Beyond User Preferences: The Short-Term Behaviour Modelling

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ABSTRACT

The context of a user is a notoriously researched topic in the recommender systems community. It greatly influences user preferences and respectively his/her behaviour. The research focuses on the actual influence affecting user and temporal preferences of users. These tell us what the user likes, but fail at describing his/her behavior. We believe that the user's actual behavior represents a great source of information, which is useful for recommendation methods. By modelling the user short-term behavior (on the level of a session), we are able to, e.g., predict the session end intent or the length of the session and respectively adjust generated recommendations. As a result, users benefit from a seamless user experience and the business utilizes its objective functions (e.g., profit).

CCS CONCEPTS

• **Information systems → World Wide Web**; **Personalization**; **Web mining**; *Personalization*;

KEYWORDS

user context, short-term behavior, personalization, user model

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1 INTRODUCTION

Personalized recommendation became an integral part of modern Web applications. User preferences serve as the basis for tailoring services and its content for specific user. This was proved to work very well in several domains [3]. Despite of this, researchers found out that user preferences are highly influenced by his/her context, e.g., time, location, mood. Context is generally defined as "a predefined set of contextual attributes, the structure of which does not change over time" [1].

The context helps us to identify an actual user state, which reflects to some extent the user's objectives. Usually, long-term preferences are modelled by user models. A user model is defined as a set of information connected with the user behaviour, attitudes and stereotypes [4]. Together, both short-term and long-term user preferences help to generate relevant recommendations.

As the researchers attention is usually addressed to user preferences, user behavior (or the behavior change) is not considered in recommender approaches. We understand the behavior as a set of actions, a user performs on the web. In other words, while preferences express what the user likes, the behavior describes how the user acts. Similarly to preferences [5, 14], we distinguish between short- (within a session) and long-term behavior.

We believe, that considering a user short-term behavior in modern recommendation approaches, will improve the user experience. Moreover, a prediction of such behavior opens new opportunities for e-commerce to adjust recommendations and to optimize the utility functions (e.g., profit). In this paper, we provide a brief discussion on pros and cons of the short-term user behavior modelling and its application to the personalized recommendation problem.

2 USER PREFERENCES VS. BEHAVIOR

The major of a research activity is focused on exploring acquisition [2], modeling [11] and further usage [8] of user preferences. These are the base for almost all modern Web-based services.

As the next step, a user context proved to be extremely helpful in the personalization [15]. As the preferences of the user are rich, the context reduces a set of preferences or items, which have to be considered by the recommender approach. Both these concepts tell us what the user likes.

On the contrary, a user behavior describes how a user acts. More specifically, the short-term behavior describes user actions within a session (in the Web context). This behavior is based on a user interaction with the content and the site structure. For instance, what time the user spent in actual session, how many items he/she visited, how many hyperlinks there are available to follow. It has been proven that the website usage information improves the personalization performance [13]. We believe that the knowledge of user typical and/or future behavior allows to improve recommendations – bringing benefits both for users and commerce as well.

Surprisingly, despite its potential, the user short-term behavior is not researched from the personalization point of view. It is clear that the behavior is also influenced by a user actual state and thus the context has to be somehow taken into account. Nevertheless, it offers plenty of research questions and challenges.

3 SHORT-TERM BEHAVIOR MODELLING

From the behavior modelling perspective, the short-term behavior (within a session) brings several opportunities for the recommendation process. The short-term behavior is similarly to user preferences, influenced by his/her context. From this point of view, the site itself (e.g., content, structure) represents a major contextual information. In the literature three aspects are usually reported as helpful to model the user behavior on a site [10]: website structure; website content and website usage.

Despite of the importance of the short-term behavior, it is always based on the long-term behavior. The short-term behavior itself describes actual user actions, but it is very noisy. There is a great chance that the user actual behavior will follow in some measure his/her historic patterns. Moreover, we act as individuals, but generally we are subjects of some actual trends (e.g., following breaking news, learning session before exams) [7]. For this reason, user actual behavior may by similar to behavior of other users.

