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A Product Recommendation System for Users Based on User Interest and User Social Context

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Abstract—**Due to the advent and popularity of the social network, peoples use to share their experiences like product reviews, ratings etc. This leads to use the new factors such as interpersonal influence and interpersonal interest similarity to solve the cold start and data sparsity problems in recommendation systems. Some factors are already used in existing systems but they have not considered fully. In this paper we are considering four social factors such as user personal interest, user interpersonal interest similarity, user social context and interpersonal influence, fused all these factors into unified recommendation model based on probabilistic matrix factorization. User personal interest factor is mainly used to recommend to the experienced users, and to solve cold start problem we considered interpersonal influence and user interpersonal interest, and we are considered social context to recommend the location specific products to the users.**

Key Words: Interpersonal influence, Social context, User interpersonal interest similarity, User personal interest.

I. Introduction

We are living in the data age. Petabytes of data pour into computer networks, various data storage devices every day from engineering, medicine, business and almost every aspects from daily life. This rapid growth data volume results the development of powerful data collection and storage devices.

Global backbone telecommunication networks carries petabytes of traffic every day. Medical field generates enormous amount of data from patient monitoring, medical records and medical imaging. Search engine supports millions of web searches and process petabytes of data every day. Communities and Social media is the one of the important data sources, generates huge amount of data.

This explosive growing, widely available data makes our time truly the data age. Various powerful tools are needed to automatically reveal valuable information from huge amount of data and to transform such data into organized knowledge. This requirement let to the birth of data mining.

Data Mining

Data mining is a searching for knowledge (interesting patterns) in data [15]. Mining is a vivid term characterizing the process that finds a small set of precious nuggets from raw material. Thus data mining become popular.

Data mining has made significant progress and covered a broad spectrum of applications since the 1980s. Today, data mining is used in a vast array of areas. Numerous commercial data mining systems and services are available.

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Data Mining Applications:

- Data Mining for Financial Data Analysis
- Data Mining for Retail and Telecommunication Industries
- Data Mining in Science and Engineering
- Data Mining for Intrusion Detection and Prevention
- Data Mining and Recommender Systems

Data Mining and Recommender System:

Today's consumers are faced with millions of goods and services when shopping online. Recommender systems help consumers by making product recommendations that are likely to be of interest to the user such as books, CDs, movies, restaurants, online news articles, and other services. Recommender systems may use either a content based approach, a collaborative approach, or a hybrid approach that combines both content-based and collaborative methods.

The content-based approach recommends items that are similar to items the user preferred or queried in the past. It relies on product features and textual item descriptions. The collaborative approach (collaborative filtering approach) may consider a user's social environment. It recommends items based on the opinions of other customers who have similar tastes or preferences as the user. Recommender systems use a broad range of techniques from information retrieval, statistics, machine learning, and data mining to search for similarities among items and customer preferences.

An advantage of recommender systems is that they provide personalization for customers of e-commerce, promoting one-to-one marketing. Amazon, a pioneer in the use of collaborative recommender systems, offers "a personalized store for every customer" as part of their marketing strategy. Personalization can benefit both consumers and the company involved. By having more accurate models of their customers, companies gain better understanding of customer needs. Serving these needs can result in greater success regarding cross-selling of related products, upselling, product affinities, one-to-one promotions, larger baskets, and customer retention.

In content-based methods, it is estimated based on the utilities assigned by the same user to other items that are similar. Many such systems focus on recommending items containing textual information, such as web sites, articles, and news messages. They look for commonalities among items. For movies, they may look for similar genres, directors, or actors. For articles, they may look for similar terms. Content-based methods are rooted in information theory.

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They make use of keywords (describing the items) and user profiles that contain information about users' tastes and needs. Such profiles may be obtained explicitly (e.g., through questionnaires) or learned from users' transactional behavior over time.

A collaborative recommender system tries to predict the utility of items for a user, u, based on items previously rated by other users who are similar to u. For example, when recommending books, a collaborative recommender system tries to find other users who have a history of agreeing with u (e.g., they tend to buy similar books, or give similar ratings for books). Collaborative recommender systems can be either memory (or heuristic) based or model based.

Recommender systems face major challenges such as scalability and ensuring quality recommendations to the consumer. For example, regarding scalability, collaborative recommender systems must be able to search through millions of potential neighbors in real time. If the site is using browsing patterns as indications of product preference, it may have thousands of data points for some of its customers. Ensuring quality recommendations is essential to gain consumers trust. If consumers follow a system recommendation but then do not end up liking the product, they are less likely to use the recommender system again.

As with classification systems, recommender systems can make two types of errors: false negatives and false positives. Here, false negatives are products that the system fails to recommend, although the consumer would like them. False positives are products that are recommended, but which the consumer does not like. False positives are less desirable because they can annoy or anger consumers. Content-based recommender systems are limited by the features used to describe the items they recommend.

II. Problem Formulation

Recommender systems for automatically suggested items of interest to users have become increasingly essential in fields where mass personalization is highly valued. The popular core techniques of such systems are collaborative filtering, content based filtering and combinations of these. Traditional Recommendation system is combining only user personal interest, interpersonal interest similarity, and interpersonal influence to recommend user interested items. These systems return the same results for every user in every situation. Personalization and recommender systems adapt information access to a model of the user, but usually are not adapted to the user context so far.

