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MASTER'S THESIS

Advanced Method Towards Conversational Recommendation

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Declaration of Authorship

I, Yisong MIAO, declare that this thesis titled, "Advanced Method Towards Conversational Recommendation" and the work presented in it are my own. I confirm that:

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- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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Abstract

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Advanced Method Towards Conversational Recommendation

by Yisong MIAO

Recommender systems are embracing conversational technologies to obtain user preferences dynamically, and to overcome inherent limitations of their static models. To build a successful *conversational recommender system* (CRS), we argue that the key lies in proper handling of interactions between the conversational component (CC) and recommender component (RC). Specifically, to build an effective CRS, we argue that three fundamental problems need to be solved: 1) what questions to ask regarding item attributes, 2) when to recommend items, and 3) how to adapt to users' online feedback. To the best of our knowledge, there lacks a unified framework that jointly solves these three problems well.

In this work, We delve into the interactions between CC and RC, with the goal of building an effective and practical CRS. Specifically, we propose a new CRS framework named *Estimation–Action–Reflection*, or EAR, which consists of three stages to better converse with users. (1) Estimation, which builds predictive models to estimate user preference on both items and item attributes; (2) Action, which learns a dialogue policy to determine whether to ask attributes or recommend items, based on Estimation stage and conversation history; and (3) Reflection, which updates the recommender model when a user rejects the recommendations made by the Action stage. We present two conversation scenarios on binary and enumerated questions, and conduct extensive experiments on two datasets from Yelp and LastFM, for each scenario respectively. Our experiments demonstrate significant improvements, corresponding to fewer conversation turns, higher recommendation hits, over the state-of-the-art method CRM (Sun and Zhang, 2018).

Keywords: Conversational Recommendation, Interactive Recommendation, Recommender System, Dialogue System

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Contents

To my Parents...

Chapter 1

Introduction

Recommender systems are emerging as an important means of facilitating users' information seeking (Koren, Bell, and Volinsky, 2009; Rendle, 2010; Rendle et al., 2009; He et al., 2017; Wang, Wang, and Yeung, 2015; Chen et al., 2017; Ebesu, Shen, and Fang, 2018). However, much of such prior work in the area solely leverages the offline historical data to build the recommender model (henceforth, the *static recommender system*). This offline focus causes the recommender to suffer from an inherent limitation in the optimization of offline performance, which may not necessarily match online user behavior. User preference can be diverse and often drift with time; and as such, it is difficult to know the exact intent of a user when he uses a service even when the training data is sufficient.

The rapid development of conversational techniques (Li et al., 2018; Liao et al., 2018; Wang et al., 2018; Lei et al., 2018) brings an unprecedented opportunity that allows a recommender system to dynamically obtain user preferences through conversations with users. This possibility is envisioned as the *conversational recommender system* (CRS), for which the community has started to expend effort in exploring its various settings. Zhang et al., 2018 built a conversational search engine by focusing on document representation. Li et al., 2018 developed a dialogue system to suggest movies for cold start users, contributing to language understanding and generation for the purpose of recommendation, but does not consider modeling users' interaction histories (e.g., clicks, ratings). In contrast, Christakopoulou et al., 2018 does considers user click history in recommending, but their CRS only handles single-round recommendation. That is, their model considers a scenario in which the CRS session terminates after making a single recommendation, regardless of whether the recommendation is satisfactory or not. While a significant advance, we feel this scenario is unrealistic in actual deployments.

In particular, we believe CRS models should inherently adopt a *multi-round* setting: a CRS converses with a user to recommend items based on his click history (if any). At each round, the CRS is allowed to choose two types of actions — either explicitly asking whether a user likes a certain item attribute or recommending a list of items. In a session, the CRS may alternate between these actions multiple times, with the goal of finding desirable items for a user while minimizing the number of interaction rounds. This multi-round setting is more challenging than the single-round setting, as the CRS needs to strategically plan its actions. To do that, we argue the core problems lie in the deep interactions between the conversational component (CC) and the recommender component (RC). In a nutshell, our model casts the CC as the component responsible for interacting with the user, while the RC is responsible for estimating user preference (e.g., generating the recommendation list). We systematically summarize three fundamental problems toward the deep interaction between CC and RC as follows:

- *What attributes to ask?* A CRS needs to choose which attribute to interrogate the user. For example, in music recommendation, it may ask "Would you like to listen to classical music?", expecting a binary yes/no response[1]. If the answer is yes, it can focus on items containing the attribute, benefitting the RC by reducing uncertainty in item ranking. However, if the answer is no, the CRS expends a conversation turn with less gain to the RC. As such, towards achieving the goal of hitting the right items with fewer turns, the CC needs to carefully consider whether the user will like the asked attribute. This is exactly the job of the RC which scrutinizes the user's historical behavior.

- *When to recommend items?* With sufficient certainty, the CC should push the recommendations generated by the RC. A good timing to push recommendations should be when 1) the candidate space is small enough; when 2) asking additional questions is determined to less useful or helpful, from the perspective of either information gain or user patience; and when 3) the RC is confident that the top recommendations will be accepted by the user. Determining the appropriate timing should take both the conversation history of the CC and the preference estimation of the RC into account.

- *How to adapt to users' online feedback?* After each turn, the user gives feedback, e.g., yes/no on the queried attribute, or accept/reject the recommended items. (1) For "yes" on the attribute, both user profile and item candidates need to be updated so as to generate better recommendations; this requires the offline RC training to take such updates into account. (2) For "no" on the attribute, the CC needs to adjust its strategy accordingly. (3) If the recommended items are rejected, the RC model needs to be updated to incorporate such a negative signal. Although adjustments may seem only to impact either the RC or CC, we show that such actions actually impact both.

Towards the deep interaction between CC and RC, we propose a new solution named *Estimation–Action–Reflection* (EAR), which consists of three stages. Note that the stages do not necessarily align with each of the above problems. (a) Estimation, which builds predictive models offline to estimate user preference on items and item attributes. Specifically, we train a factorization machine (Rendle, 2010) (FM) using user profiles and item attributes as input features. Our Estimation stage builds in two novel advances: 1) the joint optimization of FM on the two tasks of item prediction and attribute prediction, and 2) the adaptive training of conversation data with online user feedback on attributes. (b) Action, which learns the conversational strategy that determines whether to ask or recommend, and what attribute to ask. We train a policy network with reinforcement learning, optimizing the reward of shorter turns and successful recommendations based on the FM's estimation of user preferred items and attributes, and the dialogue history. (c) Reflection, which adapts the CRS with user's online feedback. Specifically, when a user rejects the recommended items, we construct new training triplets by treating the items as negative instances and update the FM in an online manner. In summary, the main contributions of this thesis are as follows:

[1]Note that it is possible to compose questions eliciting an enumerated response; i.e., "Which music genre would you consider? I have pop, funk ...". However, this is a design choice depending on the domain requirements. When describing our method here, we consider the basic single-attribute case. However in experiments, we also justify the effectiveness of EAR in asking such enumerated questions on Yelp. For the purpose of exposition, we have chosen to avoid open questions that do not constrain user response for now. Even interpreting user responses to such questions is considered a challenging task (Chen et al., 2018).

- We comprehensively consider a multi-round CRS scenario that is more realistic than previous work, highlighting the importance of researching into the interactions between the RC and CC to build an effective CRS.
- We propose a three-stage solution, EAR, integrating and revising several RC and CC techniques to construct a solution that works well for the conversational recommendation.
- We build two CRS datasets by simulating user conversations to make the task suitable for offline academic research. We show our method outperforms several state-of-the-art CRS methods and provide insight on the task.

Chapter 2

Multi-round Conversational Recommendation Scenario

2.1 Workflow of Multi-round Conversational Recommendation Scenario

Following Christakopoulou et al., 2018, we denote one trial of recommendation as a *round*. This thesis considers conversational recommendation as an inherently *multi-round* scenario, where a CRS interacts with the user by asking attributes and recommending items multiple times until the task succeeds or the user leaves. To distinguish the two, we term the setting *single-round* where the CRS only makes recommendations once, ending the session regardless of the outcome, as in Sun and Zhang, 2018; Christakopoulou et al., 2018.

