Meta Policy Learning for Cold-Start Conversational Recommendation

Zhendong Chu zc9uy@virginia.edu

Department of Computer Science University of Virginia, USA

Hongning Wang

Hw5x@virginia.edu

Department of Computer Science University of Virginia, USA

Yun Xiao XIAOYUN1@JD.COM

JD.COM Silicon Valley Research Center, USA

Bo Long Bo.long@jd.com

JD.COM, China

Lingfei Wu LWU@EMAIL.WM.EDU

JD.COM Silicon Valley Research Center, USA

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Abstract

Conversational recommender systems (CRS) explicitly solicit users' preferences for improved recommendations on the fly. Most existing CRS solutions employ reinforcement learning methods to train a single policy for a population of users. However, for users new to the system, such a global policy becomes ineffective to produce conversational recommendations, i.e., the cold-start challenge.

In this paper, we study CRS policy learning for cold-start users via meta reinforcement learning. We propose to learn a meta policy and adapt it to new users with only a few trials of conversational recommendations. To facilitate policy adaptation, we design three synergetic components. First is a meta-exploration policy dedicated to identify user preferences via exploratory conversations. Second is a Transformer-based state encoder to model a user's both positive and negative feedback during the conversation. And third is an adaptive item recommender based on the embedded states. Extensive experiments on three datasets demonstrate the advantage of our solution in serving new users, compared with a rich set of state-of-the-art CRS solutions.

Keywords: Reinforcement Learning, Conversational Recommendation, Meta Learning

1. Introduction

While traditional recommenders infer a user's preferences only based on her historically interacted items (Sarwar et al., 2001; Rendle, 2010; Koren et al., 2009; He et al., 2017), conversational recommender systems (CRS) leverage interactive conversations to adaptively profile a user's preference (Sun and Zhang, 2018; Christakopoulou et al., 2016; Lei et al., 2020a). The conversations in CRS focus on questions about users' preferences on item attributes (e.g., brands or price range of a particular type of products), in the form of pre-

defined question templates (Sun and Zhang, 2018; Lei et al., 2020a; Deng et al., 2021) or timely synthesized natural language questions (Li et al., 2018; Zhou et al., 2020). Through a series of question answering, a profile about a user's intended item can be depicted, even when the user is new to the system (Christakopoulou et al., 2016), i.e., the cold-start users, which gives CRS an edge in providing improved recommendations comparing to traditional recommendation solutions.

Christakopoulou et al. (2016) first proposed the idea of CRS. Their solution focused on deciding what item to ask for feedback, and off-the-shelf metrics, such as upper confidence bound (Auer, 2002), were explored for the purpose. Following this line, reinforcement learning (RL) based methods become the mainstream solution nowadays for CRS. Sun and Zhang (2018) built a policy network to decide whether to recommend an item, or otherwise which item attribute to ask about in each turn of a conversation. However, in these two early studies, the conversation is terminated once a recommendation is made, no matter whether the user accepts it or not. Lei et al. (2020a) studied the multi-round conversational recommendation problem, where CRS can ask a question or recommend an item multiple times before the user accepts the recommendation (considered as a successful conversation) or quits (considered as a failed conversation). This is also the setting of our work in this paper. To better address multi-round CRS, the authors of (Lei et al., 2020b) leveraged knowledge graphs to select more relevant attributes to ask across turns. Xu et al. (2021) extend (Lei et al., 2020a) by revising user embeddings dynamically based on users' feedback on attributes and items. And Deng et al. (2021) unified the question selection module and the recommendation module in an RL-based CRS solution, which simplifies the training of CRS.

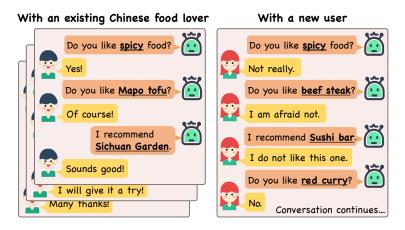


Figure 1: Example of cold-start CRS.

Although CRS is expected to address the cold-start problem in recommendation, by profiling a new user via eliciting her preference about item attributes, how to acquire the most effective feedback to profile a single user still encounters the cold-start problem. More specifically, due to the heterogeneity of different users' preferences, the same policy can hardly be optimal in finding the sequence of interactions (asking questions or making recommendations) for all users, especially for those who do not contribute to the policy training. Consider the example shown in Figure 1, a policy trained with a population of Chinese

food lovers cannot effectively serve new users who do not have any preferences on Chinese food. Once the interaction trajectory deviates from those often encountered during training, the effectiveness of the globally learnt CRS policy deteriorates, so does the quality of its recommendations.

We attribute this new challenge as the cold-start policy learning problem in CRS, which is completely non-trivial but unfortunately ignored in most previous CRS studies. The goal is clear, i.e., adapt the CRS policy for each new user; but there are at least three main technical barriers blocking us from the goal. Firstly, how to efficiently adapt a policy to new users? The tolerance of users about a prolonged conversation or bad recommendations is limited (Schnabel et al., 2018; Li et al., 2015; Gilotte et al., 2018), since all users wish to get high-quality recommendations with the least effort (e.g., least conversations) (Tétard and Collan, 2009). Hence, one cannot expect a large number of observations for CRS policy learning in a single user. Secondly, how to effectively explore user preferences for policy adaptation? As shown in Figure 1, successfully adapting a CRS policy to a new user depends on the user's preference, which however is elicited by the policy itself. This forms a chicken-and-egg dilemma (Liu et al., 2021) and adds another layer of consideration when acquiring user feedback: before identifying what item the user is looking for in a conversation, one first needs to figure out what policy best suits for the inquiry. Thirdly, how to decouple the adaptation of the conversation component and recommendation component in a CRS policy? The conversation component in a CRS policy is to profile a user by actively eliciting her feedback, while the recommendation component is to identify the most relevant recommendations based on the profile. Adaptation in both components is needed for new users, but the strategy for adapting them could be different.

