E-ConvRec: A Large-Scale Conversational Recommendation Dataset for E-Commerce Customer Service

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Abstract

There has been a growing interest in developing conversational recommendation system (CRS), which provides valuable recommendations to users through conversations. Compared to the traditional recommendation, it advocates wealthier interactions and provides possibilities to obtain users’ exact preferences explicitly. Nevertheless, the corresponding research on this topic is limited due to the lack of broad-coverage dialogue corpus, especially real-world dialogue corpus. To handle this issue and facilitate our exploration, we construct E-ConvRec, an authentic Chinese dialogue dataset consisting of over 25k dialogues and 770k utterances, which contains user profile, product knowledge base (KB), and multiple sequential real conversations between users and recommenders. Next, we explore conversational recommendation in a real scene from multiple facets based on the dataset. Therefore, we particularly design three tasks: user preference recognition, dialogue management, and personalized recommendation. In the light of the three tasks, we establish baseline results on E-ConvRec to facilitate future studies.

Keywords: Conversational Recommendation, Dialogue Corpus, User Preference Recognition

1. Introduction

Recently, Conversational Recommendation System (CRS), has attracted attention in the dialog community as it collects dynamic and interactive information from users’ requirements and provides useful recommendations (Christakopoulou et al., 2016; Sun and Zhang, 2018; Chen et al., 2019a; Radlinski et al., 2019; Lei et al., 2020a; Lei et al., 2020b; Jannach et al., 2021; Gao et al., 2021; Zhou et al., 2021). Intuitively, a high-qualified dataset is essential to facilitate the development of CRS. To drive the progress of CRS development, there are some corpora proposed recently. In general, existing corpora are constructed in roughly two ways. Some studies generate the dialogues in a Wizard-of-Oz setting (Shah et al., 2018) by connecting two crowd-workers to engage in a chat session (Moon et al., 2019; Liu et al., 2020; Xu et al., 2020; Hayati et al., 2020; Liu et al., 2021b; Liao et al., 2021). Some other studies construct datasets from user review corpus (Fu et al., 2020) or item rating website (Zhou et al., 2020). The task of conversational recommendation in E-commerce domain is far more complex compared with the above mentioned scenarios. Figure 1 shows a real-world E-commerce conversation. Several characteristics can be observed from the conversation. Firstly, users describe the sought products in broader terms and a casual way, with either explicit expressions (e.g. 14 inches, 512 SSD) or implicit words (e.g. cheaper one), resulting in difficulties in eliciting users’ preferences. Therefore, accurately recognizing user preference words in casual utterances lays the foundation for providing high-quality recommendations. Secondly, customers usually proceed in a coarse-to-fine manner to gradually make their decisions during a conversation (Fu et al., 2020). Thus, customer service staffs need to conduct effective interaction with them to collect required information or make a recommendation. To attract users’ interests, more attention should be paid to effective dialogue management during the conversation. Thirdly, there are massive personalized user profiles and product knowledge in the E-commerce domain. The auxiliary information makes it easy to trace connections from users to specific items and provides a high-quality recommendation for customers. For example, in Figure 1 customer service staffs tend to recommend a computer suitable for a student-user based on the information obtained from the user profile (e.g. 16-25 years old, undergraduate). Hence, it is also a key problem to make a personalized recommendation by fully combining user profile, product knowledge, and dialogue context into consideration.

To bridge the gap between the complex problems in real scenario and the existing artificial CRS public datasets, in this paper, we present a real-world, large-scale, and informative E-commerce conversational recommendation dataset, namely E-ConvRec. It consists of 25,440 dialogues and 775,338 utterances derived from a leading Chinese E-commerce platform. The dataset contains a wealth of information, including conversations, user profiles and product knowledge base. We hope that the natural dialogues and the en-

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1https://www.jd.com/
Figure 1: A dialogue example for E-ConvRec. This dataset provides conversation flows from real scenario of E-commerce, user profile and product KB to enrich recommendation. Moreover, three sub-tasks of user preference recognition, dialogue management, and personalized recommendation are devised to facilitate research on CRS.

riched information in E-ConvRec open plenty of room for future studies on the conversational recommendation system. Furthermore, we summarize three questions to address the aforementioned CRS paradigm: 1) What kind of products does the user prefer? 2) How should the CRS proceed the conversation by information collection or product recommendation? 3) Which product should CRS recommend to better attract users’ interests? Specifically, we devise three meaningful tasks which are user preference recognition, dialogue management, and personalized recommendation with high-qualified annotated datasets. We conduct extensive experiments and provide baselines for three tasks. Despite promising early results we get, E-ConvRec leaves ample scope to improve the CRS’s performance.