We now introduce the notation used to formalize our setting. Let $u \in \mathcal{U}$ denote a user u from the user set $\mathcal{U}$ and $v \in \mathcal{V}$ denote an item v from the item set $\mathcal{V}$. Each item v is associated with a set of attributes $\mathcal{P}_v$ which describe its properties, such as music genre "classical" or "jazz" for songs in LastFM, or tags such as "nightlife", "serving burgers", or "serving wines" for businesses in Yelp. We denote the set of all attributes as $\mathcal{P}$ and use p to denote a specific attribute. Following Sun and Zhang, 2018; Zhang et al., 2018, a CRS session is started with u's specification of a preferred attribute p^0, then the CRS filters out candidate items that contain the preferred attribute p^0. Then in each turn t ($t = 1, 2, ..., T$; T denotes the last turn of the session), the CRS needs to choose an action: *recommend* or *ask*:

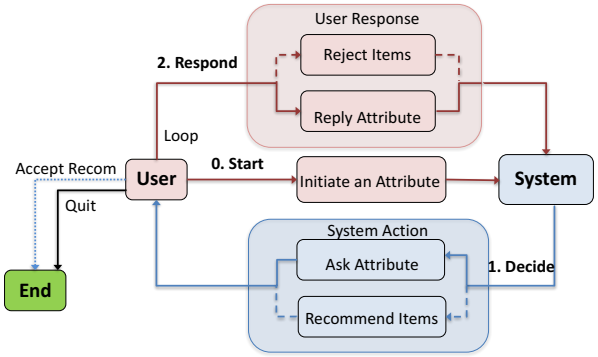


FIGURE 2.1: The workflow of our multi-round conversational recommendation scenario. The system may recommend items multiple times, and the conversation ends only if the user accepts the recommendation or chooses to quit

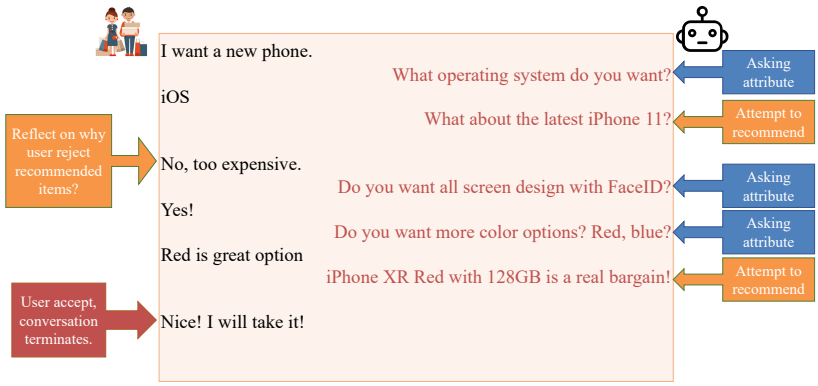


FIGURE 2.2: An example to show the workflow of multi-round conversational recommendation scenario at an online shop for electronic products. The user initiates the session with the attribute, *phone* and then session follows the workflow in Figure 2.1

- If the ACTION is *recommend*, we denote the recommended item list $\mathcal{V}^t \subset \mathcal{V}$ and the action as a_{rec}. Then the user examines whether $\mathcal{V}^t$ contains his desired item. If the feedback is positive, this session succeeds and can be terminated. Otherwise, we mark $\mathcal{V}^t$ as *rejected* and move to the next round.
- If the ACTION is *ask* (where the asked attribute is denoted as $p^t \in \mathcal{P}$ and the action as $a_{ask}(p^t)$), the user states whether he prefers items that contain the attribute p^t or not. If the feedback is positive, we add p^t into $\mathcal{P}_u$ to denote the preferred attributes the user in the current session. Otherwise, we mark p^t as *rejected*; regardless of rejection or not, we move to the next turn.

This whole process naturally forms a interaction loop (Figure 2.1) where the CRS may ask zero to many questions before making recommendations. A session terminates if a user accepts the recommendations or leaves due to his impatience. We set the main goal of the CRS as making desired recommendations within as few rounds as possible.

Let us walk through the example in Figure 2.2 which presents a multi-round conversational recommendation scenario at an online shop of electronic products. The user first initiates the session by informing an attribute he wants: *phone*. The system later asks an attribute, *operating system*, and user responds with *iOS*. The system chooses to push the recommendation of *iPhone 11*, but the user rejects it. Then the system asks two more attributes, namely *FaceID* and *color*, and finally makes a successful recommendation of *iPhone XR (Red, 128GB)*.

2.2 On the Importance of Item Attributes

One major motivation of our multi-round conversational recommendation scenario is to utilize the user's explicit feedback on attributes. Therefore, the item attributes stay at a central point in our problem setting, so we will give more explanation here.

As discussed in Section 2.1, the key components of an online platform are items, users, and attributes. Let us revisit the notation in Table 2.1: $u \in \mathcal{U}$ denotes a user u from the user set $\mathcal{U}$ and $v \in \mathcal{V}$ denotes an item v from the item set $\mathcal{V}$.

We assume that those online platforms will have many item attributes to better describe their items. We use $p \in \mathcal{P}$ to denote an attribute p from the attribute set $\mathcal{P}$. Each item v is associated with a set of attributes $\mathcal{P}_v$ which describe the properties of

TABLE 2.1: Main notations used in this thesis.

$u, \mathcal{U}$	User, and the user set
$v, \mathcal{V}$	Item, and the item set
$p, \mathcal{P}$	Attribute, and the attribute set
$\mathcal{P}_v$	Attribute set of an item v
$\mathcal{P}_u$	The set of attributes confirmed by u in a session
$\mathcal{V}_p$	The set of items that contain the attribute p
$\mathcal{V}_{cand}$	The set of candidate items
a	The action of EAR system, either a_{ask} (ask an attribute) or a_{rec} (make recommendation)

items, so apparently $\mathcal{P}_v$ is a subset of $\mathcal{P}$. In fact, the relationship between attribute set $\mathcal{P}$ and item set $\mathcal{V}$ is a bipartite graph. This bipartite structure is exploited by Zhang et al., 2020 in their work[1].

Item attributes are very important to our scenario. Let us recall another important notation, $\mathcal{P}_u$, which denotes the set of known attributes preferred by the user in an interactive session. At the very beginning, $\mathcal{P}_u$ is an empty set. With the user gives positive feedbacks on attributes being asked, $\mathcal{P}_u$ will gradually grow. This not only helps the recommender components (RC) better estimate user's preference but also helps the system to prune off irrelevant items that do not contain $\mathcal{P}_u$, which makes candidate item set $\mathcal{V}_{cand}$ smaller and thus makes the RC better make a recommendation.

Regarding our workflow in Figure 2.1, we have designed two types of questions that the system can ask users, which requires different ways for us to organize the attributes.

- **Binary question**: The system asks the user if he likes an attribute, and the user can only reply "Yes" or "No". In the above example, *FaceID* belongs to binary attributes. We directly use the attributes essentially as they are given in a specific platform (dataset).

- **Enumerated question**: The system asks the user about his preference towards a *category*. Specifically, the systems will present all possible options for this *category* to the user, and the user can choose one or multiple options from those being presented. For example, the *color* and *operating systems* are both categories being asked as enumerated question. To facilitate the evaluation of enumerated questions, we construct a 2-level taxonomy of attributes to organize them. Regarding the relationship between attributes, apparently, those attributes under the same category are semantically similar to each other. Those categories themselves are rather independent with each other. We detail our construction of such attributes in Section 4.1.1.

[1] In their work, the attribute and item are termed as key-term and arm (of bandit algorithm).

Chapter 3

Proposed Methods

EAR consists of a recommendation and conversation component (RC and CC) which interact intensively in the three–stage conversational process. The system starts working at the *estimation* stage where the RC ranks candidate items and item attributes for the user, so as to support the action decision of the CC. After the *estimation* stage, the system moves to the *action* stage where the CC decides whether to choose an attribute to ask, or make a recommendation according to the ranked candidates and attributes, and the dialogue history. If the user likes the attribute asked by the RC, the CC feeds this attribute back to the RC to make a new *estimation* again; otherwise, the system stays at the *action* stage: updates the dialogue history and chooses another action. Once a recommendation is rejected by a user, the CC sends the rejected items back to RC, triggering the *reflection* stage where the RC adjusts its estimations. After that, the system enters the *estimation* stage again.

3.1 Estimation

As discussed before, the multi-round conversational scenario brings in new challenges to the traditional RC. Specifically, the CC interacts with a user u and accumulates evidence on his preferred attributes, denoted as $\mathcal{P}_u = \{p_1, p_2, .., p_n\}$[1]. Importantly, different from traditional recommendation methods (Rendle et al., 2009; He et al., 2017), the RC here needs to make full use of $\mathcal{P}_u$ aiming to accurately predict both user's the preferred items and preferred attributes. These two goals exert positive influence on EAR, where the first directly contributes to success rate of recommendation, and the second guides the CC to choose better attributes to ask users so as to shorten the conversation. In the following, we first introduce the basic form of the recommendation method, followed by detail on how we adapt our proposed method to achieve both goals simultaneously.