In this paper, we focus on CRS policy learning for cold-start users and address it via meta reinforcement learning (Liu et al., 2021; Humplik et al., 2019; Wang et al., 2016). We propose to learn a meta policy for CRS from a population of users and adapt it to new users with only a few trials of conversational recommendations. We named the proposed solution as MetaCRS. In this solution, the meta policy can be viewed as a starting point close to every single user's personalized policy. It thus builds the basis for efficient policy adaptation with only a handful of observations in each new user. To acquire the most informative feedback for policy adaptation, we design a meta-exploration policy to identify user preferences via conversations. And to precisely model user feedback collected from conversations, we propose a Transformer-based (Vaswani et al., 2017) state encoder to integrate both positive and negative feedback on the mentioned attributes and recommended items. And based on this state representation, we explicitly adapt the recommendation component to quickly improve recommendation quality.

To evaluate the effectiveness of the proposed model, we compared MetaCRS with several state-of-the-art baselines for CRS on three public datasets. The results strongly demonstrated the advantage of our solution in making satisfactory recommendations to new users in CRS. We also conducted extensive ablation analysis on each proposed component to inspect its contribution on the improved performance: 1) the meta-exploration policy provides good user preference information for fast policy adaptation; and 2) the adapted recommendation component makes better recommendations by cooperating with the adapted conversation component.

2. Related works

Conversational recommender systems (CRS). CRS take advantage of conversations with users to elicit their preferences in real time for improved recommendations. The main research effort in CRS focuses on addressing the explore-exploit trade-off in collecting user feedback. The first attempt was made by Christakopoulou et al. (2016), where the authors employed multi-armed bandit models to acquire users' feedback on individual items. A follow-up study set an additional bandit model to select attributes to collect user feedback and employed a manually crafted function to decide when to ask questions about attributes or make recommendations (Zhang et al., 2020). To automatically identify the time of questions, Li et al. (2021) unified attributes and items in the same arm space and let a bandit algorithm determine when to do what.

Earlier CRS solutions based on bandit algorithms are often restricted to linear models, which limit the solutions' power in capturing users' diverse preferences in recommendations. Most recently, the dominating CRS solutions leverage deep reinforcement learning algorithms (Arulkumaran et al., 2017; Mnih et al., 2015) to unleash the power of CRS. Li et al. (2018) first introduced a deep RL solution to adaptively decide when to make a recommendation or otherwise what specific question to ask in each round of conversation. Lei et al. (2020a,b) extended the single-round CRS to the multi-round setting, where multiple questions and recommendations can be made in one conversation until the user accepts the recommendation or quits the conversation. Xu et al. (2021) proposed a gating mechanism to include both positive and negative user feedback for better dynamic preference modeling. Deng et al. (2021) unified the question selection module and the recommender in an RL agent. Two heuristics for attribute and item pre-selection were proposed to simplify the RL agent design. In addition to using pre-defined response templates, there are also solutions leveraging neural language models to synthesize natural language responses to make the conversation more innate (Li et al., 2018; Chen et al., 2019; Zhou et al., 2020).

All the aforementioned CRS solutions learn a global policy for all users. Even when the policy can be personalized in some of these solutions, such personalization heavily depends on a user's historical conversations or recommendation history (e.g., learning a user embedding from history as the policy's input) (Lei et al., 2020a; Deng et al., 2021; Xu et al., 2021). Such a solution becomes sub-optimal for cold-start users who do not have historical data. As we pointed out earlier, inefficient elicitation of user preference in new users leads to ineffective recommendations, which diminishes the value of CRS for cold-start users, even though it is the main motivation for CRS at the first place.

Meta learning for recommendation. Meta learning (Finn et al., 2017) has been widely used to solve the cold-start problem in recommender systems. Vartak et al. (2017) studied the item cold-start problem (i.e., how to recommend new items to users). They proposed two adaptation approaches. One learns a linear classifier whose weights are determined by the items represented to the user before and adapts the classifiers' weights for each user. Another one learns user-specific item representations and adapts the bias terms in a neural network recommender for the purpose. Lee et al. (2019) separated the representation layer and decision-making layer in a neural recommendation model, and executed local adaptation on the decision-making layer for each new user. Lu et al. (2020) enhanced meta learning with heterogeneous information network, which provides rich semantics for

fast model adaptation. Wei et al. (2020) extended collaborative filtering for meta learning, which handles new users with a few interactions. They design a dynamic sub-graph sampling method to mimic the dynamic arrival of new users when constructing the training tasks for each user. Zou et al. (2020) focused on interactive item recommendation, where the meta model is optimized by maximizing the cumulative rewards in each user. Kim et al. (2022) deployed meta learning to online update of recommender systems, where the meta learning rates are adaptively tuned on a per parameter and instance basis.

3. Preliminary

In this section, we first formulate the problem of multi-round CRS as a reinforcement learning problem, and then illustrate the concept of meta reinforcement learning and how we use it to address the cold-start challenge in CRS.

3.1 Problem Definition

In this work, we study the problem of multi-round conversational recommendation (Lei et al., 2020a), where CRS can ask questions or make recommendations multiple times before the user accepts the recommendation or quits the conversation. Similar to traditional recommender systems, CRS face a set of users \mathcal{U} and a set of items \mathcal{V} ; and we denote a specific user as u and a specific item as v. Each item v is associated with a set of pre-defined attributes \mathcal{P}_v . Attributes describe basic properties of items, such as movie genres in movie recommendations and authors in book recommendations.

We formulate the CRS problem by a Markov decision process (MDP) (Deng et al., 2021; Lei et al., 2020b), which can be fully described by a tuple (S, A, T, R). S denotes the state space, which summarizes the conversation between the system and user so far. A denotes the action space for the system, which includes recommending a particular item or asking a specific attribute for feedback. $T: S \times A \to S$ is the state transition function, and $R: S \times A \to [-R_{max}, R_{max}]$ is a bounded reward function suggesting a user's feedback on the system's actions. As we focus on meta policy learning for CRS in this work, how to best define reward is not our objective. We follow the reward function defined in (Lei et al., 2020a,b; Deng et al., 2021) to make our results comparable to previously reported results; but our solution framework is agnostic to any specific reward definitions. In particular, we include the following rewards: (1) $r_{\text{rec_suc}}$, a large positive reward when the recommended item is rejected; (3) $r_{\text{ask_suc}}$, a positive reward when the inquired attribute is confirmed by the user; (4) $r_{\text{ask_fail}}$, a negative reward when the inquired attribute is dismissed by the user; (5) r_{quit} , a large negative reward when the user quits the conversation without a successful recommendation.

