Preference Dynamics and Behavioral Traits in Fashion Domain

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***Abstract*—Users preferences evolve over the time. This so-called dynamics is a serious challenge which is widely researched in several domains. In these domains users are usually active for a long period of time and they tend to interact with a wide range of items. To make it more complicated, users preferences are likely to evolve only in some aspects, while others remain untouched. In this paper we present an analysis of user behaviour dynamics in a fashion e-shop. We identified four typical user behaviours, i.e., classes. Moreover, we explored typical user behaviour before and after the purchase. As a result, such knowledge can improve various tasks dealing with short-term dynamics, mainly in session-based recommender systems.**

***Index Terms*—user modelling, user behavior, concept drift, preference dynamics, fashion, session based recommendation**

I. Introduction

A typical user on the Web changes his/her preferences and interest over time. Such a behaviour is mostly common for domains where users are active for a long period of time. On the contrary, not only a user behavior changes, in the long term perspective also items available for interaction tend to change. A common belief, that more data leads to better performance of recommender methods fails in this setting [1]. In fact, involving a complete user interaction history may decrease recommender performance. The knowledge of user preference drift may greatly improve the performance various predictive approaches.

Learning users' preferences is a challenging task because it is under constant influence of external factors. Only a fraction of these factors can be monitored by the system. For example, a child likes a fairy tail theme of clothing but later their preference will change as he/she grows up. Recent studies identified similar effects of the time [2], [3]: *a*) change in interest, habits and trends in general community; *b*) temporal popularity of certain items; *c*) natural preferences change of individuals.

In order to reduce the preference drift influence in user modelling, researchers use temporal information in many different ways. Xiong et al. [4] introduced Bayesian probabilistic tensor factorization, which enhances traditional collaborative filtering with temporal features. Therefore, it is able to learn latent features evolving over the time on the global basis. Spiegel et al. [5] used tensor factorization on data split to predefined time periods. Users were modelled for every chunk separately. Their approach used exponential smoothing technique to lower the importance and eventually to eliminate older preferences. Both of this approaches introduced some kind of forgetting mechanism into user modelling. However, this technique does not take into account, that a dynamic of preferences varies on an individual basis. Some users may behave more conservative and on the other hand, preferences of other users may undergo rapid and fundamental changes. Rafailidis et al. [6] solved this issue by introducing the User-Preference Dynamics measure which captures the rate with which the actual preferences of each user have been shifted in comparison with older. Value of this metric is maintained for each user and it is used to weight the importance of preferences in recommendation tasks based on tensor factorization.

In this paper, we present an analysis of user behavior dynamics in fashion domain. We explore the similarity of items which user interacted with on a Web site. We identify and describe typical classes of users clustered by their behavior in informational and transactional sessions. By this analysis we answer following research questions:

- RQ1: How consistent are sessions and purchases in fashion domain?
- RQ2: Do users have characteristic behaviour traits in informational and transactional sessions?

The paper is structured as follows. Section 2 describes dataset used in analysis. In section 3 we provide our examination results of similarity of sessions, purchases and their relationship. Section 4 describes identified classes of users by their behavioral traits. The paper ends by the conclusions discussing the analysis and future work.

II. Dataset

For the analysis we used a sample of users in a typical fashion e-shop. User behaviour was described by view and purchase events over aprrox. 1.5 year period.

In the first step the dataset was preprocessed. We removed obviously incorrect events. Because of the analysis of user's purchase behavior we use in our analysis only users which made at least two purchases during examined period of time. This results to deletion of non-human events (i.e., robots). After the preprocessing step, our dataset consisted of tens of thousands users and hundreds of thousands purchases done in a few millions sessions.

The items metadata in our dataset is rather uninformative, therefore we used items categories as a main metadata source. Categories tree depth consists of four levels, while the top level splits items to women, men and kids categories. Second level describes type of clothing (e.g., t-shirts, jeans, skirts) and finally third level provides us with better understanding of variations (e.g., long and short skirts). The fourth level of category tree was truncated as this information was missing in the majority of items. With three levels, there were approx. 200 leafs in a categories tree.