3.1.1 Basic Recommendation Method

we choose the factorization machine (FM) (Rendle, 2010) as our predictive model due to its success and wide usage in recommendation tasks. However, FM considers all pairwise interactions between input features, which is costly and may introduce undesired interactions that negatively affect our two goals. Thus, we only keep the interactions that are useful to our task and remove the others. Given user u, his preferred attributes in the conversation $\mathcal{P}_u$, and the target item v, we predict how likely u will like v in the conversation session as:

$$\hat{y}(u, v, \mathcal{P}_u) = \mathbf{u}^T\mathbf{v} + \sum_{p_i \in \mathcal{P}_u} \mathbf{v}^T\mathbf{p_i}, \tag{3.1}$$

[1]We detail how to obtain such data in experiments Chapter 4.1.2.

where $\mathbf{u}$ and $\mathbf{v}$ denote the embedding for user u and item v, respectively, and $\mathbf{p}_i$ denotes the embedding for attribute $p_i \in \mathcal{P}_u$. Bias terms are omitted for clarity. The first term $\mathbf{u}^T\mathbf{v}$ models the general interest of the user on the target item, a common term in FM model (He et al., 2017). The second term $\sum \mathbf{v}^T\mathbf{p_i}$ models the affinity between the target item and user preferred attributes. We have also tried to include v's attributes $\mathcal{P}_v$ into FM, but found it brings no benefits. One possible reason is that the item embedding $\mathbf{v}$ may have already encoded its attribute information. Thus we also omit it.

To train the FM, we optimize the pairwise Bayesian Personalized Ranking (BPR) (Rendle et al., 2009) objective. Specifically, given a user u, it assumes the interacted items (e.g., visited restaurants, listened music) should be assigned higher scores than those not interacted with. The loss function of traditional BPR is:

$$L_{bpr} = \sum_{(u,v,v')\in\mathcal{D}_1} -\ln\sigma(\hat{y}(u,v,\mathcal{P}_u) - \hat{y}(u,v',\mathcal{P}_u)) + \lambda_\Theta \|\Theta\|^2 \tag{3.2}$$

where $\mathcal{D}_1$ is the set of pairwise instances for BPR training, $\mathcal{D}_1 := \{(u,v,v') \mid v' \in \mathcal{V}_u^-\}$, where v is the interacted item of the conversation session (i.e., the ground truth item of the session), $\mathcal{V}_u^- := \mathcal{V}\backslash\mathcal{V}_u^+$ denotes the set of non-interacted items of user u and $\mathcal{V}_u^+$ denotes the items interacted by u. σ is the sigmoid function, and λ_Θ is the regularization parameter to prevent overfitting.

3.1.2 Attribute-aware BPR for Item Prediction.

However, in our scenario, the emphasis of CRS is to rank the items that contain the user preferred attributes well. For example, if u specifies "Mexican restaurant" as his preferred attribute, a good CRS needs to rank his preferred restaurants among all available Mexican restaurants. To capture this, we propose to sample two types of negative examples:

$$\mathcal{V}_u^- := \mathcal{V}\backslash\mathcal{V}_u^+, \quad \widehat{\mathcal{V}}_u^- := \mathcal{V}_{cand}\backslash\mathcal{V}_u^+, \tag{3.3}$$

where $\mathcal{V}_u^-$ is the same negative samples as in the traditional BPR setting, i.e., all non-interacted items of u. $\mathcal{V}_{cand}$ denotes the current candidate items satisfying the partially known preference $\mathcal{P}_u$ in the conversation, and $\widehat{\mathcal{V}}_u^-$ is the subset of $\mathcal{V}_{cand}$ that excludes the observed items $\mathcal{V}_u^+$. The two types of pairwise training instances is defined as:

$$\mathcal{D}_1 := \{(u,v,v') \mid v' \in \mathcal{V}_u^-\}, \quad \mathcal{D}_2 := \{(u,v,v') \mid v' \in \widehat{\mathcal{V}}_u^-\}, \tag{3.4}$$

We then train the FM model by optimizing both $\mathcal{D}_1$ and $\mathcal{D}_2$:

$$L_{item} = \sum_{(u,v,v')\in\mathcal{D}_1} -\ln\sigma(\hat{y}(u,v,\mathcal{P}_u) - \hat{y}(u,v',\mathcal{P}_u)) + \sum_{(u,v,v')\in\mathcal{D}_2} -\ln\sigma(\hat{y}(u,v,\mathcal{P}_u) - \hat{y}(u,v',\mathcal{P}_u)) + \lambda_\Theta \|\Theta\|^2 \tag{3.5}$$

where the first loss learns u's general preference, and the second loss learns u's specific preference given the current candidates. It is worth noting adding the second loss for training is critical for the model ranking well on the current candidates. This is very important for CRS since the candidate items dynamically change with user feedback along the conversation. However, the state-of-the-art method CRM (Sun and Zhang, 2018) does not account for this factor, being insufficient in considering the interaction between the CC and RC.

3.1.3 Attribute Preference Prediction.

We formulate the task of the second goal of accurate attribute prediction separately. This prediction of attribute preference is mainly used in the CC to support the action on which attribute to ask (*c.f.* Sec 3.2). As such, we take u's preferred attributes in the current session into account:

$$\hat{g}(p|u, \mathcal{P}_u) = \mathbf{u}^T\mathbf{p} + \sum_{p_i \in \mathcal{P}_u} \mathbf{p}^T\mathbf{p}_i, \tag{3.6}$$

which estimates u's preference on attribute p, given u's current preferred attributes $\mathcal{P}_u$. To train the model, we also employ BPR loss, and assume that the attributes of the ground truth item v (of the session) should be ranked higher than other attributes:

$$L_{attr} = \sum_{(u,p,p') \in \mathcal{D}_3} -\ln\sigma(\hat{g}(p|u, \mathcal{P}_u) - \hat{g}(p'|u, \mathcal{P}_u)) + \lambda_\Theta \|\Theta\|^2, \tag{3.7}$$

where the pairwise training data D_3 is defined as:

$$D_3 = \{(u, p, p')|p \in \mathcal{P}_v, p' \in \mathcal{P} \backslash \mathcal{P}_v\}, \tag{3.8}$$

where $\mathcal{P}_v$ denotes item v's attributes.

3.1.4 Multi-task Training.

We perform joint training on the two tasks of item prediction and attribute prediction, which has the potential of mutual benefits since their parameters are shared. The multi-task training objective is:

$$L = L_{item} + L_{attr}. \tag{3.9}$$

Specifically, we first train the model with L_{item}. After it converges, we continue optimizing the model using L_{attr}. We iterate the two steps until convergence under both losses. Empirically, 2-3 iterations are sufficient for convergence.

3.2 Action

After the estimation stage, the action stage finds the best strategy for *when to recommend*. We adopt reinforcement learning (RL) to tackle this multi-round decision making problem, aiming to accomplish successful recommendation in shorter number of turns. It is worth noting that since our focus is on conversational recommendation strategy, as opposed to fluent dialogue (the language part), we use templates as wrappers to handle user utterances and system response generation. That is to say, this work serves as an upper bound study of real applications as we do not include the errors for language understanding and generation.

3.2.1 State Vector.

The state vector is a bridge for the interaction between the CC and RC. We encode information from the RC and dialogue history into a state vector, providing it to the CC to choose actions. The state vector is a concatenation of four component vectors

that encode signal from different perspectives:

$$\mathbf{s} = \mathbf{s}_{ent} \oplus \mathbf{s}_{pre} \oplus \mathbf{s}_{his} \oplus \mathbf{s}_{len}. \tag{3.10}$$

Each of the vector components captures an assumption on asking which attribute could be most useful, or whether now is a good time to push a recommendation. They are defined as follows:

- $\mathbf{s}_{ent}$: This vector encodes the entropy information of each attribute among the attributes of the current candidate items $\mathcal{V}_{cand}$. The intuition is that asking attributes with large entropy helps to reduce the candidate space, thus benefits finding desired items in fewer turns. Its size is the attribute space size $|\mathcal{P}|$, where the i-th dimension denotes the entropy of the attribute p_i.

- $\mathbf{s}_{pre}$: This vector encodes u's preference on each attribute. It is also of size $|\mathcal{P}|$, where each dimension is evaluated by Equation (3.6) on the corresponding attribute. The intuition is that the attribute with high predicted preference is likely to receive positive feedback, which also helps to reduce the candidate space.

- $\mathbf{s}_{his}$: This vector encodes the conversation history. Its size is the number of maximum turns T, where each dimension t encodes user feedback at turn t. Specifically, we use -1 to represent recommendation failure, 0 to represent asking an attribute that u disprefers, and 1 to represent successfully asking about an attribute that u desires. This state is useful to determine when to recommend items. For example, if the system has asked about a number of attributes for which u approves, it may be a good time to recommend.

- $\mathbf{s}_{len}$: This vector encodes the length of the current candidate list. The intuition is that if the candidate list is short enough, EAR should turn to recommending to avoid wasting more turns. We divide the length $|\mathcal{V}_{cand}|$ into ten categorical (binary) features to facilitate the RL training.

