Proposal on Virtual User Profile Generation for Explainable Recommendation

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Abstract. This paper proposes a method for providing users with the profiles of virtual users as an explanation for recommendations.
Recommender systems are one of the intelligent systems that support us in accessing vast amounts of information. Those are roughly divided into content-based filtering and collaborative filtering. Many algorithms have been studied for determining items to recommend, all of which require users' personal information such as purchase/browsing history to estimate their tastes for providing personalized recommendations. Although obtaining as much information as possible is preferable, it raises the problem of privacy concerns.
To realize personalized recommendations without collecting users' personal information, this paper proposes a recommendation framework that uses virtual user profiles. A virtual user profile describes the interests and tastes of a virtual user to items. A virtual user is extracted from large interaction data about anonymous users. Using the profiles of virtual users and their ratings to items of interest as a kind of explanation for recommendations, users are expected to find relevant items without providing their private information. This paper describes how to create a virtual user profile and shows its effectiveness through questionnaires.

Keywords: recommender systems · explainable recommendation · user profile.

1 Introduction

This paper proposes a method for providing users with the profiles of virtual users as an explanation for recommendations.

Recommender systems are one of the intelligent systems that support us in accessing vast amounts of information. Those are roughly divided into two approaches: content-based filtering and collaborative filtering. In both approaches, users' personal information such as purchasing and browsing history is required to estimate their tastes and provide personalized recommendations. As the cold-start problems and a sparsity problem imply, it is usually important to obtain as much user information as possible. However, it raises the problem of privacy concerns.

On the other hand, providing personalized service, i.e. recommending different items to different users based on their tastes, is usually considered important for improving customer satisfaction. However, it is also pointed out that if a system provides excessively personalized services, users could feel a sense of mistrust due to privacy concerns[1].

Considering the above-mentioned problems, it is difficult to further improve the performance by personalization only, in particular the acceptability of recommender systems.

Another factor affecting recommender systems' acceptability is explainability. While traditional recommendation algorithms have focused on determining the items to recommend, explainable recommendation recommends items together with the reason (explanation) about why those are recommended[2]. It is expected that explainable recommendations can improve the transparency, persuasiveness, usefulness, reliability, and user satisfaction of recommender systems[3].

As a new kind of explainable recommendation, this paper proposes a recommendation framework that uses virtual user profiles. A virtual user is an unreal user who is supposed to be representative of actual users accessing a target recommender system. A virtual user profile describes the interests and tastes of a virtual user to items. Using the profiles of virtual users and their ratings to items of interest as a kind of explanation for recommendations, users are expected to find relevant items without providing their private information. That is, virtual user profiles could contribute to the realization of personalized recommendations without collecting users' personal information.

This paper proposes a method for creating a virtual user profile from large interaction data about anonymous users and large language models. The quality of the generated user profiles is evaluated with a questionnaire.

2 Related Work

2.1 Model-intrinsic Explainable Recommendation

The explainable recommendation aims to provide users with an explanation of why items are recommended, together with the recommended items. It is classified into model-intrinsic and model-agnostic approaches[2].

Model-intrinsic approach generates an explanation based on the process a recommender system determines the item to recommend. Therefore, it is required to employ a model of which the decision process is interpretable. The interpretable models include matrix factorization-based models[4, 5], graph-based models[6, 7], and models based on rule mining[8].

Matrix factorization-based models decompose a rating matrix into a latent user matrix and a latent item matrix, both of which have low dimensions. Predicted scores for items are calculated as the dot product of a user and an item vector. Using the dot product between user vectors or item vectors as the similarity between users or items, such an explanation as "Those who are similar to you positively evaluated this item." can be generated. However, each dimension of latent user/item vectors is uninterpretable and it is difficult to explain from what viewpoint they are similar[2].

To solve this problem, Zhang et al. have proposed to generate an explanation by relating the latent factors of matrix factorization-based models to item features and user opinions extracted from user reviews[4]. Bauman et al. proposed to integrate matrix factorization-based models with the estimation of user emotion from user reviews. Emotion refers to the degree of users' satisfaction and favor reflected on their reviews.

