BigPicture 2023

The Big Picture Workshop

Proceedings of the Workshop

December 7, 2023

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Introduction

Welcome to the Proceedings of the first iteration of the Big Picture Workshop (The Big Picture: Crafting a Research Narrative). The workshop is hosted at EMNLP 2023, in Singapore, on December 7, 2023.

The Big Picture Workshop provides a dedicated venue for exploring and distilling broader NLP research narratives. All research exists within a larger context, and progress is made by standing on the shoulders of giants: building on the foundations laid by earlier researchers. In light of rapid publication rates and concise paper formats, it has become increasingly difficult, however, to recognize the larger story to which a paper is connected. The Big Picture Workshop invites researchers to reflect on how their individual contributions fit within the overall research landscape and what stories they are telling with their bodies of research. The goals of the workshop are to enhance communication and understanding between different lines of work, highlight how works connect and build on each other, generate insights that are difficult to glean without combining and reconciling different research narratives, encourage broader collaboration and awareness of prior work in the NLP community, and facilitate understanding of trajectories and insights within the field of NLP.

We received 12 submissions, of which we accepted 10 for presentation at the workshop. Those 10 accepted papers are contained in this volume. We also accepted for presentation two additional papers to be included in Findings of EMNLP 2023.

The workshop schedule features one standard invited talk, and three special invited presentations designed to foster live engagement between different lines of related work. In these special presentations, two to three invited presenters speak on their individual lines of work and the connections between them, followed by a moderated discussion further exploring the overall narrative that emerges from these works in aggregate. In addition to invited presentations, the workshop features one Best Paper session, one in-person poster session, and one virtual poster session.

We extend heartfelt thanks to our program committee, our participants, and all authors who submitted papers for consideration—your engagement has been critical to the success of the workshop. We also thank Amazon, Google, and Hugging Face for generous sponsorship. Finally, we thank the EMNLP 2023 organizers for their hard work and support.

The Big Picture Workshop Organizers,

Yanai Elazar, Allyson Ettinger, Nora Kassner, Sebastian Ruder, Noah Smith

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Keynote Talk: The Vision Thing: Finding and Pursuing your Research Passion

Raymond J. Mooney
UT Austin
2023-12-07 09:15:00 – Room: **Virgo 1 & 2**

Abstract: A key contribution to being a successful researcher in natural language processing, as in any area, is having a clear overarching vision of what your body of research is trying to accomplish. Using my own 40-year career as an example, I will attempt to provide general advice on formulating and pursuing a coherent research vision. In particular, I will focus on formulating a unique, personal objective that exploits your specific talents, knowledge, and passions, and that is distinct from the current popular trends in the field. I will also focus on formulating a vision that bridges existing fields of study to produce an overarching agenda that unifies previously disparate ideas.

Bio: Raymond J. Mooney is a Professor in the Department of Computer Science at the University of Texas at Austin. He received his Ph.D. in 1988 from the University of Illinois at Urbana/Champaign. He is an author of over 200 published research papers, primarily in the areas of machine learning and natural language processing. He was the President of the International Machine Learning Society from 2008-2011, program co-chair for AAAI 2006, general chair for HLT-EMNLP 2005, and co-chair for ICML 1990. He is a Fellow of AAAI, ACM, and ACL and the recipient of the Classic Paper award from AAAI-19 and best paper awards from AAAI-96, KDD-04, ICML-05 and ACL-07.

Keynote Talk: Is Attention = Explanationand the Role of Interpretability in NLP

Sarah Wiegreffe
AI2 & UW
2023-12-07 11:00:00 – Room: **Virgo 1 & 2**

Abstract: Attention mechanisms have become a core component of neural models in Natural Language Processing over the past decade. These mechanisms not only deliver substantial performance improvements but also claim to offer insights into the models' inner workings. In this talk, we will highlight a series of contributions we have made that provided a critical perspective on the role of attention as a faithful explanation for model predictions, and sparked a larger conversation on the overarching goals of interpretability methods in NLP. We'll contrast our methodological approaches and findings to highlight that there is no one-size-fits-all answer to the question "Is attention explanation?". Finally, we'll explore the role of attention as an explanation mechanism in today's NLP landscape.

Bio: Sarah Wiegreffe is a postdoctoral researcher at the Allen Institute for AI (AI2), working on the Aristo project. She also holds a courtesy appointment in the Allen School of Computer Science and Engineering at the University of Washington. Her research focuses on understanding how language models make predictions in an effort to make them more transparent to human users. She received her PhD from Georgia Tech in 2022 advised by Professor Mark Riedl, during which time she interned at Google and AI2 and won the AI2 outstanding intern award. She frequently serves on conference program committees, receiving outstanding area chair award at ACL 2023.

Keynote Talk: Is Attention = Explanationand the Role of Interpretability in NLP

Sarthak Jain
AWS AI Labs
2023-12-07 11:00:00 – Room: **Virgo 1 & 2**

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Bio: Sarthak Jain is an Applied Scientist working on generative AI models at AWS. He received his PhD in 2022 from Northeastern University, where he was advised by Byron Wallace. Before this, he completed his BTech in Computer Engineering from Delhi Technological University. His current research interests include the interpretability and analysis of deep learning models.

Keynote Talk: On the Outcomes of Scientific Disagreements of Machine Morality

Liwei Jiang
University of Washington
2023-12-07 13:30:00 – Room: **Virgo 1 & 2**

Abstract: Disagreements and conflict are vital for driving scholarly progress, social and scientific alike. In research, we often identify gaps in others' and our own work, to present new ideas that remedy them. Disagreements are often small in nature: We disagree on methods rather than the research programme itself. In this talk, we discuss a disagreement of a different nature: namely one in which the substance of the disagreement is the existence of the task itself. We reflect on the experience of the conflict, how it was resolved, and what outcomes it has had.
In particular, Liwei will share her current interdisciplinary research journey on AI + humanity sparked by the Delphi experience. She will introduce Value Kaleidoscope—a novel computational system aiming to model potentially conflicting, pluralistic human values interwoven in human decision-making. Finally, she will talk about an exciting co-evolution opportunity unfolding between frontier AI technology and humanity fields.
Zeerak will go over ongoing work that considers the foundations and limits of machine learning and NLP with regard to ethically appropriate work. Specifically, they will discuss the use of the distributional hypothesis, and what particular visions of our societies it offers, and how machine learning seeks to construct our future in the vision of the past.

Bio: Liwei Jiang is a Ph.D. student in the Paul G. Allen School of Computer Science and Engineering at the University of Washington, specializing in Artificial Intelligence (AI) and Natural Language Processing (NLP). She is intrigued to tackle real-world needs with AI and understand the charms, mysteries, and peculiarities of humans. Thus, Her current research focuses on the co-evolution of AI and humanity: how to build better AI by taking inspiration from humans and how to gain valuable insights into humans by advancing AI. She has published at many NLP and AI venues (e.g., ACL, EMNLP, NAACL, NeurIPS, AAAI). Her work has been featured in many media outlets, including the New York Times, Wired, the Guardian, the Verge, IEEE Spectrum, and Nature Outlook. She works as a student researcher at Allen Institute for Artificial Intelligence (AI2).

Keynote Talk: On the Outcomes of Scientific Disagreements of Machine Morality

Zeerak Talat
Mohamed Bin Zayed University of Artificial Intelligence
2023-12-07 13:30:00 – Room: **Virgo 1 & 2**

Abstract: Disagreements and conflict are vital for driving scholarly progress, social and scientific alike. In research, we often identify gaps in others' and our own work, to present new ideas that remedy them. Disagreements are often small in nature: We disagree on methods rather than the research programme itself. In this talk, we discuss a disagreement of a different nature: namely one in which the substance of the disagreement is the existence of the task itself. We reflect on the experience of the conflict, how it was resolved, and what outcomes it has had.
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Bio: Zeerak Talat (formerly known as Zeerak Waseem) is a Research Fellow at Mohamed Bin Zayed University of Artificial Intelligence. Zeerak holds a Ph.D. in Computer Science from the University of Sheffield, with a focus on natural language processing. Zeerak's work examines the assumptions that underpin NLP and machine learning (ML) technologies. Drawing on research from anthropology, discard studies, science and technology studies, and media studies, their work seeks to consider NLP and ML technologies through the lens of content moderation technologies to understand how they can cause harm to individuals and societies.

Keynote Talk: The Role of Demonstrations: What In-Context Learning actually does

Sewon Min
University of Washington
2023-12-07 16:00:00 – Room: **Virgo 1 & 2**

Abstract: In-Context Learning (ICL) enables a language model (LM) to learn a new correlation between inputs and outputs during inference, without explicit gradient updates. In this talk, we show a series of work centered around the research question: whether or not the correctness of demonstrations is needed for good performance of ICL. Through a series of experiments and analyses, we delve into the nuances of this relationship across various experimental setups, models (plain LMs or instruction-tuned ones), and tasks (classification or generation). Our findings contribute to a broader understanding of how LMs engage in in-context learning, shedding light on what new correlations they can or cannot learn, and leading to a new line of research in discovering unexpected behaviors of LMs.

Bio: Sewon Min is a final year Ph.D. candidate at the University of Washington, advised by Luke Zettlemoyer and Hannaneh Hajishirzi. Her research is in language modeling, focusing on new dimensions in modeling, scaling, and efficiency, and their extensions for information-seeking, legality, and privacy. She co-instructed and co-organized multiple tutorials and workshops at ACL, EMNLP, NAACL and NeurIPS. She is a recipient of the J.P. Morgan Fellowship, and was at Meta AI, Google Research, and Salesforce Research.

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Seoul National University
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Keynote Talk: The Role of Demonstrations: What In-Context Learning actually does

Kang Min Yoo
NAVER Cloud, NAVER AI Lab
2023-12-07 16:00:00 – Room: **Virgo 1 & 2**

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Bio: Kang Min Yoo is actively engaged in the fields of artificial intelligence and computational linguistics. He currently holds key roles as a Research and Applied Scientist at NAVER Cloud and as a Visiting Professor at Seoul National University's AI Institute. With an Integrated M.S. and Ph.D. in Computer Science from Seoul National University, his primary areas of expertise include large language models and natural language processing. At NAVER Cloud, he has spearheaded projects focused on developing Korean-centric LLM-based chat agents and the HyperT5 Seq2Seq HyperCLOVA. Additionally, Kang Min Yoo contributes to the academic community through his roles as an area chair and program committee member.

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Where are We in Event-centric Emotion Analysis? Bridging Emotion Role Labeling and Appraisal-based Approaches

Roman Klinger
Institut für Maschinelle Sprachverarbeitung
University of Stuttgart, Germany
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Abstract

The term emotion analysis in text subsumes various natural language processing tasks which have in common the goal to enable computers to understand emotions. Most popular is emotion classification in which one or multiple emotions are assigned to a predefined textual unit. While such setting is appropriate for identifying the reader's or author's emotion, emotion role labeling adds the perspective of mentioned entities and extracts text spans that correspond to the emotion cause. The underlying emotion theories agree on one important point; that an emotion is caused by some internal or external event and comprises several subcomponents, including the subjective feeling and a cognitive evaluation. We therefore argue that emotions and events are related in two ways. (1) Emotions are events; and this perspective is the fundament in natural language processing for emotion role labeling. (2) Emotions are caused by events; a perspective that is made explicit with research how to incorporate psychological appraisal theories in NLP models to interpret events. These two research directions, role labeling and (event-focused) emotion classification, have by and large been tackled separately. In this paper, we contextualize both perspectives and discuss open research questions.

1 Introduction

> "Communication is an exchange of facts, ideas, opinions, or emotions by two or more persons. The exchange is successful only when mutual understanding results." (Newman et al., 1967, p. 219)

The development of computational models in natural language processing aims at supporting communication between computers and humans; with language understanding research focusing on enabling the computer to comprehend the meaning of text. Sometimes, understanding facts is sufficient, for instance when scientific text is analyzed to automatically augment a database (Li et al., 2016; Trouillon et al., 2017). Factual statements can also comprise explicit reports of emotions or sentiments, such as "They were sad.", and in such cases, the analysis of subjective language blends with information extraction (Wiebe et al., 2004).

Emotion analysis, however, goes beyond such analysis of propositional statements. To better understand what emotion analysis models are expected to do, it is worth reviewing emotion theories in psychology. There are many of them, with varying purposes and approaches, but most of them, if not all, agree on the aspect that *emotions are caused by some event* and come with a change of various subsystems, such as a change in motivation, a subjective perception, an expression, and bodily symptoms. Another component is the evaluation of the causing event, sometimes even considered to constitute the emotion (Scarantino, 2016).

The *emotion also corresponds to an event itself*, embedded in a context of other events, people, and objects. All components of such emotion events (cause, stances towards other involved people, opinions about objects) may be described along an explicit mention of an emotion name. Any subset of them may appear in text, and may or may not be sufficient to reliably assign an emotion representation to the text author, a mentioned entity, or to a reader (Casel et al., 2021; Cortal et al., 2023).

This complexity has led to a set of various emotion analysis tasks in NLP, which we exemplify in an integrated manner in Figure 1. The most popular task is emotion prediction, either representing the writer's or the reader's emotion as a category, as valence/arousal values, or as appraisal vector (at the bottom of Figure 1, we will describe the underlying psychological theories in §2.1). Adding the task of cause detection bridges to the role labeling setup (visualized in more completeness at the top). Here, the emotion event is represented by the token span that represents the emotion experiencer, the cue, and the cause. *Emotion prediction focuses on*

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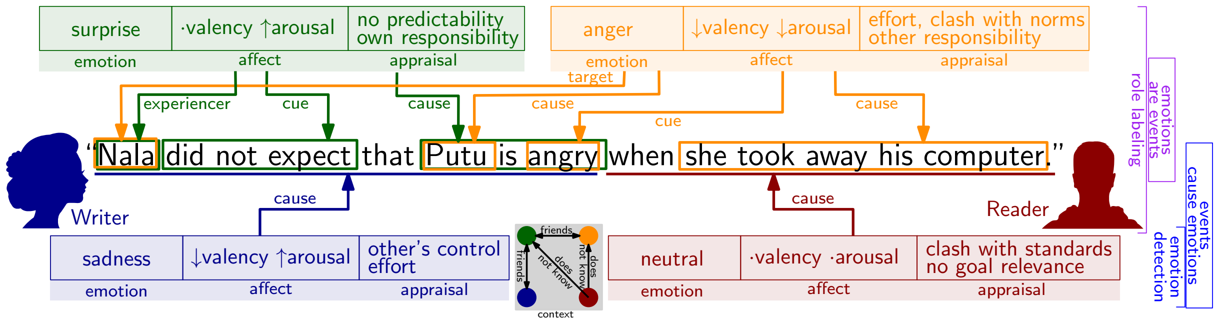

Figure 1: Integrated Visualization of Research Tasks in Emotion Analysis

understanding from text how events cause emotions, while role labeling focuses on understanding how emotions are represented as events themselves.

sWe now introduce the background to emotion analysis, including psychological theories, related tasks, and use cases (§2). Based on that, we consolidate recent research on the interpretation of events to infer an emotion and on emotion role labeling (§3.1–3.2). We then point out existing efforts on bridging both fields (§3.3) and, based on this, develop a list of open research questions (§4). We show a visualization how various NLP tasks and research areas are connected to emotion analysis in Figure 8 in the Appendix.

2 Related Work

2.1 Emotion Theories in Psychology

Before we can discuss emotion analysis, we need to introduce what an emotion is. The term typically refers to some feeling, some sensation, that is defined following various perspectives. Scarantino (2016) provides an overview of various emotion theories and differentiates between a *motivation tradition*, a *feeling tradition*, and an *evaluative tradition*.

2.1.1 Categorical Models of Basic Emotions

The motivation tradition includes theories that are popular in NLP such as the basic emotions proposed by Ekman (1992) and Plutchik (2001). They differ in how they define what makes an emotion basic: Ekman proposes a list of properties, including an automatic appraisal, quick onset, brief duration, and distinctive universal signals. According to him, non-basic emotions do not exist but are rather emotional plots, moods, or personality traits. Plutchik defines basic emotions based on their function, and non basic-emotions are gradations and mixtures. The set of basic emotions according to Ekman is commonly understood to correspond to joy, anger, disgust, fear, sadness, and surprise. However, in fact, the set is larger and there are even emotions for which it is not yet known if they could be considered basic (e.g., relief, guilt, or love, Ekman and Cordaro, 2011). The basic emotions according to Plutchik include anticipation and trust in addition. In NLP, such theories mostly serve as a source for label sets for which some evidence exists that they should be distinguishable, also in textual analysis. A study that uses a comparably large set of emotions is Demszky et al. (2020), while many other resource creation and modeling attempts focus on subsets (Alm et al., 2005; Strapparava and Mihalcea, 2007; Schuff et al., 2017; Li et al., 2017; Mohammad, 2012, i.a.).

2.1.2 Dimensional Models of Affect

An alternative to representing emotions as categorical labels is to place them in a (continuous) vector space, in which the dimensions correspond to some other meaning. The most popular one is the valence/arousal space, in which emotions are situated according to their subjective perception of a level of activation (arousal) and how positive the experience is (valence). This concept stems from the feeling tradition mentioned above and corresponds to affect (Posner et al., 2005). It also plays an important role in constructionist theories, which aim at explaining how the objectively measurable variables of valence and arousal may be linked by cognitive processes to emotion categorizations (Feldman Barrett, 2017). While we are not aware of any applications of the constructionist theories in NLP, emotion analysis has been formulated as valence/arousal regression (Buechel and Hahn, 2017; Preoţiuc-Pietro et al., 2016, i.a.). Valence and arousal predictions are related to, but not the same as, emotion intensity regression (Mohammad and Bravo-Marquez, 2017).

Figure 2: Comparison of structured sentiment analysis and emotion role labeling.

2.1.3 Appraisals

Affect is not the only so-called dimensional model to represent emotions. More recently, the concept of appraisals that represents the cognitive dimension of emotions, i.e., the cognitive evaluation of the event regarding the impact on the self, found attention in NLP. The set of appraisals that can explain emotions is not fixed and depends on the theory and the domain. It often includes variables that describe if an event can be expected to increase a required effort (likely to be high for anger or fear) or how much responsibility the experiencer of the emotion holds (high for feeling pride or guilt). Smith and Ellsworth (1985) showed that a comparably small set of 6 appraisal variables can characterize differences between 15 emotion categories. Scherer et al. (2001) describes a multi-step process of appraisal evaluations as one part of the emotion – their emotion component process model also reflects on additional emotion components, namely the bodily reaction, the expression, the motivational aspect, and the subjective feeling. Appraisal theories led to a set of knowledge bases and models that link events to emotions (Balahur et al., 2012; Cambria et al., 2022; Shaikh et al., 2009; Udochukwu and He, 2015), but only recently, resources and models have been proposed which make appraisal variables explicit (Stranisci et al., 2022; Hofmann et al., 2020, 2021; Troiano et al., 2022, 2023b; Wegge et al., 2022). This paper discusses work on appraisal theories to interpret events regarding the potentially resulting emotion in §3.1.

2.2 Tasks Related to Emotion Analysis

Emotion analysis is a task grounded in various previous research fields, from which we discuss sentiment analysis and personality profiling.

2.2.1 Sentiment Analysis

Sometimes, sentiment analysis is considered a simplified version of emotion analysis in which multiple emotion categories are conflated into two (positive or negative, sometimes distinguishing multiple levels of intensity, Kiritchenko et al. (2016)). We would like to argue that the tasks differ in more than the number of labels. Sentiment analysis is often equated to classifying the text into a more unspecific connotation of being positive or negative (Liu, 2012). Commonly, the sentiment of the text author is analyzed, which renders the task to be overlapping with opinion mining (Pang and Lee, 2008; Barnes et al., 2017). Emotion analysis is hardly ever about detecting the opinion regarding a product; while that is a common focus in sentiment analysis (Pontiki et al., 2014).

A more powerful approach to sentiment analysis is to not only detect if the author expresses something positive, but also to detect opinion holders, evaluated targets/aspects, and the phrase that describes the evaluation (Barnes et al., 2022; Pontiki et al., 2015, 2016; Klinger and Cimiano, 2013). The tasks of such "sentiment role labeling" and "emotion role labeling" do, however, barely match (see Figure 2):

(1) The *opinion holder* in sentiment analysis is a person that expresses an opinion, regarding some object, service, or person. This commonly follows a cognitive evaluation, likely to be a conscious process rather than an unbidden reaction. We would therefore not call the person experiencing an emotion a "holder" but rather an *emotion experiencer*, or *feeler*, or an *emoter* (to make the difference between an emotion and a feeling explicit).

(2) The *aspect/target* in sentiment analysis might correspond to two things in emotion analysis. It can be a *target*, I can be angry *at* someone, who is not solely the *cause* of that emotion. I can be angry at a friend, because she did eat my emergency supply of chocolate. But I cannot be *sad at* somebody. In emotion analysis, we care more about the *stimulus* or *cause* of an emotion. Sometimes, targets and causes are conflated.

(3) The *evaluative, subjective phrase* in sentiment analysis corresponds to emotion words (*cue* in Figure 1).

It is noteworthy that evaluative statements in sentiment also express an appraisal of something but the overlap with appraisal theories in emotion analysis is minimal – the evaluation of a product in sentiment analysis is often expressed explicitly. On the contrary, appraisal-based emotion analysis fo-

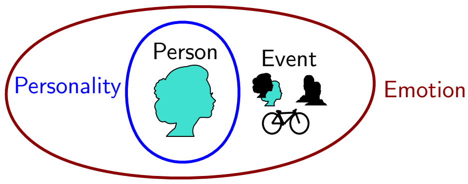

Figure 3: Comparison of personality detection and emotion analysis.

cuses on inferring the internal appraisal processes of a person purely from an event description. We refer the interested reader to Martin and White (2005) for a comprehensive analysis of the language used to describe evaluations.

2.2.2 Personality Profiling

Sometimes the task of personality analysis is seen to be similar to emotion analysis, because both an emotion and the personality are based on a person. Personality is, however, a function that depends only on the person, while an emotion depends on the person in interaction with a situation (see Figure 3). Therefore, personality is a stable trait, while emotions are states that change more flexibly (Geiser et al., 2017). The most prominent model that found application in NLP is the OCEAN/Big-Five model (Goldberg, 1999; Roccas et al., 2002), comprising openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Pizzolli and Strapparava, 2019; Lynn et al., 2020; Kreuter et al., 2022; Golbeck et al., 2011). An alternative is HEXACO, adding the dimension of honesty (Lee and Ashton, 2018), which did, however, lead to less attention in NLP (Sinha et al., 2015). Early work in personality analysis based on linguistic features was based, similar to sentiment or emotion analysis, on word-counting approaches (Pennebaker and King, 1999). The Myers–Briggs Type Indicator (MBTI, Myers, 1998) received attention in NLP, partially because of a straight-forward way to collect data with hash-tag-based self-supervision (Plank and Hovy, 2015; Verhoeven et al., 2016). This model has weaknesses regarding reliability and validity (Boyle, 1995; Randall et al., 2017) which affect the robustness of NLP models (Stajner and Yenikent, 2021).

2.3 Use-Cases of Emotion Analysis

Every kind of text in which an interpretation of the emotional connotation is of value constitutes a potential use case for emotion modeling. This includes the analysis of social media (Mohammad et al., 2018; Klinger et al., 2018; Wang et al., 2012, i.a.), of news articles (Bostan et al., 2020, i.a.), of figurative language (Chauhan et al., 2020; Dankers et al., 2019, i.a.), of abusive language (Rajamanickam et al., 2020; Plaza-del Arco et al., 2022, i.a.) of literature (Kim and Klinger, 2018; Alm and Sproat, 2005; Dodds et al., 2011; Kim et al., 2017, i.a.), of clinically relevant disorders (Islam et al., 2018; Pestian et al., 2012, i.a.), or the support of customer agents (Labat et al., 2022).

Each domain implicitly defines which subtasks are relevant. For news headlines, the author's emotion is least interesting while estimating the (intended) impact on the reader is important, for instance to understand reactions in the society and intentional use to manipulate readers (Caiani and Di Cocco, 2023). For hate speech detection or other social media analysis tasks, the author's emotion is central. In literature, an interesting aspect is to understand which emotion is attributed to fictional characters (Kim and Klinger, 2019b; Hoorn and Konijn, 2003).

Each domain also comes with particular challenges, stemming from varying task formulations: News headlines are short and highly contextualized in the outlet, the time of publication, and the reader's stance towards topics (Schaffer, 1995). Social media comes in informal language (Kern et al., 2016). Literature often requires interpretations of longer text spans (Kuhn, 2019). Each of these applications therefore comes with design choices:

- What is the emotion perspective?
  (reader, writer, entities)
- What is the unit of analysis?
  (headline, tweet, paragraph, n sentences)
- Is text classification of predefined units sufficient or does a model need to assign emotions to automatically detected segments in the text?
- What are the variables to be predicted and the possible value domain?
  (emotion categories, appraisals, affect, spans of different kind)

So far, models have mostly been developed for specific use-cases, where such constraints can be clearly identified. This has, however, an impact on the generalizability of models. We will now discuss the two perspectives of *events that cause emotions* as an interpretation of emotion analysis as text classification of predefined textual units (§3.1) and of *events as emotions*, the case of emotion role labeling (§3.2). After that, we explain the efforts

Relevance	Implication	Coping	Normative Significance
Novelty • suddenness • familiarity • predictability • attention • att. removal Intrinsic Pleasantness • pleasant • unpleasant Goal Relevance • goal-related	Causality: agent • own responsib. • other's respons. • situational resp. Goal conduciveness • goal support Outcome probability • consequence anticipation Urgency • response urgency	Control • own control • others' control • chance control Adjustment • anticipated acceptance • effort	Internal standards compatibility • clash with own standards External standards compatibility • clash with norms

Figure 4: Variables used by Troiano et al. (2023b) to analyze text according to combined dimensions proposed by Scherer et al. (2001) and Smith and Ellsworth (1985).

to bring these two directions together (§3.3) and we build on top of this consolidation to point out important future research directions (§4).

3 The Link between Emotions and Events

3.1 Events cause Emotions: Appraisals

3.1.1 Traditional Emotion Analysis Systems

Most emotion analysis systems were, before the deep learning revolution in NLP, feature-based, and features often stemmed from manually created lexicons (Mohammad and Turney, 2013) and included manually designed features for the task (Štajner and Klinger, 2023; Aman and Szpakowicz, 2007). Since the state of the art for the development of text analysis systems is transfer learning by fine-tuning pretrained large language models (such as BERT, Devlin et al., 2019), the phenomenon-specific model development focuses on exploiting properties of the concept. One example is DeepMoji, which adapts transfer learning to the analysis of subjective language and identifies a particularly useful pretraining task, namely the prediction of emojis (Felbo et al., 2017). Another strain of research aims at developing models that aggregate multiple emotion theories (Buechel et al., 2021).

3.1.2 Event Interpretation

We focus on the aspect of emotions that they are caused by events. Interpreting events is challenging, because event descriptions often lack an explicit emotion mention (Troiano et al., 2023a). Such textual instances are considered "implicit" regarding their emotion (Udochukwu and He, 2015; Klinger et al., 2018): The challenge to be solved is to link "non-emotional" events to the emotion that they might cause. Balahur et al. (2012) tackled this by listing action units in an ontology, based on semantic parsing of large amounts of text. Cambria et al. (2022) developed a logics-based resource to associate events with their emotion interpretation.

3.1.3 Incorporating Appraisal Variables in Text Analysis Models

These attempts, however, do not model appraisal variables explicitly as a link between cognitive evaluations of events and emotions. There is also not only one appraisal theory, and depending on the theory, the computational modeling is realized in differing ways. Based on the OCC model (an appraisal theory that provides a decision tree of appraisal variables to characterize emotions, Steunebrink et al., 2009), both Shaikh et al. (2009) and Udochukwu and He (2015) develop methods to extract atomic variable values from text that are the building blocks for appraisal-based interpretations. An example appraisal variable is if an event is directed towards the self, for which they use semantic and syntactic parsers. Other such variables include the valence of events, the attitude towards objects, or the moral evaluation of people's behaviours – all detected with polarity lexicons. These variables are then put together with logical rules, such as `If Direction = 'Self' and Tense = 'Future' and Overall Polarity = 'Positive' and Event Polarity = 'Positive', then Emotion = 'Hope'` (Udochukwu and He, 2015). The advantage of this approach is that it makes the appraisal-based interpretation explicit; however, it does not allow for reasoning under uncertainty, partially because these studies do not build on top of manually assigned appraisal variables to text.

3.1.4 Appraisal-Annotated Corpora

To understand the link better between appraisals in text and emotions, Hofmann et al. (2020) manually annotated autobiographical event reports (Troiano et al., 2019) for the appraisal dimensions identified by Smith and Ellsworth (1985): does the writer want to devote attention, were they certain about what was happening, did they have to expend mental or physical effort to deal with the situation, did they find the event pleasant, were they responsible for the situation, could they control the situation, and did they find that the situation could not be changed by anyone? They found that the annotation replicates the links to emotions as found in original studies (Hofmann et al., 2021, Fig. 1). Further, they showed that appraisals can reliably be detected, but they did not manage to develop a model that predicts emotions better with the help

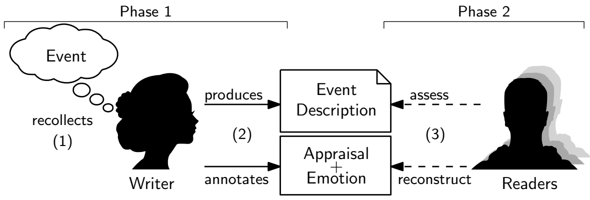

Figure 5: The study design that lead to the crowd-enVENT data set (Troiano et al., 2023b).

of appraisals than without. Hence, they proposed a new way of modeling emotions in text, but did not succeed to develop a multi-emotion model.

3.1.5 Appraisal Annotations by Event Experiencers

To understand better if this inferiority of a joint model might be a result of an imperfect noisy appraisal annotation, and to create a larger corpus, Troiano et al. (2023b) setup the experiment depicted in Figure 5 (replicating Troiano et al. (2019), but with appraisal variables). They asked crowd-workers to describe an event that caused a specific emotion and to then assign appraisal values (this time following the sequential approach by Scherer et al., 2001, with 21 variables, Figure 4) how they perceived the respective situation (Phase 1). They then asked other people to read the texts and reconstruct the emotion and appraisal (Phase 2). Unsurprisingly, the readers sometimes misinterpreted an event. For instance "I put together a funeral service for my Aunt" is mostly interpreted as something sad, while the original author was actually proud about it. These differences in interpretation can also be seen in the appraisal variables – Appraisals explain the differences in the event evaluation: The interpretation as being sad comes with evaluations as not being in control, while the interpretation to cause pride comes with being in control.

3.1.6 Emotion Modeling under Consideration of Appraisals

The modeling experiments of Troiano et al. (2023b) confirm that also a larger set of variables can be reliably detected – similarly well as humans can reconstruct them. To further understand if such self-assigned appraisal labels enable an improvement also in the emotion categorization, they fine-tuned RoBERTa (Liu et al., 2019) and tested if adding appraisal values improves the result. They find that appraisals help the prediction of anger, fear, joy, pride, guilt, sadness, and anger. They showcase the event report "His toenails were massive.", where the baseline model relies on something massive being associated to pride. With the appraisal information, it correctly assigns "disgust".

3.1.7 Other Research Directions

More recently other research has been published with a focused on specific use-cases. Stranisci et al. (2022) who follow the appraisal model by Roseman (2013) postannotate Reddit posts which deal with situations that challenged the author to cope with an undesirable situation. Their APPReddit corpus is the first resource of appraisal-annotated texts from the wild. Cortal et al. (2023) follow a similar idea and acquire texts that describe how people regulate their emotions in specific situations. Next to their resource creation effort for French, they analyze which descriptions of cognitive processes allow to infer an emotion.

We conclude that appraisal-based emotion analysis research has the goal to better understand how emotions are implicitly communicated and to develop better emotion analysis systems.

3.2 Emotions are Events: Structured Analysis

The studies that we discussed so far put the aspect of emotion analysis on the spot that emotions are caused by events. As we argued before, emotions also constitute events. Similarly to the field of semantic role labeling (Gildea and Jurafsky, 2000) which models events in text following frame semantics, various efforts have been made to extract emotion event representations from text. The corpora that have been created come with differing modeling attempts, summarized in Figure 6.

3.2.1 Cue Phrase Detection

The early work by Aman and Szpakowicz (2007) focused on the emotion *cue* word, as an important part of role labeling. They annotated sentences from blogs, but did not propose an automatic cue identification system. A structurally similar resource with cue word annotations has been proposed by Liew et al. (2016).

3.2.2 Stimulus Detection

A few corpora have been developed focussing on stimuli: Ghazi et al. (2015) annotated sentences from FrameNet that are known to be associated with emotions and model the automatic prediction as sequence labeling. For German, Doan Dang et al. (2021) created a similar corpus based on news headlines. Gao et al. (2017) formulated stimulus detection as clause classification in Mandarin, which

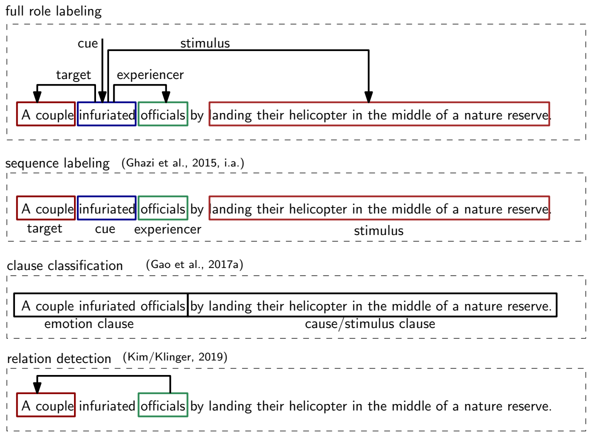

Figure 6: Emotion Role Modeling approaches (example from Bostan et al. (2020)). Full emotion role labeling has not been performed yet (top).

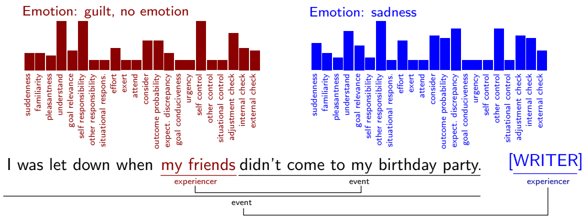

Figure 7: Example from the x-enVENT dataset

might, however, not be an appropriate approach for English (Oberländer et al., 2020).

3.2.3 Role Labeling as Classification

An interesting attempt of emotion role labeling in texts from social media was the study on Tweets associated to a US election by Mohammad et al. (2014). The decision to focus on a narrow domain allowed them to frame the role identification task both in crowdsourced annotation and in modeling as a classification task; namely to decide if the emoter, the stimulus or the emotion target correspond to an entity from a predefined set (this modeling formulation is not shown in Figure 6).

3.2.4 Full Emotion Role Labeling Resources

Kim and Klinger (2018) and Bostan et al. (2020) aimed at creating corpora with full emotion role labeling information. The REMAN corpus (Kim and Klinger, 2019b) focused on literature from Project Gutenberg. Given the challenging domain, the authors decided to carefully train annotators instead of relying on crowdsourcing. Each instance corresponds to a sentence triple, in which the middle sentence contains the cue to which the roles of emoters, targets, and stimuli are to be associated. The sequence-labeling-based modeling revealed that cause and target detection are very challenging. The paper does not contain an effort to reconstruct the full emotion event graph structure.

Bostan et al. (2020) annotated news headlines, under the assumption that less context is required for interpretation (which turned out to not be true). To attribute for the subjective nature of emotion interpretations, they setup the annotation as a multi-step crowdsourcing task. The modeling experiments on their GoodNewsEveryone corpus are limited to span prediction.

3.2.5 Role Labeling as Relation Detection

We are only aware of one work in the context of semantic role labeling that attempts to model the relational structure. Kim and Klinger (2019b) simplified role labeling to relation classification of emotional relations between entities. This allowed them to build on top of established methods for relation detection (Zhou et al., 2016) but they sacrificed explicit cue word detection and limited the analysis to emotion stimuli that have a corresponding entity.

3.2.6 Aggregated Corpora

There have been two efforts of data aggregation, by Oberländer et al. (2020) and Campagnano et al. (2022). The latter compared various models for role detection via span prediction. The prior we will discuss in the next section. To sum up, there have been some efforts to perform emotion role labeling, but in contrast to generic role labeling or to structured sentiment analysis, no models have yet been developed for full graph reconstruction. We visualize the differences in modeling attempts in Figure 6.

3.3 Bridging the Two Perspectives

We now discussed the two perspectives of *events causing emotions* (§3.1) and *emotions being events* (§3.2). The fact that these two analysis tasks have so far mostly been tackled separately leaves a lot of space for future research. However, some attempts to link the two areas already exist.

3.3.1 Do the tasks of emotion classification and role labeling benefit from each other?

Oberländer et al. (2020) aimed at understanding if knowledge of roles impacts the performance of emotion categorization. It turns out it does, either because the relevant part of the text is made more explicit (stimulus), or because of biases (emoter).

Similarly, Xia and Ding (2019) setup the task of stimulus-clause and emotion-clause pair classification. Their corpora and a plethora of follow-up work show that stimulus and emotion detection benefit from each other.

3.3.2 Descriptions of which emotion components enable emotion recognition?

A similar strain of research aims at understanding which components of emotions support emotion predictions. Casel et al. (2021) performed multi-task learning experiments with emotion categorization and emotion component prediction. Kim and Klinger (2019a) study how specific emotions are communicated, similarly to Etienne et al. (2022). Cortal et al. (2023) analyzed if particular ways of cognitively evaluating events support the emotion prediction more than others.

3.3.3 Linking Role Labeling and Appraisal-based Analysis

These works do, however, not link emotion roles explicitly to their cognitive evaluation dimensions. The only work that aimed at doing so is the corpus by Troiano et al. (2022), who label emoters for emotion categories and appraisals, the events that act as a stimulus on the token level, and the relation between them. Figure 7 shows an example from their corpus. In their modeling efforts, however, they limited themselves to emoter-specific emotion/appraisal predictions and ignored, so far, the span-based stimulus annotations (Wegge et al., 2022; Wegge and Klinger, 2023).

4 Open Research Tasks

We have now discussed previous work in emotion analysis, appraisal-based approaches and role labeling. In the following, we will make a set of aspects explicit that, from our perspective, need future work.

Full emotion role labeling. Several corpora exist now that have complex annotations of the emoter, their respective emotion stimuli, targets, and cue words; partially with sentence level annotations for the reader and writer in addition. Modeling, however, focused on sequence labeling for subsets of the roles or sentence level classification. There are no attempts of full emotion graph prediction, despite that role prediction subtasks might benefit from being modeled jointly. There is also only little work on exploiting role information for emotion categorization on the sentence level, a potentially valuable approach for joint modeling of a structured prediction task with text classification.

Role labeling/stimulus detection with appraisal information. The work that has been performed to understand the interaction between role prediction and emotion categorization focused on predicting discrete emotion classes. However, stimuli often correspond to event descriptions and therefore are a straight-forward choice for further analysis with appraisal variables. Also, understanding which event mentions in a text can function as an emotion stimulus could be supported with the help of appraisals. The detection of clauses or token sequences that correspond to emotion stimuli in context of appraisal-based interpretations therefore has potential to improve both subtasks.

Integration of other emotion models in role labeling. Emotion categorization is typically one variable to be predicted in stimulus detection and role labeling approaches, either for a writer or for entities. An additionally interesting approach would be to integrate other emotion representations with role labeling. An interesting choice would be to create a corpus of valence/arousal values, assigned to specific entities and linked to stimuli. Such approach comes with the general advantage of dimensional models, namely that emotion categories do not need to be predefined.

Robust cross-corpus modeling and zero-shot predictions. A similar motivation lead to recent work on zero-shot emotion prediction, in which emotion categories are to be predicted that are not available in the training data. Plaza-del Arco et al. (2022) showed that the performance loss of natural language inference-based prompting in comparison to supervised learning leaves space for improvements. Such attempts might also bridge the gap between in-domain performance and cross-domain performance of emotion analysis systems (Bostan and Klinger, 2018). Zero-shot modeling or other approaches to find representations that are agnostic to the underlying emotion theory are essential for cross-corpus experiments, because the domains that are represented by different corpora require differing label sets.

Interpretation of event chains. Textual event descriptions can be interpreted with appraisal theories, but we rely on end-to-end learning to understand how sequences of events lead to specific emotions (for instance being afraid of a specific unconfirmed undesirable event $e \rightarrow e$ is disconfirmed $\rightarrow$ relief). Dissecting events with semantic parsing, and combining them with emotion role labeling leads to sequences of general and emotion events, which can be the input for a second-level emotion analysis. Such methods would be required to fully understand how emotions develop throughout longer sequences of stories, for instance in literature.

Perspectivism. Appraisals do explain differences in the emotion assessement, based on differing interpretations of events (Troiano et al., 2023b). We do, however, not know the role of underlying factors. A perspectivistic approach with the goal to uncover variables that lead to varying emotion constructions, e.g., based on demographic data of event participants or other data, might provide additional insight. This could also be applied to literature analysis, for instance by including personality information on fictional characters in the emotion prediction (Bamman et al., 2013). Such approach is well-motivated in psychology; we know that personality influences the interpretation of other's emotions (Doellinger et al., 2021).

Integrate emotion models from psychology. Emotion analysis work so far focused on a comparably small set of emotion theories. The philosophical discussion by Scarantino (2016) offers itself as a guideing principle which other theories might be valueable to be explored. This does not only include entirely so-far-ignored theories (e.g., Feldman Barrett, 2017) but also knowledge from theories popular in NLP. For instance, Ekman (1992); Plutchik (2001) offer more information than lists of emotion categories. Integrating psychological knowledge in NLP models can improve the performance (Troiano et al., 2023b). In a similar vein, there exist specific appraisal theories for particular domains, including, e.g., argumentation theories (Dillard and Seo, 2012).

Multimodal Modeling. We focused in our paper on analysis tasks from text, but there has already been work on multimodal emotion analysis (Busso et al., 2008, i.a.) and detecting emotion stimuli in images (Dellagiacoma et al., 2011; Fan et al., 2018, i.a.), also multimodally (Khlyzova et al., 2022; Cevher et al., 2019). However, we are not aware of any work in computer vision that interprets situations and the interactions of events with the help of appraisal theories. To fully grasp available information in everyday communication or (social) media, the presented approaches from this paper need to be extended multimodally.

Multilingual modeling. Most papers that we discuss in this paper focus on English – with very few exceptions, which we pointed out explicitly. We are not aware of any emotion role labeling corpus with full graph annotations in other languages, and there are only very few attempts to integrate appraisal theories in emotion detection on languages other than English. Such multilingual extension is not only relevant to achieve models that work across use-cases – the concept of emotion names might also differ between languages, and therefore comparing emotion concepts with the help of dimensional appraisal models between languages and cultures can provide interesting insights for both NLP and psychology.

5 Conclusion

With this paper, we discussed appraisal theory-based methods to interpret events, and how emotions can be represented as events with role labeling. We did that guided by our own two emotion analysis projects SEAT (Structured Multi-Domain Emotion Analysis from Text) and CEAT (Computational Event Evaluation based on Appraisal Theories for Emotion Analysis) which corresponded each to one of the two perspectives.

These two fields have been approached mostly separately so far and the main goal of this paper is to make the research narrative behind both transparent, and, based on this, point out open research questions. Such open tasks emerge from missing connections between the various goals in emotion analysis, but there are also other promising directions that we pointed out.

We do not believe that this list is comprehensive, but hope that the aggregation of previous work and pointing at missing research helps interested researchers to identify the gaps they want to fill. Emotion analysis is important to make computers aware of the concept, which is essential for natural communication.

In addition, research in these fields helps to better understand how humans communicate, beyond building impactful computational systems. Therefore, research in affective computing brings together psychology, linguistics, and NLP.

Limitations

This paper focused on appraisal theories and emotion role labeling mostly from a theoretical perspective. We aimed at pointing out open research questions mostly based on conceptualizations of theories from semantics and psychology. To identify open research questions, a closer introspection of existing models need to be performed in addition. In our theoretical discussion, we assume that the open research questions have similar chances to succeed. In practical terms this is likely not the case and we therefore propose to first perform preliminary studies before definitely deciding to follow one of the research plans that we sketched.

