Finetuning Large-Scale Pre-trained Language Models for Conversational Recommendation with Knowledge Graph

Lingzhi Wang[1,2][*] **Huang Hu**[4], **Lei Sha**[3], **Can Xu**[4], **Kam-Fai Wong**[1,2], **Daxin Jiang**[4][†]

[1]The Chinese University of Hong Kong, Hong Kong, China
[2]MoE Key Laboratory of High Confidence Software Technologies, China
[3]The University of Oxford, United Kingdom
[4]Microsoft Corporation, Beijing, China
[1,2]{lzwang,kfwong}@se.cuhk.edu.hk; [3]lei.sha@cs.ox.ac.uk;
[4]{huahu,caxu,djiang}@microsoft.com

Abstract

In this paper, we present a pre-trained language model (PLM) based framework called **RID** for conversational recommender system (CRS). **RID** finetunes the large-scale PLMs such as DialoGPT, together with a pre-trained Relational Graph Convolutional Network (RGCN) to encode the node representations of an item-oriented knowledge graph. The former aims to generate fluent and diverse dialogue responses based on the strong language generation ability of PLMs, while the latter is to facilitate the item recommendation by learning better node embeddings on the structural knowledge base. To unify two modules of dialogue generation and item recommendation into a PLMs-based framework, we expand the generation vocabulary of PLMs to include an extra item vocabulary, and introduces a vocabulary pointer to control when to recommend target items in the generation process. Extensive experiments on the benchmark dataset REDIAL show RID significantly outperforms the state-of-the-art methods on both evaluations of dialogue and recommendation[1].

1 Introduction

Building an intelligent agent that can freely chat with humans and provide accurate recommendations through interactive conversations, has been one of the longest standing goals in natural language processing (NLP) and artificial intelligence (AI). Thanks to the progress in deep learning, the research on the dialogue system has been greatly advanced over the past few years. Various end-to-end neural approaches have been proposed to address the open-domain dialogue system (Vinyals and Le, 2015; Shang et al., 2015; Sordoni et al., 2015; Serban et al., 2016; Xing et al., 2017) and task-oriented ones (Bordes et al., 2017; Zhao et al., 2017; Lei et al., 2018; Peng et al., 2020). The recent breakthrough in pre-training techniques (Devlin et al., 2019; Liu et al., 2019; Radford et al., 2019; Brown et al., 2020; Dong et al., 2019) sheds a light on the future direction of dialogue system. Large-scale generative pre-training dialogue models such as DialoGPT (Zhang et al., 2020a), Meena (Adiwardana et al., 2020), BlenderBot (Roller et al., 2021) and PLATO-XL (Bao et al., 2021b), also exhibit the compelling performance.

In recent years, there are fast-growing research interests to address Conversational Recommender System (CRS) (Li et al., 2018; Sun and Zhang, 2018; Zhou et al., 2020a), due to the booming of intelligent agents in e-commerce platforms. It aims to recommend target items to users through interactive conversations. Traditional recommender systems perform personalized recommendations based on user's previous implicit feedback like clicking or purchasing histories, while CRS can proactively ask clarification questions and extract user preferences from conversation history to conduct precise recommendations. Existing generative methods (Chen et al., 2019; Zhou et al., 2020a; Ma et al., 2020; Liang et al., 2021) are generally composed of two modules, *i.e.*, a recommender module to predict precise items and a dialogue module to generate free-form natural responses containing the recommended items. Such methods usually utilize Copy Mechanism (Gu et al., 2016) or Pointer Network (Gulcehre et al., 2016) to inject the recommended items into the generated replies. On the one hand, these strategies cannot always incorporate the recommended items into the generated responses precisely and appropriately. On the other hand, most of the existing CRS datasets (Li et al., 2018; Zhou et al., 2020b; Liu et al., 2020, 2021) are relatively small (∼10K dialogues) due to the expensive crowd-sourcing labor. The end-to-end neural models trained on these datasets from scratch are

---

[1]The code will be publicly available at https://github.com/Lingzhi-WANG/PLM-BasedCRS

prone to be overfitting and have the undesirable quality on the generated replies in practice.

Encouraged by the compelling performance of pre-training techniques, we present a pre-trained language models (PLMs) based framework called **RID** to address these challenges. **RID** integrates the item **R**ecommendation **I**nto the **D**ialogue generation under the pretrain-finetune schema. Specifically, RID finetunes the powerful PLMs like DialoGPT (Zhang et al., 2020b) together with a pre-trained Relational Graph Convolutional Network (RGCN) to encode the node representation of an item-oriented knowledge graph. The former aims to generate fluent and diverse dialogue responses based on the strong language generation ability of PLMs, while the latter is to facilitate the item recommendation by learning better structural node representations. To bridge the gap between response generation and item recommendation, we expand the generation vocabulary of PLMs to include an extra item vocabulary. Then a vocabulary pointer is introduced to control when to predict a target item from the item vocabulary or an ordinary word from generation vocabulary in the generation process. The introduced item vocabulary and vocabulary pointer effectively unify the two individual modules into one PLM-based framework.

To better investigate end-to-end CRS system, we argue to evaluate the performance of recommendation by checking whether the final responses contain the target items. Existing works separately evaluate the performance of the two modules, *i.e.*, dialogue generation and item recommendation. However, copy mechanism or pointer network cannot always inject the recommended items into generated replies precisely and appropriately. The performance of the final recommendations is actually lower than that of the recommender module. For instance, the Recall@1 of recommender module in KGSF (Zhou et al., 2020a) is 3.9% while the actual performance is only 0.9% when evaluating the final integrated responses. We conduct extensive experiments on the benchmark REDIAL (Li et al., 2018). Our RID achieves a remarkable improvement on the recommendation over the state-of-the-art, and the generated responses are also significantly better on automatic metrics as well as human evaluation. Further ablation studies and quantitative and qualitative analyses demonstrate the superior performance of our approach. The contributions of this work can be summarized as follows:

- We propose a PLM-based framework called RID for conversational recommendation. RID finetunes the large-scale PLMs together with a pre-trained Relational Graph Convolutional Network (RGCN) to address the low-resource challenge in current CRS.

- By introducing an extra item vocabulary with a vocabulary pointer to control when to recommend, RID effectively unifies two components of item recommendation and response generation into a PLM-based framework.

