COOKIE: A Dataset for Conversational Recommendation over Knowledge Graphs in E-commerce

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Abstract
In this work, we present a new dataset for conversational recommendation over knowledge graphs in e-commerce platforms called COOKIE. The dataset is constructed from an Amazon review corpus by integrating both user–agent dialogue and custom knowledge graphs for recommendation. Specifically, we first construct a unified knowledge graph and extract key entities between user–product pairs, which serve as the skeleton of a conversation. Then we simulate conversations mirroring the human coarse-to-fine process of choosing preferred items. The proposed baselines and experiments demonstrate that our dataset is able to provide innovative opportunities for conversational recommendation.

1 Introduction
The rapid development of conversational systems has had substantial impact in industry, but remains under-explored in e-commerce settings. When choosing products or services, customers may easily feel overwhelmed or confused by the various technical specs and product details (Bettman et al., 1998). Recently, conversational recommender systems have been proposed to interactively and dynamically solicit information about user requirements so as to provide better recommendations (Jannach et al., 2020). At the same time, knowledge graphs have recently come to prominence to endow recommender systems with explainability and transparency (Zhang and Chen, 2018), as their graph structure makes it easy to trace connections from users to specific recommendations, and the discovered paths can be presented to the customer. However, previous work neglects user-side information as a part of the graph, only enriching product information with external knowledge bases such as Freebase (Zhao et al., 2019). Thus, it is promising to integrate user activities as well as historical user preferences into the knowledge graph such that the conversational system can better assist users to effortlessly find the best-suited products.

In practice, humans often proceed in a coarse-to-fine manner to gradually make their decisions. For example, people answer questions by first skimming the text, identifying key ideas, and then carefully reading specific parts to obtain an answer (Masson, 1983). Similarly, customers often initiate queries to an e-commerce conversational engine that describe the sought products in broader terms, e.g., categories or brand names. During the interaction with the system, the latter gradually gains a better understanding of specific user requirements and preferences pertaining to the relevant products to be chosen. Hence, the success of such a conversation hinges on the richness of the acquired knowledge by the system. In order to make

Figure 1: A knowledge-enhanced conversational recommender system aims to interact with the user to predict user preferences and make recommendations.
the user–agent conversations more reasonable and transparent, we draw on a unified knowledge graph based on the Amazon review corpus by Ni et al. (2019). Specifically, for every user, we determine the set of reachable entities connected with purchased products as essential sequential knowledge within the KG, aiming to follow natural coarse-to-fine conceptual resolution to gradually propagate the user interests.

To this end, we present a novel corpus called COOKIE: CONversational recommendation OVer Knowledge graphs in E-commerce platforms. The key contributions of this paper can be summarized as follows. 1) We highlight the importance of injecting unified knowledge graphs into conversational recommendation, and induce a corresponding dataset to encourage further research. 2) We propose a simple yet effective pipeline to construct a knowledge graph based on the Amazon review dataset and identify key entities that can be invoked to generate conversations. 3) We provide several baseline results for recommendation and next-question prediction.

2 Related Work

We review several essential features of state-of-art conversational recommendation. Zhang et al. (2018) design a multi-memory network architecture, which can ask aspect-based questions to gradually understand the user preferences. However, it fails to consider human-readable utterances as a fluent response for semantic understanding, which is replaced by either extracting the facets from the utterance or crawling the raw review contexts. In contrast, Li et al. (2018) encode a dialogue via an RNN-based neural network to extract the dialogue state. Greco et al. (2017) propose a framework based on hierarchical RL for dialogue management. These works focus on dialogue generation and recommendation. However, retrieval-based conversational engines such as AliMe (Li et al., 2017) as e-commerce assistants have proven more popular in practice. Compared to generation-based methods (Liu et al., 2019; Chen et al., 2019a), retrieval-based methods are often able to provide more fluent and informative responses (Yang et al., 2018; Yuan et al., 2019). Recently, the integration of knowledge graphs (KGs) has enabled recommendation grounded in reasoning in conjunction with conversational knowledge. Moon et al. (2019) propose an attention-based graph decoder that seeks optimal paths within a KG, and a zero-shot learning model that leverages previous sentences, dialogue, and KG contexts to re-rank candidates from the pruned decoder graph output. In Chen et al. (2019b), item-related knowledge bases with entity-linked text lead to better performance than either of them alone in dialogue generation and recommendation. Comparing to these methods, we provide an open dataset for conversational recommendation that integrates knowledge graphs so that prominent knowledge with semantics can be used to provide both personalized and explainable recommendation.

