Short Text Pre-training with Extended Token Classification for E-commerce Query Understanding

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Abstract

E-commerce query understanding is the process of inferring the shopping intent of customers by extracting semantic meaning from their search queries. The recent progress of pre-trained masked language models (MLM) in natural language processing is extremely attractive for developing effective query understanding models. Specifically, MLM learns contextual text embedding via recovering the masked tokens in the sentences. Such a pre-training process relies on the sufficient contextual information. It is, however, less effective for search queries, which are usually short text. When applying masking to short search queries, most contextual information is lost and the intent of the search queries may be changed. To mitigate the above issues for MLM pre-training on search queries, we propose a novel pre-training task specifically designed for short text, called Extended Token Classification (ETC). Instead of masking the input text, our approach extends the input by inserting tokens via a generator network, and trains a discriminator to identify which tokens are inserted in the extended input. We conduct experiments in an E-commerce store to demonstrate the effectiveness of ETC.

1 Introduction

Query Understanding (QU) plays an essential role in E-commerce shopping platform, where it extracts the shopping intents of the customers from their search queries. Traditional approaches usually rely on handcrafted features or rules (Henstock et al., 2001), which only have limited coverage. More recently, deep learning models are proposed to improve the the generalization performance of QU models (Nigam et al., 2019; Lin et al., 2020). These methods usually train a deep learning model from scratch, which requires a large amount of manually labeled data. Annotating a large number of queries can be expensive, time-consuming, and prone to human errors. Therefore, the labeled data is often limited.

To achieve better model performance with limited data, researchers resorted to the masked language model (MLM) pre-training with large amount of unlabeled open-domain data (Devlin et al., 2019; Liu et al., 2019b; Jiang et al., 2019; He et al., 2021) and achieved the state-of-the-art performance in QU tasks (Kumar et al., 2019; Jiang et al., 2021; Zhang et al., 2021; Li et al., 2021). However, open-domain pre-trained models can only provide limited semantic and syntax information for QU tasks in E-commerce search domain. In order to capture domain-specific information, Lee et al. (2020); Gururangan et al. (2020); Gu et al. (2021) propose to pre-train the MLM on a large in-domain unlabeled data either initialized randomly or from a public pre-trained checkpoint.

![bamboo charcoal bag](image1)
Original Query

![bamboo [MASK] bag](image2)
Masked Query

![organic bamboo charcoal bag](image3)
Extended Query

Figure 1: Original Query vs. Masked Query vs. Extended Query. "bamboo charcoal bag" is a bag of ‘bamboo charcoal’, while ‘bamboo bag’ is a bag made of bamboo. Masking out ‘charcoal’ will completely change the user’s search intent. On the contrary, extending the query to ‘organic bamboo charcoal bag’ does not change the user’s search intent even though the combination of ‘organic’ and ‘bamboo charcoal bag’ is not common.

Although the search query domain specific MLM can adapt to the search query distribution in some extent, it is not effective in capturing the contextual information of the search queries due to the short length of the queries. There are two major challenges:
MLM (Devlin et al., 2019) randomly replace tokens in the text by [MASK] tokens and train the model to recover them with a low masking probability (e.g., 15% in Devlin et al. (2019); Liu et al. (2019b)). Since the length of search queries is short, there will be many queries having no masked tokens during training. Even though we can ensure each query to be masked for at least one token, the percentage of mask tokens will be way much higher and thus lose much context information;

- Masking out tokens may significantly change the intent of the search queries. Figure 1 shows an example of masked token changing the intent of the query.

In this paper, we propose a new pre-training task — Extended Token Classification (ETC) to mitigate the above-mentioned issues for search query pre-training. Instead of masking out tokens in the search query and training the model to recover the tokens, we extend the search query and train the model to identify which tokens are extended. The extended query is generated by inserting tokens with a generator, which is a pre-trained masked language model. The generator takes query with randomly inserted [MASK] tokens as the input and fill in the blanks by its prediction. There are several benefits of ETC:

- It turns the language modeling task into a binary classification task on all tokens, which makes the model easier to train;
- All samples will be used to train the model, even when the probability of inserting tokens is low;
- Since the generator has already been pre-trained, the extended queries alter the meaning of the search query less frequently.