- Extensive experiments show RID significantly outperforms the state-of-the-art methods on both evaluations of dialogue generation and recommendation.

2 Related Work

Recently, extensive efforts from both academia and industry have been devoted to exploring conversational recommender systems (CRS) based on different hypotheses and application scenarios. Existing works in the literature can be mainly divided into two groups, namely attribute-based CRS and open-ended CRS. In the rest of this section, we will briefly review these works.

Attribute-based CRS. The attribute-based CRS can be viewed as a question-driven task-oriented dialogue system (Zhang et al., 2018; Sun and Zhang, 2018). This kind of systems proactively ask clarification questions about the item attributes to infer user preferences, and thus search for the optimal candidates to recommend. There are various asking strategies studied by existing works, such as entropy-ranking based approach (Wu et al., 2018), generalized binary search based approaches (Zou and Kanoulas, 2019; Zou et al., 2020), reinforcement learning based approaches (Hu et al., 2018; Chen et al., 2018; Lei et al., 2020a; Deng et al., 2021), adversarial learning based approach (Ren et al., 2020b) and graph based approaches (Xu et al., 2020; Lei et al., 2020b; Ren et al., 2021; Xu et al., 2021). Another line of research on this direction address the trade-off issue between exploration (*i.e.*, asking questions) and exploitation (*i.e.*, making recommendations) to achieve both the engaging conversations and successful recommendations, especially for the cold-start users. Some of them leverage bandit online recommendation methods to address cold-start scenarios (Li et al., 2010, 2016b; Christakopoulou et al., 2016; Li et al.,

2020), while others focus on the asking strategy with fewer turns (Lei et al., 2020a,b; Shi et al., 2019; Sun and Zhang, 2018).

Open-ended CRS. Existing works (Li et al., 2018; Lei et al., 2018; Jiang et al., 2019; Ren et al., 2020a; Hayati et al., 2020; Ma et al., 2020; Liu et al., 2020; Liang et al., 2021) on this direction explore CRS through more free-form conversations, including proactively ask clarification questions, chat with users, provide the recommendation, etc. Multiple datasets have been released to help push forward the research in this area, such as REDIAL (Li et al., 2018), TG-REDIAL (Chinese) (Zhou et al., 2020b), INSPIRED (Hayati et al., 2020) and DuRecDial (Liu et al., 2020, 2021). Li et al. (2018) make the first attempt on this direction and contribute the benchmark dataset RE-DIAL by the paired crowd-workers (*i.e.*, Seeker and Recommender). Follow-up studies (Chen et al., 2019; Zhou et al., 2020a,b) leverage the multiple external knowledge to enhance the performance of open-ended CRS. CR-Walker (Ma et al., 2020) is proposed to perform the tree-structured reasoning on the knowledge graph to introduce relevant items, while MGCG (Liu et al., 2020) addresses the transition policy from a non-recommendation dialogue to a recommendation-oriented one. Recently, Liang et al. (2021) propose NTRD to decouple the dialogue generation from the item recommendation, which combines the advantage of classic slot filling approaches and modern neural NLG approaches. Besides, Zhou et al. (2021) develop an open-source toolkit CRSLab to further facilitate the research on this direction. Most of these works utilize pointer network (Gulcehre et al., 2016) or copy mechanism (Gu et al., 2016; Sha et al., 2018) to inject the recommended items into generated replies. Our work lies in the research of open-ended CRS. While different from the previous work, we present a PLM-based framework for CRS, which finetunes the large-scale PLMs together with a pre-trained Relational Graph Convolutional Network (RGCN) to encode the node representations of an item-oriented knowledge graph.

3 Methodology

In this section, we present our proposed RID model. Figure 1 shows the model overview. We first formalize the conversational recommendation task, then elaborate the response generation model architecture and vocabulary pointer. After that, we in-
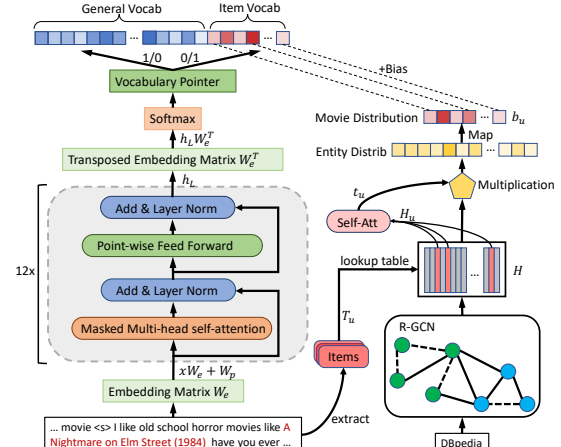

Figure 1: Model overview of RID.

troduce how to finetune the generation model with a Relational Graph Convolution Network (RGCN) pre-trained on an item-oriented knowledge graph and top-k item recommendation in beam search. Finally, we describe the model training objectives.

3.1 Problem Formalization

The dialogue context is denoted as a sequence of utterances $\{t_1, t_2, ..., t_m\}$, where m represents the length of context *i.e.*, the number of utterances. Each utterance is either given by the seeker (user) or recommender (the model), which contains the token sequence $\{w_{i,1}, w_{i,2}, ..., w_{i,n_i}\}$ $(1 \leq i \leq m)$, where w_{ij} is the j-th token in the i-th utterance and n_i is the number of tokens in i-th utterance. Note that we define the name of an item as a single token and do not tokenize it. The output tokens sequence by the model is denoted as $\{w_{n+1}, w_{n+2}, ..., w_{n+k}\}$, where k is the number of generated tokens and $n = \sum_1^m n_i$ is the total number of tokens in context. When the model conducts the recommendation, it will generate an item token w_{n+i} together with the corresponding context. In this way, recommendation item and response are generated concurrently.

3.2 Response Generation Model

In this subsection, we introduce how to extend PLMs to handle conversational recommendation task and produce items recommendation during the dialogue generation.

PLM-based Response Generation. Given the input (*i.e.*, the conversation history context $\{t_1, t_2, ..., t_m\}$), we concatenate the history utterances into the context $C = \{w_1, w_2, ..., w_n\}$ where n is the total number of tokens in the context.