Another model-intrinsic approach is based on graph-based models, which represent a relation between users and between users and items as a graph. By finding a path from a user to a recommended item, the reason why that item was recommended can be explained. As SNS (social networking services) such as X and YouTube essentially hold such network information, those are widely used as the resources for graph-based models[9, 10].

He et al. employed a network structure that represents a ternary relationship between users, items, and item's features for generating an explanation[6]. On the other hand, Heckel et al. constructed a bipartite graph representing the relationship between users and items and applied overlapping co-clustering to the graph[7]. This method can generate an explanation such as "user X purchased items B, C, D, and users Y and Z who purchased those items purchased item A as well. Furthermore, X purchased items E and F, and user W who purchased those items also purchased item A. Therefore, A is recommended to X."

2.2 Model-agnostic Explainable Recommendation

Some recommendation models determine the items to recommend based on complicated processes: it is difficult to generate explanations from such models. In such a case, a model-agnostic approach is employed. This approach generates explanations independent of recommendation models. In other words, explanations are generated as an afterthought. For example, many electric commerce sites provide an explanation like "70% of your friends purchased this item., " which is generated with basic statistics or association rules[2]. However, this approach does not provide an explanation reflecting the determination process of recommendation models and reliability and transparency tend to be low[11].

To solve this problem, LIME (Local Interpretable Model-agnostic Explanation)[12], which was proposed for giving a local interpretation of complicated models, has been employed for an explainable recommendation. LIME learns linear regression models from the input/output pair of a target model. Input features of high importance can be used for explanations. SHAP (SHapley Additive exPlanations)[13] has been proposed to increase the transparency of recommendation results based on Shapley value[14].

3 Virtual User Profile Generation

This paper proposes a virtual user profile to be used for a new kind of explanationable recommendations. Virtual user profiles are generated from a large amount of anonymous datasets about the interaction between users and items.

Although the proposed method could be applied to various kinds of items, the target items in this paper are movies: a virtual user profile describes the tastes of the user about movies. In this paper, a profile consists of three sentences about positive preference and three sentences about negative preference. Two ways of generating profiles, manual generation and semi-automatic generation using large language model (LLM) are proposed, which are respectively described in Sec. 3.1 and 3.2.

3.1 Manual Profile Generation

The manual generation method selects a candidate anonymous user from a dataset on the basis of tag information. A profile of a virtual user is also generated based on the tag information. A procedure for manually generating a virtual user profile from Movielens dataset[1] is as follows.

1. Select a candidate user u_c
2. Estimate u_c's topic distribution
3. Extract u_c's representative movies
4. Generate a profile of u_c

A Movielens dataset consists of rating information and tag information given by anonymous users. In step 1, we select a candidate user from those who gave more than 1,000 tags so that a virtual user can have enough information to describe his/her profile.

Step 2 is further divided into two sub-steps:

- Train a topic model
- Estimate u_c' topic distribution

First, each movie x_i is represented as a document d_i, which is a set of given tags by all users. By applying LDA (Latent Dirichlet Allocation)[15] to a set of documents $\{d_i\}$, topic model $\boldsymbol{\theta}_i = (\theta_{i1}, \ldots, \theta_{iK})$ (K is a number of topics) and $\boldsymbol{\phi}_k = (\phi_{k1}, \ldots, \phi_{kV})$ (V is a number of different tags) are obtained.

Using the obtained model, u_c's topic distribution $\boldsymbol{\theta}_c$ is estimated from a document d_c, which consists of 50 tags with higher TF-IDF scores than other tags. TF-IDF score of a tag t_j for d_i is calculated with Eq. 1, where tf_{ij} is the frequency that u_i uses t_j, N is the number of users, and df_j is the number of users who gave t_j.

$$tfidf_{ij} = tf_{ij} \log \frac{N}{df_j} \tag{1}$$

In step 3, u_c' positive/negative movies are selected. The conditions of positive/negative movies are as follows, where r_{ij} is the u_i's rating to a movie x_j and $\overline{r}_j$ is x_j's average rating.