We conduct experiments on an E-commerce store to demonstrate the effectiveness of ETC. We conduct fine-tuning experiments in a wide range of query understanding tasks including three classification tasks, one sequence labeling task, and one text generation task. We show that ETC outperforms open-domain pre-trained models, and search query domain specific pre-trained MLM model and ELECTRA (Clark et al., 2020) model.

2 Background

Masked Language Modeling (MLM) pre-training is first introduced in Devlin et al. (2019) to learn contextual word representations with a large transformer model (Vaswani et al., 2017). Given a sequence of tokens \( x = [x_1, \ldots, x_n] \), Devlin et al. (2019) corrupt it into \( x^{\text{mask}} \) by masking 15% of its tokens at random:

\[
m_i \sim \text{Binomial}(0.15), \quad \text{for } i \in [0, \ldots, n],
\]

\[
x^{\text{mask}} = \text{REPLACE}(x, [m_1, \ldots, m_n], \text{[MASK]})
\]

Devlin et al. (2019) then train a transformer-based language model \( G \) parameterized by \( \theta \) to reconstruct \( x \) conditioned on \( x^{\text{mask}} \):

\[
\min_{\theta} \mathbb{E} \sum_{t=1}^{n} \mathbb{1}(m_t = 1)p_G(x_t | x^{\text{mask}}),
\]

where \( p_G(x_t | x^{\text{mask}}) \) denotes the predicted probability of the \( t \)-th token being \( x_t \) given \( x^{\text{mask}} \).

Devlin et al. (2019) also introduced a next sentence prediction (NSP) pre-training task, which is shown to be not very effective in a later work (Liu et al., 2019b). In this paper, we do not discuss the NSP pre-training task.

3 Method

ETC adopts two transformer-based neural networks: a generator \( G \) and a discriminator \( D \). A raw text input is first inserted with some [MASK] tokens, and then the generator, a masked language model, fills [MASK] tokens with its prediction. The discriminator is trained to identify which tokens are generated. The encoder of the discriminator is then used as the pre-trained model for fine-tuning on downstream tasks. We summarize the extended token classification pre-training task in Figure 2.

3.1 Extended Query Generation

Each query is a sequence of tokens \( x = [x_1, \ldots, x_n] \), where the number of the tokens \( n \) is usually small for search queries. As a result, masked language models must set a high enough masking rate to make sure at least one token is masked out and the training can be really conducted with this sample. By replacing tokens with mask tokens, the semantic meaning of the search queries might be altered. Instead of masking tokens, we propose to insert [MASK] tokens in the query and use a generator to fill in the blanks. Specifically, we randomly select a set of positions \( m = [m_0, \ldots, m_n] \) with a fixed probability \( p \):

\[
m_i \sim \text{Binomial}(p), \quad \text{for } i \in [0, \ldots, n],
\]
where \( m_i = 1 \) is the selected position. For each selected position \( m_i = 1 \), we insert \([\text{MASK}]\) between \( x_i \) and \( x_{i+1} \) \(^1\). We denote the extended input with \([\text{MASK}]\) as

\[
x^{\text{temp}} = \text{INSERT}(x, m, [\text{MASK}])
\]

The generator \( G \) is a pre-trained masked language model. Given the extended \( x^{\text{temp}} \), \( G \) outputs a probability for generating a particular token \( \hat{x}_t \) for all \( x^{\text{temp}}_t = [\text{MASK}] \):

\[
\hat{x}_t \sim p_G(x_t | x^{\text{temp}})
\]

We denote the final extended input as

\[
x^{\text{extend}} = \text{INSERT}(x, m, \hat{x})
\]