Then the probability of the generated response $R = \{w_{n+1}, w_{n+2}, ..., w_{n+k}\}$ is formulated as:

$$\text{PLM}(R|C) = \prod_{i=n+1}^{n+k} p(w_i|w_1, ..., w_{i-1}). \quad (1)$$

where $\text{PLM}(\cdot|\cdot)$ denotes the PLMs of Transformer (Vaswani et al., 2017) architecture. For a multi-turn conversation, we can construct N such context-response pairs, where N is the number of utterances by the recommender. Then we finetune the PLMs on all possible (C, R) pairs constructed from the dialogue corpus. By this means, not only does our model inherit the strong language generation ability of the PLMs, but also simultaneously can learn how to generate the recommendation utterances on the relatively small CRS dataset.

PLM-based Item Generation. To integrate the item recommendation into the generation process of PLMs, we propose to expand the generation vocabulary of PLMs to include an extra item vocabulary, and devise a vocabulary pointer to control when to generate token from the ordinary vocabulary or item vocabulary. Concretely, we denote each item as a single token and add all items into the item vocabulary. Hence, our model can learn the relationship between context words and candidate items. Such a process integrates the response generation and item recommendation into a unified model that can perform the end-to-end recommendation through dialogue generation.

Vocabulary Pointer. We first preprocess the dialogue corpus and introduce two special tokens [RecS] and [RecE] to indicate the start and end positions of the item in utterance. Then we divide the whole vocabulary V into V_G and V_R, where V_G includes the general tokens (*i.e.*, tokens in the original vocabulary of PLM) and [RecS] while V_R contains the all item tokens and [RecE]. After that, we introduce a binary *Vocabulary Pointer* I_{vp} to guide the generation from V_G or V_R. The model generates tokens in V_G when $I_{vp} = 0$, and generates the tokens in V_R when $I_{vp} = 1$, which can be formulated as follows:

$$p(w = w_i) = \frac{exp(\phi_I(w_i) + \tilde{h}_i)}{\sum_{w_j \in V} exp(\phi_I(w_j) + \tilde{h}_j)} \quad (2)$$

$$\phi_I(w_j) = \begin{cases} 0, & I_{vp} = 0, w_j \in V_G \text{ or} \\ & I_{vp} = 1, w_j \in V_R, \\ -inf, & I_{vp} = 1, w_j \in V_G \text{ or} \\ & I_{vp} = 0, w_j \in V_R \end{cases} \quad (3)$$

where $\tilde{h} = h_L W_e^T$ is the feature vector before the softmax layer in Figure 1, $\tilde{h}_i$ means the feature value of the i-th token. I_{vp} is initialized as 0 at the beginning of the generation and won't change until the model produces [RecS] or [RecE]. It changes to 1 if the model produces [RecS] (*i.e.*, the model begins to generate items) and changes back to 0 if [RecE] is emitted. Such a procedure continues until the current turn is finished. With the devised *Vocabulary Pointer*, our model can alternatively switch between generating response words and recommending items based on its previous outputs in a unified fashion.

3.3 Knowledge Graph Enhanced Finetuning

Due to the difficulty of fully understanding user preferences by the conversation context, it is necessary to introduce the external knowledge to encode the user preferences when finetuning response generation model. Inspired by the previous work (Chen et al., 2019; Zhou et al., 2020a), we also employ a knowledge graph from DBpedia (Lehmann et al., 2015) and perform entity linking (Daiber et al., 2013) to the items in the dataset, which helps better model the user preferences. A triple in DBpedia is denoted by $< e_1, r, e_2 >$, where $e_1, e_2 \in \mathcal{E}$ are items or entities from the entity set $\mathcal{E}$ and r is entity relation from the relation set $\mathcal{R}$.

Relational Graph Propagation. We utilize R-GCN (Schlichtkrull et al., 2018) to encode structural and relational information in the knowledge graph to entity hidden representations. Formally, the representation of node e at $(l+1)$-th layer is calculated as follows:

$$\boldsymbol{h}_e^{(l+1)} = \sigma(\sum_{r \in \mathcal{R}} \sum_{e' \in \mathcal{E}_e^r} \frac{1}{Z_{e,r}} \boldsymbol{W}_r^{(l)} \boldsymbol{h}_{e'}^{(l)} + \boldsymbol{W}^{(l)} \boldsymbol{h}_e^{(l)}), \quad (4)$$

where $\boldsymbol{h}_e^{(l)} \in \mathbb{R}^{d_E}$ is the node representation of e at the l-th layer, and $\mathcal{E}_e^r$ denotes the set of neighboring nodes for e under the relation r. $\boldsymbol{W}_r^{(l)}$ is a learnable relation-specific transformation matrix for the embedding from neighboring nodes with relation r, while $\boldsymbol{W}^{(l)}$ is another learnable matrix for transforming the representations of nodes at the l-th layer and $Z_{e,r}$ is the partition function.

At the last layer L, structural and relational information is encoded into the entity representation $\boldsymbol{h}_e^{(L)}$ for each $e \in \mathcal{E}$. The resulting knowledge-enhanced hidden representation matrix for entities in $\mathcal{E}$ is denoted as $\boldsymbol{H}^{(L)} \in \mathbb{R}^{|\mathcal{E}| \times d_E}$. We omit the (L) in the following paragraphs for simplicity.

Entity Attention. Given a conversation context, we first collect the entities appeared in the context, and then we represent the user preference as $\mathcal{T}_u = e_1, e_2, ..., e_{|\mathcal{T}_u|}$, where $e_i \in \mathcal{E}$. After looking up the knowledge-enhanced representation table of entities in $\mathcal{T}_u$ from $\boldsymbol{H}$, we get:

$$\boldsymbol{H}_u = (\boldsymbol{h}_1, \boldsymbol{h}_2, ..., \boldsymbol{h}_{|\mathcal{T}_u|}), \qquad (5)$$

where $\boldsymbol{h}_i \in \mathbb{R}^{d_E}$ is the hidden vector of entity e_i. Then the self-attention mechanism (Lin et al., 2017) is applied to $\boldsymbol{H}_u$, which outputs a distribution α_u over $|\mathcal{T}_u|$ vectors:

$$\alpha_u = softmax(\boldsymbol{w}_{a2} tanh(\boldsymbol{W}_{a1} \boldsymbol{H}_u^T)), \qquad (6)$$

where $\boldsymbol{W}_{a1} \in \mathbb{R}^{d_a \times d_E}$ and $\boldsymbol{w}_{a2} \in \mathbb{R}^{1 \times d_a}$ are learnable parameters. Then we get the final representation for user history u as follows:

$$\boldsymbol{t}_u = \alpha_u \boldsymbol{H}_u. \qquad (7)$$

Knowledge-Aware Bias. To incorporate the knowledge from the constructed knowledge graph into our model while generating recommendation items, we first map the derived user representation $\boldsymbol{t}_u$ into the item vocabulary space $|V_R|$ as follows:

$$\boldsymbol{b}_u = \boldsymbol{t}_u \boldsymbol{H}^T \boldsymbol{M}_b, \qquad (8)$$

where $\boldsymbol{M}_b \in \mathbb{R}^{|\mathcal{E}| \times |V_R|}$ are learnable parameters. Then we add b_u to the projection outputs before softmax operation in the generation as a bias. In this way, our model can produce items in aware of their relational knowledge and thus enhance the performance of recommendation.