With this formulation, a conversation in CRS can be represented as $d = \{(a_1, r_1), ...(a_T, r_T)\}$, where T is the maximum number of allowed turns. A conversation (or an episode in the language of RL, we will use them exchangeablely) will terminate when (1) the user accepts the recommended item; or (2) the agent runs out of maximum allowed turns. At each time step t, the CRS agent, which can be fully described by a policy $\pi(a_t|s_t)$, selects an action a_t based on the current state s_t . The training objective of a CRS policy is to maximize the expected cumulative rewards over the set of observed episodes D, which can be described

by the following loss,

$$\mathcal{L}(\pi) = - \underset{d \sim P(D)}{\mathbb{E}} \Big[\sum_{t=0}^{T} R_t \Big],$$

where $R_t = \sum_{t'=t}^T \gamma^{T-t'} r(a_t)$ is the accumulated reward from turn t to the final turn T, and $\gamma \in [0,1]$ is a discount factor to emphasize rewards collected in a near term.

3.2 Meta Reinforcement Learning for CRS

Instead of learning a single global policy π , we propose to learn personalized policy π_u for each user u (new or existing) to address the cold-start challenge for CRS. The fundamental reason that almost all previous works (Lei et al., 2020a,b; Deng et al., 2021) focused on global policy learning is that they (implicitly) assumed users know all attributes of their desired items and share the same responses over those attributes; in other words, user feedback is fully determined by the item. This assumption is unrealistically strong and naive, since different users can describe the same item very differently, because of their distinct knowledge and preferences about item attributes. For example, some users choose a mobile phone for its appearance while others choose it because of its brand. As a result, a global policy can hardly be optimal for every single user, especially the new users whose preferences are not observed during global policy training. In this work, we impose a weaker and more realistic assumption about users' decision making by allowing user-specific feedback $\mathcal{R}_{\mathcal{U}}$, which calls for personalized policies. Therefore, a personalized policy for user u should minimize,

$$\mathcal{L}_{u}(\pi) = -\underset{d \sim P(\mathcal{D}_{u})}{\mathbb{E}} \left[\sum_{t=0}^{T} R_{u}(a_{t}) \right], \tag{1}$$

where \mathcal{D}_u is a collection of conversations from user u and $R_u(a_t) = \sum_{t'=t}^T \gamma^{T-t'} r_u(a_{t'})$. To find the best personalized policy π_u (parameterized by θ_u) for each new user u, instead of learning from scratch every time, we choose to learn a meta policy parameterized by θ and use it as a starting point to look for θ_u . Following the convention of meta learning, we assume a small set of conversations \mathcal{D}_u^s (i.e., the support set) for policy adaptation and another small set \mathcal{D}_u^q (i.e., the query set) for policy evaluation. Hence, the size of support set \mathcal{D}_u^s in each user u denotes the conversation budget we have to find θ_u when serving a single user. Given limited tolerance of an ordinary user to prolonged conversations, a performing solution should find the optimal θ_u with the size of \mathcal{D}_u^s as small as possible.

4. Methodology

In this section, we describe the design of MetaCRS in detail. We first introduce our two-stage meta policy learning framework designed for cold-start CRS. To assist policy learning, we develop a Transformer-based state encoder, which aims to rapidly capture a user's preference from her both positive and negative feedback in a conversation. This state representation also facilitates fast adaptation of the recommendation component in each user. Figure 2 shows the overview of MetaCRS.

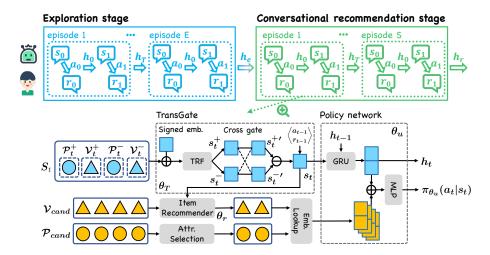


Figure 2: The workflow of MetaCRS training. Each user's support set is separated into the exploration stage and conversational recommendation stage. The last hidden state from the previous episode is passed to the next episode as its initial state throughout the course of MetaCRS in each user.

4.1 Two-stage Meta Policy Learning for CRS

Motivated by the seminal work Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017), we propose to first learn a meta CRS policy from a population of users; and then for each individual user, we adapt the meta policy to a user-specific policy with only a few trails of conversational recommendations with the user. We obtain the meta policy by maximizing the policy adaptation performance in a given set of training users. Specifically, in each user u, we perform policy adaptation on her support set \mathcal{D}_u^s , where θ_u is initialized with θ and then updated by optimizing Eq.(1) via gradient descent. The gradient for Eq.(1) is computed by the REINFORCE (Williams, 1992) algorithm based on the collected rewards in a conversation,

$$\nabla_{\theta_u} \mathcal{L}_u(\pi_{\theta_u}) = -\mathbb{E}\Big[\sum_{t=0}^T R_u(a_t) \nabla_{\theta_u} \log \pi_{\theta_u}(a_t|s_t)\Big]. \tag{2}$$

The gradient of the meta policy with respect to θ (i.e., $\nabla_{\theta} \mathcal{L}_{u}(\theta_{u})$) is computed in the same way as Eq.(2), but on the corresponding query set \mathcal{D}_{u}^{q} . In this way, the meta policy is optimized for generalization, akin to cross-validation. Note that to exactly compute the gradient for θ , we need to take a higher-order derivative in $\nabla_{\theta_{u}} \mathcal{L}_{u}(\theta_{u})$ with respect to θ on the support set as well, since θ_{u} is a function of θ . In this work, we followed the the first-order approximation methods proposed in (Finn et al., 2017; Nichol et al., 2018) to simplify the gradient computation.

In meta-learning for supervised learning tasks, e.g., image classification (Finn et al., 2017; Nichol et al., 2018; Vuorio et al., 2019), the support set and query set are predefined and therefore not determined by the learnt models. Therefore, gradient-based optimization alone is sufficient for meta model learning and adaptation. But in our problem, what we will observe in \mathcal{D}_u^s and \mathcal{D}_u^q are completely determined by the employed policy π_{θ_u} , which however

is supposed to be estimated from \mathcal{D}_u^s and \mathcal{D}_u^q . This causes the so-called *chicken-and-egg* dilemma (Liu et al., 2021) for meta policy learning which we discussed in the introduction, and calls for additional treatments beyond gradient-based policy optimization.