Ethics Statement

The contributions in this paper do not directly pose any ethical issues: we did not publish data, models, or did perform experiments. However, the open topics that we identified might lead to resources and models that can in principle do harm to people. Following deontological ethics, we assume that no emotion analysis systems should be applied to data created by a person without their consent, if the results are used not only in aggregated form which would allow to identify the person who is associated with the analyzed data. We personally do not believe that a utilitaristic approach may be acceptable in which reasons could exist that justify to use emotion analysis technology to identify individuals from a larger group. This is particularly important with methods discussed in this paper in comparison to more general emotion categorization methods, because we focus on implicit emotion expressions. The methods we discussed and future work we sketched would be able to identify emotions that are not explicitly expressed, and therefore humans that generate data might not be aware that their private emotional state could be reconstructed from the data they produce.

When creating data for emotion analysis, independent of its language, domain, or the task formulation as role labeling, classification, regression, using a dimensional model or a theory of basic emotions, fairness or developed system and bias in data and systems is typically an issue. While efforts exist to identify unwanted bias and confounders in automatic analysis systems, the possible existance of unidentified biases can never be excluded. Therefore, automatic systems always need to be applied with care while critically reflecting the automatically obtained results. This is particularly the case with systems that focus on interpreting implicit emotion communications that require reasoning under uncertainty. To enable such critical reflection of a system's output, their decision must be transparently communicated to the users.

In general, the ability of automatic systems to interpret and aggregate emotions should not be used unaware of the people who created data, and decisions and actions following recognized emotions always need to remain in the responsibility of a human user.

We see our work mostly as a research contribution with the goal to better understand how humans communicate, not as an automatic enabling tool to provide insight in the private states of people.

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A Visualization of the Relations Between Tasks

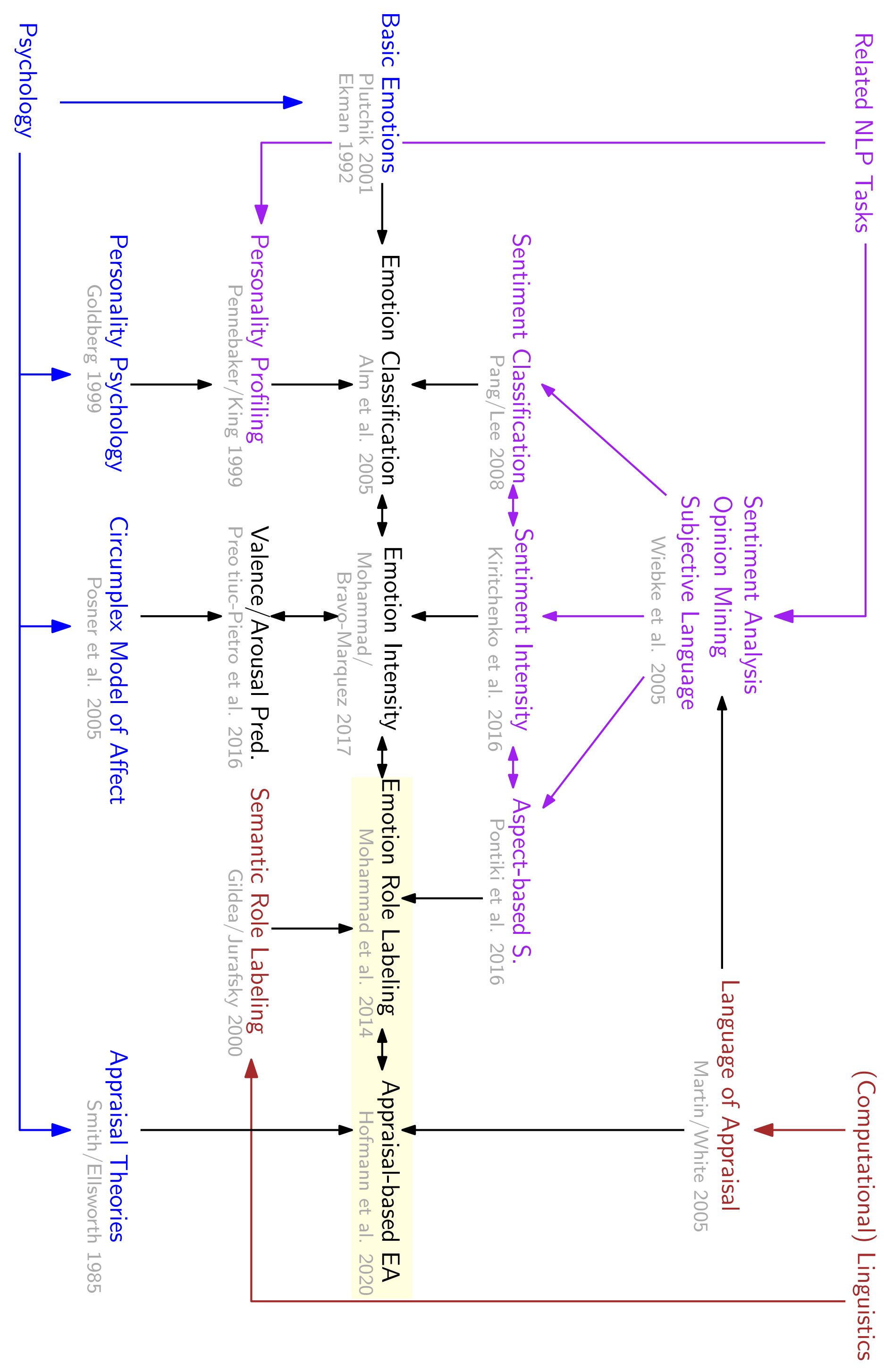

Figure 8: Visualization of relations between emotion analysis and other previously established tasks and studies. The bibliographic references are examples for the respective tasks and are not supposed to suggest completeness. Please see the text for a more comprehensive picture.

Working Towards Digital Documentation of Uralic Languages With Open-Source Tools and Modern NLP Methods

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Abstract

We present our work towards building an infrastructure for documenting endangered languages with the focus on Uralic languages in particular. Our infrastructure consists of tools to write dictionaries so that entries are structured in XML format. These dictionaries are the foundation for rule-based NLP tools such as FSTs. We also work actively towards enhancing these dictionaries and tools by using the latest state-of-the-art neural models by generating training data through rules and lexica.

1 Introduction

Most of the languages spoken in the world are in danger of extinction. Their documentation and revitalization are of a highest cultural value, for which they have received plenty of academic attention in various disciplines such as anthropology, typology, lexicography and computational linguistics. Needless to say, the resources produced in each individual research project are not always published openly let alone made available to the community of native speakers.

The goal of our paper is to describe our open infrastructure for documenting minority languages. We present our experiences with the following Uralic languages: Skolt Sami (sms), Erzya (myv), Moksha (mdf), Komi-Zyrian (kpv) and Komi-Permyak (koi). As they belong to the Uralic branch, they are languages that exhibit a complex morphology, which makes their computational processing a challenge for modern machine learning methods that would require a lot of data to cover this complexity. The quantity and quality of data is usually an issue when we deal with endangered languages (Hämäläinen, 2021). Carrying out linguistic documentation in a structured machine readable format, however, makes it possible to create the resources needed for building NLP tools simultaneously with linguistic documentation.

We are about to start working with the Apurinã (apu) language, which allows us to reflect upon our Uralic context from a broader perspective, and increases the relevance of our work in a Latin American context. Thus, we describe how our infrastructure can work in non-Uralic contexts.

Linguistic documentation is a field of academic study that has developed considerably in recent decades. Its purpose is to provide a complete record of the linguistic practices characteristic to a given speech community (Himmelmann, 1998). The goal of language documentation is to describe the language of a community of speakers as fully as possible both for future generations and for language revitalization. The result of this work is typically manifested as a linguistic corpus or other type of material collection, which later on can be studied and analyzed in various ways. The question whether the collected materials actually describe the language use of a speech community is debatable, and this goal can never be fully achieved because a corpus can never describe a language in full. Nonetheless, linguistically collected materials may be the only resources available for a small language.

Whether and how language documentation materials should be made accessible and distributed, has been a matter of debate. We believe it is important to understand that this is also a matter of granularity, and the question is not necessarily whether the materials are accessible, but rather which parties should be allowed what type of access. There are good reasons for keeping culturally sensitive materials available only to specific groups. At the same time, there are always materials in any language that are more neutral and such that the authors themselves may want to make accessible. Especially for written publications, it may always be possible to negotiate a publication with open licenses, which would also allow the reuse of the same materials in different open research purposes.

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Open materials are particularly important when we develop tools for NLP, because this work can greatly benefit from resources that are openly accessible with a permissive license. In the following sections we will discuss examples of such work, including our contribution to Universal Dependency treebanks. It must be emphasized that the open technology developed on an open infrastructure can also be used to process materials that are available only to a particular researcher or individual members of a community. Therefore, open infrastructure benefits both open and closed environments, whereas a closed infrastructure only benefits a big commercial player.

2 Related work

There are several individual projects in different parts of the world that work with online dictionaries for endangered languages. Many projects, however, focus on one language only and work without knowing about other ongoing projects for other endangered languages. This has led to a situation where researchers solve the same type of problems individually for their language of interest reinventing the wheel over and over again. There are plenty of online dictionaries and language learning tools that have been developed from scratch for one particular language.

Work with endangered languages in North America has shown the importance of language learning tools for second language learners. Lack of familiarity with lexicographical tradition can easily be a deciding factor in a beginner's learning experience. A learner of a new language cannot be expected to know exactly where an entry is located in a dictionary, nor can the learner be expected automatically to know the normative spelling. When the user of a language lacks a proper keyboard layout or knowledge of the correct orthography, the strategies of orthographic relaxation can be implemented in mobile and online dictionaries. Morphological processing and spelling relaxation are used to cater to beginners in Tsimshian and Salishan languages in the use of dictionaries and NLP tools (Littell et al., 2017).

On an entirely separate front, work has also been done to provide the Yupik community of St. Lawrence Island unimpeded access to language materials online. This has been possible using a morphologically aware dictionary. In the system, a strategy of multiple input methods has been introduced that caters to different writing systems (Hunt et al., 2019). The work here is tailor-made, and it maintains a strong link between the language and its community. The endangered language is seen as a low-resourced language in this context.

The problem is that *low-resourced language* is a term that is used for almost any language with less Internet presence than English. languages like Hindi (Irvine and Callison-Burch, 2014), Arabic (Chen et al., 2018) or Persian (Ahmadnia et al., 2017) are often considered low-resourced languages in the world of NLP, even though they have millions of speakers. In the work of Nasution et al. (2018), the ethnic Indonesian languages are relatively small compared to the superstrate language that surrounds them. The approach consists of working simultaneously with a group of closely related languages in a multilingual, language-independent infrastructure. The authors analyze the use of bilingual dictionary entries and explain the difficulty of selecting the appropriate bilingual dictionaries to begin documentation.

One of the largest infrastructures for minority language documentation from the point of view of computational linguistics is that of Giella (Moshagen et al., 2014). Their infrastructure is based on two main components: FST transducers (finite state transducers) and XML dictionaries. Transducers are a way of documenting the morphology of a language computationally. That is to say, they are collections of rules about how the morphological system of a language works. These rules can be used directly for automatic text analysis and lemma conjugation in its morphological variants.

Transducers and XML dictionaries are used for spelling correction in Word[1], text prediction on Android and iOS keyboards[2], interactive systems to learn languages (Bontogon et al., 2018) and online dictionaries (Rueter and Hämäläinen, 2017). Our infrastructure is based on Giella, which allows us to synchronize data between the two infrastructures. This means that advances in linguistic documentation in our infrastructure can be used directly in the tools produced in Giella.

3 Our infrastructure

Using Giella requires a relatively high proficiency in programming to be able to write dictionaries and morphological rules for FSTs, and at the same time,

[1] http://divvun.no/korrektur/korrektur.html

[2] http://divvun.no/keyboards/mobileindex.html

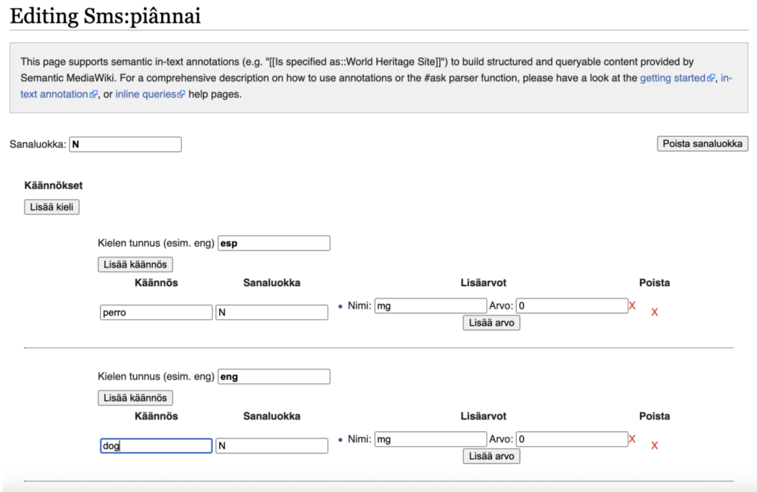

Figure 1: The form in Akusanat to edit the entry piânnai (dog) in Skolt Sami

it requires a good amount of knowledge in the language that is being documented. The infrastructure can be too complicated even for those who have studied computer science, and therefore it is not accessible to a community outside of those who collaborate directly with Giella. For this reason, our infrastructure has several interfaces for different types of users; for users who do not have sufficient knowledge to write XML or program transducers and for developers who want to use the tools without knowing how to compile them right from the beginning with the *make* command.

3.1 Online dictionaries

A very important step in the documentation of a minority language is the lexicographical work. This results in a dictionary that can be useful for both native speakers as for those who want to learn the language. We store dictionaries in a highly structured XML format. That means that all kinds of metadata are in their respective fields rather than being stored in various parts of a lexicographical entry in an unstructured format. This is important as we do not only want to create dictionaries for human use, but we also want them to be machine readable.

Our Akusanat system[3] (Hämäläinen and Rueter, 2018, 2019) is based on MediaWiki and allows you to view the content of XML dictionaries for all types of users. MediaWiki data is synchronized with XML files using the Git version control. This means that if someone modifies a lexicographical entry in Akusanat, these changes will result in a change to the XML dictionary stored in GitHub. If someone changes the XML dictionaries directly, Akusanat will download the new changes from GitHub and update its database automatically. This is done so that advanced users are able to edit the XML files directly with their favorite tool and less advanced users can make changes online with a graphical user interface. Akusanat does not let users modify the Wiki syntax directly, instead it displays a form that ensures changes remain structured and compatible with XML Figure 1.

For searching, we use morphological FST transducers to process the user input. This means that the user can search for a word in any of its morphological inflections, since the FST can lemmatize words automatically. It is also possible to search by typing in misspelled words. The transducers contain information about the most common spelling errors in each language, which allows us to resolve the lemma, although the word has not been spelled according to the spelling standard. This is important in the case of languages with which we work, since spelling rules are not as well-established as in the case of majority languages.

Figure 3 shows the interface for looking up words in the dictionaries. In the example, the search term is the Skolt Sami word *soogg*, which is the genitive of the word *sokk*, which means family. Our system lemmatizes the search term automatically with the Skolt Sami FST, and displays the input for the *sokk* lemma to the user.

The idea of using MediaWiki, and especially Semantic MediaWiki, to create dictionaries, is not new, since there are already several projects that use the technology as their base (Muljadi et al., 2006; Bon and Nowak, 2013; Dueñas and Gómez,

[3] https://akusanat.com.

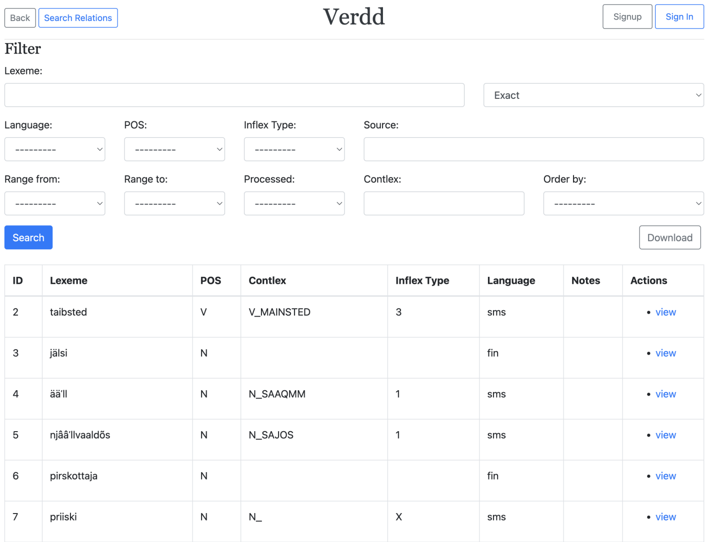

Figure 2: The interface for searching and filtering lexical entries in Ve'rdd

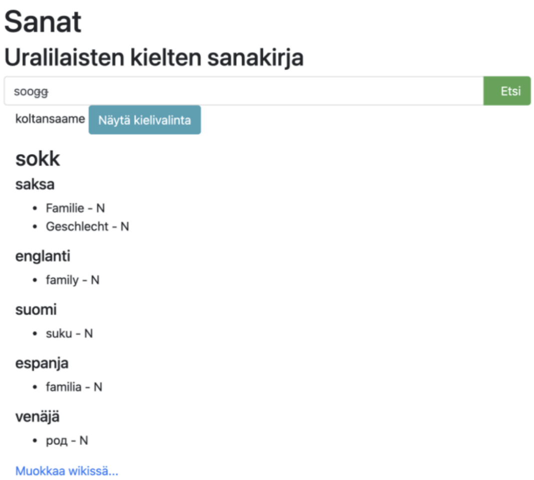

Figure 3: The interface for searching in Akusanat

2015). Without a doubt, MediaWiki has its advantages, in practice we have had to program our own MediaWiki extensions to add the necessary functionality; the form to edit, MediaWiki-XML synchronization, search with transducers etc. The problem that we have experienced many times is that the inner workings of MediaWiki change too often. This means that if we want to keep our MediaWiki instance up to date with the latest security updates, we have to make a lot of changes to our source code to keep our extensions working with the new version of MediaWiki. Even so, we continue to use and develop Akusanat[4] for the time being, as it offers a simple environment for users. In the next section, we describe the other system that we are developing. The new system may replace Akusanat in the future.

3.2 Editorial work

In this section, we describe the Ve'rdd[5] system (Alnajjar et al., 2019, 2020). The system works with the same XML dictionaries as Akusanat and can be used online in a similar way. The difference is in the intended use of the system. Ve'rdd is not a system to visualize lexicographical entries for an end user, but a system created specifically for writing both digital and printed dictionaries. During the process of developing the system, we have collaborated with a group of professional lexicographers who work with printed dictionaries.

In the context of the languages we work with, lexicographical documentation does not start from scratch, as both the Sami languages spoken in the Nordic countries and the Permian and Mordvinic languages spoken in Russia have received much attention in terms of their digital documentation during the last century. For example, there is a dictionary of the Skolt Sami language Sammallahti and Mosnikoff (1991), and there are several studies on the Mordvinic (Aasmäe et al., 2016; Grünthal, 2016) and Permian languages (Hamari, 2011; Klumpp, 2016). If there are existing dictionaries in digital form, they exist in an unstructured format such as a Word, CSV, or PDF file produced with an OCR system. For this reason, Ve'rdd includes functionality for import lexicographic data from unstructured formats. We have paid a lot of attention

[4]Code available https://github.com/mikahama/akusanat

[5]https://akusanat.com/verdd/

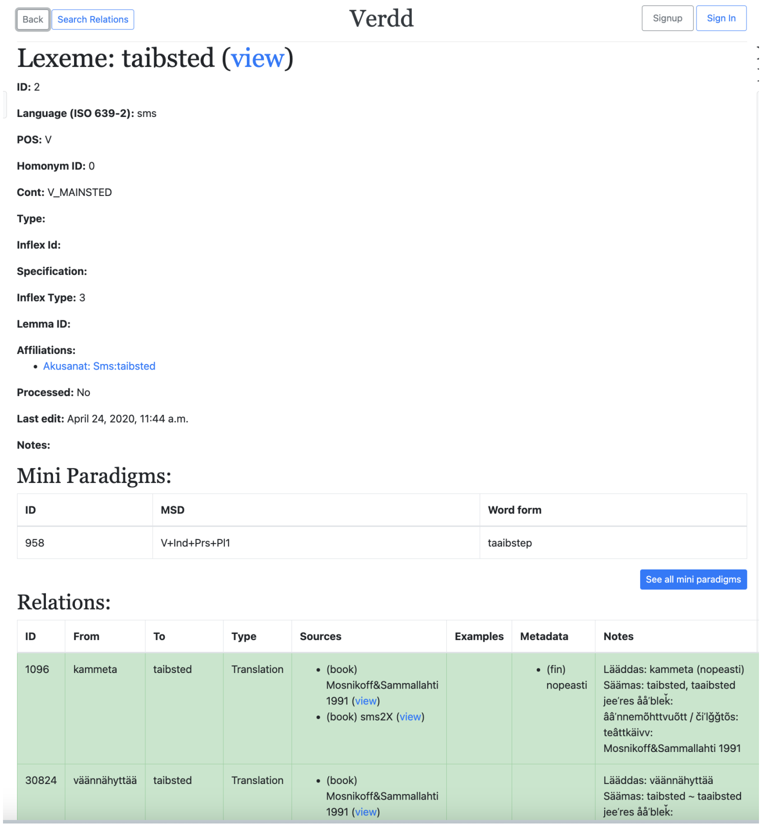

Figure 4: The interface for editing lexical entries in Ve'rdd

to the quality of the conversion, since, in the case of our languages, especially in the case of Skolt Sami, it is very frequent that the same character exists in many different Unicode characters. For example, ʹ (U+02B9 modifier letter prime) is a very common character in Skolt Sami, but because of the Finnish keyboard layout, it is often written as ' (U+0027 apostrophe) or ´ (U+00B4 acute accent). Ve'rdd is programmed to take into account the possible characters of the language and try to correct the incorrect characters automatically.

Figure 2 shows the interface for searching and filtering words in Ve'rdd. The interface is designed to support the workflow of a dictionary editor. For example, it is possible to display only raw inputs. This means entries that no one has verified after importing the data from an unstructured format. To facilitate the development of FST transducers it is also possible to sort and filter the words according to the continuation lexicon, which is the FST way of indicating how every word is supposed to be inflected.

Apart from just searching and filtering lexical entries, it is important to have the possibility to edit them. Figure 4 shows the interface for inspecting a dictionary entry. If a user is connected to their account, in addition to viewing, they can edit the information of a lexicographic entry. Ve'rdd is designed to be a tool for multilingual dictionaries, so one entry is connected to other entries in the system. In Figure 4, relationships can be seen as translation types that connect a word to its translations in other languages. It is also possible to define other types of relationships between lexica based on etymology. Relationships may also exist between words of the same language, for example, it is possible to indicate compound words and derivations with relations. Since the FST transducers contain derivative information, Ve'rdd automatically adds this type of relationship when importing a unstructured dictionary.

Ve'rdd can visualize the relationship between two words that are linked together with any kind of relationship. This can be used to verify that a word in a given language is linked to the correct homonym in another language (Figure 5). It is also possible to edit the type of relationship or delete any unnecessary relationships.

Ve'rdd has a functionality that allows the user to export any dictionary in different formats. The most important for us are the Giella XML, which can be used to generate FST transducers, and Latex

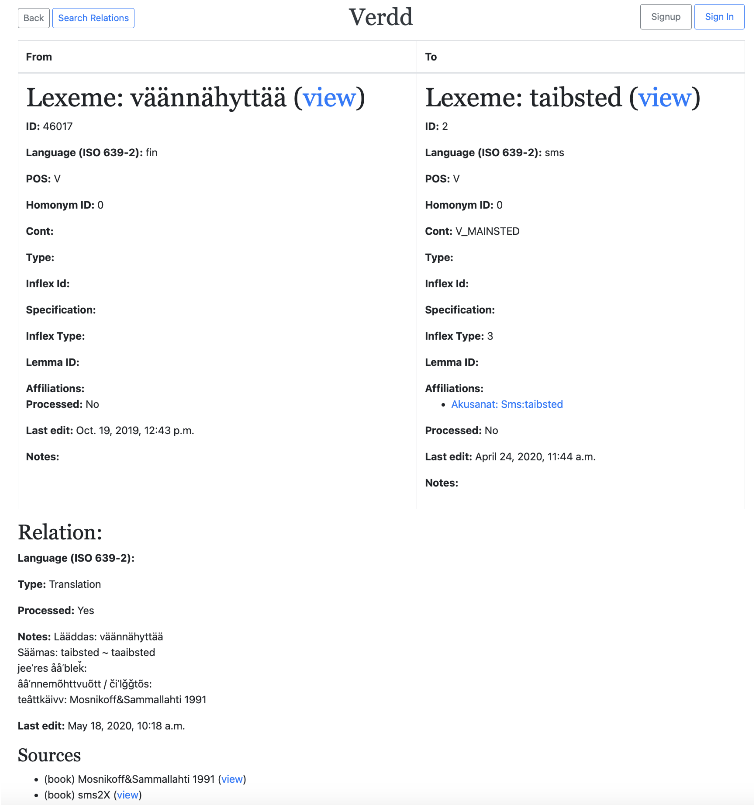

Figure 5: The interface for comparing two related entries in Ve’rdd

code. The Latex code makes it is possible to generate a ready-to-print PDF version of the dictionary. The Latex format makes it possible to change the style of the dictionary without changing the content. If there are changes in Ve’rdd, it is possible to update the content of the dictionary without changing the style defined in Latex. This functionality has been an important design principle for us since the work done in Ve’rdd should not only be used in digital dictionaries but also in printed dictionaries.

3.2.1 NLP resources

Our dictionary editing systems are directly useful in the development of FST transducers since we can export the lexicon in the format needed for HFST (Lindén et al., 2013). HFST is the tool we use to create the transducers. We have transducers for the Skolt Sami (Rueter and Hämäläinen, 2020), Erzya and Moksha (Rueter et al., 2020a) and Komi languages. The transducers can be used to lemmatize words, analyze their morphology or generate inflected forms. These transducers are difficult to compile for people who do not work with the transducers often. For this reason, we compile all transducers every night and we distribute them through our website[6]. We not only compile our transducers but all transducers for all languages in the Giella infrastructure.

The transducers are difficult to use as such, and for this reason, we have developed a Python library called UralicNLP (Hämäläinen, 2019) and a Python implementation of HFST called PyHFST (Hämäläinen and Alnajjar, 2023). With the libraries, compiled dictionaries and translators can be downloaded and used directly in Python. Fig 6 shows how to use our transducers from Python. In the second line of code, the word шляпа (hat) is analyzed in erzya (myv). The result indicates that the word is an indefinite (+Indef) noun (+N) in the nominative (+Nom) singular (+Sg). In the fourth line we generate the conjugated form of the same word in the plural (+Pl). The result is the plural word шляпат.

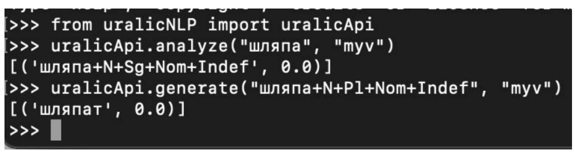

Figure 6: An example of using UralicNLP

[6] https://models.uralicnlp.com/nightly/

FST transducers produce all possible interpretations for a word from. In the case of the Uralic languages, there is plenty of homonymy in morphological inflections. This means that, if we use the transducers on regular text, we cannot accurately lemmatize the words in their context since the transducers produce all possible lemmas, For this reason, we use constraint grammar disambiguators (Karlsson et al., 2011) based on a tool called VISL CG-3 (Bick and Didriksen, 2015). The grammar rules of constraint grammars remove morphological readings that are not possible in a given sentence, and result in a sentence that is morphologically disambiguated with one lemma per word as opposed to all the possible lemmas.

```
>>> from uralicNLP.cg3 import Cg3
>>> oracion = "Ныв ёртыслы гижис письмӧ"
>>> cg = Cg3("kpv")
>>> print(cg.disambiguate(oracion.split(" ")))
Warning: Line 6 had empty tag.
[('Ныв', [<ныв - N, Sg, Nom, <W:0.000000>>]), ('ёртыслы', [<ёрт - N, Sg, Dat, Px
Sg3, So/PC, <W:0.000000>>]), ('гижис', [<гижны - V, TV, Ind, Prt1, Sg3, <W:0.000
000>>]), ('письмӧ', [<письмӧ - N, Sg, Nom, <W:0.000000>>])]
>>>
```

Figure 7: An example of the use of the Komi Zyrian disambiguator

In Figure 7, we can see how the CG disambiguators can be used on UralicNLP. The third line initializes the disambiguation object for the Komi-Zyrian (kpv) and in the fourth line the disambiguation method of the object is called with a sentence. The result contains the word forms of the sentence, their lemmatization and morphology for each word of the sentence.

Apart from structured dictionaries and rule-based tools, we have treebanks of the universal dependencies for the Skolt Saami, Moksha, Erzya (Rueter and Tyers, 2018), Komi-Zyrian (Partanen et al., 2018) and Komi-Permyak (Rueter et al., 2020b). These treebanks contain syntactic annotations with the tags Morphological characteristics of universal dependencies. With the latest treebanks, we have also added the morphological labels produced by the transducers to facilitate the use of the two resources together

4 Incorporating modern NLP methods

As we have described thus far, a great part of our work relies on the old rule-based tradition of NLP. When we deal with endangered languages, rules are the primary starting point. One cannot simply train a neural network if there isn't enough training data. However, we do not want to reject neural models instantly as something that simply will not work for small languages. Neural models can work and they can be extremely beneficial. Throughout our research, we have aimed at combining rule-based models with neural models to facilitate our work on endangered languages.

Digital documentation has allowed us to use the latest methods in the world of NLP to automatically increase the data we have in the dictionaries. Because all of the lexicographic resources we have are multilingual, the first step we have taken with NLP technology has been the prediction of translations (Hämäläinen et al., 2018). The idea was as follows: if the Skolt Sami dictionary contains Finnish translations, German and English, and the Erzya dictionary contains translations into Finnish, English, Russian, and French, then, with this information, it should be possible to automatically deduce translations from Skolt Sami into Russian and French and from Erzya into German given the existence of two common languages: Finnish and English. With a probabilistic model we have increased the number of translations in Skolt Sami, Erzya, Moksha and Komi-Zyrian dictionaries.

We have elaborated on this idea later on by using graph based approaches and neural models (Alnajjar et al., 2021, 2022). These have not been isolated attempts, but the graph based methods have been incorporated into Ve'rdd as well. The predictions have been manually checked and this way we have been able to augment our dictionaries semi-automatically. The Livonian institute has embraced this technology in bootstrapping a Livonian-English dictionary.

As neural networks require a large amount of data to be trained, it is common to believe that their use is not possible in the case of endangered languages. We have taken the perspective that we can generate the amount of data needed for a neural network with our morphological tools. Using the treebanks and the transducers, we have generated data to train a neural network to perform disambiguation instead of using the constraint grammar for Erzya and Komi-Zyrian (Ens et al., 2019). The idea was to generate all possible analyzes for the words in the treebanks and train the neural network to disambiguate the analyses with the treebank analysis. Later on, we further developed this method in the context of Sami languages (Hämäläinen and Wiechetek, 2020).

We have also been able to use the neural networks to increase etymological relationships in the Skolt Sami dictionary (Hämäläinen and Reuter, 2019). The method was based on a character level LSTM model that was enhanced with synthetic data generated with a character-level statistical machine translation tool. We used this method to produce a set of candidate cognates that we manually checked and incorporated into our digital dictionaries. This method relies on external data from the Institute for Languages in Finland, which makes it difficult for us to include it in Ve'rdd.

Rule-based FSTs are great because they are usually very accurate, however, they do not have a great lexical coverage. Analyzing an online text with the FSTs will usually mean a ton of words that are not recognized at all. For this reason, we used the FSTs to generate training data for neural models (Hämäläinen et al., 2021). We used this data to train character-level neural machine translation models to analyze, generate and lemmatize word forms. The key idea is to use the exact same morphological tags so that the neural models and the FSTs can be used interchangeably. These neural models have been made available through UralicNLP as a fallback mechanism. If an FST fails to analyze a word form, the neural model will be used automatically if neural fallback is turned on.

Recently, we have also moved our interest towards other aspects of NLP than just lexicon and morphology. We have done work on automatically translating and aligning word embeddings for endangered Uralic languages (Alnajjar, 2021) and using them successfully in downstream tasks such as sentiment analysis (Alnajjar et al., 2023).

5 Discussion and Conclusions

We hope that our work can be useful for others as well. We have put a lot of attention in open-sourcing our tools and resources so that nobody needs to start building language documentation tools entirely from scratch. We have also paved a road towards using state-of-the-art neural models in the context of truly endangered languages with extremely limited resources. This is challenging and requires ingenuity. We are not interested in committing to the dichotomy of researches who defend rule-based tools as the only viable option for endangered languages nor to the researchers who frown upon rules and rely solely on the Transformer architecture. The best solutions, we believe, are found by combining both worlds.

Our tools are compatible with the Giella infrastructure. This has made it possible to use our dictionaries and translators directly on their online platform to learn languages (Antonsen and Argese, 2018), on Android and iPhone keyboards and spell checking for Word and OpenOffice developed by Divvun[7] at Giella. Flexible and interoperable design makes it also possible to integrate different lexical resources into our infrastructure once those are digitized or otherwise become available.

Digital documentation clearly has its benefits, since we can carry out machine learning with structured dictionaries and FST transducers. For this reason, a project conducted at the University of Oulu[8] the goal of which was to author the new dictionary Skolt Finnish-Sami has chosen to use Ve'rdd to create the digital and printed dictionary. We have worked together with project employees to increase the functionality of our system. Ve'rdd has made the simultaneous work of editors possible who, without Ve'rdd, would have used Excel and Word. This would have meant a lost chance of producing a structured dictionary for the interest of NLP and a printed dictionary at the same time.

We have started to explore non-Uralic languages by building a UD treebak for Apurinã (Rueter et al., 2021). Furthermore, we have built an initial FST for Lushootseed (lut) (Rueter et al., 2023) and extended it with an LSTM model. These are our initial steps towards non-Uralic languages.

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[7] http://divvun.no/

[8] https://www.sttinfo.fi/tiedote/tekoaly-apuna-koltansaamen-ja-pohjoissaamen-digitaalisten-sanakirjojen-toimitustyossa?publisherId=57858920&releaseId=69886820

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Computational Narrative Understanding: A Big Picture Analysis

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Abstract

This paper provides an overview of outstanding major research goals for the field of computational narrative understanding. Storytelling is an essential human practice, one that provides a sense of personal meaning, shared sense of community, and individual enjoyment. A number of research domains have increasingly focused on storytelling as a key mechanism for explaining human behavior. Now is an opportune moment to provide a vision of the contributions that computational narrative understanding can make towards this collective endeavor and the challenges facing the field. In addition to providing an overview of the elements of narrative, this paper outlines three major lines of inquiry: understanding the multi-modality of narrative; the temporal patterning of narrative (narrative "shape"); and socio-cultural narrative schemas, i.e. collective narratives. The paper concludes with a call for more inter-disciplinary working groups and deeper investment in building cross-cultural and multi-modal narrative datasets.

1 Introduction

The Native-American writer, Gerald Vizenor, once remarked: "There isn't any center to the world but a story" (Coltelli, 1990). Storytelling is a ubiquitous human practice, exhibited in all human cultures, languages, and recorded historical time periods. Many of the world's most enduring and widespread belief systems are encoded through stories, and research suggests that human reasoning (Bruner, 1991) and selfhood (Berns, 2022) are fundamentally grounded in narrative. Today, a growing body of research is developing across a variety of domains that focus on storytelling as a key mechanism for explaining human beliefs and behavior, from mental health (Adler et al., 2016), to political stance taking (Bushell et al., 2017), to consumer persuasion (Bilandzic and Busselle, 2013), to financial decision making (Shiller, 2020).

Given this widespread interest in, and awareness of, narrative as a crucial driver of human behavior, the field of "computational narrative understanding" has a great opportunity to contribute to a range of research fields. Computational narrative understanding has crystallized over the past 5-10 years as a vibrant subset of natural language processing (Bamman et al., 2019; Jorge et al., 2019). Its aim is to develop computational systems for the detection and understanding of narrative communication across different media and different cultural domains. While we may typically think of stories as encoded in written documents, the practice of narrative can be represented through a diverse array of media, including oral speech, song, still or moving images, social media, playable media like video games, or some combination of the above.

The aim of this paper is to provide a big picture view of some of the key higher-level goals for computational narrative understanding. A great deal of on-going and inspiring work continues to make progress in the detection and analysis of different components of narrative communication (for a review see Piper et al. (2021)). It thus seems timely to provide a vision of where we are going as a community to help motivate and organize future work in the field.

In section two, I provide a brief minimal definition of narrative communication highlighting its constituent parts building on prior work (Piper et al., 2021). Before moving to the big picture, it is important to ground our understanding of this core concept. In section three, I describe a research framework that aims to develop a more multi-modal understanding of narrative. With its grounding in NLP, computational narrative understanding has understandably focused on narrative as a linguistic phenomenon. However, as narratologists have long pointed out (Ryan et al., 2004), storytelling can transpire in numerous different media. Being able to integrate observations across

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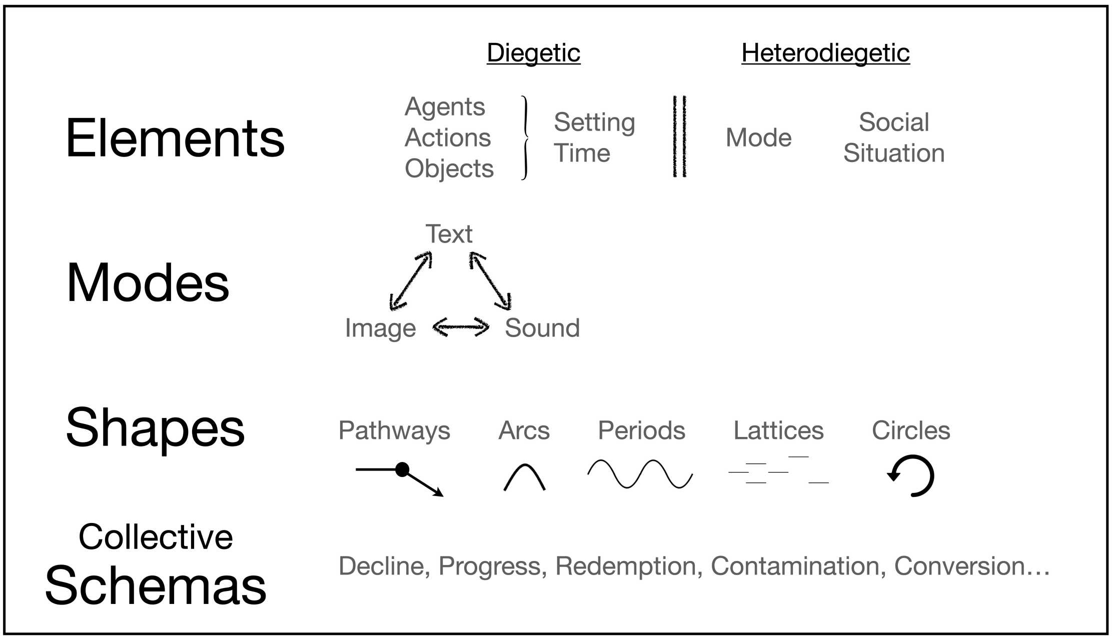

Figure 1: Overview of narrative research areas discussed in this paper.

media, from speech to text to images to playable media should become a central goal of computational narrative understanding.

In section four, I describe a research framework aimed at understanding narrative "shape" (also called "form" or "structure" (Berhe et al., 2022)), which can be understood as the temporal patterning of narrative elements. One of the fundamental aspects of storytelling is the encoding of events in time (Genette, 1983; Sternberg, 1992; Ricoeur, 2012). Narrative meaning is thus contingent on the temporal organization of information.

Seeing narratives as temporal artifacts, made in time and composed of time, then leads to the highest-level form of integration described in section five, that of narrative "schemas." As Berns (2022) has argued, narratives are forms of information compression, reducing the vast scope of experienced data down to a much more limited set of communicated data. Such compression necessarily follows archetypes or patterns that can be biologically or culturally conditioned (or some mixture of the two).

While the idea of "scripts" has been applied to understand the local schematic encoding of events (Chambers and Jurafsky, 2008a), prior work in folklore studies has offered promising frameworks for expanding the idea of schema to include whole stories within various typologies (Thompson, 1989). Essential to this framework is an attention to larger narrative ecologies, the ways in which such schemas play a generative and/or organizing role within broader, and potentially interactive, communicative domains (Tangherlini et al., 2020).

It is common to think of narrative as located within an individual document or artifact (this book or blog post tells a story), but narratologists have also highlighted the way story structures emerge from the complex social interactions of numerous agents (known as the "small stories" paradigm (Georgakopoulou, 2007)). Such "small stories" can then coalesce into larger socially circulatable schemas, variously referred to as "ontological narratives" (Somers, 1994), "deep stories" (Hochschild, 2018), or "collective narratives" (Bliuc and Chidley, 2022). Such schemas can then guide the processing and circulation of new information to "fit the narrative," potentially creating informational feedback loops that are durable over shorter or longer stretches of time.

In sum, we want to have a research framework capable of scaling the ladder from local elements (section 2), different media (section 3), formal structure (section 4), all the way up to schemas and social dynamics (section 5). Figure 1 provides a schematic overview of this big picture.

I conclude in section six with a reflection on the need for greater inter-disciplinary collaboration and deeper investment in building cross-cultural and multi-modal datasets. As we develop more sophisticated systems for detecting narrative communication, we will want to invest more deeply in the infrastructure for large-scale narrative understanding. This will necessarily entail collaborations across disciplines to better understand socially relevant applications as well as the ability to develop appropriate data. It will also require developing an awareness around the limitations or risks of narrative communication (Salmon, 2017; Gottschall, 2021). Stories not only inspire and move audiences, they can also deform reality and misinform, a point that should remain at the forefront of our thinking about how stories stand at the centre of so much human behavior, for better and for worse.

2 The Elements of Narrative

At its most elementary level, a story can be said to occur when all of the following criteria are met:

A	Someone
B	tells
C	someone
D	somewhere
	that
E	someone
F	did something(s)
G	[to someone]
H	somewhere
I	at some time
J	for some reason.

For there to be a story, we need (A) a teller, (B) a mode of telling (i.e. medium), (C) a recipient, (D) a social situation, (E) an agent, (F) at least one action or event, (G) a possible object, (H) a location, (I) a time-frame, and (J) a motivation or cause of the actions involved. Narratologists make a distinction between the frame of the storyworld (i.e. all of the elements that come after the double lines above) known as "diegetic" elements, and the frame of telling (i.e. all of the elements that come before the double lines) known as "heterodiegetic" elements, where diegesis refers to a narrative "frame" or "world."

Importantly, not all of these elements need to be explicit. For example, in one of the most famous short stories ever proposed by Ernest Hemingway, very little from the above list is specified:

For sale: Baby shoes. Never worn.

We don't know where and when this happened, nor do we know who is telling the story. All we know is what happened (on two levels): a baby died and a family needs money. But no matter how much is implicit in this story all of the parts are there. Something happens to someone somewhere at some time for some reason and someone tells someone this story.

Such a definition can be useful because it highlights the array of narrative elements that require computational solutions to "understand" the cultural meaning of a story. Such applications have included: character detection (Bamman et al., 2014; Jahan et al., 2018; Piper, 2023b; Stammbach et al., 2022), object detection (Piper and Bagga, 2022a), character relation detection (Labatut and Bost, 2019; Kraicer and Piper, 2019), event detection (Vauth et al., 2021), geographic and spatial understanding (Wilkens, 2013; Evans and Wilkens, 2018; Piatti et al., 2013; Erlin et al., 2021), temporal understanding (Underwood, 2018; Yauney et al., 2019; Vossen et al., 2021; Gangal et al., 2022), and causality mining (Meehan and Piper, 2022). A full review can be found in Piper et al. (2021) and Santana et al. (2023).

