Unsupervised Keyphrase Extraction via Interpretable Neural Networks

Rishabh Joshi[♣] [*] Vidhisha Balachandran[♣] [*] Emily Saldanha[◊]
Maria Glenski[◊] Svitlana Volkova[◊] Yulia Tsvetkov[♠]
[♣]Language Technologies Institute, Carnegie Mellon University
[◊]Pacific Northwest National Laboratory
[♠]Paul G. Allen School of Computer Science & Engineering, University of Washington
{rjoshi2,vbalacha}@cs.cmu.edu,
{emily.saldanha,maria.glenski,svitlana.volkova}@pnnl.gov,
yuliats@cs.washington.edu

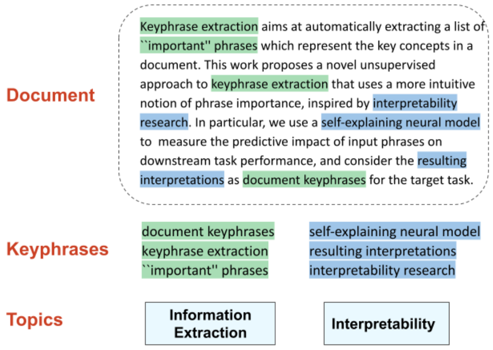
Abstract

Keyphrase extraction aims at automatically extracting a list of "important" phrases representing the key concepts in a document. Prior approaches for unsupervised keyphrase extraction resorted to heuristic notions of phrase importance via embedding clustering or graph centrality, requiring extensive domain expertise. Our work presents a simple alternative approach which defines keyphrases as document phrases that are salient for predicting the topic of the document. To this end, we propose INSPECT—an approach that uses self-explaining models for identifying influential keyphrases in a document by measuring the predictive impact of input phrases on the downstream task of the document topic classification. We show that this novel method not only alleviates the need for ad-hoc heuristics but also achieves state-of-the-art results in unsupervised keyphrase extraction in four datasets across two domains: scientific publications and news articles.[1]

1 Introduction

Keyphrase extraction is crucial for processing and analysis of long documents in specialized (e.g., scientific, medical) domains (Mekala and Shang, 2020; Betti et al., 2020; Wang et al., 2019). The task is challenging, as the notion of phrase importance is context- and domain-dependent. Therefore, developing domain-agnostic keyphrase annotation guidelines and curating representative hand-labeled datasets is not feasible. This motivates the need for generalizable unsupervised approaches to keyphrase extraction.

Unsupervised keyphrase extraction methods have used heuristic notions of phrase importance (Mihalcea and Tarau, 2004; Shang et al., 2018; Campos et al., 2018). Popular proxies for phrase importance include phrase clustering based on statistical features like word density (Florescu and Caragea, 2017a; Campos et al., 2018) and structural features like graph centrality (Bougouin et al., 2013; Ding and Luo, 2022) or more recently neural embedding clustering techniques (Bennani-Smires et al., 2018; Zhang et al., 2022; Ding and Luo, 2021; Sun et al., 2020). However, such methods do not generalize to new domains as they require experts to carefully construct domain-specific heuristics (Mani et al., 2020).



Keyphrase extraction aims at automatically extracting a list of ``important'' phrases which represent the key concepts in a document. This work proposes a novel unsupervised approach to keyphrase extraction that uses a more intuitive notion of phrase importance, inspired by interpretability research. In particular, we use a self-explaining neural model to measure the predictive impact of input phrases on downstream task performance, and consider the resulting interpretations as document keyphrases for the target task.

Figure 1: A comprehensive set of keyphrases should highlight important phrases for all major topics in a document. INSPECT identifies such keyphrases using interpretable neural models by measuring how use phrases are for predicting the topic of a text.

Historically, topic models (Blei et al., 2001; Blei and McAuliffe, 2007; Wallach, 2006) have relied on salient words and phrases in a document, which are similar to the notion of keyphrases, although to the best of our knowledge there is no prior work that identified keyphrases using topic models. In this work, we hypothesize that end-to-end neural models for topic classification latently rely on salient phrases for document representation and topic classification. Consequently, if we can interpret model decisions via highlighting salient and influential features (phrases) used for neural topic prediction, we can identify such keyphrases.

Inspired by this intuition, we propose INSPECT—a novel and simple framework to identify keyphrases by leveraging interpretable text classi-

[*] Equal Contribution
[1] Code: https://github.com/rishabhjoshi/inspect.

Findings of the Association for Computational Linguistics: EACL 2023, pages 1107–1119
May 2-6, 2023 ©2023 Association for Computational Linguistics

fiers to highlight phrases important for predicting the topics in a text. Specifically, we adapt an interpretable classifier SelfExplain (Rajagopal et al., 2021) to jointly predict the topic of an input document and to identify the salient phrases influencing the prediction. The model is distantly supervised using topic labels from off-the-shelf topic-models, eliminating the need for any human/expert annotations. We consider SelfExplain's output interpretations as keyphrases for the input document (§2).

INSPECT can be trained on documents of any domain without keyphrase annotations and using distant topic supervision, making them easily adaptable to new domains. We contribute two versions of our method: i) INSPECT— individual models trained for topic-classification for each target dataset. ii) INSPECT-GEN—a more general model pre-trained on a large in-domain corpus, without finetuning on pre-specified target datasets.

We evaluate INSPECT and INSPECT-GEN on four benchmark datasets across two domains: scientific documents and news articles (§3). Our results in §4 show that INSPECT improves keyphrase extraction performance over strong baselines by 0.8% F1 on average, without any domain-specific processing. INSPECT-GEN further improves the performance, outperforming the state of the art in unsupervised keyphrase extraction on 3 out of 4 datasets by 2.7% F1 on average. Our experiments suggest that INSPECT-GEN has strong generalization capabilities, and can be used out-of-the-box without finetuning on individual datasets. Importantly, INSPECT alleviates the need for heuristics and expert-labelled annotations, and thus can be applied to a wide range of domains and problems where keyphrase extraction is important. Our results confirm that the latent keyphrases obtained from an interpretable model correlate with human annotated keyphrases, opening new avenues for research on interpretable models for information extraction.

