Explainable Recommendation for Repeat Consumption

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ABSTRACT

Displaying appropriate explanations for recommended items is of vital importance for improving the persuasiveness and user satisfaction of recommender systems. Although a user often consumes the same item repeatedly in some domains such as music and restaurants, existing studies have focused on generating explanations for recommending novel items. In this paper, we describe the concept of explainable recommendation for repeatedly consumed items. Because of the high proportion of repeat consumption in music listening, we suggest nine kinds of explanations for song recommendations according to three factors: personal, social, and item factors. From the results of an online survey involving 622 participants, we evaluate the usefulness of these explanations.

CCS CONCEPTS

• **Information systems → Recommender systems**.

KEYWORDS

Explainable recommendation; Repeat consumption; User study

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1 INTRODUCTION

To improve the persuasiveness and user satisfaction of recommender systems (RSs), it has become an essential research topic to provide explanations for recommended items so that users can understand why they are recommended [25]: this approach is called explainable recommendation (ER) [29]. In ER, the explanations displayed to a user are typically generated from her histories of item consumption [28]. Various user studies have reported that ER enables users to more accurately select items [5] and improves user acceptance of recommended items [10].

Despite the various kinds of approaches for generating explanations in previous studies [28], most of them focused on generating explanations for recommending novel items to a user. However, in some domains such as music listening, video watching, and restaurant visiting, a user often consumes the same item repeatedly over time [2, 4], and such user behavior is called *repeat consumption*. Therefore, it is worth considering explanations for recommending items that a user has already consumed. For example, suppose that exactly five years have passed since a user listened to *Shake It Off* by *Taylor Swift* for the first time on a music streaming service. In that case, the service could recommend the song to the user with an explanation of "We recommend *Shake It Off* because exactly five years have passed since you listened to it for the first time." In typical repeat consumption, a user initially consumes an item repeatedly within a short time span; but the span gradually increases as she becomes bored with the item, and eventually she stops consuming it [4]. Even if the user has stopped listening to *Shake It Off* as a result of repeat consumption, however, the music streaming service could increase the possibility that she listens to it again by displaying an explanation like the one above. For example, listening to the song could enable her to feel nostalgia by thinking back to those days when she often listened to it. This would also be beneficial for the music streaming platform, because it could increase its revenue by encouraging users to listen to not only novel songs but also already consumed songs. Despite such possibilities, no studies have focused on ER for repeat consumption.

In light of the above, in this paper, we provide the first study of ER for repeat consumption. To generate explanations for consumed items, we consider the following three factors.

- Personal factor: this factor considers the interaction between a target user and a recommended item. For example, in the context of restaurant visiting, one possible explanation is "Exactly seven years have passed since you visited the recommended restaurant for the first time."
- Social factor: this factor considers the interaction between all users on a service and a recommended item. For example, in the context of video watching, one possible explanation is "Just now, the number of unique users watching the recommended video reached exactly 100 thousand."
- Item factor: this is an item-specific factor that is not related to the users who consumed the item. For example, in the context of music listening, one possible explanation is "Today, the artist performed the recommended song at a live concert."

According to these factors, we suggest nine kinds of explanations and evaluate their effectiveness through the results of an online survey.

Our contributions in this paper can be summarized as follows.

- To the best of our knowledge, this is the first study to propose the concept of ER for repeat consumption. We suggest nine kinds of explanations based on the above three factors: personal, social, and item factors.

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- To investigate the effectiveness of our proposed explanations, we conducted an online survey involving 622 participants in the domain of song recommendation. In the survey, first, we investigated the persuasiveness of the nine kinds of explanations. Second, because some explanations include a variable such as a time span or play count, we also evaluated the value preference for such variables.
- From the survey results, we reveal various insights for both the persuasiveness (e.g., explanations related to song popularity are more persuasive) and the value preference (e.g., a clear tendency of preferable values exists for all kinds of explanations). We also discuss how to apply these insights to repeat consumption recommendations.

2 RELATED WORK

2.1 Explainable Recommendation

Studies have reported that displaying explanations in RSs can increase persuasiveness [10] and user satisfaction [26]. One approach for ER is single-style explanations in which an RS displays explanations that involve a single source of data such as user-based or item-based similarity. Studies by Herlocker *et al.* [10], Chang *et al.* [7], and Symeonidis *et al.* [24] are classified into this approach. Another approach is hybrid explanations that combine multiple styles. That approach has been reported to be more effective than the single-style approach [19]. Although most studies on hybrid explanations have focused on visualizing various explanation styles via graphical user interfaces (GUIs) [6, 11, 12, 18, 20, 27], Kouki *et al.* [16] recently showed that text-based explanations are more persuasive than GUIs-based ones. They generated explanations based on a hybrid RS, called HyPER [14]. Unlike prior studies that aimed to generate explanations of novel items for a user, we focus here on explanations for repeat consumption. Inspired by the aforementioned insights of prior studies, in this paper, we adopt text-based explanations that can be generated in the HyPER framework as described in Section 3.1.