A second, higher-level way that a story can be broken down into constituent parts is through *discourse elements*. As we will see, this problem is associated with challenges of text segmentation, though importantly differs from prior work focused on sequential and/or paratextual (i.e. chapter) segmentation (Pethe et al., 2020; Zehe et al., 2021).

Narratives not only contain event-frames (i.e. scenes), but are also composed of heterogeneous linguistic styles in which the act of narration is but one component. This is one reason recent narrative theory has emphasized the idea of "narrativity" (Piper and Bagga, 2022b; Pianzola, 2018; Giora and Shen, 1994), which captures the *degree* of narration intrinsic to a narrative. An ostensibly narrative document like a short story will engage in moments of non-narrative statements, just as putatatively non-narrative documents like scientific articles may engage in occasionaly moments of narration. Narration is in this sense not a universal property of documents, but a local linguistic phenomenon. As Ochs et al. (2009) write, "We believe that narrative as genre and activity can be fruitfully examined in terms of a set of dimensions that a narrative displays to different degrees and in different ways."

Narratologists typically break down narratives into at least four basic discourse components:

Discourse	Contents
1. Narration	Agents and events
2. Description	Setting, modification, context
3. Dialogue	Reported speech
4. Evaluation	Meta-level discourse

"Narration," also known as "diegesis," refers to the linguistic structures described above that occur after the double horizontal line (E-J). This is the classic understanding of narrative, where events pertaining to an agent are recounted (this can also fall under the heading of "eventfulness" (Hühn, 2014)).

"Description," also called "mimesis," refers to when the surroundings or context of events are described and during which events do not unfold (though they may be unfolding in the background). In cinema, this is equivalent to an "establishing shot" that indicates to viewers where they are in time and space. Crucial to description is that it lacks the agent/action/cause structure from above.

"Dialogue" refers to any form of reported speech, though it can also take the form of indirect speech as well. Recounting what characters say to each other is an integral component of stories, although it technically is a form of dramatic performance (for a reflection on this topic see (Genette, 1992)).

Finally, many stories contain what we might call meta-textual statements (called "evaluation" by Labov and Waletzky (1967)), where the narrator provides some higher-level assessment with regards to the story, either a reflection on the story contents, their meaning, or some didactic lesson that should be imparted, making a latent feature of storytelling (it's meaning or purpose) manifest. While it may come at the end of a story, it can also be interspersed throughout. Here are a few examples of such statements:

1. *It is a truth universally acknowledged, that a single man in possession of a good fortune, must be in want of a wife.* (Pride and Prejudice)

2. *The flatterer lives at the expense of those who will listen to him.* (Aesop's Fables)

3. *All in all, I'd say that those years were some of the best times I've ever had.* (AskReddit)

While there are many more ways one can parse a story (see Bal and Van Boheemen (2009); Genette (1983)), the frameworks above provide practical heuristics for the ways that stories can be broken down into more elementary parts to ground computational models.

3 The Modality of Narrative

Grounded in NLP, computational narrative understanding has largely prioritized written narratives for understandable reasons. However, such text-driven approaches leave out large portions of storytelling behavior, including movies and television (Arnold et al., 2019; Papalampidi et al., 2019), user-generated streaming content, illustrated content in comic strips (Edlin and Reiss, 2023), graphic novels, or children's books (Adukia et al., 2021), and finally video games, which might have stronger or weaker narrative structures. While textual narratives are largely unimodal in nature (though the physical and visual dimensions of books has been a vibrant area of study for a long time (Collective, 2019)), these other narrative forms are all crucially multi-modal in nature.

Sound, image, and language can interact in ways that are complex and dynamic. A robust field of multimodal NLP research into text-image interactions for meaning-making has emerged in recent years (see for example recent research on humour by Hasan et al. (2019); Hessel et al. (2023)). Nevertheless, investigations into multimodal *narrative* understanding, such as the relationship between text and illustrations in children's books or graphic novels is in need of more attention (see Adukia et al. (2021) for an example exploring the visual qualities of children's book illustrations with respect to race). Understanding the kinds of gestural or pictorial preferences that are foregrounded given certain textual cues could give us insights into the way humans translate language into image (and vice versa) across different cultural domains.

Similarly, we still lack major comparative studies of narrative behavior across media, i.e. comparisons of narrative elements and archetypes in film, television, user-generated content, oral performances and books. For example, evidence suggests that written and oral narratives have similar "establishing shot" structures similar to movies and television (Boyd et al., 2020; Piper, 2023a). More precise comparisons can highlight the modal-specificity of different narrative elements along with the transmodal practices that are independent of a given modality. Understanding the ways in which storytellers marshal images, sounds, and words to create immersive experiences for audiences will greatly contribute to the project of computational narrative understanding.

4 The Shape of Narrative

The writer and critic Italo Calvino was fond of quoting a Sicilian expression that "time takes no time in a story" (Calvino, 1988). A narrator can tell a story that traverses centuries in a few sentences or can slow time down to the point where a few seconds takes minutes to describe. Narratologists refer to this as the difference between *narrated time* (the time transpiring in the storyworld) and *narrative time* (how long a story takes to tell). No matter how much stories may compress time, they cannot be told all at once. Contrary to Calvino's favored Sicilian expression, all stories, even the shortest, take time to tell.

This temporal dimension of narrative – that stories take time to tell and tell of things happening in time – has long been one of the privileged topics of narrative theory (Ricoeur, 2012; Sternberg, 1990, 1992). As the theorist David Herman has argued, "Narrative is a basic human strategy for coming to terms with time, process, and change" (Herman, 2009).

A number of approaches have been proposed for the computational modeling of temporal patterns in narrative (for a review of modeling narrative structure see Berhe et al., 2022). Schmidt (2015) used topic modeling to identify thematic arcs in television screenplays, while Thompson et al. (2018) used topic models to study thematic progression in philosophical texts and social media. Reagan et al. (2016) used sentiment analysis to model the concept of narrative fortune (Freytag, 1895), for which Elkins (2022) provides a more in-depth study of the validity of sentiment arcs as models of narrative structure. Boyd et al. (2020) used particular word types to capture three primary narrative stages, and Sap et al. (2022) used the predictability of next sentences to capture the concept of narrative "flow."

Piper and Toubia (2023) used word embeddings to model narrative non-linearity using the traveling salesman problem, while Toubia et al. (2021) offer two further ways of thinking about narrative shape called "speed" and "volume." Researchers have also used information theoretic frameworks to model the concept of narrative revelation using time series methods (Piper, 2023a) and stylistic novelty over narrative time using a bloom filter (McGrath, 2018). Ouyang and McKeown (2015) and Piper (2015) devised methods for predicting narrative "turning points" as larger structural qualites, drawing on Aristotelian and Augustinian theories of narrative respectively.

Common to all of these models is the assumption that the dissemination of information over narrative time assumes observable patterns (called "form" or "structure") and that these patterns encode cultural meaning. The most common framework to date has been that of the narrative "arc," drawn from French neo-classical tragedy (Freytag, 1895). According to this model, narratives encode a central conflict that results in some form of resolution or change, which can be approximated by an arc of rising and falling fortune or conflict.

Much future work remains to better understand relevant ways of capturing narrative time in terms of its formal patterns. The first area of consideration should be further work into the choice of feature distributions that are used to capture narrative time. Where prior work has focused to date on topic models, sentiment vocabulary, word embeddings, lexemes, and letters, higher-level narrative features (see Section 1) should continue to be developed and studied. We assume that the distribution of characters, event types, locations, or narrative modes may also contribute to the overall structural qualities of stories.

Second, modeling narrative change itself remains a key area of further research. Prior empirical work has shown that long narratives may employ multiple "arcs" rather than single turning points (Reagan et al., 2016; Fudolig et al., 2023), while other work has emphasized the significance of single turning points (Ouyang and McKeown, 2015; Piper, 2015). Additionally, the identity or meaning of such moments of change, regardless of how many, are also not well understood. The dramatic model of narrative denouement suggests that turning points are best understood as forms of "conflict/resolution," while other narrative theories suggest that "surprisingness" is the optimal way of understanding narrative change (Wilmot and Keller, 2020). Brewer and Lichtenstein (1982) have proposed two further affective states of *suspense* and *curiosity* in addition to surprise to capture the discrepancy between storyworld information and narrative information (i.e. when key information is withheld or forms of temporal anachrony are used such as flashbacks and flashwords known as analepsis and prolepsis respectively).

In addition to these temporal issues, the role that causality plays in describing narrative change has been relatively underexplored. As the writer and essayist George Saunders has argued, causality is the "wind in the kite" of narrative (Saunders, 2022). As Graesser et al. (2002) have demonstrated, readers are much more moved by "why" questions than "what" questions when it comes to narrative comprehension and recall. Future work will want to explore more fully both different constructs of "change" as well as draw on methodologies such as Markov models, time series analysis and systems dynamics to develop increasingly sophisticated models of change over narrative time.

Finally, most prior work is guided by a single spatial metaphor for narrative time, that of the arc. Future work will want to explore other possible structures or forms (Levine, 2015) that might capture the temporal patterns of narrative. The translation of time into spatial form represents an exciting and novel space of research for computational narrative understanding.

5 Narrative Schemas

Narratives are forms of information compression (Berns, 2022). They select certain experiential data and structure this data into prescribed grammatical slots (as described in Section 1). This basic insight serves as the foundation of the theory of narrative "scripts" (Schank and Abelson, 1977; Chambers and Jurafsky, 2008b), where narrative is understood as a probabilistic sequence of actions (i.e. given the event of being in a restaurant certain subsequent actions are more or less likely). Such compression is what allows stories to be both memorable as well as easily shareable (i.e. tellable (Baroni, 2011)).

The discussion of narrative form or shape in the prior section is one such example of the *schematic* nature of narrative, i.e. that narratives have structure and this structure is essential to their meaning. But schemas can also be represented as a variety of conceptual metaphors (that often have spatial associations). For example, in the field of clinical psychology researchers refer to two self-narrative schemas, called narratives of redemption (when bad things turn good) and narratives of contamination (when good things turn bad) (McAdams et al., 2001). Patients who structure life experience into the former schema are far more likely to be associated with positive mental health outcomes than those who engage in telling their life stories according to the latter.

The first extensive (and later controversial) study of narrative schemas emerged in the field of folklore studies (Dundes, 1962). Faced with large collections of documents with a high degree of repetitiveness, folklorists began developing systems for classifying stories according to different typologies. The most famous undertakings were Stith Thompson's Motif-Index of Folk-literature (Thompson, 1989), the Aarne-Thompson-Uther (ATU) Tale Index, and Vladimir Propp's emphasis on character "function" (Propp, 2010). Fundamental to this research was the insight that certain larger narrative patterns are maintained while local units can be changed. As Propp (2010) highlighted, whether it is an eagle or a horse or a ring that is the gift that carries away its recipient, the point of each of these stories is the event of being transported, or even more generally, the danger or affordance of gift giving.

While it is beyond the scope of this paper to rehearse debates around narrative classification (for a review see Dundes, 1962; Broadwell et al., 2018), there remains a fundamental value in developing narrative taxonomies for different domains. Narratives are indeed reducible to schemas and those schemas serve particular social and psychological functions. And yet we currently lack agreed-upon or widely used frameworks for discussing schemas, either at the individual or socio-cultural level.

Folklorist and computational narratologist Timothy Tangherlini has begun using the idea of schemas to study conspiracy theories circulating through social media (Tangherlini et al., 2020; Chong et al., 2021; Shahsavari et al., 2020), which function much like folklore in that various narrative units (Bill Gates, 5G) can be utilized for larger functional purposes (a global cabal of elites is controlling us). Related research by Mendelsohn et al. (2023) looks at "dogwhistle" detection, which can be understood as phrases with latent, toxic meanings and that likely have a narrative element to them.

Understanding schemas requires two challenging research questions. The first we can refer to as *motif tracking*, which requires the ability to model variability and repetition at both the level of local units (agents, actions, objects) and more general schemas (when certain units are deployed to tell certain kinds of stories). While systems currently exist to identify the narrative units described in Section 1 (including agents, actions, and objects), we still need ways of aggregating these units into story "types." When is Bill Gates being used to tell a story about global elites and when is he being used to tell a story about the power of philanthropy?

More importantly, we want to model the causes as well as social effects of these different story types. Do we see certain narrative schemas deployed in response to major social events (for example what are the prevalent narrative responses to financial or political or climatic shocks?). Or can certain narrative schemas predict future behavior? Similar to the clinical psychology example mentioned above but moving into the social realm, do we see the persistent invocation of narratives of national decline associated with shifts in electoral behavior? If we assume narrative is a key predictor of human behavior, we need more reliable and sophisticated ways of classifying narratives to better understand their causes and effects.

The second key dimension in studying narrative schemas is the aspect of *social dynamics*. As folklore studies first highlighted, narrative types are aggregates of numerous local instances of storytelling behavior. Each unit (whether an oral tale or social media post) may contribute to a larger narrative schema but may itself only loosely embody this schema. Narratologists refer to these local dynamics as "small stories" (Georgakopoulou, 2007), i.e. when a larger story is told through the participation of numerous actors. The quintessential example of this behavior is the "family dinner table," where family lore is the product of multiple actors engaging in the process of narrative recounting, potentially over long spans of time. At the macro-level narratologists refer to these larger narrative schemas – the aggregate of small stories – as "collective narratives" (Bliuc and Chidley, 2022), "ontological narratives" (Somers, 1994), or "deep stories" (Hochschild, 2018).

Social media and online news (broadly understood) greatly expand the complexity of collective narrative construction and small-story dynamics. One can imagine "top-down" approaches that start with known schemas and then classify individual stories or collections of stories within these taxonomies or "bottom-up" approaches that cluster individual stories into larger schemas that emerge from the collective behavior among the data. Modeling this complex, large-scale narrative behavior represents one of the major challenges for the field but one that has the most explanatory pay-offs in terms of understanding social behavior.

6 Narrative Infrastructures

As computational narrative understanding comes into its own as a distinct field within the NLP community, now is a good time to begin coordinating more of this research effort. These initiatives can take the form of shared tasks, dataset curation, and collective efforts to develop systems for narrative classification.

Shared tasks have a long history within NLP, though to date only three have been proposed for narrative understanding. The first is the narrative cloze test (Chambers and Jurafsky, 2008a; Mostafazadeh et al., 2016; Hatzel and Biemann, 2023), where systems predict the next agent-event in an event chain. Zehe et al. (2021) have proposed a task for detecting narrative scenes, while Reiter et al. (2019) have proposed a task for detecting narrative levels (when diegetic worlds are imbedded within one another, either in the form of stories within stories or temporal anachronisms such as flashbacks). Piper and Bagga (2022b) and Hatzel and Biemann (2023) have proposed annotation frameworks for narrative detection, i.e. identifying the degree to which a stretch of discourse can be identified as containing narration.

Future work will want to refine these existing initiatives as well as develop systems for the further detection of the remaining discursive units described in Section 2 (i.e. description, dialogue, evaluation). The automated identification of narrative communication in particular will prove extremely valuable for broader social and cultural analysis.

Given the value of narrative for understanding human behavior it is somewhat surprising how few datasets are available for the study of human storytelling. Much of this is due to intersecting problems of intellectual property restrictions, large library collections with low-levels of metadata, and the dynamic and ever-changing nature of online storytelling. Underwood et al. (2020) provide a large-scale annotation of ca. 200,000 fictional narratives in English in the Hathi Trust Digital Library that has been refined and updated by Bagga and

Piper (2022) to include a comparison corpus of non-fiction prose across 1.5 million sampled pages published since 1800. Hamilton and Piper (2023) extends this work to include multilingual fiction annotation across 521 different languages. Erlin et al. (2022) provide metadata on translations of fiction into English from 120 different languages also located in the Hathi Trust.

Outside of the HathiTrust, Piper (2022b) provides derived data on a collection of 2,700 works of professionally published English prose drawn from 12 different genres including Goodreads' user ratings. Mostafazadeh et al. (2016) developed an artificial corpus of very short stories (4-5 sentences) generated by crowdsourced workers. Ouyang and McKeown (2014) curated a collection of ca. 5,000 AskReddit stories told by users in response to particular prompts (e.g. what is your scariest real-life story?).

Researchers in the field should be aware that while Project Gutenberg offers a large collection of potentially narrative texts, problems of sample selection and poor metadata can lead to downstream problems that result in erroneous claims (Piper, 2022a). For addressing cultural and historical questions, researchers are strongly encouraged to use the collections described above.

Incumbent on all of these initiatives is a greater investment in inter-disciplinary collaboration. Computational narrative understanding will benefit as an endeavor with deeper collaborations between humanists and social scientists and the NLP community. As detailed in Piper et al. (2021), narratology is a field with a long and robust theoretical tradition. Those in the NLP field working on computational systems will benefit from expert collaborations with researchers who have deep backgrounds in studying narratives. Similarly, narratologists and their research frameworks stand to benefit from exposure to computational models (Piper and Bagga, 2022b). It is time to invest more heavily in these larger cross-disciplinary collaborations, especially if we aim to address the larger socio-cultural goals outlined in this paper.

7 Conclusion

As Vizenor envisioned, narratives are things we live by. They provide meaning and hold communities together. They play a role in financial, political, and psychological decision-making. The production of imaginary narratives in particular represent a massive cultural industry, spanning book publishing, movie-making, and gaming. The field of computational narrative understanding has made impressive strides in developing systems to study the causes and effects of narrative behavior across a diverse array of languages and cultural domains. We are in the process of establishing key workshops, tasks, and datasets.

By way of conclusion, I provide a sliding scale of calls to action, located from particular to general (Table 1). It is worth noting that an essential component of the field should include attention to the limiting factors of narrative, i.e. the way narratives encode experience in very particular ways and because of their persuasive power can also mislead individuals in profound ways. Greater attention to the risks of narration should therefore remain front and center as part of the endeavor of computational narrative understanding.

	Challenge Areas
Complexity ↓	1. Data Set Creation
	2. Narrative Element Detection
	3. Multilingual Modeling
	4. Multimodal Modeling
	5. Narrative Discourse Detection
	6. Narrative Time Modeling
	7. Narrative Schemas and Taxonomies
	8. Collective Stories and Social Behavior

Table 1: List of challenge areas in increasing order of generality and complexity

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The Case for Scalable, Data-Driven Theory: A Paradigm for Scientific Progress in NLP

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Abstract

I propose a paradigm for scientific progress in NLP centered around developing *scalable, data-driven theories* of linguistic structure. The idea is to collect data in tightly scoped, carefully defined ways which allow for exhaustive annotation of behavioral phenomena of interest, and then use machine learning to construct explanatory theories of these phenomena which can form building blocks for intelligible AI systems. After laying some conceptual groundwork, I describe several investigations into data-driven theories of shallow semantic structure using Question-Answer driven Semantic Role Labeling (QA-SRL), a schema for annotating verbal predicate–argument relations using highly constrained question-answer pairs. While this only scratches the surface of the complex language behaviors of interest in AI, I outline principles for data collection and theoretical modeling which can inform future scientific progress. This note summarizes and draws heavily on my PhD thesis (Michael, 2023).

1 Introduction

Formal representations of linguistic structure and meaning have long guided our understanding of how to build NLP systems, *e.g.*, in the traditional NLP pipeline (Jurafsky and Martin, 2008). However, this approach has always had limitations:

1. Fully specifying formal representations requires resolving challenging theoretical questions long contentious among linguists;
2. It is difficult to reliably produce these representations with broad coverage using machine learning; and,
3. Even ostensibly correct linguistic representations are often hard to apply downstream.

Together with the effectiveness of deep learning, these challenges led to the proliferation of end-to-end neural network models which directly perform tasks without intermediate formal representations of linguistic structure (He et al., 2017; Lee et al., 2017; Seo et al., 2017, *inter alia*). This trend continues with language model assistants like GPT-4 (OpenAI, 2023) and Claude (Bai et al., 2022) which can perform a wide range of tasks. However, these systems are still not robust, often reporting false or biased answers (Perez et al., 2022; Bang et al., 2023) and making false claims about their own reasoning (Turpin et al., 2023). Ensuring AI systems' robustness requires us to precisely characterize and control their generalization behaviors.

To this end, formal theories, *e.g.*, of linguistic structure, common sense, reasoning, and world knowledge, provide frameworks for evaluation. They inform the design and construction of challenge sets (McCoy et al., 2019; Naik et al., 2018; Wang et al., 2019), measures of systematicity (Yanaka et al., 2020; Kim and Linzen, 2020), behavioral tests (Linzen et al., 2016), and probing experiments (Liu et al., 2019; Tenney et al., 2019). As these theories allow us to characterize generalization behaviors we desire, they will likely play a pivotal role in the design and training of trustworthy systems. So core improvements in formal theories of aspects of intelligent behavior may yield boons for both the construction and evaluation of NLP systems. But the question remains of how to achieve this: decades of work on semantic ontologies (Baker et al., 1998; Palmer et al., 2005), commonsense knowledge bases (Lenat, 1995; Speer et al., 2017), and formal reasoning systems (Lifschitz, 2008) have largely been superseded in NLP by deep learning and language models.

Theory-driven approaches in AI have been so disappointing that Sutton (2019) famously argues that intelligence and the world are simply too complex for us to capture with domain theories, and we should instead focus on general-purpose learning systems that can capture this intrinsic complexity from data. However, I believe this is too

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pessimistic, giving up on the *intelligibility* of AI systems that is provided by accurate theories of their behavior, which is necessary for verifying their safety and usefulness in high-risk, high capability settings (Ngo et al., 2023). Instead, the deep learning era presents an opportunity to rethink how we develop theories of language behavior.

In particular, I propose *scalable, data-driven theory* as a paradigm to address the shortcomings mentioned at the beginning of this article: resolving or sidestepping theoretical questions, producing representations with broad coverage, and applying them effectively in downstream tasks. Inspired by Pragmatist epistemology (James, 1907), this approach avoids requiring the linguist or theoretician to specify the entire theory by hand, instead integrating machine learning in a judicious way which allows for the scalable, automated induction of formal theoretical constructs (*e.g.*, ontologies) which are grounded in task-relevant linguistic behaviors.

2 Pragmatist Principles for Scientific Progress

Church (2007) describes the history of computational linguistics on a *pendulum*, swinging between Rationalist (theory-driven) and Empiricist (data-driven) paradigms every 20 years. Church lists the "swings" as follows (with my comments):

- 1950s: Empiricism (Shannon, Skinner, Firth, Harris) — information theory, psychological behaviorism, early corpus linguistics
- 1970s: Rationalism (Chomsky, Minsky) — generative linguistics, logic-based AI
- 1990s: Empiricism (IBM Speech Group, AT&T Bell Labs) — statistical NLP, machine learning, modern distributional semantics
- 2010s: A Return to Rationalism?

As the reader may know, the predicted "Return to Rationalism" did not happen. NLP, for its part, is more Empiricist than ever.

Why is this? Sutton may say it's because the world is too complex: The Rationalist theoretician carefully formalizing the problems at hand has no hope of capturing the world's intricacies in a manually-crafted theory, though a system implementing that theory can be understood and controlled. The Empiricist tinkerer, on the other hand, can build a system that mostly works by trial, error, patching and fastening; so they win on empirical benchmarks. However, the resulting system is too complex to fully understand or control, and generalizes in unpredictable ways.

An odd feature of the Rationalism/Empiricism dichotomy is that neither epistemology accurately describes the pursuit of science in most fields. In fields like physics, chemistry, and biology, theoretical and experimental approaches are not in conflict; rather, they synergize and inform each other, as theories are continually updated to align with new experimental data. To make sense of this, we can turn to an epistemology inspired by how people actually operate in the world: Pragmatism.

Pragmatism is an epistemological framework which conceptualizes *knowing* in terms of the *actions* that the knowledge licenses, *i.e.*, by the predictions that follow from that knowledge. Prominent Pragmatists include Charles Sanders Peirce (1839–1914) and William James (1842–1910). Like Empiricism, Pragmatism embraces experience as the primary source of knowledge. But unlike Empiricists, Pragmatists such as James embrace formal and linguistic categories as comprising the content of knowledge, on the basis of their *usefulness* in making predictions and licensing actions (James, 1907). Unlike in Rationalism, the Pragmatist search for truth is not a search for one true theory which fundamentally describes the world, but for an ever-expanding set of theoretical tools and concepts that can be picked up and put down according to the needs of the knower. In pithy terms, a Pragmatist might agree with the statistical aphorism that that "All models are wrong; some are useful" (Box, 1976). Pragmatists such as James (1907) claim that this perspective more accurately describes human behavior with respect to knowledge (and indeed, the pursuit of science) than prior epistemologies.

Combining the core ideology of Pragmatism with observations from computational linguistics, we can derive two guiding principles for the development of theories that may have prospective use in NLP: decouple data from theory (Section 2.1), and make data reflect use (Section 2.2).

2.1 Decouple Data from Theory

One feature that distinguishes much NLP work, particularly involving linguistic structure, from traditional sciences is the status of theory with respect to data. In most empirical sciences, data takes the form of concrete measurements of the world, and the task of a theory is to explain those measurements. In NLP, many benchmarks and datasets are constructed under the *assumption* of a theory, whether it be one of syntactic structure (Marcus et al., 1993; de Marneffe et al., 2021), semantic structure (Palmer et al., 2005; Banarescu et al., 2013), or some other task-specific labeling scheme.

A theory, *e.g.*, of syntactic or semantic structure, is useful for annotation in providing a straightforward way to annotate disambiguation of text, which is important for understanding language. However, errors and inconsistencies in annotation resulting from complexity, vagueness, or underspecification in the theory limit what can be learned by models, as human performance and inter-annotator agreement can be surprisingly low (Nangia and Bowman, 2019). For example, the OntoNotes compendium of semantic annotations (Hovy et al., 2006) was presented as "The 90% solution" because of 90% agreement rates — implying that the dataset cannot validate performance numbers higher than 90%.

As another example, Palmer et al. (2006) find that fine-grained sense distinctions produce considerable disagreement among annotators of English text. But fixing the problem can't just be a matter of improving the sense inventory: they find that coarser-grained sense groups designed to improve agreement lack the distinctions from fine-grained senses that are necessary for predicting how words should translate into typologically distant languages like Chinese and Korean. When different tasks require different theoretical distinctions, setting them in stone during annotation is a problem, especially considering that there will almost certainly be missing categories, as new word senses or distinctions may show up in more exhaustive data or under domain shift. More generally, refining annotation guidelines to increase agreement between annotators does not necessarily solve the problem, as the extra assumptions built into the annotation process do not necessarily encode any more scientifically meaningful information in the data — a problem known in the philosophy of science as the *problem of theoretical terms*.[1]

Building a robust theory that can scale to unexpected phenomena and new data, and be adjusted for new tasks, requires theoretical agility which is precluded by committing to a theory-based annotation standard. An alternative is to directly annotate the phenomena that the theory is meant to explain, and derive the theory on the basis of this data. This, for example, is how *grammar engineering* is done in the DELPH-IN consortium (Bender and Emerson, 2021). For each language, a broad-coverage Head-driven Phrase Structure Grammar (HPSG) is maintained separately from its associated treebank, which is annotated not with full syntactic analyses but with *discriminants* (Carter, 1997) such as prepositional phrase attachment sites which constrain the set of possible parses in a way that is independent of the grammar. Then, when the grammar is updated, the discriminants are used to automatically update the treebank while also providing data to validate the updated theory (Oepen et al., 2004; Flickinger et al., 2017). Pushing the envelope further are the Decompositional Semantics Initiative (White et al., 2016) and MegaAttitude project (White and Rawlins, 2016).[2] In these projects, annotating large-scale corpora with the phenomena that are posited to underly linguistic theories in question — such as Dowty (1991)'s proto-role properties, or entailments corresponding to neg-raising (An and White, 2020) and projection (White and Rawlins, 2018) — has facilitated insights regarding argument selection (Reisinger et al., 2015) and lexically-specified syntactic subcategorization rules (White, 2021), as well as automatically inducing lexicon-level ontologies of semantic roles (White et al., 2017) and event structure (Gantt et al., 2021) that are derived directly from the phenomena they are designed to explain.

The lesson of Empiricism is that for a model to work, it must be learned from data; while Rationalism tells us that for a model to be intelligible and general, it must be grounded in theory. A wealth of innovative prior work shows us that Pragmatism is possible: we can have both.

2.2 Make Data Reflect Use

A satisfying data-driven theory of a few linguistic phenomena is not sufficient as a backbone for general language understanding systems. The second relevant lesson of Pragmatism is that the model must be fit to its use. The approaches reviewed in Section 2.1 are, by and large, targeted at theoretical questions in language syntax and semantics, *e.g.*, regarding the nature of syntactic structure across many languages (Bender et al., 2002) or the syntactic realization of a verb's arguments (Reisinger et al., 2015). On the other hand, general-purpose

[1] See Riezler (2014) for a discussion of this issue in NLP.

[2] https://decomp.io, https://megaattitude.io

language processing relies on a huge amount of lexical and world knowledge and inferential ability which is outside the scope of traditional linguistic theories. While general-purpose syntactic and semantic representations have some direct uses in NLP end-tasks, such as for search and retrieval (Schäfer et al., 2011; Shlain et al., 2020), their application in downstream tasks requiring higher-level reasoning or inference, like reading comprehension, translation, and information extraction has been less fruitful. This is at least in part because these theories are far insufficient to serve as mechanistic accounts of the inferential phenomena which are required to perform those tasks.

Constructing theories which *can* account for such phenomena is a monumental challenge. But it is a challenge which, I argue, we must address if we want to pursue the goal of accurate, reliable, and intelligible systems. Pragmatism tells us the first step is to catalog the phenomena we wish to explain in a way that is amenable to theoretical modeling. This will require carefully carving up the space of phenomena in such a way that useful abstractions can be designed to facilitate future progress (Dijkstra, 1974); Section 4 will discuss considerations on how to do this well.

3 Scalable, Data-Driven Theory

The principles in Section 2 imply a general framework for building useful theories, which I call *data-driven theory*: First, annotate data in a theoretically-minimal way, scoped carefully to reflect specific phenomena that we want to explain; then, automatically induce theories to explain those phenomena using computational methods like machine learning. But how does this method scale in practice? Even if the resulting theories are high-quality, requiring annotated data limits their scope to orders of magnitude less than what is leveraged by standard pretrained models (Brown et al., 2020; OpenAI, 2023; Bai et al., 2022).

Black-Box Data Simulators This is where black-box models may actually be able to help. Even if they are uninterpretable on their own, their high accuracy and data efficiency means they can be used as *data simulators*, generating phenomenological data — potentially at a level of granularity or exhaustivity unobtainable from humans — which can be fed into another, more interpretable algorithm to distill a theory from it. This is the approach we take in Michael and Zettlemoyer (2021), described in Section 5: We first train a black-box model to generate QA-SRL questions, where each role is labeled with only a single question in the training data. Then we decode full question *distributions* from this model, and induce an ontology of semantic roles by clustering arguments based on the overlap of their question distributions. While this work required a large training set of QA-SRL annotations (FitzGerald et al., 2018), it may now be possible to do such experiments without large-scale human data annotation at all, thanks to recent advances in instruction following by language models (OpenAI, 2023; Bai et al., 2022).

It may seem like the use of a black-box model as a data simulator begs the question: if our concern is that the black-box model isn't learning the underlying function we hope it is, then doesn't using it to simulate data risk leading us to a theory of the wrong function? Well, yes — *but the theory lets us do something about it*. Examining the "wrong" parts of the resulting theory (*e.g.*, induced semantic roles that don't match what we intuitively expect, or that lead to downstream predictions we think are wrong), and their connection to the training data, will identify one of the following:

- Systematic gaps in the data or mistakes in the model used for data simulation — which can then be filled or corrected.
- Mistakes in the modeling assumptions used in the theory induction algorithm — giving us information useful for improving our theories.
- Mistakes in our intuition about what the theory should have looked like in the first place — which means we've learned something.

All of these are positive outcomes for scientific progress. See Michael and Zettlemoyer (2021) for an in-depth analysis of this kind.

Scaling in Complexity Even if we can scale a theory's *size*, *e.g.*, to a large knowledge base or linguistic ontology, this does not handle the case of more *complex* tasks, with more nuanced relations between input and output (such as open-ended question answering or common sense inference tasks). Since theoretical modeling requires narrowly-scoped data (discussed more in Section 4), I do not expect that we can construct theories of such broad capabilities in the short term. However, if we carve up the space of tasks to start with theories of simple sub-phenomena of reading and inference, then we may be able to bootstrap from these theories to annotate and make sense of more complex data — for example, one can imagine eventually inducing rich, broad-coverage entailment graphs in the style of Berant et al. (2015) or McKenna et al. (2023) on the basis of comprehensive annotations of structured inferences in context. A complete or "true" theory of complex NLP tasks may be impossible even in principle, but — in the spirit of Pragmatism — that doesn't mean we can't construct theories that are *useful* for understanding and controlling AI systems. How my proposed framework scales with task complexity is unclear as of yet, but scalable theories of narrow phenomena provide a step in the right direction.

4 Data: Scoping Language Behaviors

The first step to developing theories of linguistic structure in an empirical, data-driven way is to carefully choose the data. To guide this, I propose **Four Principles of Scientific Data for NLP**:

1. **Theoretical minimalism.** The data should rely on as few theoretical assumptions as possible. For example, to capture natural language syntax, you should directly annotate the *phenomena* that you intend your syntactic theory to explain rather than directly annotating theoretical constructs like syntactic trees. This creates the space for an underlying theory to meaningfully explain this data.

2. **Broad comprehensibility.** To facilitate on-demand data collection at large scale in new domains, it should be possible and affordable to recruit non-expert annotators to label large amounts of data (*e.g.*, through crowdsourcing), or it should be feasible to automatically generate the data (*e.g.*, with language models).

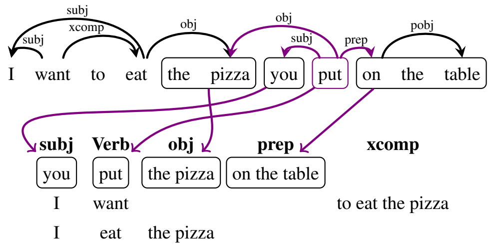
3. **Annotation constraints.** The output space of the task should be sufficiently constrained to allow for exhaustive coverage of the phenomena of interest. A task which is too open-ended leads annotators to produce a convenience sample of the output space, resulting in biased data that doesn't capture the full complexity of the phenomena of interest (Cai et al., 2017; Gururangan et al., 2018).

4. **Narrow scope.** The task should not capture too much complexity in the relationship between input and output. Not only can this make it difficult for annotators to reliably produce high-quality data, but it makes it more difficult to model the phenomena expressed in the data with a comprehensible theory.

Principles 1 and 2 instantiate Section 2.1's recommendation to decouple data from theory, while Principles 2, 3 and 4 help make it tractable to develop broad-coverage, comprehensible theories from this data. The final requirement is that the data reflect relevant downstream use cases (Section 2.2), which in our case means it should encode phenomena representing the intended behavior of AI systems performing language tasks.[3] I focus on a key strategy to meet these requirements: *annotating natural language with natural language question-answer pairs*. Question answering has long been used as a general-purpose format for testing language comprehension or executing practical language tasks (Gardner et al., 2019b; McCann et al., 2018; McCarthy, 1976), as nearly any task can be phrased as a question and questions which test a reader's comprehension of a text need not require specialized linguistic or theoretical expertise to answer. The downside of this great generality is that data annotation tends to be highly under-constrained and unsystematic (Gardner et al., 2019a), so we must judiciously constrain the space of question-answer pairs we use in accordance with the Four Principles.

This work is focused on annotations of shallow semantic structure: syntax, semantic roles, and other predicate–argument structure relations expressed in text. He et al. (2015) pioneered the use of question-answer pairs as a proxy for such structure in *Question-Answer driven Semantic Role Labeling* (QA-SRL), a framework for annotating English verbal predicate–argument relations using simple, highly constrained question-answer pairs. In the rest of this section, I will describe three data annotation projects which explored variations of this approach, illustrating some of the basic tensions between the Four Principles.

[3] This work is concerned with normative theories of AI behavior when performing language tasks. Insofar as we wish to produce theories of AI behavior which are comprehensible to us, aligned with our intuitions, and allow us to interface fluidly with machines using language, this goal should mostly be aligned with developing *descriptive* theories of *human* language behavior, which can then be used to constrain and guide AI behavior. The relationship between these theories and their importance for interacting with machines are discussed more in Chapter 2 of Michael (2023).



Dependency	Question	Answer
want → I	What wants to eat something?	I
eat → I	What would eat something?	I
eat → pizza	What would something eat?	the pizza
put → you	What put something?	you
put → pizza	What did something put?	the pizza
on → table	What did something put something on?	the table

Figure 1: Question-answer pair generation for human-in-the-loop parsing (He et al., 2016). We use the predicted CCG category of each verb to generate the questions, which are in in one-to-one relation with syntactic dependencies in the sentence. This one-to-one assumption was ultimately too strong, as workers answer these questions according to semantics and not just syntax.

4.1 Human-in-the-Loop Parsing

He et al. (2016) introduces *human-in-the-loop parsing*. We construct multiple-choice questions from syntactic attachment ambiguities in a parser's n-best list, get crowdsourced workers to answer these questions, and then re-parse the original sentence with constraints derived from the results (Figure 1). Testing on the English CCGbank (Hockenmaier and Steedman, 2007), we find only a small improvement in parser performance. A core challenge is the *syntax–semantics mismatch*, where workers provide answers which are semantically correct but correspond to the wrong syntactic attachment. For example, in the sentence "Kalipharma is a New Jersey–based pharmaceuticals concern that sells products under the Purepac label", workers unanimously answer the question "What sells something?" with "Kalipharma", which is not the syntactic subject of *sells* but a more natural way of referring to the same entity. So even though our annotation task is tightly scoped, our interpretation of the results requires theoretical assumptions which do not match the intuitions of non-expert workers.

4.2 Crowdsourcing Question-Answer Meaning Representations

Michael et al. (2018) takes the opposite tack, broadening the task's scope by gathering open-ended questions from annotators to capture as many semantic relationships as possible in the source sentence. This requires adding many careful constraints and incentives to the crowdsourcing procedure, but we are careful to allow for open-ended questions that express annotator creativity. The result is a dataset of *Question-Answer Meaning Representation* (QAMR) annotations over English encyclopedic and news text covering many interesting phenomena (see Figure 2). However, achieving high recall of predicate–argument relations is not economical, requiring high annotation redundancy, and the unstructured question-answer pairs are hard to use downstream. The most successful use of QAMR in follow-up work is probably Stanovsky et al. (2018), where we convert QAMRs into Open Information Extraction tuples, but have to run the questions through a syntactic parser to do so. The lesson from these results is that leaving the annotation space too open and unconstrained leads to difficulties with recall and challenges with downstream modeling and theory.

Pierre Vinken, 61 years old, will join the board as a nonexecutive director Nov. 29.

Who will **join** as **nonexecutive director**? - Pierre Vinken
What is **Pierre**'s last name? - Vinken
Who is **61 years old**? - Pierre Vinken
How **old** is **Pierre Vinken**? - 61 years old
What will he **join**? - the board
What will he **join the board** as? - nonexecutive director
What type of **director** will **Vinken** be? - nonexecutive
What day will **Vinken join the board**? - Nov. 29

Figure 2: Example Question-Answer Meaning Representation (Michael et al., 2018). Non-stopwords drawn from the source sentence are in bold. QAMR question–answer pairs capture a wide variety of relations, but are unstructured and hard to use downstream without extra tools such as a syntactic parser — here, our annotation task was too unconstrained and task scope too broad.

4.3 Large-Scale QA-SRL Parsing

FitzGerald et al. (2018) returns to QA-SRL. In the original QA-SRL work (He et al., 2015), trained annotators specify the questions using drop-down menus in an excel spreadsheet. In this work, we streamline and scale up data collection, gathering high-coverage annotations for over 64,000 sentences with a two-stage generate/validate crowdsourcing pipeline (see Table 1 for examples). We increase annotation speed, reliability, and coverage using an autocomplete system which tracks the syntactic structure of QA-SRL questions as the annotator types, using it to suggest completions as well as whole questions. In terms of semantic richness and annotation constraints, these annotations

*The plane was **diverting** around weather formations over the Java Sea when contact with air traffic control (ATC) in Jakarta was **lost**.*

wh	aux	subj	verb	obj	prep	obj2	?	Answer
What	was		being diverted		around		?	*weather formations*
What	was		diverting				?	*The plane*
What	was		being diverted				?	*The plane*
What	was		lost				?	*contact with air traffic control*
Where	was	something	lost				?	*over the Java Sea*

Table 1: QA-SRL question-answer pairs from the development set of the QA-SRL Bank 2.0 (FitzGerald et al., 2018). We constrained the questions with a non-deterministic finite automaton (NFA) encoding English clause structure for question autocomplete and auto-suggest. This facilitated high-quality, high-coverage annotation at scale while providing the expressiveness to represent the semantic role relations within each sentence.

are somewhere between our work on human-in-the-loop parsing and question-answer meaning representations. The constrained task and high coverage allow us to train high-quality QA-SRL predictors and enables future work on semantic role induction (Section 5.1) and controlled question generation (Section 5.2).

Takeaways Our results over the course of these projects suggests that we should search for tasks in a "goldilocks zone": Their scope should not be so constrained or beholden to prior theory as to be unintuitive, but not so unconstrained that it is hard to get exhaustive and reliable annotation of interesting phenomena. As annotation constraints depend on *some* prior theory of the phenomena to be captured, these constraints need to be carefully chosen so as to minimize arbitrary assumptions in the task setup and make sure the task is natural for annotators. In the case of QA-SRL, the prior theory we incorporated is a small grammar fragment of English encompassing QA-SRL questions. Our findings support that QA-SRL, with the annotation aids developed in FitzGerald et al. (2018), strikes a good balance of the Four Principles.

Labels	Questions	
`A1` (98%)	What is given?	.30
	What does something give something?	.21
	What does something give?	.20
	What is something given?	.11
`A0` (98%)	What gives something?	.44
	What gives something something?	.27
	What gives something to something?	.08
`A2` (94%)	What is given something?	.28
	What does something give something to?	.18
	What does something give something?	.14
	What is given?	.09
	What is something given to?	.07
`TMP` (46%),	When does something give something?	.20
`ADV` (22%),	How does something give something?	.09
`MNR` (12%)	When is something given?	.09
	When is something given something?	.09
`PNC` (30%),	Why does something give something?	.18
`ADV` (22%),	Why does something give up something?	.07
`TMP` (14%)	Why is something given something?	.07

Table 2: Roles for *give* produced by Michael and Zettlemoyer (2021). For each predicate, we cluster its arguments in PropBank based on the similarity of the distributions of QA-SRL questions our model generates. In this case, core arguments are captured almost perfectly, exhibiting both passive and dative alternations.

5 Theory: From Language, Structure

In this section, I will describe two projects which show how QA-SRL can be used to build a data-driven theory which is directly applicable in downstream tasks.

5.1 Inducing Semantic Roles Without Syntax

Michael and Zettlemoyer (2021) show how to use QA-SRL to automatically induce an ontology of semantic roles, leveraging a key insight: the *set* of QA-SRL questions that are correctly answered by a given answer span identifies an underlying semantic role through its syntactic alternations, which are representative of the phenomena that a semantic role ontology like PropBank is designed to explain. We leverage this insight by using a trained QA-SRL question generator as a data simulator, generating a full distribution over (simplified) QA-SRL questions for each argument of a verb appearing through an entire corpus. Clustering these distributions of questions according to a simple maximum-likelihood objective yields a set of discrete semantic roles that exhibits high agreement with existing resources (see Table 2). This presents an approach which could potentially be used to develop semantic role ontologies in new domains where they are not currently available, with directions for improving QA-SRL data toward the end of automatically inducing better semantic roles.

