Pre-training Tasks for User Intent Detection and Embedding Retrieval in E-commerce Search

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Abstract
BERT-style models pre-trained on the general corpus (e.g., Wikipedia) and fine-tuned on specific task corpus, have recently emerged as breakthrough techniques in many NLP tasks: question answering, text classification, sequence labeling and so on. However, this technique may not always work, especially for two scenarios: a corpus that contains very different text from the general corpus Wikipedia, or a task that learns embedding spacial distribution for a specific purpose (e.g., approximate nearest neighbor search). In this paper, to tackle the above two scenarios that we have encountered in an industrial e-commerce search system, we propose customized and novel pre-training tasks for two critical modules: user intent detection and semantic embedding retrieval. The customized pre-trained models after fine-tuning, being less than 10% of BERT-base’s size in order to be feasible for cost-efficient CPU serving, significantly improve the other baseline models: 1) no pre-training model and 2) fine-tuned model from the official pre-trained BERT using general corpus, on both offline datasets and online system. We have open sourced our datasets 1 for the sake of reproducibility and future works.

CCS Concepts
• Information systems → Query intent; Information retrieval;
• Computing methodologies → Neural networks.

Keywords
Pre-training; User intent classification; Embedding retrieval

1 Introduction
Over the recent decades, online shopping platforms (e.g., eBay, Walmart, Amazon, Tmall, Taobao and JD) have become increasingly popular in people’s daily life. E-commerce search, which helps users find what they need from billions of products, is an essential part of those platforms, contributing to the largest percentage of transactions among all channels [22]. Nowadays, along with the recent advance in large-scale Nature Language Processing (NLP) pre-trained models, NLP plays an increasingly vital role in almost every module of e-commerce search. Thus, it is essential to develop powerful pre-trained NLP models to improve the overall performance of an e-commerce search system.

Figure 1 illustrates a typical workflow of an e-commerce search system, which includes query processing (including user intent detection), semantic retrieval, and ranking. Let’s take the query “apple 13 pro max” as an example. 1) Query processing, which aims to detect the query intentions like category, brand, etc., recognizes the intention as “cellphone”. With the great advances in NLP models, BERT-style models are massively used [1, 12, 21] in the task. 2) Candidate retrieval is normally accomplished by traditional inverted index retrieval in the manner of keyword matching, while model-based semantic retrieval [8, 10, 15, 28] methods are optimized for additional results which are semantically relevant with “iphone 13 pro max”. 3) Ranking model finally orders the retrieved candidates based on thousands of factors, such as relevance, user preference, product popularity, etc.

Recent significant advances in NLP modeling techniques provide us with a few promising directions [2, 3, 20, 27, 28]. Those large-scale models, such as BERT [4], T5 [20], PaLM [3] and so on, pre-trained on large-scale corpus such as Wikipedia and simply fine-tuned on domain-specific dataset, have already been proven to be the state-of-the-art model in many NLP tasks, such as question...
Table 1: Typical e-commerce text examples that are repetitive, redundant and grammatically disastrous.

| Category | Example |
|----------|---------|
| Fresh | Fresh Of fice Business Computer Stationery Fruit V egetable Apple Banana T omato Potato Laptop PC Pencil Paper |
| Fruit | Apple Banana T omato Potato |
| Vegetable | |
| Stationery | |
| Office Business | |

In this paper, we take the pre-training technology to realize a more general solution to these problems, especially for two important components of a leading e-commerce search system, i.e., user intent detection in query processing step and semantic retrieval in candidate retrieval step, as shown in Figure 1. We do not consider ranking module in this paper since it always tends to consider user’s personalised information. But we claim the proposed method is general enough to be applied in other modules in e-commerce search.

2 Method

2.1 User Intent Detection

2.1.1 Problem Formulation. User intent detection can be formulated as a standard multi-label classification problem where the total number of labels L is usually large, i.e., 3,000, which equals the number of leaves in the hierarchical product category structure as shown in Figure 2. For a query x, our model learns a vector-valued output function $f(x) \in \mathbb{R}^d$ that produces the probability of each label. Then we obtain labels with top-k probabilities, or set a probability threshold to get a dynamic number of predicted labels.