2 The INSPECT Framework

The goal of the INSPECT framework is to extract important keyphrases in long documents. Following the hypothesis that neural text classifiers latently leverage important keyphrases for predicting topics in text, INSPECT extracts keyphrases through interpreting topic classification decisions. It builds upon an interpretable model, SelfExplain (Rajagopal et al., 2021), which learns to attribute text classification decisions to relevant phrases in the input. However, SelfExplain was designed and tested in supervised settings and for single-sentence classification; in this work we explore its extension to unsupervised keyphrase extraction from long documents. In what follows, we describe the base SelfExplain model (§2.1) and the distant supervision setup for *topic classification* (§2.4). We outline the training mechanism to jointly predict topics and highlight salient phrases in the document as model interpretations (§2.2) and finally extract the resulting phrase interpretations as important keyphrases in the document (§2.3).

2.1 Base Interpretable Model

Feature attribution methods for model interpretability include two predominant approaches, (i) post-hoc interpretations of a trained model (Jin et al., 2020; Kennedy et al., 2020; Lundberg and Lee, 2017; Ribeiro et al., 2016), and (ii) intrinsically (by-design) interpretable models (Alvarez-Melis and Jaakkola, 2018; Rajagopal et al., 2021). We adopt the latter approach, specifically SelfExplain (Rajagopal et al., 2021) as our phrase attribution model, as the model directly produces interpretations, though in principal any phrase based interpretability techniques could be employed.

SelfExplain augments a pre-trained transformer-based model (RoBERTa (Liu et al., 2019) in our case) with a local interpretability layer (LIL) and a global interpretability layer (GIL) which are trained to produce local (relevant features from input sample) and global (relevant samples from training data) interpretations respectively. The model can be trained for any text classification tasks using gold task supervision, and produces local and global interpretations along with model predictions. Since our goal is to identify important phrases from the input sample, we use only the LIL layer. The LIL layer takes an input sentence and a set of candidate phrases and quantifies the contribution of a particular phrase for prediction through the activation difference (Shrikumar et al., 2017; Montavon et al., 2017) between the phrase and sentence representations.

2.2 Keyphrase Relevance Model

SelfExplain is designed to process single sentences and uses all the phrases spanning non-terminals in a constituency parser as units (candidate phrases) for interpretation. This is computationally expensive for our use-case. To facilitate long document topic classification, we instead define the set of noun phrases (NPs) as the interpretable units, which aligns with prior work in keyphrase extraction of using noun phrases as initial candidate phrases (Shang et al., 2018; Mihalcea and Tarau, 2004; Bougouin et al., 2013). INSPECT splits a long document into constituent passages, extracts NPs as candidates, and attributes the contribution of each NP for predicting the topics covered in the passage.

For each text block $\boldsymbol{X}$ in the input document, we preprocess and identify a set of candidate phrases $\boldsymbol{CP}_X = \boldsymbol{cp}_1, \boldsymbol{cp}_2, ..., \boldsymbol{cp}_N$ where N is the number candidate phrases in $\boldsymbol{X}$. From the base RoBERTa model, we obtain contextual [CLS] representations of the entire text block $\mathbf{h}_{[CLS]}$ and individual tokens. We compute phrase representations $\mathbf{h}_1 ... \mathbf{h}_N$ for each candidate by taking the sum of the RoBERTa representations of each token in the phrase.

To compute the relevance of each phrase, we construct a representation of the input without the contribution of the phrase, $\mathbf{z}_i$, using the activation differences between the two representations. We then pass it to a classifier layer in the local interpretability module to obtain the label distribution for prediction.

$$\mathbf{z}_i = g(\mathbf{h}_i) - g(\mathbf{h}_{[CLS]}); \quad \boldsymbol{\ell}_i = f(\mathbf{W}^T \mathbf{z}_i + \mathbf{b}) \quad (1)$$

where g is the ReLU activation function and W and b are the weights and bias of the classifier. Here $\boldsymbol{\ell}_i$ denotes the label distribution obtained on passing the phrase-level representations $\mathbf{z}_i$ through a classification layer f which is either the sigmoid or the softmax function depending on the prediction task (multi-label versus multi-class). We denote the label distribution from the base RoBERTa model for predicting the output using the whole input block as $\boldsymbol{\ell}_{[CLS]}$. We train the model using the cross entropy loss $\mathcal{L}_y$ with respect to the multi-label gold topics $\boldsymbol{Y}_i$ for instance i and an explanation specific loss $\mathcal{L}_e$ using the mean of all phrase-level label distributions such that $\boldsymbol{\ell}_e = \sum_{i=1}^{P} \boldsymbol{\ell}_i$.

$$\mathcal{L}_y = -\sum_{j=1}^{N} \mathbf{y}_j \log(\boldsymbol{\ell}_{[CLS]}), \mathcal{L}_e = -\sum_{j=1}^{N} \mathbf{y}_j \log(\boldsymbol{\ell}_e) \quad (2)$$

The classifier is regularized jointly with α regularization parameter[2] using explanation and classification loss: $\mathcal{L} = (1 - \alpha)\mathcal{L}_y + \alpha\mathcal{L}_e$.

2.3 Inference

During inference, for each predicted label $y \in \boldsymbol{Y}$, where $\boldsymbol{Y}$ denotes set of all predicted labels for input text $\boldsymbol{X}$, INSPECT calculates an importance score r_i^y with respect to the predicted label y using the difference between the label distribution $\boldsymbol{\ell}_i^y$ for a candidate phrase $\boldsymbol{cp}_i$ and the one obtained using the entire input $\boldsymbol{\ell}_{[CLS]}^y$ as $r_i^y = \boldsymbol{\ell}_{[CLS]}^y - \boldsymbol{\ell}_i^y$.

This score denotes the influence of a candidate keyphrase on the predicted topic. This score denotes the influence of a phrase on the predicted topic—the closer $\boldsymbol{\ell}_i^y$ is to $\boldsymbol{\ell}_{[CLS]}^y$ the less important phrase i is for predicting the topic. Since the relevance scores are computed with respect to a particular predicted topic and it's label distribution, the scores for the same input are not comparable across different predicted topics in multi-label classification (since label distributions can vary in magnitude). To aggregate important keyphrases across all predicted topics, we pick the ones that positively impact prediction for each topic (having a positive influence score) as a set of keyphrases.

$$\boldsymbol{KP}(x) = [\boldsymbol{cp}_i \;\; \forall \; r_i^y > 0; y \in \boldsymbol{Y}; i \in \{1 : N\}]$$

2.4 Distant Supervision via Topic Prediction

Obtaining annotations for keyphrases in specialized domains is challenging for supervised keyphrase extraction (Mani et al., 2020). Instead, we train the interpretable model in a distant supervision setup for multi-class topic classification and use model interpretations to identify keyphrases, without any keyphrase annotations. Topical information about a document are known to be essential for identifying diverse keyphrases (Bougouin et al., 2013; Sterckx et al., 2015). Further, a comprehensive set of keyphrases should represent the various major topics in the document to be useful for different long document applications (Liu et al., 2010). We hypothesize that by using topic classification as our end-task, our model will learn to highlight—via interpretations it is designed to provide—important and diverse keyphrases in the input document.