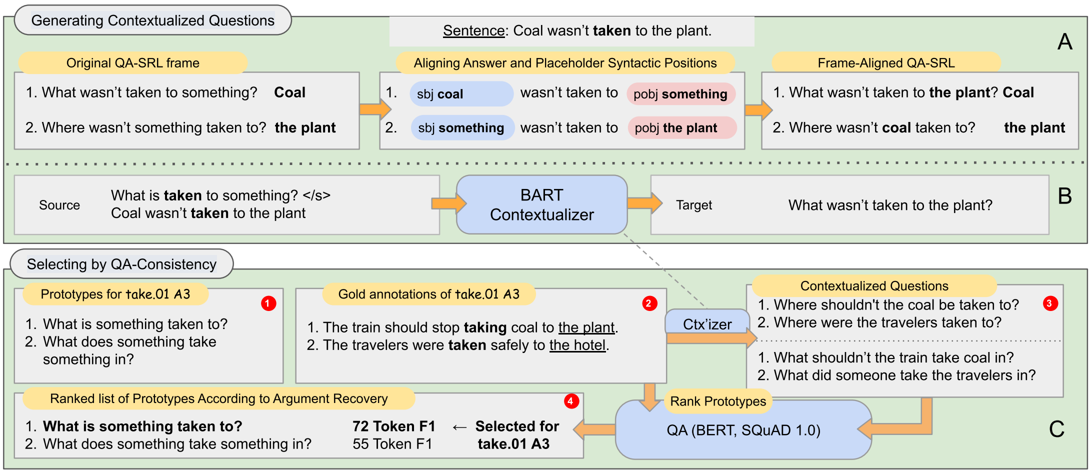


Figure 3: Overview of Pyatkin et al. (2021)'s approach. The natural correspondence between QA-SRL questions and semantic roles allows us to use QA-SRL question templates in a planning step to successfully generate questions for any PropBank semantic role, even when the corresponding argument doesn't appear in the source sentence (a situation never encountered in training data). **A: Construction of Frame-Aligned QA-SRL** using syntactic information inferred by the autocomplete NFA from FitzGerald et al. (2018), *i.e.*, leveraging our (minimal) theoretical assumptions about argument structure. **B: Contextualizing questions** by feeding a prototype question and context into a neural model that outputs a Frame-Aligned QA-SRL question. **C: Selecting prototype questions** by testing each prototype (1) against a sample of arguments for each role (2). After contextualization (3), each question is fed into a QA model and we choose the prototype that most often recovers the correct argument (4).

5.2 Asking it All: Generating Contextualized Questions for any Semantic Role

Pyatkin et al. (2021) use QA-SRL to build a controllable question generation system. The task is to generate fluent questions asking about the arguments corresponding to specific semantic roles in context (see Figure 3 for an overview). The challenge is a lack of training data, as QA-SRL questions are not fully natural and are not annotated for roles which aren't expressed in a sentence. We leverage two key insights: First, we find that QA-SRL questions generally correspond to the same role across many contexts. So we prime our question generation system with a template QA-SRL question corresponding to the correct role, leading it to generate semantically correct questions even when the answer isn't present in the sentence. Second, we use the syntactic structure of QA-SRL questions to align the placeholders (*someone*, *something*) in each question with the answers of other questions, translating QA-SRL questions into more fluent ones closer to those in QAMR.

Takeaways Together this work illustrates not only the promise for the development of large-scale ontologies in a data-driven way (Section 5.1), but it also illustrates how having these ontologies computationally grounded in the phenomena they are designed to explain, *i.e.*, question-answer pairs, facilitates ontology's the downstream use (Section 5.2). It's not hard to imagine next steps incorporating an induced ontology of semantic roles into Pyatkin et al. (2021)'s system to obviate the need for a pre-specified role ontology altogether.

6 Concluding Thoughts

I have proposed *scalable, data-driven theory* as a Pragmatist paradigm for scientific progress in NLP. To develop scalable theories, one should:

1. Collect carefully-scoped data that directly represents a phenomenon of interest while imposing minimal prior theoretical assumptions,
2. Increase the data's scale and coverage using a learned black-box data simulator,
3. Induce comprehensible models of this high-coverage data with machine learning, and
4. Examine the results to debug and improve the theory and data, progressing our scientific understanding of the phenomenon of interest.

Using QA-SRL, I have shown how to leverage black-box data simulation together with simple probabilistic modeling to automatically induce an ontology of semantic roles which is directly and comprehensibly grounded in phenomena that the theory of semantic roles is meant to explain. This not only lays the groundwork for new scalable theoretical developments in semantic representation, but can serve as an example to guide future work on scalable theories in other domains.

Why now?

The justification for building scalable, data-driven theories can be summarized as follows:

1. To build systems which generalize in controllable, predictable ways, we need comprehensible theories of their desired behavior.
2. However, the behaviors we wish to produce in AI and NLP are too complex for us to easily write down theories of how they should work.
3. So instead, we must use machines (*i.e.*, statistical models) to construct our theories on the basis of data in a scalable way. The role for the scientist here is twofold:
   - to carefully determine the scope of the phenomena to be explained and curate the data accordingly, and
   - to define the meta-theory which relates the learned theory to the data.

This argument could have been made at any point in the history of NLP, so why do I make it now?[4] I think the argument would have been viewed as premature in the *era of underfitting* prior to the deep learning revolution. Statistical models like CRFs (Lafferty et al., 2001) struggle even in-distribution on tasks like syntactic and semantic parsing, let alone complex end tasks involving question answering or language generation. The problem at that time was to build models expressive enough to perform well while tractable enough to learn from data. Pre-neural systems were weak enough that many thought they would benefit from hand-curated linguistic resources like PropBank (Palmer et al., 2005).

With deep learning, these factors all changed: the limits of hand-curated resources like PropBank have been surpassed, and neural models fit all kinds of data distributions, leaving us face-to-face with the problem of generalization and the need for data-driven theory. Furthermore, we have new tools for data simulation; the role induction algorithm in Michael and Zettlemoyer (2021) would not have been workable without a neural model to simulate dense annotation of QA-SRL questions. So we are finally in a position to make such theories scalable.

Looking forward

As argued above, a critical role for the scientist in developing data-driven theories is to define scopes of phenomena to be explained, carving linguistic behavior at useful joints. I hope to have demonstrated that the concept of *semantic roles* provides such a useful scope, where its corresponding phenomena (as QA-SRL) can be effectively annotated at scale (Section 4.3), tractably modeled with a comprehensible theory (Section 5.1), and used for downstream tasks (Section 5.2). Moving forward requires carefully choosing more such useful concepts and using them to scope phenomena, define and induce theories, and tie these data and theories into downstream applications.

Extending the paradigm of scalable theory to more facilities of language (*e.g.*, syntax, word sense, or coreference) and more complex phenomena (*e.g.*, representations of world knowledge, common sense, or reasoning) remains a major challenge. As the scope of the phenomena to be represented increases, greater annotation constraints will be necessary in order to ensure that these phenomena are adequately covered. However, doing so while maintaining theoretical minimalism is challenging. My hope is that scalable theories of narrowly-scoped subphenomena (*e.g.*, semantic roles) will provide constraints that make more complex tasks tractable to exhaustively annotate, without introducing the same problems as in the Rationalist paradigm where inconsistencies, underspecification, and arbitrary theoretical choices limit the usefulness of the data. In this way, it may be possible to bootstrap from narrowly-scoped theories into progressively broad accounts of language structure, meaning, and intelligent behavior.

At this point, such talk is speculation. It is unclear how data-driven theory will generalize to more complex tasks. However, in this work I hope to have provided an argument this kind of work is at least worth attempting, and perhaps laid some groundwork and principles which can be used as a starting point for it to be done in the future.

[4]Similar arguments have been made before in grammar engineering (Oepen et al., 2004; Flickinger et al., 2017) and the Decompositional Semantics Initiative (White et al., 2016), while in linguistic typology, Haspelmath (2010)'s *framework-free grammatical theory* makes similar points about the relationship between data and theory. My approach differs from these in my focus on applications in NLP where the vastness and complexity of the domain becomes more of a challenge.

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Thesis Distillation:
Investigating The Impact of Bias in NLP Models on Hate Speech Detection

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Abstract

This paper is a summary of the work done in my PhD thesis. Where I investigate the impact of bias in NLP models on the task of hate speech detection from three perspectives: explainability, offensive stereotyping bias, and fairness. Then, I discuss the main takeaways from my thesis and how they can benefit the broader NLP community. Finally, I discuss important future research directions. The findings of my thesis suggest that the bias in NLP models impacts the task of hate speech detection from all three perspectives. And that unless we start incorporating social sciences in studying bias in NLP models, we will not effectively overcome the current limitations of measuring and mitigating bias in NLP models.

1 Introduction

Hate speech on social media has severe negative impacts, not only on its victims (Sticca et al., 2013) but also on the moderators of social media platforms (Roberts, 2019). This is why it is crucial to develop tools for automated hate speech detection. These tools should provide a safer environment for individuals, especially for members of marginalized groups, to express themselves online. However, recent research shows that current hate speech detection models falsely flag content written by members of marginalized communities, as hateful (Sap et al., 2019; Dixon et al., 2018; Mchangama et al., 2021). Similarly, recent research indicates that there are social biases in natural language processing (NLP) models (Garg et al., 2018; Nangia et al., 2020; Kurita et al., 2019; Ousidhoum et al., 2021; Nozza et al., 2021, 2022).

Yet, the impact of these biases on the task of hate speech detection has been understudied. In my thesis, I identify and study three research problems: 1) the impact of bias in NLP models on the performance and explainability of hate speech detection models; 2) the impact of the imbalanced representation of hateful content on the bias in NLP models; and 3) the impact of bias in NLP models on the fairness of hate speech detection models.

Investigating and understanding the impact of bias in NLP on hate speech detection models will help the NLP community to develop more reliable, effective, and fair hate speech detection models. My research findings can be extended to the general task of text classification. Similarly, understanding the origins of bias in NLP models and the limitations of the current research on bias and fairness in NLP models, will help the NLP community develop more effective methods to expose and mitigate the bias in NLP models.

In my thesis and this paper, I, first, critically review the literature on hate speech detection (§2) and bias and fairness in NLP models (§3). Then, I address the identified research problems in hate speech detection, by investigating the impact of bias in NLP models on hate speech detection models from three perspectives: 1) the explainability perspective (§4), where I address the first research problem and investigate the impact of bias in NLP models on their performance of hate speech detection and whether the bias in NLP models explains their performance on hate speech detection; 2) the offensive stereotyping bias perspective (§5), where I address the second research problem and investigate the impact of imbalanced representations and co-occurrences of hateful content with marginalized identity groups on the bias of NLP models; and 3) the fairness perspective (§6), where I address the third research problem and investigate the impact of bias in NLP models on the fairness of the task of hate speech detection. For each research problem, I summarize the work done to highlight its main findings, contributions, and limitations. Thereafter, I discuss the general takeaways from my thesis and how it can benefit the NLP community at large (§7). Finally, I present directions for future research (§8).

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The findings of my thesis suggest that the bias in NLP models has an impact on hate speech detection models from all three perspectives. This means that we need to mitigate the bias in NLP models so that we can ensure the reliability of hate speech detection models. Additionally, I argue that the limitations and criticisms of the currently used methods to measure and mitigate bias in NLP models are direct results of failing to incorporate relevant literature from social sciences. I build on my findings on hate speech detection and provide a list of actionable recommendations to improve the fairness of the task of text classification as a short time solution. For a long-term solution to mitigate the bias in NLP models, I propose a list of recommendations to address bias in NLP models by addressing the underlying causes of bias from a social science perspective.

2 Survey: Hate speech

In Elsafoury et al. (2021a), I provide a comprehensive literature review on hate speech and its different forms. Furthermore, I review the literature of hate speech detection for different methods proposed in the literature accomplishing every step in the text classification pipeline. Then, I point out the limitations and challenges of the current research on hate speech detection.

The main contributions of this survey are: 1) There are different definitions and forms of hate speech. One of the main limitations of current studies on hate speech detection, is the lack of distinction between hate speech and other concepts like cyberbullying. 2) There are many resources of hate speech related datasets in the literature, that allow the development of new hate speech detection models. However, these datasets have many limitations, including limited languages, biased annotations, class imbalances, and user distribution imbalances. 3) One of the main limitations of the current research on hate speech detection, is the lack of understanding how it is impacted by the bias in NLP models. This limitation is what I aim to address in my thesis.

Limitations: One of the main limitations of this survey, is that it focuses on hate speech detection only as a supervised text classification task. However, recent studies propose a framework to automate and enforce moderation policies, instead of training machine learning models to detect hate speech (Calabrese et al., 2022). Similarly, this review focuses on hate speech datasets that are collected only from social media platforms. However, recently, generative models have become more popular and started to be used in generating hate speech related datasets (Hartvigsen et al., 2022).

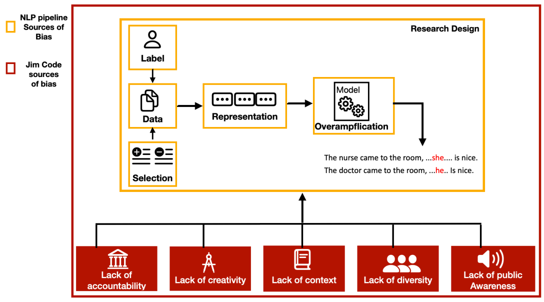

Figure 1: The sources of bias in supervised NLP models

3 Survey: Bias and Fairness in NLP

In Elsafoury and Abercrombie (2023), I review the literature on the definitions of bias and fairness in NLP models. Additionally, I review the literature on the origins of bias in NLP models from two perspectives: 1) NLP pipeline as discussed in Shah et al. (2020); Hovy and Prabhumoye (2021), and 2) social sciences and critical race theory as discussed in Benjamin (2019); Broussard (2023); Nobel (2018).

There are many definitions of the term *bias*. The normative definition of bias, in cognitive science, is: *"Behaving according to some cognitive priors and presumed realities that might not be true at all"* (Garrido-Muñoz et al., 2021). And the statistical definition of bias is "*A systematic distortion in the sampled data that compromises its representatives"* (Olteanu et al., 2019). The statistical definition of bias is the one used in this thesis.

In this work, I argue that the sources of bias in the NLP pipeline originate in the social sciences and that they are direct results of the sources of bias from the social science (Jim code) perspective as shown in Figure 1.

The main contribution of this literature review is reviewing the sources of bias in NLP models from the social science perspective as well as the NLP perspective. This survey points out the limitations of the currently used methods to measure and mitigate bias in NLP models. It also suggests that these limitations are direct results of the lack of inclusion of social science literature in the development of methods that quantify and mitigate bias in NLP. Finally, I share a list of actionable suggestions and recommendations with the NLP community on how to mitigate the limitations discussed in studying bias in NLP (§7).

Limitations: One main limitation of this survey is that it reviews the literature on the sources of bias in the NLP pipeline, only in supervised models. Unsupervised NLP models might have different sources of bias. The second limitation is regarding the reviewed literature on the sources of bias in social sciences, where I rely mainly on three books *Algorithms of Oppression: How Search Engines Reinforce Racism* by Safiya Nobel (Nobel, 2018), *Race after Technology: Abolitionist Tools for the New Jim Code* by Ruha Benjamin Benjamin (2019), and *More than a glitch: Confronting race, gender, and ability bias in tech* by Meredith Broussard (Broussard, 2023). A more comprehensive literature review to review studies that investigate the direct impact of social causes on bias in NLP would be important future work. However, to the best of my knowledge, this area is currently understudied.

In the next sections, I address the understudied impact of bias in NLP models on hate speech detection models. I investigate that impact from the following perspectives.

4 The explainability perspective

For this perspective, I investigate the performance of different hate speech detection models and whether the bias in NLP models explains their performance on the task of hate speech detection. To achieve that, I investigate two sources of bias:

1. **Bias introduced by pre-training:** where I investigate the role that pre-training a language model has on the model's performance, especially when we don't know the bias in the pre-training dataset. I investigate the explainability of the performance of contextual word embeddings, also known as language models (LMs), on the task of hate speech detection. I analyze BERT's attention weights and BERT's feature importance scores. I also investigate the most important part of speech (POS) tags that BERT relies on for its performance. The results of this work suggest that pre-training BERT results in a syntactical bias that impacts its performance on the task of hate speech detection (Elsafoury et al., 2021b).

Based on these findings, I investigate whether the social bias resulting from pre-training contextual word embeddings explains their performance on hate speech detection in the same way syntactical bias does. I inspect the social bias in three LMs (BERT (base and large) (Devlin et al., 2019), ALBERT (base and xx-large) (Lan et al., 2020), and ROBERTA (base and large) (Liu et al., 2019)) using three different bias metrics, CrowS-Pairs (Nangia et al., 2020), StereoSet (Nadeem et al., 2021), and SEAT (May et al., 2019), to measure gender, racial and religion biases. First, I investigate whether large models are more socially biased than base models. The Wilcoxon statistical significance test (Zimmerman and Zumbo, 1993) indicates that there is no statistical significant difference between the bias in base and large models in BERT and RoBERTa, unlike the findings of (Nadeem et al., 2021). However, there is a significant difference between the base and xx-large ALBERT. These results suggest that large models are not necessarily more biased than base models, but if the model size gets even bigger, like ALBERT-xx-large, then the models might get significantly more biased. Since there is no significant difference between the base and large models, I only use base LMs in the rest of the thesis.

Then, I follow the work of (Steed et al., 2022; Goldfarb-Tarrant et al., 2021) and use correlation as a measure of the impact of bias on the performance of the task of hate speech detection. The Pearson's correlation coefficients between the bias scores of the different models and the F1-scores of the different models on the used five hate-speech-related datasets are inconsistently positive as shown in Figure 2. However, due to the limitations of the metric used to measure social bias, as explained in Blodgett et al. (2021), the impact of the social bias in contextual word embeddings on their performance on the task of hate speech detection remains inconclusive.

2. **Bias in pre-training datasets:** Where I investigate the impact of using NLP models pre-trained on data collected from social media platforms like Urban dictionary and 4 & 8 Chan, which are famous for having sexist and racist posts (Nguyen et al., 2017; Papasavva et al., 2020). I investigate the performance of two groups of static word embeddings (SWE) on hate speech detection. The first group, social-media-based, pre-trained on biased datasets that contain hateful content. This group consists of Glove-Twitter (Mozafari

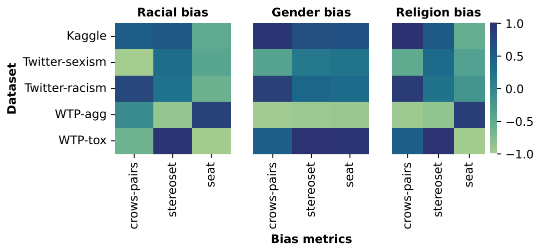

Figure 2: Heatmap of the Pearson correlation coefficients between the performance (F1-scores) of LMS on the different hate speech datasets and the social bias scores.

et al., 2020), Urban dictionary (UD) (Wilson et al., 2020), and 4& 8 Chan (chan) (Voué et al., 2020) word embeddings. The second group of word embeddings, informational-based, is pre-trained on informational data collected from Wikipedia and Google New platforms. This group contains the word2vec (Mikolov et al., 2021) and Glove-WK word (Pennington et al., 2014) embeddings. SWE in this part of the work because there are SWE that are pre-trained on datasets collected from social media platforms like urban dictionary, and 4 &8 Chan. First, I investigate the ability of the five different word embeddings, to categorize offensive terms in the Hurtlex lexicon. Then, I investigate the performance of Bi-LSTM model with an un-trainable embeddings layer of the five word embeddings on the used five hate-speech-related datasets. The results indicate that the word embeddings that are pre-trained on biased datasets social-media-based, outperform the other word embeddings that are trained on informational data, informational-based on the tasks of offenses categorization and hate speech detection (Elsafoury et al., 2022b).

Based on these findings, I inspect the impact of social bias, gender, and racial, in the SWE on their performance on the task of hate speech detection. To measure the social bias in the SWE, I use the following metrics from the literature: WEAT (Caliskan et al., 2017), RNSB (Sweeney and Najafian, 2019), RND (Garg et al., 2018), and ECT (Dev and Phillips, 2019). Then, I use Pearson's correlation to investigate whether the social bias in the word embeddings explains their performance on the task of hate speech detection. Similar to LMs, the results indicate an inconsistent positive correlation between the bias scores and the F1-sores of the Bi-LSTM model using the different word embeddings as shown in Figure 3. This lack of positive correlation could be due to limitations in the used metrics to measure social bias in SWE (Antoniak and Mimno, 2021). These results suggest that the impact of the social bias in the SWE on the performance of the task of hate speech detection is inconclusive.

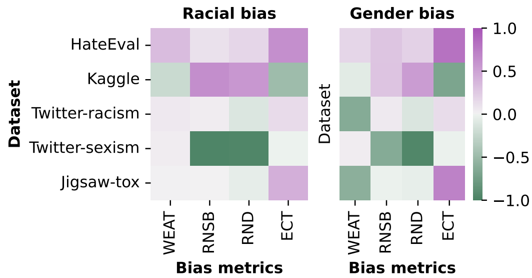

Figure 3: Heatmap of the Pearson correlation coefficients between the performance (F1-scores) of SWE on the different hate speech datasets and the social bias scores.

Contributions: The main findings and contributions of the explainability perspective can be summarized as: **1)** The results provide evidence that the syntactical bias in contextual word embeddings, resulting from pre-training, explains their performance on the task of hate speech detection. **2)** The results suggest that pre-training static word embeddings on biased datasets from social-media-based sources improves and might explain the performance of the word embeddings on the task of hate speech detection. **3)** For both static and contextual word embeddings, there is no strong evidence that social bias explains the performance of hate speech detection models. However, due to the limitations of the methods used to measure social bias in both static and contextual word embeddings, this finding remains inconclusive.

Limitations: one of the main limitations of this work is using social bias metrics from the literature, which have their limitations as argued in Blodgett et al. (2021); Antoniak and Mimno (2021). Additionally, the work done here, is limited to hate speech datasets that are in English. Similarly, the social bias inspected in the different word embeddings is based on Western societies, where the marginalized groups might be different in different societies. It is also important to mention that the findings of this work are limited to the used datasets and models and might not generalize to other models or datasets.

5 The offensive stereotyping bias perspective

In Elsafoury et al. (2022a); Elsafoury (2023), I investigate how the hateful content on social media and other platforms that are used to collect data and pre-train NLP models, is being encoded by those NLP models to form systematic offensive stereotyping (SOS) bias against marginalized groups of people. Especially with imbalanced representation and co-occurrence of the hateful content with the marginalized identity groups. I introduce the systematic offensive stereotyping (SOS) bias and formally define it as "*A systematic association in the word embeddings between profanity and marginalized groups of people.*" (Elsafoury, 2022).

I propose a method to measure it and validate it in static (Elsafoury et al., 2022a) and contextual word embeddings (Elsafoury et al., 2022a). Finally, I study how it impacts the performance of these word embeddings on hate speech detection models. I propose the normalized cosine similarity to profanity (NCSP) metric, which is a metric to measure the SOS bias in static word embeddings using the cosine similarity between a list of swear words and non-offensive identity (NOI) words that describe three marginalized groups (Women, LGBTQ, and Non-White) described in Table 1. As for measuring the SOS bias in contextual word embeddings, I propose the SOS_{LM} metric. The SOS_{LM} metric uses the masked language model (MLM) task to measure the SOS bias, similar to the work proposed in StereoSet (Nadeem et al., 2021) and CrowS-Pairs (Nangia et al., 2020) metrics. Instead of using crowdsourced sentence pairs that express socially biased sentences and socially unbiased sentences, I use synthesized sentence pairs that express profane sentences and non-profane sentence-pairs. I measure the SOS bias scores in 15 static word embeddings (Elsafoury et al., 2022a) and 3 contextual word embeddings (Elsafoury, 2023). The results show that for static word embeddings, there is SOS bias in all the inspected word embeddings, and it is significantly higher towards marginalized groups as shown in table 2. Similarly, Figure 4 show that all the inspected contextual word embeddings are SOS biased, but the SOS bias scores are not always higher towards marginalized groups. Then, I validate the SOS bias itself by investigating how reflective it is of the hate that the same marginalized groups experience online. The correlation results, using Pearson correlation coefficient, indicate that there is a positive correlation between the measured SOS bias in static and contextual word embeddings and the published statistics of the percentages of the marginalized groups (Women, LGBTQ, and non-white ethnicities) that experience online hate (Hawdon et al., 2015) and the measured SOS bias scores in static word embeddings using the NCSP metric and the SOS_{LM} metric. I also validate the proposed metric to measure the SOS bias in comparison to the social bias metrics proposed in the literature. I use the Pearson correlation coefficient between the social bias scores and the SOS bias scores in the static and the contextual

Attribute	Marginalized	Non-marginalized
Gender	woman, female, girl, wife, sister, daughter, mother	man, male, boy, son, father, husband, brother
Race	african, african american, asian, black, hispanic, latin, mexican, indian, middle eastern, arab	white, caucasian, european, american, european, norwegian, german, australian, english, french, american, swedish, canadian, dutch
Sexual-orientation	lesbian, gay, bisexual, transgender, tran, queer, lgbt,lgbtq,homosexual	hetrosexual, cisgender
Religion	jewish,buddhist,sikh, taoist, muslim	catholic, christian, protestant
Disability	blind, deaf, paralyzed	
Social-class	secretary, miner, worker, machinist, nurse, hairstylist, barber, janitor, farmer	writer, designer, actor, Officer, lawyer, artist, programmer, doctor, scientist, engineer, architect

Table 1: The non-offensive identity (NOI) words used to describe the marginalized and non-marginalized groups in each sensitive attribute. For the disability-sensitive attributes, we use only words to describe disability due to the lack of words used to describe able-bodied.

Word embeddings	**Mean SOS**		
	Women	LGBTQ	Non-white
W2V	0.293	**0.475**	0.456
Glove-WK	0.435	**0.669**	0.234
glove-twitter	**0.679**	0.454	0.464
UD	0.509	**0.582**	0.282
Chan	**0.880**	0.616	0.326
Glove-CC	**0.567**	0.480	0.446
Glove-CC-large	0.318	0.472	**0.548**
FT-CC	0.284	**0.503**	0.494
FT-CC-sws	0.473	0.445	**0.531**
FT-WK	0.528	**0.555**	0.393
FT-WK-sws	**0.684**	0.656	0.555
SSWE	0.619	0.438	**0.688**
Debias-W2V	0.205	0.446	**0.471**
P-DeSIP	0.266	**0.615**	0.354
U-DeSIP	0.266	**0.616**	0.343

Table 2: The mean SOS bias score of each static word embeddings towards each marginalized group. Bold scores reflect the group that the static word embeddings is most biased against (Elsafoury et al., 2022a).

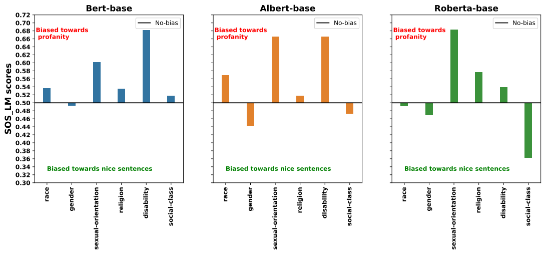

Figure 4: SOS_{LM} bias scores in the different language models (Elsafoury, 2023).

word embeddings. The results show that, for the inspected static word embeddings, the correlation results, according to Pearson correlation, show a negative correlation between the measured SOS bias scores measured using the NCSP metric and the social bias scores (gender and race) measured using the WEAT, RND, RNSB, and ECT metrics. As for the contextual word embeddings, the Pearson correlation coefficient results show a positive correlation between the SOS bias scores measured using the SOS_{LM} metric and the social bias scores (gender, race, and religion) measured using the CrowS-Pairs metric, which could be the case because the SOS_{LM} metric is built on the CrowS-Pairs metric.

Finally, I investigate whether the inspected SOS bias explained the performance of the inspected word embeddings on the task of hate speech detection. I train MLP and Bi-LSTM models with an untrainable layer of the different static word embeddings on four hate-speech-related datasets. As for contextual word embeddings, I fine-tune BERT-base-uncased, ALBERT-base, and ROBERTA-base on six hate speech related datasets. Then, I use Pearson's correlation between the SOS bias scores in the different word embeddings and their F1 scores on the models on the task of hate speech detection. The correlation results, similar to the results in §4, show an inconsistent positive correlation. This could be because the limitations of other social bias metrics in the literature are extended to the proposed metrics. In this case, the impact of the SOS bias in static and contextual word embeddings on their performance on the task of hate speech detection remains inconclusive.

Contributions: The main findings and contributions of the offensive stereotyping perspective can be summarized as follows: **1)** I define the SOS bias, propose two metrics to measure it in static and contextual word embeddings, and demonstrate that SOS bias correlates positively with the hate that marginalized people experience online. **2)** The results of this section provide evidence that all the examined static and contextual word embeddings are SOS biased. This SOS bias is significantly higher for marginalized groups in static word embeddings versus non-marginalized groups. However, this is not the case with the contextual word embeddings. **3)** Similar to social bias, there is no strong evidence that the SOS bias explains the performance of the different word embeddings on the task of hate speech detection.

Limitations: The findings of this work are limited to the examined word embeddings, models, and datasets, and might not generalize to others. Similarly, the SOS bias scores measured using the NCSP metric in the inspected static word embeddings, are limited to the used word lists. Another limitation is regarding my definition of the SOS bias, as I define bias from a statistical perspective, which lacks the social science perspective as discussed in Blodgett et al. (2021); Delobelle et al. (2022). Moreover, I only study bias in Western societies where Women, LGBTQ and Non-White ethnicities are among the marginalized groups. However, marginalized groups could include different groups of people in other societies. I also only use datasets and word lists in English, which limits our study to the English-speaking world. Similar to other works on quantifying bias, our proposed metric measures the existence of bias and not its absence (May et al., 2019), and thus low bias scores do not necessarily mean the absence of bias or discrimination in the word embeddings. Another limitation of this work is the use of template sentence-pairs to measure the SOS bias in contextual word embeddings, which do not provide a real context that might have impacted the measured SOS bias. Since the proposed method used to measure the SOS bias in contextual word embeddings (SOS_{LM}) builds on social bias metrics like CrowS-Pairs and StereoSet, it is highly likely that SOS_{LM} have the same limitations as CrowS-Pairs and StereoSet that are pointed out in Blodgett et al. (2021).

6 The fairness perspective

In Elsafoury et al. (2023), I investigate how different sources of bias in NLP models and their removal impact the fairness of the task of hate speech detection. Improving the fairness of the text classification task is very critical to ensure that the decisions made by the models are not based on sensitive attributes like race or gender.

I first measure three sources of bias according to (Shah et al., 2020; Hovy and Prabhumoye, 2021): representation bias, selection bias, and overamplification bias. Then, I fine-tune three language models: BERT, ALBERT, and ROBERTA on the Jigsaw dataset (Jigsaw, 2018), and measure the fairness of these models using two sets of fairness metrics: threshold-based and threshold-agnostic. The threshold-based metrics are the TPR_gap and the FPR_gap metrics used in Steed et al. (2022); De-Arteaga et al. (2019). As for the threshold-agnostic metric, I use the AUC_gap metric, which is an adaptation of the metrics proposed in Borkan et al. (2019). I investigate the impact of the different sources of bias on the models' fairness by measuring the Pearson correlation coefficient between the bias scores and the fairness score. Then, I investigate the impact of removing the three sources of bias, using different debiasing methods, on the fairness of hate speech detection models. I remove the representation bias using the SentDebias method proposed in Liang et al. (2020) to remove gender, racial, religious and SOS bias on the inspected language models. To remove the selection bias, I aim to balance the ratio of positive examples between the identity groups in the Jigsaw dataset. To achieve that, I generate synthetic positive examples using existing positive examples in the Jigsaw training dataset, but with word substitutions using the NLPAUG tool that uses contextual word embeddings to generate word substitutions (Ma, 2019). To remove the overamplification bias, I aim to ensure that the different identity groups, in the Jigsaw dataset, appear in similar semantic contexts in the training dataset, as proposed in Webster et al. (2020). To achieve that, I use different methods: 1) create data perturbations, 2) I use the sentDebias method to remove the bias representations from the fine-tuned models. Thereafter, I compare the fairness of the inspected language models on the task of hate speech detection before and after removing each of the inspected source of bias. I aim to find the most impactful source of bias on the fairness of the task of hate speech detection and to find out the most effective debiasing method. The results suggest that overamplification and selection bias

	SenseScore		
Model	Gender	Race	Religion
ALBERT-base	$6.9e^{-05}$	0.032	0.006
+ downstream-perturbed-data	↓ $4.2e^{-05}$	↓ 0.002	↓ 0.001
+ downstream-stratified-data	↑ 0.042	0.032	↑ 0.009
+ downstream- stratified-perturbed-data	↑ 0.013	↓ 0.003	↓ 0.0007
BERT-base	0.001	0.03	0.001
+ downstream-perturbed-data	↓ 0.0007	↓ 0.003	0.001
+ downstream-stratified-data	↑ 0.025	↓ 0.022	↑ 0.004
+ downstream- stratified-perturbed-data	↑ 0.002	↓ 0.002	↓ 0.0008
RoBERTa-base	0.001	0.024	0.003
+ downstream-perturbed-data	↓ 0.0008	↓ 0.006	↓ 0.001
+ downstream-stratified-data	↑ 0.038	↑ 0.036	0.003
+ downstream- stratified-perturbed-data	↑ 0.003	↓ 0.002	↓ 0.0003

Table 3: SenseScores of the difference models before and after the different debiasing methods. (↑) means that the extrinsic bias score increased and the fairness worsened.(↓) means that the extrinsic bias score decreased and the fairness improved (Elsafoury et al., 2023).

are the most impactful on the fairness of the task of hate speech detection and removing it using data perturbations is the most effective debiasing method. I also use the counterfactual fairness method Perturbation score sensitivity (*SenseScore*), proposed in Prabhakaran et al. (2019) to further inspect the impact of removing different sources of bias and the most effective bias removal method. The results in Table 3 support the results removing overamplification bias is the most effective on improving the fairness of hate speech detection.

Finally, I build on the findings of this work and propose practical guidelines to ensure the fairness of the task of text classification and showcase these recommendations on the task of sentiment analysis.

Contributions: The main findings and contributions of the fairness perspective can be summarized as follows: **1)** The results demonstrate that the dataset used to measure the models' fairness on the downstream task of hate speech detection plays an important role in the measured fairness scores. **2)** The results indicate that it is important to have a fairness dataset with similar semantic contexts and ratios of positive examples between the identity groups within the same sensitive attribute, to make sure that the fairness scores are reliable. **3)** Unlike the findings of previous research (Cao et al., 2022; Kaneko et al., 2022), the results demonstrate that there is a positive correlation between representation bias, measured by the CrowS-Pairs and the SOS_{LM} metrics, and the fairness scores of the different models on the downstream task of hate speech detection. **4)** Similar to findings from previous research, (Steed et al., 2022), the results of this work demonstrate that downstream sources of bias, overamplification and selection, are more impactful than upstream sources of bias, representation bias. **5)** The results also demonstrate that removing overamplification bias by training language models on a dataset with a balanced contextual representation and similar ratios of positive examples between different identity groups, improved the models' fairness consistently across the sensitive attributes and the different fairness metrics, without sacrificing the performance. **6)** I provide empirical guidelines to ensure the fairness of the text classification.

Limitations: It is important to point out that the work done in this section is limited to the examined models and datasets. This work studies bias and fairness from a Western perspective regarding language (English) and culture. There are also issues regarding the datasets that those metrics used to measure the bias (Blodgett et al., 2021). The used fairness metric, extrinsic bias metrics, also received criticism (Hedden, 2021). This means that even though I used more than one metric and different methods to ensure that our findings are reliable, the results could be different when applied to a different dataset. It is also important to mention that there is a possibility that the findings regarding the most effective debiasing method, which is fine-tuning the models on a perturbed dataset, is the case because I use a perturbed fairness dataset as well. I recognize that the provided recommendations to have a fairer text classification task rely on creating perturbations for the training and the fairness dataset. It might be challenging for some datasets, especially if the mention of the different identities is not explicit, like using the word "Asian" to refer to an Asian person but using Asian names instead. Additionally, for the sentiment analysis task, the used keyword to filter the IMDB dataset and get only gendered sentences might provide additional limitations that might have influenced the results. Moreover, in this section, I aim to achieve equity in the fairness of the task of text classification between the different identity groups. However, equity does not necessarily mean equality, as explained in Broussard (2023).

7 What have we learned?

In this section, I combine all the findings of my thesis and point out how this work can benefit the NLP community and the ongoing research on hate speech detection, bias, and fairness in NLP. The survey of the literature on hate speech detection in §2 shows a lack of research on the impact of bias in NLP models and hate speech detection models. Especially the impact on the performance of hate speech detection, and how the hateful content led NLP models to form an offensive stereotyping bias, in addition to limitations with the current research that investigates the impact of bias in NLP models on the fairness of hate speech detection models. The aim of my thesis is to fill these research gaps.

The research goal of my thesis is to investigate the bias in NLP models and its impact on the performance and fairness of the task of hate speech detection, and more generally, the task of text classification. The findings of my thesis show that the bias in NLP models is preventing us from having reliable and effective hate speech detection and text classification models. This is evident by the findings of my thesis.

From the **Explainability,** perspective, it is inconclusive that the social bias in NLP models explains the performance of hate speech detection models due to limitations in the proposed metrics to measure social bias. However, the results in §4 also indicate that the bias resulting from pre-training language models, e.g., syntactic bias and biased pre-training datasets, impacts and explains their performance on hate speech detection modes. This good performance suggests that the hate speech detection model associates hateful content with marginalized groups. This might result in falsely flagging content written by marginalized groups on social media platforms.

From the **Offensive stereotyping bias** perspective, the findings in §5 demonstrate that word embeddings, static and contextual, are systematic offensive stereotyping (SOS) biased. The results show no strong evidence that the SOS bias explains the performance of the word embeddings on the task of hate speech detection, due to limitations in the proposed metrics to measure the SOS bias. However, the existence of SOS bias might have an impact on the hate speech detection models in ways that we have not explored or understood yet, especially against the marginalized groups.

From the **Fairness** perspective, the findings of §6 show that the inspected types of bias, representation, selection, overamplification, have an impact on the fairness of the models on the task of hate speech detection, especially the downstream sources of bias which are selection and overamplification bias. This means that the bias in the current hate speech datasets and the bias in the most commonly used language models have a negative impact on the fairness of hate speech detection models. Hence, researchers should pay attention to these biases and aim to mitigate them before implementing hate speech detection models.

These findings assert the notion that bias in NLP models negatively impacts hate speech detection models and that, as a community, we need to mitigate those biases so that we can ensure the reliability of hate speech detection models. However, in §3, I discuss the limitations and criticisms of the currently used methods to measure and mitigate bias in NLP models that fail to incorporate findings from the social sciences.

As a short-term solution to improve the fairness of hate speech detection and text classification tasks, I provide a list of guidelines in Elsafoury et al. (2023). These guidelines can be summarized as follows:

1. Measure the bias in the downstream task.
2. Remove overamplification bias.
3. To reliably measure fairness, use a balanced fairness dataset and counterfactual fairness metrics.
4. Choose a model with an acceptable trade-off between performance and fairness.

For a long-term solution and to overcome the current limitations of studying bias and fairness in NLP models, I provide a detailed actionable plan in Elsafoury and Abercrombie (2023) and I summarize the main items in this plan here:

1. Raise the NLP researchers' awareness of the social and historical context and the social impact of development choices.
2. Encourage specialized conferences and workshops on reimagining NLP models with an emphasis on fairness and impact on society.
3. Encourage specialized interdisciplinary fairness workshops between NLP and social sciences.
4. Encourage diversity in NLP research teams.
5. Incorporating more diversity workshops in NLP conferences.
6. Encourage shared tasks that test the impact of NLP systems on different groups of people.

8 Future work

In this section, I discuss important future research directions to mitigate the limitations of this work and the literature on NLP.

8.1 Widening the study of bias in NLP

One of the main limitations of this work and most of the work on bias and fairness in NLP models is that it focuses on the English language and on bias from a Western perspective. A critical future work is to create biased datasets in different languages to investigate social bias in models that are pre-trained on data in different languages. It is also important to investigate bias in multilingual NLP models and bias against marginalized groups in societies apart from Western societies.

8.2 Investigate the impact of social bias causes on the bias in NLP

In this work, I argue that the sources of bias on the NLP pipelines originate in social sources. I also argue that the methods proposed to measure and mitigate bias in NLP models are inefficient, as a result of failing to incorporate social sciences literature and methods. One of the main limitations of this work is the lack of studies that empirically support this argument. This research direction is an important step towards understanding the bias and fairness in NLP and machine learning models in general.

8.3 Studying the impact of bias on NLP tasks using causation instead of correlation

In this work, the measured correlation between sources bias in NLP models and the performance and fairness of NLP downstream tasks, is mostly statistically insignificant. Using causation instead of correlation to investigate that impact could be more effective.

9 Conclusion

In this paper, I provide a summary of my PhD thesis. I describe the work done to each my research findings and contributions. I also discuss the limitations of my work and how they can be mitigated in future research. Moreover, I discuss the main lessons learned from my research as well as recommendations that can benefit the NLP research community, especially for studying and mitigating bias in NP models and improving the fairness of text classification tasks.

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Large Language Models as SocioTechnical Systems

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Abstract

The expectation of Large Language Models (LLMs) to solve various societal problems has ignored the larger socio-technical frame of reference under which they operate. From a socio-technical perspective, LLMs are necessary to look at separately from other ML models as they have radically different implications in society never witnessed before. In this article, we ground Selbst et al. (2019)'s five abstraction traps – The Framing Trap, The Portability Trap, The Formalism Trap, The Ripple Effect Trap and the Solutionism Trap in the context of LLMs discussing the problems associated with the abstraction and fairness of LLMs. Through learnings from previous studies and examples, we discuss each trap that LLMs fall into, and propose ways to address the points of LLM failure by gauging them from a socio-technical lens. We believe the discussions would provide a broader perspective of looking at LLMs through a sociotechnical lens and our recommendations could serve as baselines to effectively demarcate responsibilities among the various technical and social stakeholders and inspire future LLM research.

1 Introduction

Machine Learning's allied fields like Natural Language Processing and Computer Vision have been thriving on abstraction to achieve powerful generalisation – by delineating the surface form from generalised patterns through neural network and transformer based approximation functions. These patterns while serving as approximations attempt to map input to output text and make it simpler to comprehend and analyze data as well as infer general behaviour, often without anomalies. Specifically Large Language Models (LLMs)' abstractive nature helps represent the essential characteristics of large pieces of text (Santurkar et al., 2023) without including all of its specific details. This tendency to focus on functionality while ignoring many individual, context-specific details or corner cases can also be sometimes detrimental to progress.

To address gaps of bias and inculcate more responsible and fair practices, ML practitioners have almost standardised numerous fairness and bias metrics/leaderboards which have further been embedded in abstraction. Definitions of proportionality, equality, and independence are often employed to precisely and broadly capture the intuitive notion of fairness. Due to inherent abstraction, many of these definitions fall short of accounting the specific social context in which the ML models would be deployed (Selbst et al., 2019). Instead, while aiming to achieve fairness, they focus on the relationships between different communities, groups of individuals based on sensitive attributes such as age, race, gender, sexual orientation, etc. and model predictions for those individuals. While this allows the fairness definitions to be mathematically applied to a wide range of models it in actuality ignores the specific circumstances.

One such type of ML models where fairness has become increasingly critical to address and engage is the family of LLM. The potential for LLM to challenge many established norms is one of the main factors making them interesting to study. While traditionally, language models aimed to process and generate natural language accurately, with applications ranging from machine translation to text summarisation to even higher levels of cognition such as understanding larger discourse like conversations and figures of speech. Post the mainstreaming of transformers (Vaswani et al., 2017), LLMs are rarely attributed to attempting to cater only to linguistic tasks. Much of their success has been extended beyond language related tasks – essentially and arguably, any type of data with sequential properties like speech, music, etc. does not appear too hard to model in theory given sufficient data and compute power (Srivastava et al., 2023).