In summary, the main contributions of this paper are listed as follows:

- We contribute E-ConvRec, a real-world, natural, and informative dataset from the E-commerce domain, which consists of 25k dialogues, user profiles, and product knowledge base.
- We design three worth investigating tasks to explore conversational recommendation in the real scenario from multiple facets, supported by the dataset.
- We conduct extensive experiments and provide several baseline results for three tasks to facilitate future research. The corpus and the annotated sub-tasks will be released soon.

2. Related Work

CRS is a recommendation system that elicits the dynamic preferences of users and takes actions based on their current needs through real-time multi-turn interactions (Gao et al., 2021). The growth of this field has been consistently supported by the development of novel datasets. We present a detailed comparison of E-ConvRec with existing datasets in Table 1. Based on various resources of data collection, existing corpora can be roughly divided into two categories: 1) corpus generated by crowd-sourced workers and 2) dataset constructed from reviews or item ratings. The former one collects human-to-human and human-to-machine conversation data by recruiting crowd-sourced workers to interact in real-time under pre-defined search or recommendation settings. There are crowdsourcing sites, such as Amazon Mechanical Turk (AMT) where researchers can find participants to accomplish their data collection task (Li et al., 2018; Kang et al., 2019; Moon et al., 2019; Liu et al., 2020; Xu et al., 2020; Hayati et al., 2020; Liu et al., 2021b; Liao et al., 2021). The latter is constructed in an automatic or semi-automatic manner. Researchers utilize the real data records or reviews from popular review websites (e.g., Douban Movie, Amazon, Facebook) and simulate the recommendation scenario to
### 3. Dataset Collection and SubTasks Annotation

E-ConvRec is constructed from the real scenario application in the E-commerce domain. In this section, we will introduce the detailed information for data collection and annotation procedures for sub-tasks.

#### 3.1. Data Collection

Our data sources mainly include the following three parts: 1) The dialogue flows from online E-commerce conversation; 2) The personalized user profile; 3) Knowledge base for products. We will introduce them respectively in the following part.

**Dialogue Flows.** We first collect the dialogue dataset which contains conversations on pre-sales topics between users and customer service staff in an E-commerce scenario. We pre-select the conversations with a high intention of placing an order from a broader set of dialogues. After crawling, we de-duplicated the raw data, desensitized and anonymized private information. As illustrated in Figure 1, conversation collected from the real-world application contains more linguistic variety with natural expressions, and users involved tend to present more complicated requirements compared with the synthesized corpus.

We also analyze the number of sessions, words, and average turn to give an overview of the conversation dataset. As illustrated in Table 2, we can see that, our conversation dataset contains more than 25k sessions, including 32k cases and 775k utterances in total. Besides, the number of turns ranges from 2 to 100 for each session, with an average of 12. Figure 2 describes the histogram of dialogue length in the dataset. We only present dialogue with less than 30 turns for space limitation. It illustrates that most conversations are between 3 to 12, and the session of 7 turns has the largest portion. It indicates that, in the real application, users may be impatient, and professional customer service staffs need to make product recommendation in an appropriate timing, which is also a challenge for CRS.

**User Profile.** User profile plays a critical role in the personalized recommendation system as it encourages the CRS to make decisions tailored to each individual user’s interest without requiring the user to make an explicit query (Zhang and Koren, 2007; Massari, 2010; Ni et al., 2018). Thus, we collect the user profile from the pre-processed user profile library. During information processing, to protect user’s privacy, we anonymize the username, delete the phone number and construct the dataset. (Dodge et al., 2015; Zhou et al., 2020; Fu et al., 2020).