3.4 Recommendation in Beam Search

To enable the top-k item recommendation in the generation process, we implement it in the beam search decoding. Specifically, each time after the generation is finished, we check whether the best response in the beam contains the target items. If yes, then we choose the top-k items between [RecS] and [RecE] according to the probability scores at current time-step to calculate Recall@k.

3.5 Learning Objectives

There are learning objectives, *i.e.*, node representation learning on knowledge graph and the finetuning of response generation model. For the former, we optimize the R-GCN and the self-attention network based on the cross entropy of item prediction, which is defined as follows:

$$\mathcal{L}_{kg} = \sum_{(u,i) \in \mathcal{D}_1} -log(\frac{exp(\boldsymbol{t}_u \boldsymbol{H}^T)_i}{\sum_j exp(\boldsymbol{t}_u \boldsymbol{H}^T)_j}), \qquad (9)$$

where the item i is the ground-truth item and u is the corresponding user history, while $\mathcal{D}_1$ contains all training instances and $\boldsymbol{t}_u \boldsymbol{H}^T \in \mathbb{R}^{|\mathcal{E}|}$.

For the latter, we optimize another cross entropy loss for all generated responses, denoted as R. The following formula summarizes the process:

$$\mathcal{L}_{gen} = \sum_{(C,R) \in \mathcal{D}_2} \sum_{w_i \in R} -log(p(w_i|w_{<i}, C)), \qquad (10)$$

where $p(w_i)$ refers to Eq. 2 and $\mathcal{D}_2$ contains all (C, R) pairs constructed from the dataset.

4 Experimental Setup

Datasets. We evaluate our model on the benchmark dataset REDIAL (Li et al., 2018), which collects the human conversations on movie recommendation on Amazon Mechanical Turk (AMT) platform with pair crowd-workers (*i.e.*, Seeker and Recommender). The statistics of REDIAL dataset is shown in Table 1. As we can see, the users speak briefly (as the average token length of utterances is 6.8), and most conversations last for a long round (as the average turn number is 18.2). There are 6924 movies in total, and they are mentioned 7.5 times on average. More detailed statistics of movie mentions are shown in Figure 2(a). Most of the movies occur less than 5 times in the dataset, which indicates an obvious data imbalance problem in the REDIAL. We also show the relationship between the average number of movie mentions and the number of dialog turns in Figure 2(b). As we can see, there are only less than 2 movie mentions when the number of dialogue turns is less than 5. Cold-start problem will be discussed in Section 5.5. Finally, we following (Li et al., 2018) to split the dataset into 80-10-10, for training, validation and test (*i.e.*, original division).

Parameter Setting. We finetune the small size pre-trained DialoGPT model[2], which consists of 12 transformer layers. The dimension of embeddings is 768. It is trained on 147M multi-turn dialogues from Reddit discussion threads. For the knowledge graph (KG), both the entity embedding size and the hidden representation size are set to 128, and we set the layer number for R-GCN to 1. For BART baseline, we finetune the base model [3] with 6 layers in each of the encoder and decoder, and a hidden

---

[2] https://huggingface.co/microsoft/DialoGPT-small
[3] https://huggingface.co/facebook/bart-base

Conversations		Movies	
# of convs	10006	# of mentions	51699
# of utterances	182150	# of movies	6924
# of users	956	avg mentions	7.5
avg token length	6.8	max mentions	1024
avg turn #	18.2	min mentions	1

Table 1: Statistics of ReDial dataset. "#" means number and "avg" refers to average.

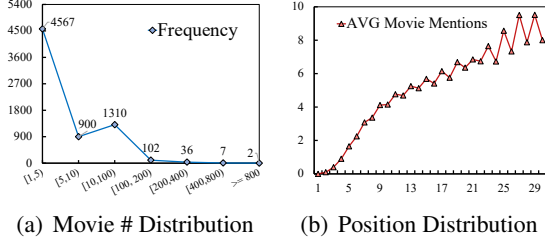(a) Movie # Distribution   (b) Position Distribution

Figure 2: For Figure 2(a), X-axis: the movie mentions range; Y-axis: movie numbers. For Figure 2(b), X-axis: turn positions; Y-axis: average movie mentions.

size of 1024. For GPT-2 baseline, we finetune the small model[4]. For all model's training, we adopt Adam optimizer and the learning rate is chosen from $\{1e-5, 1e-4\}$. The batch size is chosen from $\{32, 64\}$, the gradient accumulation step is set to 8, the warm up step is chose from $\{500, 800, 1000\}$. All the hyper-parameters are determined by grid-search.

Baselines and Comparisons. We first introduce two baselines for recommender and dialogue modules, respectively. (1) **Popularity**. It ranks the movie items according to their historical frequency in the training set without a dialogue module. (2) **Transformer** (Vaswani et al., 2017). It utilizes a transformer-based encoder-decoder to generate responses without recommender module.

We then compare the following baseline models in the experiment: (3) **ReDial** (Li et al., 2018). It consists of a dialogue generation module based on HRED (Serban et al., 2017), a recommender module based on auto-encoder (He et al., 2017), and a sentiment analysis module. (4) **KBRD** (Chen et al., 2019). It utilizes a knowledge graph from DBpedia to model the relational knowledge of contextual items or entities, and the dialogue generation module is based on the transformer architecture. (5) **KGSF** (Zhou et al., 2020a). It incorporates and fuses both word-level and entity-level knowledge graphs to learn better semantic representations for user preferences. (6) **GPT-2**. We directly finetune GPT-2 and expand its vocabulary to include the

---

[4] https://huggingface.co/gpt2

item vocabulary. (7) **BART**. We directly finetune BART and expand its vocabulary to include the same item vocabulary. (8) **DialoGPT**. We directly finetune DialoGPT and expand its vocabulary to include same item vocabulary.