### 3.2 Training the Discriminator

The training objective of the discriminator is identifying if a token is generated by the generator or not given the entire extended query. We denote the binary labels as \( y = [y_1, \ldots, y_{n^t}] \), where \( y_t = \mathbb{1}(x^{\text{temp}}_t = [\text{MASK}]) \) and \( n^t \) is the length of \( x^{\text{extend}} \). The training of \( D \) is conducted via minimizing the following training loss:

\[
\min_{\theta_D} \mathcal{L}(x, \theta_D) := \mathbb{E} \sum_{t=1}^{n^t} -y_t \log(D_\theta(x^{\text{extend}}_t, t)) - (1 - y_t) \log(1 - D_\theta(x^{\text{extend}}_t, t)) ,
\]

where \( \theta_D \) denotes the parameters of the discriminator. We remark that during the training of ETC, we only train the discriminator and keep the generator as unchanged for better efficiency.

\(^1\)If \( i = 0 \) or \( i = n \), the inserted \([\text{MASK}]\) is at the beginning or the ending of the sentence respectively.

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### 4 Experiments

We conducted experiments in an experimental system from E-commerce search domain. This paper considers the multilingual tasks and data, unless it is clearly stated. The pre-training corpus have 14 languages in total: En, De, Fr, Jp, It, Es, Zh, Pt, Ni, Tr, Cs, Pl, Ar, Sv. All the languages of the downstream tasks are included in the above 14 languages. The statistics of the data are presented in Table 1.

All implementations are based on transformers (Wolf et al., 2019). The max sequence length is set as 128 for all of the following experiments. We use an Amazon EC2 virtual machine with 8 NVIDIA A100 GPUs to conduct the experiments.

| Dataset       | Train | Dev  | Test  | Language |
|---------------|-------|------|-------|----------|
| Query         | 1.0B  | 1.1M | 1.1M  | 14       |
| NER           | 586.7K| 28.6K| 84.4K | 13       |
| Media         | 52.3M | 6.5M | 6.5M  | 9        |
| Help          | 29.8M | 3.7M | 3.7M  | 9        |
| Adult         | 10.8M | 1.3M | 1.3M  | 9        |
| Spelling      | 88.7M | 89.9K| 89.9K | 1*       |

Table 1: Number of samples of datasets and number of languages. *: Although the spelling correction task is only in English, we still use the multilingual pre-trained model for this task.

### 4.1 Pre-training

We use an E-commerce search query corpus, which consists of 1 Billion queries, for model pre-training. We first train a tokenizer on the query corpus using WordPiece (Wu et al., 2016). We use a vocabulary of 150K tokens. The tokenizer applies lower case,
We adopt the following transformer architecture for the encoder (Vaswani et al., 2017): the number of layers is 12, the hidden dimension is 386 and the intermediate size of the feed-forward layer is 1536. The total number of parameters of the encoder is 79M. Note that, the adopted structure is the same MiniLM model (Wang et al., 2020). Such an architecture is even smaller than the usual transformer-base (Vaswani et al., 2017). We adopt such a small architecture mainly due to the real word application consideration, where there are latency constraints. We use the RA Dam Optimizer (Liu et al., 2019a) with \( \beta = (0.9, 0.999) \), a learning rate of \( 10^{-4} \), a weight decay of 0.01 and a dropout ratio of 0.1. The batch size is 64 per GPU and the number of gradient accumulation steps is 2. We adopt the cosine learning rate schedule (Loshchilov and Hutter, 2016).

We first train a masked language model with the above encoder from scratch. The number of training steps is 1M. After MLM training, we take the MLM model as the generator, and use the MLM encoder to initialize the encoder of the discriminator. And then we conduct ETC training for 1M step. The sampling ratio \( p \) is 15\% in ETC. Note that during the training of ETC, we fix the generator and do not apply dropout to the generator.

### 4.2 Downstream Application

To evaluate the quality of the pre-trained models, we fine-tune the pre-trained model in following five query understanding tasks:

- **Named Entity Recognition (NER)** is the task of detecting mentions of real-world entities from text and classifying them into predefined types (e.g., brand, color, product in E-commerce domain). There are 12 different E-commerce entity types. It is a sequence labeling problem, we fine-tune the pre-trained encoder with a randomly initialized linear token-classification layer. We use the span-level \( F_1 \) score to evaluate the model performance.

