On the role of resources in the age of large language models

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Abstract

We evaluate the role of expert-based domain knowledge and resources in relation to training large language models by referring to our work on training and evaluating neural models, also in under-resourced scenarios which we believe also informs training models for "well-resourced" languages and domains. We argue that our community needs both large-scale datasets and small but high-quality data based on expert knowledge and that both activities should work hand-in-hand.

1 Introduction

In the recent years large language models based on transformers that are trained end to end and automatically capture the structure of language have achieved remarkable performance (Devlin et al., 2018; Brown et al., 2020). Indeed there is an ongoing debate as to whether level of semantics that these systems obtain. On the one hand, some researchers argue that systems trained on linguistic form alone are limited to being "statistical parrots" (Bender and Koller, 2020) and others argue the correspondence between language use and situations in the world enables these systems to access meaning (Sahlgren and Carlsson, 2021).[1]. Alongside the debate in relation to the semantics these systems encode, several questions have been raised in relation to their training and usage.

Large language models require a lot of data to train and to do that an approach in natural language processing has been to utilise (sometime indiscriminately) all the data that is available. However, access to the data is heavily biased to the data that can be found online, e.g. Wikipedia, or data that can be collected with crowd-sourcing platforms. Such selection of data on which the models are trained does not represent all possible contexts of language use or groups of society producing language which results in undesired and exaggerated thematic (Agrawal et al., 2017) and social bias (Bender et al., 2021) in the models. Moreover, although the performance improvements of LLMs across a range of tasks has come in tandem with a massive growth in the dataset and model sizes and the compute used to train these systems (see, e.g. (Kaplan et al., 2020)), it is recognised that quality data is core to these improvements and there are some projections based on the current rate of growth in data requirements that we may run out of quality training data in the near future (Villalobos et al., 2022). Indeed, a response to this challenge can be seen in the significant amount of current research focused on how to automatically curate quality data from huge web crawl datasets (Penedo et al., 2023).

In addition to access to large datasets of text (and images), training such models is also costly in terms of time and available computational resources, both factors which are only available to a few world languages where English is over-represented.

On the other hand, curating of datasets in terms of collecting high-quality data and their annotation with linguistically-motivated annotation schemes has a long tradition in natural language processing. Transformer models learn linguistic structure end-to-end and systems using automatically learned contextualised embedding surpass models with expert-engineered features which raises a question whether all the years of hard expert work is superfluous. But can we be really sure that the models really have learned useful linguistic structure (Conneau et al., 2018)? Is that structure the same what we expect (Dobnik et al., 2018)? Since annotation of resources is directly connected with linguistics, which focuses on understanding of differences between languages and therefore explores a variety of world languages, the annotation work provides a good cross-linguistic coverage but

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[1]See (Kelleher and Dobnik, 2022) for more on this debate.

frequently datasets have a limited coverage of examples and may not be large enough for training machine learning models. Another benefit of a close relation of this approach to linguistics is that the annotation categories are motivated by our (expert) understanding of how these languages work so the resulting representations are well-motivated and interpretable.

In this presentation we evaluate the previous questions about the role of data and resources for modern natural language processing in the light of our experience with building resources for under-resourced language from ground up. We highlight the idea that in such scenarios both kinds of resources are useful and in fact shows that they have complementary weaknesses and strengths. It follows that modern and future natural language processing must be informed by expert domain knowledge about language and linguistics as without these we are not able to evaluate the data that these models are utilising nor interpret what semantics or bias the models might have captured nor we can improve the models in a motivated way either indirectly (by neural architecture choice) or directly (by injection of labels).

2 The need for (deeper) semantics

One of the primary objective functions used for training large foundational language models is to predict the next word or a missing word from the surrounding context. This objective function indirectly priorities several linguistic perspectives. The of semantics that is learned in this way can be characterised as being primarily *distributional* (in the sense of (Firth, 1957)), *thematic* (rather than *taxonomic*, see (Kacmajor and Kelleher, 2020)), and *topical* (in the sense of topic as word co-occurrence (Manning and Schutze, 1999)).