Potential bias in the currently learnt policy prevents it from being effective in acquiring the most informative feedback for meta policy learning and adaptation. Hence, we propose to separate the policy adaptation procedure in each user into an exploration stage and a conversational recommendation stage, and design their corresponding policies. To avoid ambiguity, we refer to the policy for exploration stage as the meta-exploration policy (denoted as π_{θ_e}), and the policy for conversational recommendation stage as the CRS policy (denoted as π_{θ_e}). This is similar to the explore-then-commit strategy (Garivier et al., 2016; Lattimore and Szepesvári, 2020) in bandit literature. But note that our meta-exploration policy is not personalized, as its sole goal is to quickly identify what kind of user the system is interacting with. Hence, we choose to estimate it from the whole set of training users. In particular, we reserve the first few episodes in each user's support set for our exploration stage, denoted as exploration set \mathcal{D}_u^e . The size of \mathcal{D}_u^e is a hyper-parameter to be tuned for different CRS applications. Observations in \mathcal{D}_u^e will only be used to estimate the meta-exploration policy π_{θ_e} .

In MetaCRS, the meta-exploration policy π_{θ_e} , meta CRS policy π_{θ} and personalized CRS policies $\{\pi_{\theta_u}\}_{u\in\mathcal{U}}$ are realized by the same RNN-based policy network architecture (Hopfield, 1982; Duan et al., 2016; Wang et al., 2016) with Gated Recurrent Units (GRUs) (Bahdanau et al., 2014; Duan et al., 2016), but we estimate different parameters for them respectively. To avoid ambiguity, we will use the learning of meta-exploration policy π_{θ_e} as an illustrating example; and the same procedure applies to the learning of other policies.

Specifically, at the t-th turn of an episode, we observe a new state and encode it using a state encoder. We leave the discussion about our state encoding in Section 4.2. The encoded state s_t is provided as input to the policy network. The output h_t of the GRU is fed to a fully connected layer followed by a softmax function to produce the action distribution for $\pi_{\theta_e}(a_t|s_t)$. In each user, by the end of each episode, the GRU's last output hidden state h_T is passed to the user's next episode as its initial state, such that this user's conversation history with the system can be continuously used to jump start her next conversation. Enabled by this design, information collected from the exploration stage (denoted as h_e) is passed over to the conversational recommendation stage to profile who the user is, and then from the conversational recommendation stage (denoted as h_r) to the query set to suggest what the user's preference could be. This sequential process is depicted in Figure 2.

The policy networks for π_{θ} and $\{\pi_{\theta_u}\}_{u\in\mathcal{U}}$ are trained via the meta learning procedure described at the beginning of this section, on top of the rewards defined in Section 3.1. But the meta-exploration policy π_{θ_e} is trained with a specially designed reward function, as its sole purpose is to identify what kind of user the system is serving. Inspired by (Liu et al., 2021; Kamienny et al., 2020; Humplik et al., 2019), we adopt pre-trained user embeddings $\{e_u\}_{u\in\mathcal{U}}$ obtained on users with historical observations (i.e., training users) to design the exploration reward,

$$r_e(s_t) = \log P(e_u|s_t) - \log P(e_u|s_{t-1}),$$
 (3)

^{1.} If the conversation ends before the maximum turn, h_T stands for the latent state at the successful recommendation.

where $P(e_u|s_t) = \frac{\exp(h_t^\top e_u)}{\sum_{u \in \mathcal{U}} \exp(h_t^\top e_u)}$. Note here we use the GRU's output hidden state h_t to predict the user embedding, just as how we use it to compute the action distribution in the policies. Specifically, we obtain $\{e_u\}_{u \in \mathcal{U}}$ from a Factorization Machine model (Lei et al., 2020a) trained on observed user-item interactions in training users. More details about this user embedding learning can be found in Section 5.1. The insight behind our exploration reward design is that we promote the actions that help us identify a specific user during the exploration stage. Following the suggestion from (Liu et al., 2021; Kamienny et al., 2020; Humplik et al., 2019), we also add a cross entropy loss on the meta-exploration policy network's latent state h_t to regularize the estimation of θ_e ,

$$\mathcal{L}_e(\pi_{\theta_e}) = -\mathbb{E}\Big[\sum_{t=0}^T R_e(s_t) + \sum_{t=0}^T \log P(e_u|h_t)\Big],\tag{4}$$

where $R_e(s_t)$ is the accumulated discounted reward based on Eq.(3) from turn t. The gradient of the first term is also computed by the REINFORCE algorithm.

4.2 TransGate State Encoder

Previous CRS solutions seldom directly encode negative feedback (i.e., the rejected attributes and items) into states (Deng et al., 2021; Lei et al., 2020a). But for cold-start CRS, especially in the early stage of policy adaptation, it is more likely to collect negative feedback. Ineffective modeling of negative feedback will slow down policy adaption. Moreover, positive and negative feedback posits distinct information about users' preference, and thus calls for different treatments. In MetaCRS, we employ a Transformer to encode the complicated relations among positive and negative feedback in an ongoing conversation into a state, with a cross gate mechanism to differentiate the impact from positive and negative feedback. We name this state encoder as TransGate.