- **Media Query Identification** is the task of identifying the weather the user is looking for a media product via the search query. As it is a binary unbalanced classification problem, we fine-tune the pre-trained encoder with a randomly initialized linear classification layer and use \( F_1 \) score to evaluate the model performance.

- **Help Query Identification** is the task of identifying non-product related questions from other search queries. As it is a binary unbalanced classification problem, we fine-tune the pre-trained encoder with a randomly initialized linear classification layer and use \( F_1 \) score to evaluate the model performance.

- **Adult Query Identification** is the task of identifying the weather the user is looking for adult product. As it is a binary unbalanced classification problem, we fine-tune the pre-trained encoder with a randomly initialized linear classification layer and use \( F_1 \) score to evaluate the model performance.

- **Spelling Error Correction** is the task of correcting the spelling errors in the search queries. It is a text generation task, we use a non-auto-regressive model which consists of the pre-trained encoder and a linear classification layer with the label space as the entire vocabulary. We use accuracy (the percentage of correctly fixed queries) as the metric to evaluate the model performance.

**Hyper-parameters**: the number of epoches is 10 for the NER task and 2 for other tasks. The batchsize is 128 per GPU for the spelling error correction task, and 256 per GPU for other tasks. We use the RA Dam Optimizer (Liu et al., 2019a). The learning rate is selected from \( \{2 \times 10^{-5}, 5 \times 10^{-5}, 5 \times 10^{-5}, 1 \times 10^{-4}, 2 \times 10^{-4}\} \) according to the validation set performance. We do not apply weight decay during fine-tuning. The dropout ratio is 0.1.

### 4.3 Baselines

We compare ETC with the following open-domain multilingual pre-trained models:

- **Multilingual DistilBERT** (Sanh et al., 2019)
- **Multilingual MiniLM** (Wang et al., 2020)
- **InfoXLM-Large** (Chi et al., 2021a)

We also compare ETC with the following in-domain pre-trained models:

- **MLM** is the masked language modeling pre-training (Devlin et al., 2019) on the search query domain.

- **ELECTRA** is the reproduction of Clark et al. (2020) on the in domain query data. In our reproduction, we fix the generator, which is a pre-trained MLM model. The encoder of the discriminator is also initialized from the pre-trained MLM model.

- **ETC** is our method. The same as the ELECTRA model, we take the MLM model as the generator, which is a pre-trained MLM model. The encoder of the discriminator is also initialized from the pre-trained MLM model.

All in-domain pre-trained models are pre-trained
## 4.4 Main Results

Our main results are shown in Table 2. First of all, the in-domain pre-trained MLM models outperform all the open-domain pre-trained models, including the InfoXLM-large, which has 550M parameter. Such a comparison indicates that our in-domain baselines are very strong.

Among all the in-domain pre-trained models, ETC achieves the best performance in all 5 tasks. It’s worthy noticing that ELECTRA perform even worse than the MLM model. Clark et al. (2020) claims that ELECTRA can improve the pre-training mainly because two reasons: 1. the task is defined over all input tokens rather than just the small subset that was masked out, and 2. the binary classification task is easier than the language modeling task. As we show here, that is not the case of pre-training on short search queries. ETC and ELECTRA are similar in terms of both aspects: 1. applying loss on all tokens in the sequence, and 2. reducing the entire label space from the entire vocabulary to a binary classification. Unlike ELECTRA hurting the performance, ETC can improves the performance. Such a comparison demonstrates that the benefit of ETC mainly comes from extending the short text.