While certain domains like news articles have extensive datasets with human annotated topic labels, others like scientific articles or legal documents require significant effort for human annotation. INSPECT can be trained using annotated topic labels when they exist. In other domains where such annotations are scarce, INSPECT can be trained using labels extracted unsupervisedly using topic models

[2] $\alpha = 0.5$

Dataset	Type	Split	Total docs	Avg words per doc	Avg keyphrases per doc
SciERC	Scientific	Train	350	130	16
		Dev	50	130	16
		Test	100	134	17
SciREX	Scientific	Train	306	5601	353
		Dev	66	5484	354
		Test	66	6231	387
SemEval17	Scientific	Train	350	160	21
		Dev	50	193	27
		Test	100	186	23
500N-KPCrowd	News	Train	400	430	193
		Dev	50	465	86
		Test	50	420	116
BBC News	News	All	2225	385	-
ICLR	Scientific	All	8317	6505	-

Table 1: Description about the datasets. Average words and keyphrases per document are rounded to the nearest whole number. ICLR and BBC News are used in INSPECT-GEN setting for training and don't have any labelled keyphrase data.

(Gallagher et al., 2017). Experiments in §4 show results using both settings.

3 Experimental Setup

3.1 Evaluation Datasets

We evaluate INSPECT in two domains using four popular keyphrase extraction datasets—scientific publications (SemEval-2017 (Augenstein et al., 2017a), SciERC (Luan et al., 2018), SciREX (Jain et al., 2020)) and news articles (500N-KPCrowd (Marujo et al., 2013)). Dataset details and statistics are shown in Table 1.

3.2 Topic Labels

We create distant supervision for INSPECT by labeling the above datasets using document topics as labels. We leverage existing topic annotations when such annotations exist. In the 500N-KPCrowd news based dataset, we use existing topic labels (tags or categories such as Sports, Politics, Entertainment) in a one-class classification setting. For the scientific publications domain, we use topic models (Gallagher et al., 2017) to extract $T = 75$ topics where each document can be labeled with multiple topics. The scientific domain datasets are trained in a multi-label classification setup.

3.3 Training Data and Settings

We train INSPECT in two settings:

1. **INSPECT** - Here we assume availability of training documents for each of our datasets. We train the model for topic prediction using only the documents and topic labels from the training set of each dataset obtained using the approach outlined in §3.2). The training data in this setting, is most closely aligned to the test data, as the documents are of the same topic distribution.

2. **INSPECT-Gen** - We assume no access to training documents and train the model on a large external set of documents of a similar domain (ICLR papers for scientific, BBC News for news) but not necessarily of similar topic distribution as the test data (eg. SemEval-2017 has Physics papers). We use ICLR OpenReview dataset with topics obtained using off-the-shelf topic modeling [3] for the scientific domain and BBC News corpus (Greene and Cunningham, 2006) with pre-labelled topics for the news domain.

The model from each setting is then evaluated on the held-out test data of each evaluation dataset.

For the external data, we collect over 8,317 full papers from ICLR and obtained 75 topic labels using topic modeling[4]. We removed 22 topic labels that were uninformative (list in Appendix Table 6) and used the rest to train our model in a multi-label classification setup. The BBC News corpus (Greene and Cunningham, 2006) consists of 2,225 news article documents, each annotated with one of five topics (business, entertainment, politics, sport, or tech).

We pre-process each document (for training and inference) by splitting it into text blocks of size 512 tokens, where consecutive blocks overlap with a stride size of 128. Following Shang et al. (2018),

[3] https://github.com/gregversteeg/corex_topic

[4] https://github.com/gregversteeg/corex_topic

for each block we consider all Noun Phrases (NPs) as candidate phrases and extract them using a Noun Phrase extractor from the Berkeley Neural Parser[5]. All hyperparameters were chosen based on development set performance on SciERC. Our final models were trained with a batch size of 8 a learning rate of 2e-5 for 10 epochs.The classification layer dimension was 64 and α was 0.5. We provide more implementation details, including hyperparameter search in Appendix §A.2.

3.4 Baselines

We compare our method against seven unsupervised keyphrase extraction techniques — TF-IDF (Florescu and Caragea, 2017a), TopicRank (Bougouin et al., 2013), Yake (Campos et al., 2018), AutoPhrase (Shang et al., 2018; Liu et al., 2015), UKE-CCRank (Liang et al., 2021), MDERank (BERT)[6] (Zhang et al., 2022) and SifRank (Sun et al., 2020). Out of the chosen baselines, Yake, TF-IDF and AutoPhrase are statistical, TopicRank is graph-based and SifRank, UKE-CCRank and MDERank are neural embedding based methods. For INSPECT setting, we compare with baselines that only use training data documents—TF-IDF, TopicRank, Yake, AutoPhrase, UKE-CCRank and MDERank. For the INSPECT-GEN setting, we compare with TF-IDF and AutoPhrase trained on our external corpora and SifRank which uses the external corpora to obtain prior likelihood scores for the phrases.

Following prior work and task guidelines (Augenstein et al., 2017a; Jain et al., 2020), INSPECT produces **span level** keyphrases and distinguishes each occurrence of a keyphrase. In contrast, methods like SifRank, AttentionRank, UKE-CCRank and MDERank are phrase level keyphrase extractors which don’t provide span level outputs. To maintain common evaluation, we adapt these methods to span level keyphrase extraction by matching each output keyphrase to all occurrences of the phrase in the document. As our method applies a cutoff on relevance scores and picks any phrase with a positive relevance score as a keyphrase, we cannot be directly compared with baselines which rank candidate phrases and pick top-K phrases as important. To establish a fair setting for evaluation, we choose the average of the number of keyphrase predictions from our model as the ’K’ across all baselines.

Dataset	Method	F1 Score		
		Micro	**Macro**	**Weighted**
SciERC	RoBERTa	0.842	0.651	0.767
	INSPECT	0.836	0.658	**0.771**
SciREX	RoBERTa	0.609	0.404	0.641
	INSPECT	0.628	0.442	**0.697**
SemEval17	RoBERTa	0.819	0.613	0.731
	INSPECT	0.822	0.611	**0.744**
500N-KPCrowd	RoBERTa	0.916	0.880	0.910
	INSPECT	0.938	0.904	**0.939**
ICLR	RoBERTa	0.729	0.456	0.699
	INSPECT	0.743	0.492	**0.733**
BBC News	RoBERTa	0.880	0.851	0.876
	INSPECT	0.902	0.886	**0.894**

Table 2: Proxy Task (Topic prediction) performance. Our INSPECT method outperforms a strong RoBERTa baseline on Micro, Macro and Weighted F1 scores.

