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

Yiming Qiu †, Chenyu Zhao †, Han Zhang, Jingwei Zhuo, Tianhao Li, Xiaowei Zhang, Songlin Wang, Sulong Xu, Bo Long and Wen-Yun Yang *

JD.com, Beijing, China & Shenzhen, China & Mountain View, USA

{qiuyiming3, zhaochenyu8, zhanghan33, zhuojingwei1, litianhao5, zhangxiaowei9, wangsonglin3, xusulong, bo.long, wenyun.yang}@jd.com

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

ACM Reference Format:

Yiming Qiu[†], Chenyu Zhao[†], Han Zhang, Jingwei Zhuo, Tianhao Li, Xiaowei Zhang, Songlin Wang, Sulong Xu, Bo Long and Wen-Yun Yang *. 2022. Pretraining Tasks for User Intent Detection and Embedding Retrieval in Ecommerce Search. In *Proceedings of the 31st ACM International Conference on Information and Knowledge Management (CIKM '22), October 17–21, 2022*,

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

CIKM '22, October 17–21, 2022, Atlanta, GA, USA

© 2022 Association for Computing Machinery. ACM ISBN 978-1-4503-9236-5/22/10...\$15.00 https://doi.org/10.1145/3511808.3557670

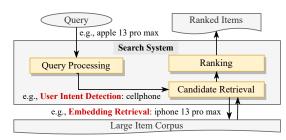


Figure 1: Major stages of an e-commerce search system.

Atlanta, GA, USA. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3511808.3557670

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

¹ https://github.com/jdcomsearch/jd-pretrain-data

[†] Both authors contribute equally

^{*} corresponding author

Table 1: Typical e-commerce text examples that are repetitive, redundant and grammatically disastrous.

带芽人参种子人参苗子西洋参种子长白山人参种子药材种子 (Ginseng seeds with buds Ginseng seeddings Western ginseng seeds Changbai Mountain ginseng seeds Medicinal seeds) 鸡毛掸子家用车用鸡毛扫灰清洁用品汽车拖把不掉毛掸子除尘 (Feather Duster Household Car Use Chicken Feather Dust Sweeping Cleaning Supplies Car Mop No Lint Duster Dust Removal) 巴沙鱼片5斤装冷冻鱼片淡水龙利鱼柳新鲜无刺无骨鱼肉做酸菜鱼2500g (Baas Fish Fillet Skg Frosen Fish Fillet Freshwater Longli Fish Fillet Fresh Boneless Fish Meat Sauerkraut Fish 2500g)

answering [25, 26], text classification [17, 23], sequence labeling [14, 24], etc., which inspire us to apply BERT-based pre-training models to the e-commerce search system. In the view of NLP, nowadays e-commerce search system faces the following challenges that we are going to tackle in this paper.

- Free-form text refers to the user typed texts (e.g., customer typed queries and merchant typed product descriptions) that does not follow grammar rules. On the one hand, the customer typed queries may be ambiguous for the system to identify exact user intent, since the system could be confused by word order (e.g., milk chocolate or chocolate milk), typos or unclear expressions. On the other hand, product descriptions typed by the merchant may be composed of a handful of short text segments that do not follow grammar strictly, like the product titles shown in Table 1. As a result, BERT models pre-trained on Wikipedia or other corpus that follow grammar strictly directly on this problem are not suitable for this case. In Section 3, we will show the unsatisfied performance of the direct application of the pre-trained BERT models.
- Long-tail query has introduced additional difficulties in our model learning: 1) there are a lot of long-tail queries, and 2) the training examples for each long-tail query are far from enough. As a typical example, the query "Goliath", is a cold-start brand in our e-commerce platform. It is quite difficult to identify its product category intent and retrieve relevant products due to the lack of supervised training data. Thus, several long-tail related studies have emerged: an across-context attention mechanism for long-tail query classification [29], a dual heterogeneous graph attention network to improve long-tail performance in e-commerce search [18] and a systematical study of the long-tail effect in recommendation system [19].

