Social Network Recommendation Based-on User Context

# Abstract

# Introduction

With the development of social networks, the extreme explosion of information makes it increasingly difficult for users to obtain what they want. Therefore, social networks recommendation system becomes an important mechanism for active service. To meet users’ individual requirements, the system should extract content from a lot of information in line with user needs and interests.

Traditional recommendation technologies [1] mainly contain content-based and collaborative filtering recommendation and the hybrid recommendation technology. In social networks, collaborative filtering methods are unable to fully characterize the complex relationship in social networks. For social networks recommendation, the researchers introduced trust-base and influence-base methods to leverage social networks the relationship between users, so that the social networks recommended more precise.

Both the traditional and the existing social networks recommendation methods recommend with two-dimensional matrix such as the observed user ratings matrix, the user feature matrix, the item features matrix to predict the user ratings matrix describing the users’ preference for items. These two-dimensional recommendation mechanisms ignore the influence of user context on user behavior. Only user and project dimensions are considered but the context dimension.

In our real life, people communicate with who they like and talk about what they are interested in according to the prevailing situation. That is, in a dynamic environment, user-user influence and user preference of topic will change with the social situation. For example, when a person has trouble, he would choose older experienced people exchanges, and the topic may change from his usual favorite sports to a life philosophy class. And when he is working, he will turn to his work colleagues, sharing the contents of work-related. However, same in work time, if it is Friday, the day before the weekend, he and his colleagues’ talking content may be more to do with the weekend activities.

In the social networks similar with real life, the main factors affecting user behavior have three aspects as shown in Figure 1. Figure 1 shows entire social network information when user surfing on the social networks. According to the social context, item sender and its contents, by filtering social networks information, user will choose the items they like the current social context. For example in Sina Weibo, when an user receive an item posted by one of his friends, he usually will quickly scan who send it and its content, and decide whether he is interested in the item and to re-tweet it according to the current social context. If at work, he may cares more about some professional items from expect authors he follows and if at home, he may prefer his close friends items and items about his personal hobbies. So when establish the social networking user behavior model, it is necessary to take into account: (1) the user's personal preferences, (2) the impact between users and (3) the user social context.

In order to improve the accuracy of social networks recommendation, we propose a context-based three-dimensional model, in which the third dimension of user context is introduced into the existing user-item two-dimensional model.

We conducted experiments on the existing social networks Sina Weibo to do the recommended model validation. Firstly we crawled Sina micro blogging data, and then analyzed the data to identify the social context data, the sender information and the item content. For situational awareness of today's social networking for is limited, the situational data mainly include location data aware by mobile device, time data, and the mood data both from Sina Weibo mood service and facial expression analysis of user. Our experimental data is divided into training and testing sets, using the most commonly recommended metrics MAE and RMSE as the evaluation criteria. We show that the real word social context contribute to the precise of social networking recommendation.

This paper is organized as follows. Section 2 provides an overview of some recommendation approaches and related work. Section 3 describes how specific user, item and social context to are abstract and modeled and our context-based social networking recommendation model is formulated. Section 4 describes our experimental design and experimental results, followed by the conclusion and future work in Section 6.

# Related work

In this section we review several major recommendation approaches, including traditional recommendation system which are mainly based on collaborative filtering technology and some social recommendation system.

Traditional recommendation approaches [1] mainly contain content-based method and the commonly-used approach collaborative filtering and the hybrid approaches. Collaborative filtering is the most widely used and mature recommended method. Collaborative filtering can be divided into neighborhood-based (based on user or item) and model-based collaborative filtering. User-based collaborative filtering approach [?] primarily based on the assumption that similar users have similar tastes of a certain item. Use the history item rating to find neighbors similar with the current user and then predict the ratings with the user-neighbors’ ratings. Similarly, item-based collaborative filtering predicts the rating based on the ratings of item-neighbors which are rated by active user. The neighborhood-based collaborative filtering mainly use Pearson Correlation Coefficient [13] and the Vector Space Similarity [?] algorithm to compute the similarity of user and item. Model-based collaborative filtering methods use existing user rating matrix to train a recommended model predict user preferences instead of directly calculate the ratings as neighborhood-based. The mainly used algorithms include Personality Diagnosis [17], Bayesian Network Model [8] and Clustering Model [].