III. User Preference Dynamics

Long- and short-term preference modelling is closely related to preference dynamics. While long-term preferences represent user's general preference which is formed progressively and is somewhat stable. On the other hand, the short-term preferences are unstable from their nature and may change on a day-to-day basis [7]–[9]. This non stationary learning problem is referred as *concept drift*. *Zliobaite* [10] identified and presented four types of the preferences change: *a*) sudden drift, *b*) gradual drift, *c*) incremental drift, *d*) reoccurring contexts.

One of the important tasks is to quantify the effect of dynamics. We opt fot the Jaccard similarity index (Equation 1), which measures relative size of the overlap of two finite sets A and B. We used *item vectors* describing items categories as sets for Jaccard similarity estimation. This measure is in fact complementary to UPD measure used by Rafailidis et al. [6].

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \quad (1)$$

As a result we obtain expression of the dynamics, which gains values in range from 0 to 1 and represents how much some action, i.e., item is similar to other. Thanks to the categories hierarchy, it is clear, that items from different categories have non-zero similarity (if they share common parent category).

In our study we explore the user behaviour on the level of sessions. To represent a user preference in the session (or purchase with several items) we aggregated all actions within a session (or purchase) by a union of *item vectors*.

A. Purchase Preferences Characteristics

A purchase is considered to be the strongest interest indicator. Thanks to this the inter-purchase similarities change, may indicate a possible concept drift. As we can see (Figure 1) there is a high similarity of consecutive purchases compared to purchases which happened further in the past. Actually, this is expected, since we base on the hypothesis that user preferences evolve over the time.

Moreover, there are other aspects which are worth to discuss. E-shop users may return purchased items, which they did not like. Hence, their needs were not satisfied by the purchase and they are looking for alternatives (in order to fulfill his/her purchase task). Another typical behaviour for this e-shop (also thanks the above described feature) is to purchase a related, therefore similar, products in the post-purchase stage [11].

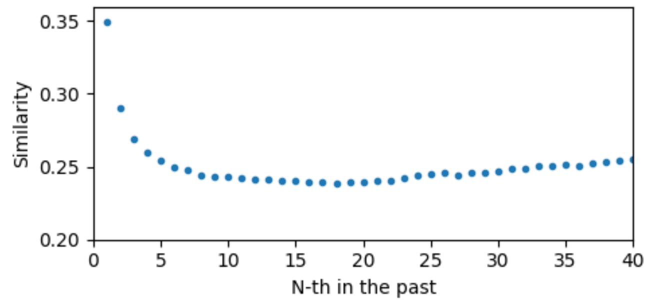

Fig. 1. The average similarity of purchase compared to previous user purchases. The similarity of consecutive purchases (leftmost) decreases over the time. Further in the past (larger N values), the purchase similarity tends to increase a bit, which is caused by the seasonality.

Following the history (looking further in the past) we can observe purchases to start to be slightly more similar to the last purchase. We attribute this effect to the seasonality. E.g., during the summer, users buy new t-shirts, while in the winter warm clothes are preferred.

To further explore the consistency level of users purchases, e.g., the average similarity of purchases made by a user, we adjusted the dataset. For this purpose, we have excluded users who made less than 4 purchases (52% of all users).

Figure 2 shows that users tend to have lower similarity of consecutive purchases compared to average similarity of all purchases compared each to other. This means that long-term preference is more stable than short-term preferences change on purchase-by-purchase basis. Considering that the consecutive purchases similarity is low but the overall purchase similarity is higher, we can hypothesise that a concept drift of reoccurring contexts is present. There are almost 2% of users, who have perfect match between consecutive purchases, hence there are users who buy items of the same type each time. On the other hand, there are some users (more than 1%) who have zero similarity. This number is low because users make most of their purchases from the same top-level category, which defines their gender, so zero similarity occurs very rare.

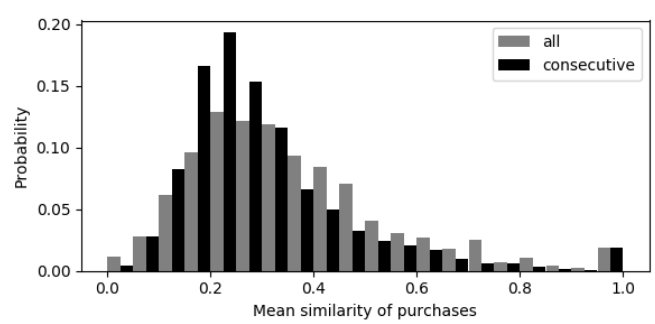

Fig. 2. Average purchase similarity and corresponding probability of the occurrence. The differences between all and consecutive purchases similarities are presented.