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 personalized 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

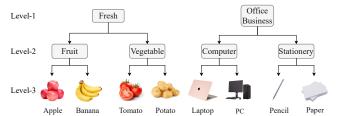


Figure 2: Product Category Hierarchy.

as shown in Figure 2. For a query x, our model learns a vectorvalued output function $f(x) \in \mathbb{R}^L$ 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 pretraining 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 pretraining 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 mulit-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.

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

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.

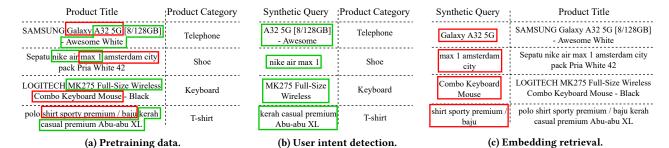


Figure 3: Illustration of pre-training tasks where we take random substring from item title as synthetic query.

Table 2: Dataset Statistics.

| Dataset | # Examples | # Queries | # Items | # Categories |
|-------------------------|------------|-----------|---------|--------------|
| Pre-training | 566,161 | _ | 566,161 | 112 |
| User Intent Fine-tuning | 180,008 | 180,008 | - | 97 |
| Retrieval Fine-tuning | 667,665 | 200,001 | 83,672 | - |
| Overall eval | 10,000 | 10,000 | 69,855 | 94 |
| Long-tail eval | 10,000 | 10,000 | 12,312 | 88 |

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 we find it makes no noticeable difference in retrieval performance. 2) MLM task again refers to the standard BERT pretraining 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 pretrained 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

| | | | U | | |
|-----------------------------------|-----------------------------------|--------------------------------|--|--|--|
| | Query | RSX+MLM | BERT-zh | Related Pre-training Title | |
| | 秀才装 | 古装 | 中国历史 | 男式中国风秀才装演出服蓝色 | |
| User Intent Detection | (Xiucai dress) ¹ | (Ancient Costume) | (Chinese History) | (men's blue Chinese style Xiucai dress) | |
| Oser Intent Detection | 房子出售 | 房子 | 礼品,装修设计 | 精装修两室新装修房子出售 | |
| | (house for sale) | (House) | (Gifts, Decoration) | (house with two bedrooms for sale) | |
| | 卡农线3518 | 卡农线2米QS3518T2 | 卡侬头音频线 | 卡农线1米QS3518T2 | |
| Embedding Retrieval Recall@1 Case | (XLR line 3518) | (XLR line 2 meters QS3518T2) | (XLR head audio cable) | (XLR line 1 meters QS3518T1) | |
| | 惠普953xl墨盒原装 | 953XL墨盒4色装 | 惠普(HP) 72号墨盒3WX08A | 惠普953XL墨盒HP | |
| | (original HP 953xl ink cartridge) | (953XL ink cartridge 4 colors) | (Hewlett-Packard (HP) No. 72 ink cartridge 3WX08A) | (Hewlett-Packard 953XL ink cartridge HP) | |

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

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

| Pre-train method | Overall | | | | Long-tail | | | |
|-------------------------|---------|-------|-------|-------|-----------|-------|-------|-------|
| rie-train method | P | R | F1 | N | P | R | F1 | N |
| No pre-train (4-layer) | 0.664 | 0.860 | 0.668 | 0.751 | 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 |
| FSC+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 | 0.787 | 0.817 | 0.737 | 0.951 | 0.782 | 0.829 |

importantly, the carefully designed pre-training task RSC is more proper 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 FSC 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. Again, we now can conclude that, due to the different text distribution between Wikipedia and e-commerce data, a customized pre-training task instead of the official pre-trained BERT-zh model is essential for e-commerce user intent detection.