3 Dataset Construction and Task

In this section, we describe the pipeline to construct COOKIE and the corresponding task definition. Before that, we first describe the key desiderata. Manually verified: Most commercial conversational engines principally rely on template-based utterance generation (e.g., Alexa Skills, DialogueFlow, etc.). This requires substantial development effort, which however is tied to a particular model. Manually verified data has the advantage of allowing the data construction to be completed separately from model development and learning. Reliability: Although conversations may be simulated, the generated questions and user responses should be reasonable. Personalization: One of the cornerstones of recommendation is that the results are personalized, accounting for the specific historical records available for each user. Thus, even for two otherwise identical conversations, we expect diverse recommendation results based on the user’s past activities. Goal-Oriented: Users of e-commerce platforms tend to be impatient and hence the conversation should not be lengthy, as opposed to open-domain chatbot-style dialogue. Rather than getting the user involved in a long conversation spanning many rounds, a key objective is to satisfy the user’s needs as efficiently as possible and quickly identify personalized target items.

Existing methods for conversational recommender systems are either based on dialogue state tracking (Sun and Zhang, 2018; Lei et al., 2020), which typically represents the dialogue state by facet attributes of items, or on dialogue semantic modeling (Zhang et al., 2018), which focuses on understanding the semantics of the dialogue via language models. We draw on the KG structure and on the dialogue and try to unify these two philosophies.
The goal is to predict the next utterance while simultaneously addressing next-question prediction as well as the final recommendation task.

The four domains of our dataset are Cellphones & Accessories, Grocery & Gourmet, Toys & Games, and Automotive (see Table 1). Each category is a separate domain of the e-commerce platform and is hence considered as an independent sub-dataset. The pipeline involves first constructing a knowledge graph, followed by the process of key entity extraction and finally conversation synthesis.

Unified Knowledge Graph Construction. We start from a recent collection of Amazon reviews (Ni et al., 2019). The extracted facts can mainly be categorized into two groups: user activities and product meta-data. For user activity related facts, we extract user review keywords and liked styles of products following Zhang et al. (2014, 2018). This yields multiple categories of user records (purchases, comments, etc.) and abundant product information (price, aspects, category, brand, etc.). The unified knowledge graphs in this work not only capture user activities towards products but also incorporate rich product meta-information.

Key Entity Extraction. Once the KG is constructed, the next step is to consider each ground truth user–product interaction and extract relevant key entities from the knowledge graph that motivate the purchase decision. In Fig. 1, for instance, the key entities highlighted in red include product categories, attributes such as healthy, etc. Each sequence of key entities later serves as a skeleton for the respective dialogue, guiding a coarse-to-fine selection process in which the entities determine which feature is considered in each conversational turn. Therefore, we sort the entities by node degree, and then select the KG entities that are reachable from the given user and product within one or two hops. The underlying intuition is that since the conversational system aims to help users to gradually figure out their preferences, the system starts from larger degree entities, as these are more prominent, well-known, and often more generic. As the conversation proceeds, the latent needs of users are progressively clarified such that it becomes easier to consider key entities with a smaller degree, i.e., more particular fine-grained ones.

Conversation Synthesis. The next step is to generate dialogue for the recommendation interactions. For each ground truth user–product pair, we compose the corresponding conversations based on the skeleton formed by the respective sequence of key entities. In particular, we transform the key entities into questions via human-specified templates $Q(.)$ generated from Wiseman et al. (2018), which are manually verified and require simple Yes/No-style answers from the user. Apart from simplifying the dataset creation and subsequent prediction, it also makes sense to assume that those users seeking assistance rather than directly selecting an item tend to be unfamiliar with the product details and are unable to provide detailed requirements. In this case, Yes/No questions are a natural way of narrowing down the search space.

We simulate a conversation procedure in a coarse-to-fine manner to construct the dataset. Formally, we define a $T$-turn knowledge-enhanced conversation as

$$C^{(T)} = (q_0, (q_1, a_1, e_1), \ldots, (q_T, a_T, e_T)),$$

where $q_0$ is the query initiated by the user, $q_t$ ($t = 1, \ldots, T$) is the $t$-th question given by the agent, and $a_t$ ($t = 1, \ldots, T$) is the $t$-th answer given by the user. Assume that each question $q_t$ is associated with an entity $e_t \in E$, where $E$ denotes the entity set of an knowledge graph $G$. Given $C^{(T)}$, we will expect the model to make two kinds of predictions at step $T + 1$: next-question prediction and recommendation. For these, we need the set of candidate questions $Q^{(T+1)}$, candidate key entities $E^{(T+1)}$, and candidate items $V$. The details for constructing these for our dataset are as follows. For each user $u_i$ and item $v_j$ purchased by that user, we take as input a sequence of $T + 1$ key entities $\{e_0, \ldots, e_T\}$, as obtained in the previous section, along with a sequence of corresponding answers $\{a_1, \ldots, a_T\}$. Here, $e_0$ is a key entity identified from the user query, so there is no corresponding answer for it. We first construct the
Table 2: F1@10 results of next-question prediction. Evaluation based on samples of 100 negative products as candidates.