During data construction, apart from dialogue information, most datasets provide additional information to improve CRS’s performance. OpenDialKG (Moon et al., 2019) imports knowledge graph sources from Freebase, aiming to model of dialogue logic by walking over the knowledge graph. GoDialKG (Moon et al., 2019) and TG-ReDial (Zhou et al., 2020) import user data to capture human-level reasoning for the personalized recommendation. DuRecDial (Liu et al., 2020) leverages multi-type of dialogues in conversation recommendation and DuRecDial 2.0 (Liu et al., 2021b) prepares bi-lingual corpus for the task. From the perspective of the application domain, most of the corpora such as ReDial (Li et al., 2018) and INSPIRED (Hayati et al., 2020) focus on movie recommendation. MGConvRex (Xu et al., 2020) concentrates on restaurant booking and MMCong (Liao et al., 2021) presents multi-domain conversation during traveling. However, in most of the mentioned domains, the recommendation is quite straightforward. This is largely due to the fact that, during movie or restaurant recommendations, the user’s intention is usually under-control and their requirements can be easily defined in limited aspects. Compared with them, the conversational recommendation in the E-commerce domain is quite different. Faced with millions of customers and thousands of different categories of products, the CRS not only needs to interpret various expressed requirements from users but are also required to bridge the gap between user’s description and tens of attributes information corresponding to each individual product. Even though COOKIE (Fu et al., 2020) takes the first step to present an E-commerce recommendation dataset, it only covers on four categories of products, which limits the complexity in this domain.

| Dataset   | #Dialogue | #Utterance | #Domain       | Language | Source          | Extra Info |
|-----------|-----------|------------|---------------|----------|-----------------|------------|
| Facebook_Rec | 1M        | 6M         | Movie         | EN       | item rating     | KB         |
| GoRecDial  | 10,006    | 182,150    | Movie        | EN       | crowd-sourced   | KB         |
| OpenDialKG | 15,673    | 91,209     | Movie, book, etc. | EN       | crowd-sourced   | KB         |
| DuRecDial  | 10,190    | 155,447    | Movie, food, etc. | ZH       | crowd-sourced   | User data, KB |
| TG-ReDial  | 10,000    | 129,392    | Movie        | ZH       | item rating     | User data, KB |
| MGConvRex  | 7.6K+     | 73K        | Restaurant    | EN       | crowd-sourced   | User data  |
| INSPIRED   | 1.001     | 35,811     | Movie        | EN       | crowd-sourced   | -          |
| DuRecDial 2.0 | 16,482   | 255,346    | Movie, music, etc. | EN-ZH   | crowd-sourced   | -          |
| MMConv     | 5106      | 39,759     | Travel       | EN       | crowd-sourced   | User data, KB |
| COOKIE     | -         | 11.6M      | E-commerce   | EN       | item review     | KB         |
| E-ConvRec  | 25,440    | 775,338    | E-commerce   | ZH       | natural dialogue| User data, KB |

Table 1: Comparison of E-ConvRec with other Conversational Recommendation Datasets.
Table 2: Session statistics.

| Statistic              | Value  |
|------------------------|--------|
| Total cases            | 32,609 |
| Total sessions         | 25,440 |
| Total turns            | 305,441|
| Average turns per session | 12    |
| Max turns              | 100    |
| Min turns              | 2      |
| Total utterances       | 775,338|
| Max utterances         | 180    |
| Min utterances         | 3      |
| Total words            | 6,782,956|
| Average words per utterance | 8.7   |

Figure 2: The distribution of dialogue with respect to the number of dialogue turns.

detailed address information, and remove all fields that related to the user identification. We further convert their identifications into string of 10 random characters in our dataset.

In general, 20 different types user profiles are provided. The user profiles are collected in two ways: some of the attributes are collected from their personal information during their registrations, such as user level, sex, age, marital status, education and profession, etc. The others are analyzed based on their historical shopping activities such as brand preference, average payment per month, purchasing power, Top 3 purchased categories with the largest values in last three months, etc. Detailed examples can be found in Figure 3. It’s observed that, during popular item recommendation, the user profile such as average payment monthly may play a key role as it provides insights for user’s preference on product price.

Table 3 shows the coverage of our provided user profile and product KB. The extracted KB covers 118k product items and the user profile provides anonymized information for 24k users.