Given that the semantics of these models is primarily based on co-occurrence an interesting question to ask is whether (or at least how far) can co-occurrence bring a model in terms of semantics. A review of the literature probing on neural embeddings (Conneau et al., 2018) and on the BERT architecture in particular (Rogers et al., 2020) indicates that neural embeddings do encode a range of linguistic information, in particular topic and syntax. However, a relatively under-explored aspect of these systems is their ability to capture and encode semantic phenomena, such as idiomaticity (Nedumpozhimana et al., 2022). One reason

for this lack of research is the relative paucity of large scale annotated benchmarks for semantic phenomena. For example, many probing experiments build on the benchmark datasets set out in (Conneau et al., 2018), however the tasks covered by these datasets are primarily syntactic in nature (Klubicka and Kelleher, 2022). There is some evidence that BERT does encode semantic phenomena (Nedumpozhimana and Kelleher, 2021). However, in the current context of large language models trained on massive datasets the question of whether *more is different* is holds for linguistic semantics arises?

Some researchers have argued that BERT rediscovers the classical NLP pipeline, with the earlier layers encoding syntactic information and later layers semantic (Tenney et al., 2019). However, a number of recent studies have found that the performance of BERT-based transformer models across a range of standard NLP benchmark dataset is robust to word-order perturbations (see e.g. (Pham et al., 2021), (Gupta et al., 2021)). These results suggest transformer based models such as BERT rely on relatively shallow surface level information such as topic rather than syntactic information. Moreover, this suggests current NLP benchmarks are not challenging enough to comprehensively assess linguistic semantic (Sinha et al., 2021). The difficulties in developing robust benchmark datasets has been raised in the discussions around the recent work by (Jiang et al., 2023) that reported a set of experiments that demonstrate that a simple *gzip*-based text classification method outperforms BERT and a number of other deep neural network NLP models on a range of text classification tasks using standard datasets.

3 The need for data

Training of large language models requires a lot of data that spans over different contexts of language use and social groups in order to capture (some kind of) knowledge of language for natural language generation and interpretation and to avoid unwanted social and contextual bias. However, as discussed in the previous section even for well-resourced language models such as English it is still not clear whether this has been achieved as data selection and coverage of thematic and social contexts that are used in the training data has not yet been (to our knowledge) systematically evaluated. Equally, approaching the same problem from

the engineering perspective it has been impossible to collect enough data or build a model large enough to test whether such an endeavour is theoretically and practically possible at all (Villalobos et al., 2022).

This need for data and its limitations becomes much more evident when we examine the under-resourced scenarios that we looked at. Arabic natural language processing is an interesting case. Modern Standard Arabic (MSA) is a standardised form of Arabic used in printed media and news and is supported well in terms of natural language models and resources. However, there are also several local varieties spoken over a large geographical span. In addition, Arabic may be also spoken (and written in social media) and code-switched with several other varieties and even different languages. Some of these have received more attention than others in NLP. For example, there has been a good support for the Egyptian variety but very little support for Algerian and the individual varieties in the Levantine area. Another interesting aspect of Arabic linguistic landscape is that it differs between regions/countries in what situation contexts different varieties are used, what other varieties are present in these contexts and how similar these varieties are.

Speakers/writers in Algeria (Adouane and Dobnik, 2017) use social media where varieties that were typically spoken in personal everyday communication are now written with Arabic script on a limited phone keyboard. There is no standard spelling for these varieties and the practical limitation of using different keyboards introduce high level of variation in the way these varieties are written by different users in different contexts on different social media. A further level of of variation is added when these varieties are code-switched with MSA and other languages, in case of Algerian with Berber, French and English, all written in the same script. Hence, one of the first tasks to tackle the bootstrapping of resources for Algerian was to build a code-switching detector based on a limited expert-annotated corpus using probabilistic (HMM) and bi-gram feature classification models.

On the other hand, Levantine dialects (Abu Kwaik et al., 2018b) are various closely related Arabic dialects that are spoken and written in social media but such context makes them hard to distinguish from each other as phonological form which underlies a lot of discriminating power

is missing (Abu Kwaik et al., 2018a). Finally, Wolaytta (Gebreselassie and Dobnik, 2022), is one of several languages spoken in Ethiopia, belongs to the Omotic family of African languages which is different from Amharic, an official national language which belongs to the Semitic family of languages and for which most NLP resources exits. Wolaytta is mostly used in spoken form in personal communication and radio and has been standardised in the written form in school texts and religious textbooks. In terms of NLP resources, there is no social media but they are radio programmes , school textbooks, religious literature and a Wolaytta-English dictionary.