In social networks, collaborative filtering approaches are unable to fully characterize the complex graph-based relationship in social networks and make full use of social knowledge. Recently, for social networks recommendation, researchers introduced a trust-based [2] [9] [11] [22] and influence-based [4] [10] [16] [18] approaches to take advantage of the relationship of users in the social network to get more accurate prediction. Trust-base recommendation is based on the assumption of homogeneity principle that the user has similar tastes with his trusted people, which is not entirely realistic. This approach is only applicable to trust mechanism network rather than the real social networks. While Huang [10] introduced a social network between users mutually influencing factors, but ignored the user's own factors. Jiang [4] took into account the context of social networks, proposed a new social network user behavior model, that user behavior among users affected by the user's preferences and interaction between the two, a more comprehensive characterization of the user behavior in social networks, but ignored in different contexts, the influence between users and user preferences are changing. Calculation of the recommended methods of efficiency, so that all of the matrix decomposition methods [6] [7] and the normalized matrix [5] The method has also been proposed to calculate the mass of the social network data, in order to improve computational efficiency. But whether it is traditional recommendation methods and existing social networks are recommended for the observed user ratings matrix, the user feature matrix, the project features such as two-dimensional matrix matrix processing, resulting in predictable user ratings matrix to describe the user for an item preference. These two-dimensional recommendation mechanisms ignore the context of user behavior, user and project considered only two dimensions, without considering the context of this dimension. In this article I will situational impact on users and user preferences between the role of the application of our recommendation in social networks.

# Social Recommendation Model Based-on Context

## Context Definition

Definition of context in different areas will be different. We use the definition of Schmidt [20]: A context describes a situation and the environment a device or user is in. A context is identified by a unique name. For each context a set of features is relevant.

In social networks, Context describes the user state and the situation when users browse the social network, including external and internal factors. The context when user browse the social network with the external environment is limited including the time and place and the internal factor of user can be described as mood. For example, a user might browse social networking information at home, in work places or in public places, in different period of the day, with different mood such as happy, worried or no feeling.

## Context-based 3 Dimensional Model

Dimensions are used to represent the range of recommendation space. In addition to user dimension U and item dimension I, there is context dimension C. Recommendation dimensional space S is the Cartesian product of user, item and context dimensions:

In traditional recommendation systems, rating on the item indicates how much user like the item. Different recommendation approach predicts by calculating the 2-dimensional rating matrix of user and item dimensions.

In 3-dimensional recommendation model with social context dimension, we predict with recommended space S. Figure 2 the 3-dimensional rating matrix may exhibit user rating of an item in a certain context. But in social networks, R is the adoption matrix, that is, value 1 of indicates user i adopted item j and value 0 indicates no adoption. So.

The recommendation space S can be intuitively represented by the following 3-dimensional of Figure 3, each small square represents a user adopts of an item in a context. In this paper we refer it as adoption matrix R.

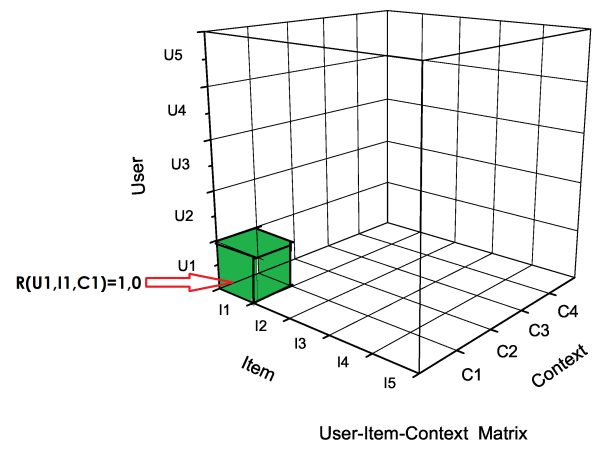


Figure 2: User-Item-Context Matrix

## Social Recommendation Algorithm

Context-based social network recommendation is to predict the user-item-context adoption matrix R, then recommend items by the values in R.

According to the analysis of user behavior in social networks in Figure 1, we propose a 3-dimensional social network recommendation model based on the social context as shown in Figure 3. The model takes two main factors into account: First the user-user influence in different context, and second the personal preference in different context. The original adoption matrix R (User-Item) you need from the user preferences and influence among users of both calculated (divided into User-Item Influence Matrix and User-Item Preference matrix), and the expansion of two-dimensional score matrix R to three-dimensional, the User-Item User-Item-Context becomes three-dimensional matrix, then decomposed into User-Item-Context Influence matrix I and User-Item-Context Preference matrix P.

According to historical data, we use LDA [] to calculate the project Item computing its topic distribution, resulting in different contexts Item Item Latent Feature Matrix, based on user adoption program in historical data, can be calculated in different contexts of users the preference of different Latent (User Latent Feature Matrix), at the same time, which can be calculated User-Item-Context Preference matrix (1). On the other hand, according to the adopted sender information items, calculated User-User-Context Influence matrix, and then combined with the actual sender of the project conditions Item (Item Sender Matrix) to obtain User-Item-Context Influence matrix (2). Edited by (1) (2) calculated User-Item-Context scoring matrix. This can be based on the matrix and the user's current context for users recommended.

In our model, we assume that the user whether to adopt a project depends on four factors: a content item itself, two projects sender, three user preferences on the project, and 4 was situational.

First, we define users with m, n of the project, k kinds of scenarios. Project matrix M represents the sender (Item Sender Matrix), Mij = 1 means that the user uj send the project pi; matrix N is the user inter-impact matrix (User-User-Context Influence Matrix), matrix Nijk expressed ui uj in the user situational ck influence. Matrix G represents users in different contexts for different projects latent preferences (User Latent Context Matrix), the matrix S represents the distribution of projects on the topic (Item Latent Matrix). So that we can pass Hadamard product (MN) ° (SG) to approximate the matrix R user adoption.