3.2. Task Formulation

As demonstrated in Figure 1, customers often proceed in a coarse-to-fine manner to gradually make their decisions during conversation flows. As they often initiate queries by describing the sought products in broader terms, e.g., category or brand name (Fu et al., 2020). As the dialogue goes on, CRS gradually grasps the users’ specific requirements and preferences referring to the relevant products to be recommended. Naturally, we form them into three tasks: **User Preference Recognition** focuses on eliciting as many user preferences as possible; **Dialogue Management** tends to estimate the dialogue policy at per conversation step. Whereas **Personalized Recommendation** focuses on decision making tailored to each individual user’s interest.

**User Preference Recognition.** The preference words in the query can depict the user’s preference for an item. And then, customer service staffs match appropriate items catering to user needs and recommend them to the user. Therefore, recognizing the preference words is an indispensable part of the conversation recommendation.

![Figure 4: Examples of Product KB.](image)

Table 3: User and product statistics.

| Statistic  | Value  |
|------------|--------|
| Total items| 118,086|
| Total users| 24,358 |
| Users without the profile | 348 |
| Items without the KB | 21,907 |

**Product Knowledge Base.** Product Knowledge Base (KB) provides abundant information about a product. Recently study (Fu et al., 2020) also proves its effectiveness to CRS with its explainability and transparency, which easily bridges the gap between user’s description and product. Inspired by this, we crawl KB information of products mentioned in the conversation from the E-Commerce platform. To enrich information variety, we also collect knowledge from other products in the same category which are sold in the same online shop. Specifically, the extracted KB contains the product name, category, product title and various attributes and their values (e.g., screen size: 5.7 inch, Color: Silver). Figure 4 shows two examples of product KB.
Empowered by real-time comparative words and 7.05% have negative words. 99.97% include category words, 0.51% involve comparisons, 91.91% of sessions contain descriptive words, and 2k+ negative words. In the 25k+ sessions, we acquire strong inter-annotator agreement. We acquire 67k+ description timing. In addition, the intention of user sessions which contain utterances with the positive recommendation timing. In the future, we also label the intention for each query in the dialogues with a in-house intent classifier of E-commerce domain. The classifier contains five intents, and it’s trained with BERT (Devlin et al., 2018). Table 4 shows the distribution of 5 intentions (The other intention includes Time for shipping, Invoice Policy, Usage Consultation, etc.). The classification accuracy reaches 92% on the test set of intention dataset, indicating the quality of the classifier.

| Intent                | Data distribution |
|-----------------------|-------------------|
| Inform Preference     | 28.25 %           |
| Request Attributes    | 22.35%            |
| Don’t care            | 6.45 %            |
| Confirmation          | 10.35 %           |
| Other                 | 32.60 %           |

Table 5: Distribution of user’s intents in E-ConvRec.

Personalized Recommendation. On the E-commerce application, we naturally assume that if the customer eventually purchases the item we recommend, it indicates a successful recommendation. Therefore, the task of conversational recommendation is designed to judge whether the user will buy a candidate product based on user profile, product KB and conversation content (context before the recommendation moment). Personalized recommendation is formulated as a ranking task. During data construction, we label the purchased product related to the conversation as positive sample (ground-truth). We also mine at most 30 hard negative samples, including the products which appeared within the conversation but not purchased by the user, or those of the same category and sold in the same online shop.