3.5 Evaluation Metrics

Topic Prediction Evaluation: To ensure high-quality interpretations from our model, it is imperative that it performs well on topic prediction. We first evaluate INSPECT’s performance on topic prediction using micro, macro, and weighted F1 score of the classifier’s predictions compared to true labels across all labels.

Keyphrase Extraction Evaluation: For our primary evaluation of keyphrase extraction, we evaluate using span match of our predictions and the true labels (human annotated keyphrases). In addition to measuring quality of keyphrases, this evaluation also measures the quality of explanations from our interpretable topic model by measuring how well the keyphrases extracted by INSPECT align with human annotated keyphrases. Prior works (Shang et al., 2018; El-Beltagy and Rafea, 2009; Bougouin et al., 2013) have mainly focused on *exact match* performance. However, a recent survey highlights that the measure is highly restrictive (Papagiannopoulou and Tsoumakas, 2019) as simple variations in preprocessing can misalign phrases giving an inaccurate representation of the model’s capabilities (Boudin et al., 2016).

Alternatively, *partial span match* using the word level overlap between the predicted and gold span ranges, has also been explored (Rousseau and Vazirgiannis, 2015). But, it is sometimes lenient in scoring. Papagiannopoulou and Tsoumakas (2019) suggest *average of the exact and partial matching* as an appropriate metric based on empirical studies. Therefore, we evaluate performance using the average of the exact and partial match F1 scores

[5] https://pypi.org/project/benepar/

[6] As of Oct 2022, the authors have not released their model.

Dataset	Method	Exact Match F1	Partial Match F1	Avg Exact Partial F1
SciERC	TF-IDF	0.0627	0.2860	0.1743
	TopicRank	0.2533	**0.5680**	0.4110
	Yake	0.2230	0.5125	0.3678
	AutoPhrase	0.0961	0.3145	0.2053
	UKE CCRank	**0.3584**	0.4804	0.4194
	MDERank	0.3092	0.5102	0.4097
	INSPECT	0.3108	0.5524	**0.4316**
SciREX	TF-IDF	0.1521	0.3690	0.2605
	TopicRank	0.2298	0.4122	0.3210
	Yake	0.1840	0.3734	0.2787
	AutoPhrase	0.1814	**0.4236**	0.3025
	UKE CCRank	0.0419	0.0759	0.0589
	MDERank	0.1241	0.3776	0.2509
	INSPECT	**0.2397**	0.4127	**0.3262**
SemEval17	TF-IDF	0.0610	0.2698	0.1654
	TopicRank	0.2240	0.4312	0.3276
	Yake	0.1687	0.3644	0.2665
	AutoPhrase	0.0790	0.3404	0.2097
	UKE CCRank	0.2427	0.345	0.2938
	MDERank	0.2529	0.4818	0.3673
	INSPECT	**0.2594**	**0.5185**	**0.3889**
500N-KPCrowd	TF-IDF	0.1034	0.3520	0.2277
	TopicRank	0.1060	0.2346	0.1703
	Yake	0.1380	0.3551	0.2465
	AutoPhrase	0.1590	0.3608	0.2599
	UKE CCRank	**0.1729**	0.2873	0.2303
	MDERank	0.1522	**0.4197**	**0.2859**
	INSPECT	0.1608	0.3920	0.2764

Table 3: Span-match results for unsupervised keyphrase extraction across datasets in the INSPECT setting. Best performance is indicated in Bold. **Our model ourperforms baselines on average of exact and partial F1 scores.**

between predicted and true phrases keyphrases.

4 Results

4.1 Topic Prediction with INSPECT

First, we compare INSPECT's effectiveness in classifying the topics with the corresponding non-interpretable encoder baseline, using micro, macro, and weighted F1 score of the classifier's predictions compared to gold standard annotations. The results in Table 2 show that our approach outperforms a strong RoBERTa (Liu et al., 2019) baseline for topic prediction across all of our evaluation datasets. The difference is more pronounced in larger datasets (SciREX, ICLR, and BBC News), and strong performance on the topic classification task provides confidence that highlighted interpretations are for relevant and major topics in the text.

4.2 Keyphrase Span Match Performance

Next, we study the utility of INSPECT in highlighting keyphrases via model interpretations. The results for INSPECT are detailed in Table 3 and, for INSPECT-GEN in Table 4.

Results in Table 3 show that even with access to only training set of documents from each dataset, on 3 out of 4 datasets INSPECT outperforms all baselines with ∼0.8 average F1 improvements. In the news domain (500-KPCrowd dataset) INSPECT performs comparably to prior best method. INSPECT has low exact match scores but higher partial match scores indicating misalignments between predicted and gold spans. Additionally, 500N-KPCrowd annotates all instances of a keyphrase as a reference span which favours phrase level methods like AttentionRank in the current evaluation setup. In SciREX, we observe very poor performance of UKE CCRank as it ranks common phrases like “image”, “label”, “method”, etc, very high.

In the INSPECT-GEN setting, with access to a larger dataset of external documents, our model outperforms prior methods in 3 out of 4 datasets with ∼2.7 points average F1 improvements. In the 500N-KPCrowd dataset, INSPECT performs comparably to SifRank with improved Partial Match F1. As Table 4 illustrates, we notice that the model consistently performs better in the INSPECT-GEN setting when compared with the INSPECT setting, showing that the method benefits from more training data. We particularly see large improvements over the INSPECT setting in the scientific datasets, showing that training on a larger set of documents

Dataset	Method	Exact Match F1	Partial Match F1	Avg Exact Partial F1
SciERC	TF-IDF	0.2162	0.4434	0.3298
	AutoPhrase	0.2416	0.6130	0.4273
	SifRank	0.2248	**0.7357**	0.4803
	INSPECT-GEN	**0.4371**	0.7114	**0.5743**
SciREX	TF-IDF	0.1780	0.4008	0.2894
	AutoPhrase	0.2583	**0.4993**	**0.3788**
	SifRank	0.1234	0.3957	0.2595
	INSPECT-GEN	**0.2601**	0.4893	0.3747
SemEval17	TF-IDF	0.1810	0.3398	0.2604
	AutoPhrase	0.1104	0.4874	0.2989
	SifRank	0.2804	**0.6336**	0.4570
	INSPECT-GEN	**0.3246**	0.6218	**0.4732**
500N-KPCrowd	TF-IDF	0.1398	0.3578	0.2488
	AutoPhrase	0.1701	0.3918	0.2805
	SifRank	**0.1847**	0.4125	**0.2986**
	INSPECT-GEN	0.1776	**0.4194**	**0.2985**

Table 4: Span-match results for unsupervised keyphrase extraction in INSPECT-GEN (trained on ICLR and BBC News corpus). Best performance is indicated in Bold. **INSPECT outperforms most baselines**.

helps generalize the model in this setting. Our results further show that variations in topic distribution between training and test data don't significantly impact results. INSPECT can thus benefit from large unlabeled documents from similar domains to improve results.

