Vocabulary Transfer for Biomedical Texts

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Abstract

Vocabulary transfer is a transfer learning sub-task in which language models fine-tune with the corpus-specific tokenization instead of the default one, which is being used during pretraining. This usually improves the resulting performance of the model, and in the paper, we demonstrate that vocabulary transfer is especially beneficial for medical text processing. Using three different medical natural language processing datasets, we show vocabulary transfer to provide up to ten extra percentage points for the downstream classifier accuracy.

1 Introduction

The transformer introduced in Vaswani et al. (2017) gave rise to a large family of models as GPT (Radford et al., 2018, 2019) or BERT (Devlin et al., 2019), T5 (Raffel et al., 2020), XLM-RoBERTa (Conneau et al., 2020), ELECTRA (Clark et al., 2019) and many more. The performance of such models tends to improve with the size, and training of such architectures from scratch requires a lot of computational power and huge datasets. Thus, most practical implementations use transfer learning: a huge pretrained model is fine-tuned on a smaller dataset collected for a specific downstream task. This fuels interest in transfer learning procedures and gives rise to various approaches and practices to raise the transfer’s effectiveness, see Raffel et al. (2020).

This paper demonstrates that vocabulary transfer is helpful for natural language processing in the medical domain. Typical language model training procedure may be divided into three huge parts: tokenization - transforming text from letters to ids of tokens from predefined vocabulary, pretraining - unsupervised language model training with huge corpus, usually on masked language modeling (MLM) or next sentence prediction (NSP) tasks and fine-tuning - training model on a target downstream task. Conventionally, tokenization used for language models is the same for pretraining and fine-tuning and includes thousands of tokens. These could be smaller chunks of words (down to the size of a single letter) and more extended tokens directly corresponding to certain words. In Samenko et al. (2021) authors suggest that using new downstream-specific tokenization for fine-tuning might be beneficial for the performance of the resulting model. Naturally, dataset-specific tokenization could be especially useful for the use cases when the downstream dataset significantly differs from the dataset on which the pretraining is performed.

Vocabulary transfer seems especially relevant when the dataset used for fine-tuning has many words and parts of words, which are rare in the pretraining dataset and frequent in the downstream one. In this case, better transfer of the existing knowledge could be especially relevant. For example, "entomophobia" is a specific phobia characterized by an excessive or unrealistic fear of one or more insect classes. Though it is reasonably rare in generic texts, proper disambiguation might be relevant for medical purposes. We use several datasets to check if vocabulary transfer improves the model’s performance on such datasets that significantly differ from the generic natural language. Namely, we experiment with text classification as a downstream task in biological domain (Mujtaba et al., 2019; Gao et al., 2021; Hughes et al., 2017) on three datasets: MeDAL (Wen et al., 2020) - large medical dataset for abbreviation disambiguation, OHSUMED (Hersh et al., 1994) - medical dataset for classification cardiovascular diseases and Kaggle Medical Texts Dataset1 - medical dataset for classification different conditions of a patient: digestive system diseases, cardiovascular diseases, neoplasms, nervous system diseases, and general pathological conditions. We demonstrate that vocabulary transfer improves the result-

1https://www.kaggle.com/chaitanyakck/medical-text
ing performance on the downstream task by up to ten percentage points.

## 2 Vocabulary transfer

In Samenko et al. (2021) the authors introduce vocabulary transfer as a process of finding such dataset-specific tokenization $\tilde{V}$, its initialization, and a fine-tuning procedure for it that would result in the superior performance of a given NLP model. We will use the following notation. The vocabulary of tokens $V = \{t_k, v_k\}^M_0$ is obtained as a result of a pretraining phase. Here $t_k$ stands for some chunk of text that forms a token, and $v_k$ is an embedding that corresponds to it. The new vocabulary $\tilde{V} = \{\tilde{t}_k, \tilde{v}_k\}^N_0$ is used for the fine-tuning.

To transfer pretrained knowledge about old tokens to the new, corpus-specific tokens, one could have some heuristic procedure of token matching. In this paper, we test two token initialization heuristics. First, if a token in the new vocabulary coincides with some token in the old one, we can assign its old embedding. We denote this vocabulary transfer as matched. At the same time, some of the new tokens could be split into a partition of several tokens from the original tokenization. For every such token in a new vocabulary, we build all possible partitions that consist of the old vocabulary tokens. We choose a partition with a minimal number of tokens out of these partitions. If there is more than one partition with the same amount of tokens, we choose the one that includes the most extended token. We initialize the corresponding token from the new vocabulary with the old vocabulary embeddings averaged over the chosen partition for every selected partition. We call this transfer averaged.