For our RID, in addition to the full model (9) **RID**, we also evaluate two variants: (10) **RID *w/o* VP**, where we remove the vocabulary pointer; and (11) **RID *w/o* KG**, where the knowledge graph part is removed.

Evaluation Metrics. As we discussed above, the previous works evaluate the recommender and dialogue modules separately. Following the previous setting (Chen et al., 2019; Zhou et al., 2020a), we evaluate the recommender module by Recall@k (k = 1, 10, 50). Besides, we also evaluate Recall@k in an end-to-end manner, *i.e.*, to check whether the final produced response contains the target item. For the dialogue module, automatic metrics include: (1) **Fluency**: perplexity (PPL) measures the confidence of the generated responses. (2) **Relevance**: BLEU-2/4 (Papineni et al., 2002) and Rouge-L (Lin, 2004). (3) **Diversity**: Distinct-n (Dist-n) (Li et al., 2016a) are defined as the number of distinct n-grams divided by the total amount of words. Specifically, we use Dist-2/3/4 at the sentence level to evaluate the diversity of generated responses. Besides, we also employ Item Ratio introduced in KGSF (Zhou et al., 2020a) to measure the ratio of items in the generated responses.

5 Experimental Results

In this section, we first report the comparison results on recommendation and response generation, respectively. Then we discuss the human evaluation results. After that, we show an example to illustrate how our model works, followed by further qualitative analysis.

5.1 Results on Recommendation

The main experimental results for our RID and baseline models on recommendation side are presented in Table 2. And we can draw several observations from the results.

There is a significant gap between the performance of the recommender module and the performance of the final integrated system. KGSF, the state-of-the-art model, achieves 3.9% Recall@1 in the recommender module evaluation but yields only 0.9% in the evaluation of the final produced

Models	Eval on Rec Module			End-to-End Eval		
	R@1	R@10	R@50	R@1	R@10	R@50
Baselines						
Popularity	1.2	6.1	17.9	1.2	6.1	17.9
ReDial	2.4	14.0	32.0	0.7	4.4	10.0
KBRD	3.1	15.0	33.6	0.8	3.8	8.8
KGSF	3.9	18.3	37.8	0.9	4.2	8.8
GPT-2	-	-	-	1.4	6.5	14.4
BART	-	-	-	1.5	-	-
DialoGPT	-	-	-	1.7	7.1	13.8
RID	-	-	-	**3.1**	**14.0**	**27.0**

Table 2: Main comparison results on recommendation. R@k refers to Recall@k (k=1, 10 and 50).

Models	R@1	R@10	R@50	Item Ratio	BLEU	Rouge-L
RID	**3.1**	**14.0**	**27.0**	**43.5**	**20.7**	**17.6**
RID *w/o* VP	1.8	8.8	19.5	17.8	18.5	14.6
RID *w/o* KG	2.3	9.4	20.1	39.8	17.7	12.9

Table 3: Comparison results on ablation study.

Models	Dist-2	Dist-3	Dist-4	IR	BL-2	BL-4	Rouge-L	PPL↓
Baselines								
Transformer	14.8	15.1	13.7	19.4	-	-	-	-
ReDial	22.5	23.6	22.8	15.8	17.8	7.4	16.9	61.7
KBRD	26.3	36.8	42.3	29.6	18.5	7.4	17.1	58.8
KGSF	28.9	43.4	51.9	32.5	16.4	7.4	14.3	131.1
GPT-2	35.4	48.6	44.1	14.5	17.1	7.7	11.3	56.3
BART	37.6	49.0	43.5	16.0	17.8	9.3	13.1	55.6
DialoGPT	47.6	55.9	48.6	15.9	16.7	7.8	12.3	56.0
RID	**51.8**	**62.4**	**59.8**	**43.5**	**20.4**	**11.0**	**17.6**	**54.1**

Table 4: Automatic metrics on generated responses. IR denotes the Item Ratio.

Models	Fluency	Informative	Coherence	Kappa
HUMAN	1.95	1.71	**1.71**	**0.74**
ReDial	1.92	1.32	1.23	0.70
KBRD	1.95	1.39	1.31	0.77
KGSF	1.91	1.02	0.95	0.65
RID	**1.98**	**1.71**	1.63	0.54

Table 5: Human evaluation results.

responses. This indicates that the integration strategies utilized by previous methods have significant harm on the recommendation performance.

Finetuning PLMs on the small CRS dataset is effective. As we can see, compared to non-PLM based methods, directly finetuning GPT-2/BART/DialoGPT on the REDIAL achieves the obvious performance gain on recommendation.

Our RID model significantly outperforms the SOTAs on recommendation performance. As shown in Table 2, our RID achieves the best Recall@k (k = 1, 10, 50) scores under the end-to-end evaluation, which demonstrates the superior performance of the PLMs with the unified design.

5.2 Results on Dialogue Generation

Since CRS aims to recommend items during natural conversations, we conduct both the automatic and human evaluations to investigate the quality of generated responses by RID and baselines.

Automatic Evaluation. Table 4 shows the main comparison results on Dist-2/3/4, BLEU-2/4, Rouge-L and PPL. As we can see, RID significantly outperforms all baselines on Dist-n, which indicates that *PLM helps generate more diverse responses.* Previous works suffer from the low-resource issue due to the small crowd-sourcing CRS dataset and tend to generate boring and singular responses. On the other hand, *our RID model tends to recommend items more frequently*, as the Item Ratio score of RID is much higher than those of baselines. Besides, our RID and PLM-based methods consistently achieve remarkable improvement over non-PLM based methods on all metrics, which demonstrates the superior performance of PLMs on dialogue generation.