### Table 2: Main Experiment Results on 5 QU tasks. All results obtained in this table are the average of 5 runs. We also did unpaired t-test between ETC and the second best method for all tasks. The improvement are statistically significant, where the p-value < 0.05.

| Model (# of param.) | NER: $F_1$ | Media: $F_1$ | Help: $F_1$ | Adult: $F_1$ | Spell Correction: Acc. |
|---------------------|------------|-------------|------------|-------------|------------------------|
| **Public Open-Domain Model** |
| MiniLM (117M)       | 69.45%     | 91.82%      | 88.88%     | 97.36%      | 76.00%                 |
| DistilBert (134M)   | 68.73%     | 91.83%      | 88.07%     | 97.38%      | 76.81%                 |
| InfoXLM-Large (558M)| 73.29%     | 92.16%      | 89.52%     | 97.41%      | 77.00%                 |
| **In-Domain Model** |
| MLM (79M)           | 73.67%     | 92.51%      | 89.42%     | 97.55%      | 80.89%                 |
| ELECTRA (79M)       | 72.26%     | 92.41%      | 89.08%     | 97.16%      | 80.61%                 |
| ETC (79M)           | **74.23%** | **92.62%**  | **89.95%** | **97.71%**  | **81.17%**             |

Table 3: $F_1$ scores of different languages on NER task. For ETC, we also denote the performance gain over MLM in the second line. We highlight the languages where the performance gain is over 1%.

from scratch and only use the query data. The tokenizer is also the same for all in-domain pre-trained models. For fair comparison the in-domain MLM model is trained for 2M steps. Note that the MLM generator used in ELECTRA and ETC are only trained for 1M steps, and the discriminator is trained for another 1M steps.

### 4.5 Training Efficiency

We also study the training efficiency of the ETC. Specifically, we compare the fine-tuning performance on the NER task between MLM and ETC at different number of iterations. Note that MLM is trained for 2M steps, while ETC is trained for 1M and is continually trained from MLM checkpoint at 1M step. The result is summarized in Figure 3.

As can be seen, the NER $F_1$-score of MLM starts to saturated at around 1.5M steps. Continual MLM can only give very limited performance gain. In contrast, ETC can keep improving the performance.
4.6 Multilingual Analysis

We study how ETC would perform for different languages. Specifically, we exam the fine-tuning performance of different languages on the NER task, where there are 13 difference languages. The results are presented in Table 3.

As can be seen, ETC uniformly outperform MLM across all languages. ETC is particularly helpful for Jp, Pt, and Sv, where it achieves more than 1\% $F_1$ score improvement.

4.7 Few-shot Experiments

We conducted few-shot experiments on the NER task to demonstrate the effectiveness of ETC. Specifically, we fine-tune the pre-trained models on randomly sub-sampled training data and validate/test on the same validation/test set. The results are presented in Table 4. We observe that ETC outperforms the MLM pre-trained model on all splits of data. It achieves the best performance improvement on the 0.1\% data setting. Interestingly, we found the performance gains on 1\%, 10\%, 100\% are rather similar. Such a finding demonstrates that when scaling up the fine-tuning training data, the performance gain from ETC over MLM would not diminishes quickly.

| Model   | 0.1\%  | 1\%    | 10\%   | 100\%  |
|---------|--------|--------|--------|--------|
| # Samples | 0.6K | 5.9K | 58.6K   | 586.7K  |
| MLM     | 61.90\% | 66.36\% | 70.73\% | 73.67\% |
| ETC $(F_1$ gain) | 62.74\% | 66.91\% | 71.23\% | 74.23\% | +0.84\% | +0.55\% | +0.50\% | +0.56\% |

Table 4: $F_1$ scores on NER task with randomly sub-sampled training data. The first row is the sub-sampling ratios.

5 Related Work

Self-Supervised Pre-training There are two main streams of pre-training language models: 1. language modeling (LM), such as GPT-2 and GPT-3 (Radford et al., 2019; Brown et al., 2020); 2. masked language modeling (MLM), such as BERT. MLM usually perform better for language understanding tasks, while LM usually perform better in language generation tasks.