INSPECT improves performance in settings with human annotated topics (news) as well as when topics are extracted using unsupervised topic modeling (scientific). Additionally, most baselines rely on carefully constructed pre- and post-processing to eliminate common phrases and produce high-quality candidates (Liang et al., 2021; Ding and Luo, 2021; Sun et al., 2020). In contrast, INSPECT achieves competitive results without domain expertise and processing for extracting quality keyphrases. Therefore, INSPECT can be easily adapted to new domains without human annotations for topics and with minimal domain knowledge, as we show across two domains.

Our results demonstrate that phrase attribution techniques from interpretability literature can be leveraged to identify high-quality document keyphrases by measuring predictive impact of input phrases on topic prediction. These results also show that our interpretable model in INSPECT produces high quality keyphrases as phrase explanations which correlate with human annotated keyphrases, evaluating the interpretablity aspect of our framework. Crucially, as these keyphrases correlate with human annotated keyphrases, our results validate our initial hypothesis that neural models latently use document keyphrases for tasks like topic classification.

	Recall	
Type	Exact	Partial
Metric	60.65	78.34
Task	58.27	90.45
Material	72.17	86.69
Scientific Term	78.87	95.13
Method	65.31	95.41
Generic	63.16	86.06

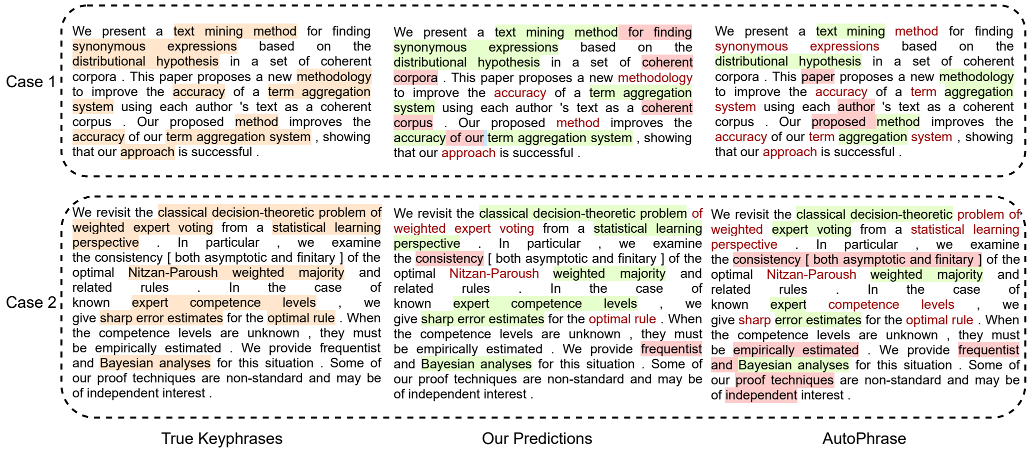
Table 5: Exact and partial span match recall scores for different types of keyphrases on the SciERC dataset.

5 Discussion

Here, we present an analysis on the common error types in INSPECT and discuss the strengths and weaknesses of INSPECT using qualitative examples.

Entity Type Analysis: We leverage the entity type information in SciERC to observe the performance of INSPECT on specific types of keyphrases. From Table 5, we see that INSPECT performs best on keyphrases labelled as *Scientific Terms* and *Materials*. *Generic* phrases and *Metrics* are usually not representative of topical content, and thus, our method performs poorly on them. On manual analysis, we noticed that many phrases marked as *Task* are very unique and infrequent, making them harder to identify. A high partial match recall but a low exact match recall for *Method* type suggest that many predicted keyphrases are misaligned with the gold labels. We believe that alternative downstream tasks can be explored in future to help tailor our approach to capture specific types of entities, based on application requirements.

Qualitative Analysis In Figure 2 we show two randomly selected abstracts from the SciERC



We present a text mining method for finding synonymous expressions based on the distributional hypothesis in a set of coherent corpora . This paper proposes a new methodology to improve the accuracy of a term aggregation system using each author 's text as a coherent corpus . Our proposed method improves the accuracy of our term aggregation system , showing that our approach is successful .

We present a text mining method for finding synonymous expressions based on the distributional hypothesis in a set of coherent corpora . This paper proposes a new methodology to improve the accuracy of a term aggregation system using each author 's text as a coherent corpus . Our proposed method improves the accuracy of our term aggregation system , showing that our approach is successful .

We present a text mining method for finding synonymous expressions based on the distributional hypothesis in a set of coherent corpora . This paper proposes a new methodology to improve the accuracy of a term aggregation system using each author 's text as a coherent corpus . Our proposed method improves the accuracy of our term aggregation system , showing that our approach is successful .

We revisit the classical decision-theoretic problem of weighted expert voting from a statistical learning perspective . In particular , we examine the consistency [both asymptotic and finitary] of the optimal Nitzan-Paroush weighted majority and related rules . In the case of known expert competence levels , we give sharp error estimates for the optimal rule . When the competence levels are unknown , they must be empirically estimated . We provide frequentist and Bayesian analyses for this situation . Some of our proof techniques are non-standard and may be of independent interest .

We revisit the classical decision-theoretic problem of weighted expert voting from a statistical learning perspective . In particular , we examine the consistency [both asymptotic and finitary] of the optimal Nitzan-Paroush weighted majority and related rules . In the case of known expert competence levels , we give sharp error estimates for the optimal rule . When the competence levels are unknown , they must be empirically estimated . We provide frequentist and Bayesian analyses for this situation . Some of our proof techniques are non-standard and may be of independent interest .