Human Evaluation. To further investigate the effectiveness of our RID, we conduct a human evaluation experiment, where two crowd-workers are employed to score on 100 context-response pairs that are randomly sampled from the test set. Then, we collect the generation results of our model and the baseline models and compare their performance on the following three aspects: (1) **Fluency**. Whether the response is organized in regular English grammar and easy to understand. (2) **Informativeness**. Whether the response is meaningful and not a "safe response", and repetitive responses are regarded as uninformative. (3) **Coherence**. Whether the response is coherent with the previous context. The crowd-workers give a score on the scale of [0, 1, 2] to show the quality of the generated sentences, and higher scores indicate better qualities. We use the following three criteria in PLATO (Bao et al., 2021a) and the scoring details are provided in Appendix.

We calculate the average score for each model, as well as the ground truth that humans give. As shown in Table 5, our model shows better performance than all the baselines. Interestingly, ground-truth Human cannot get a 100% correctness in all the four evaluation metrics and our RID achieves even better fluency performance than Human. The reason may be that words and phases sent by human annotators on AMT platform sometimes are the casual usage popular on Internet, which have

the wrong grammars. For the fluency, all models generate fluent utterances and show similar performance. For the informativeness, our RID achieve much better performance than the baselines, which indicates RID tends to generate more meaningful responses.

5.3 Ablation Study

We then report the performance comparisons on our model's variants. Table 3 shows the end-to-end recommendation performance and generation results. Removing the vocabulary pointer leads to significant drops on R@k and Item Ratio. *This indicate Vocabulary Pointer (VP) introduced in RID is crucial to the performance of item recommendation.* The reason is that the generation process would lose the guidance to switch between general tokens and recommended items without the help of the vocabulary pointer. Besides, we can also found that *knowledge graph enhanced finetuning helps achieve better recommendation performance.* Introducing the node representations learned on the knowledge graph is beneficial to a better user preference modeling, which could further enhance the recommendation performance.

5.4 Qualitative Analysis

In this subsection, we present a conversation example to illustrate how our model works in practice. More examples are included in Appendix.

In Figure 6, the *Seeker* states that he likes scary movies. Our model successfully captured the keyword of "scary" and recommends a famous scary movie "*It (2017)*" while the state-of-the-art model KGSF produces a safe response "Hello!", which shows our RID can generate the responses that are more coherent with the context. Interestingly, after the *Seeker* says he watched the old "*It (1990)*", our model recommends another horror movie "*Psycho (1960)*" also released in the last century. The possible reason is that RID infers the seeker is interested in old horror movies. The example in Figure 6 shows that our RID tends to generate a more informative response than KGSF. In addition, we find that KGSF always generates "I would recommend *Item*" (*Item* is replaced with *Get out (2017)* in this example) and "I would recommend it.". The first response pattern successfully integrates the movie item into the response, while the second fails to make a complete recommendation, which reveals the drawback of the copy mechanism in KGSF.

Conversation Example	
User:	I like to watch scary movies
Human:	Tell me what kind of movie do you like? Did you watch *It (2017)*? And *It (1990)*?
KBRD:	Hi, what kind of movies do you like?
KGSF:	Hello!
RID:	Have you seen *It (2017)*?
User:	I have seen the old one
Human:	Did you watch *The Exorcist (1973)*?
KBRD:	*Get Out (2017)*
KGSF:	I would recommend *Get Out (2017)*
RID:	How about *Psycho (1960)*?
User:	I have not seen the new one I do like the exorcist
Human:	Ok, you should watch the new one even though I would rather the old one. And did you watch *The Last Exorcism (2010)*? I hope I have helped
KBRD:	I haven't seen that one
KGSF:	I would recommend it
RID:	Yes, it was good. I hope you enjoy it. Have a good day. Bye
User:	No I have not but it sounds scary! Thank you for the suggestions!
Human:	You should try them. you're welcome
KBRD:	bye
KGSF:	Bye
RID:	You're welcome bye

Table 6: A conversation example on *movie item* recommendation. The responses of **KBRD**, **KGSF** and **RID** are from the test results for corresponding models. **Human** responses are ground-truth.

5.5 Further Analysis

Analysis on Data Imbalance. As we discussed aforementioned, the movie occurrence frequency shows an imbalanced distribution over different movies (see Figure 2(a)). To investigate the effect, we report the Recall@30 and Recall@50 scores over movie mentioned times in Figure 3(a). As we can see, the recall scores for low-frequency movies (with mentioned times less than 10) are much lower than those high-frequency movies (with > 100 mentions). However, most of the movies (5467 out of 6924 movies) in the REDIAL dataset are low-frequency movies, which leads to relatively low results in the overall performance.

Analysis on Cold Start. Figure 2(b) shows that the REDIAL dataset suffers from the cold-start problem. It is hard for models to recommend precise items in the first few turns of the conversation. We report the Recall@30 and Recall@50 scores of our RID over different dialogue turns in Figure 3(b). Generally, we can see that the recall scores are getting better with richer information

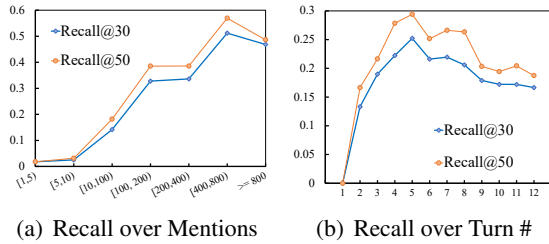(a) Recall over Mentions   (b) Recall over Turn #

Figure 3: Y-axis: Recall. For Fig. 3(a), X-axis: Movie mentions range. For Fig. 3(b), X-axis: turn numbers.

gradually obtained from dialogue interactions. The scores begin to drop when there are more than 5 turns. The possible reason is that as the conversation goes deeper, the Seekers are no longer satisfied with the recommended high-frequency movies but prefer more personalized recommendations, which makes it more difficult to predict in practice.

6 Conclusion

This paper presents a novel PLM-based framework called **RID** for CRS, which integrates the item recommendation into the generation process of PLM. Specifially, we finetunes the large-scale PLMs together with a pre-trained relational graph convolutional network on an item-oriented knowledge graph. To unify the response generation and item recommendation into the existing PLMs, we expand the generation vocabulary of PLMs to inlcude an extra item vocabulary, and devise a vocabulary to control when to generate a ordinary word from generation vocabulary or an item from item vocabulary. Extensive experiments on a CRS benchmark dataset REDIAL show that our proposed RID significantly outperforms the state-of-the-art methods.

References

Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, et al. 2020. Towards a human-like open-domain chatbot. *arXiv preprint arXiv:2001.09977*.