It is worth noting that besides $\mathbf{s}_{his}$, the other three vectors are all derived from the RC component. We claim that this is a key difference from existing conversational systems (Zhang et al., 2018; Li et al., 2018; Sun and Zhang, 2018; Christakopoulou et al., 2018; Liao et al., 2018); i.e., the CC needs to take information from the RC to decide the dialogue action. In contrast to EAR, the recent conversational recommendation method CRM (Sun and Zhang, 2018) makes decisions based only on the belief tracker that records the preferred attributes of the user, which makes it less informative. As such, CRM is less effective especially when the number of attributes is large (their experiments only deal with 5 attributes, which is insufficient for real-world applications).

3.2.2 Policy Network and Rewards

The conversation action is chosen by a policy network in our CC. In order to demonstrate the efficacy of our designed state vector, we purposely choose a simple policy network — a two-layer multi-layer perceptron, which can be optimized with the standard policy gradient method. It contains two fully-connected layers and maps the state vector $\mathbf{s}$ into the action space. The output layer is normalized to be a probability distribution over all actions by $softmax$. In terms of the action space, we follow the previous method Sun and Zhang, 2018, which includes all attributes $\mathcal{P}$

and a dedicated action for recommendation. To be specific, we define the action space as $\mathcal{A} = \{a_{rec} \cup \{a_{ask}(p)|p \in \mathcal{P}\}\}$, which is of size $|\mathcal{P}| + 1$. After the CC takes an action at each turn, it will receive an immediate reward from the user (or user simulator). This will guide the CC to learn the optimal policy that optimizes long-term reward. In EAR, we design four kinds of rewards, namely: (1) r_{suc}, a strongly positive reward when the recommendation is successful, (2) r_{ask}, a positive reward when the user gives positive feedback on the asked attribute, (3) r_{quit}, a strongly negative reward if the user quits the conversation, (4) r_{prev}, a slightly negative reward on every turn to discourage overly lengthy conversations. The intermediate reward r_t at turn t is the sum of the above four rewards, $r_t = r_{suc} + r_{ask} + r_{quit} + r_{prev}$.

We denote the policy network as $\pi(a^t \mid \mathbf{s}^t)$, which returns the probability of taking action a^t given the state $\mathbf{s}^t$. Here $a^t \in \mathcal{A}$ and $\mathbf{s}^t$ denote the action to take and the state vector of the t-th turn, respectively. To optimize the policy network, we use the standard policy gradient method (Sutton et al., 2000), formulated as follows:

$$\theta \leftarrow \theta - \alpha \bigtriangledown \log \pi_\theta(a^t \mid \mathbf{s}^t) R_t, \tag{3.11}$$

where θ denotes the parameter of the policy network, α denotes the learning rate of the policy network, and R_t is the total reward accumulating from turn t to the final turn T: $R_t = \sum_{t'=t}^{T} \gamma^{T-t'} r_{t'}$, where γ is a discount factor which discounts future rewards over immediate reward.

3.3 Reflection

This stage also implements the interaction between the CC and RC. It is triggered when the CC pushes the recommended items $\mathcal{V}^t$ to the user but gets rejected, so as to update the RC model for better recommendations in future turns. In the traditional static recommender system training scenario (Rendle et al., 2009; He et al., 2017), one issue is the absence of true negative samples, since users do not explicitly indicate what they dislike. In our conversational case, the rejection feedback is an explicit signal on user dislikes which are highly valuable to utilize; moreover, it indicates that the offline learned FM model improperly assigns high scores to the rejected items. To leverage on this source of feedback, we treat the rejected items $\mathcal{V}^t$ as negative samples, constructing more training examples to refresh the FM model. Following the offline training process, we also optimize the BPR loss:

$$L_{ref} = \sum_{(u,v,v') \in \mathcal{D}_4} -\ln \sigma(\hat{y}(u, v, \mathcal{P}_u) - \hat{y}(u, v', \mathcal{P}_u)) + \lambda_\Theta \|\Theta\|^2 \tag{3.12}$$

where $\mathcal{D}_4 := \{(u, v, v') \mid v \in \mathcal{V}_u^+ \wedge v' \in \mathcal{V}^t\}$. Note that this stage is performed in an online fashion, where we do not have access to the ground truth positive item. Thus, we treat the historically interacted items $\mathcal{V}_u^+$ as the positive items to pair with the rejected items. We put all examples in D_4 into a batch and perform batch gradient descent. Empirically, it takes 3-5 epochs to converge, sufficiently efficient for online use.

Note that although it sounds reasonable to also update the policy network of the CC (since the rejection feedback implies that it is not an appropriate timing to push recommendation), we currently do not perform this due to high difficulty of online updating RL agent and leave it for future work.

Chapter 4

Experiments

EAR is built based on the guiding ideology of interaction between the CC and RC[1]. To validate this ideology, we first evaluate whole system to examine the overall effect brought by the interaction. Then, we perform ablation study to investigate the effect of interaction on each individual component. Specifically, we have the following research questions (RQ) to guide experiments on two datasets.

- **RQ1.** How is the overall performance of EAR comparing with existing conversational recommendation methods?
- **RQ2.** How do the attribute-aware BPR and multi-task training of the *estimation* stage contribute to the RC?
- **RQ3.** Is the state vector designed for the CC in the *action* stage appropriate?
- **RQ4.** Is the online model update of the *reflection* stage useful in obtaining better recommendation?

4.1 Settings

4.1.1 Datasets

We conduct experiments on two datasets: Yelp[2] for business recommendation and LastFM[3] for music artist recommendation. First, we follow the common setting of recommendation evaluation (He et al., 2017; Rendle et al., 2009) that reduces the data sparsity by pruning the users that have less than 10 reviews. We split the user–item interactions in the ratio of 7:2:1 for training, validation and testing. Table 4.1 summarizes the statistics of the datasets.

For the item attributes, we preprocess the original attributes of the datasets by merging synonyms and eliminating low frequency attributes, resulting in 590 attributes in Yelp and 33 attributes in LastFM. In real applications, asking about attributes in a large attribute space (e.g., on Yelp dataset) causes overly lengthy conversation. We therefore consider both the binary question setting (on LastFM) and enumerated question (on Yelp). To enable the enumerated question setting, we build a two-level taxonomy on the attributes of the Yelp data. For example, the *parent attribute* of {“wine", “beer", “whiskey”} is “alcohol”. We create 29 such parent attributes on the top of the 590 attributes, such as “nightlife”, “event planning services”, “dessert types” etc. In the enumerated question setting, the system choose one parent attribute to ask. This is to say, we change the size of the output space of

[1] All codes and datasets can be found at http://ear-conv-rec.github.io
[2] https://www.yelp.com/dataset/
[3] https://grouplens.org/datasets/hetrec-2011/

TABLE 4.1: Dataset statistics.

Dataset	#users	#items	#interactions	#attributes
Yelp	27,675	70,311	1,368,606	590
LastFM	1,801	7,432	76,693	33

the policy network to be $29 + 1 = 30$. At the same time, it also displays all its child attributes and ask the user to choose from them (the user can reply with multiple child attributes). Note that choosing what kinds of questions to ask is an engineering design choice by participants, here we evaluate our model on both settings.

4.1.2 User Simulator For Multi-round Scenario.

Because the conversational recommendation is a dynamic process, we follow Zhang et al., 2018; Sun and Zhang, 2018) to create a user simulator to enable the CRS training and evaluation. We simulate a conversation session for each observed interaction between users and items. Specifically, given an observed user–item interaction (u, v), we treat the v as the ground truth item to seek for and its attributes $\mathcal{P}_v$ as the oracle set of attributes preferred by the user in this session. At the beginning, we randomly choose an attribute from the oracle set as the user's initialization to the session. Then the session goes in the loop of the "model acts – simulator response" process as introduced in Section 2. We set the max turn T of a session to 15 and standardize the recommendation list length $\mathcal{V}^t$ as 10.

4.1.3 Training Details

Following CRM (Sun and Zhang, 2018), the training process is divided into offline and online stages. The offline training is to build the RC (i.e., FM) and initialize the policy network (PN) by letting them optimize performance with the offline dialogue history. Due to the scarcity of the conversational recommendation dialogue history, we follow CRM (Sun and Zhang, 2018) to simulate dialogue history by building a rule-based CRS to interact with the simulator introduced in Section 4.1.2. Specifically, the strategy for determining which attribute to ask about is to choose the attribute with the maximum entropy. Each turn, the system chooses the recommendation action with probability $10/max(|\mathcal{V}|, 10)$ where $\mathcal{V}$ is the current candidate set. The intuition is that the confidence of recommendation grows when the candidate size is smaller. We train the RC to give the ground-truth item and oracle attributes higher ranks given the attribute confirmed by users in dialogue histories, while training the policy to mimic the rule-based strategy on the history. Afterwards, we conduct online training, optimizing the PN by letting EAR interact with the user simulator through reinforcement learning.

