Recommender System for Developing New Preferences and Goals

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ABSTRACT

The research topic is to investigate how recommender systems can help people develop new preferences and goals. Recommender systems nowadays typically use historical user data to predict users' current preferences. However, users might want to develop new preferences. Traditional recommendation approaches would fail in this situation as these approaches typically provide users with recommendations that match their current preference. In addition, users are not always aware of preference development due to the issue of filter bubbles. In this case, recommender systems could also be there to help them step away from their bubbles by suggesting new preferences for them to develop. The research will take a multidisciplinary approach in which insights from psychology on decision making and habit formation are paired with new approaches to recommendation that included preference evolution, interactive exploration methods and goal-directed approaches. Moreover, when evaluating the success of such algorithms, (longitudinal) experiments combining objective behavioral data and subjective user experience will be required to fine-tune and optimize recommendation approaches.

CCS CONCEPTS

• **Information systems → Users and interactive retrieval**; **Personalization**; **Recommender systems**; • **Human-centered computing → User studies**.

KEYWORDS

recommender system; preference developing; user goals; behavior change; user-centric evaluation

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1 INTRODUCTION

Users' preferences are not fixed [16] and users might want to develop new preferences or goals [6] every now and then. For example, developing new music tastes from pop to classical or a healthier eating habit. Traditional recommender system approaches fail in this situation because these approaches typically give recommendations matching users' current preferences. While current recommender systems are able to go beyond accuracy [23] by including both diversity and novelty to expand users' horizons [2], the two measures might not be enough to incur behavior change. Recommender systems for developing new preferences should provide users with more explicit guidance and support towards new preferences rather than just introducing new or diverse items as most of the current diversification and novelty approaches do.

Preference development and behavior change often correlate with each other. In the health domain, when a user is making efforts to change her unhealthy eating behaviors, she is also developing new healthier eating preferences. Similarly, in the music domain, when developing a new music taste, the user is also changing her music listening behaviors. The difference is that in the health domain, we usually want people to develop preference in a certain direction, i.e., from unhealthy behaviors to healthy behaviors, while in the music domain, there is no such direction.

Psychological research on behavior change shows that people change their behavior in stages [32]. According to the Transtheoretical Model (TTM), there are five main stages in the whole process of behavior change, namely precontemplation, contemplation, preparation, action, and maintenance, and different process of change are required to move the user through different stages. For example, the change from the precontemplation stage to the contemplation stage requires conscious awareness of wanting to change.

Based on the TTM, we combine the stages of change with two possible preference development situations: user-initiated and system-initiated. In user-initiated situations, the user comes to the system with a motivation to change and is able to express her new preferences in a direct way, e.g., through a simple user interface to indicate the new taste. Given the direct input, the system can then help the user with the new preference development. In such situations, users normally have already thought about a specific goal and passed from the precontemplation to the contemplation stage. However, users do not always realize the need for change. For example, they might sometimes get stuck in their filter bubbles. In system-initiated situations, recommender systems are there not only to provide recommendations but also to initiate new preferences for users to develop (move them from precontemplation stage to contemplation stage).

Domain is another factor to consider when designing this type of recommender systems since the goal of behavior change and the way how people change their behavior could be different in

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different domains and would thus influence the recommendation approaches used.

By combining insights from recommender algorithms and interactive recommender system design with behavior change models, we would like to build recommender systems that can support users to develop new preferences and goals in different domains and preference development situations.

2 RELATED WORK

In this section, we discuss the related aspects in the existing recommender systems that can support the development of new preferences or goals.