| Users’ utterances                                                                                   | Table 4: Examples for user preference words annotation: descriptive words, category words, comparative words and negative words. |
|------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|
| (Do you have the lipstick that girls wear in your shop?)                                             | We hire three crowd-sourced workers who are familiar with E-commerce customer services, to help us annotate the data. The annotators are requested to tag the user preference words from queries. We provide the product knowledge base and category lexicon for workers as references for the annotators. Generally, product attributes and values, usage scenarios, user groups, brands, and categories are considered as preference words. We define four kinds of preference words, including descriptive preference words, category words, negative preference words (i.e. don’t want black), and comparative preference words (i.e. less than 300). Table 4 illustrates a detailed example from the annotation. After the data annotation, we merge the instances from three crowd-sourced workers to obtain a diverse and high-quality preference words corpus. We assign 9k sessions to each crowd-sourced worker and collect 1k cross-annotated sessions. We follow the previous works (Bowman et al., 2015; Chen et al., 2019b) to employ the Fleiss Kappa (Fleiss, 1971) as an indicator, where \( p_e = \frac{p_c - p_a}{1-p_a} \) is calculated from the observed agreement \( p_c \) and the agreement by chance \( p_a \). We obtain a Fleiss Kappa = 0.87, which indicates strong inter-annotator agreement. We acquire 67k+ descriptive words, 137k+ category words, 133 comparative words and 2k+ negative words. In the 25k+ sessions, 91.91% of sessions contain descriptive words, 99.97% include category words, 0.51% involve comparative words and 7.05% have negative words. |
| (I don’t like dark red.)                                                                            | Dialogue Management. Empowered by real-time interactions, CRS can directly acquire users’ needs. After gathering users’ preferences well enough, the system should make the proper recommendation at the golden time, otherwise, users will lose their patience. Accurately predicting recommendation timing can greatly improve the user experience. Thus for the dialogue management, we specifically focus on the task of recommendation timing prediction (Timing to ask user’s preference proactively is also effective dialogue policy, however, we leave it into future work due to space limitation). According to statistics, there are totally 23,932 sessions which contain utterances with the positive recommendation timing. In addition, the intention of user can be helpful for determining whether or not to recommend items to the user. To facilitate the research in the future, we also label the intention for each query in the dialogues with a in-house intent classifier of E-commerce domain. The classifier contains five intents, and it’s trained with BERT (Devlin et al., 2018). Table 5 shows the distribution of 5 intentions (The other intention includes Time for shipping, Invoice Policy, Usage Consultation, etc.). The classification accuracy reaches 92% on the test set of intention dataset, indicating the quality of the classifier. |
| (Is it lighter than the previous one?)                                                               | We define four kinds of preference words, including descriptive preference words, category words, negative preference words (i.e. don’t want black), and comparative preference words (i.e. less than 300). Table 4 illustrates a detailed example from the annotation. After the data annotation, we merge the instances from three crowd-sourced workers to obtain a diverse and high-quality preference words corpus. We assign 9k sessions to each crowd-sourced worker and collect 1k cross-annotated sessions. We follow the previous works (Bowman et al., 2015; Chen et al., 2019b) to employ the Fleiss Kappa (Fleiss, 1971) as an indicator, where \( p_e = \frac{p_c - p_a}{1-p_a} \) is calculated from the observed agreement \( p_c \) and the agreement by chance \( p_a \). We obtain a Fleiss Kappa = 0.87, which indicates strong inter-annotator agreement. We acquire 67k+ descriptive words, 137k+ category words, 133 comparative words and 2k+ negative words. In the 25k+ sessions, 91.91% of sessions contain descriptive words, 99.97% include category words, 0.51% involve comparative words and 7.05% have negative words. |
| (I don't want black one, I want a bright color one.)                                                 | Dialogue Management. Empowered by real-time interactions, CRS can directly acquire users’ needs. After gathering users’ preferences well enough, the system should make the proper recommendation at the golden time, otherwise, users will lose their patience. Accurately predicting recommendation timing can greatly improve the user experience. Thus for the dialogue management, we specifically focus on the task of recommendation timing prediction (Timing to ask user’s preference proactively is also effective dialogue policy, however, we leave it into future work due to space limitation). According to statistics, there are totally 23,932 sessions which contain utterances with the positive recommendation timing. In addition, the intention of user can be helpful for determining whether or not to recommend items to the user. To facilitate the research in the future, we also label the intention for each query in the dialogues with a in-house intent classifier of E-commerce domain. The classifier contains five intents, and it’s trained with BERT (Devlin et al., 2018). Table 5 shows the distribution of 5 intentions (The other intention includes Time for shipping, Invoice Policy, Usage Consultation, etc.). The classification accuracy reaches 92% on the test set of intention dataset, indicating the quality of the classifier. |
| (Please recommend another mobile phone with a price lower than 300.)                               | We hire three crowd-sourced workers who are familiar with E-commerce customer services, to help us annotate the data. The annotators are requested to tag the user preference words from queries. We provide the product knowledge base and category lexicon for workers as references for the annotators. Generally, product attributes and values, usage scenarios, user groups, brands, and categories are considered as preference words. We define four kinds of preference words, including descriptive preference words, category words, negative preference words (i.e. don’t want black), and comparative preference words (i.e. less than 300). Table 4 illustrates a detailed example from the annotation. After the data annotation, we merge the instances from three crowd-sourced workers to obtain a diverse and high-quality preference words corpus. We assign 9k sessions to each crowd-sourced worker and collect 1k cross-annotated sessions. We follow the previous works (Bowman et al., 2015; Chen et al., 2019b) to employ the Fleiss Kappa (Fleiss, 1971) as an indicator, where \( p_e = \frac{p_c - p_a}{1-p_a} \) is calculated from the observed agreement \( p_c \) and the agreement by chance \( p_a \). We obtain a Fleiss Kappa = 0.87, which indicates strong inter-annotator agreement. We acquire 67k+ descriptive words, 137k+ category words, 133 comparative words and 2k+ negative words. In the 25k+ sessions, 91.91% of sessions contain descriptive words, 99.97% include category words, 0.51% involve comparative words and 7.05% have negative words. |
| (I want a new phone, but this kind is too expensive.)                                               | Dialogue Management. Empowered by real-time interactions, CRS can directly acquire users’ needs. After gathering users’ preferences well enough, the system should make the proper recommendation at the golden time, otherwise, users will lose their patience. Accurately predicting recommendation timing can greatly improve the user experience. Thus for the dialogue management, we specifically focus on the task of recommendation timing prediction (Timing to ask user’s preference proactively is also effective dialogue policy, however, we leave it into future work due to space limitation). According to statistics, there are totally 23,932 sessions which contain utterances with the positive recommendation timing. In addition, the intention of user can be helpful for determining whether or not to recommend items to the user. To facilitate the research in the future, we also label the intention for each query in the dialogues with a in-house intent classifier of E-commerce domain. The classifier contains five intents, and it’s trained with BERT (Devlin et al., 2018). Table 5 shows the distribution of 5 intentions (The other intention includes Time for shipping, Invoice Policy, Usage Consultation, etc.). The classification accuracy reaches 92% on the test set of intention dataset, indicating the quality of the classifier. |