2.2 Repeat Consumption

Although most RS studies have traditionally aimed to recommend novel items to a user [1], users are known to consume the same item repeatedly over time in various domains. For example, in music listening and location check-ins, averages of 69% and 51% of a user's consumption, respectively, consist of items already consumed by the user [4]. Because of such popularity of repeat consumption, several studies have developed models for simulating repeat consumption behavior [2, 4, 8] or proposed methods for recommending previously consumed items [9, 13, 21, 22]. By analyzing repeat consumption behavior, Benson *et al.* [4] reported that each item has its own *lifetime* for a user: at the beginning of the lifetime, the temporal gap between item consumption events is small; at the end of the lifetime, however, the gap becomes large, and eventually the user becomes bored with the item. Such boring items are usually removed from the recommendation candidates. However, we believe that if we recommend these boring items with explanations, they might be consumed again by the user, and this would also be beneficial for the service platform to increase its revenue. Hence, our study is a first step toward investigating whether some types of explanations are persuasive enough to motivate a user to revisit already consumed items.

3 EXPLANATIONS FOR REPEAT CONSUMPTION RECOMMENDATION

In this section, we first give an overview of the HyPER framework [14] and describe how to apply it to our problem. We then describe the three factors that we consider and nine kinds of explanations for repeat consumption recommendation.

3.1 Overview of HyPER

HyPER [14] is a hybrid RS that uses probabilistic soft logic (PSL) [3] and develops recommendation models through a set of *rules*. An example of a rule is "If user u has listened to song s_1 and s_1 is similar to song s_2, then u would listen to s_2." HyPER automatically learns to balance the different rules and computes the probability that a user accepts each item. It then generates explanations from *explanation styles*, each of which corresponds to a rule. For example, the aforementioned example rule is used for an item-based explanation style, which generates a concrete explanation like "We recommend *Shake It Off* because it is similar to *King of Anything*, which you like." One characteristic of HyPER is its extensibility: it can incorporate any kind of style that can be written as a rule. By taking advantage of this, in the following subsection, we propose nine explanation styles and their rules to support recommendation explanations for repeat consumption.

3.2 Explanation Styles

In this paper, we assume a scenario in which an item that a user has already consumed is recommended to her. Under this scenario, we aim to display an explanation of why the item is recommended for repeat consumption. To this end, we consider three factors involving the item: personal, social, and item factor. We use song recommendation as a target domain, because repeat consumption is especially salient in music listening [4]. Although we describe a total of nine explanation styles with example explanations, as listed in Table 1, we acknowledge that there can be other explanation styles. However, note that our goal here is not to list all possible explanation styles; rather, we aim to suggest examples of possible explanations based on the three factors. We believe that these factors can help any service platform to consider explanations for recommending consumed items according to service-specific characteristics.

3.2.1 Personal Factor. The personal factor considers the interaction between a target user and a recommended song. As the user repeatedly listens to the same song, the service platform stores logs. By using the logs, we propose four explanation styles for the personal factor: P-first, P-last, P-together, and P-total. P-first and P-last are related to the elapsed time: P-first uses a rule of "If exactly x years have passed since user u listened to song s for the first time on the service, u would listen to s"; P-last is based on a rule of "If exactly x years have passed since user u listened to song s last, u would listen to s." Here u is the target user, and s is a song repeatedly consumed by u. In the example explanations of Table 1,

Table 1: Nine explanation styles and example explanations.

