Train No Evil: Selective Masking for Task-guided Pre-training

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Abstract

Recently, pre-trained language models mostly follow the pre-training-then-fine-tuning paradigm and have achieved great performances on various downstream tasks. However, due to the aimlessness of pre-training and the small in-domain supervised data scale of fine-tuning, the two-stage models typically cannot capture the domain-specific and task-specific language patterns well. In this paper, we propose a selective masking task-guided pre-training method and add it between the general pre-training and fine-tuning. In this stage, we train the masked language modeling task on in-domain unsupervised data, which enables our model to effectively learn the domain-specific language patterns. To efficiently learn the task-specific language patterns, we adopt a selective masking strategy instead of the conventional random masking, which means we only mask the tokens that are important to the downstream task. Specifically, we define the importance of tokens as their impacts on the final classification results and use a neural model to learn the implicit selecting rules. Experimental results on two sentiment analysis tasks show that our method can achieve comparable or even better performance with less than 50% overall computation cost, which indicates our method is both effective and efficient. The source code will be released in the future.

1 Introduction

Pre-trained Language Models (PLMs) have achieved superior performances on various NLP tasks (Baevski et al., 2019; Joshi et al., 2019; Liu et al., 2019; Yang et al., 2019; Clark et al., 2020) and have attracted wide research interests. Inspired by the success of GPT (Radford et al., 2018) and BERT (Devlin et al., 2019), most PLMs follow the pre-training-then-fine-tuning paradigm, which adopts unsupervised pre-training on large general-domain corpora to capture the general language patterns and supervised fine-tuning to adapt to downstream tasks.

However, on one hand, the unsupervised pre-training is time-consuming and compute-intensive, which is very inefficient for solving a specific downstream task. On the other hand, limited by the aimlessness of pre-training and the small scale of in-domain supervised data used in fine-tuning, the PLMs typically cannot effectively capture the domain-specific and task-specific language patterns, such as terminologies in legal tasks, which are critical for downstream tasks.

To learn the domain-specific language patterns, some previous works (Beltagy et al., 2019; Huang et al., 2019) pre-train a BERT-like model from scratch using large-scale in-domain data. However, they are still very compute-intensive and require large-scale in-domain corpora, which is hard to obtain in many domains. There are also some
works (Phang et al., 2018) which add intermediate supervised pre-training after the general pre-training, whose pre-training task is similar to the downstream task but has a larger dataset, so that they can learn some task-specific language patterns. But, Wang et al. (2019) shows that the intermediate pre-training often negatively impacts the transfers to downstream tasks.

Inspired by the LM fine-tuning in ULMFiT (Howard and Ruder, 2018), we add a task-guided pre-training stage between general pre-training and fine-tuning to capture domain-specific language patterns. The overall training process is shown in Figure 1. In task-guided pre-training, we train masked language modeling (Masked LM) (Devlin et al., 2019) on mid-scale in-domain unsupervised data, which is constructed by collecting other datasets in the same domain. In this way, PLMs can utilize more data to better learn domain-specific language patterns (Alsentzer et al., 2019; Lee et al., 2019; Sung et al., 2019; Xu et al., 2019). However, the conventional Masked LM randomly masks tokens, which is inefficient to capture the task-specific patterns. Hence, we propose a selective masking strategy for task-guided pre-training, whose main idea is selectively masking the important tokens for downstream tasks.

Intuitively, some tokens are more important than others for solving a specific task, and the important tokens vary among specific tasks (Ziser and Reichart, 2018). For instance, in sentiment analysis, emotional tokens such as “like”, “hate” are critical for determining the sentiments of texts (Ke et al., 2019). While in relation extraction, predicates and verbs are typically more significant. Therefore, selectively masking and predicting the important tokens instead of randomly masking massive tokens can help the PLM efficiently learn the task-specific language patterns and significantly reduce the computation cost of task-guided pre-training.

Our selective masking strategy adopts black-box attacks to find task-specific important tokens and then trains a neural model to learn the implicit selecting rules. Specifically, inspired by the previous work (Li et al., 2019) on measuring the importance of a token for downstream tasks, we define the importance of a token as the change of classification confidence after removing the token from the sequence. However, this method relies on the labels in downstream datasets whose sizes are often limited for task-guided pre-training. To better utilize mid-scale in-domain unsupervised data as shown in Figure 1, we train a neural network to imitate the scoring function and learn the implicit selecting rules, so that we can select the tokens to be masked without labels.

Since our task-guided pre-training method enables the model to efficiently learn the domain-specific and task-specific language patterns, it is unnecessary to fully train the model in the general pre-training stage. Hence, our overall pre-training time cost of the two pre-training stages can be smaller than those of conventional PLMs.

We conduct experiments on two real-world sentiment analysis tasks: MR and SemEval14. Experimental results show that our method is both efficient and effective. Our method can achieve comparable and even better performances than the conventional pre-train-then-fine-tune method with less than 50% of overall computation cost.