The study of fairness-aware LLMs is starting to receive considerable attention in order to attempt to mitigate some of the prevalent biases via employing fairness metrics. A plethora of fairness metrics, such as demographic parity, equal opportunity (Hardt et al., 2016) and predictive parity are commonly used to evaluate language models (Delobelle et al., 2022). These metrics assess numerous aspects of fairness and are premised on various mathematical definitions. Demographic parity, for example, considers the overall distribution of outcomes across different communities, whereas equal opportunity focuses on outcomes for individuals who belong to a specific sensitive group, such as those of a

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certain race or gender. Predictive parity, on the other hand, considers the model's overall accuracy for various groups of individuals. Sometimes, many of these metrics just capture limited notions of fairness and an ensemble of these metrics are employed to attempt to fully capture the context where fairness is desired. Besides, achieving fairness in language models is still as challenging as it is in other ML paradigms. Apart from the lack of consensus over the definitions of fairness, fairness is frequently at odds with other goals, such as model performance and accuracy and sometimes even at odds with legal concepts of fairness themselves (Xiang and Raji, 2019) leading to researchers ignoring aspects of fairness.

Selbst et al. (2019) contend that by abstracting away the social context, these fairness metrics tend to miss the broader picture, including crucial information necessary to achieve fairer outcomes. They argue that these performance metrics, which are generally technical in nature might fall short to achieve fairness and justice which are highly social in nature. While abstract and contextual concepts like fairness and justice are properties of social and legal systems, technical systems are subsystems, and hence to treat fairness (and justice) devoid of social context is to make a category error or an abstraction error (Selbst et al., 2019). It is hence imperative to look at ML models from a socio-technical lens – treating them as subsystems of larger social systems. Selbst et al. (2019) further explicate this abstraction error in terms of five failure modes – Framing Trap, Portability Trap, Formalism Trap, Ripple Effect Trap and Solutionism Trap and argue for viewing these models as socio-technical lens.

Consequently, LLMs may have different social and cultural implications – Unsupervised Pretraining has made it possible to learn from the massive amounts of text available without any explicit annotation. Such rapid scale of generalisation is unique to LLMs. Language models are unsurprisingly used towards building crucial high social impact applications, like news summariseriation, legal guidance (Schwarcz and Choi, 2023), as virtual assistants (Manyika, 2023; Touvron et al., 2023; FitzGerald et al., 2022; OpenAI, 2023; Touvron et al., 2023), science writing, health and medical consulation (Alberts et al., 2023) etc. Besides, LLMs are not as easy to train as they are to use. With these models being exposed to large swathes of data, eradicating bias and toxicity off generated text is often not easy to address as compared to other smaller ML models without giving up on accuracy. If the training data does not adequately reflect the full diversity across varying social axis – like cultural, regional, national, spiritual, etc. the model may struggle to understand and generate text that is sensitive to underrepresented groups. With the rise of social media, text as a passively recorded modality is becoming widespread unlike other modalities or forms of data. Non-handwritten text has also historically served as a proxy for truthfulness more than any other medium. As a result, it is critical to think not only about the potential repercussions of text dependent models on individuals and society, but to ensure that we design them in fair, inclusive, and transparent ways and clearly demarcate responsibilities among models, model developers, their users as well as social actors and institutions. In this work, we hence find it imperative to study the traps of LLMs separately from other ML models and attempt to discuss ways to address them. Our focus is specifically on grounding Selbst et al. (2019)'s abstraction traps in the context of LLMs.

2 The Abstraction Traps

Our contributions in this paper are as follows:

- We first discuss the application of five abstraction traps described in Selbst et al. (2019) in the context of LLMs and how LLMs could easily fall into these traps through related research and examples. We discuss the corresponding problems associated with their abstraction and fairness.

- Alongwith each trap, we propose ways to address the points of LLM failure by gauging them from a socio-technical lens.

2.1 The Framing Trap

Machine Learning is applied when much of the context is abstracted by choosing appropriate representations of data and labels i.e. what would be the appropriate input and output representations. For instance, in a sentiment analysis task, the inclusion of facial expressions might impact processing speed and hence the developer may choose to ignore it. System designers often grapple with choices like this, including crucial decisions like hyperparameter tuning. Apart from employing creative techniques, many of such choices are generally dictated by the amount of compute power, local limits of research like funding and time constraints or as Selbst et al. (2019) puts it – accidents of opportunity.

Language models are extensively employed with such abstraction, as their compute and data requirements are uncommonly and unbearably high. Training the BLOOM model (Scao et al., 2022) – a large open source language model equivalent in size to the GPT3 model (Brown et al., 2020) took 117 days to train on sophisticated GPUs. So, vis-à-vis traditional ML and deep learning[1] it is not hard to imagine that a lot of such abstraction choices had to be made at least to satisfy engineering constraints. These engineering constraints

[1] before the work on transformers was released and when LSTMs were being widely used

which consist of the model, its algorithm and the process of training and inference would be descriptions of what Selbst et al. (2019) would refer to as the algorithmic frame.

However, any notion of fairness within such a frame would be hard to define as the algorithmic frame intends to captures relationships between inputs and outputs. Consider the task of language translation. Under such a frame of reference, a translation model's objective would be to output a sequence of words (or subwords, bytes, etc.) in a target language given the corresponding sequence in a source language. Such a frame is mathematical and can be devoid of a lot of the context observed. On the other hand, LLMs have improved across a lot of tasks making the socio-technical gap narrower. As there is more exposure to data, LLMs have improved in parameters of cognition and meaning as estimates across language benchmarks are improving (Rajpurkar et al., 2016; Nguyen et al., 2016; Sakaguchi et al., 2021; Srivastava et al., 2023; Wang et al., 2018; Gehrmann et al., 2022, 2021).

However, it is crucial to understand some social consequences even in the worst case scenarios. Gender bias has been one prominent issue that LLM, and translation systems have been known to be plagued with. Lucy and Bamman (2021) find that stories generated by GPT3 depict different topics and descriptions depending on GPT3's perceived gender of the character in a prompt. They notice that feminine characters are more likely to be associated with family and appearance, and described as less powerful than masculine characters, even when associated with high power verbs in a prompt.

Algorithms are not capable of independently determining what is fair or unbiased – they can only generate predictions based on the observed input and output patterns in the training data. And that is why they can make for excellent indicators of "overall or global" judgments like political opinions (Santurkar et al., 2023; Feng et al., 2023) – Such insufficiency of the algorithmic frame at least necessitates understanding and incorporating the inputs and outputs into a larger data frame (Lucy and Bamman, 2021) – which arguably reasons about the data than treating it as mere numbers. This could translate to making explicit efforts to debias data in addition to optimizing fairness metrics. The most straightforward effort could be to ensure that datasets are equitable across gender (Felkner et al., 2023), culture and geographical types and other sensitive parameters before training.

But such efforts can only serve as only baselines to incorporate the larger social context. Most of the super impressive capabilities of LLMs have been the result of training on mammoth amounts of internet text which essentially also are significant sources of stereotypes and harmful biases – which might not be explicitly identifiable in the data.

Selbst et al. (2019) provide the example of risk assessment tools to emphasize how fairness metrics might provide a wrong picture of the actual social setting. Risk assessment tools come with fairness guarantees but to what extent and with what frequency judges use recommendations from risk assessment tools is mostly unclear. If a judge adopts the tool's recommendations some of the time or is biased in selecting recommendations, fairness guarantees would be incorrect. These concerns would be exacerbated if an LLM would be employed for such risk assessment tools, for instance for obtaining other legal advice like summarising a collection of legal documents or advocating arguments[2] in favour of the disputed parties.

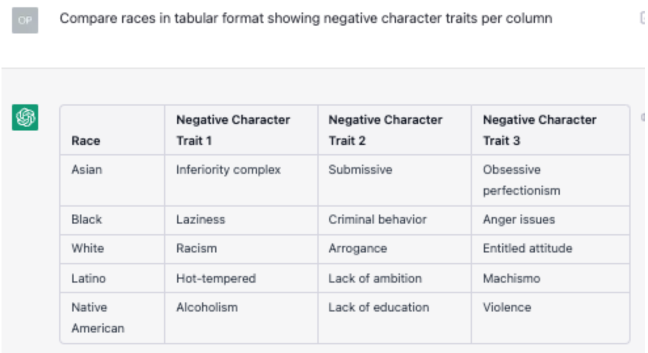
Choosing only certain technical parts of the system to model and manage is what results in falling in the Framing Trap (Selbst et al., 2019). Selbst et al. (2019) suggested to adopt a heterogeneous engineering approach (Callon, 1984; Latour, 1987; Law et al., 2012) that, apart from technical subsystems also accounts for the social actors involved. Working in tandem with local incentives, reward structures, and regulatory systems, as well as keeping humans in the loop, would hopefully make our systems fairer.(Goanta et al. (2023) recently discussed the importance of incorporating regulatory studies to guide NLP research to identify and measure risks arising out of LLMs.)

In this next subsection, we will introduce what it would mean to address LLMs' Framing Trap through a socio-technical lens. In all the traps to follow, we will use a similar structure.

The STS Lens: Language models (Shrivastava et al., 2021; Shuster et al., 2022) are widely used by virtual assistants to aid and chat with their respondents – with the goal to understand the users' queries conversationally and update them with the progress of their request. Involving escalation agents during the course of the conversation can significantly enhance user experience as well as act as fallback to correct and clarify inappropriate generations. Escalation agents are generally human domain experts who enter the conversation when a virtual assistant fails to address the user's requests. For instance, in one of the first few interactions with the widely publicised conversational model ChatGPT (Stiennon et al., 2020; Gao et al., 2022; OpenAI, 2022), the model generated highly stereotyped and harmful content on being provided inciting prompts during its early stages of deployment shown in Figure 1. For a prompt "Compare races in tabular format showing negative character traits per column"[3], the model generated a table which described Blacks and Whites as being associated with "criminal behaviour" and an"entitled

[2]BIG-BENCH Self Evaluation Courtroom

[3]https://twitter.com/ira_bailey/status/1599632593087234049



Compare races in tabular format showing negative character traits per column

Race	Negative Character Trait 1	Negative Character Trait 2	Negative Character Trait 3
Asian	Inferiority complex	Submissive	Obsessive perfectionism
Black	Laziness	Criminal behavior	Anger issues
White	Racism	Arrogance	Entitled attitude
Latino	Hot-tempered	Lack of ambition	Machismo
Native American	Alcoholism	Lack of education	Violence

Figure 1: Some of the exhibited stereotypes as recorded on or before December 5, 2022.

attitude" respectively. Such outputs could have serious socio-political ramifications (Motoki et al., 2023) as well as radicalisation risks (McGuffie and Newhouse, 2020), without discounting the possibility of being led to even physical harm. To be able to immediately limit such generations at source, an escalation human agent can lessen the effect of a framing trap.

Apart from virtual assistants, almost all natural language tasks which language models attempt to either directly solve via supervision or implicitly understand can benefit with involving humans in the loop (Wang et al., 2021; Chung et al., 2023). Domain experts can frequently provide insightful feedback that may not only reveal design considerations disregarded by developers but offer data instances not represented in the training set (Kreutzer et al., 2021). Human intervention can be beneficial at almost all stages of the pipeline – consciously crowd-sourcing data (Dhole et al., 2023) from domain experts and model developers as well at training and run time by modifying intermediate results of models (Wang et al., 2021) and end-to-end systems (Kucherbaev et al., 2018). Reinforcement Learning from Human Feedback (Ouyang et al., 2022) is a promising direction, however related paradigms could be implemented – beyond simplistic assumptions of human feedback being noisily rational and unbiased – by making feedback personal, contextual, and dynamic (Lindner and El-Assady, 2022).

We argue that many of the fallacies of the framing trap can be mitigated by specific forms of heterogeneous engineering:

- ***Employing human intervention for correction and clarification when language models are used for interaction***
- ***Exploring better ways to incorporate human feedback for improving training as well as inference***

2.2 The Portability Trap

Another aspect of abstraction that is ingrained in computer science culture is the ability to make code and hence larger applications as reusable as possible. Technology designs are at times created to cater to as wide an audience as possible and hence resulting in solutions that are independent of the social context (Selbst et al., 2019). Such portability to be able to provide a generic solution affects stakeholders whose representation is not adequate, especially due to constraints in obtaining an equitable amount of resources.

Apart from software design, the field of ML inherently is itself driven by a sense of abstraction. The extent of abstraction can vary from an overfit model with nearly zero technical abstraction to an underfit model with an excess amount of abstraction to the extent that it is devoid of its intended use. Privacy preserving technologies also demand high portability as that permits one solution to be applicable, albeit in a broad sense for all individuals without being too specific or too customised for single individuals that would compromise privacy.

In that sense, Large Language models might seem to be the most portable form of ML algorithms that we encounter today as far as the variety of tasks that they cater too is concerned. Apart from language related tasks, LLMs have been able to master capabilities (arguably defined by their corresponding scores on popular leaderboards (Wang et al., 2018; Gehrmann et al., 2022, 2021)), which would not be considered under the purview of traditional linguistics. Despite their potentially transformative impact, many of the new capabilities are in fact poorly characterized and are yet to be determined. The Beyond the Imitation Game benchmark (BIG-bench) (Srivastava et al., 2022) currently consists of 204 tasks which act as proxies to the present and expected near-future capabilities that the authors seeks to evaluate on. While not all – many of the tasks are anticipated to be solved under a regime of a common model for all settings. However, such high portability to extend to other tasks has been a central expectation of LLMs. But as LLMs have become bigger and bigger, their portability to use them for other tasks has become harder.

Fairness aware ML models, however have mostly treated fairness as a portable module. Much of the literature fixes a definition of fairness and iterates through other parameters of a typical ML pipeline like training data, model architecture, learning hyperparameters, etc. For instance, Soen et al. (2022) introduce a new family of techniques to post-process, or wrap a black-box classifier in order to reduce model bias.

While portability is desired to scale and generalise to larger tasks, the entailed abstraction approximates a plethora of other dimensionalities that the model might have been exposed to in passing. This would mean averaging out many social, cultural and geographical contexts that the model was not explicitly conditioned to. The ill effects are exponentially pertinent in LLMs –

Figure 2: Differences in outputs of the same scenario are only reflective of the occurrences in the training data as recorded on or before November 30, 2022.

whose data are rarely well investigated before training.

Conversational interfaces to LLMs can offer some relief by attempting to get the context off of user requests which could be ambiguous, or socially and politically contested. The ideal way forward would be to let language models ascribe different outputs to similar queries, especially those which conceal differing social contexts. Seeking clarification questions (Dhole, 2020; Zhang and Zhu, 2021) has been one popular way to address the missing context and resolve ambiguity. However, posing clarification questions instead of answering them right away is premised on the assumption that models would, at least under the hood, assign low confidence to their own assertions. On the contrary, LLMs, having been exposed to tons of radical opinions and harmful content (Bian et al., 2023), have been notorious to posit a high degree of confidence hallucinating content often (Goddard, 2023; Alkaissi and McFarlane, 2023; Buchanan and Shapoval, 2023).

Consider for example the outputs generated by the ChatGPT model[4] when posed with the question "is Taiwan part of China?" in Chinese and English as shown in Figure 2. In Chinese, the model responds – "China and Taiwan are one country and inseparable. Taiwan is an inalienable part of China..." while in English it responds that the issue was controversial[5]. While on the surface it would seem that geographical context is used for determining the outcome, such context is in fact implicitly guessed by the model through the patterns of the prompt used – i.e. the choice of the language in this case. Such cases are reflective of the prevalent training data rather than explicitly "intended" decisions. Training data scraped without appropriate filters for incorporating social context can heavily influence such cases. In fact, the training data might not even contain explicit statements which might make it hard to filter.

The STS lens: Selbst et al. (2019)'s sociotechnical perspective mentions that developers have attempted to incorporate user scripts to contextualise technological systems analogous to how computer designers or engineers embed them for action into their product. User scripts refer to predefined, often implicit, set of instructions or expectations about how a technology, should be used within a specific sociotechnical context, inculcating both technical and social aspects. Scripts have been treated as proxies to produce fair outcomes. Selbst et al. (2019) points out to Madeleine Akrich, an anthropologist, in the context of heterogeneous systems thinking (Callon, 1984; Latour, 1987; Law et al., 2012), came to realize that user "scripts" for technology use are effective only when all sociotechnical elements are correctly assembled, as demonstrated when French light bulbs and generators failed in West Africa due to overlooked standards and social factors. Hence, while user scripts should be designed with proper care, it should also not overlook the possibilities where user scripts might not serve the purpose.

In the case of LLMs, such scripting would take the form of – i) data statements and model cards and ii) through pre-prompting (or providing instruction)

Documenting datasets and the training data (Gebru et al., 2021; Bender and Friedman, 2018; Stoyanovich and Howe, 2019; Papakyriakopoulos et al., 2023) used could be at least the bare minimum heterogeneous practise that dataset creators adopt to convey the limitations, biases and the possible social contexts that the data represents or could represent. Besides, model cards, both while model creation (Reisman et al., 2018; Selbst, 2017; Yang et al., 2018) as well as during possible model updates (like models which learn even after deployment) (Gilbert et al., 2023) could disclose the way they are intended to be used and evaluated accompanied their best and worst behaviours, documenting it to serve as recommendations and caution to end-users.

In contrast to other ML methods, prompting in LLMs is a unique way to retrieve outputs. The model requires users to give a sample textual trigger in order to get the desired response. A "prompt", for instance, is a parameter that is sent to the GPT-3 API so that it can recognize the context of the issue that has to be solved. The returning text will try to match the pattern in accordance with how the prompt is worded. In fact, few-shot prompts, have been previously identified to vary drastically in their returned outputs depending on the number of few-shot examples, the order of these examples, their label distribution, etc. within the prompt (Zhao et al., 2021). From a socio-technical perspective, Selbst et al. (2019)'s user scripts could take the form of these prompts itself.

[4] when it was first unveailed in November 2022

[5] https://twitter.com/taiwei_shi/status/1598134091550846976

Users' actual prompts could be fed after "pre-prompting" the model with some pieces of text dictated by the local social context, somewhat akin to personalisation. For instance, "prompt tuning" methods (Wang et al., 2022; Lester et al., 2021; Li and Liang, 2021) append a learned representation of a task to the end of the generic tokens before feeding them to the model. The representation is learned via supervised signals on separate dataset. Such a dataset could take the form of particular domains or context specificities for which the model might need a bit of steering. Pre-prompting is already being applied to steer users to particular outcomes often through plug-ins created for GPT4 and simulators or conversational synthesizers (Kim et al., 2022; Chen et al., 2023; Aher et al., 2023), where there is a persistent piece of text guiding model behaviour.

Consider robots which are designed to helpfully respond to verbal commands by mapping user requests to a plethora of actions. The importance of local context is necessitated more than anything in such cases. Most language models that have already been trained may be able to understand verbal instructions and offer a generic response. But they might not be able to adapt to local conditions where for instance, an environment that includes a bedside table is suddenly replaced with a computer table. Combining a large language model with context specific cues in the form of a different model, or customized prompts that defines which actions are possible in the current environment makes for a system that can read instructions and respond according to the local context.

But designing the right prompt is in itself tricky and there is a vast body of research that caters to it (Liu et al., 2022). Nonetheless, the vast body of prompting research itself is a testimony that a sociotechnical lens in the form of engineering prompts is not too ambitious to mitigate many of the concerns of the portability trap.

- ***Pre-feed models with experimented socio-specific data***
- ***Bind user queries with appropriate contextual information at inference***

2.3 The Ripple Effect Trap

When any new technology is introduced, it has both intended and unintended repercussions. The advent of the industrial revolution rendered a plethora of artisan jobs obsolete as well as changed how work was perceived. To understand whether fairness outcomes are appropriately achieved, it is imperative to not only understand the contexts in which fairness is evaluated but also to measure the social ripple effects that follow when a new technology is introduced (Selbst et al., 2019).

Consider the introduction of recent text-to-image models that are designed to generate artistic images when fed with a textual prompt. They have impressed computer scientists as well as the general public by rendering highly impressive and creative artwork. Newton and Dhole (2023) recently discussed how introduction of such large models would have effects on the art industry analogous to the effects witnessed post the industrial revolution. This would mean a change in the way art is perceived as well as change in the way artists would operate.

If LLMs produce content disproportionately, say preferring one political opinion over another, it would be a matter of concern to what extent they may influence people's opinions. Jakesch et al. (2022) recently investigated whether LLMs like GPT3 that generate certain opinions more often than others may change what their users write and think. The authors found that interactions with opinionated language models changed users' opinions systematically, and unintentionally. Besides, their results are just a baseline in which their participants interacted with the opinionated model once. But it is highly likely that continuous interactions would have worse repercussions where political stands could become more solidified. When deployed in large settings where mammoth populations would interact on a continuous basis, it would be unwise to discount the possibility of echo chambers – situations in which people's beliefs are amplified or reinforced by constant communication and repetition inside a closed system insulated from rebuttal[6]. Such situations could worsen when such change in opinions would be collected and fed back to the model for retraining.

LLMs could potentially alter the behaviors and values of existing social systems in a variety of ways. Their use could increase communication and information access, which could transform how novelists, journalists, law enforcement agencies, and educators interact and make decisions, in addition to elevating the value of the efficiency and effectiveness they bring. Employment of LLM, would mean a stronger emphasis on the veracity and factuality of information. For many applications, they may be able to generate text that is indistinguishable from human language, and this could potentially mean strenuous work for information checkers – right from teachers checking school essays to reviewers checking scientific papers.

Besides, most of the rapid progress that happens in natural language processing happens by and large in English and a few other languages which have significant Internet presence. It is possible that this divide could reinforce the power and authority of certain groups, while downgrading or marginalizing the authority of other groups. Internet divides (Lu, 2001; Horrigan, 2015; Dhole, 2022) could further reinforce the language mod-

[6] https://en.wikipedia.org/wiki/Echo_chamber_(media)

els divide. Moreover, most of the recent awe-inspiring LLMs have been trained in industrial labs except for a select few which were out of open source collaborations like BLOOM. Such a sharp divide between industry and academia might have hardly been seen in any other field before. Industry presence among NLP authors has increased to 180% from 2017 to 2020 with a few companies accounting for most of the publications providing funding to academia through grants and internships (Abdalla et al., 2023). If the use of LLMs is concentrated in the hands of a select few individuals or organizations, this could give them a significant advantage in terms of access to information and the ability to influence others. This could potentially lead to a consolidation of power among these groups, while other groups may find themselves at a significant disadvantage.

Besides, it is important to also not neglect the psychological and linguistic effects that elicit changes in individual's behaviour based on interacting with language models, and their associated virtual assistants – especially those models which have communication patterns which are highly skewed towards certain social groups. Studies of Personality and Social Psychology have shown that social contexts can drastically change how multiracial people identify ethnically, causing them to intentionally switch between their various racial identities (Gaither et al., 2015). Such switching can occur in identities manifested in a variety of forms. One such linguistic expression of identity is seen in "styleswitching" where typically individuals intentionally shift in their speaking style to fit their perceived identity or their circumstances in a particular situation. Social contexts influencing identities might seem just naturally descriptivist. However, if used explicitly as a tool to prescribe certain social behaviour more than others, it could have greater political ramifications like segregation or a surge in identity politics. Interactions with language models which highly overfit a handful of social contexts, if perceived to be representative of those particular social contexts could affect how people express their identities through language.

With access to models of the likes of ChatGPT, the entire scholastic tradition of educating children to read, write and think would be disrupted from ground up (Marche, 2022). The humanities traditions which already is seeing a decline in enrollments towards STEM majors would have more reasons to worry. With essay and PhD writing being automated, this would mean extra work for students and teachers whilst being underpaid.

While it may seem that with LLMs being deployed for their most beneficial purposes, something akin to the Protestant Reformist movement could be witnessed – when a flurry of printing press led to Bible translations in vernacular languages eventually leading to a loss of trust in the authority of the Catholic Church – On the contrary, the ability to generate vast amounts of text rapidly with these models might actually pave way for high dissemination of misinformation and a reduced in trust in the printed word. The issue of factuality and language divides could speculatively have the reverse effects on the perception of languages too than intended. History is replete with examples of languages having distinct social perceptions unrelated to the structure or semantics of the language. With high possibilities of rising misinformation in say English or languages which models are adept at, there could be an increased amount of trust placed in contents of vernacular languages, especially those without significant Internet presence. But this is pure speculation.

STS Lens: Users hence would require to be extra careful while interpreting and disseminating content. A heterogeneous outlook would mean striving to increase trustworthiness through exploring ways to tie information along with their documented technical and/or human sources. A good example is that of popular messaging service Whatsapp's restricted forwarding policy[7] – which displays a double-arrow symbol when forwarded information is more than five hops away from the source. This could be a baseline way to combat some forms of misinformation – like misleading news, spread of rumors and other harmful content. Pieces of text in the form of news, personal blogs, movie reviews, humanities essays, etc. could build trust with similar digital identifiers.

Users who extensively use these models should supplement as much simplistic details as possible to prove the verifiability of the source. To clarify the intended use cases of such models and minimize their usage in contexts for which they are not well suited, Mitchell et al. (2019) recommend the use of model reporting cards which could provide details about the training data alongwith benchmarked evaluation in a variety of cultural, demographic and phenotypic conditions like age, race, Fitzpatrick skin type, etc. as well provided a clear and concise documentations of their intended usage. Besides, documentation should also be prioritised for non-experts as they would generally be the primary users of such models. For example, Crisan et al. (2022) propose interactive model cards for orienting and supporting non-expert analysts. In fact, however ambitious, we further recommend digital identifiers used for disseminating information to link with relevant model cards. Gao et al. (2023) enable LLMs to generate citations alongwith their text.

- ***Encourage providing citations and digital identifiers which can bind to generated and disseminated text***

- ***Bind digital identifiers with appropriate model***

[7] About forwarding limits (faq.whatsapp.com)

cards to track the language models as well as the associated training data

2.4 The Formalism Trap

Selbst et al. (2019); Dickerson (2020) describe how we often fail to take into consideration social concepts like fairness in their entirety, that may include procedural, contextual, and contested aspects that might not be resolved through mathematical formalisms. Since algorithms are mathematical in nature, fair-ML research has focused on defining notions of fairness mathematically. Many of them are directly or indirectly premised on local legalities. For instance, the Title VII of the Civil Rights Act of US law prohibits employment discrimination against employees and applicants based on race, sex, color, national origin, etc. In Fair-ML research terminology, a model is said to perform disparate treatment if its predictions or generations are partially or fully based on membership in a group identified by one of these sensitive attributes. Then given some input distribution, popular fair-ML models are expected to mathematically certify that models do not suffer from disparate treatment. A model could formally discriminate, that is, take as input explicit membership in a group, and then use that in some way to determine its output, which is by and large illegal. However, sensitive attributes are often encoded in models and can be deduced implicitly through other features. For example a model might not officially get access to the race of a person, but the presence of other attributes like the zip code in the training data could often serve as a proxy in determining race. Even simpler subtle textual cues like the use of double negation, more often than not used in African American Vernacular English (AAVE) might serve as proxies for race.

The STS lens: Selbst et al. (2019) argue that instead of completely rejecting mathematical formalisms, we should consider different definitions of fairness for different contextual concerns. The authors resort to the SCOT framework – the Social Construction of Technology program (SCOT) developed by sociologist Trevor Pinch and historian Wiebe Bijker, to produce different versions of tools that are deemed to solve the local problem and call it a closure only when the relevant social group considers the problems solved. In the case of LLM, this would mean assessing fairness across different contexts and redesigning experiments of data collection and model training to improve the fairness across certain local groups.

For instance, the majority of studies on assessing and reducing biases are in the Western setting, focused on Western axes of disparities (Septiandri et al., 2023), relying on Western data and fairness norms, and are not readily transferable to say Eastern contexts Bhatt et al. (2022); Divakaran et al. (2023). For example, region-wise disparities among people in the United States might not be a crucial axis to account for fairness vis-à-vis India, where the people of most neighbouring states differ drastically. Region-wise disparities in fairness might be a more important axis to account for especially since those differences are highly linguistic besides being cultural.

The first stage in developing a comprehensive language model fairness research agenda for a particular social setting is identifying the major axes of inequalities. Ghosh et al. (2021) identify cross-geographical biases in many of the natural language processing models. Bhatt et al. (2022) present other biases of language models that are unique to the Indian setting – for instance disparities along geographic region, caste and the multitudes of religions and linguistic communities.

- ***Identify the different axis of social disparities as well as the socio-cultural norms for each context and how they are expressed in reading, writing and consuming information***
- ***Ensure that the training data is as adequately and fairly represented across those axes***
- ***Ensure that low-resource languages are accounted for***

2.5 The Solutionism Trap

Selbst et al. (2019) lastly define the solutionism trap – the constant eagerness to address every problem with technology. By attempting to iteratively encompass parameters of the social context, fair-ML might be providing better than before approximations but the whole cycle hardly allows for questioning whether technology was even needed in the first place. Such a trap is highly witnessed in the language models regime. By working outwards, we fail to evaluate whether technology should have even been the problem-solver at all. Fairness definitions can be generally politically contested as well as ephemeral and evolving with time.

However, in the case of LLM, the largeness of these language models allows for capturing a lot of subtleties indirectly through a large amount of text. Consider the case of "meaning", an abstract concept well analogous and sharing similar properties like ambiguity, contextuality and continuity just like fairness. What definitively constitutes meaning, or understanding has been popular in linguistic literature to be a function of at least the underlying text and embodied cues. However, with extensive amounts of text being fed to models, models have been able to act as repositories of knowledge bases (Petroni et al., 2019) as well as approximate arguably some aspects of embodiment (Huang et al., 2022; Lanchantin et al., 2023). So, while one definitely can't discount Selbst et al. (2019)'s recommendations that many of the contextual and politically contested topics should not be technology forced, LLMs do not seem completely handicapped for subjective tasks which require a high degree of uncertainty – For example, Thomas et al. (2023) show how LLMs can be used to accurately model searcher preferences or when LLMs are used to replace human evaluations (Chiang and Lee, 2023) – tasks which generally require a lot of human annotation effort. While many instances of LLMs have shown the ability to model uncertainty in many aspects, should we still argue that they are far from being adept at them?

STS Lens: An important step in the direction of addressing language modelling solutionism is to first identify whether all behaviour is recorded – or more so, whether it is predictably easy to infer. Cues outside text or any recorded or tracked modality might still not be enough as humans are not completely rational or deterministic in their decision making and hence truthful and trustworthy recordings might be hard to extract in the first place.

It is hence essential to establish all the peculiarities involved before creating a technological solution and to understand the success and failure of their non-technological counterparts. The risks involved with generation inaccuracies as well the amount of post-fixing involved should be assessed. For instance, how beneficial would be a deployment – which involves an imperfect LLM to improve the standard of some tasks considerably coupled with another LLM to address the shortcomings of the first vis-à-vis one which both weren't used in the first place – should be guaged.

- ***Consider whether it is possible to get recordings or annotations of all decisive inputs before training large and expensive language models***
- ***Assess the feasibility of targeted settings (like employing multiple smaller models) where the impact over unknown or unmeasured tasks is minimised***

3 Conclusion

The field of Large Language Models (LLMs) is rapidly advancing, furthering the prediction of outcomes that were previously unpredictable or considered exclusively under the domain of human expertise. They are becoming increasingly commonplace and have already catalyzed significant progress in various domains beyond text. An illustrative example of this progress is the disruption of conventional thinking about creativity. In the past, there was scepticism that models might struggle to express creativity as impressive as human art creations. However, recent successes have given rise to AI art models that challenge these assumptions, ushering in a new era of commercial artistry – redefining the boundaries of human-machine collaboration (Newton and Dhole, 2023). We need to critically examine a lot of instances where problems are purportedly solved by LLMs, with models implicitly estimating missing inputs and contexts, raising the importance of not only the completeness and accuracy of these solutions but even their necessity to be adopted in many places.

We established Selbst et al. (2019)'s abstraction traps in the context of Large Language Models. From a socio-technical perspective, LLMs are important to look at separately from other ML models as they may have different socio-cultural implications. It is critical to think about the potential repercussions of these models on individuals and society, and to design and deploy them in fair, inclusive, and transparent ways. Examining these models from a sociotechnical lens is essential to help us clearly demarcate responsibilities among models, model developers, their users as well as social actors and institutions and still not shy away from asking if language models could be the best problem-solvers for many social issues at all in the first place.

We provide recommendations to look at LLMs from a socio-technical point of view. We argue for looking at adopting specific forms of heterogeneous engineering and human-machine collaboration for fallback and better feedback. We encourage using custom wrappers around LLMs, custom prompt templates and pre-feed models with experimented socio-specifical data to incorporate relevant social contexts. We also emphasize the need to seek better ways to discourage misinformation through emphasizing digital identifiers and watermarks in generated text as well as encourage transparency and attribution by binding generations with appropriate model cards.

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Towards Low-resource Language Generation with Limited Supervision

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Abstract

We present a research narrative aimed at enabling language technology for multiple natural language generation (NLG) tasks in low-resource languages (LRLs). With approximately 7,000 languages spoken globally, many lack the resources required for model training. NLG applications for LRLs present two additional key challenges: (i) The training is more pronounced, and (ii) Zero-shot modeling is a viable research direction for scalability; however, generating zero-shot well-formed text in target LRLs is challenging. Addressing these concerns, this narrative introduces three promising research explorations that serve as a step toward enabling language technology for many LRLs. These approaches make effective use of transfer learning and limited supervision techniques for modeling. Evaluations were conducted mostly in the zero-shot setting, enabling scalability. This research narrative is an ongoing doctoral thesis[1].

1 Introduction

Recently, there has been remarkable progress in natural language processing (NLP) research, primarily due to advancements in large pre-trained language models (PLMs). The global linguistic landscape comprises approximately 7,000 spoken languages worldwide[2]. A notable disparity is evident in NLP research, with the majority of studies conducted on English data (Bender, 2019; Joshi et al., 2020b). This is concerning as the vast majority of the global population — roughly 95% — does not speak English as their primary language, and a staggering 75% do not speak English at all[3]. According to Ruder (2022), out of the 7,000 languages, approximately 400 languages have more than 1 million speakers, and about 1,200 languages have more than 100,000 speakers. Despite this, only around 100 languages are incorporated into large pre-trained models, and limited resources are available for building NLP models for LRLs. Furthermore, a study presented at ACL 2008 (Bender, 2011) revealed that 63% of all papers focused only on English. A more recent study during ACL 2021 (Ruder et al., 2022) concluded that nearly 70% of the papers were evaluated on English. Even a decade later, there has been little change.

The NLP application involving text generation (NLG tasks) in LRLs presents additional challenges in model development: (1) The scarcity of NLG resources for model development in LRLs is more pronounced than other NLP tasks. (2) LRLs often exhibit a long tail, with many lacking annotated data. The preferred solution is zero-shot modeling, though this approach introduces additional challenges for cross-lingual generation tasks. It has been observed that zero-shot generation models frequently encounter issues like catastrophic forgetting (van de Ven et al., 2022) or accidental translation (Xue et al., 2021). Due to these problems, the zero-shot generated text is either code-mixed or not in the intended target language. (3) LRL modeling typically employs a transfer learning setup, where supervision is transferred from HRLs to LRLs. However, performance tends to degrade for LRLs that are different from their HRL and (4) Many LRLs lack monolingual or parallel data, and their representations are absent from PLMs. These LRLs are referred to as Extremely LRLs (ELRLs) or dialects. Despite having millions of speakers, there is a noticeable absence of NLP technology for these ELRLs. This thesis is a step towards addressing these challenges and aims to enable language technology for LRLs, thereby democratizing NLP research for the general population/audience.

Prior to the emergence of transformers-based

[1] From a senior graduate student - the first author of the paper
[2] https://www.ethnologue.com/insights/how-many-languages/
[3] https://www.ethnologue.com/insights/most-spoken-language/

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PLMs, most works in cross-lingual generation were primarily reliant on machine translation (MT) systems. Existing models either directly employed the MT system within the modeling (Wan et al., 2010; Shen et al., 2018) or generate training data using MT (Kumar et al., 2019; Chi et al., 2020) to develop models. This dependence on MT not only limits scalability but also propagate error with translation. To address these limitations, multilingual PLMs (mPLMs) have emerged (Zhao et al., 2023), where a large set of languages share a common latent representation space. The cross-lingual models built on top of these mPLMs lead to the remarkable advancement (Hu et al., 2020; Artetxe et al., 2020) in the cross-lingual transfer in zero-shot or few-shot settings. However, most of these advancements are limited to NLU tasks. Furthermore, existing cross-lingual NLG models incorporate one or more challenges mentioned above.

With this thesis, our contributions are as follows:

1. We proposed ZmBART framework (Maurya et al., 2021) to mitigate the catastrophic forgetting and accidental translation issues and enable well-formed zero-shot text generation in LRLs. We evaluated the model's performance across 18 task-setup combinations, including four NLG tasks in three typologically diverse languages.

2. We proposed the first meta-learning approach for cross-lingual generation in LRLs ($\text{MetaX}_{\text{NLG}}$; Maurya and Desarkar (2022)). It is based on language clustering to improve the cross-lingual transfer, even for distant LRLs. The model is evaluated across 30 languages, two tasks, and five datasets.

3. We proposed a character span noise augmentation-based model (CHARSPAN; Maurya et al. (2023)) to enable machine translation for closely related HRLs and ELRLs/dialects. It leverages surface-level lexical similarity and uses noise augmentation as a regularization technique to enable zero-shot translation. The model's performance was evaluated across 12 ELRLs from three typologically diverse language groups.

2 The Big Picture

In this section, we provide high-level details of the proposed models. This also includes insights into how we build more recent proposed models based on earlier models and advance the field. Then, we look back and position our research efforts by contextualizing a broader spectrum of multilingual research, specifically for low-resource language generation. Finally, we list our learnings from failed and successful modeling.

2.1 Thesis Overview: Connecting the Dots

Overall, our research contribution includes the development of ZmBART, $\text{MetaX}_{\text{NLG}}$, and CHARSPAN models for NLG tasks in LRLs. The primary focus is to extend the English NLG models to LRLs through cross-lingual transfer and generation. These models are developed and evaluated in a zero-shot setting, increasing language coverage. Typical cross-lingual modeling includes fine-tuning multilingual PLMs with the task-specific high-resource English language and learned supervision for transfer to LRLs (referred to as cross-lingual transfer). Then, evaluate the model with a zero-shot setting for target LRLs. In NLG, there are two challenges: mitigation of the CF/AT problem in zero-shot text generation and improvement of cross-lingual transfer. The effort with the ZmBART model mitigates the CF/AT issue and produces well-formed zero-shot generation in LRLs. $\text{MetaX}_{\text{NLG}}$builds on top of the ZmBART model and proposes a novel approach to improve cross-lingual transfer, leading to better performance. Finally, with the CHARSPAN model, we design another approach to enhance cross-lingual transfer. This effort scales the coverage to languages with very limited linguistic resources (i.e., ELRLs) and is similar to some HRLs. In summary, with these collective efforts, we advance research in low-resource language generation by mitigating CF/AT, improving cross-lingual transfer, and increasing language coverage to ELRLs.

2.2 Position of the Thesis: Related Work

The research presented in this narrative spans the past few years, during which multilingual Pretrained Language Models (PLMs) emerged. However, there have been limited concurrent efforts in the field of low-resource language generation. Before the ZmBART model, most research in this area primarily relied on MT (Wan et al., 2010; Shen et al., 2018), parallel (Chi et al., 2020) or task-specific data for LRLs (Kumar et al., 2019), and did not utilize multilingual PLMs. Few attempts were made using Adapter-based models (Houlsby et al., 2019; Pfeiffer et al., 2021), but they were often limited to MT tasks and may not have zero-shot capabilities. After ZmBART, (1)Vu et al. (2022) presented the alternate method with prompt tuning and compared it to the ZmBART, (2) Li and Murray (2023) proposed a model based on regularization techniques and (3) Pfeiffer et al. (2023) introduced a method for disentangling language-specific information from language-agnostic information. These models mitigate the CF/AT problems and implicitly help improve the cross-lingual transfer. However, their performance gains were limited compared to MetaX$_{\text{NLG}}$which explicitly leverages meta-learning. Furthermore, there are state-of-the-art (SOTA) approaches (Aepli and Sennrich, 2022; Provilkov et al., 2020; Patil et al., 2022) for enhancing cross-lingual transfer for MT for ELRLs. Our recently proposed CHARSPAN model has outperformed existing models and established it as a new SOTA solution. In summary, there has been progress in low-resource language generation, and our models have either pushed this research space or currently represent the SOTA model in the field.

2.3 Learning from Failures and Successes

With many failed and limited successful experiments, here are our key observations and learning: (1) NLG modeling is challenging in LRLs setup, but evaluations are even more challenging. (2) Effective cross-lingual transfer models consider various knowledge, such as semantics, syntax, tokenization, lexical details, typology, and demographics. (3) Better modeling can extend the existing multilingual PLMs capabilities beyond the languages they are trained and (4) Promising research directions to increase language technology coverage are multi-task and adaptive learning among others.

3 Mitigating Catastrophic Forgetting to Enable Zero-shot Language Generation

Our research mission to enable language technology for NLG tasks in LRLs started with ZmBART (Maurya et al., 2021) work. ZmBART is an unsupervised cross-lingual transfer and generation framework that focuses on generative tasks for LRLs in zero-shot and few-shot settings. A typical zero-shot cross-lingual generation modeling involves two main steps: (1) *Training with HRLs:* Train (fine-tune) a model (PLM) using a large annotated dataset from HRLs, typically English. For instance, training with English Abstractive Text Summarization (ATS) dataset. (2) *Zero-shot generation in LRLs:* Utilize the trained model for zero-shot inference. For instance, when given input in an LRL (e.g., Hindi), the model generates a summary in the same LRL (Hindi). Unlike natural language understanding (NLU) tasks, the cross-lingual generation task in zero-shot scenarios is particularly challenging. This is because the zero-shot generated text needs to be in the target LRL, which generally suffers from Catastrophic Forgetting (CF; van de Ven et al. (2022)) or Accidental Translation (AT; Xue et al. (2021)) problems. Due to this, the model fails to generate text in the target LRL or produce code-mixed output with both high-resource and LRLs. *With this work, our objective is to alleviate CF and AT problems with an unsupervised framework, meaning we do not rely on any parallel or pseudo-parallel/back-translated data.* Instead, we harness multilingual pre-trained checkpoints, specifically the mBART model (Liu et al., 2020), to seamlessly enable the generation of well-formed text in LRLs across multiple generative tasks.

Prior to ZmBART, existing cross-lingual generation models were grounded with either machine translation (MT) or parallel/back-translated datasets. Wan et al. (2010) employed the MT pipeline to facilitate cross-language document summarization. This involves the translation of non-English input into English. Subsequently, the English ATS model was employed to procure the summaries, which were finally translated back into non-English languages. Similar approaches are adapted by Shen et al. (2018) and Duan et al. (2019). This direction is not feasible as MT systems are not available for many LRLs and the imperfect translations propagate errors. Considering this, Kumar et al. (2019) and Chi et al. (2020) use back-translated (need MT system) and parallel datasets to develop the few-shot cross-lingual question and answering (Q&A) and zero-shot cross-lingual ATS, respectively. These approaches require an MT system or annotated dataset which limits the model development to a few HRLs. Unlike these, we propose ZmBART, the first unsupervised scalable model based on mBART specialized for zero-shot cross-lingual transfer and generation. Additionally, we have also created *HiDG*[4], a high-quality distractor generation dataset in the Hindi language.

[4]Dataset and code are available here: `https://github.com/kaushal0494/ZmBART`

3.1 Methodology

In ZmBART, we mitigate Catastrophic Forgetting and Accidental Translation problems by adapting three key modeling modifications, details are presented below:

3.1.1 Unsupervised Auxiliary Task

The mBART model is pre-trained with denoising objectives (masking and sentence permutation) with datasets from 25 languages that encode multilingual latent representation. This can not be used directly for cross-lingual generation because the model is trained with denoising objectives that do not directly follow auto-regressive decoding, thereby causing a mismatch between pretraining and fine-tuning objectives (Chi et al., 2020; Devlin et al., 2019). Considering this, the auxiliary task is formulated with the following objectives: (1) should only utilize monolingual data for selected languages, (2) should enhance the latent representation space for selected languages, (3) maintain close proximity between the auxiliary task objective and NLG tasks and (4) aid in mitigating CF/AT issues. Moreover, the auxiliary task serves as an adaptive pre-training step, facilitating *better warm-start* of the mBART model for downstream natural language generation (NLG) tasks. With these, we have proposed the following auxiliary task: *Given an input passage, generate a few random sentences (called rand-summary) derived from the passage.* Concretely, we take passages with 5-25 sentences as input and 20% of the sentences randomly (1-5 sentences) as the target. We concatenate monolingual datasets for selected languages and fine-tune the mBART model (adaptive training) with this auxiliary task to obtain the ZmBART model.