Factor	Style	We recommend *Shake It Off* by *Taylor Swift* because:
Personal factor	P-first	Exactly *five years* have passed since you listened to it for the first time.
	P-last	Exactly *three years* have passed since you listened to it last.
	P-together	Around the same time, you frequently listened to it and *Applause* by *Lady Gaga*, which you listened to just now.
	P-total	You will have played it *100* times when you listen to it next.
Social factor	S-total	Its total play count by all users reached *one million*.
	S-unique	The number of unique users who listened to it reached *100 thousand*.
	S-favorite	The number of users who added it to their Favorites reached *10 thousand*.
Item factor	I-release	Exactly *five years* have passed since it was released.
	I-live	*Today*, *Taylor Swift* performed it at a live concert.

words in italics are variables. Therefore, *five years* in the explanation of P-first could be *three years*, *seven years*, or even *10 years*. One possible way to set appropriate values would be to enable users to set them according to their personal preferences. It would also be possible for the music streaming service to set particular values in common for all users. We evaluate the preferences for these values in Section 4.3. As for P-together, the explanation is generated from the co-occurrence of songs in a user's play history. Let s' denote another song that has been repeatedly consumed by u. Then, the rule is "If u listened to s' just now and has frequently listened to s' along with s, u would listen to s." The co-occurrence of songs can be detected by using session information [23] in the user's play logs. We assume that these three styles would be persuasive because they would enable the user to feel nostalgia by thinking back to those days when she often listened to the recommended song. Finally, P-total considers personal play counts, with a rule of "If u's total play count for s would reach x by playing s next, u would listen to s." We think that this style would also be persuasive, because the user would feel a sense of achievement if she knew the play count information.

3.2.2 Social Factor. The social factor considers the interaction between all users on the service and a recommended song. We suggest three styles based on this factor: S-total, S-unique, and S-favorite. S-total uses a rule of "If s's total play count by all users has reached x, u would listen to s," while S-unique adopts a rule of "If the number of unique users who have listened to s has reached x, u would listen to s." As for S-favorite, on music streaming services, users can usually use a *Favorites* function that enables them to mark any song as a favorite. Thus, S-favorite is based on a rule of "If the number of users who added s to Favorites has reached x, u would listen to s." Our assumption on the persuasiveness of these styles is that the user would want to listen to s again if she knew a familiar song had been played or chosen as a favorite by so many users.

3.2.3 Item Factor. Lastly, the item factor considers item-specific information that is independent of users on the music streaming service. The first style, I-release, adopts a rule of "If exactly x years have passed since s was released, u would listen to s." We assume that this style would be persuasive because such information would make the user think of the song's anniversary. For the second style, I-live, we assume that the user would want to listen to a song that the artist recently performed at a concert because she would enjoy a "live" feeling by listening to it. Therefore, this style uses a rule of "If the artist performed s at a live concert x days ago, u would listen to s." One way to collect concert-related information is by mining Twitter, because it is common for concert attendees to tweet about performed songs [17].

4 USER STUDY

In this section, we answer the following two research questions by conducting an online survey involving 622 participants.

- **RQ1** How do the explanation styles affect the explanation persuasiveness?
- **RQ2** For each explanation style, is there any tendency in terms of preferred values of the variable in the explanation?

4.1 Participants

We recruited 679 participants for our survey via an online research company. All the participants were Japanese and listened to music at least one day per week via any online music streaming service. The participants answered our questionnaire through a web browser. We paid about 13.9 USD (1,500 JPY) to each participant. Although 679 participants joined the survey, to make the analysis results more reliable, we removed the answers from 57 participants: 39 of them gave the same answer to all questions (e.g., choosing "1" for all questions), and 18 of them submitted improper responses to an open-ended answer format (e.g., "xxxxxx"). Of the remaining 622 participants, 296 were male (10s: 8; 20s: 60; 30s: 82; 40s: 73; 50s: 73), and 326 were female (10s: 10; 20s: 67; 30s: 91; 40s: 82; 50s: 76).

4.2 Persuasiveness of Explanation Styles

First, to answer **RQ1**, we investigated the persuasiveness of each of the nine explanation styles introduced in Section 3.2. In this investigation, we aimed to evaluate the persuasiveness purely according to the explanation style. To this end, each explanation described the recommended song as "song A" to remove any bias regarding the song. In addition, to remove any bias regarding particular values of the time (P-first, P-last, I-release, and I-live), play count (P-total and S-total), or user count (S-unique and S-favorite), we asked the participants to assume any values they liked. Thus, in the case of P-first, for example, we showed the participants a description like the following.

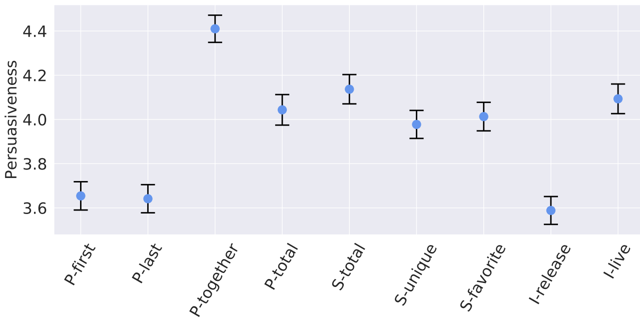

Figure 1: Mean persuasiveness for each explanation style, with standard errors.