[1] https://grouplens.org/datasets/movielens/

- $r_{ij} \geq 4 \wedge |r_{ij} - \overline{r}_j| \geq 1 \rightarrow x_j$ is positive
- $r_{ij} \leq 2 \wedge |r_{ij} - \overline{r}_j| \geq 1 \rightarrow x_j$ is negative

In step 4, Sentences describing u_c's positive/negative aspects about movies are manually generated using $\boldsymbol{\theta}_c$ and positive/negative movies as clues. We generate three sentences for each of the positive/negative aspects.

3.2 Profile Generation with LLM

This subsection describes a semi-automatic generation method using LLM. As LLM, this paper employs ChatGPT[2]. This method considers two approaches: individual user-based and user group-based approaches. The procedure for generating a virtual user profile is as follows.

1. Select a candidate user u_c or user group U_c
2. Extract u_c's representative movies
3. Generate a profile of u_c/U_c using ChatGPT

In Step 1, Matrix Factorization[16] is applied to a rating matrix obtained from Movielens dataset. Randomly dividing the dataset into training data and test data, RMSE (Root Mean Square Error) on test data is calculated per user using the model trained with the training data. u_c is selected from those who rated 1000 or more movies and RMSE is equal to or less than 0.75. U_c includes u_c and u_c's 10 most similar users, where similarity between users is calculated based on cosine similarity between users' latent vectors obtained by Matrix Factorization.

The individual user-based approach selects u_c's 10 positively-rated (4 or higher ratings) and 10 negatively-rated (2 or lower ratings) movies. While the user group-based approach also selects 20 movies in similar way, average ratings over U_c are used to judge positive/negative.

In Step 3, 20 movies selected in Step 2 are inputted to ChatGPT with the following prompt[3].

> Followings are movies a user was positively or poorly rated. Create a profile text based on his/her preferences and tastes.
> Conditions:
>
> - The profile should include three positive aspects and three negative aspects using bullet points.
> - Each aspect should be about 100 characters.
> - Avoid abstract expressions and focus on factual content.
> - Each aspect should describe different contents.

[2] https://chat.openai.com/
[3] It is translated from Japanese to English.

Positively-rated movies:
- American Beauty (1999)
...

Negatively-rated movies:
- Mission: Impossible 2 (2000)
...

4 Experiments

Questionnaire-based experiments are conducted to evaluate the generated virtual user profiles in terms of validity and usefulness. Validity is judged by whether or not respondents can estimate the virtual users' preference for movies from their profiles. The usefulness for recommendations is investigated by analyzing how respondents use the virtual user profiles as clues for estimating their unwatched movies. In particular, we also examine whether or not different virtual users with different taste are used as clues for estimating movies in different ways.

4.1 Validity evaluation of virtual user profiles

In a questionnaire, a profile of a virtual user is presented together with the following 20 movies.

- PV: 5 movies that the virtual user rated as 4 or higher.
- NV: 5 movies that the virtual user rated as 2 or lower.
- PO: 5 movies that other users evaluated positively
- NO: 5 movies that other users evaluated negatively

As PO and NO, we selected famous movies of which the average rating in the dataset is 4 or higher (2 or lower). The title of a movie and the links to its summary page in allcinema[4] and Kinema Junpo[5] are presented in the questionnaire without an explanation about how those movies were selected.

After reading the summaries for each of the movies, a respondent was asked to answer the following questions.

- Q1: Do you think a user with the presented profile will like this movie?
- Q2: Select sentences in the profile based on which you answered to Q1 (multiple answers possible).

The answer to Q1 is given on a 5-point scale (5: strongly agree, 1: strongly disagree). A respondent is asked to answer Q2 when the answer to Q1 is not 3 (neither agree or disagree). It is also allowed to answer nothing for Q2.

The following four profiles are evaluated with the questionnaire.

[4] https://www.allcinema.net/
[5] https://www.kinejun.com/

– Manual: a profile generated manually (Sec. 3.1). Sentences do not refer to movies.
– Manual-M: a profile generated manually (Sec. 3.1). Sentences refer to movies as examples.
– LLM-S: a profile generated by using LLM (Sec. 3.2) from a single user.
– LLM-G: a profile generated by using LLM (Sec. 3.2) from a user group.