2.1 Behavioral change oriented recommender system

Not much work in the field recommender system is directly related to behavior change. In one of the earliest work, Farrell [7] suggest to use only personal history to support making lifestyle changes. However, they also noted several significant challenges to implement this approach, such as the cold-start problem and the low coverage in the user's history. More recently, several Rasch-based recommender systems are designed in both health [33, 35] and energy domain [39, 40] to support users to make behavioral changes by providing them with tailored advice based on the user's ability and the behavioral difficulty. The benefit of the Rasch-based recommender system is that it can measure all behavior difficulties and user abilities in one scale [35]. In the energy domain, Starke et al. [39] found that users preferred to take easy energy-saving measures below their ability and that tailoring advice to a user ability could increase the feasibility of the recommended measures. Similarly in the health domain, Schäfer and Willemsen also found that tailoring nutrition goals to users' ability could lead to higher success rate on the target goal [35].

2.2 Guided exploration towards new preference

In the music domain, rather than designing a behavior change oriented recommender system, several guided exploration tools are built to help people explore new items that they might be interested in and further build new preferences towards them.

Within the context of automatic playlist generation [38], Flexer et al. [8] have proposed an approach which allows users to discover new songs by creating smooth transition (e.g., from one genre to another) between start song and end song based on audio similarity. The Boil the Frog [1] app developed by Lamere also allows users to create a seamless playlist between any two artists to discover new music tracks or artists. More recently, the music exploration tool by Taramigkou et al. [41] enables users to explore new music tracks from their current preferences to the desired genre by following a path built from others' preferences. The recommended path is the shortest path from the user's current preference to the target genre, identified in a user preference graph with nodes corresponding to users and edges representing user to user similarity.

[1]http://static.echonest.com/BoilTheFrog/

2.3 Dealing with filter bubble, blind spots and echo chamber

The issue of filter bubbles [30] has been long discussed in the field of recommender system. Recently, some visualization approaches have been implemented to present users their filter bubbles (blind spots) and might further serve as a way to encourage them to explore new items. Nagulendra and Vassileva visualized the personalized stream filtering mechanism in Online Social Networks with a bubble metaphor [27, 28] and found that visualization could help users understand the filtering mechanism. Tintarev et al. [19, 46] put their focus on highlighting the gap between the user's current profile with the overall profile of all users and found that the proposed visualization could improve users' exploration [19].

In the news domain, various presentation tools have been developed to nudge people to read more diverse news or viewpoints [25, 26, 31] to mitigate the issue of echo chambers. Rather than focusing on how to nudge people to read more diverse by presentation, some recent work has put focus on what to recommend by making challenging information more acceptable [12, 43].

2.4 Summary

Research on behavioral change related recommender systems is limited. Exploration serves as a way to help users find new items rather than support them to make behavioral changes or develop new preferences. The Rasch-based recommender system is able to support users to make behavioral changes by providing tailored advice that matches their current ability but it is not designed for developing new preferences. In this project, we go beyond these approaches by building recommender systems that can support users in developing new preferences based on the domains and preference development situations (user-initiated or system-initiated). We will discuss our research directions in the next section in detail.

3 RESEARCH DIRECTIONS

Based on whether the preference development is user-initiated or system-initiated, our two main research questions are:

- RQ1: How recommender systems can help users to develop new preferences when they already have a specific goal in mind in a user-initiated situation?
- RQ2: How recommender systems can help users to develop new preferences when they do not have a new goal in a system-initiated situation?

Before further stepping into specific research questions, we first would like to list the recommendation goals for the recommender systems that are designed to help people develop new preferences in different domains and situations in Table 1. Each recommendation goal is related to one research question that will be discussed next.

3.1 User-initiated preference change RQ1

The first research question concerns how recommender systems can help users to develop new preferences in a user-initiated situation when they already have a specific goal in mind.