## 3 Data

Table 2 summarizes the parameters of the datasets that we experiment with.

| Dataset   | Number of Records | Number of Labels |
|-----------|-------------------|------------------|
| MeDAL     | 24 005            | 5 886            |
| OHSUMED   | 13 929            | 23               |
| Kaggle    | 28 880            | 5                |

Table 1: Parameters of the datasets used for experiments. MeDAL is the largest of the three, with the highest total amount of texts and highest total amount of labels.

Similarly to Wen et al. (2020) we use only a small share of MeDAL dataset, for which there is specifically one disambiguation solution for every given text. Thus, the datasets are as follows: MeDAL has the highest number of labels with approximately four examples per one label only, Kaggle Dataset of Medical Text has only five labels with a vast amount of samples for each, while OHSUMED has 23 labels.

## 4 Experiments

We run a series of experiments with the base version of BERT model on three different medical datasets. First, we discuss how to adopt new dataset-specific vocabulary via an intermediary MLM step. Then we run several experiments with various parameters.

### 4.1 Fine-tuning Transferred Vocabulary

Token matching is not enough for vocabulary transfer. One also has to establish some procedure to fine-tune the model with new dataset-specific tokenization. A natural way is to run an MLM on the downstream dataset before training a final classifier. In this subsection, we compare the performance of averaged vocabulary transfer with and without the intermediary MLM step.

Table 2 summarizes the performance of BERT with a vocabulary of 16 000 tokens with averaged vocabulary transfer on the task of medical diagnosis prediction.

| Fine tuning          | Classifier Accuracy | MLM + Classifier Accuracy |
|----------------------|---------------------|---------------------------|
| Standard             | 77.4                | 80.4                      |
| Averaged tokens      | 81.9                | 83.1                      |

Table 2: Accuracy of downstream classifiers for MeDAL. Fine-tuning BERT with new, corpus-specific tokenization improves the performance with and without the intermediary MLM step. Pre-training BERT as an MLM before training of actual classifier improves the performance further.

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Both for standard fine-tuning and vocabulary transfer intermediary MLM brings up to three extra percentage points on the downstream accuracy. We see this pattern on all datasets. Thus we suggest running MLM as an intermediary step when transferring vocabulary. In the following Subsection, we experiment with various vocabulary sizes and matching procedures.

MeDAL is a medical disambiguation dataset that includes the diagnosis’s shorted version in the input text. Here we treat it as a natural language classification problem to make an illustrative comparison with the other two datasets.

As MeDAL has a very specific structure, MLM might be especially effective due to some form of a data leak. However, this is not the case since the complete answers are not included in the input texts. Instead, vocabulary transfer allows the model to have dataset-specific tokens that assist overall performance.
4.2 Vocabulary Size and Matching

In this subsection, we report experiments with OHSUMED and Kaggle medical datasets. Tables 3-7 summarize the obtained results.

One could see that vocabulary transfer significantly improves downstream performance for all vocabulary sizes on both datasets. The results here are provided for different learning rates 1e-4, 1e-5, and 1e-6, and for all learning rates, vocabulary transfer shows impressive results. Figure 1 summarizes the resulting accuracy of the models on the test and shows confidence intervals after five independent reruns.

5 Discussion

One could notice several essential aspects of vocabulary transfer for medical texts. First, the intermediary MLM step is always helpful, even over old predefined tokenization. One could speculate that some tokens that are rare in common English but are helpful for medical NLP are adjusted through the intermediate MLM step. This step gives two to three extra percentage points regarding the downstream accuracy.

Second, matching coinciding tokens and running intermediary MLM steps is almost as good as a more sophisticated averaging heuristic. Conservatively, such matching gives extra three to nine percentage points in terms of the downstream accuracy. Maybe, there is a better and more robust procedure out there, but it seems that the most straightforward vocabulary transfer for medical NLP can boil down to three steps:

- tokenize the dataset;
- substitute matching tokens with the embeddings learned in pre-training;
- run an MLM and fine-tune the model with new tokens.

Finally, averaging the tokens that could be represented as a union of old ones tends to give one or two extra percentage points in the downstream accuracy.

6 Conclusion

This paper demonstrates that vocabulary transfer could be beneficial for medical natural language processing. We show how different steps of vocabulary transfer affect resulting performance on the task of classification using three medical datasets. Vocabulary transfer seems to be effective on all three datasets.

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