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

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

| Pre-train method | Overall | | | | Long-tail | | | |
|-------------------------|---------|--------|--------|--------|-----------|--------|--------|--------|
| | R@50 | P@50 | R@100 | P@100 | R@5 | P@5 | R@10. | P@10 |
| No pre-train (4-layer) | 0.6342 | 0.2103 | 0.7489 | 0.1460 | 0.6295 | 0.1831 | 0.7406 | 0.1164 |
| No pre-train (12-layer) | 0.6415 | 0.2145 | 0.7531 | 0.1481 | 0.6342 | 0.1863 | 0.7480 | 0.1188 |
| MLM (12-layer) | 0.6416 | 0.2159 | 0.7590 | 0.1497 | 0.6445 | 0.1890 | 0.7555 | 0.1199 |
| BERT-zh (12-layer) | 0.6575 | 0.2185 | 0.7689 | 0.1508 | 0.6603 | 0.1943 | 0.7649 | 0.1215 |
| RSR (12-layer) | 0.6685 | 0.2216 | 0.7792 | 0.1526 | 0.6730 | 0.1982 | 0.7806 | 0.1245 |
| RSR+MLM (4-layer) | 0.6604 | 0.2189 | 0.7703 | 0.1506 | 0.6690 | 0.1964 | 0.7713 | 0.1223 |
| RSR+MLM (12-layer) | 0.6682 | 0.2219 | 0.7786 | 0.1525 | 0.6728 | 0.1990 | 0.7806 | 0.1247 |

Table 6: Online A/B test.

| | GMV | UCVR | UCTR |
|---------------------|---------|---------|---------|
| Intent Detection | +0.799% | +1.032% | +0.811% |
| Embedding Retrieval | +0.623% | +0.291% | +0.012% |

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 *RSR* + *MLM* task seems not helping much on top of the *RSR* 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 shows a few good cases which benefit from *RSR* task. For instance, "XLR line 3518" is a long-tail query which consists of product and model words. Intuitively, *RSR* task facilitates the pre-training model with the key attribute information taken from item title, which enables the fine-tuned model to retrieve items with correct attributes.

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 pretraining 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

¹ Xiucai is an ancient Chinese academic degree.

pre-trained models and outperform the official pre-trained BERT models, on both offline evaluation and online A/B test.

References

- Fengyu Cai, Wanhao Zhou, Fei Mi, and Boi Faltings. 2021. SLIM: Explicit Slot-Intent Mapping with BERT for Joint Multi-Intent Detection and Slot Filling. arXiv preprint arXiv:2108.11711 (2021).
- [2] Wei-Cheng Chang, X Yu Felix, Yin-Wen Chang, Yiming Yang, and Sanjiv Kumar. 2019. Pre-training Tasks for Embedding-based Large-scale Retrieval. In International Conference on Learning Representations.
- [3] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2022. Palm: Scaling language modeling with pathways. arXiv preprint arXiv:2204.02311 (2022).
- [4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018).
- [5] Ruiqi Guo, Philip Sun, Erik Lindgren, Quan Geng, David Simcha, Felix Chern, and Sanjiv Kumar. 2020. Accelerating large-scale inference with anisotropic vector quantization. In *International Conference on Machine Learning*. PMLR, 3887–3896.
- [6] Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. 2015. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.025312, 7 (2015).
- [7] Elad Hoffer and Nir Ailon. 2015. Deep metric learning using triplet network. In International workshop on similarity-based pattern recognition. Springer, 84–92.
- [8] Po-Sen Huang, Xiaodong He, Jianfeng Gao, Li Deng, Alex Acero, and Larry Heck. 2013. Learning deep structured semantic models for web search using clickthrough data. In Proceedings of the 22nd ACM international conference on Information & Knowledge Management. 2333–2338.
- [9] Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2019. Billion-scale similarity search with gpus. IEEE Transactions on Big Data 7, 3 (2019), 535–547.
- [10] Sen Li, Fuyu Lv, Taiwei Jin, Guli Lin, Keping Yang, Xiaoyi Zeng, Xiao-Ming Wu, and Qianli Ma. 2021. Embedding-based Product Retrieval in Taobao Search. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. 3181–3189.
- [11] Yuming Li, Pin Ni, Junkun Peng, Jiayi Zhu, Zhenjin Dai, Gangmin Li, and Xuming Bai. 2019. A joint model of clinical domain classification and slot filling based on RCNN and BiGRU-CRF. In 2019 IEEE International Conference on Big Data (Big Data). IEEE, 6133-6135.
- [12] Yiu-Chang Lin, Ankur Datta, and Giuseppe Di Fabbrizio. 2018. E-commerce product query classification using implicit user's feedback from clicks. In 2018 IEEE International Conference on Big Data (Big Data). IEEE, 1955–1959.
- [13] Jingzhou Liu, Wei-Cheng Chang, Yuexin Wu, and Yiming Yang. 2017. Deep learning for extreme multi-label text classification. In Proceedings of the 40th international ACM SIGIR conference on research and development in information retrieval. 115–124.
- [14] Yijin Liu, Fandong Meng, Jinchao Zhang, Jinan Xu, Yufeng Chen, and Jie Zhou. 2019. GCDT: A Global Context Enhanced Deep Transition Architecture for Sequence Labeling. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 2431–2441.
- [15] Yiqun Liu, Kaushik Rangadurai, Yunzhong He, Siddarth Malreddy, Xunlong Gui, Xiaoyi Liu, and Fedor Borisyuk. 2021. Que2Search: Fast and Accurate Query and Document Understanding for Search at Facebook. In Proceedings of the 27th ACM