B. Sessions Preferences Characteristics

The second strongest implicit feedback type is the view of an item. However, on the single item basis it is quite hard to differentiate between the noise and real user preferences. To over come this issue usually a set of user actions, i.e., session is used for analysis. In other words, related actions share a common intent and thus should be processed together [12]. In our analysis, a session is a sequence of actions joined by temporal heuristic [13]. To make it clear, two consecutive actions are joint into a single session if they occur in less than 30 minutes. Any action made more than 30 minutes after its preceding action is considered as a new session.

Given two following sessions, assuming that in each of these sessions a user viewed two categories sharing common second-level parent, similarity of value 0.5 means, that the user viewed one of the categories in both of these sessions. Figure 3 shows negative correlation between similarity of compared sessions and increasing distance between these sessions. Majority of sessions similarities is around value of 0.47. The similarity is 0.82 if we take in account only top-level categories. Immediate session neighbours have 0.54 average similarity and sessions with distance 5 have average similarity 0.43, which is still fair similarity.

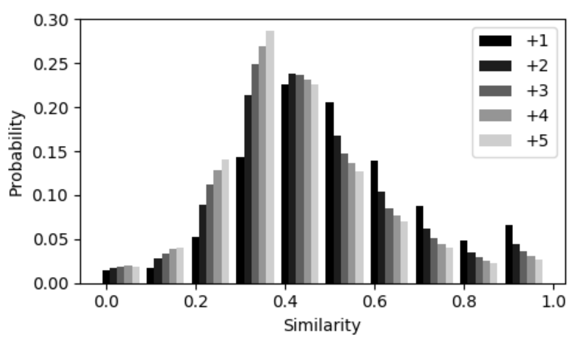

Fig. 3. Sessions similarity compared to its neighbourhood in a distance up to 5. E.g. *+1* label means that compared session is immediate follower and *+5* label means that compared session is 5-th afterwards.

When we calculated the similarity of a session and its neighborhood, we did not take into account any global bias. Later, we have discovered few large and several small peaks in similarity metrics across the dataset (Figure 4). Both of these peaks occurred in December, just before Christmas. We believe that it is caused by browsing or purchasing items for a third person, for example as a gift. Other small deviations may be caused by massive online advertisement campaigns held by the e–shop. The user might click on an advertisement but it does not necessarily mean he/she shifted his/her preferences. Therefore, this kind of sessions and purchases should not be considered when modelling user preferences.

C. Relationship of Sessions and Purchases

There is fair chance of high similarity between two consequent sessions. As shown in Figure 5, we see increased

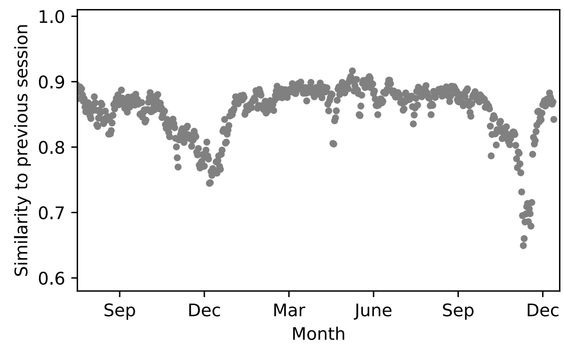

Fig. 4. Average similarity of sessions during the year. Similarities are calculated based on the top-level categories. The similarity drops (in December) are caused by the Christmas gifts purchases.

