Knowledge Graph Contrastive Fusion for Product Search Relevance

Authors

Abstract

Product Search Relevance (PSR) is a fundamental and essential function in e-commerce. However, due to lack of information caused by short text, external knowledge is usually necessary to help model understand query intent and product essence. To tackle this problem, Knowledge Graph (KG) is usually utilized to improve model performance. However, naively fuse knowledge from KG still cannot solve the problem fundamentally. In this paper, we propose a novel framework to fuse knowledge in KG into PSR models based on contrastive learning called Knowledge Graph Contrastive Fusion (KGConFu), which outperforms orther baseline methods. Besides, we also release a Chinese PSR dataset with KG structure.

1 Introduction

Knowledge Graph (KG) has been deployed in a large amount of companies nowadays. In e-commerce scenario, KGs can benefit a lot of downstream tasks, such as Product Search Relevance (PSR), recommendation, Question Answering etc (QA). The core idea of fusing KG into PSR model is that with the help of knowledge, model can deeply understand query intent and product essence, which means knowledge in KG can help model learn the world better. However, current knowledge fusion methods cannot make full use of the Knowledge Graph and essentially understand textual information.

The overview of KG in e-commerce is depicted in Figure 1. Generally speaking, there is usually a taxonomy to organize items and concepts in e-commerce KG. This taxonomy is usually manually defined and coarse-grained. To better understand user need and describe products, more fine-grained e-commerce related concepts are usually constructed. For concepts in KG, some necessary relations, such as synonym and related_to, are also defined to clarify the relationship between different concepts.

This framework is applied in (Luo et al. 2020, 2021) and our scenario. Specifically, in our scenario, the product taxonomy is a manually constructed tree structure connected by isA relationships. Apart from the taxonomy, fine-grained e-commerce concepts are also constructed.

Currently, there are many approaches to fuse KG knowledge into model, such as string concatenation, Knowledge Graph Embedding (KGE), etc. However, these methods can only fuse knowledge in a shallow form. In our application scenario, there are still challenges cannot be solved by these methods.

In e-commerce, products are usually linked to KG by human efforts or models, and both method will inevitably introduce noise. For instance, product "Beer Partner 180g/bag" (a kind of snack) can be mis-linked on the path of "Snacks - cakes and pastries - bread" in KG. Ideally, knowledge is fused to improve model performance. However, fusing such kind of noisy knowledge in a direct manner do harm to model performance easily. Even though knowledge is correct, fused in-direct knolwedge can also cause semantic drift, and this kind of knowledge is another form of noise. We define this challenge as **Noisy Knowledge Challenge** in this paper. Besides, KG contains different kinds of knowledge to be mined. Lots of hidden knowledge, including hypernyms, hyponyms, synonyms, and KG structure, is waiting to be further exploited. However, current methods cannot fully mine knowledge from KG, which causes **Underutilized Knowledge Challenge**. Another challenge is that when using current fusion approach, although correct knowledge is utilized, knowledge can still be ignored by model. For example, for the query product pair ¡"Green onion", "Seaweed-flavored shallots green onion 65g" (a kind of snack) ¿, even though the path of "Seaweed-flavored shallots green onion 65g" in KG "Snacks - Fried food/puffed food - Others", is concatenated to the product name, the similarity between this query-product-pair is still high, which means model ignored the fused knowledge. This challenge is defined as **Knowledge Ignorance Challenge**. This challenge is normally caused by lexical dominant problem.

In order to solve these challenges, we design a novel KG fusion method with contrastive learning call Knowledge Graph Contrastive Fusion (KGConFu). Our key contributions are as follows:

- **A Novel KG Fusion Method**. We propose a novel fusion method to inject knowledge in KG into PSR model. It is worth mentioning that this KGConFu method can not only be applied in e-commerce scenario but all other related tasks with KGs, such as QA task with KG.
- **Effectiveness**. According to our experiments, KGConfu