We revisit the classical decision-theoretic problem of weighted expert voting from a statistical learning perspective . In particular , we examine the consistency [both asymptotic and finitary] of the optimal Nitzan-Paroush weighted majority and related rules . In the case of known expert competence levels , we give sharp error estimates for the optimal rule . When the competence levels are unknown , they must be empirically estimated . We provide frequentist and Bayesian analyses for this situation . Some of our proof techniques are non-standard and may be of independent interest .

Figure 2: Two data points randomly chosen from the SciERC dataset. Orange spans represent gold standard annotations. Green spans in the predictions represent correctly predicted spans, whereas red spans are spans wrongly predicted as being keyphrases and red text are keyphrases that the model did not identify.

dataset. We see that INSPECT tends to extract longer phrases compared to AutoPhrase, which tends to extract mostly unigrams or bigrams. Overall, our approach is able to extract more relevant phrases than the baseline. Both INSPECT and AutoPhrase tend to miss generic phrases like 'approach' (e.g., as seen in case 1). Case 2 also demonstrates the INSPECT's ability TO predict complete phrases, like 'classical decision-theoretic problem', instead of AutoPhrase's prediction – 'classical decision-theoretic' which is incomplete. From both these examples, we see that INSPECTis usually able to correctly extract Scientific Terms, and struggles to extract Generic phrases and Metrics. This can be attributed to the usage of topic models to extract the content's topical information.

6 Related Work

Unsupervised keyphrase extraction is typically treated as a ranking problem, given a set of candidate phrases (Shang et al., 2018; Campos et al., 2018; Florescu and Caragea, 2017a). Broadly, prior approaches can be categorized as statistical, graph-based, embedding-based, or language model based methods; Papagiannopoulou and Tsoumakas (2019) provide a detailed survey.

Statistical methods exploit notions of information theory directly. Common approaches include TF-IDF based scoring (Florescu and Caragea, 2017a) of phrases with other co-occurrence statistics to enhance performance (Liu et al., 2009; El-Beltagy and Rafea, 2009). Campos et al. (2018) shows the importance of incorporating statistical information of the context of each phrase to improve performance. Statistical approaches typically treat different instances of a phrase equally, which is a limitation.

Graph-based techniques, on the other hand, broadly aim to form a graph of candidate phrases connected based on similarity to each other. Then core components of the graph are chosen as key phrases. Amongst these, PageRank (Brin and Page, 1998) and TextRank (Mihalcea and Tarau, 2004) assign scores to nodes based on their influence. A common extension is to use weights on the edges denoting the strength of connection (Wan and Xiao, 2008; Rose et al., 2010; Bougouin et al., 2013). Position Rank (Florescu and Caragea, 2017b) and SGRank (Danesh et al., 2015) combine the ideas from statistical, word co-occurrence and positional information. Some approaches, especially applied in the scientific document setting, make use of citation graphs (Gollapalli and Caragea, 2014; Wan and Xiao, 2008), and external knowledge bases (Yu and Ng, 2018) to improve keyphrase extraction. In this work, we focus our approach on a general unsupervised keyphrase extraction setting applicable to any domain where such external resources may not be present.

Finally, embedding based techniques (Bennani-Smires et al., 2018; Papagiannopoulou and Tsoumakas, 2018; Zhang et al., 2022) make use of word-document similarity using word embeddings (Sun et al., 2020; Liang et al., 2021), while language-model based techniques use word prediction uncertainty to decide informativeness (Tomokiyo and Hurst, 2003). Ding and Luo (2021) uses attention scores to calculate phrase importance with the document in an unsupervised manner.

7 Conclusion and Future Work

In this work, we introduced INSPECT, a novel approach to unsupervised keyphrase extraction. Our framework uses a neural model that explains text classification decisions to extract keyphrases via phrase-level feature attribution. Using four standard datasets in two domains, we show that INSPECT outperforms prior methods and establishes state-of-art results in 3 out of 4 datasets.. Through qualitative and quantitative analysis, we show that INSPECT can produce high-quality and relevant keyphrases. INSPECT presents applications of interpretable models beyond explanations for humans.

8 Limitations

Our method uses model explanations for each predicted topic to highlight keyphrases in text. A direct limitation of this method is that our importance scoring is topic-specific and cannot be used to provide an overall rank across topics. Our method therefore cannot provide a ranked list of top-5 or top-10 keyphrases as often done in prior work. While this is a limitation, our current technique of producing a set of all predicted keyphrases is useful in domains like scientific articles where keyphrases are used for downstream applications. Further, as our method produces topic-specific keyphrases, it could potentially miss some keyphrases which are not associated to any predicted topic. Therefore, our approach is beneficial in settings where topic prediction is accurate and feasible to ensure high quality and good coverage of keyphrases. Finally, this work was also limited by the specific choice of the downstream task - namely, topic prediction. Other downstream tasks, like summarization, can potentially help us gain additional insights from attribution.

Acknowledgements

We would like to thank Justin Lovelace, Sachin Kumar, Shangbin Feng, Dheeraj Rajagopal and other members of Tsvetshop Lab for feedback on the paper. This research is supported in part by the Office of the Director of National Intelligence (ODNI), Intelligence Advanced Research Projects Activity (IARPA), via the HIATUS Program contract #2022-22072200004. This material is also funded by the DARPA CMO under Contract No. HR001120C0124 and by the United States Department of Energy (DOE) National Nuclear Security Administration (NNSA) Office of Defense Nuclear Nonproliferation Research and Development (DNN R&D) Next-Generation AI research portfolio. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of ODNI, IARPA, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright annotation therein.

References

David Alvarez-Melis and Tommi S Jaakkola. 2018. Towards robust interpretability with self-explaining neural networks. *Neurips*.

Isabelle Augenstein, Mrinal Das, Sebastian Riedel, Lakshmi Vikraman, and Andrew McCallum. 2017a. SemEval 2017 task 10: ScienceIE - extracting keyphrases and relations from scientific publications. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 546–555, Vancouver, Canada. Association for Computational Linguistics.

Isabelle Augenstein, Mrinal Das, Sebastian Riedel, Lakshmi Vikraman, and Andrew McCallum. 2017b. SemEval 2017 task 10: ScienceIE - extracting keyphrases and relations from scientific publications. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 546–555, Vancouver, Canada. Association for Computational Linguistics.

Kamil Bennani-Smires, Claudiu Musat, Andreea Hossmann, Michael Baeriswyl, and Martin Jaggi. 2018. Simple unsupervised keyphrase extraction using sentence embeddings. *arXiv preprint arXiv:1801.04470*.

