User Timeline and Interest-Based Collaborative Filtering on Social Network

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Abstract. A lot of users and large amount of information have been posted and shared through on-line systems. User timeline and interest are important features on recommendation systems (e.g., user likes watching action movies in the morning, and likes watching drama movies in the afternoon however he/she likes watching thriller movies in the evening) and also on social network. There are some recommendation applications have been developed on social network to support users selecting what kind of wanted items based on user timeline and interest. However, there is not any approaches based on user timeline and interest have been proposed that user interest have been separated into partitions of user interest. Thus, a recommendation mechanism will be applied on social networks based on extracting user timeline and user interest that is necessary. In this paper, we propose a new approach that user interest will be determined on a set of time partitions.

Keywords: Recommendation systems · Context · User timeline · User interest

1 Introduction

Nowadays, social networking sites (SNS) are good choice to post and share what on their mind is, what they did or their plan to group, community and the world. The data on SNS is growing rapidly as Big Data. There are many applications have been developed on SNS by using social metadata. Recommendation technique is being suitable approach for e-commercial systems. It helps users to overcome the overload information on the web. User is suggested related items that it predicts that they will be interested in. On the social network, these suggestions can be shared to other people who is in the group (e.g., friends, family) or community.

User context contains a set of particular situations that user interact with the system. Context-based recommendation is an approach to improve user satisfaction in particular context. Thus, the context extraction is an important task to

P.C. Vinh and V. Alagar (Eds.): ICCASA 2015, LNICST 165, pp. 132–140, 2016.
DOI: 10.1007/978-3-319-29236-6_14

understand user activities on the systems. In previous work, we have proposed a context-based recommendation approach based on social context. However, we did not mention about the partitions of time. We just considered time feature as watched history [1].

We consider the following table:

Table 1. User-item model

	Titanic	Ghost rider	Apollo 13	Spider man	Frozen	Lion King
u_1	5	4		3		
u_2	5		3			
u_3				5	5	
u_4					5	4

Table 1 shows user-item model. In traditional collaborative filtering, we just measure the similarity between two users to find potential movies to recommend. However, if considering user watched history as timeline and time is separated into partitions. We have the table as follows:

Table 2. User model in partitions of day

	Morning	Afternoon	Evening
u_1	(“Titanic”, 5, t_{11})	(“Spider man”, 3, t_{12})	(“Ghost rider”, 4, t_{13})
u_2	(“Apollo 13”, 3, t_{21})		(“Titanic”, 5, t_{22})
u_3		(“Frozen”, 5, t_{31})	(“Spider man”, 5, t_{32})
u_4	(“Frozen”, 5, t_{41}), (“Lion King”, 4, t_{42})		

Table 2 shows a description about user model in partition of day. The day is separated by three partitions, morning, afternoon and evening. Each partition shows a set of movies that each user watched, movie rating and watched time, respectively. Each movie is described by title, a list of genres, director, a list of actors and auxiliary information such as country, language, runtime, and so on. User can rate movie from 1 to 5. Watched time identifies time that user begin watching movie. Making the partition of time will measured by using this parameter. The table has 4 users u_1, u_2, u_3, u_4. In this example, user u_1 has watched three movies in his/her timeline. Based on watched time and partition of day, we separated them into partitions, “Titanic” in the morning, “Spider man” in the afternoon and “Ghost rider” in the evening. The key question is how to apply collaborative filtering in this scenario.

Extracting user interest in a particular context is very necessary for recommending a list of items that user may be interested in at any one moment. There are many approaches to construct user preference. However, user interest may be change over time. Thus, the capturing them is a challenge in recommendation systems. In order to face this problem, in this paper we propose a new approach to determine user interest over time. In our approach, user interest will be determined on a set of time partitions with a set of pair item attribute and value.

Therefore, we focus on two major tasks in this paper:

- Taking into account user interest in partitions of time
- Extending collaborative filtering approach based on them.

The outline of this paper is organized as follows. In Sect. 2, we represent related work. In Sect. 3, we discuss about user timeline and user interest features in social context and in recommendation systems and also present collaborative filtering recommendation approach based on integrated user interest and partition of time. Finally, in Sect. 4, we conclude our proposal and suggest future work.

2 Related Work

Context-based recommendation systems try to improve user interest in particular context [2–6]. The contextual information has been exploited and applied to improve the quality of recommendation systems and discussed by Adomavicius et al. [2]. In [3] they introduced a new context-aware recommendation approach. User profile has been splited into several possibly overlapping sub-profiles as micro-profiling. Each profile represents users in particular contexts. However, they have just focused on calculating the similarity based on user rating. A new approach recommendation systems has been proposed in [5]. Braunhofer et al. [6] has been proposed a new approach for recommendation task by selecting music suited for a place of interest by using emotional tags and developed a mobile application.