To reflect all these characteristics, in our previous work, we proposed a domain independent short-term user model [9]. Following the idea of the short-term and long-term behavior, our model consists (Fig. 1) of several time layers (e.g., day, week), two parts (personal – reflecting a behavior of modelled user; global – reflecting a behavior of all users). Moreover, several additional attributes are stored to help describe the (temporal) actual session (e.g., time spent within the session).

As a result, we monitor several comparative characteristics for every time layer (e.g., hour, day, week) and part (comparison to user previous behavior and also to all users). As the model considers only characteristics (e.g., number of sentences, images), model is domain independent.

Afterwards the short-term behavior of the user is modelled, we often want to predict the user future behavior. From the website point of view, the user session end intent is an important task. In the e-commerce this is observed from the long-term perspective (e.g., contract renewal) and referred as the user attrition [12]. On the Web, this is quite a novel task, which needs to be further explored [6].

In our previous works, we made first steps to explore the user session end intent prediction [7]. We used a binary linear classifier over a stream of actions from news and e-learning domains. As our results indicate, thanks to proposed model, we are able to predict the user end intent within three actions in advance (precision 82%) [9]. This is a promising result, which indicates that proposed model adapts various domain characteristics and reflects slight changes of the user behavior.

Hand by hand with the session end intent prediction, the time spent prediction on the site seems to be a promising task. In some domains, not only number of actions, but also an approximated time, the user will browse may bring better user experience and business potential. All of these tasks use the user short-term behavior and we believe that will improve the quality of web services.

4 CONCLUSIONS

There are no doubts that the user short-term behavior is an important source of information and knowledge, describing the user. Together with the user context and his/her preferences allow modern Web-based services react to actual user surroundings and tastes.

The short-term behavior modelling [9] aims at capturing slight behavior changes by comparing actual to historical user behavior and also to the behavior of the rest of users. The knowledge of user future actions allows us to differentiate recommendations, e.g., for a user who will perform two actions before leaving the session and a user who will perform 20 actions within a session. For instance, an educational system should recommend an important learning object for a student, who is about to leave the system. On the contrary, more exercises can be recommended to a student performing a long session. Such an approach is clearly beneficial for the students by trying to maximize their knowledge in the specific amount of time.

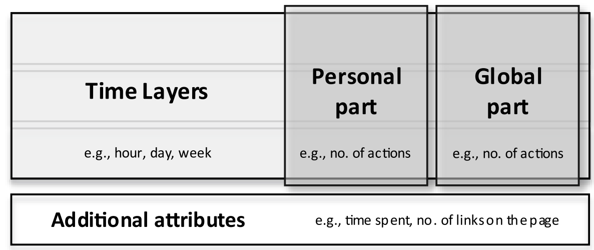

Figure 1: The idea of short-term behavior user model [9].

Similarly, based on the session end intent prediction, a content provider can decide which personalized adverts (considering user context) should be displayed to the customer. Another example of application such a concept is to offer a discount or special offer.

Based on our experience, with the short-term behavior modelling, we identified following challenges:

Short-term behavior modelling. User behavior is a valuable source of information for modern web-based services. We believe, that similarly to the user preferences also a user behavior is influenced by his/her context. Considering the user context can further improve the short-term modelling and its consequent applications.

Session end intent prediction. As our experiments showed, we are able to predict the user short-term behavior on a website. A more sophisticated machine learning approach may further improve the performance. On the other hand, one of the implicit requirements is the prediction in online time (as we need to react to the actual user session). These two aspects need to be balanced.

Spend time prediction. In some domains, also a time, the user will spend by browsing, represents a valuable information. Two basic approaches have to be explored – a classification to predefined classes (e.g., time intervals) and a regression in order to approximate specific time.

Short-term behavior boosted recommendation. The most interesting application of the short-term behavior is its considering in recommendation. There are several options as to selecting different recommender method or to prioritize specific items. This application is mostly appreciated by the commerce.

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