We use scenario vector Cx (c1, c2, ..., ck) represents contexts x, where c1, c2, ..., ck denote context of x in the value of k kinds of scenarios.

For projects latent distribution matrix S, we use LDA model content for each project topic modeling, vector Ta represents a topic of project distribution, all of the project's topic distribution vectors constitute the matrix S.

Users in different contexts of user u v vector H as follows:

Where S (u, v) is a user u, v to a collection of items, A (u) the adoption of a collection of items the user, Ca 'for the user to apply project a' vector of the situation. All of these vectors constitute a three-dimensional matrix N.

Users in different contexts favored topic of the project distributed two-dimensional matrix as follows:

Where A (u) user adoption of a collection of items, Ca 'user adoption project a' situation when vector, Ta ​​'as the topic distribution vectors. All of these constitute proof two-dimensional three-dimensional matrix G.

G represents users in different contexts for different projects latent preferences: Known user u, items a, when his situation x. Find x situations preference for users of the project:

User influence matrix I:

Where V (u, a) all forwarded items a set of users to user u, A (u) is a collection of items adopted by user u, S (u, v) is a user u, v to a collection of items, Ca 'is user adoption project a 'situation when vectors.

Preference matrix P:

Which T\_a a topic for the project distribution vector, C\_a evaluation context for the project a valued, equally C\_a 'project a' scene when adopted vector value, A (u, a) for the user to send all outside except a collection of items, | A (u, a) | is the number of elements in the collection.

# Experiments

In this section, we use real social network data conducted experiments to compare with other recommendation methods.

## Datasets

We use existing social networks Sina Weibo experimental data and the recommended model validation. Sina Weibo is China's famous social networks like Twitter, people can focus on their own interest, and then send these men received information, the user can collection, forwarding and praise these tweets. Information can be sent with the expression, location information, Sina microblogging also provides an interface to send mood. First we crawl Sina microblogging data, and then analyze the data in the context of identifying data, the sender and the project content. Because today's social networking channels for situational awareness and content more limited, mainly situational data including location-aware mobile device data, time data, and the user interface to send by Sina mood mood and expression analysis of user data in the resulting situation. Experimental data statistics as follows:

|  |  |
| --- | --- |
| Statistic | Value |
| User Number |  |
| Tweet Item Number |  |
| Forward Behavior Number |  |

Table 1: Statistics of Sina Weibo

Experimental Target: Our experiments require the user to predict the item being read. Experimental setup: with other network users to browse the static information of the differences in social networks, the user can see the information is updated in real time, the user may not be able to see all the information sent to him. We can not get users online time, but also can not get the user to read microblogging contextual information in real time, but only according to the user's behavior to determine the user's existing online time and contextual information. So we act according to the user's effective (eg published microblogging, forwarding, collection microblogging come) to determine the user is online, for each active behavior, we define an effective period of time online session (before and after the act for some time), which means that in this period of time users online. We extract from Sina microblogging three scenarios information (time, place, mood), because the user behavior does not necessarily contain all the contextual information, we will act contains two or more effective as a situational behavior, shown in Figure 4, in which conduct an effective period of time other users' actions as valid behavior, while the behavior from the user context information obtained last this time period. The valid time period information set, compared to other equally effective method.

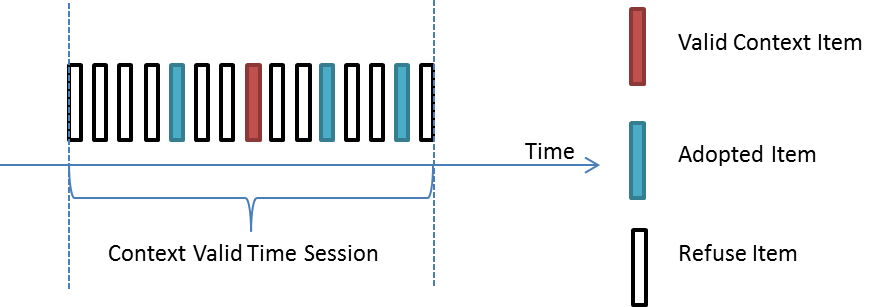


Figure 4: Timeliness of Context Data

Our experimental data is divided into training and test sets, from the training set is calculated using our model between users on different contexts influence among users and projects feature matrix, different situations the user feature matrix. While for us to extract from the test set valid time period. The user then compare algorithms and our model calculation.

## Metics

We use the commonly used measurement metrics Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) as the evaluation criterion to measure the recommendation accuracy by calculating the deviation between the real and prediction adoption. The smaller value of MAE and RMSE means the higher quality.

MAE metric is defined as follows:

RMSE metric is defined as follows:

where means that the real user i adoption information of item j in the adoption context k, represents predicted user adoption, and T represents the number of the test adoption.

## Comparisons

# Conclusion and Future Work

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