Arianna Betti, Martin Reynaert, Thijs Ossenkoppele, Yvette Oortwijn, Andrew Salway, and Jelke Bloem. 2020. Expert concept-modeling ground truth construction for word embeddings evaluation in concept-focused domains. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 6690–6702, Barcelona, Spain (Online). International Committee on Computational Linguistics.

David M. Blei and Jon D. McAuliffe. 2007. Supervised topic models. In *NIPS*.

David M. Blei, A. Ng, and Michael I. Jordan. 2001. Latent dirichlet allocation. *J. Mach. Learn. Res.*, 3:993–1022.

Florian Boudin, Hugo Mougard, and Damien Cram. 2016. How document pre-processing affects keyphrase extraction performance. In *NUT@COLING*.

Adrien Bougouin, Florian Boudin, and Béatrice Daille. 2013. TopicRank: Graph-based topic ranking for keyphrase extraction. In *Proceedings of the Sixth International Joint Conference on Natural Language Processing*, pages 543–551, Nagoya, Japan. Asian Federation of Natural Language Processing.

Sergey Brin and Lawrence Page. 1998. The anatomy of a large-scale hypertextual web search engine. *Computer Networks*, 30:107–117.

Ricardo Campos, Vítor Mangaravite, Arian Pasquali, Alípio Mário Jorge, Célia Nunes, and Adam Jatowt. 2018. A text feature based automatic keyword extraction method for single documents. In *European conference on information retrieval*, pages 684–691. Springer.

Soheil Danesh, Tamara Sumner, and James H. Martin. 2015. SGRank: Combining statistical and graphical methods to improve the state of the art in unsupervised keyphrase extraction. In *Proceedings of the Fourth Joint Conference on Lexical and Computational Semantics*, pages 117–126, Denver, Colorado. Association for Computational Linguistics.

Haoran Ding and Xiao Luo. 2021. AttentionRank: Unsupervised keyphrase extraction using self and cross attentions. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1919–1928, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Haoran Ding and Xiao Luo. 2022. Agrank: Augmented graph-based unsupervised keyphrase extraction. In *AACL*.

Samhaa R. El-Beltagy and Ahmed Rafea. 2009. Kp-miner: A keyphrase extraction system for english and arabic documents. *Information Systems*, 34(1):132–144.

Corina Florescu and Cornelia Caragea. 2017a. A new scheme for scoring phrases in unsupervised keyphrase extraction. In *European Conference on Information Retrieval*, pages 477–483. Springer.

Corina Florescu and Cornelia Caragea. 2017b. Positionrank: An unsupervised approach to keyphrase extraction from scholarly documents. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1105–1115.

Ryan J Gallagher, Kyle Reing, David Kale, and Greg Ver Steeg. 2017. Anchored correlation explanation: Topic modeling with minimal domain knowledge. *Transactions of the Association for Computational Linguistics*, 5:529–542.

Sujatha Das Gollapalli and Cornelia Caragea. 2014. Extracting keyphrases from research papers using citation networks. In *Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence*, AAAI'14, page 1629–1635. AAAI Press.

Derek Greene and Pádraig Cunningham. 2006. Practical solutions to the problem of diagonal dominance in kernel document clustering. In *Proc. 23rd International Conference on Machine learning (ICML'06)*, pages 377–384. ACM Press.

Sarthak Jain, Madeleine van Zuylen, Hannaneh Hajishirzi, and Iz Beltagy. 2020. Scirex: A challenge dataset for document-level information extraction. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*.

Xisen Jin, Zhongyu Wei, Junyi Du, Xiangyang Xue, and Xiang Ren. 2020. Towards hierarchical importance attribution: Explaining compositional semantics for neural sequence models. In *International Conference on Learning Representations*.

Brendan Kennedy, Xisen Jin, Aida Mostafazadeh Davani, Morteza Dehghani, and Xiang Ren. 2020. Contextualizing hate speech classifiers with post-hoc explanation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5435–5442, Online. Association for Computational Linguistics.

Xinnian Liang, Shuangzhi Wu, Mu Li, and Zhoujun Li. 2021. Unsupervised keyphrase extraction by jointly modeling local and global context. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 155–164, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Jialu Liu, Jingbo Shang, Chi Wang, Xiang Ren, and Jiawei Han. 2015. Mining quality phrases from massive text corpora. In *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, pages 1729–1744.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Zhiyuan Liu, Wenyi Huang, Yabin Zheng, and Maosong Sun. 2010. Automatic keyphrase extraction via topic decomposition. In *EMNLP*.

Zhiyuan Liu, Peng Li, Yabin Zheng, and Maosong Sun. 2009. Clustering to find exemplar terms for keyphrase extraction. In *Proceedings of the 2009 conference on empirical methods in natural language processing*, pages 257–266.

Yi Luan, Luheng He, Mari Ostendorf, and Hannaneh Hajishirzi. 2018. Multi-task identification of entities, relations, and coreference for scientific knowledge graph construction. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3219–3232, Brussels, Belgium. Association for Computational Linguistics.

Scott M. Lundberg and Su-In Lee. 2017. A unified approach to interpreting model predictions. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, page 4768–4777, Red Hook, NY, USA. Curran Associates Inc.

Kaushik Mani, Xiang Yue, Bernal Jimenez Gutierrez, Yungui Huang, Simon Lin, and Huan Sun. 2020. Clinical phrase mining with language models. In *2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pages 1087–1090. IEEE.

Luis Marujo, Márcio Viveiros, and João Paulo da Silva Neto. 2013. Keyphrase cloud generation of broadcast news. In *Proceeding of Interspeech 2011: 12th Annual Conference of the International Speech Communication Association.*

Dheeraj Mekala and Jingbo Shang. 2020. Contextualized weak supervision for text classification. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 323–333, Online. Association for Computational Linguistics.

Rada Mihalcea and Paul Tarau. 2004. Textrank: Bringing order into text. In *Proceedings of the 2004 conference on empirical methods in natural language processing*, pages 404–411.

Grégoire Montavon, Sebastian Lapuschkin, Alexander Binder, Wojciech Samek, and Klaus-Robert Müller. 2017. Explaining nonlinear classification decisions with deep taylor decomposition. *Pattern Recognition*, 65:211–222.

Eirini Papagiannopoulou and Grigorios Tsoumakas. 2018. Local word vectors guiding keyphrase extraction. *Information Processing & Management*, 54(6):888–902.

Eirini Papagiannopoulou and Grigorios Tsoumakas. 2019. A review of keyphrase extraction. *CoRR*, abs/1905.05044.