2.1.2 Pre-training Tasks. As shown in Figures 3a and 3b, the pre-training tasks consist of two sequential ones: 1) Random Substring Classification (RSC) refers to the task that we take a random substring from an item title as a synthetic query, and predict the category of the synthetic query as the item’s category. Formally, we randomly select a start position of item title according to a uniform distribution between 0 and title length, and take a substring of random length $l$ sampled again from a uniform distribution from 1 to a maximum length parameter (5 in our model). 2) Masked Language Model (MLM) refers to the standard BERT pre-training task [4] that randomly masks tokens and learns to recover the masked tokens. We do not adopt the next sentence prediction (NSP) task which is not fit for our scenario, since MLM is more suitable for learning contextualized information. We follow the standard MLM setting which randomly masks 15% tokens and substitutes 80% of them with [MASK] token and 10% with random tokens.

2.1.3 Fine-tuning. The fine-tuning step is very similar to the above pre-training, except for the following two differences: 1) we collect the fine-tuning data by aggregating user click log data, where we collect the most user clicked product categories accounting for up to 90% of total clicks. Thus, a training instance in the fine-tuning step may consist of a query and several categories, which makes the fine-tuning tasks a multi-label classification problem instead of a single-label classification problem in the pre-training step. 2) We apply the softmax temperature strategy [6] to maximize the margin between positive and negative categories. Specifically, we use a temperature 1/3 in our model.

2.2 Embedding Retrieval

2.2.1 Problem Formulation. Industrial practitioners usually use the two-tower model structure [10, 15, 28] and approximate nearest neighbor search [5, 9] libraries to enable fast online retrieval. A typical two-tower model can be formulated as follows.

$$f(q, s) = Q(q)^T S(s)$$  \hspace{1cm} (1)

where a given query q is input of a query tower $Q$ to generate a query embedding $Q(q) \in \mathbb{R}^d$, and an item is input of an item tower $S$ to generate an item embedding $S(s) \in \mathbb{R}^d$. Typically, a triplet loss [7] including a query, a positive item and a negative item, is optimized during the training. In our work, pre-training and fine-tuning optimize the same loss function but using different data as described below.
2.2.2 Pre-training Tasks. As shown in Figures 3a and 3c, here we use two pre-training tasks similarly as above user intent detection: 1) Random Substring Retrieval (RSR) task takes a random substring from an item title as a synthetic query to retrieve the item. An option here is to mask the substring in the item title in order to guide the model to learn semantics instead of word matching. However, in practice it finds no noticeable difference in retrieval performance. 2) MLM task again refers to the standard BERT pre-training task. As same as user intent detection, we do not include NSP task in our scenario as well.

2.2.3 Fine-tuning. We perform fine-tuning using standard click log data with unique pairs of query and clicked item title. The negative item in the triplet loss is collected in an in-batch negative fashion, which is a common practice in previous works [2, 28].

3 Experiment

3.1 Setup

3.1.1 Dataset. Table 2 shows the statistics of our training and evaluation data, which are all collected from user click log on single “Level-1” category’s items within 60 days. The user intent detection model and semantic retrieval model are pre-trained on the same pre-training dataset, which is collected by item title and product category from our e-commerce commodity pool, but fine-tuned on two different datasets. These two datasets are both collected from user click log with different fields, where user intent detection model uses the search query and product category of clicked item and semantic retrieval model uses the search query and clicked item title.

Then, the two proposed methods are both evaluated on two evaluation datasets, each of which contains 10,000 queries. The overall evaluation dataset contains randomly sampled queries and the long-tail evaluation dataset contains only long-tail queries to measure the model performance on them. Note that this dataset, open sourced for the sake of reproducibility of our work or other academic studies, is only a subset of the full dataset used to train the online model in Section 3.4.