User profiling with temporal dynamics has been considered in this approach. Another time-based approach has been proposed in [4,7,8]. Xiang et al. [4] try to capture user preference over time. They focus on explicitly user profiling in long-term and short-term preferences by using implicit datasets. In [7], they proposed a new recommendation method based on time-framed user clustering and association mining.

There are a lot of applications have been developed and posted on social network including recommendation applications. A lot of users and large amount of information have been posted and shared through social networks. The applications will be relied on these information to understand user interest to make more better recommendation. In [9], they investigate the importance and usefulness of tag and time information for predicting users preference on social tagging systems. Abel et al. [10] compare many different strategies for user profiling of personalized recommendations in the social web based on the published Twitter messages and try to understand it changing over time. In [11], a statistical user interest models has been represented in social media.

3 User Timeline and Interest-Based Collaborative Filtering Recommendation Systems

In order to understand our approach, we denote as follows:

- U is a set of users
- I is a set of items
- A is a set of item attributes
- V is a set of attribute values
- R is a set of user ratings

Definition 1 (Recommendation Framework). *Recommendation framework on social network is defined as a tuple:*

$$S = \langle U, I, R, T \rangle$$

where, T is a timeline.

Definition 2 (Partition of Time). *Partition of time is defined as follows:*

$$P = \{(t_1, t_2) | \forall t_1, t_2 : (t_2 - t_1) \geq \lambda\}$$

In our approach, user timeline is separated into partitions of time, denoted P, for example, in Table 2, $P = \{(4:00AM, 12:00AM), (12:01PM, 20:00PM), (20:01PM, 3:59AM)\}$ and we can represent it as follows: $P = \{morning, afternoon, evening\}$. In order to easy represent our example, we denote: $p_1 \longleftarrow morning, p_2 \longleftarrow afternoon, p_3 \longleftarrow evening$. Figure 1 shows an illustration for partition of time.

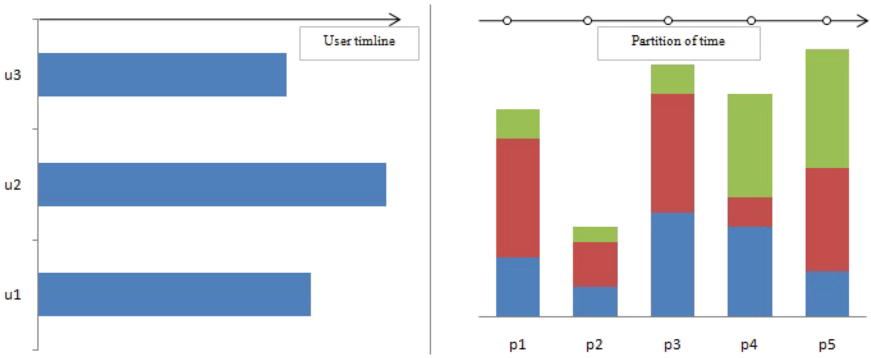

Fig. 1. Partition of time for three users

Depending on each time partition, we collect a set of items for each user on each partition. Each user partition contains a set of items that selected item time belongs to the same time partition.

Definition 3 (Partition of User). *Given user u, the partition of user is defined as follows:*

$$P_u = \{(i, r, t)_p | \forall p \in P, i \in I, r \in R : t \in T\}$$

As Table 2, u_1 watched three movies, each movie is in one partition. We have: $P_{u_1} = \{($"Titanic", 5, $t_{11})_{p_1}$, ("Spider man", $3, t_{12})_{p_2}$, ("Ghost rider", 4, $t_{13})_{p_3}\}$

Therefore, there is a set of items on partition p for all users will expressed as follows:

$$p = \{(u, i, r) | \forall u \in U, i \in I, r \in R : i \in p_u\}$$

For example, in Table 2, we have:

$p_1 = \{(u_1,$"Titanic", 5), (u_2, "Apollo 13", 3), (u_4,"Frozen", 5), (u_4,"Lion King", 4)$\}$

$p_2 = \{(u_1,$ "Spider man", 3), (u_3, "Frozen", 5)$\}$

$p_3 = \{(u_1,$ "Ghost rider", 4), (u_2, "Titanic", 5), (u_3, "Spider man", 5)$\}$

3.1 User Timeline and User Interest

In the both social network and recommendation systems usually contain important features, user timeline and user interest. Timeline feature is a collection user interactions that is organized the following time feature. It is counted from first login to system to now. It contains a set of time intervals including user contents. For example, on Facebook, user timeline is grouped by year. We can see a set of user events via month highlight. It expresses a lot of related information in that month such as number of friends, number of photos and a list of posted events. Another example on recommendation system as Facebook application is proposed in [1], called my movie history. User timeline is represented one by one for each movie. However, in this approach, we have not taken timeline into account partition of times (i.e., time windows) and integrated interest of user.