All hyper-parameters are tuned on the validation set. We set the embedding size of FM as 64. We employ the multi-task training mechanism to optimize FM as described in Section 3.1.4, using SGD with a regularization strength of 0.001. The learning rate for the first task (item prediction) and second task (attribute prediction) is set to 0.01 and 0.001, respectively. The size of the two hidden layers in the PN is set as 64. When the pre-trained model is initialized, we use the REINFORCE algorithm to train the PN. The four rewards are set as: r_{suc}=1, r_{ask}=0.1, r_{quit}=-0.3, and r_{prev}=-0.1, and the learning rate α is set as 0.001. The discount factor γ is set to be 0.7.

4.1.4 Baselines.

As our multi-round conversational recommendation scenario is new, there are few suitable baselines. We compare our overall performance with the following three:

- **Max Entropy**. This method follows the rule we used to generate the conversation history in Section 4.1.2. Each turn it asks the attribute that has the maximum entropy among the candidate items. It is claimed in Dhingra et al., 2017 that maximum entropy is the best strategy when language understanding is precise.
- **Abs Greedy** (Christakopoulou, Radlinski, and Hofmann, 2016). This method recommends items in every turn without asking any question. Once the recommendation is rejected, it updates the model by treating the rejected items as negative examples. According to Christakopoulou, Radlinski, and Hofmann, 2016, this method achieves equivalent or better performance than popular bandit algorithms like Upper Confidence Bounds Auer, 2002 and Thompson Sampling Chapelle and Li, 2011.
- **CRM** (Sun and Zhang, 2018). This is a state-of-the-art CRS. Similar to EAR, it integrates a CC and RC by feeding the belief tracker results to FM for item prediction, without considering much interactions between them. It is originally designed for single-round recommendation. To achieve a fair comparison, we adapt it to the multi-round setting by following the same offline and online training EAR.

It is worth noting that although there are other recent conversational recommendation methods (Zhang et al., 2018; Li et al., 2018; Christakopoulou, Radlinski, and Hofmann, 2016; Liao et al., 2018), they are ill-suited for comparison due to their different task settings. For example, Zhang et al., 2018 focuses on document representation which is unnecessary in our case. It also lacks the conversation policy component to decide when to make what action. Li et al., 2018 focuses more on language understanding and generation. We summarize the settings of these methods in Table 5.1 and discuss differences in Section 5.

4.1.5 Evaluation Metrics

We use the success rate (SR@t) (Sun and Zhang, 2018) to measure the ratio of successful conversations, i.e., recommend the ground truth item by turn t. We also report the average turns (AT) needed to end the session. Larger SR denotes better recommendation and smaller AT denotes more efficient conversation. When studying RC model of offline training, we use the AUC score which is a surrogate of the BPR objective (Rendle et al., 2009). We conduct one-sample paired t-test to judge statistical significance.

4.2 Performance Comparison (RQ1)

Figure 4.1 shows the recommendation Success Rate* (SR*) @t at different turns ($t = 1$ to 15), SR* denotes the comparison of each method against the strongest baseline CRM, indicated as $y = 0$ in the figure. Table 4.2 shows the scores of the final success rate and the average turns. As can be clearly seen, our EAR model significantly outperforms other methods. This validates our hypothesis that considering extensive

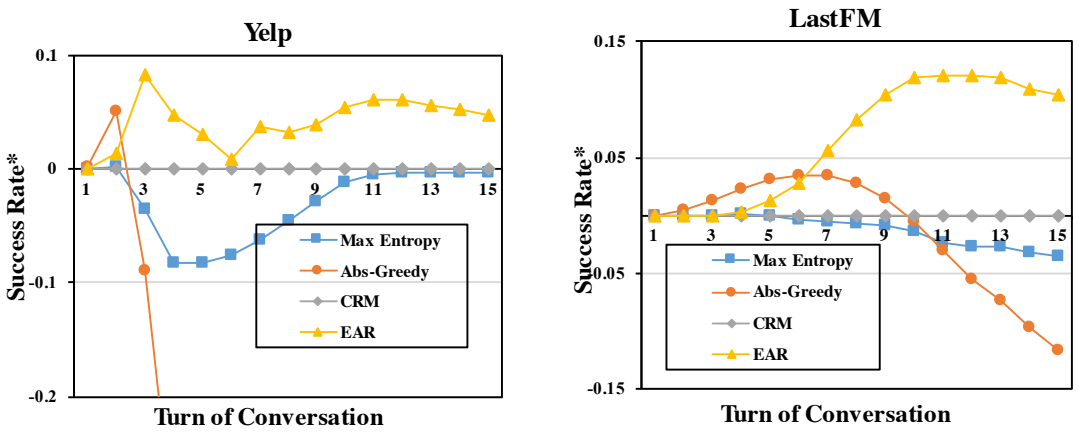


FIGURE 4.1: Success Rate* of compared methods at different conversation turns on Yelp and LastFM (RQ1).

TABLE 4.2: SR@15 and AT of compared methods. * denotes that improvement of EAR over other methods is statistically significant for $p < 0.01$ (RQ1).

	LastFM		Yelp	
	SR@15	**AT**	**SR@15**	**AT**
Abs Greedy	0.209	13.63	0.271	12.26
Max Entropy	0.290	13.61	0.919	5.77
CRM	0.325	13.43	0.923	5.33
EAR	**0.429***	**12.45***	**0.971***	**4.71***

interactions between the CC and RC is an effective strategy to build conversational a recommender system. We also make the following observations:

Comparing with Abs Greedy, the three attribute-based methods (EAR, Max Entropy and CRM) have nearly zero success rate at the beginning of a conversation ($t < 2$). This is because these methods tend to ask questions at the very beginning. As the conversation goes, Abs Greedy (which only recommends items) gradually falls behind the attribute-based methods, demonstrating the efficacy of asking attributes in the conversational recommendation scenario. Note that Abs Greedy has much weaker performance on Yelp compared to LastFM. The key reason is the setting of Yelp is to ask enumerated question, and user's response with multiple finer-grained attributes sharply shrinks the candidate items.

CRM generally underperforms our EAR methods. One of the key reasons is that its state vector cannot help CC to learn sophisticated strategy to ask and recommend, especially in a much larger action space, i.e., the number of attributes (nearly 30 in our experiments versus 5 in theirs Sun and Zhang, 2018). This result suggests that in a more complex *multi-round* scenario where the CC needs to make a comprehensive utilization of both the CC (e.g., considering dialogue histories) and RC (considering statistics like attribute preference estimation) when formulating a recommendation strategy.

Interestingly, Figure 4.1 indicates that in Yelp, EAR's gain over CRM enlarges in Turns 1–3, shrinks in Turns 4–6 and widens again afterwards. However, in LastFM it has a steadily increasing gain. This interesting phenomenon reveals that our EAR system can learn different strategies in different settings. In the Yelp dataset, the CRS asks enumerated questions where the user can choose finer-grained attributes,

TABLE 4.3: Offline AUC score of FM, FM with attribute-aware BPR (FM+A) and with multi-task training for item recommendation and attribute prediction (FM+A+MT). * denotes that improvement of FM+A+MT over FM and FM+A is statistically significant for $p < 0.01$ (RQ2).

	LastFM		Yelp	
	Item	**Attribute**	**Item**	**Attribute**
FM	0.521	0.727	0.834	0.654
FM+A	0.724	0.629	0.866	0.638
FM+A+MT	**0.742***	**0.760***	**0.870***	**0.896***

resulting a sharp reduction in the candidate space. The strategy that the EAR system learns is more aggressive: it attempts to ask attributes that can sharply shrink the candidate space and make decisive recommendation at the beginning turns when it feels confident. If this aggressive strategy fails, it changes to a more patient strategy to ask more questions without recommendations, causing less success in the medial turns (e.g., Turns 5–7). However, this strategy pays off in the long term, making recommendation more successful in the latter half of conversations (e.g., after Turn 7). At the same time, CRM is only able to follow the strategy of trying to ask more attributes at the beginning and making recommendations later. In the LastFM dataset, the setting is limited to binary attributes, leading to less efficiency in reducing candidate space. Both EAR and CRM adapt and ask more questions at the outset before making recommendations. However, as EAR incorporates better CC and RC to model better interaction, it significantly outperforms CRM.

4.3 Effectiveness of Estimation Designs (RQ2)

There are two key designs in the estimation stage that trains the recommendation model FM offline: the attribute-aware BPR that samples negatives with attribute matching considered, and the multi-task training that jointly optimizes item prediction and attribute prediction tasks. Table 4.3 shows offline AUC scores on the two tasks of three methods: FM, FM with attribute-aware BPR (FM+A), and FM+A with multi-task training (FM+A+MT).

As can be seen, the attribute-aware BPR significantly boosts the performance of item ranking, being highly beneficial to rank the ground truth item high. Interestingly, it harms the performance of attribute prediction, e.g. on lastFM, FM+A has a much lower AUC score (0.629) than FM (0.727). The reason might be that the attribute-aware BPR loss guides the model to specifically fit to item ranking in the candidate list. Without an even optimization enforced for the attribute prediction task, it may suffer from poor performance. This implies the necessity of explicitly optimizing the attribute prediction task. As expected, the best performance is achieved when we add multi-task training on. FM+A+MT significantly enhances the performance of both tasks, validating the effectiveness and rationality of our multi-task training design.