> On a music streaming service, you have previously listened to song A. One day, song A is recommended to you with the following explanation: "Song A is recommended to you because exactly five years have passed since you listened to it for the first time on this service." Here, "five years" is just an example, and you can assume any time span you like, such as half a year, one year, or seven years.[1]

For each explanation style, the participants were asked to rate its persuasiveness on a scale of 1 to 7 (1: not persuasive at all; 7: very persuasive). The explanation styles were displayed in a random order to each participant. For participants who gave an explanation style a rating of 5-7 (i.e., those who thought that the explanation style was persuasive), we also provided an open-ended answer format for freely describing why they thought it was persuasive.

Figure 1 shows the mean persuasiveness for each explanation style. It can be observed that the nine styles can be divided into two groups: a high-persuasiveness group (hereafter, "High group") that includes P-together, P-total, S-total, S-unique, S-favorite, and I-live, and a low-persuasiveness group (hereafter, "Low group") that includes the remaining three styles. Because the persuasiveness of any style in the High group is statistically higher than that of any style in the Low group at $p < 0.05$ by Tukey's HSD test, a clear difference in persuasiveness exists between the two groups.

In the High group, P-together has the highest persuasiveness: the value is statistically higher ($p < 0.05$) than those of the remaining seven styles except for S-total. As expected, the most popular reason for persuasiveness was about nostalgia. Although the most popular reasons for P-first and P-last were also about nostalgia, as we had assumed, both styles belong to the Low group. In the situation of P-together, the user can continuously listen to nostalgic songs (i.e., one played by her and another recommended by the service), while in P-first and P-last, the user feels nostalgia only from the recommended song. Thus, P-together would enable the user to more deeply feel nostalgia, resulting in its higher persuasiveness. For P-total, the most popular reason was that the user could realize again, when she knew her total play count, how much she loved the song. Our expected reason (that she could feel a sense of achievement) was the second most popular. Regarding the social factor, all explanation styles (S-total, S-unique, and S-favorite) are in the High group, and no significant difference was observed between their persuasiveness. For all of these styles, the reason with the highest frequency was that the user could perceive the popularity of the song. More specifically, in the case of S-total, for example, a participant answered, "I become happy to know that a familiar song has been played so many times, so I want to listen to the recommended song." Finally, for I-live, in addition to our assumed reason (that the user could enjoy a "live" feeling), another reason related to the artist's desire (e.g., "A song performed at a live concert is one that the artist wants people to hear, so I want to listen to it.") was also popular. Given a target user, the explanation styles that are persuasive enough to her should be used to recommend songs. To save the cost of such personalization, however, it would also be beneficial for music streaming platforms to simply use styles in the High group.

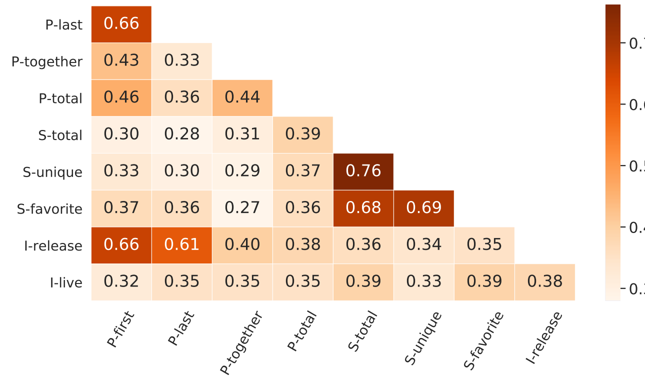

Figure 2: Pearson's correlation of persuasiveness between explanation styles. All correlations are significant at $p < 0.001$.

Figure 2 shows the Pearson's correlation of persuasiveness between explanation styles. P-first, P-last, and I-release have relatively high correlation values with each other. This means that, although they belong to the Low group, there was a group of participants who regarded the time-related styles as persuasive. Therefore, a service platform can estimate that if a user listens to a song recommended according to a time-related style, she would also accept songs recommended by other time-related styles. We can also observe another group of participants who especially prioritized popularity-related styles, because S-total, S-unique, and S-favorite have high correlation values with each other. On the other hand, the correlation values between the time and popularity-related styles are relatively low. That is, the two participants groups were exclusive to some extent.