At turn t, we can accumulate four kinds of feedback from a user in this conversation: (1) \mathcal{P}_t^+ , attributes confirmed by the user; (2) \mathcal{V}_t^+ , candidate items satisfying all accepted attributes; (3) \mathcal{P}_t^- , attributes dismissed by the user; (4) \mathcal{V}_t^- , items rejected by the user. Collectively, we denote $\mathcal{S}_t = \{\mathcal{P}_t^+, \mathcal{V}_t^+, \mathcal{P}_t^-, \mathcal{V}_t^-\}$. We first map elements in \mathcal{S}_t into vectors with an embedding layer: $\{e_p^+|p\in\mathcal{P}_t^+\}, \{e_v^+|v\in\mathcal{V}_t^+\}, \{e_p^-|p\in\mathcal{P}_t^-\}$ and $\{e_v^-|v\in\mathcal{V}_t^-\}$, where attribute and item embeddings are pre-trained with training users' historical observations. Candidate items and rejected items are aggregated separately to reduce the sequence length,

$$e_{\mathcal{V}}^{+} = \frac{1}{|\mathcal{V}_{t}^{+}|} \sum_{v \in \mathcal{V}_{t}^{+}} e_{v}^{+}, \ e_{\mathcal{V}}^{-} = \frac{1}{|\mathcal{V}_{t}^{-}|} \sum_{v \in \mathcal{V}_{t}^{-}} e_{v}^{-}.$$

In the original Transformer (Vaswani et al., 2017), elements are encoded with position embeddings. But in our case, the order among the elements is not important, but encoding the sign of user feedback (i.e., accepted or rejected) is critical. Inspired by position embeddings, we propose to encode user feedback into signed embeddings $\{e^+, e^-\}$. We add e^+ to positive elements and e^- to negative elements in \mathcal{S}_t . We consider candidate items as positive. Then, we feed the obtained embeddings into L Transformer layers. For simplicity, we remain the notations of transformed embeddings unchanged. We then aggregate the

positive and negative elements separately to obtain an embedding for positive feedback and an embedding for negative feedback,

$$s_t^+ = \frac{1}{1 + |\mathcal{P}_t^+|} (e_{\mathcal{V}}^+ + \sum_{p \in \mathcal{P}_t^+} e_p^+), \ s_t^- = \frac{1}{1 + |\mathcal{P}_t^-|} (e_{\mathcal{V}}^- + \sum_{p \in \mathcal{P}_t^-} e_p^-).$$

The positive feedback embedding and negative feedback embedding may contain overlapped information, which would confuse policy learning. For example, an item that already satisfies all confirmed attributes so far can still be rejected by the user. We propose a cross gate mechanism to further differentiate the positive and negative information,

$$s_t^{+\prime} = s_t^+ \odot g^-, \ s_t^{-\prime} = s_t^- \odot g^+,$$

where \odot denotes the element-wise product and $\{g^+, g^-\}$ are defined as,

$$g^+ = \sigma(\mathbf{W}_1 s_t^+ + \mathbf{b}_1), \quad g^- = \sigma(\mathbf{W}_2 s_t^- + \mathbf{b}_2),$$

where $\sigma(\cdot)$ denotes the sigmoid function and $\{W_1, W_2, b_1, b_2\}$ are learnable parameters. We obtain the final state embedding by,

$$s_t = s_t^{+\prime} - s_t^{-\prime}.$$

The set of parameters for the TransGate encoder is denoted as θ_T , which is learnt from the conversations with training users. We should note once learnt this encoder is shared globally by all users without personalization. The state embedding is then concatenated with the encoding of $\langle a_{t-1}, r_{t-1} \rangle$ as the input to the RNN-based policy network. In particular, the action embedding is directly read off based on the pre-trained attribute and item embeddings, and we set a linear layer to encode the reward.

In each turn, we use all the candidate items \mathcal{V}_{cand} (i.e., \mathcal{V}_t^+) and attributes \mathcal{P}_{cand} to construct the action space, where \mathcal{P}_{cand} is the entire attribute set excluding \mathcal{P}_t^+ and \mathcal{P}_t^- . Deng et al. (2021) reported that a very large action space always slowed down policy learning. To generate a reasonable action space, we follow the manually crafted rules from (Deng et al., 2021) to select K_A attributes from \mathcal{P}_{cand} and select the top- K_I items provided by a state-based item recommender, which is described in the next section.

4.3 State-aware Item Recommender

Previous studies use a pre-trained recommender through the course of CRS (Lei et al., 2020a,b; Xu et al., 2021), as their focus is mostly on deciding when to make a recommendation or otherwise what question to ask. A pre-trained recommender restricts the CRS policy to accommodate the recommender's behavior, which adds unnecessary complexity for policy adaptation. In MetaCRS, we choose to adapt the recommendation component as well. We set a learnable item recommender to rank candidate items based on the state embedding from the TransGate encoder. The ranking score of an item v is calculated by,

$$w_t(v) = e_v^{\top}(\boldsymbol{W}_3 s_t + \boldsymbol{b}_3),$$

where $\{W_3, b_3\}$ are learnable parameters for the recommender, collectively denoted as θ_r . We perform local adaptation of θ_r to obtain a personalized recommender for each user.

Algorithm 1: Optimization algorithm of MetaCRS

```
Input: User population \mathcal{U}, learning rates \alpha, \beta, meta parameters \theta, \theta_e, \theta_R, \theta_T; while not Done do

Sample a batch of users \mathcal{U}_b \sim P(\mathcal{U});
for each u \in \mathcal{U}_b do

Collect \mathcal{D}_u^e and h_e by executing \pi_{\theta_e};
Initialize \theta_u = \theta, \theta_r = \theta_R;
Collect \mathcal{D}_u^s and h_r by executing \pi_{\theta_u} with h_e;
Evaluate \nabla_{\theta_u} \mathcal{L}_u and \nabla_{\theta_r} \mathcal{L}_r using \mathcal{D}_u^s;
Compute adapted parameters with gradient descent: \theta_u = \theta_u - \alpha \nabla_{\theta_u} \mathcal{L}_u,
\theta_r = \theta_r - \alpha \nabla_{\theta_r} \mathcal{L}_r ;
Collect \mathcal{D}_u^q by executing \pi_{\theta_u} with h_r;
end
Update \theta, \theta_R, \theta_T using each \mathcal{D}_u^q by minimizing \mathcal{L}_u, \mathcal{L}_r;
Update \theta_e, \theta_T using each \mathcal{D}_u^e by minimizing \mathcal{L}_e;
end
```

We update the item recommender by minimizing the following cross entropy loss once a successful conversation concludes,

$$\mathcal{L}_r(\theta_r) = -\frac{1}{T_s} \mathbb{I}(T_s \le T) \sum_{t=0}^{T_s} \log \frac{\exp(w_t(v_s))}{\sum_{|\mathcal{V}_t^+|} \exp(w_t(v))}, \tag{5}$$

where T_s is the index of the successful turn and v_s is the accepted item. This loss function encourages the adapted recommendation component to identify the finally accepted item as early as possible in a conversation. We denote the meta parameters of θ_r as θ_R .