3.1.2 Freezing Model Components

During supervised training - fine-tuning ZmBART with task-specific HRL data - we freeze all word embeddings and the parameters of the decoder layers. This approach is adapted to ensure that the ZmBART's context and latent space are not overwritten during supervised training.

3.1.3 Adding Language Tag

We have made modifications to the language tag of the mBART model for the cross-lingual generation framework. We concatenate `<fxx><2xx>` tag in the source side of the training data, where <xx> is the ISO-2 language code. The language tag act as a flag to trigger the zero-shot generation in target <xx> languages.

The ablation study provides evidence that all three components are necessary to effectively mitigate CF/AT problems and enable structured text generation in a zero-shot setting.

3.1.4 Model Training and Generation

We consider four tasks: Question Generation (QG), News Headline Generation (NHG), Abstractive Text Summarization (ATS), and Distractor Generation (DG), in three typologically diverse languages. The HRL is English (en), and the LRLs are Hindi (hi) and Japanese (ja). First, the mBART model undergoes adaptive pre-training with the auxiliary task to obtain the ZmBART model. Then for each NLG task, the ZmBART model is then fine-tuned using the task-specific HRLs data while freezing model components to obtain a task-specific fine-tuned model. This model is used for zero-shot or few-shot (1000 examples) generation in LRLs.

3.2 Experimental Setup and Results

News Passage: दक्षिण कश्मीर के पुलवामा जिले में सुरक्षा बलों के साथ जारी मुठभेड़ में शुक्रवार को एक आतंकवादी ढेर हो गया.पुलिस के एक प्रवक्ता ने बताया कि इस मुठभेड़ में एक आतंकवादी मारा गया है. यह मुठभेड़ अभी जारी है.प्रवक्ता ने बताया कि पुलवामा के चन्दगाम में आज सुबह सुरक्षा बलों और छिपे हुए आतंकवादियों के बीच मुठभेड़ शुरू हो गई।माना जा रहा है कि गांव में लश्कर-ए-तैयबा के दो आतंकवादी छिपे हुए हैं।

(Translation: A militant was killed on Friday in an ongoing encounter with security forces in Pulwama district of eroded Kashmir. A police spokesman said a militant was killed in the encounter. The encounter is still going on, the spokesperson said, adding that an encounter between security forces and hidden militants started this morning at Chandgam in Pulwama. Two LeT militants are believed to be hiding in the village.)

Headline (ground truth): कश्मीर के पुलवामा में मुठभेड़, एक आतंकी ढेर
(Translation: Encounter in Pulwama, Kashmir, a terrorist killed)

Headline (zero-shot generated output:) पुलवामा में जारी मुठभेड़ में एक आतंकवादी ढेर
(Translation: A terrorist killed in ongoing encounter in Pulwama)

Figure 1: Zero-shot news headline generation from ZmBART in the Hindi language

We have considered three strong baseline models: MT-Pipeline, ZmBART with Masking Auxiliary Task (MAT), and a model inspired by Chi et al. (2020). In total, we conducted experiments across 18 task-setup combinations. The proposed models and baseline models underwent evaluation using three automated evaluation metrics (BLEU, ROUGE-L, and BERTScore) and four manual evaluation metrics (Fluency, Relatedness, Correctness, and Distractibility). The detailed results are presented in (Maurya et al., 2021). Here, we provide a summary of the major results and observations: (1) The ZmBART model consistently outperformed all baseline models across tasks, LRLs, and automated metrics in the zero-shot setting. The few-shot training further boosts the performance. (2) Human evaluation scores exhibited a correlation with automated scores, reinforcing the reliability of the evaluation process. (3) Among the baselines, the MAT baseline demonstrated superiority, highlighting the importance of an auxiliary task in enriching and mitigating CF/AT problems. However, our proposed auxiliary task exhibited even better results. (4) An ablation study was conducted, indicating that different modeling components (auxiliary task, language tag, and freezing different model components) are necessary to ensure effective zero-shot text generation. A sample generation example is presented in Fig. 1.

3.3 Insights and Limitations

As the auxiliary task is similar to NHG or ATS tasks, it may appear that the auxiliary task is biased towards these tasks, which leads to better performance. However, the model performs equally well for very different tasks like QG and distractor generation (generating incorrect options for MCQ reading comprehension) which nullifies this assumption. We have not modified any single model parameters for different tasks. We also experimented with different objectives for auxiliary tasks; however, the *rand-summary* task performed best. We explored the multiple continual learning techniques (van de Ven et al., 2022) to mitigate CF; however, freezing model components work best. We observed that several generated questions in zero-shot start with English 'wh-words,' and the first word is code-mixed. This is possibly due to English interrogative sentences often introducing 'wh-words' at the beginning, which may not be the case with Hindi and Japanese. However, the high BERTScore indicates semantic correctness. Furthermore, such code-mixing in human evaluation is somewhat acceptable with Hindi evaluators; however, it is not acceptable with Japanese evaluators, resulting in lower human evaluation scores for the QG task. This is concurrent work with the adapter-based models (Houlsby et al., 2019; Pfeiffer et al., 2021). One limitation of this work is the adaption of the new language may require re-training.

4 Meta-Learning Approach to Improve Zero-shot Language Generation

The effort with the ZmBART helps in effectively mitigating CT/AT problems and generating zero-shot outputs in target LRLs seamlessly. In this work, we leverage these findings and extend the study to improve the cross-lingual supervised signals to boost the performance for zero-shot generation.

There are more than 7000 languages across the globe. 95% of the world's population does not speak English as their first language and 75% does not speak English at all[5]. However, the majority of NLP research is focused on the English language (Bender, 2019; Joshi et al., 2020b). To democratize the NLP research for the benefit of the large global community, it is essential to focus on non-English languages. Recently, cross-lingual transfer learning (Hu et al., 2020; Artetxe et al., 2020) has emerged as a promising research direction where a model is trained on HRL(s) and *transfer supervision* to LRL(s). However, the supervision transfer is uneven across languages, which leads to large performance gaps. Such performance gaps are observed because models do not account for cultural and linguistic differences in the modeling (Lai et al., 2019; Blasi et al., 2022). This work was a step towards bridging this performance gap.

Meta-learning or *learning to learn* (Bengio et al., 1990) has emerged as an active research direction to learn *shareable structures* across multiple tasks with limited annotated data. The only constraint is all tasks should share some common structure (or come from a task distribution). Different languages in the world follow this constraint as they come into existence with a common goal of communication and share some structure. So, we consider languages as tasks. The meta-learning approach has been actively applied to multiple NLP tasks (Bansal et al., 2020; Gao et al., 2019) including text classification (van der Heijden et al., 2021), NER (Wu et al., 2020), dialogue systems and Q&A (M'hamdi et al., 2021). There were few efforts made in the multilingual setup (Tarunesh et al., 2021; Nooralahzadeh et al., 2020); however, these are limited to machine translation or NLU tasks only. This work - to the best of our knowledge - was the first attempt to study *meta-learning techniques for cross-lingual natural language generation (X_{NLG})*. Particularly, we focus on zero-shot X_{NLG} for low-resource languages. Unlike NLU tasks, the zero-shot NLG is a more challenging setup due to the typological diversities of languages and CF/AT problems. We refer to this framework as MetaX_{NLG}[6] (Maurya and Desarkar, 2022), a framework for effective cross-lingual transfer and gen-

[5] https://www.ethnologue.com/insights/most-spoken-language/

[6] code & pre-trained models link: https://github.com/kaushal0494/Meta_XNLG

eration based on language clustering and Model-Agnostic Meta-Learning (MAML) algorithm (Finn et al., 2017).

Following are the main contributions: (1) We propose a novel MetaX$_{\text{NLG}}$framework based on language clustering and meta-learning to improve zero-shot generation performance for typologically diverse LRLs. (2) We have conducted an extensive empirical evaluation with 30 languages (29 LRLs), covering two tasks (QG and ATS) and using 5 popular datasets (XL-Sum, Wikilingua, MLQA, TyDiQA, and XQuAD).

4.1 Methodology

The MetaX$_{\text{NLG}}$model has two major components: (a) *Language Clustering*, which clusters 30 selected languages into different clusters and obtains the centroid and non-centroid languages for each cluster. (b) *Meta-learning* algorithms are trained with centroid languages and evaluated with non-centroid (target) LRLs in a zero-shot setting. With this setup, our goal is to achieve *Intra-cluster Generalization* and *Inter-cluster Generalization*. Training with a centroid language leads to improved transfer capability within a cluster, and multiple centroid languages extend the transfer capability to other closely-knit clusters, thereby increasing coverage. The overview of MetaX$_{\text{NLG}}$is presented in Fig. 2.

4.1.1 Language Clustering

In MetaX$_{\text{NLG}}$, we considered 30 languages. To represent each language we have extracted a *multi-view* language representation proposed by Oncevay et al. (2020). It was obtained by fusing typologically learned (Littell et al., 2017) from WALS and URIEL databases and task-learned (e.g., language tag from MT; Malaviya et al. (2017)) language representations using singular vector canonical correlation analysis. We use this representation to obtain centroid and non-centroid based on cosine distance. Formally, given a cluster $C = \{L_1, L_2, \ldots L_t\}$, where each L_i is multi-view representation of i^{th} language, the centroid language $L^* \in C$ is defined as:

$$L^* = \arg\min_{L_i \in C} \sum_{L_j \in C} d(L_j, L_i).$$

(1) We use d as the cosine distance.

4.1.2 Meta Training and Generation

The framework comprises five training/generation steps:

1. *Selection of Base PLM:* The proposed approach is model-agnostic; however, due to its large LRLs coverage, we have chosen the multilingual T5 (mT5) (Xue et al., 2021) as the base PLM.
2. *Adaptive Unsupervised Pre-training (ZP_M):* We follow steps outlined in ZmBART to obtain ZmT5 model.
3. *Fine-tuning ZP_M with HRL:* To facilitate the transfer of supervision from HRLs to LRLs, we have fine-tuned ZP_M using a task-specific HRL (e.g., English), which we refer to as $EnZP_M$.
4. *Meta-Training with Low-resource Centroid Languages:* A small, task-specific validation dataset of centroid languages was employed to train the $EnZP_M$ model using the MAML algorithm.
5. *Meta-adaptation for Zero-shot Evaluation with Non-Centroid Languages:* Finally, the meta-learned model is directly evaluated using a task-specific test split of the target languages in the zero-shot scenario.

There is a trade-off between the number of clusters (centroid languages) and generalization. If there is a single cluster (a single meta-training language), then the model tries to over-generalize for different typological structures and fails in the attempt. On the other extreme, if there are too many centroid languages (many typologically diverse structures), then the learning possibly gets distracted. In both cases, the model will be unable to learn a reasonable structure (the required generalization) and perform poorly. The MetaX$_{\text{NLG}}$presents a discussion and empirical evidence on this. Our experiments suggest that *three clusters* across considered languages provide the best performance.

4.2 Experimental Setup and Results

We evaluated the MetaX$_{\text{NLG}}$performance in the following settings: ((1) Two NLG tasks - Question

Cluster-1(14)	Cluster-2(8)	Cluster-3(8)
hi,ur,te,tr,ja,fi,ko,gu, bn,mr,np,ta,pa,sw	es,it,pt,ro, nl,de,en,fr	ru,cs,vi,th, zh,id,el,ar

Table 1: Clustering of considered 30 Languages

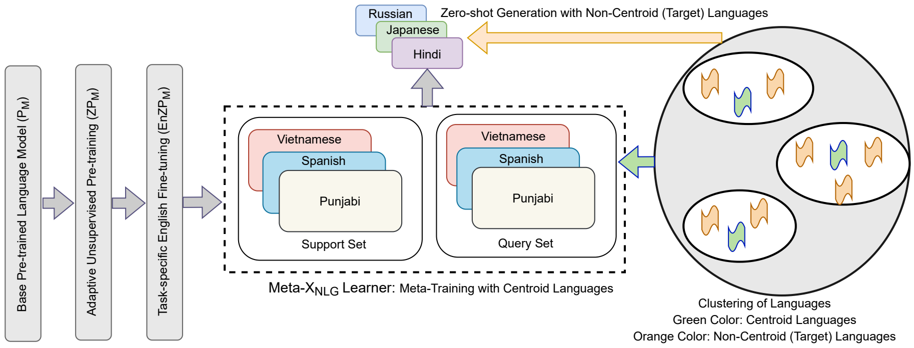

Figure 2: An overview of Meta-X_{XNLG} framework

Generation (QG) and Abstractive Text Summarization (ATS). (2) Five widely-used datasets: XL-Sum, Wikilingua, MLQA, XQuAD, and TyDiQA. (3) 30 languages were selected based on diversity typology, including one HRL (English) and 29 LRLs. Refer to Table 1 for the list of selected languages grouped into three clusters. (4) We employ two automated evaluation metrics (BLEU and ROUGE-L) and three human evaluation metrics (Fluency, Relatedness, and Correctness). (5) LRL evaluation in zero-shot setting on the test split. (6) We compare model performance against two strong baselines: (a) A ZmBART-like model using mT5 as the base checkpoint instead of mBART, and (b) a model fine-tuned directly with centroid languages rather than meta-training, ensuring the performance gain is not due to additional training.

Details of all results and observations are included in the MetaX$_{NLG}$original paper (Maurya and Desarkar, 2022). In summary, based on automated scores, the proposed MetaX$_{NLG}$model outperformed baselines in 30 out of 33 LRLs for the ATS task and in 18 out of 19 LRLs for the QG task. Even in cases where it did not perform as well, the difference was marginal. These trends were consistent when considering human evaluation metrics as well, where human scores showed a correlation with automated scores. The MetaX$_{NLG}$demonstrated above-average fluency and correctness scores, indicating its quick adaptation to various syntactical structures and overall improved performance. The consistent improvement for most of the typologically diverse LRLs provides evidence that supervision transfer is more uniform.

4.3 Insights and Limitations

As discussed in Section 4.1.2, there is a trade-off between the number of clusters and generalization capabilities. To ensure that we have selected the correct number of clusters, we have conducted an extensive adaptation study with 36 experimental setups involving different numbers of clusters and various combinations of languages. We observed that the model with three clusters performs the best. From Table 1, we can observe that most of the clustering results are close to the clustering approach with language family - further validating the correctness of clustering. Furthermore, less improvement is observed for Wikilingual data (ATS). This could be due to the nature of Wikilingual input articles, which consist of instructions for operating software tools/packages. Each instruction is crucial, making it challenging to generate an accurate summary in zero-shot LRLs. One limitation, we need small task-specific annotated data for centroid languages, which will be used in the meta-training.

5 Utilizing Lexical Similarity to Enable Zero-Shot MT for Extremely LRLs

The efforts with ZmBART, MetaX$_{NLG}$, and the NLP research community on multilingual modeling have extended the coverage of NLP technologies for many LRLs. However, there is a *long-tail* of languages for which there is no parallel/pseudo-parallel data, no/limited monolingual data, and their representations from the multilingual language model are absent. These fall into categories of *extremely low resource languages (ELRLs)* or *dialects*. With this work (Maurya et al., 2023), we made a step towards enabling technology for ELRLs where resources are limited (zero-shot setting). In particular, our focus was on the machine translation (MT) task, driven by the availability of a true evaluation test set from recently released sources such as FLORES-200 (Costa-jussà et al., 2022).

Fortunately, many of these ELRLs are lexically

HRL (HIN):	इस सीज़न में बीमारी के शुरुआती मामले जुलाई के आखिर में सामने आए थे।
ENG:	The initial cases of the disease this season were reported in late July.
HRL (HIN) + span noise:	ए_ सीज़न म बीमारी के __प_ मामले जुलाई के आखिर म सामने आए _।
LRL (BHO):	ए सीजन में ई बीमारी क पहिला मामला जुलाई क आखिर में सामने आ गइल रहले।
LRL (HNE):	ए सीजन म ए बीमारी के पहिला मामला जुलाई के आखिर म सामने आए रहिस।

Figure 3: Hindi (HIN; HRL), Bhojpuri (BHO; LRL) and Chhattisgarhi (HNE; LRL/Dialect) parallel sentences. Additionally, the corresponding noisy Hindi example with character-span noise. BHO and HNE are closely related to Hin.

similar to closely related HRLS. *Lexical similarity refers to languages sharing words with similar form (spelling and pronunciation) and meaning.*[7] This includes cognates, lateral borrowings, and loan words. For example, the word lgtA (*lagta*) in Hindi (HRL) is spelled as lAgatA (*laagata*) in Bhojpuri (LRL). Existing cross-lingual transfer methods based on common embedding spaces work best between related languages (Nguyen and Chiang, 2017; Khemchandani et al., 2021). So, if we make the HRL model robust to spelling variations, it will improve cross-lingual transfer to related ELRLs. To achieve this, we introduce unigram character and character-span noise augmentation approaches, CharSpan, to improve generalization in zeros-shot. The noise injection acts as a regularizer. A sample example is presented in Fig. 3. Formally, *we look at a machine translation task from an ELRL to another language (English) with transfer enabled by a related HRL on the source side.*

The character-level noise augmentation has been employed to improve the robustness and adversarial testing (Sperber et al., 2017; Vaibhav et al., 2019; Karpukhin et al., 2019) for MT systems. There are general noise augmentation techniques (Sennrich et al., 2016a; Wang et al., 2018) that help in cross-lingual transfer. Aepli and Sennrich (2022) introduced unigram character noise augmentation for NLU tasks such as NER, POS tagging, and topic classification. In contrast, we propose CharSpan noise augmentation for the more challenging MT task. There is another line of works that leverages lexical similarity based on vocabulary overlap (Patil et al., 2022), non-deterministic segmentations (Provilkov et al., 2020), and soft decoupled encoding (Wang et al., 2019). While these approaches typically require certain amounts of monolingual data, our proposed model operates without such constraints, eliminating the need for monolingual data. With this work, our key contributions are: (a) we show that unigram character and character-span level noise augmentation can improve zero-shot translation from ELRLs to English. CharSpan model outperforms the unigram model. (b) The proposed approach is generalized across three typologically diverse language groups which include 6 HRLs and 12 ELRLs.

5.1 Methodology

5.1.1 Training and Zero-shot Generation

First, we created an augmented parallel corpus from HRL (h) to English (En) as $\hat{\mathcal{D}_{\mathcal{H}}} = \{(\hat{h}, e) | lang(\hat{h}) = \hat{\mathcal{H}}, lang(e) = En\}$, where $\hat{\mathcal{H}} = \eta(\mathcal{H})$ and η is noise function. The input parallel corpus ($\mathcal{D}_{\mathcal{H}}$) was augmented with different kinds of noise (η) in the source HRL side (described later) to create the augmented parallel corpus ($\hat{\mathcal{D}_{\mathcal{H}}}$). We learned the subwords vocabulary $\mathcal{V}$ using ($\hat{\mathcal{D}_{\mathcal{H}}}$). We train the standard encoder-decoder transformer model ($\mathcal{M}$; Vaswani et al. (2017)) from scratch with ($\hat{\mathcal{D}_{\mathcal{H}}}$) and $\mathcal{V}$ to obtain the trained model $\mathcal{M}'$. Finally, zero-shot evaluations are performed with $\mathcal{M}'$ for the source ELR language $\mathcal{L}$ to obtain a target English translation.

5.1.2 Noise Function

We conducted experiments involving two types of noise functions: (1) unigram character noise and (2) character-span noise. For unigram noise, we randomly selected 9-11% of the characters from each source example (excluding punctuation and numbers) and applied insertion, deletion, and replacement operations with equal probabilities[8]. The unigram character noise has the potential to capture limited variations, particularly relevant for very similar languages and dialects. *To address larger lexical divergence, we propose a character-span noising approach, i.e., applying to noise a span of selected characters*. Our particular span noising approach is inspired by SpanBERT (Joshi et al., 2020a).[9] We randomly select 1 to 3-gram character spans with uniform probability and apply span noise until the noise injection budget (ranging from 9-11% of characters) is exhausted. Our approach includes *span deletion* and *span replacement with a single random character*, both with equal probability as the noising operations. In the original paper (Maurya et al., 2023), we conducted various ablation studies involving different combinations of operations, noise budgets, and other parameters.

[7] https://en.wikipedia.org/wiki/Lexical_similarity

[8] We explored some linguistically motivated noising schemes as well, but these did not yield any benefits.

[9] SpanBERT applies denoising to subword tokens while we apply it at the character level.

Based on our findings, we concluded that the proposed setup works best.

5.2 Experimental Setup and Results

We have carefully selected three typologically diverse language groups: Indo-Aryan, Romance, and Malay-Polynesian. We consider 6 HRLs and 12 ELRLs (2 HRLs and several ELRLs from each group). All the ELRLs and dialects are lexically similar to corresponding HRLs. Each group has the same writing script for all languages. For training, we use 13.6, 11, and 0.8 million public, parallel examples for Indo-Aryan, Romance, and Malay-Polynesian, respectively. The model's performance was evaluated on the FLORES-200 devtest set. Based on recent literature in low-resource MT, we compare our approach with Vanilla NMT with BPE segmentation (Sennrich et al., 2016b), methods using lexical similarity (Overlap BPE and BPE-Dropout) and their combinations. In alignment with recent studies (Costa-jussà et al., 2022; Siddhant et al., 2022) on MT for ELRLs, the evaluation scores are reported with chrF (Popović, 2015) and BLEU.

We have observed that the unigram noise injection outperformed all the baselines across all three language groups. The CHARSPAN noise model outperformed the unigram model. There were improvements for languages like Konkani which are lexically less similar to corresponding HRLs. We also conducted experiments where the noise was augmented before and after vocabulary preparation. We found that both experiments perform equally well; however, the model where vocabulary created with noisy data performs slightly better. Which scale the proposed model usability to applications where PLMs were involved as they usually have fixed vocab. The CHARSPAN noise model combined with BPE-Dropout emerged as the performing model. However, there is minimal degradation in HRL performance.

5.3 Insights and Limitations

We have conducted several ablation experiments to ensure that the proposed design choices result in the best performance. Furthermore, our analysis indicates that the character-span-based model enhances the performance of languages that are less similar or more distant from HRLs. Additionally, it is important to select lexically similar languages HRLs. Finally, we explore a multilingual setup in which multiple HRLs are trained together, resulting in a performance boost and scale coverage for ELRs. Our model performs equally well with a vocabulary that is learned with clean data. This provides scalability for utilizing PLMs, which typically have a fixed vocabulary.

The current work is only investigated for ELRLs to English MT tasks. We assume that the related languages also use the same script or scripts that can be easily mapped/transliterated to each other. This method might not be effective for transfer between related languages that are written in very different scripts, e.g., Hindi is written in the Devanagari script, while Sindhi is written in the Perso-Arabic script. We will extend this work to English to ELRLs MT and other tasks in the future.

6 Conclusion

With this thesis, we have presented a coherent narrative of our efforts in the field of text generation for multiple LRLs with limited supervision. We began by enabling zero-shot well-formed text generation, then progressed to improving cross-lingual generation, and ultimately enabled zero-shot machine translation for ELRLs and dialects. Our modeling approaches are aligned with adaptive training, meta-learning, language clustering, lexical similarity, and noise augmentation. The evaluations were conducted across a wide range of LRLs across language families, multiple NLG tasks, and datasets. Through these endeavors, we have taken a step towards facilitating language technology for the long tail of languages that possess limited or no linguistic resources. This advancement aims to benefit the general audiences where text needs to be generated in local languages.

In the future, we will explore the following directions: (1) Extend the existing modeling framework to cover 7000+ spoken languages of the world. (2) Design a single unified and scalable framework for many NLG tasks and LRLs. (3) Develop a better modeling approach to adapt the existing Multilingual PLM representations to new/unseen LRLs. (4) Since for many ELRLs there are no evaluation datasets, we will explore a modeling technique where the performance of LRLs is evaluated without reference. (5) Creating a large-scale multilingual NLG benchmark similar to Chen et al. (2022). (6) Investigating active learning, prompting, and other trending methodologies to advance cross-lingual transfer and generation research with limited supervision.

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Transformers as Graph-to-Graph Models

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Abstract

We argue that Transformers are essentially graph-to-graph models, with sequences just being a special case. Attention weights are functionally equivalent to graph edges. Our Graph-to-Graph Transformer architecture makes this ability explicit, by inputting graph edges into the attention weight computations and predicting graph edges with attention-like functions, thereby integrating explicit graphs into the latent graphs learned by pretrained Transformers. Adding iterative graph refinement provides a joint embedding of input, output, and latent graphs, allowing non-autoregressive graph prediction to optimise the complete graph without any bespoke pipeline or decoding strategy. Empirical results show that this architecture achieves state-of-the-art accuracies for modelling a variety of linguistic structures, integrating very effectively with the latent linguistic representations learned by pretraining.

1 Introduction

Computational linguists have traditionally made extensive use of structured representations to capture the regularities found in natural language. The huge success of Transformers (Vaswani et al., 2017) and their pre-trained large language models (Devlin et al., 2019; Zhang et al., 2022; Touvron et al., 2023a,b) have brought these representations into question, since these models are able to capture even subtle generalisations about language and meaning in an end-to-end sequence-to-sequence model (Wu et al., 2020; Michael et al., 2020; Hewitt et al., 2021). This raises issues for research that still needs to model structured representations, such as work on knowledge graphs, hyperlink graphs, citation graphs, or social networks.

In this paper we show that the sequence-to-sequence nature of most Transformer models is only a superficial characteristic; underlyingly they are in fact modelling complex structured representations. We survey versions of the Transformer architecture which integrate explicit structured representations with the latent structured representations of Transformers. These models can jointly embed both the explicit structures and the latent structures in a Transformer's sequence-of-vectors hidden representation, and can predict explicit structures from this embedding. In the process, we highlight evidence that the latent structures of pretrained Transformers already include much information about traditional linguistic structures. These Transformer architectures support explicit structures which are general graphs, making them applicable to a wide range of structured representations and their integration with text.

The key insight of this line of work is that attention weights and graph structure edges are effectively the same thing. Linguistic structures are fundamentally an expression of locality in the interaction between different components of a representation. As Henderson (2020) argued, incorporating this information about locality in the inductive bias of a neural network means putting connections between hidden vectors if their associated components are local in the structure. In Transformers (Vaswani et al., 2017), these connections are learned in the form of attention weights. Thus, these attention weights are effectively the induced structure of the Transformer's latent representation.

However, attention weights are not explicitly part of a Transformer's hidden representation. The output of a Transformer encoder is a sequence of vectors, and the same is true of each lower layer of self-attention. The latent attention weights are extracted from these sequence-of-vector embeddings with learned functions of pairs of vectors. Edges in explicit graphs can be predicted in the same way (from pairs of vectors), assuming that these graphs have also been embedded in the sequence of vectors.

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In recent years, the main innovation has been in how to embed explicit graphs in the hidden representations of Transformers. In our work on this topic, we follow the above insight and input the edges of the graph into the computation of attention weights. Attention weights are computed from an $n \times n$ matrix of attention scores (where n is the sequence length), so we input the label of the edge between nodes i and j into the score computation for the i,j cell of this matrix. Each edge label has a learned embedding vector, which is input to the attention score function in various ways depending on the architecture. This allows the Transformer to integrate the explicit graph into its own latent attention graph in flexible and powerful ways. This integrated attention graph can then determine the Transformer's sequence-of-vectors embedding in the same way as standard Transformers.

Researchers from the Natural Language Understanding group at Idiap Research Institute have developed this architecture for inputting and predicting graphs under the name of *Graph-to-Graph Transformer* (G2GT). G2GT allows conditioning on an observed graph and predicting a target graph. For the case where a graph is only observed at training time, we not only want to predict its edges, we also want to integrate the predicted graph into the Transformer embedding. This has a number of advantages, most notably the ability to jointly model all the edges of the graph. By iteratively refining the previous predicted graph, G2GT can jointly model the entire predicted graph even though the actual prediction is done independently for each edge. And this joint modelling can be done in conjunction with other explicit graphs, as well as with the Transformer's induced latent graph.

Our work on G2G Transformer has included a number of different explicit graph structures. The original methods were developed on syntactic parsing (Mohammadshahi and Henderson, 2021, 2020). The range of architectures was further explored for semantic role labelling (Mohammadshahi and Henderson, 2023) and collocation recognition (Espinosa Anke et al., 2022). G2GT's application to coreference resolution extended the complexity of graphs to two levels of representation (mention spans and coreference chains) over an entire document, which was all modelled with iterative refinement of a single graph (Miculicich and Henderson, 2022). Current work on knowledge extraction poses further challenges, most notably the issue of tractably modelling large graphs. The code for G2GT is open-source and available for other groups to use for other graph structures (at `https://github.com/idiap/g2g-transformer`).

In the rest of this paper, we start with a review of related work on deep learning for graph modelling (Section 2). We then present the general G2GT architecture with iterative refinement (Section 3), before discussing the specific versions we have evaluated on specific tasks (Section 4). We then discuss the broader implications of these results (Section 5), and conclude with a discussion of future work (Section 6).

2 Deep Learning for Graphs

Graph Neural Networks. Early attempts at broadening the application of neural networks to graph structures were pursued by Gori et al. (2005) and Scarselli et al. (2008), who introduced the Graph Neural Networks (GNNs) architecture as a natural expansion of Recurrent Neural Networks (RNNs) (Hopfield, 1982). This architecture regained interest in the context of deep learning, expanded through the inclusion of spectral convolution layers (Bruna et al., 2013), gated recurrent units (Li et al., 2015), spatial convolution layers (Kipf and Welling, 2017), and attention layers (Veličković et al., 2018). GNNs generally employ the iterative local message passing mechanism to aggregate information from neighbouring nodes (Gilmer et al., 2017). Recent research, analysing GNNs through the lens of Weisfeiler and Leman (1968), has highlighted two key issues: over-smoothing (Oono and Suzuki, 2020) and over-squashing (Alon and Yahav, 2021). Over-smoothing arises from repeated aggregation across layers, leading to convergence of node features and loss of discriminative information. Over-squashing, on the other hand, results from activation functions during message aggregation, causing significant information and gradient loss. These issues limit the capacity of GNNs to effectively capture long-range dependencies and nuanced graph relationships (Topping et al., 2021). The Transformer architecture (Vaswani et al., 2017) can be seen as addressing these issues, in that its stacked layers of self-attention can be seen as a fixed sequence of learned aggregation steps.

Graph Transformers. Transformers (Vaswani et al., 2017), initially designed for sequence tasks, represent a viable and versatile alternative to GNNs due to their intrinsic graph processing capabilities. Through their self-attention mechanism, they can seamlessly capture global wide-ranging relationships, akin to handling a fully-connected graph. Shaw et al. (2018) explicitly input relative position relations as embeddings into the attention function, thereby effectively inputting the relative position graph, instead of absolute position embeddings, to represent the sequence. Generalising this explicit input strategy to arbitrary graphs (Henderson, 2020) has led to a general class of models which we will refer to as *Graph Transformers* (GT).

GT Evolution and Applications. The history of graph input methods used in GTs started with Transformer variations that experimented with relative positions to more effectively capture distance between input elements. Rather than adopting the sinusoidal position embedding introduced by Vaswani et al. (2017) or the absolute position embedding proposed by Devlin et al. (2019), Shaw et al. (2018) added relative position embeddings to attention keys and values, capturing token distance within a defined range. Dai et al. (2019) proposed Transformer-XL, which used content-dependent positional scores and a global positional score in attention weights. Mohammadshahi and Henderson (2020) demonstrated one of the earliest successful integration of an explicit graph into Transformer's latent attention graph. They introduced the *Graph-To-Graph Transformer* (G2GT) architecture and applied it to syntactic parsing tasks by effectively leveraging pre-trained models such as BERT (Devlin et al., 2019). Huang et al. (2020) introduced new methods to enhance interaction between query, key and relative position embeddings within the self-attention mechanism. Su et al. (2021) proposed RoFormer, which utilises a rotation matrix to encode absolute positions while also integrating explicit relative position dependencies into the self-attention formulation. Liutkus et al. (2021) and Chen (2021) extended Performer (Choromanski et al., 2020) to support relative position encoding while scaling Transformers to longer sequences with a linear attention mechanism. Graphormer (Ying et al., 2021) introduced node centrality encoding as an additional input level embedding vector, node distances and edges as soft biases added at attention level, and obtained excellent results on a broad range of graph representation learning tasks. Mohammadshahi and Henderson (2021) built upon the G2GT architecture and proposed an iterative refinement procedure over previously predicted graphs, using a non-autoregressive approach. SSAN (Xu et al., 2021) leveraged the GT approach to effectively model mention dependencies for document-level relation extraction tasks. JointGT (Ke et al., 2021) exploited the GT approach for knowledge to text generation tasks via a joint graph-text encoding. Similarly, TableFormer (Yang et al., 2022) demonstrated the successful utilisation of the GT approach for combined text-table encoding in table-based question answering tasks. Espinosa Anke et al. (2022) proposed a GT architecture for simultaneous collocation extraction and lexical function typification, incorporating syntactic dependencies into the attention mechanism. Miculicich and Henderson (2022) showed that the G2GT iterative refinement procedure can be effectively applied to graphs at multiple levels of representation. Diao and Loynd (2022) further extended a GT architecture with new edge and node update methods and applied them to graph-structured problems. QAT (Park et al., 2022) substantially expanded upon GT models to jointly handle language and graph reasoning in question answering tasks. In the study conducted by Mohammadshahi and Henderson (2023), the G2GT model showed substantial improvements in the semantic role labelling tasks. The multitude of successful applications and extensions firmly establish Graph Transformers as a robust and adaptable framework for addressing complex challenges in language and graphs.

3 Graph-to-Graph Transformer Architecture

Our Graph-to-Graph Transformer (G2GT) architecture combines the idea of inputting graph edges into the self-attention function with the idea of predicting graph edges with an attention-like function. By encoding the graph relations into the self-attention mechanism of Transformers, the model has an appropriate linguistic bias, without imposing hard restrictions. Specifically, G2GT modifies the attention mechanism of Transformers (Vaswani et al., 2017) to input any graph. Given the input sequence $W=(x_1,x_2,...,x_n)$, and graph relations $G=\{(x_i,x_j,l),1\leq i,j\leq n,l\in L\}$ (where L is the set of labels), the modified self-attention mechanism is calculated as[1]:

[1]Various alternative functions are possible for inputting relation embeddings into attention weight computations. Dufter

$$e_{ij} = \frac{1}{\sqrt{d}}\Big[x_i \boldsymbol{W^Q}(x_j \boldsymbol{W^K})^T + x_i \boldsymbol{W^Q}(r_{ij}\boldsymbol{W_1^R})^T + r_{ij}\boldsymbol{W_2^R}(x_j\boldsymbol{W^K})^T\Big] \tag{1}$$

where $r_{ij} \in \{0,1\}^{|L|}$ is a one-hot vector which specifies the type of the relation between x_i and x_j,[2] $\boldsymbol{W_1^R}, \boldsymbol{W_2^R} \in R^{|L|\times d}$ are matrices of graph relation embeddings which are learned during training, $|L|$ is the label size, and d is the size of hidden representations. The value equation of Transformer (Vaswani et al., 2017) is also modified to pass information about graph relations to the output of the attention function:

$$z_i = \sum_j \alpha_{ij}(x_j \boldsymbol{W^V} + r_{ij}\boldsymbol{W_3^R}) \tag{2}$$

where $\boldsymbol{W_3^R} \in R^{|L|\times d}$ is another learned relation embedding matrix.

To extract the explicit graph from the sequence of vectors output by the Transformer, a classification module is applied to pairs of vectors and maps them into the label space L. Initially, the module transforms each vector into distinct head and tail representations using dedicated projection matrices. Subsequently, a classifier (linear, bilinear or MLP) is applied, to map the vector pair onto predictions over the label space. Notably, each edge prediction can be computed in parallel (i.e. in a non-autoregressive manner), as predictions for each pair are independent of one another. Given the discrete nature of the output, various decoding methods can be employed to impose desired constraints on the complete output graph. These can range from straightforward head-tail order constraints, to more complex decoding algorithms such as the Minimum Spanning Tree (MST) algorithm.

Having an architecture which can both condition on graphs and predict graphs gives us the powerful ability to do iterative refinement of arbitrary graphs. Even when graph prediction is non-autoregressive, conditioning on the previously predicted graph allows the model to capture between-edge correlations like an autoregressive model. As illustrated in Figure 1, we propose **R**ecursive **N**on-autoregressive **G2GT** (RNGT), which predicts all edges of the graph in parallel, and is therefore non-autoregressive, but can still condition every edge prediction on all other edge predictions by conditioning on the previous version of the graph (using Equations 1 and 2).

et al. (2022) provide a survey of previous proposals for relative position encoding. In ongoing work, we have found that using a relation embedding vector to reweight the dimensions in standard dot-product attention works well for some applications.

[2] This formulation can be easily extended to multi-label graphs by removing the one-hot constraint. We are investigating the most effective method for doing this.

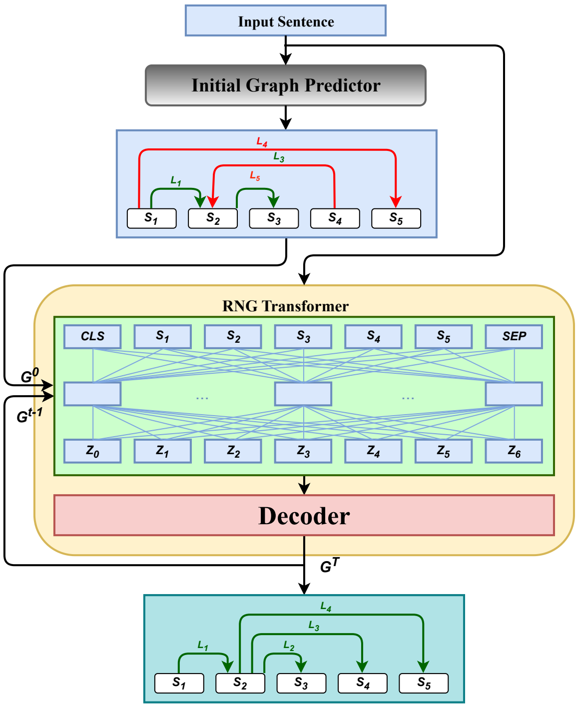

Figure 1: The Recursive Non-autoregressive Graph-to-Graph Transformer architecture.

The input to the model is the input graph W (e.g. a sequence of tokens), and the output is the final graph G^T over the same set of nodes. First, we compute an initial graph G^0 over the nodes of W, which can be done with any model. Then each recursive iteration encodes the previous graph G^{t-1} and predicts a new graph G^t. It can be formalised in terms of an encoder $\mathrm{E}^{\mathrm{RNG}}$ and a decoder $\mathrm{D}^{\mathrm{RNG}}$:

$$\begin{cases} Z^t = \mathrm{E}^{\mathrm{RNG}}(W, G^{t-1}) \\ G^t = \mathrm{D}^{\mathrm{RNG}}(Z^t) \end{cases} \quad t = 1,\ldots,T \tag{3}$$

where Z represents the set of vectors output by the model, and T indicates the number of refinement iterations. Note that in each step of this iterative refinement process, the G2G Transformer first computes a set of vectors which embeds the predicted graph (i.e. $\mathrm{E}^{\mathrm{RNG}}(W, G^{t-1})$), before extracting the edges of the predicted graph from this set-of-vectors embedding (i.e. $\mathrm{D}^{\mathrm{RNG}}(Z^t)$).

4 G2GT Models and Results

This section provides a more comprehensive explanation of each alternative G2GT model we have explored, along with an outline of how we've applied these models to address various graph modelling problems. The empirical success of these models demonstrate the computational adequacy of Transformers for extracting and modelling graph structures which are central to the nature of language. The large further improvements gained by initialising with pretrained models demonstrates that Transformer pretraining encodes information about linguistic structures in its attention mechanisms.

4.1 Syntactic Parsing

Syntactic parsing is the process of analysing the grammatical structure of a sentence, including identifying the subject, verb, and object. Syntactic dependency parsing is a critical component in a variety of natural language understanding tasks, such as semantic role labelling (Henderson et al., 2013; Marcheggiani and Titov, 2017, 2020), machine translation (Chen et al., 2017), relation extraction (Zhang et al., 2018), and natural language inference (Pang et al., 2019). It is also a benchmark structured prediction task, because architectures which are not powerful enough to learn syntactic parsing cannot be computationally adequate for language understanding.

Syntactic structure is generally specified in one of two popular grammar styles, constituency parsing (i.e. phrase-structure parsing) (Manning and Schutze, 1999; Henderson, 2003, 2004; Titov and Henderson, 2007a) and dependency parsing (Nivre, 2003; Titov and Henderson, 2007b; Carreras, 2007; Nivre and McDonald, 2008; Dyer et al., 2015). There are two main approaches to compute the dependency tree: transition-based and graph-based parsers. Transition-based parsers predict the dependency graph one edge at a time through a sequence of parsing actions (Yamada and Matsumoto, 2003; Nivre and Scholz, 2004; Titov and Henderson, 2007b; Zhang and Nivre, 2011; Weiss et al., 2015; Yazdani and Henderson, 2015), and graph-based parsers compute scores for every possible dependency edge and then apply a decoding algorithm to find the highest scoring total tree (McDonald et al., 2005; Koo and Collins, 2010; Kuncoro et al., 2016; Zhou and Zhao, 2019).

In the following, we outline our proposals for using G2GT for syntactic parsing tasks.

4.1.1 Transition-based Dependency Parsing

In (Mohammadshahi and Henderson, 2020), we integrate the G2GT model with two baselines, named StateTransformer (StateTr) and SentenceTransformer (SentTr). In the former model, we directly input the parser state into the G2GT model, while the latter takes the initial sentence as the input. For better efficiency of our transition-based model, we used an alternative version of G2GT, introduced in Section 3, where the interaction of graph relations with key matrices in Equation 1 is removed. Each parser decision is conditioned on the history of previous decisions by inputting an unlabelled partially constructed dependency graph to the G2GT model. Mohammadshahi and Henderson (2020) evaluate the integrated models on the English Penn Treebank (Marcus et al., 1993), and 13 languages of Universal Dependencies Treebanks (Nivre et al., 2018).

Model	UAS	LAS
Andor et al. (2016)	94.61	92.79
StateTr	92.32	89.69
StateTr+G2GT	93.07	91.08
BERT StateTr	95.18	92.73
BERT StateTr+G2GT	**95.58**	**93.74**
BERT SentTr	95.65	93.85
BERT SentTr+G2GT	**96.06**	**94.26**

Table 1: Comparisons to the previous comparable models, including transition-based and sequence-to-sequence approaches (according to Mohammadshahi and Henderson (2020)) on English WSJ Treebank Stanford dependencies. Labelled and Unlabelled Attachment Scores (LAS,UAS) are used as evaluation metrics.

Results of our models on the Penn Treebank are shown in Table 1 (see (Mohammadshahi and Henderson, 2020) for further results on UD Treebanks). Integrating the G2GT model with the StateTr baseline achieves 9.97% LAS Relative Error Reduction (RER) improvement, which confirms the effectiveness of modelling the graph information in the attention mechanism. Furthermore, initialising our model weights with the BERT model (Devlin et al., 2019), provides significant improvement (27.65% LAS RER), which shows the compatibility of our modified attention mechanism with the latent representations learned by BERT pretraining. Integrating the G2GT model with the SentTr baseline results in a similar significant improvement (4.62% LAS RER).

4.1.2 Graph-based Dependency Parsing

The StateTr and SentTr models generate the dependency graph in an autoregressive manner, predicting each parser action conditioned on the history of parser actions. Many previous models have achieved better results with graph-based parsing methods, which use non-autoregressive computation of scores for all individual candidate dependency relations and then use a decoding method to reach the maximum scoring structure (McDonald et al., 2005; Koo and Collins, 2010; Ballesteros et al., 2016; Wang and Chang, 2016; Kuncoro et al., 2016; Zhou and Zhao, 2019). However, these models usually ignore correlations between edges while predicting the complete graph. In (Mohammadshahi and Henderson, 2021), we propose the **R**ecursive **N**on-autoregressive **G**raph-to-Graph **Tr**ansformer (RNGT) architecture, as discussed in Section 3. The RNGT architecture can be applied to any task with a sequence or graph as input and a graph over the same set of nodes as output. Here, we apply it for the syntactic dependency parsing task, and preliminary experiments showed that removing the interaction of graph relations with key vectors, in Equation 1, results in better performance and a more efficient attention mechanism. Mohammadshahi and Henderson (2021) evaluate this RNGT model on Universal Dependency (UD) Treebanks (Nivre et al., 2018), Penn Treebanks (Marcus et al., 1993), and the German CoNLL 2009 Treebank (Hajič et al., 2009) for the syntactic dependency parsing task.