4.4 Ablation Studies on State Vector (RQ3)

What information helps in decision making? Let us examine the effects of the the four forms of information included in EAR state vector $\mathbf{s}$ (Equation 3.10), by ablating

TABLE 4.4: Performance of removing one component of the state vector (Equation 3.10) from our EAR. * denotes that improvement of EAR over model with removed component is statistically significant for $p < 0.01$ (RQ 3).

	Yelp				LastFM			
	SR@5	SR@10	SR@15	AT	SR@5	SR@10	SR@15	AT
$-\mathbf{s}_{ent}$	0.614	0.895	0.969	4.81	**0.051**	0.190	0.346	12.82
$-\mathbf{s}_{pre}$	0.596	0.857	0.959	5.06	0.024	0.231	0.407	12.55
$-\mathbf{s}_{his}$	0.624	0.894	0.949	4.79	0.021	0.236	0.424	12.50
$-\mathbf{s}_{len}$	0.550	0.846	0.952	5.44	0.013	0.230	0.416	12.56
EAR	**0.629***	**0.907***	**0.971***	**4.71***	0.020	**0.243***	**0.429***	**12.45***

TABLE 4.5: Performance after removing the online update module in the reflection stage. * denotes that improvement of EAR over removing update module is statistically significant for $p < 0.01$ (RQ4).

	Yelp				LastFM			
	SR@5	SR@10	SR@15	AT	SR@5	SR@10	SR@15	AT
-update	0.629	0.905	0.970	4.72	0.020	0.217	0.393	12.67
EAR	**0.629**	**0.907**	**0.971**	**4.71**	**0.020**	**0.243***	**0.429***	**12.45***

each information type from the feature vector (Table 4.4).

Comparing the performance drop of each method, we uncover differences that corroborate the intrinsic difference between the two conversational settings. The most important factor is question type: i.e., $\mathbf{s}_{ent}$ for LastFM (binary question) and $\mathbf{s}_{len}$ for Yelp (enumerated question). The entropy($\mathbf{s}_{ent}$) information is crucial for LastFM, it is in line with the claim in Dhingra et al., 2017 that the maximum entropy is the best strategy when language understanding is precise. If we ablate $\mathbf{s}_{ent}$ on LastFM, although it reaches 0.051 in SR@5, future SR greatly suffers, due to the system's over-agressiveness to recommend items before obtaining sufficient relevant attribute evidence. As for the enumerated question setting (Yelp), the candidate list length ($\mathbf{s}_{len}$) is most important, because the candidate item list shrinks more sharply and $\mathbf{s}_{len}$ is helpful when deciding when to recommend.

Apart from entropy and candidate list length, the remaining two factors – i.e., attribute preference, conversation history – both contribute positively. Their impact is sensitive to datasets and metrics. For example, the attribute preference ($\mathbf{s}_{pre}$) strongly affect SR@5 and SR@10 on Yelp, but does not show significant impacts for SR@15. This inconsistency provides an evidence for the intrinsic difficulty of decision making in the conversational recommendation scenario, which however has yet to be extensively studied.

4.5 Investigation on Reflection (RQ4)

To understand the impact of online update in the reflection stage, we start from the ablation study. Table 4.5 shows the variant of EAR that removes online update. We find that the trends do not converge on two datasets: the updating strategy helps a lot on LastFM but has very minor effect on the Yelp dataset.

Questioning this interesting phenomenon, we examine the individual items on Yelp. We find that the updating does not always help ranking, especially when the offline model already ranks the ground truth item high (but not at top 10). In this

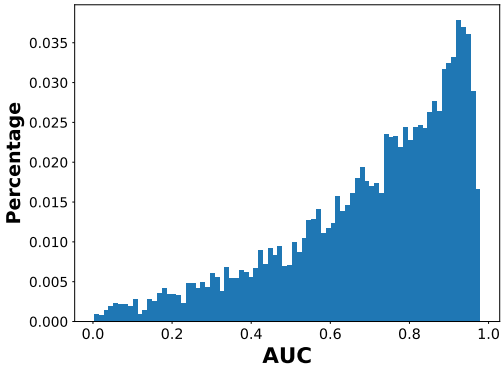


FIGURE 4.2: Percentage of bad updates w.r.t. the offline model's AUC on the users on Yelp (RQ4).

case, doing updates is highly likely to pull down the ranking position of the ground truth item. To gain statistical evidence for this observation, we term such updates as *bad updates*, and show the percentage of bad updates with respect to the offline model's AUC on the users. As seen from Figure 4.2, there is a clear positive correlation between bad updates and AUC score. For example, $\sim$3.5% of the bad updates come from users with an offline AUC of 0.9.

This explains why online update works well for LastFM, but not for Yelp: our recommendation model has a better performance on Yelp than LastFM (0.870 v.s. 0.742 in AUC as shown in Table 4.3). This means the items on Yelp are more likely to get higher AUC, resulting in worse updates. More such observations and analyses will help further the community understanding the efficacy of online updates. Although bandit algorithms have devoted to exploring this question (Kuleshov and Precup, 2014; Chu et al., 2011; Li, Karatzoglou, and Gentile, 2016; Gentile, Li, and Zappella, 2014; Wu et al., 2016), the issue has largely been unaddressed in the context of conversational recommender system.

Chapter 5

Related Work

The offline **static recommendation** task is formulated as estimating the affinity score between a user and an item (He et al., 2017). This is usually achieved by learning user preferences through the historical user-item interactions such as clicking and purchasing. The representative methods are Matrix Factorization (MF) (Koren, Bell, and Volinsky, 2009) and Factorization Machine (FM) (Rendle, 2010). Neural FM (He and Chua, 2017) and DeepFM (Guo et al., 2017) have improved FM representation ability with deep Nerual Networks. He et al., 2016; Bayer et al., 2017; Ebesu, Shen, and Fang, 2018 utilize user's implicit feedback, one common way is to optimize BPR loss (Rendle et al., 2009). However, as discussed in Section 1, such static recommendation methods suffers from the intrinsic limitations of being not able to capture user dynamic preferences.

This intrinsic limitation motivates **online recommendation**. Its target is to adapt the recommendation results with user online behaviors (Li and Karahanna, 2015). Much effort has been devoted to model it as a multi-arm bandit problem (Kuleshov and Precup, 2014; Auer, Cesa-Bianchi, and Fischer, 2002; Li, Karatzoglou, and Gentile, 2016; Gentile et al., 2016; Wu et al., 2016; Wang, Wu, and Wang, 2017; Wu, Iyer, and Wang, 2018; Zhao, Zhang, and Wang, 2013; Zhang et al., 2020), strategically demonstrating items to users for feedbacks. Zhang et al., 2020 makes the preliminary effort to extend the bandit framework to query attributes. While achieving remarkable progresses, the bandit-based solutions still not sufficient : 1). Such methods focus on exploration-exploitation trade-off in cold-start settings. However, in warm start scenario, capturing user dynamic preference is also crucial as her preference drifting is common; 2). The mathematical formation of multi-arm bandit problem limit such method only recommend one item each time. This constraint limit its applications as we usually need to recommend a list of item to users.

The envisionment of **conversational recommender system** provides a new possibility for capturing user dynamic feedbacks as it enables a system to interact with users using natural languages. However, it also poses challenges to academia researchers, leading to various settings and problem formulations (Christakopoulou, Radlinski, and Hofmann, 2016; Li et al., 2018; Liao et al., 2018; Christakopoulou et al., 2018; Zhang et al., 2018; Sun and Zhang, 2018; Priyogi, 2019; Liao et al., 2019; Yu, Shen, and Jin, 2019; Ayundhita, Baizal, and Sibaroni, 2019; Sardella et al., 2019; Zhang et al., 2020; Zhang et al., 2019; Tran et al., 2020). Table 5.1 gives a summarization of the key factors of thoes works.[1] Generally, most works considers conversational recommendation in a simplified settings. For example, Christakopoulou, Radlinski, and Hofmann, 2016; Yu, Shen, and Jin, 2019 only allow the CRS to recommend items without asking the user about their preferred attributes. The Q&R work (Christakopoulou et al., 2018) proposes to jointly optimize the two tasks of attribute prediction and item prediction but constrain the whole conversation in two

[1] An updating paper list can be found at: https://yisong.me/readpapers/convrec/

TABLE 5.1: Summary of characteristics of recent formally published conversational recommenders: 1) whether asks attributes, 2) question space, 3) any explicit strategy on recommendation timing, 4) any multi-round recommendations, 5) the main focus.