ELECTRA (Clark et al., 2020) recently draws a lot of attention. Clark et al. (2020) propose to replace the masked language modeling task by replaced token detection task. It improves not only sample-efficiency, but also fine-tuning performance. Recently, Chi et al. (2021b) applied ELECTRA to train multilingual pre-trained model. He et al. (2021) combines ELECTRA with the DeBERTa architecture and achieved SOTA performance on GLUE benchmark (Wang et al., 2019). In this paper, we show that ELECTRA is not effective for search queries. Given the success of ELECTRA in general, such a finding is exceptional. It suggests that the success in general domain is not always transferable to a specific domain.

Query Understanding QU is an important task since the appearance of search engine (Moore et al., 1995; Lau and Horvitz, 1999; Boldasov et al., 2002). Some typical tasks are query intent classification, named entity recognition, ontology linking, spelling correction and query reformulation. The earliest systems heavily rely on domain lexicons and hand-crafted features (e.g., regular expression, grammar rules) (Dowding et al., 1994). Thanks to the advance in computing power, deep learning becomes trending in the QU (Nigam et al., 2019; Lin et al., 2020). More recently, pre-trained language model has been widely adopted in QU (Jiang et al., 2021; Kumar et al., 2019; Zhang et al., 2021; Li et al., 2021). These work only adopts models pre-trained in open-domain, e.g., BERT. Some recent works have developed pre-training methods for E-commerce domain (Zhang et al., 2020; Zhu et al., 2021), but they are designed for understanding the long documents, e.g., product description, and none of them is particularly designed for query, which is short text.

The advances of QU is usually lagged behind of other NLP tasks since the lack of availability of related data in academic community. We hope this paper could inspire more research in this domain.
6 Conclusion
In this paper, we propose a new pre-training task – Extended Token Classification (ETC) to learn representation for short text, such as search queries. Different from existing pre-training task, ETC takes into consideration the short length of the text and improves the pre-training efficiency. Our thorough experiments in E-commerce search domain demonstrate that ETC outperforms existing methods in terms of fine-tuning performance on 5 QU tasks.

Ethical Impact
ETC is a general framework for pre-training on short text, such as search queries. ETC neither introduces any social/ethical bias to the model nor amplifies any bias in the data. In all the experiments, we use internal data on an E-commerce search platform without knowing customers’ identity. No customer/seller specific data is disclosed. We build our algorithms using public code bases (transformers and PyTorch). We do not foresee any direct social consequences or ethical issues.

References
Michael V Boldasov, Elena G Sokolova, and Michael G Malkovsky. 2002. User query understanding by the inbase system as a source for a multilingual nl generation module. In International Conference on Text, Speech and Dialogue, pages 33–40. Springer.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165.

Zewen Chi, Li Dong, Furu Wei, Nan Yang, Sksam Singhal, Wenhui Wang, Xia Song, Xian-Ling Mao, Heyan Huang, and Ming Zhou. 2021a. InfoXLM: An information-theoretic framework for cross-lingual language model pre-training. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3576–3588. Online. Association for Computational Linguistics.

Zewen Chi, Shaohan Huang, Li Dong, Shuming Ma, Sksam Singhal, Payal Bajaj, Xia Song, and Furu Wei. 2021b. Xlm-e: Cross-lingual language model pre-training via electra. arXiv preprint arXiv:2106.16138.

Kevin Clark, Minh-Thang Luong, Quoc V Le, and Christopher D Manning. 2020. Electra: Pre-training text encoders as discriminators rather than generators. arXiv preprint arXiv:2003.10555.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT, pages 4171–4186.

John Dowding, Jean Mark Gawron, Doug Appelt, John Bear, Lynn Cherry, Robert Moore, and Douglas Moran. 1994. Gemini: A natural language system for spoken-language understanding. arXiv preprint cmp-lg/9407007.

Yu Gu, Robert Tinn, Hao Cheng, Michael Lucas, Naoto Usuyama, Xiaodong Liu, Tristan Naumann, Jianfeng Gao, and Hoifung Poon. 2021. Domain-specific language model pretraining for biomedical natural language processing. ACM Transactions on Computing for Healthcare (HEALTH), 3(1):1–23.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A Smith. 2020. Don’t stop pretraining: Adapt language models to domains and tasks. arXiv preprint arXiv:2004.10964.