Due to the space limitation, only the presented movies and the virtual user profiles in the case of LLM-S are shown in Table 1 and 2, respectively.

Table 1. Movies presented in a questionnaire: generated with LLM from a single user.

Group	Movie	Genre
PV	The Sixth Sense (1999)	Thriller
	Braveheart (1995)	Action, Drama, War
	Shakespeare in Love (1998)	Comedy, Romance
	The Princess Bride (1987)	Action, Adventure, Comedy, Romance
	Schindler's List (1993)	Drama, War
NV	Teenage Mutant Ninja Turtles	Action, Children's Fantasy
	Stuart Little (1999)	Children's, Comedy
	Superman III (1983)	Action, Adventure, Sci-Fi
	Last Action Hero (1993)	Action, Comedy
	Robocop 2 (1990)	Action, Crime, Sci-Fi
PO	To Kill a Mockingbird (1962)	Drama
	Double Indemnity (1944)	Crime, Film-Noir
	On the Waterfront (1954)	Crime, Drama
	Cinema Paradiso (1988)	Comedy, Drama, Romance
	The Third Man (1949)	Mystery, Thriller
NO	Battlefield Earth (2000)	Action, Sci-Fi
	Pokémon the Movie 2000 (2000)	Animation, Children's
	Mr. Magoo (1997)	Comedy
	Lawnmower Man 2: Beyond Cyberspace (1996)	Sci-Fi, Thriller
	Exorcist II: The Heretic (1977)	Horror

Table 3 shows the results of Q1. Each cell shows the average rating and the standard deviation (in parentheses) to the presented movies. The column 'Virtual user' shows the results for movies positively/negatively rated by the virtual user (PV/NV), and 'Other users' shows the results for those by other users (PO/NO). The questionnaire for each profile was evaluated by 50 different respondents.

It is shown that for both of virtual user and other users, the respondents' average ratings for positively rated movies is higher than that for negative movies. When comparing the difference between their average ratings for positively rated movies and that for negatively rated ones, the difference of PO and NO is larger

Table 2. Virtual user profiles generated with LLM from a single user. (translated into English.)

Polarity	Sentences
Positive	- I put a high priority on emotional empathy and psychological depiction. I am moved by the deep character development and storytelling. For example, I enjoy works that depict inner conflicts and social satire, such as “American Beauty." - I am captivated by movies that have thrills, tension, and dramatic developments. I am passionate about action-packed films like “Jurassic Park" and “Terminator 2: Judgment Day." - Movies are a form of entertainment, and I enjoy films that are filled with humor and excitement. I like movies with fun elements, such as “Back to the Future" and “Men in Black."
Negative	- I am not interested in works with predictable stories or mundane characters. I get bored with forced plots and dull developments, like those in “Mission: Impossible 2" and “Batman Forever." - I am sensitive to movies that lack realism or feature unnatural acting. I am disappointed by tonal inconsistencies and shallow performances, like in “Mars Attacks!" and “Batman & Robin." - I am not interested in works that lack entertainment value or emotional impact. For example, I am disappointed by films without appealing characters or thematic depth, such as “Powder" and “Three Amigos!"

Table 3. Result of Q1. SD shown in parentheses.

	Virtual user		Other users	
Profile	PV	NV	PO	NO
Manual	3.06(0.468)	2.96(0.608)	3.14(0.426)	2.86(0.545)
Manual-M	3.26(0.668)	2.79(0.834)	3.31(0.616)	2.63(0.748)
LLM-S	3.30(1.073)	2.95(0.944)	3.12(0.970)	2.94(0.988)
LLM-G	3.24(0.984)	3.03(1.060)	3.33(0.948)	2.94(1.077)

than that of PV and NV except for LLM-S. This result is rationale because the respondents could use a general reputation of famous movies in addition to the information obtained from the virtual user profiles. As PO and NO are selected from famous movies, the respondents could rate those movies more easily than PV and NV. Although the difference was relatively small except for LLM-S, the fact that the respondents rated PV higher than NV shows the validity of the presented virtual user profiles.