3.1.2 Metrics. Our models are evaluated by the metrics of precision (P), recall (R), f1 score (F1), and the normalized discounted cumulative gains (NDCG or N) for user intent detection task, and precision at top k (P@k) and recall at top k (R@k) for semantic retrieval task. Intuitively, precision measures the accuracy of predicted query categories of user intent or retrieved items, recall measures the proportion of correctly predicted categories or retrieved items out of true labels, and normalized discounted cumulative gains is a conventional metric for ranking tasks, as well as extreme multi-label classification problems [13].

3.1.3 Baselines. We compare our customized pre-trained model with three baselines:

- **No pre-train** stands for the model trained directly on the fine-tuning dataset without any pre-training stage. Since the original pre-trained BERT model with 12 layers is infeasible for CPU serving, but only feasible for expensive GPU serving, we explore the variant with 4-layer smaller BERT encoder. Here we conduct 4 and 12 layers No pre-train model experiments for a fair comparison.
- **BERT-zh** stands for the official pre-trained BERT Chinese model [4] fine-tuned directly on our dataset.
- **Full String Classification (FSC)** stands for the model pre-trained with full item title instead of the random substring, which only suits the intent classification model. Here we only conduct the experiment with 12-layer BERT encoder.

Note that all models are optimized by AdamW [16] optimizer, and trained with weighted decayed learning rate from 1e-4 and batch size of 1024.

3.2 User Intent Detection

We compare the performance of our proposed method with all baseline models in Table 4, where we can observe that the different versions of our proposed methods, by varying pre-training tasks (RSC, RSC+MLM) and by varying the network depth (4 and 12 layers), all significantly improve the baseline methods, **No pre-train** and **BERT-zh**. Specifically, we can make the following observations: 1) our 12-layer’s RSC+MLM model improves the baseline no pre-train model by 10.4% in F1 and 6.0% in NDCG and the baseline BERT-zh model by 4.6% in F1 and 3.3% in NDCG, on the overall dataset. Note that these three models share exactly the same network structure and only differ in training methods. Thus, these experimental results show that the pre-training tasks are extremely necessary for obtaining a state-of-the-art user intent detection model, and more
importantly, the carefully designed pre-trained task RSC is more properly than the official pre-trained BERT in our scenario of user intent detection task in e-commerce search. We believe this is due to the highly different text in e-commerce data from the standard language in Wikipedia where the official BERT Chinese model is trained from. 2) The proposed methods achieve even larger improvements on the long-tail dataset. We believe that the sampled queries by RSC task could potentially mock the long-tail queries with variant text format. 3) The computationally efficient 4-layer model, though slightly worse than 12-layer model, still outperforms BERT-zh model and No pre-train model by large gains. Thus, it is a practical trade-off to deploy the 4-layer model in our online production system. 4) By comparing the RSC+MLM, MLM and RSC models, we can see that RSC+MLM improves MLM by 7.7% in F1 and 4.0% in NDCG, but RSC+MLM improves RSC by only 0.5% in F1 and -0.1% in NDCG, on the overall dataset. These results indicate that our proposed pre-training task RSC is extremely vital for significant improvements and the standard MLM used in the original BERT pre-training does not help much for our task. 5) RSC improves RSC by 3.6% in F1 and 2.6% in NDCG on the overall dataset. We believe this result benefits from more closed length distributions between query and item title.

We illustrate a few good cases in Table 3. As we can see, a query “Xiucai dress” is wrongly predicted as the category “Chinese History” by BERT-zh model, while correctly categorized into the category “Ancient Costume” by our RSC+MLM model, which potentially learns from the title text where “Xiucai dress” co-occurs with other clothes related words.

### 3.3 Embedding Retrieval

Table 5 presents the performance comparisons between baseline models and our customized pre-training models, measured by R@k and P@k with k=50 and 100 for overall dataset, while k=5 and k=10 for long-tail dataset since long-tail queries have less clicked items in our training dataset. Similar conclusions can be made as the above user intent detection model: the necessity of customized pre-training tasks, larger improvement on long-tail queries, and practical tradeoff of the 4-layer model. The only difference here we observe is that the RSC + MLM task seems not helping much on top of the RSC task, even though the standalone version MLM slightly improves no pre-train model. This result actually coincides with previous findings [2] that MLM pre-training task does not help much for embedding retrieval.