2 Methodology

In this section, we describe task-guided pre-training and selective masking strategy in detail. For convenience, we denote general unsupervised data, in-domain unsupervised data, downstream supervised data as $D_{\text{General}}, D_{\text{Domain}}$ and $D_{\text{Task}}$.

2.1 Training Framework

As Figure 1 shows, our overall training process consists of three stages:

- **General pre-training** is identical to the pre-training of BERT (Devlin et al., 2019). In this stage, we randomly mask 15% tokens of $D_{\text{General}}$ and train the model to reconstruct the original text. With the help of our method, we do not need to fully train the model as the original BERT does, which significantly reduces the computation cost.

- **Task-guided pre-training** trains the model on $D_{\text{Domain}}$ with selective masking to efficiently capture the domain-specific and task-specific patterns. In this stage, we apply a selective masking strategy to solely mask the important tokens, and then train the model to reconstruct the input. The details of selective masking are introduced in Section 2.2.

- **Fine-tuning** is to adapt the model to the downstream task. This stage is identical to the conventional PLMs.

2.2 Selective Masking

In our task-guided pre-training, we adopt the selective masking strategy instead of random mask-
We define the important tokens as those having large impacts on the classification results. Specifically, given a sequence of tokens \( s = (w_1, w_2, \ldots, w_n) \), let \( y_i \) denote its target classification label and \( P(y_i | w_1, w_2, \ldots, w_n) \) denote the classification confidence given by the PLM fine-tuned on the task. Note that the PLM used here is the model after the general pre-training stage described in Section 2.1, not a fully pre-trained PLM. The criterion to confirm the importance of the token \( w_i \) is:

\[
\begin{align*}
| P(y_i | w_1, w_2, \ldots, w_n) - P(y_i | w_1, w_2, \ldots, w_{n-1}) | < \delta \\
| P(y_i | w_1, w_2, \ldots, w_n) - P(y_i | w_1, w_2, \ldots, w_{i-1}) | \geq \delta
\end{align*}
\]

Given the criterion, we apply a heuristic method to find important tokens. In the beginning, the input sequence is initialized to an empty sequence. Then we sequentially add each token to the sequence and test the sequence on the above criterion. If the current sequence satisfies the criterion after adding token \( w_i \), we know that \( w_i \) is an important token and then remove \( w_i \) from the sequence. Otherwise, we keep \( w_i \) in the sequence.

Note that different from Li et al. (2019), our method ensures whenever a token \( w_i \) is tested, other tokens in the sequence are not important, which is essential for the criterion.

**Finding important tokens**

Finding important tokens is essential for the criterion. To show that our strategy can significantly reduce the computation cost of pre-training, we choose the model early stopped at 100k, 200k, and 300k steps and the fully pre-trained model (1M steps).

**In task-guided pre-training**, we use the pure text of two text classification datasets Yelp (Zhang et al., 2015) and Amazon (He and McAuley, 2016) as our in-domain unsupervised data \( D_{\text{Domain}} \), which are both hundreds of times larger than the supervised data MR and SemEval14.

**In fine-tuning**, we fine-tune the model for 10 epochs and choose the version with the highest accuracy on the dev set.

### 3.2 Experimental Results

#### Efficiency

We report our accuracy-pre-training-step lines of all four combinations of downstream tasks and \( D_{\text{Domain}} \) in Figure 2. From the experimental results, we can observe that:

1. Our method achieves comparable or even better performances on all 4 settings with less than 50% pre-training costs, which indicates our selective masking task-guided pre-training method is both efficient and effective.

2. Our selective masking strategy consistently outperforms the random selecting strategy, which indicates that our selective masking works well to capture the task-specific language patterns.

3. In the 4 settings, our model performs best in SemEval14 + Yelp, in which our model outperforms the fully pre-trained BERT_{BASE} by 1.4% with only half of the training steps. While in MR+Yelp, the model performs worst, in which our accuracy drops 1.94% compared with the fully pre-trained model. This is because the text domains...
of SemEval14 and Yelp are much more similar (both restaurant reviews) than those of MR and Yelp (movie reviews and restaurant reviews). It indicates that the similarity between $D_{\text{Domain}}$ and $D_{\text{Task}}$ is critical for our task-guided pre-training to capture the domain-specific and task-specific patterns, which is intuitive.

**Effectiveness**

To evaluate the effectiveness of task-guided pre-training, we continue to pre-train the fully pre-trained BERT BASE on the in-domain data. From the results shown in Table 1, we have the following observations:

1. Compared to the fully pre-trained model, our task-guided pre-training achieves significant improvements in 3 settings no matter which kind of masking strategies is used, which shows the task-guided pre-training can help the model to capture the domain-specific patterns. In the MR+Yelp setting, the random masking harms the model performance, which indicates not all patterns in $D_{\text{Domain}}$ can benefit downstream tasks.