Regarding the variance of answers, the standard deviation of NV/NO is larger than PV/PO except for LLM-S, which indicates that negative evaluations have greater individual differences than positive evaluations.

When comparing the results of Manual and Manual-M, the difference between PO/PV and NO/NV for Manual-M is larger than that for Manual. Furthermore, the standard deviation for Manual-M is larger than Manual, which was caused because the respondents tended to rate 1 or 5 rather than moderate rating (2-4). These results indicate the effectiveness of including movie titles in virtual user profiles.

It is also observed that the standard deviation for LLM-S/LLM-G is larger than that for Manual/Manual-M. Although the reason is not clear, the difference of the respondents might be one of the reasons.

Table 4. Result of Q2 for manual generation methods.

Sentence	Manual	Manual-M
Pos-1	137	240
Pos-2	205	219
Pos-3	156	183
Neg-1	77	199
Neg-2	193	205
Neg-3	180	240
None	340	195

Table 4 shows the result of Q2 for manual generation methods (Manual and Manual-M). 'Pos-' and 'Neg-' respectively indicate the positive and negative sentences in the virtual user profile, and 'None' indicates when the respondents selected no sentence. The value in the cell shows the number of times the sentence was selected.

It is shown in Table 4 that the variance in the number of answers per sentence by Manual is larger than that by Manual-M. The average number of answers per sentence is 158 for Manual and 214 for Manual-M. Furthermore, the number of selecting no sentence (None) for Manual is much larger than Manual-M. These results also suggest that mentioning movies makes a profile more informative.

As the common characteristics of both methods, it was also observed that the respondents tended to select positive/negative sentences as the evidence for estimating positive/negative ratings. This result suggests that the respondents used the presented sentences as a clue for their judgment by correctly understanding the contents.

Table 5. Result of Q2 for semi-automatic generation methods.

Sentence	LLM-S	LLM-G
Pos-1	130	260
Pos-2	258	257
Pos-3	229	303
Neg-1	170	127
Neg-2	174	176
Neg-3	147	152
None	218	237

Table 5 shows the result of Q2 for semi-automatic generation methods (LLM-S and LLM-G). It is shown in Table 5 that the number of respondents varies in the case of LLM-G compared to LLM-S. It is mainly caused by the fact that respondents tended to select more positive sentences than negative ones. As popular movies were included in positive sentences of LLM-G, those were supposed to be selected as evidence. Compared with Manual-M, the number of respondents who selected no sentence increased. Although semi-automatic generation methods can mitigate the cost of generating profiles, this result suggests room for improving the quality of profiles generated by LLM-S and LLM-G. For example, the respondents tended not to select negative sentences in the case of LLM-S and LLM-G compared to Manual-M. Table 6 shows negative sentences generated by Manual-M and LLM-G. Comparing Table 2 and Table 6, sentences generated by Manual-M were relatively short, which might cause the result.

Similar to the result of manual generation methods, it was observed that the respondents tended to select positive/negative sentences as the evidence for estimating positive/negative ratings. This result suggests that the respondents used the presented sentences as a clue for their judgment by correctly understanding the contents.

4.2 Evaluation of Usefulness

A questionnaire-based evaluation is conducted to investigate the usefulness of the generated user profiles for explainable recommendations. The profiles of four virtual users of different tastes are presented together with their ratings to some movies. Respondents are asked to answer whether or not they want to watch the movies. We used LLM-G for generating user profiles.

The questionnaire have 10 questions, each of which consists of the following items.

- Title of a movie
- Links to the movie's summaries in allcinema and Kinema Junpo

Table 6. Negative sentences in virtual user profiles.

Profile	Negative sentences
Manual-M	- I don't like movies that are based on stereotypes or biased thinking, such as 'Showgirls' (1995). - I don't like movies with monotonous storylines and love romances, such as 'Speed' (1994). - I don't particularly like comedy and entertainment movies for children, while I enjoy movies like 'Up' (2009) that deal with themes such as family and relationships with society, which make adults think.
LLM-G	- In comedy films, I'm not particularly interested in movies that incorporate vulgar humor or meaningless gags. For example, 'Austin Powers: The Spy Who Shagged Me' and 'Police Academy' do not match my taste. - In science fiction movies, I get disappointed by boring plots, unnatural settings, and shallow characters. For example, 'Super Mario Bros.' and 'Mission to Mars' seemed to lack compelling elements. - In fantasy movies, I don't really relate to movies that lack originality or a deep message. For example, 'Robin Hood: Prince of Thieves' and 'Bicentennial Man' were disappointing.