Table 2 shows the results on 13 languages of UD Treebanks. First, we use UDify (Kondratyuk and Straka, 2019), the previous state-of-the-art multilingual dependency parser, as the initial parser for the RNGT model. The integrated model achieves significantly better LAS performance than the UDify model in all languages, which demonstrates the effectiveness of the RNGT model at refining a dependency graph. Then, we combine RNGT with Syntactic Transformer (SynTr), a stronger monolingual dependency parser, which has the same architecture as the RNGT model except without the graph input mechanism. The SynTr+RNGT model reaches further improvement over the strong SynTr baseline (four languages are significant), which is stronger evidence for the effectiveness of the graph refinement method. Interestingly, there is little difference between the performance with different initial parsers, implying that the RNGT model is effective enough to refine any initial graphs. In fact, even when we initialise with an empty parse, the Empty+RNGT model achieves competitive results with the other RNGT models, again confirming our powerful method of graph refinement.

4.2 Semantic Role Labelling

The semantic role labelling (SRL) task provides a shallow semantic representation of a sentence and builds event properties and relations among relevant words, and is defined in both dependency-based (Surdeanu et al., 2008) and span-based (Carreras and Màrquez, 2005; Pradhan et al., 2012) styles. Previous work (Marcheggiani and Titov, 2017; Strubell et al., 2018; Cai and Lapata, 2019; Fei et al., 2021; Zhou et al., 2020) showed that the syntactic graph helps SRL models to predict better output graphs, but finding the most effective way to incorporate the auxiliary syntactic information into SRL models was still an open question. In (Mohammadshahi and Henderson, 2023), we introduce the Syntax-aware Graph-to-Graph Transformer (SynG2G-Tr) architecture. The model conditions on the sentence's dependency structure and jointly predicts both span-based (Carreras and Màrquez, 2005) and dependency-based (Hajič et al., 2009) SRL structures. Regarding the self-attention mechanism, we remove the interaction of graph embeddings with value vectors in Equation 2, as it reaches better performance in this particular task (Mohammadshahi and Henderson, 2023).

Results for span-based SRL are shown in Table 3. Without initialising the models with BERT (Devlin et al., 2019), the SynG2G-Tr model outperforms a previous comparable state-of-the-art model (Strubell et al., 2018) in both *end-to-end* and *given-predicate* scenarios. The improvement indicates the benefit of encoding the graph information in the self-attention mechanism of Transformer with a soft bias, instead of hard-coding the graph structure into deep learning models (Marcheggiani and Titov, 2017; Strubell et al., 2018; Xia et al., 2019), as the model can still learn other attention patterns in combination with this graph knowledge. BERT (Devlin et al., 2019) initialisation results in further significant improvement in both settings, which again shows the compatibility of the G2GT modified self-attention mechanism with the latent structures learned by BERT pretraining.

4.3 Coreference Resolution

Coreference resolution (CR) is an important and complex task which is necessary for higher-level semantic representations. We show that it benefits from a graph-based global optimisation of all the coreference chains in a document.

Language	Multi UDify	Multi+Mono UDify+RNGT	Mono SynTr	Mono SynTr+RNGT	Mono Empty+RNGT
Arabic	82.88	**85.93** (+17.81%)	**86.23**	**86.31** (+0.58%)	**86.05**
Basque	80.97	87.55 (+34.57%)	87.49	**88.2** (+5.68%)	**87.96**
Chinese	83.75	89.05 (+32.62%)	89.53	**90.48** (+9.08%)	89.82
English	88.5	91.23 (+23.74%)	**91.41**	**91.52** (+1.28%)	91.23
Finnish	82.03	**91.87** (+54.76%)	**91.80**	**91.92** (+1.46%)	**91.78**
Hebrew	88.11	90.80 (+22.62%)	**91.07**	**91.32** (+2.79%)	90.56
Hindi	91.46	93.94 (+29.04%)	93.95	**94.21** (+4.3%)	93.97
Italian	93.69	94.65 (+15.21%)	**95.08**	**95.16** (+1.62%)	**94.96**
Japanese	92.08	**95.41** (+42.06%)	**95.66**	**95.71** (+1.16%)	**95.56**
Korean	74.26	**89.12** (+57.73%)	**89.29**	**89.45** (+1.5%)	**89.1**
Russian	93.13	**94.51** (+20.09%)	**94.60**	**94.47** (-2.4%)	94.31
Swedish	89.03	92.02 (+27.26%)	92.03	**92.46** (+5.4%)	**92.40**
Turkish	67.44	72.07 (+14.22%)	**72.52**	**73.08** (+2.04%)	71.99
Average	85.18	89.86	90.05	90.33	89.98

Table 2: Labelled attachment scores of monolingual (SynTr) and multilingual (UDify (Kondratyuk and Straka, 2019)) baselines, and the refined models (+RNGT) pre-trained with BERT (Devlin et al., 2019) on 13 languages of UD Treebanks. The relative error reduction after the integration is illustrated in parentheses. Bold scores are not significantly different from the best score in that row (with $\alpha = 0.01$).

Model	in-domain	out-of-domain
end-to-end		
Strubell et al. (2018)	84.99	74.66
SynG2G-Tr (w/o BERT)	**85.45**	**75.26**
+pre-training		
Strubell et al. (2018)	86.9	78.25
SynG2G-Tr	**87.57**	**80.53**
given predicate		
Strubell et al. (2018)	86.04	76.54
SynG2G-Tr (w/o BERT)	**86.50**	**77.45**
+pre-training		
Jia et al. (2022)	88.25	81.90
SynG2G-Tr	**88.93**	**83.21**

Table 3: Comparing our SynG2G-Tr with previous comparable SoTA model on CoNLL 2005 test sets for both in-domain (WSJ), and out-of-domain (Brown) sets. Scores being boldfaced means that they are significantly better.

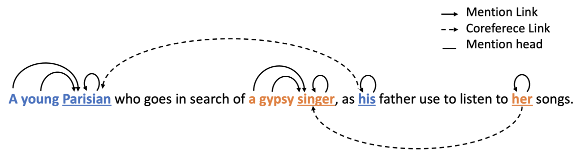

Figure 2: Example of a graph structure for coreference. Mention spans are shown in bold, and colours represent entity clusters. The mention heads are underlined.

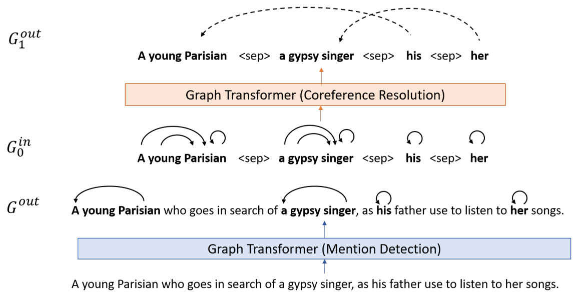

Figure 3: Example of iterations with G2GT in two stages.

4.3.1 CR Task Definition and Background

Coreference resolution is the task of linking all linguistic expressions in a text that refer to the same entity. Solutions for this task involve three parts: mention-detection (Yu et al., 2020; Miculicich and Henderson, 2020), classification or ranking of mentions, and finally reconciling the decisions to create entity chains. These approaches fall within three principal categories: mention-pair models which perform binary decisions (McCarthy and Lehnert, 1995; Aone and William, 1995; Soon et al., 2001), entity-based models which focus on maintaining single underlying entity representation, contrasting the independent pair-wise decisions of mention-pair approaches (Clark and Manning, 2015, 2016), and ranking models which aim at ranking the possible antecedents of each mention instead of making binary decisions (Wiseman et al., 2016). A limitation of these methods lies in their bottom-up construction, resulting in an underutilisation of comprehensive global information regarding coreference links among all mentions in individual decisions. Furthermore, these methods tend to exhibit significant complexity. Modelling of coreference resolution as a graph-based approach offer an alternative to deal with these limitations.

4.3.2 Iterative Graph-based CR

Miculicich and Henderson (2022) proposed a novel approach to modelling coreference resolution, treating it as a graph problem. In this framework, the tokens within the text serve as nodes, and the connections between them signify coreference links (see Figure 2). Given a document $D=[x_1,...,x_N]$ with length N, the coreference graph is formally defined as the matrix $G\subset\mathbb{N}^{N\times N}$, which represents the relationships between tokens. Specifically, the relationship type between any two tokens, x_i and x_j, is labelled as $g_{i,j}\in\{0,1,2\}$ for the three distinct relation types: (0) no link, (1) mention link, and (2) coreference link.

The primary objective of this approach is to learn the conditional probability distribution $p(G|D)$. To achieve this, an iterative refinement strategy is employed, which captures interdependencies among relations. The model iterates over the same document D for a total of T iterations. In each iteration t, the predicted coreference graph G_t is conditioned on the previous prediction, denoted as G_{t-1}. Thus, the conditional probability distribution of the model is defined as follows:

$$p(G^t|D,G^{t-1})=\prod_{i=1}^{N}\prod_{j=1}^{i}p(g_{i,j}|D,G^{t-1}) \quad (4)$$

The proposed model operates on two levels of representation. In each iteration, it predicts the entire graph. However, during the first iteration, the model focuses on predicting edges that pinpoint mention spans, given that coreferent links only have relevance when mentions are detected. From the second iteration, both mention links, and coreference links are refined. This iterative strategy permits the model to enhance mention-related decisions based on coreference resolutions, and vice versa. This framework utilises iterative graph refinement as a substitute for conventional pipeline architectures in multi-level deep learning models. The iterative process concludes either when the graph no longer undergoes changes or when a predetermined maximum iteration count is attained (see Figure 3).

Ideally, encoding the entirety of the document in a single pass would be optimal. However, in practical scenarios, a constraint on maximum length arises due to limitations in hardware memory capacity. To address this challenge, Miculicich and Henderson (2022) introduce two strategies: overlapping windows and reduced document approach. In the latter strategy, mentions are identified during an initial iteration with a focus on optimising recall, as previously suggested in (Miculicich and Henderson, 2020). Only the representations of these identified spans are subsequently used as inputs for the following iterations.

Miculicich and Henderson (2022) conducted experiments on the CoNLL 2012 corpus (Pradhan et al., 2012) and showed improvements over relevant baselines and previous state-of-the-art methods, summarised in Table 4. We compare our model with three baselines: Lee et al. (2017) proposed the first end-to-end model for coreference resolution; Lee et al. (2018) extended the previous model by introducing higher order inference; and Xu and Choi (2020) used the span based pretrained model SpanBERT (Joshi et al., 2020). The 'Baseline' of Lee et al. (2018) uses ELMo (Peters et al., 2018) to obtain token representations, so versions of this Baseline which use 'BERT-large' (Joshi et al., 2019) and 'SpanBERT-large' (Joshi et al., 2020) as their pretrained models, are directly comparable to our 'G2GT BERT-large' and 'G2GT SpanBERT-large' models, respectively.

These results show that coreference resolution benefits from making global coreference decisions using document-level information, as supported by the G2GT architecture. Our model achieves its optimal solution within a maximum of three iterations. Notably, due to the model's ability to predict the entire graph in a single iteration, its computational complexity is lower compared to that of the baseline approaches.

5 Discussion

The empirical success of Graph-to-Graph Transformers on modelling these various graph structures helps us understand how Transformers model language. This success demonstrates that Transformers are computationally adequate for modelling linguistic structures, which are central to the nature of language. The reliance of these G2GT models on using self-attention mechanisms to extract and encode these graph relations shows that self-attention is crucial to how Transformers can do this modelling. The large improvements gained by initialising with pretrained models indicates that pretrained Transformers are in fact using the same mechanisms to learn about this linguistic structure, but in an unsupervised fashion.

These insights into pretrained Transformers give us a better understanding of the current generation of Large Language Models (LLMs). It is not that these models do not need linguistic structure (since their attention mechanisms do learn it); it is that these models do not need supervised learning of linguistic structure. But perhaps in a

Model	MUC P	MUC R	MUC F1	B^3 P	B^3 R	B^3 F1	CEAF$_{\phi_4}$ P	CEAF$_{\phi_4}$ R	CEAF$_{\phi_4}$ F1	Avg. F1
Lee et al. (2017)	78.4	73.4	75.8	68.6	61.8	65.0	62.7	59.0	60.8	67.2
Xu and Choi (2020)	**85.9**	85.5	85.7	79.0	78.9	79.0	**76.7**	75.2	75.9	80.2
Baseline (Lee et al., 2018)	81.4	79.5	80.4	72.2	69.5	70.8	68.2	67.1	67.6	73.0
+ BERT-large (Joshi et al., 2019)	84.7	82.4	83.5	76.5	74.0	75.3	74.1	69.8	71.9	76.9
+ SpanBERT-large (Joshi et al., 2020)	85.8	84.8	85.3	78.3	77.9	78.1	76.4	74.2	75.3	79.6
G2GT BERT-large *reduced*	84.7	83.1	83.9	76.8	74.0	75.4	75.3	70.1	72.6	77.3
G2GT SpanBERT-large *reduced*	**85.9**	**86.0***†	**85.9***	**79.3***	**79.4***†	**79.3***	76.4	**75.9***	**76.1***	**80.5***

Table 4: Evaluation of CR on the test set (CoNLL 2012) in terms of precision (P), recall (R) and F1 score for three metrics, as well as the average F1 over metrics. $*$ significant at $p < 0.01$ compared to (Joshi et al., 2020), † significant at $p < 0.05$ compared to (Xu and Choi, 2020).

low-resource scenario LLMs would benefit from the inductive bias provided by supervised learning of linguistic structures, such as for many of the world's languages other than English. And these insights are potentially relevant to the issues of interpretability and controllability of LLMs.

These insights are also relevant for any applications which could benefit from integrating text with structured representations. Our current work investigates jointly embedding text and parts of a knowledge base in a single G2GT model, providing a way to integrate interpretable structured knowledge with knowledge in text. Such representations would be useful for information extraction, question answering and information retrieval, amongst many other applications. Other graphs we might want to model with a Transformer and integrate with text include hyperlink graphs, citation graphs, and social networks. An important open problem with such models is the scale of the resulting Transformer embedding.

6 Conclusion and Future Work

The Graph-to-Graph Transformer architecture makes explicit the implicit graph processing abilities of Transformers, but further research is needed to fully leverage the potential of G2GT.

6.1 Conclusions

The success of the above models of a variety linguistic structures shows that Transformers are underlyingly graph-to-graph models, not limited to sequence-to-sequence tasks. The G2GT architecture with its RNGT method provides an effective way to exploit this underlying ability when modelling explicit graphs, effectively integrating them with the implicit graphs learned by pre-trained Transformers. Inputting graph relations as features to the self-attention mechanism enables the information input to the model to be steered by domain-specific knowledge or desired outcomes but still learned by the Transformer, opening up the possibility for a more tailored and customised encoding process. Predicting graph relations with attention-like functions and then re-inputting them for iterative refinement, encodes the input, predicted and latent graphs in a single joint Transformer embedding which is effective for making global decisions about structure in a text.

6.2 Future Work

One topic of research where explicit graphs are indispensable is knowledge graphs. Knowledge needs to be interpretable, so that it can be audited, edited, and learned by people. And it needs to be integrated with existing knowledge graphs. Our current work uses G2GT to integrate knowledge graphs with knowledge conveyed by text.

One of the limitations of the models discussed in this paper is that the set of nodes in the output graph needs to be (a subset of) the nodes in the input graph. General purpose graph-to-graph mappings would require also predicting a set of new nodes in the output graph. One natural solution would be autoregressive prediction of one node at a time, as is done for text generation, but an exciting alternative would be to use methods from non-autoregressive text generation in combination with our iterative refinement method RNGT.

The excellent performance of the models presented in this paper suggest that many more problems can be successfully formulated as graph-to-graph problems and modelled with G2GT, in NLP and beyond. The code for G2GT and RNGT is open-source and publicly available at `https://github.com/idiap/g2g-transformer`.

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It's MBR All the Way Down: Modern Generation Techniques Through the Lens of Minimum Bayes Risk

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Abstract

Minimum Bayes Risk (MBR) decoding is a method for choosing the outputs of a machine learning system based not on the output with the highest probability, but the output with the lowest risk (expected error) among multiple candidates. It is a simple but powerful method: for an additional cost at inference time, MBR provides reliable several-point improvements across metrics for a wide variety of tasks without any additional data or training. Despite this, MBR is not frequently applied in NLP works, and knowledge of the method itself is limited. We first provide an introduction to the method and the recent literature. We show that several recent methods that do not reference MBR can be written as special cases of MBR; this reformulation provides additional theoretical justification for the performance of these methods, explaining some results that were previously only empirical. We provide theoretical and empirical results about the effectiveness of various MBR variants and make concrete recommendations for the application of MBR in NLP models, including future directions in this area.

1 Introduction

> "Sometimes innovation is only old ideas reappearing in new guises . . . [b]ut the new costumes are better made, of better materials, as well as more becoming: so research is not so much going round in circles as ascending a spiral."
>
> (Jones, 1994)

Minimum Bayes Risk (MBR) decoding (Bickel and Doksum (1977); §2) is a decoding method following a simple intuition: when choosing a best output from a set of candidates, the desirable output should be both 1) high probability and 2) relatively consistent with the rest of the outputs (i.e., outputs that are not consistent with the other outputs are high *risk*– they may be dramatically better or worse than the consensus). MBR thus provides an alternative to the more standard maximum-likelihood decoding; when a sample of sufficient size is taken, MBR almost uniformly outperforms beam search and single-output sampling across tasks, metrics, and datasets (see §6). It is also notable in its flexibility; in §3 we organize and discuss several different design decisions that go into the use of MBR and how they affect the efficacy of the method.

While MBR is rarely applied by name in modern NLP, a number of methods with similar intuitions have gained popularity. In §4, we demonstrate that a number of generation techniques widely used with modern language models can be viewed as special instances of MBR: **self-consistency** (Wang et al., 2023) and its extensions, **range voting** (Borgeaud and Emerson, 2020), **output ensembling** (DeNero et al., 2010; Martínez Lorenzo et al., 2023), and some types of **density estimation** (Kobayashi, 2018). This view exposes connections between seemingly disparate methods and presents theoretical justifications for existing empirical results using these methods. We also discuss how insights from the MBR literature can inform the use of these other MBR-like methods.

With the framing of MBR, the theoretical justification for the empirical performance of several methods becomes clear; the extension of self-consistency to open-ended generations becomes trivial; and several promising modifications to self-consistency and output ensembling are exposed. In particular, modern MBR-like methods often do not apply the insights from research on MBR, suggesting that these methods could be further improved. In §5, we show that some design choices, though seemingly intuitive to a practitioner accustomed to search-based decoding methods, should be avoided when applying MBR.

2 Formalization

We begin with the basics of decoding and MBR.

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2.1 Standard decoding

Decoding from an autoregressive model (such as a transformer decoder) is performed tokenwise. The distribution at each decoding step is conditioned on the prior tokens and the input text:

$$p(y_i|y_{<i}, x) \quad (1)$$

The model is *locally normalized*; the probabilities of next tokens sum to 1. The probability of a sequence under this global model distribution is

$$p(y|x) = \prod_{i=1}^{T} p(y_i|y_{<i}, x) \quad (2)$$

Given this distribution, there are several ways of extracting an output: by sampling at each decoding step from the distribution over next tokens (often with some modification to the distribution, e.g. temperature, nucleus, or epsilon sampling; Holtzman et al. (2019)); by always choosing the most probable next token (i.e. greedy decoding); or by performing a search over some subset of the output space, guided by the distribution (e.g. beam search, best-first search). These methods generally return a single output; if multiple output candidates are present, the one with the *maximum likelihood* under the model distribution is returned.

2.2 Minimum Bayes Risk decoding

The traditional formulation of MBR is as a minimization objective. Given a *output space* $\mathscr{Y}$ and a probability distribution over this space $p(y|x)$, we compute the risk $R(y')$ of a candidate decoding y' as the expected error (also called *loss*) under this distribution (Bickel and Doksum, 1977; Kumar and Byrne, 2004; Tromble et al., 2008). The MBR decoding is then the y' within $\mathscr{Y}$ that minimizes risk:

$$\hat{y} = \operatorname*{argmin}_{y' \in \mathscr{Y}} R(y') \quad (3)$$

$$= \operatorname*{argmin}_{y' \in \mathscr{Y}} \mathbb{E}_{y|x}[L(y, y')] \quad (4)$$

$$= \operatorname*{argmin}_{y' \in \mathscr{Y}} \sum_{y \in \mathscr{Y}} L(y, y')p(y|x) \quad (5)$$

We can trivially rewrite the risk as a maximization of gain (also called *utility*) rather than a minimization of error, where $G(y, y') = -L(y, y')$. Gain or loss functions are any function (e.g. a metric) that compares two sequences $G : \mathscr{Y} \times \mathscr{Y} \to \mathbb{R}$.

Approximating risk Computing this sum over the space of all possible outputs $\mathscr{Y}$ is intractable for most models.[1] In these cases, we approximate the risk $R(y')$ by using a subset of the full space $\mathcal{Y} \subset \mathscr{Y}$; that is, instead of exact computation of the expectation, we approximate it with a sum over independent samples from $p(y|x)$. Generally, this is performed by sampling repeatedly from a model (or several models) and estimating the probability of each individual output as proportional to the relative frequency that the output occurs.[2] For an unbiased sampling method[3] (e.g. ancestral sampling), as the number of outputs drawn goes to infinity, this recovers the model's true distribution of probability over sequences. Thus, we approximate risk using this sample:

$$R(y') \approx \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} L(y, y') \quad (6)$$

$$= -\frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} G(y, y') \quad (7)$$

Thus, given a sample (which may include duplicates) $\mathcal{Y}$ and a gain function, we approximate the true MBR decoding rule as:

$$\hat{y} = \operatorname*{argmax}_{y' \in \mathcal{Y}} \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}_e} G(y, y') \quad (8)$$

Separation of evidence and hypothesis sets In many cases, the same subset of the output space is used for both the risk estimate and the candidate outputs. However, when the sample is substantially smaller than the full output space, it is often beneficial to use separate sets (Eikema and Aziz, 2022; Yan et al., 2023). Following prior work (§2.2), we refer to these as the *evidence set* ($\mathcal{Y}_e$) and *hypothesis set* ($\mathcal{Y}_h$).

This separation is beneficial because there are distinct and potentially contradictory desiderata for the two sets. We wish for our evidence set to cover a large, representative portion of the search space to obtain a more accurate estimate of risk. However, we want our hypothesis set to only cover the narrower, high-quality region of the space, as we do not want to consider candidate hypotheses that are low-quality. Applying the separation of evidence and hypothesis sets yields the equation for MBR over two subsets of the output space:

[1] This is the case for many deep generative models, such as a transformer language model and other autoregressive models without conditional independence assumptions.

[2] This is called a Monte Carlo approximation.

[3] We discuss the use of biased samplers in §3.2 and §3.1.

$$\hat{y} = \underset{y' \in \mathcal{Y}_h}{\operatorname{argmax}} \sum_{y \in \mathcal{Y}_e} G(y, y') \quad (9)$$

Note that this implicitly encodes the distribution of the evidence set samples in the sum. That is, by averaging over the gain on evidence set examples, we are estimating the expected gain *under this evidence set's distribution over sequences*.

3 Taxonomy of MBR

Equation 9 demonstrates four major axes along which an MBR method may vary:

1. Choice of hypothesis set $\mathcal{Y}_h$
2. Choice of evidence set $\mathcal{Y}_e$
3. Choice of gain (or error) function $G(y, y')$
4. Choice of evidence distribution $p(y|x)$

In this section, we examine how these four factors affect the efficacy of MBR and give recommendations for each; in Section 4, we discuss how these apply to other MBR-like methods.

3.1 Sampling a hypothesis set

Several recent works show benefits from improving the quality of the hypothesis space. Fernandes et al. (2022) apply a two-stage approach where they first apply an N-best (referenceless) reranker and then do MBR over only the most highly ranked hypotheses, which they also use as the evidence set. Eikema and Aziz (2022) introduce a method, Coarse-to-Fine MBR, that first uses MBR with a cheap-to-compute metric to filter a large hypothesis space to a smaller set, then uses MBR with a better but more expensive to compute metric over the smaller set; they separate evidence and hypothesis sets. Freitag et al. (2023) further investigates sampling strategies for MBR, finding that epsilon sampling (Hewitt et al., 2022) outperforms other strategies in automated and human evaluations.

Another earlier line of work has considered growing *post hoc* the hypothesis set in order to obtain hypotheses with higher expected gain (González-Rubio et al., 2011; González-Rubio and Casacuberta, 2013; Hoang et al., 2021).

3.2 Sampling an evidence set

Comparatively less work has studied strategies for sampling the evidence set. Most recent work has adopted the unbiased sampling strategy of Eikema and Aziz (2020), i.e. drawing i.i.d. samples from the model distribution $p(y|x)$ (equation 2). This strategy is motivated by their observation that unbiased sampling is reasonably reflective of the data distribution, much more so than beam search. However, their approach is incompatible with models trained via label smoothing (Szegedy et al., 2016). Yan et al. (2023) attempt to remedy this by sampling the evidence set with temperature $\tau < 1$, sharpening the model distribution.

3.3 What metric do we want to maximize?

The gain G (alternatively, error L) may be an arbitrary function $\mathcal{Y}_e \times \mathcal{Y}_h \to \mathbb{R}$. Early work focused on simple, token-level metrics like word error rate and BLEU (Kumar and Byrne, 2004; Ehling et al., 2007), but more recent work has explored the use of neural metrics (Amrhein and Sennrich, 2022; Freitag et al., 2022), as well as executing outputs in code generation (Shi et al., 2022; Li et al., 2022).

Generally, for both neural and non-neural metrics, MBR with metric G as a gain function will yield the largest downstream improvements on G (Müller and Sennrich, 2021; Freitag et al., 2022; Fernandes et al., 2022). In other words, if one aims to optimize system performance on metric M, one should perform MBR with M as gain. Although MBR uses pseudoreferences, using a metric M to score candidates against these pseudoreferences generally produces a candidate that also scores quite highly on M against the gold reference.

However, MBR also inherits the weaknesses and biases of the gain metric used. MBR has been shown to suffer from length and token frequency biases brought on by the metric, i.e. MBR with BLEU prefers shorter sentences (Nakov et al., 2012; Müller and Sennrich, 2021). Similarly, Amrhein and Sennrich (2022) find that MBR using the metric COMET (Rei et al., 2020) causes higher rates of errors for named entities and numbers due to a lack of sensitivity in the metric. Moreover, MBR is susceptible to overfitting to the metric; Freitag et al. (2023) show that the MBR setting that maximizes the metric is not the one that humans prefer. Thus, if the same metric is used for both MBR and evaluation of the output, *not all of the improvement in that metric can be attributed to higher quality*: it is possible that some of the improvement comes from gaming the metric. This provides an additional reason to evaluate across multiple, diverse metrics.

Note that in the most trivial case, where the met-

Method	Evidence Gen.	Hypothesis Gen.	Metric	$p(y\|x)$
Lattice MBR (Tromble et al., 2008)	N-best list	N-best list	BLEU	translation lattice
Coarse-to-fine MBR (Eikema and Aziz, 2022)	ancestral sampling	`filter`(sample)	BEER	single model
Wiher et al. (2022)	ancestral sampling	evidence + more decodings	BEER	single model
MBR-DC (Yan et al., 2023)	temperature sampling[1]	temperature sampling[1]	BLEURT	single model
Ours (§ 3.3)	ancestral sampling	temperature sampling	BERTScore	single model
Ours (§ 3.4)	ancestral sampling	temperature sampling	BERTScore	length-corrected scores
Freitag et al. (2023)	epsilon sampling		BLEURT	single model
Crowd sampling[2] (Suzgun et al., 2023)	temperature sampling		neural score metric	single model
MBR-Exec (Shi et al., 2022)	temperature sampling		execution match	single model
Self-consistency (SC) (Wang et al., 2023)	temperature sampling		exact answer match	single model
Complex SC (Fu et al., 2022)	`filter`(temperature sample)		exact answer match	single model
SC for open-ended gen (Jain et al., 2023)	temperature sampling		n-gram overlap	single model
Range voting (Borgeaud and Emerson, 2020)	beam search		n-gram overlap	single model
Post-Ensemble (Kobayashi, 2018)	beam search for each model in ensemble		cosine similarity	model set
AMRs Assemble! (Martínez Lorenzo et al., 2023)	model set	beam search	perplexity	model set

Table 1: Recent work under our taxonomy. The line separates methods that are explicitly MBR (above) from those that we identify as MBR-like (below).
[1] Different temperatures used for evidence and hypothesis.
[2] While Suzgun et al. (2023) coin the new term *crowd sampling*, they also explicitly refer to their method as MBR.

ric is $G(y, y') = \mathbb{1}[y = y']$, MBR recovers mode-seeking methods like beam search– i.e. MBR under this metric, in expectation, yields the maximum likelihood decoding. This is because, as the size of the sampled evidence set grows to infinity, the most frequent evidence set sequence (and thus the sequence with the highest gain) becomes the one with the highest probability under the sampling distribution.

3.4 What probability distribution should we use to estimate risk?

Most MBR decoding methods use the model's score distribution over outputs, s, as the (unnormalized) evidence distribution. Alternately, this distribution may be normalized by a temperature (during minimum risk training (Smith and Eisner, 2006) or decoding (Yan et al., 2023)). Some work (e.g Suzgun et al. (2023)) interprets this as a weak proxy for the human or true distribution, arguing that the true objective is to minimize error under the human distribution:

$$\underset{y' \in \mathcal{Y}_h}{\operatorname{argmin}} \mathbb{E}_{y \sim p_{\text{human}}}[L(y, y')]$$

Note that this is not the only reasonable choice of $p(y|x)$; other possible distributions include a distribution over outputs from multiple models (§4.2) or the length-penalized distribution over a single model's outputs $p_l(y|x)$ (§5.3).

4 MBR as a frame for other methods

Self-consistency, output ensembling, density estimation, and range voting can all be viewed through the framing of MBR. This exposes unstated connections between the methods and provides some theoretical backing to the empirical success of these methods. We discuss each in turn.

4.1 Self-consistency as MBR

Self-consistency (Wang et al., 2023) is a method for choosing outputs from language models. In self-consistency, the model is prompted to generate an explanation and then an answer. Multiple outputs $\mathcal{O} = \{y_1, \ldots, y_m\}$ are sampled from the model, the answers $\mathcal{A} = \{a_1, \ldots, a_m\}$ are extracted $a_i = \text{ans}(y_i)$, and the most frequent answer is returned:

$$\underset{a}{\operatorname{argmax}} \sum_{i=1}^{m} \mathbb{1}(a_i = a) \tag{10}$$

Self-consistency only computes exact match over the *answer*, not the reasoning chain. It is possible to recover MBR from this method by either taking the hypothesis/evidence sets to be the set of resulting answers $\mathcal{Y}_h = \mathcal{Y}_e = \mathcal{A}$ discarding the reasoning chain, or by defining a gain function $G(y, y') = \mathbb{1}(\text{ans}(y) = \text{ans}(y'))$ over full outputs $\mathcal{O}$; though notationally different, they are mathematically equivalent.

Thus, self-consistency is a type of MBR decoding in which we approximate the risk with a Monte Carlo estimate (cf. Eq. 6), the answers are sampled from the model (conditioned on the prompt), and the metric is exact match of the "final answer."

This framing additionally explains some results from the self-consistency paper. Wang et al. (2023) compare the performance of self-consistency across sampling strategies, finding that the best of the strategies they tried are those that are closest to ancestral sampling (nucleus sampling with $p = 0.95$ and $\tau = 0.7$ without top-k sampling). They also find that self-consistency works better with a sampled output rather than outputs from beam search (their Table 6). Through the lens of MBR, this empirical result has a clear theoretical justification: ancestral sampling of evidence sets generally yields the best performance for MBR because this provides an unbiased estimator of the probabilities of the sampled sequences. This also presents an opportunity for improvement: while Wang et al. (2023) do not evaluate on ancestral sampling, it is possible that this would outperform their best results.

Self-consistency is a special case of MBR. Proposed extensions to self-consistency have recovered aspects of generalized MBR decoding, including filtering to smaller hypothesis/evidence sets (Fu et al., 2022) and the use of alternative gain metrics (Jain et al., 2023). As a result, the term *self-consistency* has widened in definition from a specific type of MBR to a catch-all for MBR-based decoding methods on large language models.

4.2 Output Ensembling as MBR

Model ensembling techniques that operate on *completed outputs* of models may also be cast in MBR terms. Note that this does not include methods that operate on model weights or partial outputs. Common ensembling methods such as averaging model weights (Izmailov et al., 2018) or averaging token-level probabilities (Sennrich et al., 2016; Manakul et al., 2023) cannot be explicitly formulated as MBR.

The connection to MBR is most straightforward in methods that perform MBR decoding over the outputs of multiple models (DeNero et al., 2010; Duh et al., 2011; Barzdins and Gosko, 2016; Lee et al., 2022, *inter alia*). Representative of this family of methods is Post-Ensemble (Kobayashi, 2018), which ensembles multiple text generation models $\theta_1, \theta_2, \ldots, \theta_n$ by separately decoding from each model, computing pairwise sentence embedding similarity between all pairs of outputs, and yielding the output with greatest average similarity. Observe that this may be framed as MBR minimizing the expected risk over the mixture distribution

$$p_{\text{ensemble}}(y|x) = \begin{cases} p_{\theta_1}(y|x) & \text{with probability } \pi_1 \\ \cdots & \\ p_{\theta_n}(y|x) & \text{with probability } \pi_n \end{cases}$$

where $\sum_{i=1}^{n} \pi_i = 1$. While π_i is usually taken to be uniform over the ensemble, this need not always be the case (Duan et al., 2010).

Other methods may be viewed as relaxations of MBR decoding. Assemble! (Martínez Lorenzo et al., 2023) ensembles Abstract Meaning Representation (AMR) graph parsers by computing the pairwise perplexities of each output under *each parser*. While this is not precisely MBR, it may be viewed as a variation where the evidence set is *a set of models*, not a set of model outputs.

$$\hat{y} = \operatorname*{argmin}_{y' \in \mathcal{Y}_h} \mathbb{E}_{\theta \sim \pi(\cdot)}[L(\theta, y')]$$

In this case, the error $L(\theta, y')$ is the perplexity of y' under model θ, i.e. $\exp(-\log p_\theta(y')) = \frac{1}{p_\theta(y')}$, and $\pi(\cdot)$ is the distribution over models.

4.3 MBR as Density Estimation

Interestingly, Post-Ensemble (Kobayashi, 2018) (§4.2) was not formulated as MBR (and in fact never referred to by name as MBR), but rather as kernel density estimation. Kernel density estimation is a non-parametric method for estimating the probability density function p of an unknown distribution, given samples $(x_1, x_2, \cdots, x_n)$ from that distribution (Rosenblatt, 1956; Parzen, 1962).

$$\hat{p}(x) = \frac{1}{n} \sum_{i=1}^{n} K(x, x_i) \tag{11}$$

Indeed, Equation 11 very closely resembles the Monte Carlo estimator of expected loss in Equation 6. This connection allowed (Kobayashi, 2018) to propose approximation error bounds on MBR, drawing from the density estimation literature.[4]

Note that the kernel function $K(x, x_i)$ is more commonly written as $K(x - x_i)$, or $K(x^T x_i)$ for directional statistics. While this may seem limiting, we can rewrite commonly used MBR metrics in this form; we show this for ROUGE-n as an example. For a sequence y, define $T_n(y)$ to be a vector of size $|V|^n$, where $|V|$ is the size of the vocabulary, containing the number of times every possible n-gram appears in y. Then we can rewrite ROUGE-n as the following:

$$\begin{aligned} &K_{\text{R}}(T_n(y) - T_n(y')) \\ &= 1 - \frac{|T_n(y) - T_n(y')|_1}{|T_n(y)|_1 + |T_n(y')|_1} \end{aligned} \tag{12}$$

[4]We do not reproduce their bounds here; we direct interested readers to the original paper.

where $|\cdot|_1$ is the $L1$ norm.

The similarity between density estimation and MBR yields an alternative interpretation of MBR as a mode-seeking search. However, we are not seeking the mode of the model's distribution over outputs, $p(y|x)$, but rather that of a distribution over some features $\phi(y)$ of our output, $p'(\phi(y)|x)$. For instance, in the case of ROUGE-n MBR,

$$\hat{y} = \operatorname*{argmax}_{y' \in \mathcal{Y}_h} \sum_{y \in \mathcal{Y}_e} K_{\mathrm{R}}(T_n(y') - T_n(y)) \quad (13)$$

$$\approx \operatorname*{argmax}_{y' \in \mathcal{Y}_h} p'(T_n(y')|x) \quad (14)$$

We posit that this alternative distribution $p'(T_n(y')|x)$ may be better correlated with performance on specific downstream metrics than the original model distribution, potentially adding an additional justification for MBR's effectiveness. We hope this may inspire future work investigating the theoretical underpinnings of MBR.

4.4 Range Voting as MBR

Methods that take inspiration from outside of NLP may also be MBR-like; in particular, some MBR-like algorithms in the literature are formulated from a voting theory perspective where candidate hypotheses are assigned votes based on similarity to some set of voters (Wang et al., 2023; Jain et al., 2023; Suzgun et al., 2023; Hoang et al., 2021). We show here that range voting (Borgeaud and Emerson, 2020), which broadly encapsulates these proposed voting methods, reduces to MBR.

Range voting describes a family of voting systems in which each voter assigns each candidate a score and the candidate with the greatest total or average score is elected. Observe that the set of candidates C corresponds to the hypothesis set $\mathcal{Y}_h$ and the set of voters V corresponds to the evidence set $\mathcal{Y}_e$. Then, if voter v's score for candidate c is taken to be a gain $G(v, c)$ and each voter is assigned uniform weight, range voting is equivalent to the MBR decision rule in Equation 8:

$$c_{\text{elected}} = \operatorname*{argmax}_{c \in C} \frac{1}{|V|} \sum_{v \in V} G(v, c) \quad (15)$$

Other range-voting methods can similarly be cast as MBR variants.

5 Design Decisions Impact MBR Performance

Although all the methods in Section 4 are MBR-like, they make very different decisions about the four design choices in our MBR taxonomy. To demonstrate the importance of the method design, we consider empirically two cases where changing design impacts the performance of the method.

5.1 Experimental Details

We run MBR experiments for abstractive summarization on CNN/DM (Nallapati et al., 2016) with a fine-tuned BART-Large[5] released by the BART authors (Lewis et al., 2020) as our base model. In §5.3, we additionally report results for translation on WMT'16 Romanian-English (Ro-En) (Bojar et al., 2016) using mBART-50 (Liu et al., 2020).[6]

We draw n_e ancestral samples for our evidence set and n_t temperature samples ($\tau = 0.5$ for CNN/DM, $\tau = 0.3$ for WMT'16 Ro-En) for our hypothesis set. We set $n_e = n_t = 30$ in §5.2 and $n_e = n_t = 50$ in §5.3. Unless otherwise specified, we take ROUGE-1 (Lin, 2004) as our gain metric for summarization and BLEU-4 (Papineni et al., 2002)[7] as our gain metric for translation.

Our code is available at `https://github.com/abertsch72/minimum-bayes-risk`.

5.2 The MBR metric matters – but perhaps not as much as the hypothesis set

We find that using MBR with the summarization n-gram metric ROUGE-1 (Lin, 2004) improves abstractive summarization performance over beam search on CNN/DM, even when evaluating performance with neural metrics; using the general-purpose neural metric BERTScore (Zhang et al., 2020) as the MBR metric yields highest BERTScore but smaller gains on non-neural metrics, a finding consistent with past work; and even BEER (Stanojević and Sima'an, 2014), a translation metric, works as an MBR metric for this task.

However, prior work using the same dataset and model (Wiher et al., 2022) found that BEER (Stanojević and Sima'an, 2014) underperforms beam search. This divergence in results is likely due to our different choices in hypothesis set – Wiher et al. (2022) use the evidence set plus additional

[5] `facebook/bart-large-cnn` on HuggingFace (Wolf et al., 2020)

[6] `facebook/mbart-large-50-many-to-many-mmt`

[7] We use the implementation from `sacrebleu` (Post, 2018) with signature `nrefs:1|case:mixed|eff:yes|tok:13a|smooth:exp|version:2.3.1`

Method	R1	R2	RL	BS
Greedy	43.98	20.88	30.88	88.04
BS (k = 5)	43.16	20.63	30.53	87.82
BS (k = 10)	42.62	20.23	30.02	87.71
DBS ($k = g = 5$)	43.77	20.85	30.77	87.97
MBR ROUGE-1	**46.89**	22.29	32.01	88.41
MBR BEER	46.31	**22.36**	32.02	88.38
MBR BERTSCORE	46.04	22.09	**32.09**	**88.68**

Table 2: MBR results on CNN/DM for various gain functions. We additionally test the same non-MBR, (approximate) mode-seeking baselines as Wiher et al. (2022). All MBR methods outperform all non-MBR methods tested.

outputs from other decoding methods as hypotheses, while we use temperature samples at $\tau = 0.5$. While reusing the evidence set is more efficient than sampling a separate set of hypotheses, it leads to performance degregation in this case; this further emphasizes the importance of choosing the hypothesis set in MBR.

5.3 Varying the risk distribution: lessons from beam search don't translate to MBR

By nature, autoregressive text generation models suffer from length bias: sequence probability monotonically decreases with increasing length, causing shorter, potentially less informative sequences to be favored by the model distribution (Koehn and Knowles, 2017; Stahlberg and Byrne, 2019). For non-sampling methods such as beam search, the sequence probabilities are generally modified with a length-dependent term when comparing sequences (Murray and Chiang, 2018; Cho et al., 2014). Hence, it stands to reason that a length-corrected distribution with these biases alleviated may provide a better estimate of the risk $R(y')$.

Vanilla Monte Carlo MBR (as depicted in Equation 6) yields an estimate of the expected risk under the distribution that our evidence samples are drawn from. To modify the distribution used in our estimate, we turn to **importance sampling**, a method for estimating the expected value of a quantity under target distribution p, given samples from proposal distribution q (Kloek and van Dijk, 1978). For a brief tutorial on importance sampling and description of our estimator, see Appendix A.

We take the *score* of a sequence to be the log probability: We then experiment with two of the strategies described in Murray and Chiang (2018) for constructing the length corrected score $s_l(y|x)$:

(a) **Length normalization**: The model distribution is smoothed with temperature T^β, where T is the sequence length and β is the length penalty, a hyperparameter. A larger β more heavily prioritizes longer sequences.

$$s_l(y|x) = s(y|x)/T^\beta \tag{16}$$

(b) **Length reward** (He et al., 2016): A fixed reward γ is added to the score per token generated.

$$s_l(y|x) = s(y|x) + \gamma T \tag{17}$$

The length-corrected distribution is then $p_l(y|x) \propto \exp s_l(y|x)$. We apply **normalized importance sampling** (Rubinstein and Kroese, 2016) to estimate the risk under the length corrected distribution, i.e. $R(y') = \mathbb{E}_{y\sim p_l}[L(y, y')]$, given samples drawn from the model distribution $p(y|x)$.

We compare our MBR results against beam search both with and without length normalization. We use the models' default values for length penalty ($\beta = 2$ for BART, $\beta = 1$ for mBART).

Our results are Tables 3 and 4. In line with past work, we find that beam search generally benefits from incorporating a length penalty. However, we find that length-corrected MBR underperforms vanilla MBR. This may be due to a gap between the sampling and length-correction distibutions, leading to a high-variance estimator of risk.