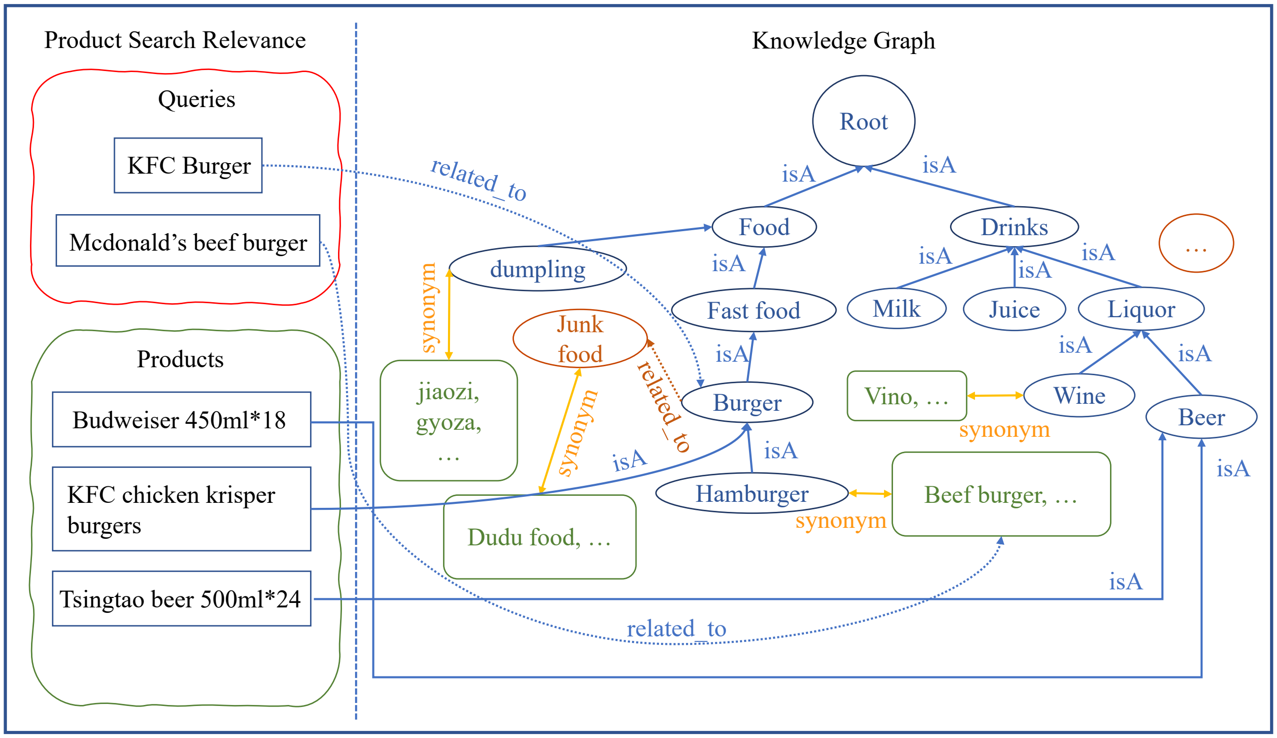

Figure 1: Overview of *Knowledge Graph based Product Search Relevance (KGPSR) Task*.

can successfully fusion KG into PSR model and benefits PSR task. KGConFu outperforms all other baseline methods for KGPSR task.

- **PSR Dataset**. In this paper, we release a new PSR data set with KG structure. As far as we know, we are the first to release such a a Chinese data set with KG structure.

2 Knowledge Graph based Product Search Relevance Task

The *KGPSR* task focuses on utilizing KG to improve PSR task. PSR task is clarified as follows. Given a set S of n query-product pairs,

$$\{< q_1, p_1 >, < q_2, p_2 >, ..., < q_n, p_n >\}$$

each pair consists of two terms, q_i and p_i. q_i is user query and p_i is the name of product. The goal of PSR task is to compute the relevance score of each query-prodcut pair.

In KGPSR task, q_i and p_i are linked on KG $G = \{V, E\}$, where V is a set of e-commerce concept nodes and E is a set of relationships. Specifically, products are mainly linked on the product taxonomy and queries are mainly linked on the e-commerce commonsense concept graph. The goal of KGPSR task is to utilize KG as much as possible to benefit PSR task in e-commerce.

3 Knowledge Graph based Product Search Relevance Dataset

4 Knowledge Graph Contrastive Fusion

5 Experiments

In this section, we discuss the experiments settings of KGConFu

5.1 Baselines

Sentence-BERT Sentence-BERT (SBERT) is a bi-encoder structure model.

SBERT-KGP The most naive method to utilize KG in KGPSR is to concatenate the path of query and products in KG.

SBERT-KGE Another method to utilize KG in KGPSR is utilze KG through embedding.

5.2 Experimental Setup

We train 5 epochs. We deploy all experiments on Nvidia V100 32G GPU. BERT-related models are initialized from the pretrained Google BERT-base (Chinese) and tuned with 2e-5 learning rate, 128 batch size, 32 sequence length.

5.3 Overall Results

The overall experiment result is in Table.

5.4 Ablation Study

This is Ablation Study.

Table 1: The AUC score of our *KGConFu* framework and other baseline methods. The best results are bolded, the best baseline results are starred.

Methods	Dev Set	Test Set
Sentence-BERT ‡	0.75743033	0.75967766
Sentence-BERT-KGP ‡	0.7511580	0.757357
Sentence-BERT-KGE ‡		
KGConFu ‡	0.777169	0.776680
KGConFu-KGP ‡	0.7706973	0.7698543
KGConFu-KGE ‡		

[1] ...

Table 2: The ablation study *KGConFu* framework.

Methods	Dev Set	Test Set
KGConFu	0.777169	0.776680
KGConFu w/o QCL	0.	0.
KGConFu w/o PCL	0.	0.

[1] ...

6 Related Work

6.1 Product Search Relevance

PSR ...

6.2 Knowledge Graph Fusion

For some tasks, especially domain-specific task, external knowledge is necessary. KG contains a wealth of knowledge and is beneficial to those downstream tasks. How to effectively fuse knowledge into model becomes a popular research direction in recent years. (Luo et al. 2021) propose a multi-task encoder-decoder Knowledge Graph Embedding (KGE) framework to provide representations for nodes and edges from AliCoCo2 and improve PSR model performance by concatenating concept embeddings to the BERT word embeddings. ERNIE (Sun et al. 2019) ... KBERT (Weijie Liu 2020) injects triples into the sentences as domain knowledge. KI-BERT (Faldu et al. 2021) infuse knowledge context from multiple knowledge graphs for conceptual and ambiguous entities into transformer-based language models during fine-tuning. K-ADAPTER (Wang et al. 2020) utilizes adapter to inject different kinds of knowledge into large pre-trained models.

6.3 Contrastive Learning

7 Conclusion and future work

In this paper, we ... Besides, we propose KGPSR dataset...

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