Now we are finally equipped to illustrate the complete learning solution for MetaCRS in Algorithm 1. In the inner for-loop, we perform policy adaption to obtain the personalized CRS policy (including item recommender). In the outer while-loop, we update all meta parameters. To simplify the gradient computation, we treat the inherited initial hidden state h_T from the latest episode as a constant. In practice, we update the local parameters once an episode is executed, as we find empirically it works better than updating once after the whole \mathcal{D}_u^s is finished. When serving new users in the meta-test phase, we fix $\{\theta_e, \theta_T\}$ and only execute local adaptation (the inner for-loop part in Algorithm 1) with the corresponding parameters initialized by $\{\theta, \theta_R\}$.

5. Experiments

To fully demonstrate the effectiveness of MetaCRS in solving the cold-start CRS problem, we conduct extensive experiments to study the following four research questions (RQ):

- **RQ1**: Can MetaCRS achieve better performance than state-of-the-art methods when handling new users?
- **RQ2**: Does our meta reinforcement learning based adaptation strategy work better than other adaptation strategies?

- RQ3: How quickly can MetaCRS obtain a good personalized policy for each user?
- RQ4: How does each proposed component contribute to the final performance of MetaCRS?

5.1 Datasets

We evaluate MetaCRS on three multi-round conversational recommendation benchmark datasets (Lei et al., 2020a,b; Deng et al., 2021; Zhang et al., 2021) and summarize their statistics in Table 1.

- LastFM (Bertin-Mahieux et al., 2011) is a music recommendation dataset. Lei et al. (2020a) manually categorized the original attributes into 33 coarse-grained attributes.
- BookRec (He and McAuley, 2016) is a book recommendation dataset. We further process the original dataset by selecting top 35 attributes according to their TF-IDF scores across items and filter out items with too few attributes.
- MovieLens (Harper and Konstan, 2015) is a movie recommendation dataset. We performed the same pre-processing as on BookRec dataset.

	LastFM	BookRec	MovieLens
#Users	1,801	1,891	3,000
# Items	7,432	4,343	5,974
#Attributes	33	35	35
#Interactions	72,040	75,640	120,000
Avg. $ \mathcal{P}_u $	7	8	12
Avg. $ \mathcal{P}_v $	4.07	8.15	5.02
Avg. $ \mathcal{P}_o $	5.44	5.30	4.25

Table 1: Summary statistics of datasets.

We randomly split the users for training, validation and testing with the ratio 80%:10%:10%, such that the evaluation set only contains new users. Similar to (Lei et al., 2020a,b; Deng et al., 2021), we developed a user-simulator to generate conversations based on the observed user-item interactions in the dataset. We describe the simulator in detail in Section 5.2.1. On each dataset, we obtained user, item and attribute embeddings (denoted as $e_{\mathcal{U}}, e_{\mathcal{V}}, e_{\mathcal{P}}$) using a variant of Factorization Machine (FM) proposed in (Lei et al., 2020a) on training users' observed user-item interactions. However, the average number of observed interactions in each user in original datasets is too small to study the personalized policies (e.g., 13.2 per user on average on LastFM dataset). As part of our simulation, we generated 40 user-item interactions for each user by sampling items proportional to the score $e_u^{\top}e_v$, to create more interaction data for our evaluation purpose.

5.2 Experimental Settings

5.2.1 User simulator

CRS needs to be trained and evaluated via interactions with users. We built upon (Lei et al., 2020a,b; Deng et al., 2021) to create our user simulator for the purpose. In each conversational session, one user-item pair (u, v) is first selected, and we treat the item v as the ground-truth target for recommendation. Previous simulator designs assumed all users

Table 2: Comparison of CRS performance among different models on three datasets. We categorize baselines into 3 groups. * stands for the best performance in each group.

		MaxE	EAR	FPAN	SCPR	UNI	MetaCRS
LastFM	SR@10 AT	$\begin{vmatrix} 0.137 \\ 9.71 \end{vmatrix}$	$0.428 \\ 8.62$	0.508* 8.08*	0.432 8.70	$0.441 \\ 8.52$	$\begin{array}{c} 0.713 \\ 6.18 \end{array}$
BookRec	SR@10 AT	0.206 9.64	$0.320 \\ 9.01$	0.397* 8.31*	0.329 9.11	$0.358 \\ 9.00$	$\begin{array}{c} 0.487 \\ 8.06 \end{array}$
MovieLens	SR@10 AT	0.262 9.46	0.552 7.98	0.589 7.81*	0.545 7.89	0.596* 8.01	$\begin{array}{c c} 0.745 \\ 6.27 \end{array}$

		UNI-FT	UNI-IA	MP UF	UR-FT	UR-IA	MetaCRS
LastFM	SR@10 AT	$\begin{vmatrix} 0.413 \\ 8.76 \end{vmatrix}$	$0.445 \\ 8.51$	$ \begin{array}{c c c} 0.468^* & 0.64 \\ 8.25^* & 7.02 \end{array} $		0.678^* 6.85^*	$\begin{array}{c c} 0.713 \\ 6.18 \end{array}$
BookRec	SR@10 AT	0.353 8.93	$0.358 \\ 9.01$	$ \begin{array}{c c c} 0.364^* & 0.38 \\ 8.82^* & 8.58 \end{array} $		0.420* 8.41*	0.487 8.06
MovieLens	SR@10 AT	0.552 8.09	0.605 7.89	0.615* 0.68 7.81* 7.00		0.704* 6.88*	$0.745 \\ 6.27$

will respond in the same way to all attributes of item v (i.e., confirming every entry in \mathcal{P}_v). This setting is unrealistically restrictive and eliminates the necessity of personalized policies. To demonstrate the utility of personalized policy learning, we design a user-centric simulator that supports user-specific feedback in each conversation.

Specifically, we used the pre-trained user and item embeddings to generate each user's preferred attribute set $\{\mathcal{P}_u\}_{u\in\mathcal{U}}$, by selecting the top-ranked attributes for each user based on the score $e_u^{\top}e_p$. In each turn, the system decides to ask a question about an attribute or recommend a list of items. The user will only confirm the overlapped attributes in $\mathcal{P}_o = \mathcal{P}_u \cap \mathcal{P}_v$, and dismiss all others. On the BookRec dataset, the original entries in \mathcal{P}_v is too generic to be informative, i.e., too many attributes appear in almost all items. We decided to also increase \mathcal{P}_v on this dataset by adding top-ranked attributes for each item based on the score $e_v^{\top}e_p$. We also report the mean value of $|\mathcal{P}_u|$, $|\mathcal{P}_v|$ and $|\mathcal{P}_o|$ resulted from our simulation on each dataset in Table 1.