4. Experiments

To evaluate the validity of our E-ConvRec dataset from multiple facets, in this section, we conduct extensive experiments for the three tasks mentioned in Section 3.2. Next, we introduce the experiment setup and experimental results for each task.

4.1. User Preference Recognition

User preference recognition can be formulated as a sequence labeling task, similar to the named entity recognition (NER). Compared with English NER, Chinese NER is more challenging as the mainstream approaches are based on characters and without word
segmentation. Recently, the lattice structure has been proved to be an effective structure as it utilizes the word boundary information and avoids the error propagation from pre-processed word segmentation (Zhang and Yang, 2018). Here, we verify the mainstream Chinese NER models enhanced by the auxiliary word information.

Data Preparation. We select 26k high-quality queries with annotated preference words from 25k dialogues in E-ConvRec. We divide the data into training, validation, and test set in the ratio of 8:1:1. To leverage auxiliary word information, we collect a lexicon (i.e. E-comm dict) in E-commerce domain with the vocabulary size of 722k based on the product KB mentioned in Section 3.1. As comparison, we also leverage the public CTB dict, an open-domain dictionary with 700k words, to examine the lexicon-enhanced sequence labelling methods.

Baselines. Hence, we select several lexicon-enhanced NER models as the baselines:

- **LSTM+CRF** (Huang et al., 2015) - It is a classical baseline for NER. We use the BMES schema as tag set and integrate extra word boundary information into the embedding layer. In this way, the character representation can be augmented with the embedding of its corresponding words.

- **Simple-Lexicon** (Ma et al., 2019) - This model integrates the lexical information with a soft lexicon mechanism. By categorizing the matched words and condensing the word sets, it captures the matched lexicon features.

- **Multi-Digraph** (Ding et al., 2019) - In this work, a neural multi-digraph model is proposed to learn how to combine the gazetteer information and resolve conflicting matches with context information.

- **FLAT** (Li et al., 2020) - This model converts the lattice structure into a flatten sequence. Equipped with Transformer and well-designed position encoding, FLAT can fully leverage the lattice information during sequence labelling and present an excellent parallelization performance.

- **LEBERT** (Liu et al., 2021a) - This work proposes Lexicon Enhanced BERT for Chinese sequence labeling, which directly injects lexicon information into Transformer layers in BERT with a Lexicon Adapter.