Pengcheng He, Jianfeng Gao, and Weizhu Chen. 2021. Debertav3: Improving deberta using electro-style pre-training with gradient-disentangled embedding sharing. ArXiv, abs/2111.09543.

Peter V Henstock, Daniel J Pack, Young-Suk Lee, and Clifford J Weinstein. 2001. Toward an improved concept-based information retrieval system. In Proceedings of the 24th annual international ACM SIGIR conference on Research and development in information retrieval, pages 384–385.

Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Tuo Zhao. 2019. Smart: Robust and efficient fine-tuning for pre-trained natural language models through principled regularized optimization. arXiv preprint arXiv:1911.03457.

Haoming Jiang, Danqing Zhang, Tianyu Cao, Bing Yin, and Tuo Zhao. 2021. Named entity recognition with small strongly labeled and large weakly labeled data. arXiv preprint arXiv:2106.09777.

Mukul Kumar, Youna Hu, Will Headden, Rahul Goutam, Heran Lin, and Bing Yin. 2019. Shareable representations for search query understanding. arXiv preprint arXiv:2001.04345.

Tessa Lau and Eric Horvitz. 1999. Patterns of search: analyzing and modeling web query refinement. In UM99 user modeling, pages 119–128. Springer.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2020. Biobert: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics, 36(4):1234–1240.

Zheng Li, Danqing Zhang, Tianyu Cao, Ying Wei, Yiwei Song, and Bing Yin. 2021. Metats: Meta teacher-student network for multilingual sequence
labeling with minimal supervision. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3183–3196.

Heran Lin, Pengcheng Xiong, Danqing Zhang, Fan Yang, Ryoichi Kato, Mukil Kumar, William Headen, and Bing Yin. 2020. Light feed-forward networks for shard selection in large-scale product search.

Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. 2019a. On the variance of the adaptive learning rate and beyond. *arXiv preprint arXiv:1908.03265*.

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

Ilya Loshchilov and Frank Hutter. 2016. Sgdr: Stochastic gradient descent with warm restarts. *arXiv preprint arXiv:1608.03983*.

Robert Moore, Douglas Appelt, John Dowding, J Mark Gawron, and Douglas Moran. 1995. Combining linguistic and statistical knowledge sources in natural-language processing for atis.

Priyanka Nigam, Yiwei Song, Vijai Mohan, Vihan Lashman, Weitian Ding, Ankit Shingavi, Choon Hui Teo, Hao Gu, and Bing Yin. 2019. Semantic product search. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2876–2885.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *ArXiv*, abs/1910.01108.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *NIPS*, pages 5998–6008.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019. Glue: A multi-task benchmark and analysis platform for natural language understanding.

Wenhui Wang, Furu Wei, Li Dong, Hangbo Bao, Nan Yang, and Ming Zhou. 2020. Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers. *ArXiv preprint arXiv:2002.10957*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. *ArXiv*, pages arXiv–1910.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*.

Danqing Zhang, Zheng Li, Tianyu Cao, Chen Luo, Tony Wu, Hanqing Lu, Yiwei Song, Bing Yin, Tuo Zhao, and Qiang Yang. 2021. Queaco: Borrowing treasures from weakly-labeled behavior data for query attribute value extraction. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 4362–4372.

Denghui Zhang, Zixuan Yuan, Yanchi Liu, Zuohui Fu, Fuzhen Zhuang, Pengyang Wang, Haiqeng Chen, and Hui Xiong. 2020. E-bert: A phrase and product knowledge enhanced language model for e-commerce. *arXiv preprint arXiv:2009.02835*.

Yushan Zhu, Huaixiao Zhao, Wen Zhang, Ganqiang Ye, Hui Chen, Ningyu Zhang, and Huajun Chen. 2021. Knowledge perceived multi-modal pretraining in e-commerce. In *Proceedings of the 29th ACM International Conference on Multimedia*, pages 2744–2752.