5.2.2 Baslines

To fully evaluate the effectiveness of MetaCRS, we compared it with a set of strong baselines. We categorized the baselines into three groups for different comparison purposes.

To answer RQ1, we compared MetaCRS with the state-of-the-art CRS methods, which form our first group of baselines:

• Max Entropy (MaxE) is a rule-based method suggested in (Lei et al., 2020a). In each turn, the attribute with maximum entropy is to be asked or top-ranked items are to be recommended based on the rule.

- EAR (Lei et al., 2020a) is a three-stage solution consisting estimation, action and reflection steps. It updates the conversation and recommendation components using reinforcement learning.
- **FPAN** (Xu et al., 2021) extends the EAR model by utilizing a user-item-attribute graph to enhance the offline representation learning. User embeddings are revised dynamically based on users' feedback on items and attributes in the conversation.
- **SCPR** (Lei et al., 2020b) reformulates the CRS problem as an interactive path reasoning problem on the user-item-attribute graph. Candidate attributes and items are selected according to their relations with collected user feedback on the graph.
- UNICORN (UNI) (Deng et al., 2021) integrates the conversation and recommendation components into a unified RL agent. Two heuristics for pre-selecting attributes and items in each turn are proposed to simplify the RL training.

All these methods rely on pre-trained user embeddings to make recommendations or construct states, which are not available in new users. To apply them to new users, we used the average embedding of all training users as the embedding for new users in these baselines. This group of baselines are learnt on training users and then evaluated on the testing users. To study the impact of different adaptation strategies as asked in RQ2, we compared our meta reinforcement learning based method with the following two popularly used strategies:

- **Fine-tuning (FT)**: We first pre-train a global policy on all training users. During testing, we fine-tune the policy on the whole support set of all new users.
- Independent adaptation (IA): We first pre-train a global policy on all training users. For each new user, we perform continual training on her support set to obtain a personalized policy.

We applied the FT and IA strategy on UNICORN, which is the most recently developed and unified reinforcement learning solution, producing two new baselines **UNI-FT** and **UNI-IA**. We found policy gradient was more effective and efficient than UNICORN's original Q-learning based method in our experiments. Hence, we applied policy gradient for model update in these three baselines. We also compared with one variant of MetaCRS, in which the state-based item recommender is removed, and only the policy network is locally adapted. For its item recommendation, we used the same heuristic as UNICORN, by using the pre-trained user/item embeddings, and then selecting the top-ranked items to form the action space. We denote this variant as **MP**.

In the third group of baselines, to further study the impact of state-aware item recommender in the general CRS solutions, we added our TransGate and state-based item recommender to UNICORN. We denote this variant as **UR**. Additionally, to study its impact on different adaptation strategies, we also performed fine-tuning and independent adaptation on UR, producing another two baselines, named as **UR-FT** and **UR-IA**.

5.2.3 Evaluation metrics

We followed the widely-used metrics in previous works (Lei et al., 2020a,b; Deng et al., 2021) to evaluate the CRS solutions. We evaluated the average ratio of successful episodes within T turns by success rate (SR@T). We also evaluated average turns in episodes (AT).

A better policy is expected to recommend successfully with less turns. The length of failed conversations is counted as T.

5.2.4 Implementation Details

We performed the training of meta policy on training users, and local adaptation on validation and testing users. We selected the best model according to its validation performance. The query sets of testing users are used to obtain the final performance for comparison. We set the rewards as: $r_{\text{rec_suc}} = 1$, $r_{\text{rec_fail}} = -0.1$, $r_{\text{ask_suc}} = 0.1$, $r_{\text{rec_fail}} = -0.1$, $r_{\text{quit}} = -0.3$. In MetaCRS, we took 5 episodes in the exploration stage and 10 episodes in the conversational recommendation stage by default. We set K_I , K_A and K_{rec} to 10. We performed standard gradient decent in local adaptation with a learning rate of 0.01, and updated the meta parameters using the Adam optimizer with a learning rate of 0.005 and L_2 regularization coefficient 1e-6. The discount factor γ is set to 0.999. In MP, we took 5 episodes in the exploration stage and 25 episodes in the conversational recommendation stage, because we found too few episodes are not enough to get a good local model in MP. To make a fair comparison, we run 30 episodes per new user for adaptation on UNI-FT and UNI-IA, and 15 episodes on UR-FT and UR-IA. The size of query set is fixed to 10. The maximum turn T in each episode is set to 10. We sample 5 users in each epoch when training MP and MetaCRS.

5.3 Overall Performance

We report the comparison results across all methods in Table 2. We can first clearly observe that MetaCRS outperformed all the baselines with large margins. First of all, MetaCRS outperformed all baselines in the first group, which proves a single global policy cannot handle new users and demonstrates the benefit of learning personalized policies. Interestingly, we observe that FPAN performed the best in most cases in this group. Different from EAR, FPAN updates user embeddings dynamically with users' positive and negative feedback on attributes and items by two gate modules, which enables dynamic item recommendation as in MetaCRS. This provides FPAN additional generalization power on new users and even outperform solutions that adapts to new users, e.g., those in our second group of baselines.

In the second group, we can observe that MP outperformed the two popularly used adaptation strategies, even without the help of the item recommender. The meta policy in MP is trained to maximize the adaptation performance on new users, but the global policy in UNI-FT and UNI-IA is trained to maximize the performance of existing users. It is thus not easy to adapt such a global policy, especially when new users' preferences could be different from existing users'. Comparing to UNICORN, We can clearly observe that simply fine-tuning the global model (i.e., UNI-FT) may even hurt the performance. UNI-IA performs better than the original global policy and UNI-FT. But again as the global policy is not trained for generalization, it is hard to find good personalized policies for new users starting from such a global policy. In our experiment, MetaCRS actually used less data to adapt than UNI-FT and UNI-IA, because the first 5 episodes are used to explore user preferences. But with the meta policy and our meta-exploration policy, MetaCRS can find better personalized policies with fewer adaptation episodes.