Experimental Results. We use F1 score as evaluation metric and present the results in Table 6. Due to the various speaking habits in real-world dialogues, there are plenty of colloquial expressions involved in our dataset, making preference words recognition a challenging task. Table 6 demonstrates the performance of state-of-the-art NER models on this task. It’s observed that LEBERT and FLAT outperform other models by utilizing the lexicon information in a more effective approach. Meanwhile, Table 6 shows the contribution of different dictionaries. Compared with CTB, the domain-specific dictionary E-comm dict helps most of the models obtain further improvements, including LSTM + CRF, Multi-Digraph and FLAT. And FLAT obtains the best performance in this task. It also suggests that how to construct a high-quality in-domain lexicon would be an important research topic in the future.

| Model              | w/ CTB dict | w/ E-comm dict |
|--------------------|-------------|----------------|
| LSTM + CRF         | 74.00       | 75.29          |
| Simple-Lexicon     | 76.30       | 75.89          |
| Multi-Digraph      | 76.37       | 77.40          |
| FLAT               | 76.60       | 79.24          |
| LEBERT             | 78.91       | 78.53          |

Table 6: Evaluation results of user preference recognition.

4.2. Dialogue Management

Data Preparation. We sample 87,270 turns of utterances for recommendation time prediction, in which 39,254 are positive samples. We randomly select at most two utterances within the same session as the negative samples. The training, validation, and test set are split in an 8:1:1 ratio.

Baselines. We formulate the recommendation timing prediction as a binary text classification task. Therefore, we select several representative methods for text classification as the baseline models.

- **TextCNN** (Kim, 2014) - In this model, the convolutional neural network (CNN) is applied to text classification. Multiple kernels of different sizes are used to extract the salient information in sentences.

- **TextRNN** (Liu et al., 2016) - This model adopts a recurrent neural network (RNN) for text classification. The structure of the model is flexible and can be replaced with various components.

- **TextRCNN** (Lai et al., 2015) - This model replaces the CNN module into TextCNN with an additional RNN layer to acquire context information and reduce noise. In addition, the maximum pooling layer is used to capture the important parts of the text.

Specifically, we train GloVe (Pennington et al., 2014) vectors with a large size of data collected from dialogues and item titles. The pre-trained character embedding from Glove serves as the initial representation for each character token in the sentence. We implement above baselines based on the open-source classification toolkit:

3https://ai.tencent.com/ailab/nlp/en/embedding.html
4https://github.com/Tencent/NeuralNLP-NeuralClassifier
| Method       | Precision | Recall | F1   |
|-------------|-----------|--------|------|
| TextRCNN    | 72.61     | 48.44  | 58.11|
| TextRNN     | 69.86     | 57.78  | 63.25|
| TextCNN     | 70.10     | 58.62  | 63.85|
| TextCNN+Intent | 72.08   | 59.73  | 65.33|

Table 7: Recommendation timing prediction evaluation results.

| Model  | Feature   | AUC  | T@1  | T@5  | T@10 |
|--------|-----------|------|------|------|------|
| DeepFM | BF        | 69.77| 15.65| 44.70| 61.94|
|        | BF+IF     | 80.19| 33.56| 63.85| 76.28|
|        | BF+CF     | 74.53| 22.07| 54.80| 70.93|
|        | BF+IF+CF  | 83.17| 37.06| 70.20| 81.46|
| FGCNN  | BF        | 70.73| 16.87| 45.50| 62.81|
|        | BF+IF     | 78.50| 35.44| 63.31| 74.87|
|        | BF+CF     | 73.63| 22.02| 53.83| 69.39|
|        | BF+IF+CF  | 80.82| 37.28| 68.24| 78.74|

Table 8: Conversational recommendation evaluation results. “T@1” stands for Top@1.

**Experimental Results.** We adopt precision, recall and F1 as evaluation metrics. Table 7 shows experimental results on four baseline methods. The three models present comparable results on our dataset. Intuitively, the intention of user should be an indicator to the recommendation timing. To investigate the contribution of user’s intent information, we append the auxiliary intent feature mentioned in Section 3.2 into TextCNN and compare its performance with other methods. Experimental result shows that intent information can bring further improvement.

### 4.3. Personalized Recommendation

We formulate the personalized product recommendation as a click-through rate (CTR) prediction task. The mainstream approach is to extract various features and catch deep feature interactions with deep neural networks. Here, we first introduce the data preparation.