	1. Q?	**2. Question Space**	**3. Explicit**	**4. Multi-round**	**5. Main Focus**
Online bandits (Christakopoulou, Radlinski, and Hofmann, 2016; Wu et al., 2016; Wu, Iyer, and Wang, 2018)	×	N.A.	×	*Yes*	Exploration-exploitation trade-off in item selection
REDIAL (NIPS'18) Li et al., 2018	*Yes*	Free texts	×	*Yes*	End-to-end generation of natural language response
KMD (MM'18) (Liao et al., 2018)	*Yes*	Free texts	×	*Yes*	End-to-end generation of text and image response
Q&R (KDD'18) (Christakopoulou et al., 2018)	*Yes*	Attributes	×	×	Question asking and single-round recommendation
MMN (CIKM'18) (Zhang et al., 2018)	*Yes*	Attributes	×	*Yes*	Attribute-product match in conversational search
CRM (SIGIR'18) (Sun and Zhang, 2018)	*Yes*	Attributes	*Yes*	×	Shallow combination between CC and RC
VDARIS (KDD'19) (Yu, Shen, and Jin, 2019)	×	N.A.	×	×	User's click and comment on recommended items
EAR (our method)	*Yes*	Attributes	*Yes*	*Yes*	Deep interaction between CC and RC

turns: one turn asking questions and the second turn making recommendations. The CRM (Sun and Zhang, 2018) extends the conversation to multi-turns but still follows the sing-round setting: it only recommends items once, and ends the session regardless of success or not. The MMN (Zhang et al., 2018) focuses on document representation, aiming to learn better matching function for attributes and products description under a conversation setting. Unfortunately, it does not build a dialogue policy maker to decide when to ask and when to make recommendations. However, the situations for various real applications are more complex: the CRS needs to strategically ask attributes and make recommendations multiple times as long as getting successful recommendations in the shortest turns. We called as multi-round scenario. In recent works, only Li et al., 2018 considers this multi-round scenario, but it focus on language understanding and generations, without paying much attention to explicitly model the conversational strategy.

Different from existing works, we focus on dialogue strategy in the multi-round recommendation scenario and design a model based on the ideology that CC and RC, the two essential components, need to achieve deep interactions. To the best of our knowledge, we are the first to systematically model such interactions.

Chapter 6

Conclusion

In this thesis, we make contributions to both the framing of the research problem and methods for addressing it.

From the perspective of the research problem, we redefine conversational recommendation by introducing a more realistic scenario: the multi-round conversational recommendation scenario. We believe the biggest strength of conversational recommendation is utilizing the user's explicit feedbacks in the conversation – the feedbacks on both attributes and items. However, previous works did not find a good mechanism to fully exploit such an advantage. As discussed in Chapter 5, there are two lines of previous works: 1) the line of works related to online bandit algorithms which can only make recommendations of items, but therefore cannot leverage the user's feedback on attributes; and 2) the emergent trend of studies on the conversational recommendation. These works mostly consider the single-turn scenario, and forgo modeling the feedback on items but are also impractical for real-world use. Therefore, our multi-round conversational recommendation scenario is very meaningful as it is an intersection of both lines: 1) it empowers the classic bandit algorithm by querying user's explicit feedback on attributes; and 2) it considers a realistic application scenario that can recommend items multiple times. While newly-introduced, our multi-round conversational recommendation scenario has already set a standard for several following works (e.g., Lei et al., 2020; Li et al., 2020).

From the perspective of methods, we introduce a novel framework called EAR (Estimation – Action – Reflection) to address this multi-round conversational recommendation problem. In EAR, the RC and CC work closely to support each other (termed *deep interaction*) to achieve the goal of accurate recommendation in fewer turns. We decompose the task into three key problems, namely, what to ask and what to recommend, when to recommend, finally how to adapt to user feedback. In each stage of the EAR system, we design the method to carefully account for the interactions between RC and CC. Through extensive experiments on two datasets, we justify the effectiveness of EAR, providing additional insights into the conversational strategy and online updates.

This work represents the first step towards exploring how the CC and RC can collaborate closely to provide quality recommendation service in the multi-round conversational scenario. There are loose ends for further investigations especially for incorporating user feedback. For example, when the user rejects the asked attribute, our current EAR updates actions by only refreshing the state vector that encodes the dialogue history. In the future, we are interested to extend our EAR system in the following directions:

Adapt to domain-specific elements: Now we have only evaluated our EAR system on two large datasets that have been studied by the community over several years. However, there might be many domain-specific elements or new features if we deploy a system online. EAR may have difficulties dealing with them, the main

reason being that our existing EAR framework relies heavily on a *"warm-start"* environment. Specifically, the estimation stage is trained using sampled data; the action stage is also trained offline before being evaluated. To tackle cold-start issues, EAR can learn from recent work such as ConUCB (Zhang et al., 2020) and ConTS (Li et al., 2020) which formalize conversational recommendation as a contextual bandit problem. EAR can also draw inspiration from recent advances in transfer learning to transfer the strategy learned from the existing environment to new environments (Taylor and Stone, 2009).

Online evaluation with real users: Evaluating our system online with real users would be a very valuable research effort. So far all our experiments are conducted through user simulator. Such a simulator has a strong assumption: the user only likes one item. Such an assumption has many biases: (1) The user would reject one item v if it does not match the one we set. This is biased since the user may actually like v, but that v is not recorded in the dataset; (2) The user's preference may change during the conversation. Without real user experiments, it is impossible to address this bias. However, real user evaluation is difficult, thus we leave it to future work.

Extend our EAR framework to other conversational IR tasks: Recently there is an emergent trend to push traditional Information Retrieval (IR) tasks into conversational ones. Notably, the CoQA dataset proposed by Reddy, Chen, and Manning, 2019 has inspired many research efforts on conversational question answering. Recently search engines are also pushed into conversational fashion, Ren et al., 2020 have created a dataset called SaaC (Search as a Conversation) to promote the study on conversational search. Fortunately, our EAR framework is very extendable and future researchers can carry on the deep interaction ideology and simply replace RC (recommender component) with their task-specific component (e.g. QA component, search engine, etc.).

Appendix A

Sample of Interactions of Different Systems in Evaluation

To increase the clarity of the thesis, we attach the real samples of interactions of the two datasets used in the evaluation. [1]

A.1 Yelp Dataset

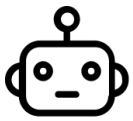
We firstly randomly sample an interaction that happens between the user with ID 10574 and the item with ID 4256, and show the interaction log between user and different models (i.e. EAR, CRM, Max Entropy and Abs Greedy).

We then show a few interesting cases that EAR system is not successful, which points directions for future researchers to study.

We summarize these samples here:

- Figure A.1 shows a sample interaction of EAR system on Yelp dataset between the user with ID 10574 and the item with ID 4256. The user accepts EAR's recommendation after 4 turns, after EAR asks 3 attribuites.
- Figure A.2 shows a sample interaction of CRM model on Yelp dataset between the user with ID 10574 and the item with ID 4256. The user accepts the system's recommendation after 5 turns, we can see that CRM system does not ask effective question as EAR system.
- Figure A.3 shows a sample interaction of Max Entropy model on Yelp dataset between the user with ID 10574 and the item with ID 4256. We can see that the conversation goes too long and the user quits. The reason is that the model cannot ask effective attributes and the candidate item space is too large for Max Entropy model to make recommendation.
- Figure A.4 shows a sample interaction of Abs Greedy model on Yelp dataset between the user with ID 10574 and the item with ID 4256. The user accepts the recommendation after 6 turns.
- Figure A.5 shows a sample interaction of EAR system on Yelp dataset between the user with ID 21243 and the item with ID 25168. This session is not successful and the user quits after 15 turns. The main reason is that, there is one attribute called *Event Planning Services* that EAR system did not ask to further reduce the candidate items. A possible explanation is that *Event Planning Services* is an attribute with low frequency, thus the system has not learned to utilize it.

[1] More samples can be found in the /EAR/yelp/data/interaction-log directory in the codebase.



I want some sandwiches.

Which city are you in?

Las Vegas

What nationalities of food do you want?
We have Chinese, Indian, French ...

No Specific!

What star rating do you want? 1-5

4!

Recommend 10 items!

I like the 4th item, accepted!

FIGURE A.1: Sample interaction of EAR system on Yelp datasets between the user with ID 10574 and the item with ID 4256.

- Figure A.6 shows a sample interaction of EAR system on Yelp dataset between the user with ID 10146 and the item with ID 67471. This session is not successful and the user quits after 15 turns. The main reason is that, there is very few attributes for this item. Although the EAR system has exploited all the attributes, it still cannot effective reduce the candidate items. This is also a feedback for future researcher that, it is challenging to due with items with few attributes.

A.2 LastFM Dataset

We randomly sample an interaction that happens between the user with ID 678 and the item with ID 3119, and show the interaction log between user and different models (i.e. EAR, CRM, Max Entropy and Abs Greedy).

We then show a few interesting cases that EAR system is not successful, which points directions for future researchers to study.

