A Multi-Factor Classification Framework for Completing Users' Fuzzy Queries (Student Abstract)

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Abstract

Intent identification is the key technology in dialogue system. However, not all online queries are clear or complete. To identify users' intents from those fuzzy queries accurately, this paper proposes a multi-factor classification framework on the query level. Experimental results on our online serving system *JIMI* demonstrate the effectiveness of our proposed framework.

Introduction

Recently, the intelligent customer service and chatting robots have been widely used in E-commerce online serving. They provide answers or solutions for users at any time based on the intents detected from user queries. Therefore, it is critical for robots to better understand user intents(Zhang et al. 2019), especially when the user expression is fuzzy.

For example, "I cannot open" is a fuzzy query from an online user. Previous approaches view this as an intent classification or FAQ (frequently asked question) retrieval task(E et al. 2019), which is coarse without making deeper use of the semantic information of user query. Therefore, when encountering this very example, these approaches can hardly identify its intent, resulting in answering the user with a general response, such as "What can I do for you".

In this paper, we propose a multi-factor classification framework on the query level to help our online serving system *JIMI* better understand user queries. We annotate each representative query with four factors besides the intents, i.e., predicate, object, adjunct and querytype to obtain the factor-intent relationship. Compared with the coarse intent-level representation framework(Zhang et al. 2020), our query-level framework contains deeper semantic meaning. When facing exactly the same example, the additional predicted factors will be given by the proposed framework. In this case, there are only predicate ("open") and querytype ("state-negative") being revealed. Since this factor combination can be contained in several intents, our framework will provide those intents as candidate selections for users to complete or clarify their intents.

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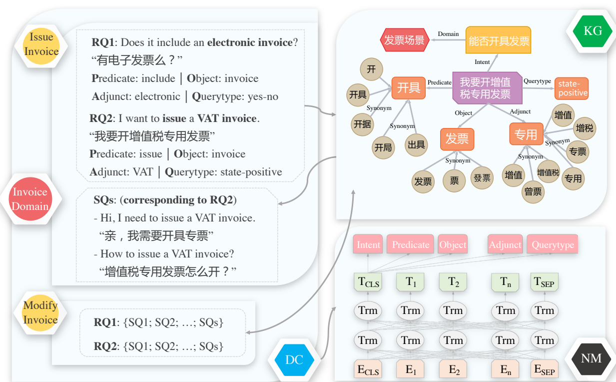

Figure 1: The overall architecture of the proposed framework. Inside KG, there are five elements, i.e., domain (red), intent (yellow), representative query (purple), factors (orange) and synonyms (coffee).

Proposed Framework

Figure 1 shows the overall architecture of our proposed multi-factor classification framework. It can be decomposed into three parts, i.e., data construction (DC in blue), knowledge graph (KG in green) and neural model (NM in black).

Data Construction

We first build up the intent system upon the business knowledge in each domain, since the online service answers user queries based on intents. In Figure 1, take Domain Invoice (red in DC) as an example, it contains about one hundred intents (yellow in DC). We select limited business knowledge points as representative queries (RQs) to help clarify the boundary among intents. Additionally, to increase the coverage of the online QA system, we collect user queries with high frequency as similar queries (SQs) for each representative query, in which RQ-SQ relationship can be obtained conveniently. Then we start to construct the corpus in multi-factor format. Different from previous works, we annotate the representative queries manually with four factors instead of directly annotating the intents. For example, RQ2 "I want to issue a VAT invoice" can be decomposed

Model	Trigger Rate	Click Rate	Accuracy
Previous	1.35%	11.16%	73.67%
Ours	**3.89%**	**18.33%**	**80.88%**

Table 1: Comparison between the previous and our proposed framework.

into issue (predicate), invoice (object), VAT (adjunct) and state-positive (querytype).

Knowledge Graph

After manual annotation of representative queries, each factor has its own synonyms. Next, a knowledge graph containing relationships among the domain, intents, representative queries, factors and synonyms can be obtained. With this graph, the factors within the similar queries can be automatically annotated through the RQ-SQ relationship. For example, two SQs corresponding to RQ2 in Figure 1 will inherit RQ2's factors with restrictions. In this way, we build a corpus without much human annotation quickly and we believe that the noise caused by the auto-annotation could help generalize the model to some extent.

Neural Model

Following (Devlin et al. 2019), we modify Bert into a multi-task form, since there are intent and factor classification tasks in this scenario. Therefore, each online query will have its own predicted factors and intent. When the intent is not convincing enough, which indicates the current query is fuzzy, the factors show its effect on how to complete it.

Experiment

Data Setting and Parameters

In our experiment, we build our corpus containing 23 domains upon our online serving system *JIMI*. Eventually, we manually annotate 900 representative queries on average for each domain including average 38 predicates, 32 objects, 31 adjuncts and 17 querytypes respectively. We collect similar queries from online logs in the past two months with frequency over 4 times to obtain about 9,000 similar queries each domain with auto-annotation, which reduces the annotation costs largely.

We choose the Chinese Bert model [1] as the basis of the proposed framework. With certain modifications, Bert is able to adapt to both intent and factor classification tasks. We finetune the model on the data mentioned above, with the same parameter settings as the original.

Experimental Results

With the above settings, the proposed framework achieves 85% on average in terms of accuracy for each factor in each domain. We test our framework in Domain Invoice online. As shown in Table 1, our proposed framework outperforms the previous Bert-base (Devlin et al. 2019) FAQ matching framework by 2.54%, 7.17% and 7.21% in terms of the trigger rate, click rate and accuracy respectively, which demonstrates the effectiveness of our proposed framework.

[1] https://github.com/ymcui/Chinese-BERT-wwm

Figure 2: An example of completing a fuzzy query online.

Figure 2 shows an example on how our proposed framework can help the users complete their fuzzy expressions online. In the beginning, the user questions "how about this invoice", where we know that predicate and adjunct are missing. Based on the existing factors, several related intents can be retrieved. Our proposed framework provides candidate selections within these intents. The user selects the one which is able to complete his intent and our system answers him with the predefined answer properly.

Conclusions and Future Work

In this paper, we proposed a multi-factor classification framework on query level, which is helpful to complete users' fuzzy queries and to clarify their intents. In the future, we look forward to generalizing better answers with the key factors provided by the framework with further exploration.

References

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