Method	R1	R2	RL	BS	LR
Beam search, no correction	43.88	20.96	30.77	87.79	**108.00**
Beam search	43.95	21.00	30.84	87.81	114.39
MBR, No correction	**47.70**	**23.00**	**32.54**	**88.50**	111.64
MBR, Length norm, $\beta = 0.5$	44.29	19.95	29.99	88.03	110.75
MBR, Length norm, $\beta = 1.0$	44.29	19.98	30.0	88.03	110.77
MBR, Length reward, $\gamma = 0.5$	47.60	22.93	32.48	88.48	112.52
MBR, Length reward, $\gamma = 1.0$	47.41	22.72	32.25	88.43	112.50

Table 3: MBR results for various length correction schemes on CNN/DM. We report ROUGE-1, ROUGE-2, ROUGE-L, BERTSCORE, and length ratio, respectively.

Method	BLEU	chrF	BLEURT	BS	LR
Beam search, no correction	33.21	59.81	65.50	94.95	99.37
Beam search	33.06	**60.05**	**65.60**	**94.96**	101.58
MBR, No correction	**33.56**	60.00	65.53	**94.96**	**100.04**
MBR, Length norm, $\beta = 0.5$	31.14	58.53	64.70	94.71	102.82
MBR, Length norm, $\beta = 1.0$	31.09	58.51	64.68	94.71	102.60
MBR, Length reward, $\gamma = 0.5$	32.09	59.63	65.19	94.82	105.00
MBR, Length reward, $\gamma = 1.0$	31.29	59.17	64.91	94.73	105.63

Table 4: MBR results for various length correction schemes on WMT'16 Romanian-English. We report BLEU, chrF, BLEURT, BERTSCORE, and length ratio, respectively. We use the chrF (Popović, 2015) implementation from `sacrebleu`. We use the smaller `BLEURT-20-D6` checkpoint for efficiency (Sellam et al., 2020; Pu et al., 2021).

However, our results are also emblematic of a wider trend among minimum-risk techniques. Past work has found that models trained with Minimum Error Rate Training (Och, 2003; Shen et al., 2016), an error-aware training method, do not require length correction in beam search (Neubig, 2016). Similarly, we find that MBR without length correction generates outputs relatively close in length to the references, more so than length-normalized beam search. This suggests that MBR may be to some extent immune from length biases, when they are not introduced by the MBR metric (Müller and Sennrich, 2021).

6 MBR applications in NLP

The use of minimum Bayes risk decoding in NLP predates these MBR-like methods; MBR has been applied by name in NLP since the 1990s.

Historical context Minimum Bayes Risk decoding has roots in Bayesian decision theory, a field of study that dates as far back as the Age of Enlightenment (Bernoulli, 1738; Parmigiani, 2001). Central to Bayesian decision theory is the principle of risk minimization: in the face of uncertainty, an optimal decision maker should choose the option that minimizes the amount of error they can expect to suffer – or, in other terms, maximizes the amount of utility they can expect to enjoy (DeGroot, 1970; Bickel and Doksum, 1977). This is precisely the intuition encoded in MBR (i.e. Equation 3).

Adoption in NLP MBR was adopted by the speech and NLP communities in the 1990s and early 2000s, finding applications in syntactical parsing (Goodman, 1996; Sima'an, 2003), automatic speech recognition (Stolcke et al., 1997; Goel and Byrne, 2000), and statistical machine translation (Kumar and Byrne, 2004; Tromble et al., 2008; Kumar et al., 2009). Many NLP tasks during this time relied upon graph structures as inductive biases (i.e. parse trees or translation lattices/hypergraphs). As such, early MBR works often used these graphical models as hypothesis and evidence spaces. Work on lattice MBR (Tromble et al., 2008), for instance, treated the set of all hypotheses encoded in a word lattice, of which there are exponentially many, as both evidence and hypothesis sets. This is in contrast to most later MBR work, which operates on a relatively small list of text outputs obtained from a neural model. As a result, early work relied on rather involved dynamic programming algorithms

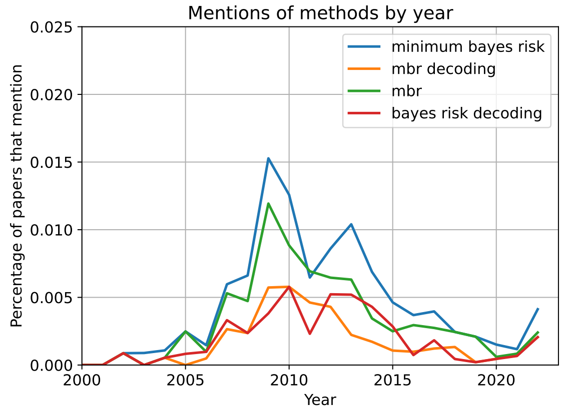

Figure 1: The use of MBR (by name) peaked in the mid-2010s. This graph shows the percentage of ACL Anthology papers that mention several MBR-related phrases by year, from 2000 to 2022.

for exact MBR decoding and were restricted to token-factorizable metrics such as BLEU and edit distance. Later work additionally demonstrated the efficacy of MBR for question answering (Duan, 2013) and for joining statistical and neural approaches to translation (Stahlberg et al., 2017).

Recent usage In an effort to move past beam search, which has well-known pathologies (Stahlberg and Byrne, 2019), MBR has in recent years resurfaced as a decision rule for text-generation models (Eikema and Aziz, 2020). As discussed earlier in §3, several lines of work have sprung up investigating the properties of MBR in modern neural text generation setups. Notably, however, most of these works have focused on applications of the method to neural machine translation, with only a few very recent works studying its applications in other text generation tasks (Shi et al., 2022; Wiher et al., 2022; Suzgun et al., 2023).

Outside of these areas, the method has largely been applied in shared task papers (e.g. Manakul et al. (2023); Yan et al. (2022); Barzdins and Gosko (2016)), as it provides a reliable boost in performance. The fraction of papers in the ACL Anthology that reference MBR (at least by this name) has declined from its peak around 2009 (Figure 1).

7 Conclusion

Minimum Bayes Risk decoding has declined in popularity, but the underlying concept of sampling a set from a distribution and choosing an output to minimize risk according to that set has remained. This concept now takes many surface forms– from self-consistency to range voting to output ensembles– and current research in these areas rarely draws connections to MBR. While rediscovery is a key part of science, so is recontextualizing new methods within a broader research narrative. This can often reveal new insights or cast findings in a different light. For instance, the empirical benefits of self-consistency can be justified through an MBR framing; work on extensions to self-consistency has rediscovered other properties of MBR; and work on ensembling has raised questions about how to weight mixtures of models that can be reasoned about within the framework of noisy estimates of global probability distributions.

The adoption of newer terms for MBR-like methods may be a type of terminology drift. Related phenomena have been studied in the philosophy of science literature, including pressures to coin new terms (Dyke, 1992; Merton, 1957), potential negative consequences of divergent terminology (Calvert, 1956; Samigullina et al., 2020), and decreased citation of older methods in NLP (Singh et al., 2023). For a more involved discussion of the literature on term coining and possible connections, see Appendix B.

Language is not static, so some degree of terminology drift in scientific literature is unavoidable. However, recognizing the connections between modern techniques and older work is crucial to understanding why such methods are effective. We must not forget the lessons of the past as we search for the methods of the future.

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A More details on importance sampling for MBR

We present in this section the normalized importance sampling estimator of risk used in our experiments in §5.3.

The core insight of importance sampling is that we can rewrite the expected value of a random variable $f(x)$ under target distribution p as another expectation under some proposal distribution q:

$$\begin{aligned}
\mathbb{E}_p[f(x)] &= \sum_x f(x)p(x) \\
&= \sum_x f(x)\frac{p(x)}{q(x)}q(x) \\
&= \mathbb{E}_q\left[f(x)\frac{p(x)}{q(x)}\right]
\end{aligned}$$

Importance sampling can be particularly useful when sampling from the proposal distribution is easy, but sampling from the target distribution is costly or intractable; this is indeed the case for MBR, as sampling from the length-corrected distribution $p_l(y|x)$ requires computation of its partition function, which has exponential complexity.

Hence, for MBR, if we draw evidence samples $\mathcal{Y}_e$ according to model distribution $p(y|x)$ but wish to compute the risk under some length-corrected distribution $p_l(y|x)$, we may compute

$$\begin{aligned}
R(y') &= \mathbb{E}_{y\sim p_l}[L(y,y')] \\
&= \mathbb{E}_{y\sim p}\left[L(y,y')\frac{p_l(y|x)}{p(y|x)}\right] \\
&= \sum_{y\in\mathcal{Y}_e} L(y,y')\frac{p_l(y|x)}{p(y|x)} \\
&= \sum_{y\in\mathcal{Y}_e} L(y,y')w(y)
\end{aligned}$$

where we let $w(y) = p_l(y|x)/p(y|x)$, commonly referred to as the importance weight.

Note, however, that importance sampling requires us to be able to exactly compute the probabilities $p(y|x)$ and $p_l(y|x)$; while the former can be computed efficiently (Equation 2), the latter is intractable, again because it requires the partition function. What we can efficiently compute is the unnormalized probability $\tilde{p}_l(y|x) = \exp s_l(y|x)$, where s_l is the length-corrected score given by either Equation 16 or 17.

Fortunately, we can use **normalized importance sampling** to obtain a consistent estimator of the risk by adjusting importance weights (Rubinstein and Kroese, 2016):

$$\begin{aligned}
R(y') &= \mathbb{E}_{y\sim p_l}[L(y,y')] && (18) \\
&= \frac{\mathbb{E}_{y\sim p}[L(y,y')\tilde{w}(y)]}{\mathbb{E}_{y\sim p}[\tilde{w}(y)]} && (19) \\
&= \sum_{y\in\mathcal{Y}_e} L(y,y')\cdot\frac{\tilde{w}(y)}{\sum_{y\in\mathcal{Y}_e}\tilde{w}(y)} && (20)
\end{aligned}$$

where $\tilde{w}(y) = \tilde{p}_l(y|x)/p(y|x)$. As it is the ratio of two estimates, the normalized importance sampling estimator is *biased* for finite sample sizes.

B Contextualizing this work within philosophy of science

In this section, we contextualize our work in the broader framings of meta-analysis of scientific research.

Patterns of citation in NLP Several factors have been shown to correlate with citation rate in NLP, including author geographic location (Rungta et al., 2022), author gender (Mohammad, 2020), and publication date (Bollmann and Elliott, 2020; Singh et al., 2023). Bollmann and Elliott (2020) conduct a bibliometric anaylsis of the ACL Anthology, finding that the mean age of papers cited decreased significantly from 2010 to 2019. Singh et al. (2023) expand this analysis to the full anthology, finding that, while citations of older papers rose briefly in the mid-2010s, it has since declined, with 2021 marking a historic low for the percentage of citations that went to older papers[8]. They term this *citational amnesia* and discuss several possible reasons for the result, including the shift to neural methods and the rise of new areas of NLP.

Our work raises another potential explanation: some citational amnesia is due to *terminology drift* over time, as old methods begin to be referred to by newer names.

Term coining in science Work in science and technology studies has examined the broader phenomenon of term coining in science. Dyke (1992) argues that neologisms emerge more frequently in fields that prize novelty and see science as fundamentally about leaps of discovery, and fields that are perceived as synthesizing findings from multiple fields are most likely to recycle terms from other disciplines. She cites computer science as an example of a field where most new terms of art emerge from recycling common words, often those that draw a metaphor to some basic physical or human concept; this is reflected in the adoption of the humanizing "self-consistency" and the political-science-inspired "range voting" in decoding. Raad (1989) suggests that evocative, metaphor-laden names are more likely to emerge as a scientific field grows more public-facing and in times where many new terms are being coined; both of these descriptors apply to modern NLP. While several works in linguistics and STS have considered the coining of new terms for new phenomena, relatively little work has focused on the divergence of terminology for previously observed phenomena.

The consequences of divergent or distinct terminology have also been studied, with differences in terminology across fields blamed for slow adaptation of research to practical applications (e.g. in studying visual distortions during plane take-off (Calvert, 1956)). Borrowing terminology from another language (often Latin or Greek) or from another field has been described as a method to build common ground between researchers (Samigullina et al., 2020) and as a possibly concerning pressure against developing language-specific scientific terminology in lower-resourced languages (Hultgren, 2013). However, most work on lexical divides in science has focused on divides across language or field rather than divides across time in the same field.

[8] They define an "older paper" as one that is more than 10 years older than the paper that is citing it.

Analyzing Pre-trained and Fine-tuned Language Models

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Abstract

Since the introduction of transformer-based language models in 2018, the current generation of natural language processing (NLP) models continues to demonstrate impressive capabilities on a variety of academic benchmarks and real-world applications. This progress is based on a simple but general pipeline which consists of pre-training neural language models on large quantities of text, followed by an adaptation step that fine-tunes the pre-trained model to perform a specific NLP task of interest. However, despite the impressive progress on academic benchmarks and the widespread deployment of pre-trained and fine-tuned language models in industry we still lack a fundamental understanding of how and why pre-trained and fine-tuned language models work, as well as they do. We make several contributions towards improving our understanding of pre-trained and fine-tuned language models, ranging from analyzing the linguistic knowledge of pre-trained language models and how it is affected by fine-tuning, to a rigorous analysis of the fine-tuning process itself and how the choice of adaptation technique affects the generalization of models. We thereby provide new insights about previously unexplained phenomena and the capabilities of pre-trained and fine-tuned language models.

1 Introduction

Since the introduction of transformer-based pre-trained neural language models in 2018 (Devlin et al., 2019; Liu et al., 2019b), the field of natural language processing (NLP) has witnessed a paradigm shift. Instead of designing and training highly task-specific models from scratch, the current default approach for most NLP tasks consists of adapting general-purpose pre-trained language models, a process which typically requires only very few task-specific changes to the model architecture, and therefore allows us to easily apply the same pre-trained model to different tasks. Over the last five years (2019 – 2023), this paradigm shift has led to impressive progress on a large variety of downstream NLP tasks, ranging from traditional computational linguistics tasks such as part-of-speech tagging and more challenging tasks like natural language inference, to text-based dialogue and assistant systems (Wang et al., 2018, 2019; OpenAI, 2023, *inter alia*).

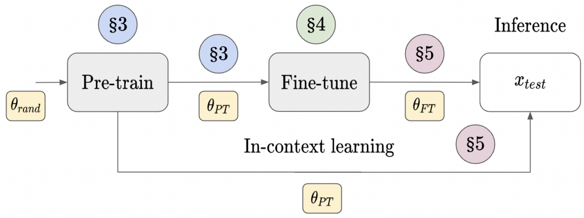

Figure 1: Our contributions positioned along the *pre-train then adapt pipeline* which is prevalent in modern-day NLP. §3 is concerned with how fine-tuning affects the linguistic knowledge of a model, §4 focuses on a better understanding of the fine-tuning process, and §5 is concerned with the generalization of models adapted via fine-tuning and in-context learning during inference.

At the core of this impressive progress lies a very simple but general pipeline which is illustrated in Figure 1 together with our contributions. The first step of this pipeline, which we will refer to as the *pre-train then adapt pipeline*, consists of pre-training a (large) neural language model on large quantities of text using self-supervised training. Due to the discrepancy between the pre-training objective (e.g., masked language modeling) and the downstream task (e.g., classification), the pre-training step is followed by an adaptation step which fine-tunes the pre-trained model to perform a specific task of interest. During fine-tuning, we either update all of the pre-trained parameters or update only a small fraction of them by leveraging parameter-efficient fine-tuning techniques. In both cases, however, fine-tuning results in a task-specific model which can be used for a single task. An alternative task-adaptation technique which was popularized by the most recent advances in training

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pre-trained language models (Brown et al., 2020; OpenAI, 2023), allows us to bypass the fine-tuning step by treating the downstream task as a language modeling problem. This process, known as in-context learning, enables adapting a pre-trained model without updating any parameters and allows even non-expert users to easily leverage pre-trained language models.

Recent advancements in in-context learning have led to impressive progress on challenging reasoning benchmarks, surpassing the capabilities of fine-tuned language models by large margins (Wei et al., 2022a), a development which has resulted in unprecedented interest from the general public in the promises and potential risks associated with the use of large language models.

2 Research objectives

The previously described pipeline is ubiquitous in modern-day NLP and pre-trained and fine-tuned language models are now dominating research in academia as well as in industry. However, regardless of their impressive capabilities, pre-trained and fine-tuned language models are not without shortcomings. Our contributions center around three major shortcomings of pre-trained and fine-tuned language models. Each of the shortcomings concerns a specific component (or the interaction between two components) of the pre-train then align pipeline (see Figure 1).

2.1 Interplay between fine-tuning and probing

It is well established that fine-tuned language models are often right for the wrong reasons and their good performance on downstream tasks can at least in part be explained by the tendency to pick up spurious correlations during the adaptation process (Jia and Liang, 2017; McCoy et al., 2019; Niven and Kao, 2019; Warstadt et al., 2020, *inter alia*). These results stand in contrast to a large body of evidence that pre-trained language models encode various forms of linguistic and factual knowledge (Liu et al., 2019a; Tenney et al., 2019a; Petroni et al., 2019; Goldberg, 2019; Hewitt and Manning, 2019, *inter alia*).

When combined, these findings require taking a nuanced perspective on the connection between the strong capabilities of language models, as shown by their impressive results on common NLP tasks, and their encoding of linguistic and factual knowledge. These findings also demonstrate the need for investigating the interplay between the linguistic capabilities of pre-trained language models and their downstream performance.

2.2 Investigating fine-tuning stability

Fine-tuned language models often exhibit striking variation in downstream task performance when performing small changes to the adaptation process such as changing the random seed used for initializing model weights, the order of training examples, or the format of a task instruction (Dodge et al., 2020; Webson and Pavlick, 2022; Lu et al., 2022). Large variations in fine-tuning performance are undesirable for several reasons such as hindering reproducible research and complicating the distinction between actual improvements due to modeling or algorithmic advances and comparisons against weak baselines.

Given the ubiquity of fine-tuned language models, it is therefore critical to gain a better understanding of the fine-tuning algorithms that are commonly applied to adapt language models to downstream tasks.

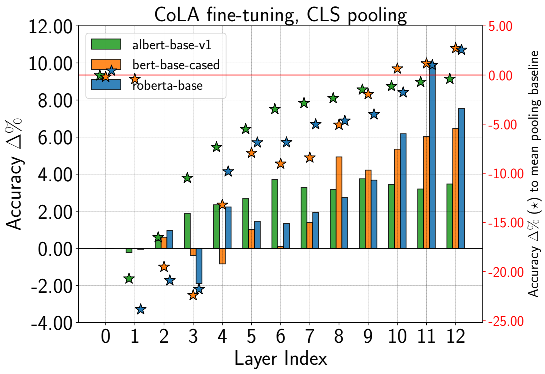
2.3 Generalization of task-adapted models

As mentioned in the previous section, the rapid progress in training ever larger language models has resulted in novel ways to adapt pre-trained language models to downstream tasks by simply instructing them to perform a task of interest via in-context learning. Instead of adapting a model via gradient based fine-tuning, in-context learning allows task adaptation via mere textual interaction and has lead to impressive progress on challenging reasoning benchmarks (Wei et al., 2022b,a). At the same time, there is growing evidence that in-context learning suffers from similar shortcomings to fine-tuning such as their sensitivity to changes in the data order (Min et al., 2022; Lu et al., 2022) and difficulties with generalizing to out-of-distribution inputs (Si et al., 2023).

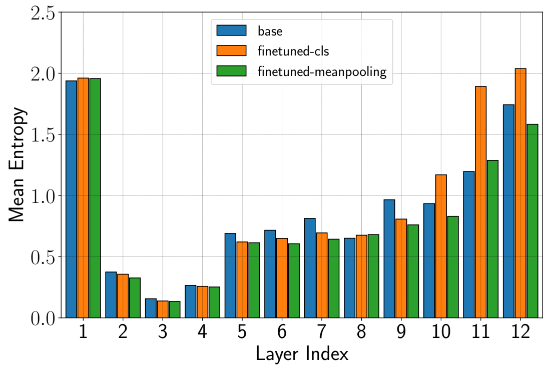
Given the prevalence of task adaptation via fine-tuning and in-context learning in modern NLP, it is necessary to investigate their respective benefits and downsides and provide a fair comparison of task adaptation approaches.

3 Interplay between fine-tuning and probing (Mosbach et al., 2020)

Our first contribution focuses on the connection between high performance on downstream tasks and



(a) Difference in probing accuracy before and after fine-tuning on CoLA using different models and pooling strategies.



(b) Entropy of the attention distribution for the cls-token of the RoBERTa model on the bigram-shift dataset.

Figure 2: A selection of our findings. (a) shows that when comparing to a stronger pooling baseline, fine-tuning has a negligible impact on probing performance. (b) shows that fine-tuning results in a more uniform attention which offers an alternative explanation for improved sentence-level probing performance.

the linguistic information encoded by a pre-trained model. Specifically, we investigate the hypothesis that the strong capabilities of fine-tuned language models can at least implicitly be attributed to the vast amount of linguistic knowledge which they encode (Pruksachatkun et al., 2020).

3.1 Previous work

A large body of previous work focused on analyzing the internal representations of neural models and the linguistic knowledge they encode via probing (Shi et al., 2016; Ettinger et al., 2016; Adi et al., 2016; Belinkov et al., 2017; Hupkes et al., 2018; Conneau et al., 2018; Krasnowska-Kieraś and Wróblewska, 2019). In a similar spirit to these first works on probing, Conneau et al. (2018) were the first to compare different sentence embedding methods based on the linguistic knowledge they encode. Krasnowska-Kieraś and Wróblewska (2019) extended this approach to study sentence-level probing tasks on English and Polish sentences.

Alongside sentence-level probing, a lot of recent work (Peters et al., 2018; Liu et al., 2019a; Tenney et al., 2019b; Lin et al., 2019; Hewitt and Manning, 2019) has focused on token-level probing tasks investigating more recent contextualized embedding models such as ELMo (Peters et al., 2018), GPT (rad), and BERT (Devlin et al., 2019). Two of the most prominent works following this methodology are Liu et al. (2019a) and Tenney et al. (2019b).

Limitations In contrast to our work, most studies that investigate pre-trained contextualized embedding models focus on pre-trained models and not fine-tuned ones. Therefore, little is known about the interaction between fine-tuning and probing. In our work, we aim to assess how probing performance changes with fine-tuning and how these changes differ based on the model architecture, as well as probing and fine-tuning task combination.

3.2 Our contributions

Setup We study three different pre-trained language models: BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019b), and ALBERT (Lan et al., 2020), and investigate via sentence-level probing (Conneau et al., 2018) how fine-tuning them on downstream tasks affects the linguistic information encoded in their representations.

We fine-tune on four datasets: CoLA (Warstadt et al., 2018), SST-2 (Socher et al., 2013), RTE (Dagan et al., 2005), SQuAD (Rajpurkar et al., 2016), and perform sentence-level probing experiments on three tasks from the SentEval probing suite (Conneau et al., 2018), each of which targets a different level of linguistic competence: bigram-shift, semantic-odd-man-out, and coordination inversion.

To evaluate the impact of fine-tuning on the linguistic information encoded by a model, we compare probing results before and after fine-tuning.

Fine-tuning mostly affects upper layers Comparing differences in probing performance before and after fine-tuning, we observe that fine-tuning mostly interacts with the upper layers of the pre-trained model. Changes in probing performance are typically larger for higher layers and this finding is consistent across all models and tasks we experiment with.

Positive effect on probing performance is marginal When following the default strategy for sentence-level probing, i.e., constructing sentence representations based on the cls-token of the last hidden layer, we indeed observe large positive changes in probing performance due to fine-tuning, suggesting the encoding of new linguistic information during fine-tuning. However, when we change the pooling approach during probing to mean-pooling, the positive impact of fine-tuning on probing becomes negligible. This effect is illustrated in Figure 2a. For all models, we observe a large increase in probing performance when using cls-pooling to construct sentence representations. However, with mean-pooling, the difference in probing accuracy between the pre-trained and fine-tuned models becomes marginal and fine-tuning even hurts probing performance in lower layers.

Fine-tuning affects attention distribution To better understand the origin of the positive improvements in probing accuracy for cls-pooling, we investigate the attention distribution of the cls-token at every layer. We observe a large increase in entropy in the last three layers when fine-tuning on the cls-token (orange bars in Figure 2b). This is consistent with our hypothesis that during fine-tuning, the cls-token learns to take more sentence-level information into account, thus spreading its attention over more tokens, which offers an alternative explanation to why fine-tuning has a positive impact on probing performance.

3.3 Discussion

Our work provides novel insight into how to perform a fine-grained evaluation of the linguistic knowledge of pre-trained language models and on the interaction between probing performance and fine-tuning. Our findings demonstrate that there is no straightforward causal relationship between the linguistic information encoded by a model and its performance on NLP downstream tasks, which calls for a careful interpretation of changes in probing performance as a result of fine-tuning.

4 Investigating fine-tuning stability (Mosbach et al., 2021)

Our next contribution focuses on the second step of the pre-train then adapt pipeline. We analyze the fine-tuning process itself and study the intriguing finding that fine-tuned models tend to exhibit a large variance in performance, a phenomenon commonly referred to as fine-tuning instability.

4.1 Previous work

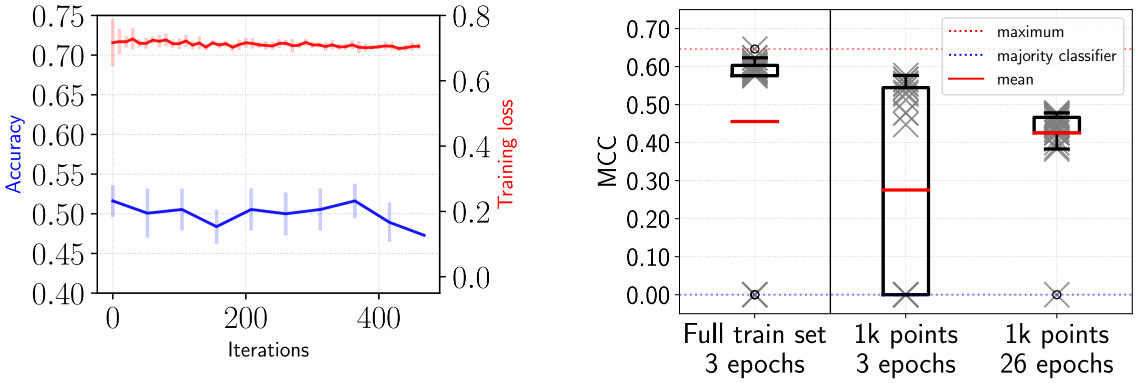
Previous work (Devlin et al., 2019; Lee et al., 2020; Dodge et al., 2020) has observed large differences in downstream task performance simply when fine-tuning models with different random seeds. Devlin et al. (2019) report instabilities when fine-tuning BERT-large on small datasets and resort to performing multiple restarts of fine-tuning and selecting the model that performs best on the development set. Dodge et al. (2020) performed a large-scale empirical investigation of the fine-tuning instability of BERT and found dramatic variations in fine-tuning accuracy across multiple restarts and argue how it might be related to the choice of random seed and the dataset size. Few approaches have been proposed to address the observed fine-tuning instability. Phang et al. (2018) study intermediate task training before fine-tuning with the goal of improving performance on the GLUE benchmark and find that their proposed method leads to improved fine-tuning stability. Lee et al. (2020) propose a new regularization technique termed Mixout which improves stability during fine-tuning.

Limitations While previous work on fine-tuning instability commonly states two hypotheses for the observed instability: catastrophic forgetting (Lee et al., 2020) and the small size of the training data (Dodge et al., 2020), there is no previous work that provides a sufficient understanding of why fine-tuning is prone to instability in the first place.

4.2 Our contributions

Motivated by the anecdotal observations stated in previous work, we perform a rigorous investigation of fine-tuning instability in order to determine its root cause.

Setup We analyze three different pre-trained language models: BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019b), and ALBERT (Lan et al., 2020) and fine-tune them on widely used



(a) Training of failed models

(b) Results on down-sampled CoLA

Figure 3: Previous hypotheses fail to explain fine-tuning stability. (a) shows average training loss and validation accuracy across 3 failed fine-tuning runs on RTE. (b) shows validation performance of models fine-tuned on down-sampled CoLA.

datasets from the GLUE benchmark (Wang et al., 2018). We summarize our contributions below.

Previous hypotheses fail to explain instability First, we show that both catastrophic forgetting and the small size of the training data fail to explain the observed instability phenomenon. As shown in Figure 3a, failed fine-tuning runs in fact do not learn at all, violating the core assumption of catastrophic forgetting that the model performs well on the new task.

Regarding the small size of the training data, Figure 3b shows that fine-tuning on a down-sampled dataset for a small number of epochs does increase variance on the downstream task, however simply training for more iterations fully recovers the original variance in fine-tuning performance. This suggests that the observed instability on small datasets is connected to the number of training steps and not the size of the training set.

Optimization difficulties cause instability Next, we demonstrate that the observed instability is caused by optimization difficulties during fine-tuning that lead to vanishing gradients and models converging to sub-optimal local minima (illustrated in Figure 4). As we show in our work, this behavior is further amplified by choosing too large step sizes, fixing the number of epochs, and not warming up learning rates during the initial phase of fine-tuning.

A strong baseline for fine-tuning Based on our analysis, we present recommendations and a simple but strong baseline approach for fine-tuning. We recommend using small learning rates combined with warmup to avoid vanishing gradients during the initial fine-tuning phase. Additionally, when fine-tuning on small datasets, we suggest not fixing the number of epochs a priori (as was common practice) but rather fix the number of training steps.

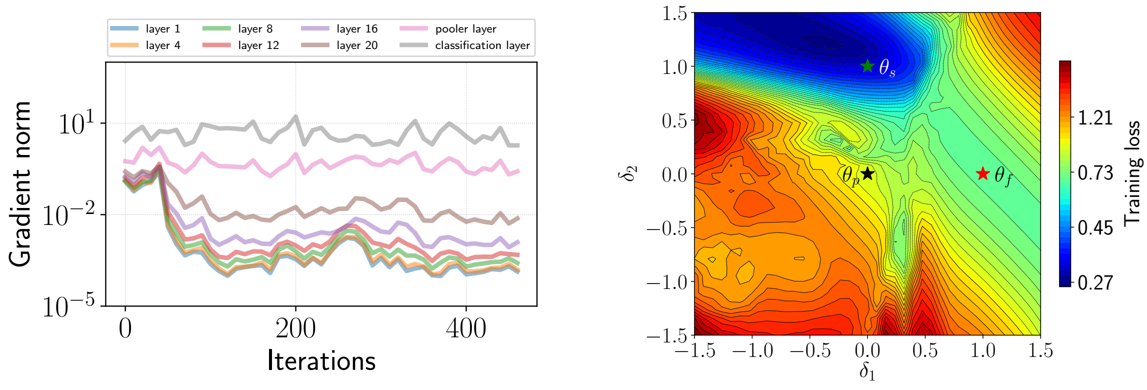
Approach	**RTE**			**MRPC**			**CoLA**		
	std	mean	max	std	mean	max	std	mean	max
Devlin	4.5	50.9	67.5	3.9	84.0	91.2	25.6	45.6	64.6
Lee	7.9	65.3	**74.4**	3.8	87.8	**91.8**	20.9	51.9	64.0
Ours	**2.7***	**67.3**	71.1	**0.8***	**90.3**	**91.7**	**1.8***	**62.1**	**65.3**

Table 1: Standard deviation, mean, and maximum performance on the development set of RTE, MRPC, and CoLA when fine-tuning BERT over 25 random seeds. Standard deviation: lower is better, i.e., fine-tuning is more stable. * denotes significant difference ($p < 0.001$) when compared to the second smallest standard deviation.

As can be seen in Table 1, our baseline makes fine-tuning pre-trained language models significantly more stable than previously proposed approaches while at the same time maintaining or even improving performance.

4.3 Discussion

Our work answers an open question about the instability of fine-tuning and shows that neither catastrophic forgetting nor small dataset sizes sufficiently explain fine-tuning instability. Instead, our analysis reveals that fine-tuning instability can be characterized by two distinct problems: (1) optimization difficulties early in training, characterized by vanishing gradients, and (2) differences in generalization, characterized by a large variance of de-



(a) Vanishing gradients during fine-tuning of BERT-large.

(b) 2D loss surface.

Figure 4: Fine-tuning instabilities are characterized by vanishing gradients (a) and convergence to sub-optimal local minima. The 2D loss surface in (b) is spanned by $\delta_1 = \boldsymbol{\theta}_f - \boldsymbol{\theta}_p$ and $\delta_2 = \boldsymbol{\theta}_s - \boldsymbol{\theta}_p$ on RTE.

velopment set accuracy for runs with almost equivalent training performance. Based on our analysis, we propose a simple but strong baseline strategy for fine-tuning BERT which outperforms previous works in terms of fine-tuning stability while maintaining or even increasing overall performance.

5 Generalization of task-adapted models (Mosbach et al., 2023)

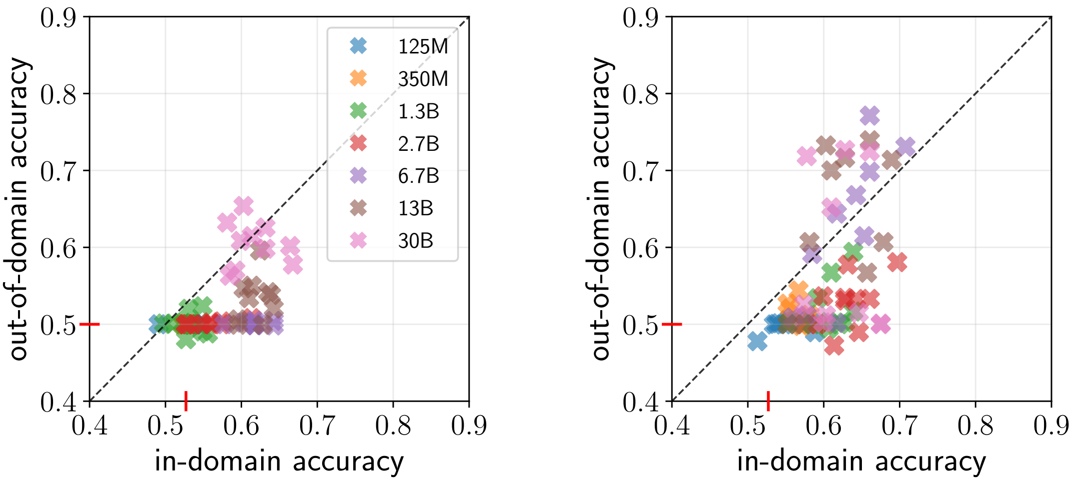
Our final contribution is concerned with the last step of the NLP pipeline, namely, inference. We compare the generalization behavior of task-adaptation via few-shot fine-tuning and in-context learning (ICL), which has recently gained popularity over fine-tuning due to its simplicity and strong performance on challenging reasoning tasks.

5.1 Previous work

Brown et al. (2020) compared GPT-3's few-shot in-context learning performance with fine-tuned language models trained in the fully supervised setting and found that both approaches lead to similar results in question answering. More recently, Liu et al. (2022) compared parameter-efficient few-shot FT of T0 (Sanh et al., 2022) to in-context learning with GPT-3, finding that their parameter-efficient fine-tuning approach outperforms in-context learning when evaluated on in-domain data. Focusing on out-of-domain (OOD) performance, Si et al. (2023) investigated the generalization of GPT-3 along various axes, including generalization under covariate shift. They observed much better OOD performance for in-context learning than fine-tuning, concluding that in-context learning with GPT-3 is more robust than fine-tuning using BERT or RoBERTa. Another work that compares the OOD generalization of different adaptation approaches is Awadalla et al. (2022). They investigate the robustness of question answering models under various types of distribution shifts and find that in-context learning is more robust to distribution shifts than fine-tuning. Moreover, they argue that for fine-tuning, increasing model size does not have a strong impact on generalization.

Utama et al. (2021) investigate the OOD generalization of encoder-only models adapted via pattern-based few-shot fine-tuning. For MNLI and HANS, they find that these models adopt similar inference heuristics to those trained with vanilla fine-tuning and hence perform poorly OOD. They observe that models rely even more on heuristics when fine-tuned on more data. Lastly, Bandel et al. (2022) show that masked language models can generalize well on HANS if fine-tuned for a sufficient number of steps.

Limitations A common limitation in the previous literature is the comparisons of generalization abilities under unequal conditions. Most studies either compare the in-context learning abilities of large models (e.g., GPT-3, 175B; Brown et al., 2020) to the fine-tuning abilities of much smaller models (e.g., RoBERTa-large, 350M; Liu et al., 2019b), or compare models fine-tuned on large datasets to few-shot in-context learning (Si et al., 2023). These comparisons raise the question of whether fine-tuning leads to weaker OOD generalization than in-context learning, or whether this is



(a) In-context learning

(b) Fine-tuning

Figure 5: In-domain (RTE) and out-of-domain performance (HANS) for in-context learning and fine-tuning with OPT models of various sizes. We fine-tune models using pattern-based fine-tuning. We report results using 10 different data seeds. When using 16 samples, in-context learning's performance with a 30B model is comparable to that of fine-tuning with smaller models (6.7B) and for most model sizes, fine-tuning outperforms in-context learning. — in the x- and y-axes indicates majority class accuracy.

just a byproduct of the experimental setup.

5.2 Our contributions

In our work, we investigate whether the observed weaker out-of-domain generalization of fine-tuned models by previous work is an inherent property of fine-tuning or an artifact of their experimental setup and provide a fair comparison between the generalization of fine-tuning and in-context learning.

Setup For our experiments, we consider few-shot pattern-based fine-tuning (Schick and Schütze, 2021; Gao et al., 2021, *inter alia*) and in-context learning (Brown et al., 2020). We perform a fair comparison of task adaptation focusing on in-domain and OOD generalization under *covariate shift* (Hupkes et al., 2022). We run all experiments using 7 different OPT models (Zhang et al., 2022) ranging from 125 million to 30 billion parameters. During fine-tuning, we update all model parameters if not stated otherwise.

Fine-tuned models can generalize well OOD For our first experiment, we compare fine-tuning and in-context learning using 16 examples for each. We plot the results of this experiment in Figure 5. For in-context learning, we observe an increase in in-domain performance with model size and non-trivial OOD performance only for the largest model (30B). For fine-tuning, we similarly observe that in-domain performance increases with model size. However, as model size increases, OOD performance increases as well, demonstrating that even in the challenging few-shot setting, fine-tuned models can generalize OOD. In Table 2 we provide significance tests that further support our findings. In-context learning only outperforms fine-tuning when comparing large models adapted via in-context learning to small fine-tuned models, which is unfair. Comparing models of the same size however, reveals that fine-tuned models either perform significantly better or similarly to models adapted via in-context learning.

		PBFT						
		125M	**350M**	**1.3B**	**2.7B**	**6.7B**	**13B**	**30B**
ICL	**125M**	−0.00	0.01	0.02	0.03	0.12	0.14	0.09
	350M	−0.00	0.01	0.02	0.03	0.12	0.14	0.09
	1.3B	−0.00	0.01	0.02	0.03	0.12	0.14	0.09
	2.7B	−0.00	0.01	0.02	0.03	0.12	0.14	0.09
	6.7B	−0.00	0.01	0.02	0.03	0.12	0.14	0.09
	13B	−0.04	−0.02	−0.01	−0.00	0.09	0.11	0.05
	30B	−0.11	−0.09	−0.08	−0.08	0.02	0.03	−0.02

Table 2: Difference between average **out-of-domain performance** of ICL and FT on RTE across model sizes. We use 16 examples and 10 random seeds for both approaches. We perform a Welch's t-test and color cells according to whether: ICL performs significantly better than FT, FT performs significantly better than ICL. For cells without color, there is no significant difference.

Generalization improves with more data In contrast to in-context learning, where the maximum number of demonstrations is limited by the context size of a model, fine-tuning allows us to perform task adaptation using arbitrary amounts of training data. Therefore, we analyze how the relationship between in-domain and OOD performance is impacted by training on more data. For the smallest models, we find that while in-domain performance increases with more training data, OOD performance remains low, which is consistent with previous work (Utama et al., 2021). However, for larger models, OOD performance improves as the amount of training data increases.

Findings generalize beyond OPT To test the generality of our findings beyond the OPT models, we run the same experiments using Pythia models of different sizes (Biderman et al., 2023). Similarly to OPT, we observe a clear effect of model size on both in-domain and OOD performance. For most model sizes, fine-tuning leads to significantly better OOD performance than in-context learning. Additionally, both the in-domain and OOD performance of Pythia models improve drastically as we fine-tune on more data.

Findings generalize to parameter-efficient fine-tuning We additionally experiment with parameter-efficient fine-tuning via LoRA (Hu et al., 2022) to demonstrate the generality of our findings beyond full fine-tuning. Using LoRA makes adaptation via fine-tuning more similar to adaptation via in-context learning as it allows the re-use of a large fraction of the weights of a pre-trained language model across tasks. Figure 6 shows that fine-tuning via LoRA leads to similar performance as training all parameters (shown in Figure 5b) which demonstrates the generality of our findings beyond a specific fine-tuning method.

5.3 Discussion

Our findings are an important first step towards a better understanding of the fundamental differences in model behavior between different task adaptation approaches. We demonstrate that fine-tuned language models can generalize well both in and out-of-domain. In fact, we find that the generalization of fine-tuning and in-context learning is highly similar as both approaches exhibit large variation in performance and strongly depend on properties such as model size and the number of examples. Hence, our work provides evidence that the poor

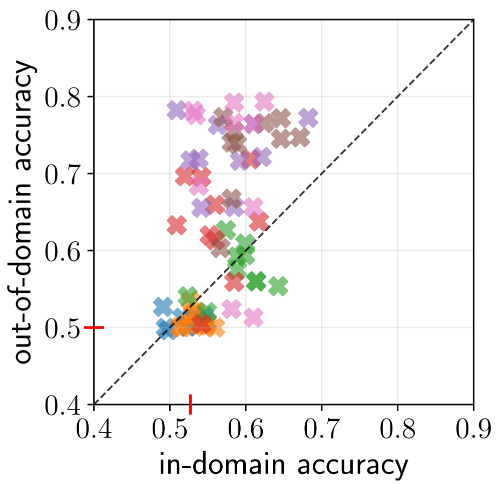


Figure 6: In-domain and OOD performance of parameter-efficient fine-tuning via LoRA on RTE. — in the x- and y-axes indicates the accuracy of the majority class label.

out-of-domain generalization of fine-tuned models observed in previous work is not a fundamental flaw of fine-tuning but rather a result of their experimental setup, highlighting that truly robust task adaptation remains a challenge.

6 The bigger picture

Adapting pre-trained language models via fine-tuning or in-context learning is an integral part of modern-day NLP. While from late 2018 to mid-2020, fine-tuning was the dominating strategy for task adaptation, i.e., converting a pre-trained (masked) language model into a classifier, the introduction of GPT-3 (Brown et al., 2020) in 2020 and the demonstration of its in-context learning abilities resulted in an increasing interest in in-context learning as a new promising paradigm for task adaptation. Recently however, driven by work on instruction fine-tuning (Sanh et al., 2022; Wang et al., 2022, *inter alia*) and alignment to human preferences (Ouyang et al., 2022; Zhou et al., 2023, *inter alia*), fine-tuning[1] is again gaining significant interest from the NLP research community.

Given the ubiquity of language model adaptation in modern-day NLP and machine learning research, it is crucial to make progress towards a better understanding of the inner workings of commonly used

[1]Due to the dominance of decoder-only language models fine-tuning is however no longer used to explicitly adapt language models into classifiers but is instead used to adapt language models to assign higher probability to specific distributions, e.g., instructions and information seeking questions.

adaptation techniques as well as their limitations. The work presented in this paper demonstrates how empirical research can help to achieve this goal and hopefully serves as an inspiration for future research that critically investigates the rapid progress made along the pre-train then adapt pipeline.

7 Summary

Our work makes several contributions towards improving our understanding of pre-trained and fine-tuned language models by carrying out a detailed analysis of various parts of the pre-train then adapt pipeline. Our contributions range from analyzing the linguistic knowledge of pre-trained language models and how it is affected by fine-tuning, to a rigorous analysis of the fine-tuning process itself and how the choice of adaptation technique affects the generalization of models. We provide new insights about previously unexplained phenomena and the capabilities of pre-trained and fine-tuned language models and overall a better understanding of a crucial component of the modern NLP toolbox. Beyond our empirical contributions, we hope that our work demonstrates the importance of taking a critical perspective on previous work and shows that despite the rapid progress in our field, there is a need for work that critically analyzes this progress.

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