Definition 4 (User Timeline). *Timeline of user u, T_u, is defined as follows:*

$$T_u = \{t | t \in T : t_1 < t_2, \forall t_1, t_2 \in T\}$$

User timeline establishes including user interactions that will help the system to refine user profiling. In this approach, we try to extract user interest by using pair of values, item attributes and attribute values. Item description contains rich information to understand what user is interested in. For example, a certain user has high watching frequency on "Steven Spielberg" movies in movie recommendation systems then we can predict that this user want to watch action movies and be directed by this director. Thus, genre (e.g., action) and director (e.g., Steven Spielberg) are dominant item attributes including values in this case, respectively.

Definition 5 (User Interest). *User interest is a representation of dominant values based on a set of item attributes and values. It is defined as follows:*

$$UI = \{(a, v, p) | a \in A, v \in V, p \in P : (a, v) \in Dom(u, I_u)\}$$

where, $Dom(u, I_u)$ is a function to find out which dominant values.

In this paper, user interest will be determined with partitions of time (e.i.,time windows). The size of partition is defined depending on user context. The Algorithm 1 shows process to extract the partition of user.

Algorithm 1. Extracting partition of user

```
T = user timeline
read λ
P_u ← ∅
P ← Partition (λ)
for all t ∈ T do
    t_1 ← t
    if (t − t_1) ≤ λ then
        p ← (t_1, t)
        if p ∉ P then
            P ← P ∪ p
        end if
        P_u ← P_u ∪ (i, r, t)_p
    end if
end for
return P_u
```

3.2 Collaborative Filtering Approach

In this section, we will explain our approach based on user timeline and user interest. In traditional collaborative filtering, the similarity between two users is computed based on entire items of two users to make recommendation at current time. However, the similarity on period of time may be different in some cases. Thus, the accurately predicted results is not closed to user interest. In order to apply collaborative filtering method to our model, we have to measure similarity between two users based on partitions of user including user interest.

Definition 6 (User Similarity). *Given two users u_1, u_2, a set of partitions P and user interest UI, the similarity between two users is computed as follows:*

$$sim(u_1, u_2) = \frac{\sum_{p \in P} sim(u_1, u_2)_p}{card(P)} \tag{1}$$

where,

$$sim(u_1, u_2)_p = \frac{\sum_{v \in V_{u_1 u_2}} card(v_{u_1}) card(v_{u_2})}{\sqrt{\sum_{v \in V_{u_1 u_2}} card(v_{u_1})} \sqrt{\sum_{v \in V_{u_1 u_2}} card(v_{u_2})}} \tag{2}$$

Depending on density of selected items of users, we separate in many different time such as day (e.g., morning, afternoon,evening), month (e.g., weeks), year (e.g., seasons). The current time will consider to decide which is the best choice for final recommendation results. For example, we consider the similarity between two users on their time, $sim(u_1, u_2) = 0.85$, $sim(u_1, u_3) = 0.6$, it means that they have the high similarity. However, if we consider them in certain partition of time (current time belongs to this partition), denoted p, we have: $sim(u_1, u_2)_p = 0.2$, $sim(u_1, u_3)_p = 0.8$. It leads to the final recommendation results are different and not accurate.

The similarity is computed based on frequency of attribute values on a set of items that users have already selected. The value vectors will be defined to compute the similarity. We have the partition of user algorithm based on a set of partitions for each user in Algorithm 1. Next, we present our algorithm of collaborative filtering method.

Algorithm 2. User timeline and interest-based collaborative filtering

```
User u_1
Extracting P_{u_1}
Dom(u_1, I_{u_1})_{P_{u_1}}
for all u_2 ∈ U do
    Extracting P_{u_2}
    Dom(u_2, I_{u_2})_{P_{u_2}}
    for all p ∈ P_{u_1,u_2} do
        Sim(u_1, u_2)_{p_{u_1,u_2}}
    end for
    Sim(u_1, u_2)
end for
L ← Rec(u, I')
return L
```

In this approach, the number of computed similarities among users will be decreased. Instead of computation all candidates, we will focus on the partition that current time belongs to.

4 Concluding Remarks

Context-based recommendation systems is an approach for dynamic scenario recommendation to bring more satisfied to users. There are many context features in recommendation systems and social networks. In this paper, we have focused on partitioning user timeline and user interest. User interest is considered with time feature in each partition. In this approach, a user interest model on partitions of time have been built based on a set of attribute values and dominant values. An collaborative filtering recommendation algorithm has been proposed to find out a set of items for recommendation.

In future work, we will present our experimental results by using our collected data and datasets [12] and our dataset. Also we have comparison with other approaches.

Acknowledgment. This research is funded by QuangBinh University. This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (NRF-2014R1A2A2A05007154). Also, this research was supported by the MSIP(Ministry of Science, ICT and Future Planning), Korea, under the ITRC(Information Technology Research Center) support program (IITP-2015-H8501-15-1018) supervised by the IITP(Institute for Information &communications Technology Promotion).

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