- SIGKDD Conference on Knowledge Discovery & Data Mining. 3376-3384.
- [16] Ilya Loshchilov and Frank Hutter. 2018. Decoupled Weight Decay Regularization. In International Conference on Learning Representations.
- [17] Zhibin Lu, Pan Du, and Jian-Yun Nie. 2020. VGCN-BERT: augmenting BERT with graph embedding for text classification. In European Conference on Information Retrieval. Springer, 369–382.
- [18] Xichuan Niu, Bofang Li, Chenliang Li, Rong Xiao, Haochuan Sun, Hongbo Deng, and Zhenzhong Chen. 2020. A dual heterogeneous graph attention network to improve long-tail performance for shop search in e-commerce. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 3405–3415.
- [19] Gal Oestreicher-Singer and Arun Sundararajan. 2012. Recommendation networks and the long tail of electronic commerce. Mis quarterly (2012), 65–83.
- [20] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683 (2019).
- [21] Michael Skinner and Surya Kallumadi. 2019. E-commerce Query Classification Using Product Taxonomy Mapping: A Transfer Learning Approach.. In eCOM@ SIGID
- [22] Daria Sorokina and Erick Cantu-Paz. 2016. Amazon Search: The Joy of Ranking Products. In SIGIR. 459–460.
- [23] Chi Sun, Xipeng Qiu, Yige Xu, and Xuanjing Huang. 2019. How to fine-tune bert for text classification?. In China national conference on Chinese computational linguistics. Springer, 194–206.
- [24] Henry Tsai, Jason Riesa, Melvin Johnson, Naveen Arivazhagan, Xin Li, and Amelia Archer. 2019. Small and Practical BERT Models for Sequence Labeling. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 3632–3636.
- [25] Zhiguo Wang, Patrick Ng, Xiaofei Ma, Ramesh Nallapati, and Bing Xiang. 2019. Multi-passage BERT: A Globally Normalized BERT Model for Open-domain Question Answering. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 5878–5882.
- [26] Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019. End-to-End Open-Domain Question Answering with BERTserini. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations). 72–77.
- [27] Han Zhang, Hongwei Shen, Yiming Qiu, Yunjiang Jiang, Songlin Wang, Sulong Xu, Yun Xiao, Bo Long, and Wen-Yun Yang. 2021. Joint Learning of Deep Retrieval Model and Product Quantization based Embedding Index. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval. 1718–1722.
- [28] Han Zhang, Songlin Wang, Kang Zhang, Zhiling Tang, Yunjiang Jiang, Yun Xiao, Weipeng Yan, and Wen-Yun Yang. 2020. Towards personalized and semantic retrieval: An end-to-end solution for e-commerce search via embedding learning. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 2407–2416.
- [29] Junhao Zhang, Weidi Xu, Jianhui Ji, Xi Chen, Hongbo Deng, and Keping Yang. 2021. Modeling Across-Context Attention For Long-Tail Query Classification in E-commerce. In Proceedings of the 14th ACM International Conference on Web Search and Data Mining. 58-66.