2. In all settings, our selective masking strategy consistently outperforms the random masking strategy, even on the setting of MR+Yelp. It indicates that our selective masking strategy can still effectively capture helpful task-specific patterns even when the $D_{\text{Domain}}$ is not so close to the $D_{\text{Task}}$.

3.3 Case Study

To analyze whether our selective masking strategy can successfully find important tokens, we conduct a case study, which is shown in Table 2. In this case, we use MR as the supervised data and Yelp as the unsupervised in-domain data. As shown in Table 2, our selective masking strategy successfully selects emotional tokens, which are important for this task, on both supervised and unsupervised data.

4 Conclusion

In this work, we present a new pre-training method, called task-guided pre-training with selective masking, which is added between general pre-training
and fine-tuning. With task-guided pre-training, models can effectively and efficiently capture domain-specific and task-specific patterns, which benefits the specific downstream task.

Experimental results show that our methods can achieve better performances with less computation. There are still three important directions for future work: (1) Applying task-guided pre-training to general domain data when the in-domain data is limited. (2) Integrating the selecting rules of different downstream tasks for more efficient pre-training. (3) Exploring more general measurements for task-specific patterns.

References

Emily Alsentzer, John Murphy, William Boag, Wei-Hung Weng, Di Jindi, Tristan Naumann, and Matthew McDermott. 2019. Publicly available clinical BERT embeddings. In Proceedings of ClinicalNLP.

Alexei Baevski, Sergey Edunov, Yinhan Liu, Luke Zettlemoyer, and Michael Auli. 2019. Cloze-driven pretraining of self-attention networks. In Proceedings of EMNLP.

Iz Beltagy, Kyle Lo, and Arman Cohan. 2019. SciBERT: Pretrained language model for scientific text. In Proceedings of EMNLP.

Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. Electra: Pretraining text encoders as discriminators rather than generators. In Proceedings of ICLR.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL.

Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In Proceedings of WWW.

Jeremy Howard and Sebastian Ruder. 2018. Universal language model fine-tuning for text classification. In Proceedings of ACL.

Kexin Huang, Jaa Alotasaar, and Rajesh Ranganath. 2019. ClinicalBERT: Modeling clinical notes and predicting hospital readmission. arXiv:1904.05342.

Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S Weld, Luke Zettlemoyer, and Omer Levy. 2019. SpanBERT: Improving pre-training by representing and predicting spans. arXiv preprint arXiv:1907.10529.

Pei Ke, Haozhe Ji, Siyang Liu, Xiaoyan Zhu, and Minlie Huang. 2019. SentiLR: Linguistic knowledge enhanced language representation for sentiment analysis. arXiv preprint arXiv:1911.02493.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2019. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics.

Jinfeng Li, Shouling Ji, Tianyu Du, Bo Li, and Ting Wang. 2019. TextBugger: Generating adversarial text against real-world applications. In Proceedings of NDSS.

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.

Bo Pang and Lillian Lee. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In Proceedings of ACL.

Jason Phang, Thibault Fève, and Samuel R Bowman. 2018. Sentence encoders on stilts: Supplementary training on intermediate labeled-data tasks. arXiv preprint arXiv:1811.01088.

Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androusooulos, and Suresh Manandhar. 2014. SemEval-2014 task 4: Aspect based sentiment analysis. In Proceedings of SemEval14.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. In Proceedings of Technical report, OpenAI.

Chul Sung, Tejas Dhamecha, Swarnadeep Saha, Tengfei Ma, Vinay Reddy, and Rishi Arora. 2019. Pre-training BERT on domain resources for short answer grading. In Proceedings of EMNLP.

Alex Wang, Jan Hula, Patrick Xia, Raghavendra Pappagari, R. Thomas McCoy, Roma Patel, Najoung Kim, Ian Tenney, Yinghui Huang, Katherin Yu, Shuning Jin, Berlin Chen, Benjamin Van Durme, Edouard Grave, Ellie Pavlick, and Samuel R. Bowman. 2019. Can you tell me how to get past sesame street? Sentence-level pretraining beyond language modeling. In Proceedings of ACL.

Yichong Xu, Xiaodong Liu, Chunyuan Li, HoiFung Poon, and Jianfeng Gao. 2019. DoubleTransfer at MEDIQA 2019: Multi-source transfer learning for natural language understanding in the medical domain. In Proceedings of BioNLP.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le. 2019. XLNet: Generalized autoregressive pretraining for language understanding. In Proceedings of NeurIPS.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In Proceedings of NeurIPS.
Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In Proceedings of ICCV.

Yftah Ziser and Roi Reichart. 2018. Pivot based language modeling for improved neural domain adaptation. In Proceedings of NAACL.