Similar conclusions can be made by comparing MetaCRS and the third group. Moreover, our proposed state encoder and item recommender significantly boosted the performance of UNICORN as shown in the results for the last group of baselines. This clearly demonstrates the necessity of fine-grain modeling of users' both positive and negative feedback and creating personalized recommendation component.

5.4 Ablation Study

5.4.1 Impact of support set size.

Since policy adaptation is performed on support sets, it is important to study how many episodes are needed to obtain good personalized policies (RQ3). To this end, we gradually increase the size of support sets with a step size 5. We remain the size of exploration episodes unchanged since 5 episodes are empirically sufficient for pinning down the target user's preference. Due to space limit, we only reported the results on the LastFM and BookRec dataset in Figure 3, and similar results were also observed on the MovieLens dataset. With a larger support set, the success rate increases considerably and the number of average turn also reduces. This is expected since more observations can be collected to better adapt the meta policy for each user. And this result also demonstrates the promise of personalized CRS policy learning: the quality of recommendation increases rapidly as the users get engaged with the system, which leads to a win-win situation for both users and system.

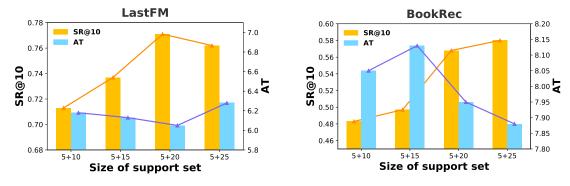


Figure 3: Performance comparisons w.r.t. size of support set.

5.4.2 Impact of different MetaCRS components.

In this section, we study the contribution of different components in MetaCRS to answer RQ4. Firstly, we evaluate the model's performance without local adaptation, which essentially evaluates the meta policy. Secondly, we remove the meta-exploration policy and directly execute policy adaptation. This setting shows how a dedicated exploration strategy affects policy adaptation. Finally, we replace the TransGate module with a simple linear layer to study how state representation learning affects the CRS performance. In particular, the positive and negative embeddings are obtained by taking the average embeddings of all positive and negative elements separately.

We present the results in Table 3. Firstly, we can observe the performance before adaptation is not bad, or even better than most of our baselines in Table 2, which means

Table 3: Ablation analysis in MetaCRS.

	LastFM		BookRec		MoiveLens	
	SR@10	AT	SR@10	AT	SR@10	AT
¬adaptation	0.632	6.68	0.378	8.56	0.630	7.31
\neg exploration	0.677	6.64	0.411	8.37	0.738	6.65
$\neg TransGate$	0.678	6.41	0.428	8.51	0.724	6.95
MetaCRS	0.713	6.18	0.487	8.06	0.745	6.27

the meta policy in MetaCRS already captures some important patterns in interacting with users. We can further compare the learnt meta policy with UR, which shares the same state encoder and item recommender, but was trained globally. UR is slightly better than the meta policy in MetaCRS. The reason is UR is trained to maximize performance on training users and generalized by the i.i.d. assumption. But the meta policy is trained to maximize the adapted policies' performance, not its own performance on new users. Hence, when the testing users share reasonable similarity with training users, UR can be helpful. But we can observe a large performance gain after adaptation, which proves the meta policy successfully serves as a good starting point for fast adaptation. Next, it is clear that without the exploration stage the performance degenerates. It confirms recognizing who the system is serving is critical for a successful adaptation. We finally evaluate the effectiveness of TransGate, without which the performance degenerates on all three datasets. This demonstrates the necessity of fine-grained modeling of user feedback, especially the negative feedback, for understanding users' preferences.

5.4.3 Case study

Additionally, we performed a qualitative study to analyze the behavior of different CRS models (shown in Figure 4) on the LastFM dataset. We compared MetaCRS with its own meta policy to show the difference before and after policy adaptation, and also the strongest baseline FPAN. The natural language questions and user responses are generated by predefined templates. We can observe all policies identify the user's preference on rock music successfully. The meta policy asks some frequent attributes in the dataset, like pop and punk. FPAN also identifies the user's preference on rock in the second turn, but it decides to ask Indie and Alternative in the following turns. Indie and Alternative frequently appear with rock music in different users. This pattern is successfully captured by FPAN; but it does not apply to this specific user, and thus fails FPAN. With the help of policy adaptation, MetaCRS successfully identifies the user's preference on rock music in 1990s within 3 turns, which is the key attribute to find the target artist Coldplay (first debuted in 1996). This case shows the effectiveness of MetaCRS in learning personalized policies and the improvement in the recommendation.

6. Conclusion

In this work, we present a meta reinforcement learning based solution to handle the problem of CRS policy learning in cold-start users. We learn a meta policy for generalization and

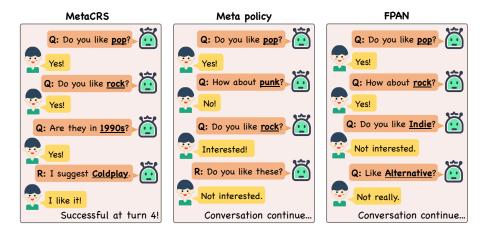


Figure 4: Conversations generated by three CRS models for the same user and target artist. Questions are marked as \mathbf{Q} , and recommendations are marked as \mathbf{R} .

fast adaptation on new users. We developed three important components to ensure the efficiency and effectiveness of policy adaptation. First, a dedicated meta-exploration policy is introduced to identify the most informative user feedback for policy adaptation. Second, a Transformer-based state encoder implicitly models a user's both positive and negative feedback collected in a conversation to precisely profile user preference. Third, an adaptive recommendation component is built on the state representation to quickly improve recommendation quality for new users. Extensive experiments demonstrate the effectiveness of our solution when serving new users, compared with a set of state-of-the-art CRS solutions.

Currently our policy adaptation is performed independently across users; to further reduce its sample complexity, collaborative policy adaptation among users can be introduced to leverage observations among both new and existing users. As previous works reported improved CRS performance using a knowledge graph (KG), it is also interesting to study how personalized policy learning can benefit from KGs, e.g., adapts the entity relations in each user or design the meta-exploration strategy based on the KG.

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