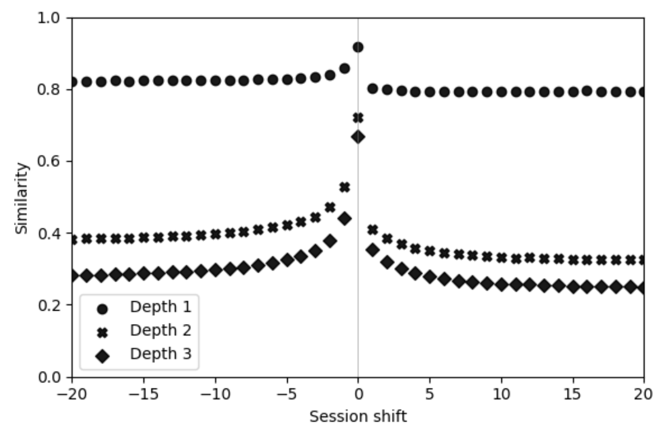

Fig. 5. Average similarity of purchase and its surrounding sessions. Purchase happened at zero value on horizontal axis. Preceding sessions are on the left from zero and following sessions are on the right. Surprisingly, there is increased similarity in post-purchase stage.

similarity of purchases to its neighbour sessions with peak at the zero, i.e., in a session in which a purchase happened. It illustrates a high consistency of characteristics of browsed items right before purchase. In other words, users browse similar items to what they intent to purchase. Similarly, there is also a similarity increase of few preceding sessions. It suggests that users may split their purchase task into multiple sessions. They browse several item alternatives and purchase it later.

Surprisingly, we also can see increased similarity in post-purchase stage (Figure 5). This effect has at least two explanations. After receiving purchased good, users evaluate their expectations and reality [14]. E.g., the user wants to compare item images on a Web site again and compare it to actual looks. Another perspective is that users search for other alternatives of items (because of goods return), thus they can challenge their belief of good purchase. Alternatively, two purchases made in a short period of time may increase a similarity of two consecutive purchases.

IV. User Behavioral Traits

Based on the user behaviour, three types of sessions were identified by Broder [15]: *a*) navigational, *b*) informational, *c*) transactional. In behalf of *RQ2*, informational and transactional sessions are interesting. During an informational session, a user's intent is to acquire information, e.g., about items in e-shop. Transactional sessions are those, when a user intends to make some kind of transaction, e.g., buy items.

Furthermore, there are two classes of users distinguished by their extreme cognitive style: navigators and explorers [16]. Only 3% of users are extreme explorers, users who visit large number of pages which contents varies highly. On the other hand, 17% of users are extreme navigators, users who complete tasks sequentially in a direct path from query submission to the problem resolution, i.e., low variance in page contents. Other 80% of users are characterized by a large diversity of behavioral patterns.

Moreover, we distinguish two basic classes of users by their decision-making style: satisficers and maximizers [17], [18]. Satisficers choose an alternative of desired item which is "good enough". On the contrary, maximizers optimize their knowledge about alternatives and choose the best possible option.

We used this knowledge to model user behavioral patterns and cluster users to classes by their common behavioral traits in transactional and informational sessions respectively.

Before the clustering process, we explored several attributes candidates which we rejected after few iterations, because those attributes had not significant influence on resulting clusters (e.g., order frequency) or did not describe behavioral habits (e.g., a purchase or session count).

Finally, we have used following clustering attributes:

A) transactional duration - average duration of transactional sessions (i.e., sessions with purchase event);
B) views count - average item views during single session;
C) duration rate - rate of transactional and informational session duration;
D) views rate - rate of item views in transactional and informational sessions;
E) transactional consistency - similarity of purchase and its transactional session;
F) informational similarity - similarity of transactional session and its preceding informational session.

We have identified four classes as shown in Table I. The smallest class consists of extreme users (2.1%) having characteristics of *explorers* [16]. Additionally, *class 2* (13.8%) and *class 3* (20.2%) have parameters characterizing behavioral traits of satisficers and maximizers respectively. The rest of population (63.9%) is classified into mixed behavioral traits class.

In fact, *satisficers* are distinguished only by the increased views count in transactional sessions. Therefore, if we merge *class 0* and *class 2*, we would get almost 80% of users characterized by a diversity of behavioral traits, which corresponds with findings of White and Drucker [16].