| Method   | Cellphones&Accessories | Grocery&Gourmet | Toys&Games | Automotive |
|----------|------------------------|----------------|------------|------------|
| BPR      | 0.540                  | 0.521          | 0.498      | 0.487      |
| KGAT     | 0.593                  | 0.622          | 0.637      | 0.581      |
| OpenDialKG | 0.480                | 0.502          | 0.446      | 0.498      |
| KBRD     | 0.424                  | 0.475          | 0.366      | 0.409      |

Table 3: Recall@2 results on next-question prediction. Evaluation using samples of 100 negative products as candidates.

| Method   | Cellphones&Accessories | Grocery&Gourmet | Toys&Games | Automotive |
|----------|------------------------|----------------|------------|------------|
| DMN      | 0.414                  | 0.429          | 0.392      | 0.388      |
| DAM      | 0.448                  | 0.501          | 0.462      | 0.490      |
| MSN      | 0.584                  | 0.617          | 0.595      | 0.587      |
| OpenDialKG | 0.670                | 0.710          | 0.555      | 0.797      |
| KBRD     | 0.666                  | 0.702          | 0.703      | 0.713      |

4 Baselines and Experiments

In this section, we evaluate the recommendation and next-question prediction tasks over our constructed conversation dataset, where each sub-dataset is divided into training (60%), validation (20%), and test portions (20%). In terms of methods, for the recommendation task, we compare Bayesian personalized ranking BPR (Rendle et al., 2009), the knowledge graph attention network KGAT (Wang et al., 2019), an adaptation of the OpenDialKG (Moon et al., 2019) DialKG Walker model, and an adaptation of KBRD (Chen et al., 2019b). For next-question prediction, we compare the popular response ranking methods DMN (Yang et al., 2018), DAM (Zhou et al., 2018), and MSN (Zhou et al., 2018). We also invoked the adapted versions of OpenDialKG and KBRD on this task, where both of them exploit the knowledge graphs to better leverage sentence, dialogue, and KG structural features. We adopt pre-trained TransE (Bordes et al., 2013) as the encoding for each entity within the KG and word embeddings are trained using the word2vec (Mikolov et al., 2013) skip-gram model.

4.1 Recommendation

The recommendation quality results of different models are given in Table 2. Among the methods, BPR optimizes a pairwise ranking only considering user–product pairs, while KGAT integrates the knowledge graph reasoning for recommendation. The best results are obtained by our modified KBRD baseline.

4.2 Next-Question Prediction

At the same time, learning to ask an appropriate question is another important indicator of evaluating whether the model successfully identifies the user needs. Compared to generation-based methods (Liu et al., 2019; Chen et al., 2019a), retrieval-based methods are able to provide more fluent and informative responses (Yang et al., 2018; Yuan et al., 2019). The question prediction in conversational recommendation seeks to better narrow down the user’s needs and effectively retrieve the best-matching products. The experimental results are given in Table 3. OpenDialKG and KBRD obtain the best results here. It should be noted that, due to computational resource constraints, how to fully utilize the unified KG structure to avoid comprehensive reasoning either based on semantic fea-
tures of historical dialogue or the overall structure of the KG are key challenges.

5 Conclusion

We introduce the new COOKIE dataset for conversational knowledge-enhanced recommendation. Our work is the first exploration of creating a conversational dataset for recommendation that simulates user feedback with regard to a knowledge graph. Compared to previous work, it enables more realistic conversational recommendation as well as explainability.

In this work, we assume customers are rational and patient in their interactions with the intelligent agent. In future work, we hope to introduce more challenging tasks, where the user is able to provide more diverse responses with richer semantics and varying sentiment towards product attributes, or present product-specific requests.

We make our data available at https://github.com/zuohuif/COOKIE with further updates and maintenance. Besides, we will also provide the results of baseline methods in order to support and encourage further research on conversational agents for e-commerce settings.

References

James R. Bettman, Mary Frances Luce, and John W. Payne. 1998. Constructive Consumer Choice Processes. Journal of Consumer Research, 25(3):187–217.

Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yakhnenko. 2013. Translating embeddings for modeling multi-relational data. In Advances in neural information processing systems, pages 2787–2795.

Qibin Chen, Junyang Lin, Yichang Zhang, Ming Ding, Yukuo Cen, Hongxia Yang, and Jie Tang. 2019a. Towards knowledge-based recommender dialog system. ArXiv, abs/1908.05391.