Comparing these cases we can see that there are large linguistic differences between these target varieties and the language used in the closest set of contexts for which NLP resources exist and also that we have limited records of of contexts in which they are used either be cause data is missing or because the variety is not used in those contexts. Consequently, building NLP resources had to rely on a large support from expert linguistic and social knowledge because the training examples were limited we relied on simple machine learning methods such as Bayesian classification which in conjunction with the expert knowledge gave satisfactory results.

4 The need for the right method

Different (i) contexts of language use, (ii) relation to the closest variety for which NLP resources exits, (iii) availability of data, (iv) availability of expert annotation required very different tools and approaches to build resources and NLP applications for these varieties. For example, using character and sub-word models and CNNs, weak supervision (bootstrapping from an existing labeller, self-training) (Adouane et al., 2018b; Abu Kwaik et al., 2020), injecting background knowledge from lexicon and pre-trained sub-word embeddings (Adouane et al., 2018a), pre-training (Abu Kwaik et al., 2022), text normalisation with alignment of tokens (Adouane et al., 2019b), data augmentation (Adouane et al., 2019a). It is often the case that a simple model works better than a more complex model, most likely because it is able to generalise better from a limited data (Abu Kwaik et al., 2019a,b). In sum, understanding language and its context is important even at the age of large language models to make an informed choice what

model should be used when.

5 Are "well-resourced" languages also under-resourced?

We argued previously that there is still an open question whether language model have in fact reached understanding of language as they have not been exposed to all contexts of language use. Hence, we are facing with similar under-resourced scenarios also in cases of "well-resourced" languages where existing large language models are applied in contexts or tasks for which the model has not been initially trained on. Language is continuously changing and speakers/writers are creative, especially in social media (Noble et al., 2021). Hence, pre-trained language models may become quickly outdated.

Our work on generating spatial descriptions of images shows that since pre-training of visual features such as ResNet (He et al., 2016), Faster-RCNN (Ren et al., 2015) and CLIP (Radford et al., 2021) that are trained to identify objects affects what is model able to learn about predicting relations which are likely to be hallucinated from a language model, simply because the model has not been pre-trained in this way and until such features are explicitly identified (Ghanimifard and Dobnik, 2019). A significant body of work on language and vision has focused on generation of image descriptions that focus on a single sentence. Extending the task to multi-sentence generation requires application of different models (Ilinykh and Dobnik, 2020).

Adaption of pre-trained models from the image captioning domain on object classification (where objects are in the attention focus of the scene) to the domain of situated language (where a robot without a specific model of visual and thematic attention) is very different reveals that visual information in such cases is used quite differently than in an image captioning scenario (Ilinykh et al., 2022).

Finally, a comparison of generated noun phrases in generated multi-sentence descriptions to human descriptions (Ilinykh and Dobnik, 2022) reveals a difference. Models are more general predictors than humans across the board and opt for more general descriptions of objects than humans. This is because they are trained on a single task, but also within this task they are biased to find a single generalisation following a training objective covering all of the examples equally, whereas in reality

humans might use descriptions that are more general or more specific on a case-to-case bases. Since general descriptions are more frequent than the specific ones, they always win. Overall, it appears that a very fine grained knowledge of language data is required to capture all the contexts.

6 Conclusions

Training language and vision and language models is useful but so is production of high quality domain specific resources as both tasks are complementary. We might want to rethink how to train such models – having one large model is practical, but perhaps not the end of the NLP story and more work is required to examine the limits of models to capture a variety of possible contexts. Expert-based knowledge is highly relevant for selecting content data, creating datasets, and evaluating contexts in which models are trained. Similarly, expert-based resources are relevant to make informed choices about the model architectures and to support training of end-to-end models by feature engineering and selection. This also includes application of pre-trained feature representations. Understanding architectures, models and training regimes allows us to define the limits of what linguistic knowledge can be represented and learned and should inform data preparation and annotation work. Although significant work has been done on evaluating the models for acquired linguistic knowledge, more targeted fine-grained evaluation of models is necessary to achieve the models fit to the previous requirements, with targeted positive and negative linguistic examples (beyond the level of granularity of a Turing test as implemented in the GLUE benchmarks (Wang et al., 2019)), which is one of our current efforts.

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