In this case, we identify two approaches (see Table 1) to move users from their current preferences to their target preference: one is to recommend items directly from the target preference, while

	User-initiated	System-initiated
Music	(1) Recommend items directly from the new genre *RQ1-(a)* (2) Recommend a path to follow, *RQ1-(b)*	Recommend new genres that they might be interested in and motivate them to make the change *RQ2*
Life-style	Recommend a path to follow *RQ1-(b)*	Recommend healthier life styles *RQ2*

Table 1: Recommendation goal in different domains and situations

the other is to recommend a path for the user to follow so that she can move gradually from their current preferences to the target preference step by step. The first approach is suitable for the case when the user comes to the system and asks directly to develop a new taste, which is more likely a case in the music domain. While in the life-style domain, behavior change always takes steps. For example, it is hard for people who used to eat unhealthy food every day to develop completely new healthy eating habits in a short time. The second approach enables users to develop a new preference gradually by following the recommended path. The two sub-research questions are:

- RQ1-(a): What could be recommended if the user wants to build a new preference directly from the new music genre?
- RQ1-(b): How to recommend a path for the user to follow and what would be the appropriate steps for the user to take towards the new preferences s/he want to develop?

3.1.1 RQ1-(a). We investigated the first sub-question in our first study. In the study, we asked users to select a music genre to explore and studied what kind of recommendations can better serve users to explore a new music taste [21]. We evaluated the three different recommendation methods in an online user study with Spotify API [2]: one non-personalized method which recommends the most representative tracks of the genre, one fully personalized method which recommends tracks that from the new genre match best with the user's current preferences on audio features built with the Gaussian mixture model, and one mixed method which serves a trade-off between the two.

We found that perceived helpfulness for exploring the new genre is positively related to perceived accuracy and representativeness. The results suggest that a tradeoff is needed of tracks that are sufficiently representative of the new genre, while on the other hand close enough to users typical preferences (in terms of the features). Furthermore, users who scored high on the on Musical Sophistication Index [24] for active engagement (MSAE) perceived the mixed method to be more helpful. The results also suggest that we should take users' domain knowledge/expertise into account when designing such systems to help users attain their new tastes.

3.1.2 RQ1-(b). From the recommender system perspective, this question considers recommending the optimal path for users to follow in order to help them build new preferences. From the behavioral change perspective, the recommended path could also be seen as a sequence of short-term goals and concrete actions that needed to be carried out to achieve the long-term goal [48].

We would like to investigate this sub-question in two different domains. In the health domain, our idea is to first build a Rasch-scale that could be used to set up the short-term goal for a user according to her current ability [35] on her way towards the long-term goal. In addition to relying on Rasch-scale for tailoring goals, the system should also be able to adjust the next goal based on how well the user achieved her last goal. We can also refer the recommended path of change of the current user from the path of change of similar users with similar goals, which is similar to collaborative filtering [5]. The same approach is also applicable in the music domain, although we might face a problem of data sparsity. This approach requires long-term datasets to compute recommendations. In the music domain, there are two available long-term datasets: Last.fm [3] Dataset - 1K [4], which records the whole listening habits (from August 2006 till May 2009) for nearly 1,000 users, and LFM-1b Dataset [37], which records a large number of listening histories from about 120 thousand users. In the music domain, the recommended path can also be derived from a tag/genre similarity graph as built by Paul Lamere [20] based on genre co-occurrence, in which each node represents a genre and each edge represents the similarity between the genre. We will build a genre similarity graph by counting the co-occurrences of genres within artists [13] from Spotify. The preference change path can then be extracted from the graph. For example, it could be the shortest path from the user's current preferences to the target preference. To build this method, we will dig into graph/network-based recommendation algorithms.

In addition, users' personal characteristics (as listed below) should also be taken into consideration when deciding the optimal path and steps for developing new preferences.