– User profiles of four virtual users
– Ratings to the movie by the virtual users

After reading the summary, a respondent is asked to answer the followings.

– Q1: Have you watched the movie?
– Q2: Do you think the ratings by the virtual users are consistent with their profiles?
– Q3: Do you want to watch the movie?
– Q4: Select sentences in the profiles based on which you answered to Q3 (multiple answers possible).

The answer to Q1 is given as Yes or No. No includes the case when they might have watched the movie but do not remember the content. When the answer to Q1 is Yes, a respondent is asked to answer Q2, otherwise answer Q3 and Q4. The answer to Q3 is given on a 5-point scale (5: really want to watch it, 1: don't want to watch it at all). It is also allowed to answer nothing to Q4. Table 7 shows the titles of the presented movies and ratings by the virtual users.

Table 8 shows the result of the questionnaire. Each column corresponds to positive/negative sentences of the virtual users, and a row corresponds to positive/negative ratings by the respondents. Each cell shows the frequency the corresponding sentences were selected.

It is observed that User1 tended to be selected more than other users. One of the reasons is that the profile of User1 was shown at the top of the questionnaire. However, there was no difference among other users: the order effect is not so strong except for the first user.

As an overall tendency, negative sentences tended to be selected when the respondents gave negative ratings. On the other hand, positive sentences were

Table 7. Presented movies and ratings by virtual users.

Movie	Genre	Ratings			
The Mask	Comedy, crime, fantasy	4	3	3	3
True Lies	Action, adventure, comedy, romance	4	4	3	5
Mary Poppins	Children's, comedy, musical	3	4	4	4
Annie Hall	Comedy, romance	4	3	4	4
Mars Attacks!	Action, comedy, Sci-Fi, war	4	3	3	4
Sneakers	Crime, drama, Sci-Fi	4	4	4	2
The Lost World: Jurassic Park	Action, adventure, Sci-Fi, thriller	2	4	3	4
Starship Troopers	Action, adventure, Sci-Fi, war	2	5	3	3
The Big Lebowski	Comedy, crime, mystery, thriller	4	4	2	5
Armageddon	Action, adventure, Sci-Fi, thriller	4	4	3	4

Table 8. Number of profiles selected when giving positive/negative ratings.

Virtual user	User1		User2		User3		User4		Total
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	
Positive	38	17	21	8	8	2	14	8	116
Negative	27	45	29	22	16	24	16	41	220
Total	65	62	50	30	24	26	30	49	336

selected regardless of ratings. This tendency suggests that if respondents have a different taste for movies from a virtual user, they can refer to the virtual user for filtering uninteresting movies.

Regarding the difference among virtual users, the positive sentences of User2 were selected more than its negative sentences. User4 has the opposite tendency: its negative sentences were selected more than its positive sentences. Such a tendency was not observed in the case of User1 and User3. It was also observed that for all virtual users except User1, more positive sentences were selected when giving negative ratings than when giving positive ratings. This tendency is significant for User2 and User3. These results suggest that different virtual users had different characteristics and were used as clues for rating movies in different ways.

5 Conclusion

This paper proposed a method for providing users with the profiles of virtual users as an explanation for recommendations.

A virtual user profile describing the interests and tastes of a virtual user to items are generated from large interaction data about anonymous users. Manual-based approach and semi-automatic approach with LLM were proposed for generating the virtual user profile.

The generated profiles were evaluated with questionnaires. The result shows the validity of the generated profiles. Regarding the usefulness of explainable recommendations, it was confirmed that different virtual users had different characteristics and were used as clues for estimating movies in different ways.

Future works include the development of a user interface based on virtual user profiles and user experiments to evaluate its effectiveness.

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