**Data Preparation.** This task requires rich information from users, products, and dialogues. Therefore, we integrate three different types of features for comparison. The basic features (BF) include user features and product attribute features. Out of the 20 types of user profiles, we select 14 most relevant features to the recommendation task. We also select top 30 high-frequency attributes from the product KB and cover at most 500 high-frequency attribute values as features. The product discussed in the current conversation should reflect the user’s interest to some extent. Based on this motivation, three interactive features (IF) are involved between products mentioned in the dialogues and candidate products. The first feature is used to judge whether the candidate product appears in the conversation. If so, the corresponding feature is 1. The second interactive feature is the average attribute similarity of the product mentioned in the dialogue and the candidate product. (The similarity score is defined as the number of the same attribute values between two products divided by the number of all different attributes). The third interactive feature is the average Jaccard similarity (Jaccard, 1912) calculated from the title between products in the dialogue and the candidate product.

The context feature (CF) consists of two parts: we first calculate average cosine similarity between the preference words and the candidate product attribute values with Glove word embedding. Then we apply BERT (Devlin et al., 2018) to encode the utterance containing the preference words in the dialogue and the title of the candidate product and calculate average the cosine similarity between them. Both two features measure the similarity between dialogue context and product candidates.

We sample 1,073,216 data samples from the corpus. After filtering data without user profile and product KB, the number of total samples is adjusted to 876,335. The number of positive samples is 30,891, and all others are the negative samples (for each positive sample, there are nearly 30 negatives). We divide the data into training, validation, and test set on a scale of 8:1:1.

**Baselines.** We adopt follow two deep CTR models as our baselines:

- **DeepFM** (Guo et al., 2017) - This model combines a Factorization Machine (FM) with a neural network to learn both low-order and high-order feature interactions, which avoids artificial features being injected into the shallow part of the model.

- **FGCNN** (Liu et al., 2019) - This model consists of feature generation and deep classifier. Feature generation leverages CNN to generate local patterns and recombines them to generate new features. Deep classifier learns interactions between the raw features and new generated features and makes prediction.

**Experimental Results.** We adopt AUC (Area Under ROC) and Top@K as metrics to evaluate the model. Table 8 shows that the performances of both DeepFM and FGCNN are improved significantly after combining with more features, indicating the different kinds of features are complementary. Meanwhile, Table 8 also demonstrates the contribution of each kind of feature in a cumulative way. In general, DeepFM with BF, IF, CF features obtains the best performance in this task.

### 4.4. Case Study

To further explore the performance of different models for personalized recommendation, we present two cases on this task. As shown in Fig 5(a), with only BF and CF, DeepFM gives a recommendation with high price which exceeds the user’s expectation (the average pay monthly is 6,072 RMB in user profile). Whereas, given only basic features (BF) and interactive feature (IF), the second model recommends the items with the
proper price but fails to capture the context features such as dark color in the conversation. In this case, user utilizes some words to explicitly express his/her needs (e.g. take clear pictures, dark color), which is challenging for system to understand. Whereas some other preference words (e.g. memory should be more than 200G) can be directly linked to the attributes in the product KB. Finally, benefiting from the combinations of basic feature, contextual feature, and interactive feature, the third model can make a correct recommendation. This illustrates that the bridging conversational corpus, user’s portrait, and product KB is the key factor for successful recommendation.

Fig[5]b presents a bad case where all the models fail to capture the user’s intention for the recommendation. As illustrated from the example, though the user recognizes single-door refrigerator as a good candidate, it explicitly describes the demand for a larger size fridge with the phrase we have a big family. Thus all the models fail to understand the user’s real intention. This case also indicates the complexity and variety for recommendation conversation presented in E-ConvRec.

5. Conclusions and Future Work

In this work, we contribute the Chinese conversational recommendation dataset which is large-scale, informative, and collected from the real scenario of E-commerce domain. To explore conversational recommendation in a real scene from multiple facets based on the dataset, we design three worth studying tasks which cover the critical problems of CRS. Extensive experiments are conducted and baselines are provided for these tasks. The experimental results indicate there is still a long way to go to solve the real scenario conversational recommendation problem. More in-depth researches on personalized preference recognition, multiturn dialogue strategies, and response generation are needed in the future. Moreover, we will enrich the dataset annotations (e.g., emotions, richer intentions) in the future.
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