Latent Explanation and Critiquing for Conversational Recommender Systems

ESC499 Thesis Proposal

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**Introduction**

Critiquing is a method for conversational recommendation that adapts recommendations in response to user preference feedback. In this setting, user will be iteratively provided with item recommendation and attribute description for that item: a user may either accept or critique the attributes to generate new recommendation.

Explainable recommendation refers to personalized recommendation algorithms that provide recommendation results and explanations, offering interpretability and transparency to help understand, diagnose and refine recommendation algorithm [1]. Explanation algorithms are developed and evaluated together with critiquing to improve recommendation performance.

**Objective**

In the above settings, we would like to build iterative critiquing algorithms that (1) minimize the number of iterations before reaching users’ satisfactory (i.e. recommend users with their target item), (2) understand user/item’s intrinsic characteristic as explanation to our recommendation.

**Related Works**

Historical critiquing works were largely based on constraint- and utility-based methods for modifying recommendations w.r.t. these critiqued attributes, including incremental critiquing that consider the cumulative effect of iterated critiquing interactions[2], and experience-based methods that attempts to collaboratively leverage critiquing interactions from multiple users[3] etc. Some recent works also explored speech- and dialog-based interfaces for critiquing-style frameworks [4]. Latent embeddings as critiquing method are also revisited and built upon in the thesis [8, 9, 10, 11]

**Approach**

Existing algorithms that leverage latent user preference representation to update recommendations are often nontrivial to interpret and debug given the nature of learned representations from linear regressions [6] or auto-encoders [10]. Considering the following two scenarios where

1. a user with some preferences showed in history, can we understand this user’s preference with a personalized keyphrases, and interpret why we made this explanation from latent representations?
2. a user might show preference to Japanese restaurants from user preference history and made a critique against spicy cuisines, would the updates from the latent representation show that this user appears more similar to users who likes non-spicy cuisines including possibly Japanese food?

Given the above questions, we are interested in looking into how *simple, interpretable, yet empirically comparable (against deep-learning based formulation)* algorithms such as matrix-based similarity framework with Nearest-Neighbour can trace both the source of explanations and the direct impact of critiquing. We would also like to further explore the Attention based algorithms to properly weight multi-step critique feedback that are not necessarily independent, nor of equal weights.

We would like to build and test the above-mentioned ideas based on three publicly available dataset: Yelp academic review, BeerAdvocate, and Amazon CDs&Vinyl, all contains more than 100,000 reviews and product rating records.

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