Preference Elicitation Strategy for Conversational Recommender System

Bilih Priyogi
RMIT University, Melbourne, Australia
bilih.priyogi@rmit.edu.au

ABSTRACT

Traditionally, recommenders have been based on a single-shot model based on past user actions. Conversational recommenders allow incremental elicitation of user preference by performing user-system dialogue. For example, the systems can ask about user preference toward a feature associated with the items. In such systems, it is important to design an efficient conversation, which minimizes the number of question asked while maximizing the preference information obtained. Therefore, this research is intended to explore possible ways to design a conversational recommender with an efficient preference elicitation. Specifically, it focuses on the order of questions. Also, an idea proposed to suggest answers for each question asked, which can assist users in giving their feedback.

CCS CONCEPTS

• **Information systems → Recommender systems**;

KEYWORDS

recommender system, conversational, preference elicitation

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1 INTRODUCTION

Recommender systems aim to guide users in a personalized way to interesting or useful items drawn from a large space of possible options [6]. Traditionally, recommenders have been based on a single-shot model based on user rating or purchase history [2, 7]. However, user preference might change from time to time based on internal and external factors. Therefore, it might be useful to ask users for more information directly. It is known that users might be willing to give more clarification about their preference [1, 8].

Conversational recommenders allow iterative interaction between user and system to clarify preferences. Two major approaches emerge, the item-based and feature-based question. Item-based approach asks users to express their preference over items [1, 3, 4]. On the other hand, a feature-based approach is questioning about user preference over features (or facets, attributes) [5, 9]. Both approaches possess similar key problems: what question should be asked and how to incorporate user feedback to improve recommendation accuracy. It is critical for conversational recommenders to gain user feedback efficiently, which means avoiding to ask too many questions and ensuring questions are asked in sensible order.

This research focus in a setting which the system uses a slot filling approach to create a structured dialogue in natural language. The slot is filled with a feature from a set of features associated with the items, as a question. For example:

- User: I want to go to a restaurant.
- System: What <feature = "cuisine"> do you like?
- User: I like <value = "Asian">.
- System: Here are some recommendations for you.

In such setting, the system needs to prioritize a feature to ask (out of all available features) which will allow it to narrow down recommendation candidates effectively. Moreover, given a question at a particular time, users may not always have a specific preference. So, it might be useful to give suggestions about feature values that may interest users. The hypothesis is that such suggestions may lower users cognitive effort in giving feedback.

Specifically, the intended novel contribution of this research are: (1) Propose question selection strategy based on past user preference and current context (item distribution); (2) Propose answer suggestions strategy for each question asked; (3) Experiment on different approaches to utilize user feedback, such as for filtering constraint and for updating user preference model; (4) Investigate the benefit obtained of using such strategy, within the user and system perspective. Ongoing experiments are conducted to test the performance of the proposed strategy to elicit user preference and improve the recommendation quality.

2 RESEARCH QUESTION

This section will briefly describe four specific research questions:

(1) How to select questions from all available item features?
(2) How to select useful answer suggestions from all related feature values?
(3) How to utilize users' feedback to improve recommendation?
(4) How does the proposed preference elicitation strategy benefit the conversational recommenders?

2.1 Question Selection Strategy

Conversational recommenders should prioritize questions based on its ability to uncover user preference and narrow down recommendation candidates effectively. This research aims to design preference elicitation strategy which can take advantage of any

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available past user preference, such as user rating or purchase history. Specifically, the question selection problem will be regarded as a feature selection problem, which means that users will be asked about their preference over possible values of an item's feature.

2.2 Answer Suggestion Strategy

We hypothesize that a set of answer suggestions can assist users in eliciting their preference. Note that a high effort in giving feedback can make users disinterested with a conversational recommender.

2.3 Utilizing User Feedback

After user feedback received, the next crucial phase is to utilize it for improving recommendation quality. We intend to experiment on two approaches: using feedback as a simple filtering constraint and using feedback to build a user preference model.

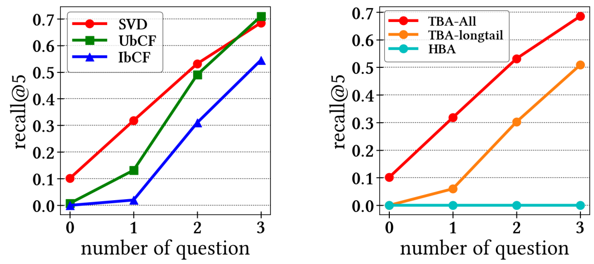
2.4 Benefit in Recommender Performance

Previous works in conversational recommender focus to improve the system efficiency and accuracy, as a separate task. Efficiency means to minimize interaction length, or the number of question asked, to present relevant items to users. Whereas, this research aims to explore and discover the trade-off in balancing the efficiency and accuracy (precision and recall) on conversational recommender.

3 ONGOING EXPERIMENT

Offline experiments have been conducted to address the research questions. A set of proposed question selection and answer suggestion selection strategies are tested with Movielens (movie) and Yelp (restaurant) dataset. For each simulated user, one most recent item is taken from her rating history as a test item, while others serve as training data. Initially, a personalized recommendation list is generated by an underlying recommender. We experiment with three different underlying recommenders: User-based Collaborative Filtering (UbCF); Item-based Collaborative Filtering (IbCF); and Singular Value Decomposition (SVD). Possible questions (features) are sorted based on its probability to narrow down the recommendation list. The user is asked with a number of question to elicit her preference. Then, user answer will be used as a filtering constraint to prune incompatible items. We tried two methods to derive a simulated user answer: Target-based Answer (TBA) which use feature value from the test item; History-based Answer (HBA) which use feature value(s) from three most recently rated items. Performance evaluated based on recall at top-5 recommended items. Note that the test item is considered as the only relevant item.

Fig. 1a shows the average performance of the proposed methods on different underlying recommender using TBA to simulate answer. Then, using SVD as the underlying recommender, we compare the performance of the two methods to simulate user answer as shown in Fig. 1b . We also investigated the performance on non-popular or longtail items as displayed in Fig. 1b. Overall results indicate that the proposed methods can improve recommendation accuracy as more question asked. Note that even when the initial top-5 recommendation fails (zero recall@5), our methods still can assist users in refining the recommendation list. Moreover, HBA failed to give any improvement which means user history does not necessarily reflect current user preference over features.



(a) (b)

Figure 1: Result with Movielens dataset: Performance on (a) Different Underlying Recommender (b) Different User Answer Simulation & Item Popularity with SVD Recommender.

4 FUTURE WORK

We plan to do an online experiment with real users. The online experiment is intended to study several aspects: (1) Are users eager to interact with a conversational recommender?; (2) Whether users perceived the proposed question and answer suggestion as useful in improving recommendation?; (3) In the experiment, we varied the probability of user answer accuracy. How is this related to the real-world situation?; (4) In this work, we took the system's perspective and prioritize questions based on its probability to narrow down recommendation list. However, the top question does not necessarily make sense for users, such as asking for a specific year or decade before recommending movies. So, to what extent it affects users in interacting with the recommender?.

Furthermore, we plan to explore other ways to incorporate user feedback into the recommendation process. Presumably, user preference over feature can be modeled, and user feedback can provide more information to update this model. Moreover, while in the current experiment we only consider item distribution to prioritize questions, it might be useful to consider the probability of being responded by users and the user preference model.

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