- *Broadness of current preferences:* The broadness of people's current preferences will influence their new preferences development [14]: it is easier for people with extensive experience to build new preferences than those with limited experience.
- *Personality traits:* Oreg [29] established a scale for measuring the individual difference in resistance to change with a four-facet structure. One of his studies investigated the relationship between resistance to change and each personality dimension of the Big Five Factor model [10, 11]. For example, individuals who scored low on openness to experience were more likely to be high on resistance to change. In the field of recommender system, it is also suggested to consider personality for recommendation diversity [4, 22, 43, 44, 47] and novelty since individuals' attitudes towards new and diverse experience would vary [3, 44].
- *Domain knowledge/expertise:* Domain knowledge or expertise is considered to be an important personal characteristic to measure in the user-centric evaluation framework [18]. It is shown that domain knowledge would affect perceived accuracy [15, 18] (although the effect is not consistent across the studies) and perceived diversity [18]. In our first study, we also found that users' music expertise would affect their perceived helpfulness of the

[2]https://developer.spotify.com/documentation/web-api

[3]https://www.last.fm/

[4]https://www.dtic.upf.edu/ ocelma/MusicRecommendationDataset/lastfm-1K.html

recommendation approaches for helping them explore the new taste [21].

3.2 RQ2

The second research question concerns how recommender systems can help users to develop new preferences from a system-initiated perspective. Unlike the user-initiated situation in which users have already thought about the change and reached the contemplation stage, users in the system-initiated situation usually do not have the idea of developing new preferences in their mind. Again we divide the research question into two sub-questions:

- RQ2-(a) What kinds of new preferences/goals could we suggest to users in order to efficiently motivate them to make the change?
- RQ2-(b) How should the suggestions about the new preferences or goals be presented to the user?

3.2.1 RQ2-(a). This sub-question investigates the new preferences that should be suggested to users in order to efficiently motivate them to make the change. Previous work by Starke et al. suggests to increase users' motivation for energy saving by making the change in small behavior steps [39, 40]. Inspired by their work, we consider to recommend new tastes that are within small change steps. For example, in the music domain, we are already testing whether suggesting a new genre close to the users' current preferences (calculated from genre co-occurrence similarity) could better help them with the change. While for food recommendation, it would mean to suggest a healthier recipe but not so different from what the user is used to take. For example, suggesting spaghetti to people who are used to take hamburgers before recommending them salads [35, 36].

3.2.2 RQ2-(b). Inside this sub-question, we will investigate how to give the suggestions towards the new preference of the user. We consider to combine suggestions with explanation since explanation [45] could help users to understand why this new genre or lifestyle is recommended (transparency), increase their trust in the system and further encourage/persuade them to try the new tastes. Furthermore, inspired by the nudging ways [1] used in the field of HCI to incur users' behavior change, we also consider to combine the idea of a nudge [42] into the system design to help users to try new music tastes/healthier lifestyles [34]. One relevant example is the shopping website designed to nudge people to eat healthier by suggesting similar alternatives as what they put in the shopping cart but lower in calories [9].

3.3 User-centric evaluation

We will evaluate our approaches with the user-centric evaluation framework by Knijnenburg et al. [17, 18]. However, as it takes time for people to change their behavior or develop new preferences, we will also measure people's self-reported behavior as used in many behavior change related studies [39] and further develop our approach within systems that allow longitudinal measurements.

3.4 Discussion

In this section, we have discussed our research questions in detail based on the type of preference development: user-initiated in RQ1 and system-initiated in RQ2. However, we would like to note here that there could also be a case in which the user would have a general idea of developing new preference but do not have a specific goal to achieve. For example, a user might want to broaden his/her music tastes, but do not have a specific goal in mind. The situation can be seen as a combination of user-initiated and system-initiated situation. It is related to RQ1 in a sense that it is user-initiated, while it is also related to RQ2 as users could be less clear about what their goals are and need the system to suggest some goals for them. To answer this question, we need to combine results and insights from both RQ1 and RQ2.

4 CONCLUSION

In this paper, we present a project about how to utilize recommender systems to help users to develop new preferences and goals. We have identified two different situations (user-initiated and system-initiated) in which users would need recommender systems to support them with the change and discussed how recommender systems could help in the two preference development situations and domains. We have also noted that it is necessary to combine the psychological perspective on behavioral change with the current recommendation techniques for designing such a system. The novel contribution of this work is to go beyond traditional recommendation approaches by supporting users to develop new preferences and goals.

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