We summarize these samples here:

- Figure A.7 shows a sample interaction of EAR system on LastFM dataset between the user with ID 678 and the item with ID 3119. The user accepts the recommendation after 7 turns, after asking 3 questions and trying to make recommendation of 4 times.
- Figure A.8 shows a sample interaction of CRM model on LastFM dataset between the user with ID 678 and the item with ID 3119. The user quits because the conversation goes too long. The reason is that CRM model does not learn effective strategy to ask attributes to shrink the candidate item space.
- Figure A.9 shows a sample interaction of Max Entropy model on LastFM dataset between the user with ID 678 and the item with ID 3119. The user accepts the recommendation after 10 turns.

I want some sandwiches.

Which city are you in?

Las Vegas

What nationalities of food do you want?
We have Chinese, Indian, French ...

No Specific!

What star rating do you want? 1-5

4!

What price range do you want? 1-5

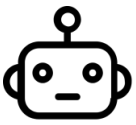
4!

Recommend 10 items!

I like the 8th item, accepted!

FIGURE A.2: Sample interaction of CRM model on Yelp datasets between the user with ID 10574 and the item with ID 4256.

- Figure A.10 shows a sample interaction of Abs Greedy model on LastFM dataset between the user with ID 678 and the item with ID 3119. The user quits because the conversation goes too long (15 turns). It is a usual case for Abs Greedy model because it does not ask attributes to shrink the candidate items.
- Figure A.11 shows a sample interaction of EAR system on LastFM dataset between the user with ID 44 and the item with ID 5916. This session is not successful and the user quits after 15 turns. The reason is quite similar to the case in A.5, there is an attribute with ID 16, and it is a low frequency attribute that EAR system have difficulty asking.
- Figure A.12 shows a sample interaction of EAR system on LastFM dataset between the user with ID 1331 and the item with ID 4837. This session is not successful and the user quits after 15 turns. The reason is quite similar to the case in A.6, there is only 2 attributes with the target items (i.e. attribute 754 and 13), thus the candidate item size is still very large after the system has exploited all the attribute information. This is again a feedback for future researchers to pay attention to items with few attributes.



I want some sandwiches.

Which city are you in?

Las Vegas

What star rate do you want? 1-5

5!

Do you want some fast food?
We have burgers, fries ...

No!

What nationalities of food do you want?
We have Chinese, Indian, French ...

No Specific!

What star rating do you want? 1-5

4!

Do you want some desserts?
We have Ice Cream, Yogurts ...

No!

What price range do you want? 1-5

4!

Do you want alcohol?

No!

...
Consistently asking attributes...

The conversation is too long.
I quit!

FIGURE A.3: Sample interaction of Max Entropy model on Yelp datasets between the user with ID 10574 and the item with ID 4256.

I want some sandwiches.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

I like the 8th item, accepted!

FIGURE A.4: Sample interaction of EAR system on Yelp datasets between the user with ID 10574 and the item with ID 4256.

I want some Mexican.

Which city are you in?

Phoenix

What Nationalities of food do you like?

Mexican!

What star rating do you want? 1-5

5!

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

What price range do you want? 1-5

4!

Recommend 10 items!

...

Recommend for 4 times, all rejected.

Ask 2 more rounds of attributes
Still got rejected.

Recommend 10 items!

I don't want that!

FIGURE A.5: Sample interaction of EAR system on Yelp datasets between the user with ID 21243 and the item with ID 25168.

I want some Mexican.

Which city are you in?

Phoenix

What Nationalities of food do you like?

Mexican!

What star rating do you want? 1-5

5!

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

What price range do you want? 1-5

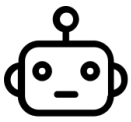
4!

...

Recommend for 6 times, all rejected.

User quits.

FIGURE A.6: Sample interaction of EAR system on Yelp datasets between the user with ID 10146 and the item with ID 67471.



I want attribute 1.

Got you, do you want attribute 73?

Yes!

Got you, do you want attribute 79?

Yes!

Got you, do you want attribute 754?

Yes!

Recommend 10 items!

Rejected!

Recommend 10 items!

Rejected!

Recommend 10 items!

Rejected!

Recommend 10 items!

I like the 3rd item, accepted!

FIGURE A.7: Sample interaction of EAR system on LastFM datasets between the user with ID 678 and the item with ID 3119.

I want attribute 1.

Got you, do you want attribute 73?

Yes!

Got you, do you want attribute 79?

Yes!

Got you, do you want attribute 191?

Yes!

Recommend 10 items!

Rejected!

Recommend 10 items!

Rejected!

Keeps making recommendation ...

...

The conversation is too long!

I quit.

FIGURE A.8: Sample interaction of CRM model on LastFM datasets between the user with ID 678 and the item with ID 3119.

I want attribute 1.

Got you, do you want attribute 73?

Yes!

Got you, do you want attribute 79?

Yes!

Got you, do you want attribute 754?

Yes!

Got you, do you want attribute 24?

No!

Got you, do you want attribute 181?

No!

Got you, do you want attribute 81?

No!

Got you, do you want attribute 210?

Yes!

Got you, do you want attribute 352?

Yes!

Got you, do you want attribute 527?

No!

Recommend 10 items!

I like the 4th item, accepted!

FIGURE A.9: Sample interaction of Max Entropy model on LastFM datasets between the user with ID 678 and the item with ID 3119.

I want attribute 1.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Recommend 10 items!

Rejected.

Keeps making recommendation ...

...

The conversation is too long!
I quit.

FIGURE A.10: Sample interaction of Abs Greedy model on LastFM datasets between the user with ID 678 and the item with ID 3119.

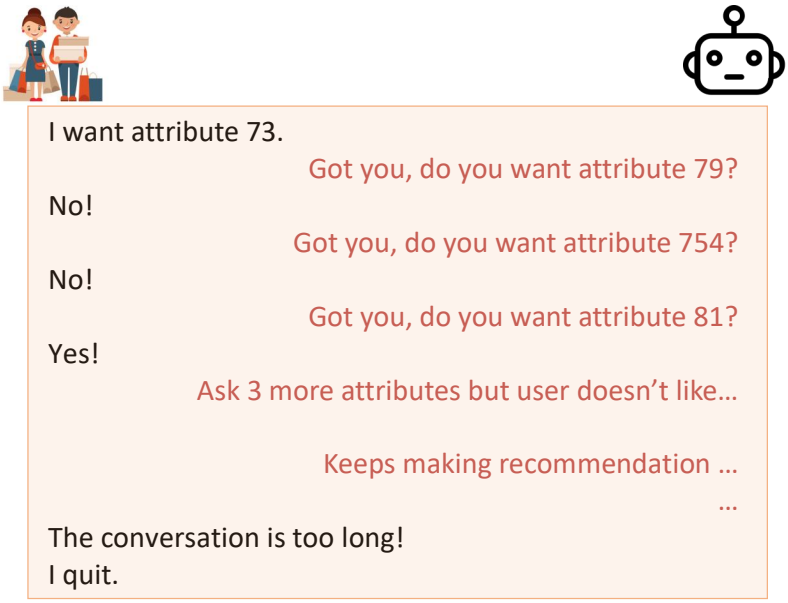


FIGURE A.11: Sample interaction of EAR system on LastFM datasets between the user with ID 44 and the item with ID 5916.

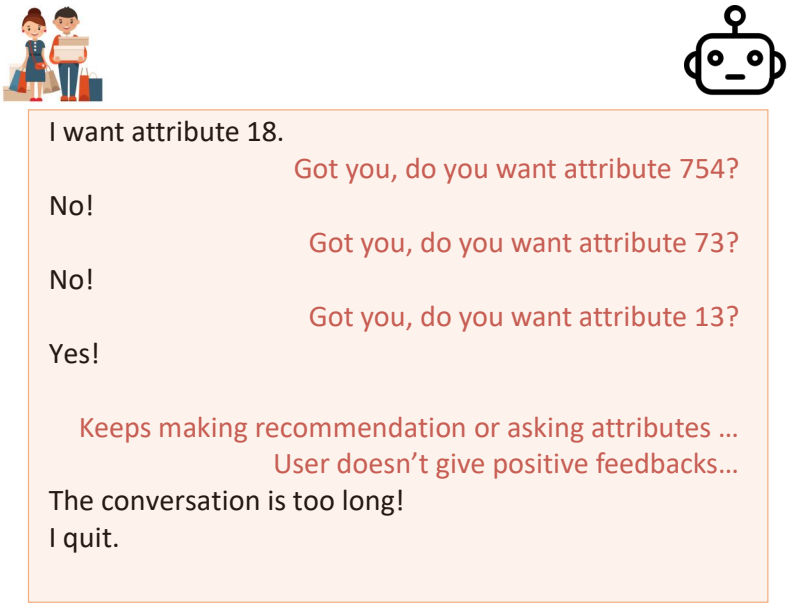


FIGURE A.12: Sample interaction of EAR system on LastFM datasets between the user with ID 1331 and the item with ID 4837.

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