Siqi Bao, Huang He, Fan Wang, Hua Wu, Haifeng Wang, Wenquan Wu, Zhen Guo, Zhibin Liu, and Xinchao Xu. 2021a. PLATO-2: Towards building an open-domain chatbot via curriculum learning. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 2513–2525, Online. Association for Computational Linguistics.

Siqi Bao, Huang He, Fan Wang, Hua Wu, Haifeng Wang, Wenquan Wu, Zhihua Wu, Zhen Guo, Hua

Lu, Xinxian Huang, et al. 2021b. Plato-xl: Exploring the large-scale pre-training of dialogue generation. *arXiv preprint arXiv:2109.09519*.

Antoine Bordes, Y-Lan Boureau, and Jason Weston. 2017. Learning end-to-end goal-oriented dialog. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Qibin Chen, Junyang Lin, Yichang Zhang, Ming Ding, Yukuo Cen, Hongxia Yang, and Jie Tang. 2019. Towards knowledge-based recommender dialog system. 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 1803–1813, Hong Kong, China. Association for Computational Linguistics.

Yihong Chen, Bei Chen, Xuguang Duan, Jian-Guang Lou, Yue Wang, Wenwu Zhu, and Yong Cao. 2018. Learning-to-ask: Knowledge acquisition via 20 questions. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2018, London, UK, August 19-23, 2018*, pages 1216–1225. ACM.

Konstantina Christakopoulou, Filip Radlinski, and Katja Hofmann. 2016. Towards conversational recommender systems. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016*, pages 815–824. ACM.

Joachim Daiber, Max Jakob, Chris Hokamp, and Pablo N Mendes. 2013. Improving efficiency and accuracy in multilingual entity extraction. In *Proceedings of the 9th International Conference on Semantic Systems*, pages 121–124.

Yang Deng, Yaliang Li, Fei Sun, Bolin Ding, and Wai Lam. 2021. Unified conversational recommendation policy learning via graph-based reinforcement learning. *arXiv preprint arXiv:2105.09710*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of

deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 13042–13054.

Jiatao Gu, Zhengdong Lu, Hang Li, and Victor O.K. Li. 2016. Incorporating copying mechanism in sequence-to-sequence learning. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1631–1640, Berlin, Germany. Association for Computational Linguistics.

Caglar Gulcehre, Sungjin Ahn, Ramesh Nallapati, Bowen Zhou, and Yoshua Bengio. 2016. Pointing the unknown words. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 140–149, Berlin, Germany. Association for Computational Linguistics.

Shirley Anugrah Hayati, Dongyeop Kang, Qingxiaoyang Zhu, Weiyan Shi, and Zhou Yu. 2020. INSPIRED: Toward sociable recommendation dialog systems. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8142–8152, Online. Association for Computational Linguistics.

Junhua He, Hankz Hankui Zhuo, and Jarvan Law. 2017. Distributed-representation based hybrid recommender system with short item descriptions. *arXiv preprint arXiv:1703.04854*.

Huang Hu, Xianchao Wu, Bingfeng Luo, Chongyang Tao, Can Xu, Wei Wu, and Zhan Chen. 2018. Playing 20 question game with policy-based reinforcement learning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3233–3242, Brussels, Belgium. Association for Computational Linguistics.

Shaojie Jiang, Pengjie Ren, Christof Monz, and Maarten de Rijke. 2019. Improving neural response diversity with frequency-aware cross-entropy loss. In *The World Wide Web Conference, WWW 2019, San Francisco, CA, USA, May 13-17, 2019*, pages 2879–2885. ACM.

Jens Lehmann, Robert Isele, Max Jakob, Anja Jentzsch, Dimitris Kontokostas, Pablo N Mendes, Sebastian Hellmann, Mohamed Morsey, Patrick Van Kleef, Sören Auer, et al. 2015. Dbpedia–a large-scale, multilingual knowledge base extracted from wikipedia. *Semantic web*, 6(2):167–195.

Wenqiang Lei, Xiangnan He, Yisong Miao, Qingyun Wu, Richang Hong, Min-Yen Kan, and Tat-Seng Chua. 2020a. Estimation-action-reflection: Towards deep interaction between conversational and recommender systems. In *WSDM '20: The Thirteenth ACM International Conference on Web Search and Data Mining, Houston, TX, USA, February 3-7, 2020*, pages 304–312. ACM.

Wenqiang Lei, Xisen Jin, Min-Yen Kan, Zhaochun Ren, Xiangnan He, and Dawei Yin. 2018. Sequicity: Simplifying task-oriented dialogue systems with single sequence-to-sequence architectures. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1437–1447, Melbourne, Australia. Association for Computational Linguistics.

Wenqiang Lei, Gangyi Zhang, Xiangnan He, Yisong Miao, Xiang Wang, Liang Chen, and Tat-Seng Chua. 2020b. Interactive path reasoning on graph for conversational recommendation. In *KDD '20: The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020*, pages 2073–2083. ACM.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016a. A diversity-promoting objective function for neural conversation models. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 110–119, San Diego, California. Association for Computational Linguistics.

Lihong Li, Wei Chu, John Langford, and Robert E. Schapire. 2010. A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th International Conference on World Wide Web, WWW 2010, Raleigh, North Carolina, USA, April 26-30, 2010*, pages 661–670. ACM.

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: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018, December 3-8, 2018, Montréal, Canada*, pages 9748–9758.

Shijun Li, Wenqiang Lei, Qingyun Wu, Xiangnan He, Peng Jiang, and Tat-Seng Chua. 2020. Seamlessly unifying attributes and items: Conversational recommendation for cold-start users. *arXiv preprint arXiv:2005.12979*.

Shuai Li, Alexandros Karatzoglou, and Claudio Gentile. 2016b. Collaborative filtering bandits. In *Proceedings of the 39th International ACM SIGIR con-*

ference on Research and Development in Information Retrieval, SIGIR 2016, Pisa, Italy, July 17-21, 2016, pages 539–548. ACM.