Qibin Chen, Junyang Lin, Yichang Zhang, Ming Ding, Yukuo Cen, Hongxia Yang, and Jie Tang. 2019b. Towards knowledge-based recommender dialog system. ArXiv, abs/1908.05391.

Claudio Greco, Alessandro Suglia, Pierpaolo Basile, and Giovanni Semeraro. 2017. Converse-et-impera: Exploiting deep learning and hierarchical reinforcement learning for conversational recommender systems. In IJCAI.

Dietmar Jannach, Ahtsham Manzoor, Wanling Cai, and Li Chen. 2020. A survey on conversational recommender systems. arXiv preprint arXiv:2004.00646.

Wenqiang Lei, Xiangnan He, Yisong Miao, Qingyun Wu, Richang Hong, Min-Yen Kan, and Tat-Seng Chua. 2020. Estimation-action-reflection: Towards deep interaction between conversational and recommender systems. Proceedings of the 13th International Conference on Web Search and Data Mining.

Feng-Lin Li, Minghui Qiu, Hailing Qin, Xiong-wei Wang, Xing Gao, Jun Huang, Juwei Ren, Zhongzhou Zhao, Weipeng Zhao, Lei Wang, Guwei Jin, and Wei Chu. 2017. Alime assist: An intelligent assistant for creating an innovative e-commerce experience. Proceedings of the 2017 ACM on Conference on Information and Knowledge Management.

Raymond Li, Samira Ebrahimi Kahou, Hannes Schulz, Vincent Michalski, Laurent Charlin, and Chris Pal. 2018. Towards deep conversational recommendations. In Advances in Neural Information Processing Systems 31 (NIPS 2018).

Zhiqiang Liu, Zuohui Fu, Jie Cao, Gerard de Melo, Yik-Cheung Tam, Cheng Niu, and Jie Zhou. 2019. Rhetorically controlled encoder-decoder for modern chinese poetry generation. In ACL.

Michael E. J. Masson. 1983. Conceptual processing of text during skimming and rapid sequential reading. Memory & Cognition, 11:262–274.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositional-ity. In Advances in neural information processing systems, pages 3111–3119.

Seunghwan Moon, Pararth Shah, Anuj Kumar, and Rajen Subba. 2019. OpenDialKG: Explainable conversational reasoning with attention-based walks over knowledge graphs. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 845–854.

Jianmo Ni, Jiacheng Li, and Julian McAuley. 2019. Justifying recommendations using distantly-labeled reviews and fine-grained aspects. 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), pages 188–197.

Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. Bpr: Bayesian personalized ranking from implicit feedback. In Proceedings of the 25th conference on uncertainty in artificial intelligence, pages 452–461. AUAI Press.

Yueming Sun and Yi Zhang. 2018. Conversational recommender system. In SIGIR ’18.

Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua. 2019. Kgat: Knowledge graph attention network for recommendation. In KDD.

Sam Wiseman, Stuart M. Shieber, and Alexander M. Rush. 2018. Learning neural templates for text generation. In EMNLP.
Liu Yang, Minghui Qiu, Chen Qu, Jiafeng Guo, Yongfeng Zhang, W. Bruce Croft, Jun Huang, and Haiqing Chen. 2018. Response ranking with deep matching networks and external knowledge in information-seeking conversation systems. *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*.

Chunyuan Yuan, Wenjie Zhou, MingMing Li, Shangwen Lv, Fuqing Zhu, Jizhong Han, and Songlin Hu. 2019. Multi-hop selector network for multi-turn response selection in retrieval-based chatbots. In *EMNLP/IJCNLP*.

Yongfeng Zhang and Xu Chen. 2018. Explainable recommendation: A survey and new perspectives. *Found. Trends Inf. Retr.*, 14:1–101.

Yongfeng Zhang, Xu Chen, Qingyao Ai, Liu Yang, and W Bruce Croft. 2018. Towards conversational search and recommendation: System ask, user respond. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 177–186. ACM.

Yongfeng Zhang, Guokun Lai, Min Zhang, Yi Zhang, Yiqun Liu, and Shaoping Ma. 2014. Explicit factor models for explainable recommendation based on phrase-level sentiment analysis. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*, pages 83–92. ACM.

Wayne Xin Zhao, Gaole He, Kunlin Yang, Hongjian Dou, Jin Huang, Siqi Ouyang, and Ji-Rong Wen. 2019. Kb4rec: A data set for linking knowledge bases with recommender systems. *Data Intelligence*, 1(2):121–136.

Xiangyang Zhou, Lu Li, Daxiang Dong, Yi Liu, Ying Chen, Wayne Xin Zhao, Dianhai Yu, and Hua Wu. 2018. Multi-turn response selection for chatbots with deep attention matching network. In *ACL*. 