Table 3: Good cases in user intent detection and embedding retrieval.

| Query                      | RSC+MLM | BERT-zh | Related Pre-training Task |
|----------------------------|---------|---------|---------------------------|
| (Xiucai dress)              |         |         |                           |
| (Yuming Qiu et al. 2022)   |         |         |                           |
| (house for sale)            |         |         |                           |
| (Gifs, Decoration)          |         |         |                           |
| (house with two bedrooms)   |         |         |                           |

Table 4: User intent detection comparative results with baseline methods.

| Pre-train method               | Overall | Long-tail |
|-------------------------------|---------|-----------|
|                               | P R F1 N | P R F1 N  |
| No pre-train (4-layer)        | 0.664 0.860 0.668 0.791 | 0.581 0.947 0.641 0.755 |
| No pre-train (12-layer)       | 0.680 0.860 0.683 0.757 | 0.595 0.939 0.656 0.760 |
| MLM (12-layer)                | 0.716 0.865 0.710 0.777 | 0.640 0.950 0.696 0.787 |
| BERT-zh (12-layer)            | 0.765 0.855 0.741 0.784 | 0.670 0.939 0.718 0.786 |
| RSC+MLM (12-layer)            | 0.772 0.856 0.751 0.791 | 0.699 0.946 0.748 0.805 |
| RSC (12-layer)                | 0.808 0.868 0.782 0.818 | 0.721 0.956 0.770 0.831 |
| RSC+MLM (4-layer)             | 0.782 0.870 0.765 0.808 | 0.704 0.954 0.754 0.816 |
| RSC+MLM (12-layer)            | 0.818 0.864 0.287 0.817 | 0.737 0.951 0.782 0.829 |

Table 5: Semantic embedding retrieval comparative results with baseline methods.

| Pre-train method               | Overall | Long-tail |
|-------------------------------|---------|-----------|
|                               | P R F1 N | P R F1 N  |
| No pre-train (4-layer)        | 0.654 0.820 0.230 0.199 | 0.749 0.840 0.140 |
| No pre-train (12-layer)       | 0.641 0.214 0.141 0.124 | 0.731 0.848 0.148 |
| MLM (12-layer)                | 0.641 0.219 0.140 0.120 | 0.730 0.848 0.147 |
| BERT-zh (12-layer)            | 0.627 0.218 0.138 0.116 | 0.729 0.846 0.145 |
| RSC (12-layer)                | 0.685 0.252 0.156 0.130 | 0.779 0.837 0.152 |
| RSC+MLM (4-layer)             | 0.660 0.218 0.156 0.130 | 0.770 0.838 0.152 |
| RSC+MLM (12-layer)            | 0.682 0.219 0.156 0.130 | 0.776 0.838 0.152 |

Table 6: Online A/B test.

| Intent Detection | GMV | UCVR | UCTR |
|------------------|-----|-----|------|
|                  | +0.263% | +0.293% | +0.012% |

3.4 Online A/B Test

Motivated by achieving real world impact from the very beginning, we conduct A/B test on a leading e-commerce search system, using 20% of the entire site traffic during a period of 30 days. Due to the confidential business information protection, we only report the relative improvements in Table 6, where the online baseline models are BiGRU [11] for user intent detection and DSPR [28] for embedding retrieval. The gross merchandise value (GMV), the number of unique order items per user (UCVR), and the click-through rate (CTR) are significantly improved.

4 Conclusion

In this paper, we have proposed carefully designed, customized pre-training tasks for two critical modules, user intent detection and embedding retrieval in a leading e-commerce search system, since the e-commerce text data are very different from general corpus such as Wikipedia where the official BERT is trained from. As a result, our customized pre-trained models significantly improve no pre-trained models and outperform the official pre-trained BERT models, on both offline evaluation and online A/B test.
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