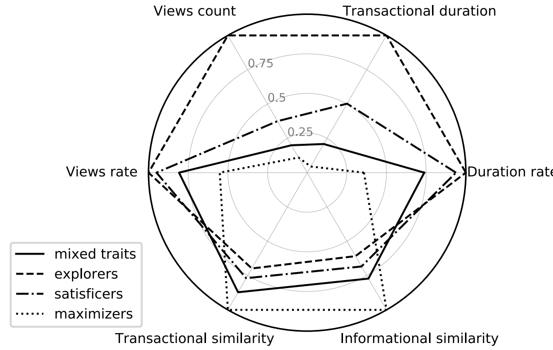

Fig. 6. Vizualisation of clusters characteristics. There are obvious differences between parameters of individual clusters, which results to four classes of users: mixed behavioral traits, explorers, satisficers, maximizers.

TABLE I
Users clusters brief characteristic and their population rate in dataset

Label	Population	Characteristics
0	63.9%	mixed behavioral traits
1	2.1%	explorers
2	13.8%	satisficers
3	20.2%	maximizers

Another perspective to differences of each class are presented in Figure 6. We describe these classes in more details in the rest of this section.

a) Class 0 – mixed behavioral traits: Based on the used attributes, we could not distinguish a majority of users. That is the reason we created a class of users with mixed behavioral traits. There is almost no difference in item views count and session duration in transacational and informational sessions of these users. Transactional consistency is fairly high, it is a double of informational similarity.

b) Class 1 – explorers: This small class of extreme users has characteristics of *explorers* trait (i.e., page views count and high variance) and their population rate also reflects other research by White [16]. They have 4.5 times more item views then average of other classes and 2 times longer transactional duration than *class 2* (96 minutes on average), which should be characterized by plenty of item views and long transactional duration.

c) Class 2 – satisficers: These are users similar to the *class 0*. The difference is that users in this class tend to have slightly higher number of item views, mainly in transactional sessions which also have higher dissimilarity compared to informational sessions. Hence, these users purchase without prior informational sessions. These are characteristics of satisficers [17].

d) Class 3 – maximizers: 20% of users are characterized by a short, only 4 minutes on average, duration of transactional sessions. Also they have very high transactional consistency (80%) and the highest informational similarity (47%). They do 70% of browsing in informational sessions. These are characteristics of maximizers [17].

V. Conclusions

User preference dynamics is a serious challenge which deserves attention of researchers. We believe that results revealed in our paper may be useful in various tasks dealing with short-term dynamics, mainly in session-based recommender systems.

We examined user interactions with items in the purpose of quantifying consistency of users' interest. On average, there is 54% match of viewed products in two consecutive sessions. This is fair level of consistency though, we did not take into account global decreases which occur mainly during the Christmas or in time of massive advertisement campaigns. Most of users have a low consistency of consecutive purchases but occasionally higher values occur. This results into increased average level of match up to 35%. It may support other researches claims of buying related items in post-purchase stage. Although, there are 2% of users who have perfect match between all purchases. The similarity of two random purchases is higher than similarity of two consecutive purchases, moreover we showed that similarity of orders in time, starts to increase after reaching local minimum. These observations indicate the presence of reoccurring contexts of concept drift. Therefore, we see potential in further investigation of these effects and eventually mining of concept drift patterns. We also showed that users tend to have an increased consistency of item views in the post-purchase stage. We provided few explanations even though none of them has been verified.

We discovered four classes of behavioral traits in which users may be assigned to. Characteristics of identified classes and its population rates correspond with findings in earlier studies. We identified users trying maximize their utility of purchase by investigating a big load of alternatives in the pre-purchase stage. It is typically done in informational sessions and their transactional sessions are usually very short. This class is significantly big, since it includes 20% of all users. We believe this users should be treated in different manner when session-based recommender systems are used.

In the future work we see a huge potential in further investigation of effect shown in this paper. All our experiments evaluate a rate of consistency of users' interest based on the similarity of categories. Therefore we propose to represent items and also sequences of user interactions in a latent space. We believe that the consistency analysis with this representation of items and interactions will be more informational.

Since researchers still do not agree in what are actual boundaries of a session, as future work, we plan to use the metric of consistency. In this way we can find relations between multiple sequences of user's interactions, which can be merged into potentially longer sequence of actions executed in purpose of fulfilling the *purchase task*.

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