4.3 Value Preference in Explanations

Except for P-together, explanations generated from the other eight styles have variables related to time (P-first, P-last, I-release, and I-live), the play count (P-total and S-total), or the user count (S-unique and S-favorite). To answer **RQ2**, we investigated the value preferences for the variables in these styles. For each explanation

[1]If a user does not remember that she has listened to song A, it should be recommended as a novel song. Therefore, in this survey, we asked the participants to assume that they remembered the recommended song. One approach to distinguish whether a user remembers a song would be to refer to its play count; we leave evaluation of that approach as future work.

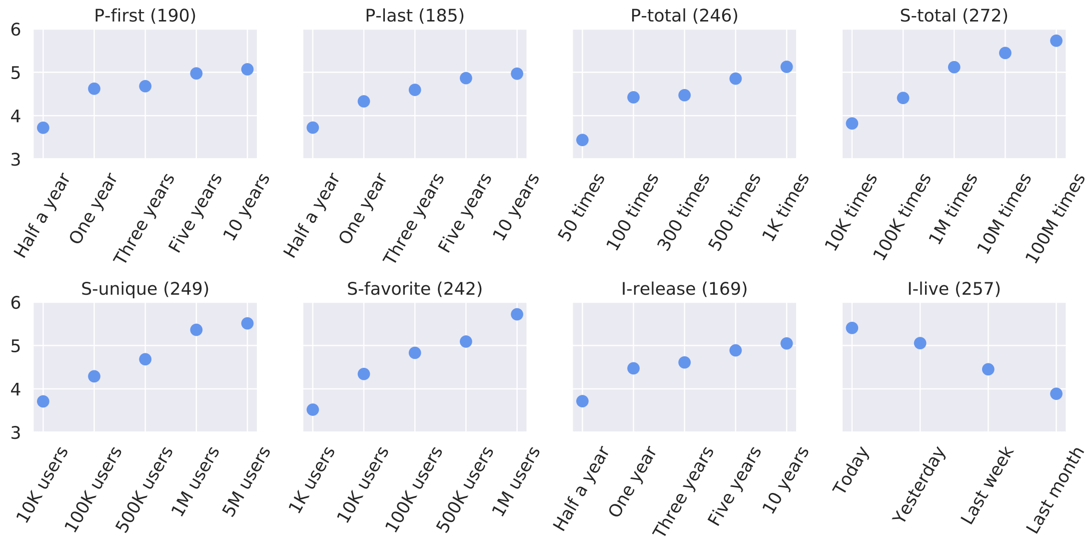

Figure 3: Mean preferences for each candidate value of a variable. The range of the y-axis is the same for all charts. The numbers in parentheses indicate the number of participants who gave their preference.

style, four or five candidate values of the variable were displayed to the participants. For example, for P-total, the candidate values were 50, 100, 300, 500, and 1K times. For each value, the participants rated their preference on a scale of 1 to 7 (1: not preferable at all; 7: very preferable). We also provided an open-ended answer format for describing the reason for a preference. For each style, we asked for preference rating from participants who gave a rating of 5-7 for the style's persuasiveness, as described in Section 4.2.

For all eight styles with variables, Figure 3 shows all candidate values and the mean preference for each value. For all styles, the mean value monotonically increases or decreases as the candidate value increases (x-axis). These results indicate a clear tendency toward a value preference. According to the free descriptions of the reasons for these preferences, in the cases of P-first and P-last, for example, the participants preferred a longer time span because it provided a stronger feeling of nostalgia. Similarly, for the popularity-related styles (S-total, S-unique, and S-favorite), higher values were preferred because they enabled a stronger feeling of a song's popularity. In contrast, for I-live, the participants preferred a shorter time span, because by listening to the recommended song within a shorter time span, they could feel stronger identification with the artist. From these results, for each explanation style, a music streaming platform could set a variable value whose mean preference is higher than, say, 4.0.

5 CONCLUSION

In this paper, we proposed the concept of explainable recommendation for repeat consumption. We suggested nine explanation styles and conducted an online survey to investigate the persuasiveness of these styles and value preferences in explanations. Here, we acknowledge some limitations of this study: (1) we investigated only the domain of song recommendation; (2) we manually generated non-personalized explanations; and (3) in the online survey, all participants were Japanese. Nonetheless, we believe that this study is a worthwhile contribution to the ER field as a first step toward investigating the usefulness of ER for repeat consumption. Moreover, these limitations indicate the possibilities of this research topic and can guide future work. In fact, initial studies on ER for hybrid RSs also had limitations (1) [16] and (2) [15], but those studies contributed to later studies. Similarly, limitation (3) can lead to future work such as investigating the differences in persuasiveness for each explanation style among countries.

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