Dheeraj Rajagopal, Vidhisha Balachandran, E. Hovy, and Yulia Tsvetkov. 2021. Selfexplain: A self-explaining architecture for neural text classifiers. *ArXiv*, abs/2103.12279.

Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "why should i trust you?": Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.*

Stuart Rose, Dave Engel, Nick Cramer, and Wendy Cowley. 2010. Automatic keyword extraction from individual documents. *Text mining: applications and theory*, 1:1–20.

François Rousseau and Michalis Vazirgiannis. 2015. Main core retention on graph-of-words for single-document keyword extraction. In *European Conference on Information Retrieval*, pages 382–393. Springer.

Jingbo Shang, Jialu Liu, Meng Jiang, Xiang Ren, Clare R Voss, and Jiawei Han. 2018. Automated phrase mining from massive text corpora. *IEEE Transactions on Knowledge and Data Engineering*, 30(10):1825–1837.

Avanti Shrikumar, Peyton Greenside, and Anshul Kundaje. 2017. Learning important features through propagating activation differences. In *International Conference on Machine Learning*, pages 3145–3153. PMLR.

Lucas Sterckx, Thomas Demeester, Johannes Deleu, and Chris Develder. 2015. When topic models disagree: Keyphrase extraction with multiple topic models. *Proceedings of the 24th International Conference on World Wide Web.*

Yi Sun, Hangping Qiu, Yu Zheng, Zhongwei Wang, and Chaoran Zhang. 2020. Sifrank: A new baseline for unsupervised keyphrase extraction based on pre-trained language model. *IEEE Access*, 8:10896–10906.

Takashi Tomokiyo and Matthew Hurst. 2003. A language model approach to keyphrase extraction. In *Proceedings of the ACL 2003 Workshop on Multiword Expressions: Analysis, Acquisition and Treatment - Volume 18*, MWE '03, page 33–40, USA. Association for Computational Linguistics.

Hanna M. Wallach. 2006. Topic modeling: beyond bag-of-words. *Proceedings of the 23rd international conference on Machine learning.*

Xiaojun Wan and Jianguo Xiao. 2008. Single document keyphrase extraction using neighborhood knowledge. In *AAAI*, volume 8, pages 855–860.

Wenbo Wang, Yang Gao, He-Yan Huang, and Yuxiang Zhou. 2019. Concept pointer network for abstractive summarization. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3076–3085.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.

Yang Yu and Vincent Ng. 2018. Wikirank: Improving keyphrase extraction based on background knowledge. *arXiv preprint arXiv:1803.09000.*

Linhan Zhang, Qian Chen, Wen Wang, Chong Deng, ShiLiang Zhang, Bing Li, Wei Wang, and Xin Cao. 2022. MDERank: A masked document embedding rank approach for unsupervised keyphrase extraction. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 396–409, Dublin, Ireland. Association for Computational Linguistics.

A Appendix

A.1 Evaluation Datasets

SemEval-2017 (Augenstein et al., 2017a) consists of 500 abstracts taken from 12 AI conferences covering Computer Science, Material Science, and Physics. The entities are annotated with Process, Task, and Material labels, which form the fundamental concepts in scientific literature. Identification of the keyphrases was subtask A of the ScienceIE SemEval task (Augenstein et al., 2017b).

SciERC (Luan et al., 2018) extends SemEval-2017 by annotating more entity types, relations, and co-reference clusters to include broader coverage of general AI. The dataset was annotated by a single domain expert who had high (76.9%) agreement with three other expert annotators on 12% subset of the dataset.

SciREX (Jain et al., 2020) is a document-level information extraction dataset, covering entity identification and n-ary relation formation using salient entities. Human and automatic annotations were used to annotate 438 full papers with salient entities, with a distant supervision from the Papers With Code[7] corpus. This dataset can help verify the performance of models on full papers.

500N-KPCrowd (Marujo et al., 2013) is a keyphrase extraction dataset in the news domain. This data consists of 500 articles from 10 topics annotated by multiple Amazon Mechanical Turk workers for important keywords. Following the baselines on this datasets, we pick keywords that were among the top two most frequently chosen by the human annotators. Since no span-level information for these keywords is given, we annotate all occurrences of the chosen keywords in the document to obtain a list of span labels, which we use to evaluate all the models.

A.2 Implementation Details

Here, we present the hyper-parameters for all experiments along with their corresponding search space. We chose all hyperparameters based on the development set performance on the SciERC dataset. We considered RoBERTa (Liu et al., 2019) and XL-NET (Yang et al., 2019) based encoders and finally chose RoBERTa for faster compute times. We experimented with learning-rates from the set of 1e-5,2e-5,5e-5,1e-4 and 2e-4. We chose 2e-5 as the final learning rate. Our batch size of 8 was chosen after experimenting with 4, 8, 12 and 16. The size of the weights matrix in the classification layer was chosen to be 64 from a set of 16,32,64 and 128. The α parameter used for regularization was fixed at 0.5. We tried values between 0.1 and 0.9 and did not find signifcant difference. We saved the model based on best weighted F1 on the topic prediction task. All training runs took less than 3 hours on 2 Nvidia 2080Ti GPUs, except on the ICLR dataset, which took 8 hours. All results are from a single run.

[7] https://paperswithcode.com/

S.No.	Top words from removed topic
1	proposed;propose novel;propose;proposed method;method
2	generalization;study;analysis;suggest;provide
3	outperforms;existing;existing methods;outperforms stateoftheart;methods
4	state;art;state art;shortterm;current state
5	effectiveness;demonstrate effectiveness;source;effectiveness proposed;student
6	training;training data;training set;training process;model training
7	experimental;experimental results;results;results demonstrate;experimental results demonstrate
8	experiments;extensive;extensive experiments;experiments demonstrate;conduct
9	performance;improves;significantly;improve;improved
10	recent;shown;recent work;recent advances;success
11	achieves;introduce;competitive;achieves stateoftheart;introduce new
12	trained;model trained;models trained;networks trained;trained using
13	present;paper present;present novel;work present;monte
14	widely;parameters;widely used;proposes;paper proposes
15	simple;benchmark datasets;benchmark;propose simple;simple effective
16	prior;approach;sampling;continuous;prior work
17	program;introduces;programs;future;paper introduces
18	solve;challenging;able;complex;challenging problem
19	challenge;current;challenges;open;current stateoftheart
20	rate;good;good performance;l;regime
21	works;previous works;existing works;focus;scenarios
22	evaluate;evaluation;tackle;tackle problem;evaluate method

Table 6: 22 Generic topics removed from the 75 topic labels learned using topic modeling on ICLR data.