Zujie Liang, Huang Hu, Can Xu, Jian Miao, Yingying He, Yining Chen, Xiubo Geng, Fan Liang, and Daxin Jiang. 2021. Learning neural templates for recommender dialogue system. *arXiv preprint arXiv:2109.12302*.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Zhouhan Lin, Minwei Feng, Cícero Nogueira dos Santos, Mo Yu, Bing Xiang, Bowen Zhou, and Yoshua Bengio. 2017. A structured self-attentive sentence embedding. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Zeming Liu, Haifeng Wang, Zheng-Yu Niu, Hua Wu, and Wanxiang Che. 2021. Durecdial 2.0: A bilingual parallel corpus for conversational recommendation. *arXiv preprint arXiv:2109.08877*.

Zeming Liu, Haifeng Wang, Zheng-Yu Niu, Hua Wu, Wanxiang Che, and Ting Liu. 2020. Towards conversational recommendation over multi-type dialogs. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1036–1049, Online. Association for Computational Linguistics.

Wenchang Ma, Ryuichi Takanobu, Minghao Tu, and Minlie Huang. 2020. Bridging the gap between conversational reasoning and interactive recommendation. *arXiv preprint arXiv:2010.10333*.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Baolin Peng, Chunyuan Li, Jinchao Li, Shahin Shayandeh, Lars Liden, and Jianfeng Gao. 2020. Soloist: Few-shot task-oriented dialog with a single pretrained auto-regressive model. *arXiv preprint arXiv:2005.05298*.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Pengjie Ren, Zhumin Chen, Christof Monz, Jun Ma, and Maarten de Rijke. 2020a. Thinking globally, acting locally: Distantly supervised global-to-local knowledge selection for background based conversation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8697–8704.

Xuhui Ren, Hongzhi Yin, Tong Chen, Hao Wang, Zi Huang, and Kai Zheng. 2021. Learning to ask appropriate questions in conversational recommendation. *arXiv preprint arXiv:2105.04774*.

Xuhui Ren, Hongzhi Yin, Tong Chen, Hao Wang, Nguyen Quoc Viet Hung, Zi Huang, and Xiangliang Zhang. 2020b. Crsal: Conversational recommender systems with adversarial learning. *ACM Transactions on Information Systems (TOIS)*, 38(4):1–40.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, and Jason Weston. 2021. Recipes for building an open-domain chatbot. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 300–325, Online. Association for Computational Linguistics.

Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In *European semantic web conference*, pages 593–607. Springer.

Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C. Courville, and Joelle Pineau. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, February 12-17, 2016, Phoenix, Arizona, USA*, pages 3776–3784. AAAI Press.

Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. 2017. A hierarchical latent variable encoder-decoder model for generating dialogues. In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA*, pages 3295–3301. AAAI Press.

Lei Sha, Lili Mou, Tianyu Liu, Pascal Poupart, Sujian Li, Baobao Chang, and Zhifang Sui. 2018. Order-planning neural text generation from structured data. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018*, pages 5414–5421. AAAI Press.

Lifeng Shang, Zhengdong Lu, and Hang Li. 2015. Neural responding machine for short-text conversation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the*

7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1577–1586, Beijing, China. Association for Computational Linguistics.

Chen Shi, Qi Chen, Lei Sha, Hui Xue, Sujian Li, Lintao Zhang, and Houfeng Wang. 2019. We know what you will ask: A dialogue system for multi-intent switch and prediction. In *CCF International Conference on Natural Language Processing and Chinese Computing*, pages 93–104. Springer.

Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 196–205, Denver, Colorado. Association for Computational Linguistics.

Yueming Sun and Yi Zhang. 2018. Conversational recommender system. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, SIGIR 2018, Ann Arbor, MI, USA, July 08-12, 2018*, pages 235–244. ACM.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008.

Oriol Vinyals and Quoc Le. 2015. A neural conversational model. *arXiv preprint arXiv:1506.05869*.

Xianchao Wu, Huang Hu, Momo Klyen, Kyohei Tomita, and Zhan Chen. 2018. Q20: Rinna riddles your mind by asking 20 questions. *Japan NLP*.

Chen Xing, Wei Wu, Yu Wu, Jie Liu, Yalou Huang, Ming Zhou, and Wei-Ying Ma. 2017. Topic aware neural response generation. In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA*, pages 3351–3357. AAAI Press.

Hu Xu, Seungwhan Moon, Honglei Liu, Bing Liu, Pararth Shah, Bing Liu, and Philip Yu. 2020. User memory reasoning for conversational recommendation. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 5288–5308, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Kerui Xu, Jingxuan Yang, Jun Xu, Sheng Gao, Jun Guo, and Ji-Rong Wen. 2021. Adapting user preference to online feedback in multi-round conversational recommendation. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, pages 364–372.

Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020a. DIALOGPT : Large-scale generative pre-training for conversational response generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 270–278, Online. Association for Computational Linguistics.

Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020b. DIALOGPT : Large-scale generative pre-training for conversational response generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 270–278, Online. Association for Computational Linguistics.

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, CIKM 2018, Torino, Italy, October 22-26, 2018*, pages 177–186. ACM.

Tiancheng Zhao, Allen Lu, Kyusong Lee, and Maxine Eskenazi. 2017. Generative encoder-decoder models for task-oriented spoken dialog systems with chatting capability. In *Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue*, pages 27–36, Saarbrücken, Germany. Association for Computational Linguistics.

Kun Zhou, Xiaolei Wang, Yuanhang Zhou, Chenzhan Shang, Yuan Cheng, Wayne Xin Zhao, Yaliang Li, and Ji-Rong Wen. 2021. CRSLab: An open-source toolkit for building conversational recommender system. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 185–193, Online. Association for Computational Linguistics.

Kun Zhou, Wayne Xin Zhao, Shuqing Bian, Yuanhang Zhou, Ji-Rong Wen, and Jingsong Yu. 2020a. Improving conversational recommender systems via knowledge graph based semantic fusion. In *KDD '20: The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020*, pages 1006–1014. ACM.

Kun Zhou, Yuanhang Zhou, Wayne Xin Zhao, Xiaoke Wang, and Ji-Rong Wen. 2020b. Towards topic-guided conversational recommender system. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 4128–4139, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Jie Zou, Yifan Chen, and Evangelos Kanoulas. 2020. Towards question-based recommender systems. In

Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval, SIGIR 2020, Virtual Event, China, July 25-30, 2020, pages 881–890. ACM.

Jie Zou and Evangelos Kanoulas. 2019. Learning to ask: Question-based sequential bayesian product search. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management, CIKM 2019, Beijing, China, November 3-7, 2019*, pages 369–378. ACM.