Location is one of the most important parameter of user context which implies extensive knowledge about an individual's interests and behavior with respect to location, thereby providing with opportunities to better understand users in a social structure according to not only online user behavior but also the user mobility and activities in the physical world. For instance, if a person searching for a nearby restaurant, according to traditional recommendation system he may get good restaurant according to his interest but that recommended restaurant may not met his expectations.

Under such a circumstance, a location recommender system is a valuable. By using location based recommendation system users can get good recommendations.

II. Related Work

Gediminas et al. [3] proposed a recommendation system named Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions, here in this system classifies the recommender system into three main categories content-based, collaborative, and hybrid recommendation approaches and also describes various limitations of previous recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications.

Venugopal et al. [4] proposed new recommendation system named A New Personalized Product Recommender System Using Stacking and Memory Based Collaborative Algorithm, here they proposed a superfine model named as PRAS (Personalized Recommender and Alert System), which combines user profile, their interpersonal and intrapersonal interest similarity along with the interpersonal influence to overcome the huge cold start challenge and NP hard problem. Due to the Sparsity problem traditional Collaborative filtering with only feedback information will suffer from unsatisfactory performance, so researchers have proposed to utilize auxiliary information such as item content, to alleviate the data sparsity problem in collaborative system Collaborative topic regression (CTR) is one of these methods which has achieved promising performance by successfully integrating both feedback information and item content information. Hao et al. [5] proposed a new system named Relational Collaborative Topic Regression for Recommender Systems, here they develop a novel hierarchical Bayesian model called Relational Collaborative Topic Regression (RCTR), which extends CTR by seamlessly integrating the user-item feedback information, item content information, and network structure among items into the same model.

Meng et al. [6] proposed a new system named Scalable Recommendation with Social Contextual Information in this system, they investigate the social recommendation problem on the basis of psychology and sociology studies, which exhibit two important factors: individual preference and interpersonal influence. First present the particular importance of these two factors in online behavior prediction. Then propose a novel probabilistic matrix factorization method to fuse them in latent space.

Paolo et al. [7] proposed a new system called Trust-aware Recommender Systems, However due to data sparsity of the input ratings matrix, the step of finding similar users often fails, so Paolo Massa and Paolo Avesani proposed to replace this step with the use of a trust metric, an algorithm able to propagate trust over the trust network and to estimate a trust weight that can be used in place of the similarity weight.

Ting et al. [8] proposed a system named content recommendation system based on private dynamic user profile, this system mines private data to client site and update private dynamic user profile at client side. Based on personal recommendation system the information classification and filtering are done automatically. The intelligent information process is transparent and effective which makes the users life easy. In future they are planning to make this system take additional contextual information such as time place and job of user information into consideration when recommending the related information.

Jie et al. [9] proposed a recommendation system named Location-based and preference-Aware Recommendation Using Sparse Geo-Social Networking Data. In this system offers more effective recommendation than baselines while having good efficiency of providing recommendation. They used Preference-aware selection algorithm. Chia et al. [10] proposed a recommendation system named A Context-Aware recommender System Based on Social Media, in this system they used Modified collaborative filtering Algorithm to solve cold starting and utilizing rich resources of user generated content.

Linas et al. [11] proposed a new system named Context Relevance Assessment for Recommender Systems, here in this system they used statistical methodology algorithm it shows how the uncertain relationship between context and decision can be explored and measured by using their approach in a different decision making scenario. Context Aware Recommender Systems: A Service Oriented Approach is proposed by Abbar et al. [12] here they used automatic context discovery algorithm to show how personalization service can be deployed in order to provide advanced context-aware recommender systems.

With the advent and popularity of social network, more and more users like to share their experiences, such as ratings, reviews, and blogs. Recommendation via User's Personality and Social Contextual is a new recommendation system proposed by He Feng et al. [13] here the new factors of social network like interpersonal influence and interest based on circles of friends bring opportunities and challenges for recommender system (RS) to solve the cold start and sparsity problem of datasets. Here they used three social factors, personal interest, interpersonal interest similarity and interpersonal influence, fuse into a unified personalized recommendation model based on probabilistic matrix factorization.

Katrien et al. [14] proposed a new recommendation system named Context-Aware Recommender Systems for Learning: A Survey and Future Challenges here they try to assess the degree to which their proposed work in Technology Enhanced Learning (TEL) recommender systems has achieved. Here first they present a context framework that identifies relevant context dimensions for TEL applications.

III. THE APPROACH

The proposed personalized recommendation approach fuses four social factors: user personal interest, interpersonal interest similarity, user social context and interpersonal influence to recommend user interested items. The illustration of our approach is shown in Fig. 1. Among the four factors, user personal interest and interpersonal interest similarity are the main contributions of the approach and all related to user interest. Thus, we introduce user interest factor firstly. And then, we infer the objective function of the proposed personalized recommendation model. At last, we give the training approach of the model. Hereinafter we turn to the details of our approach.

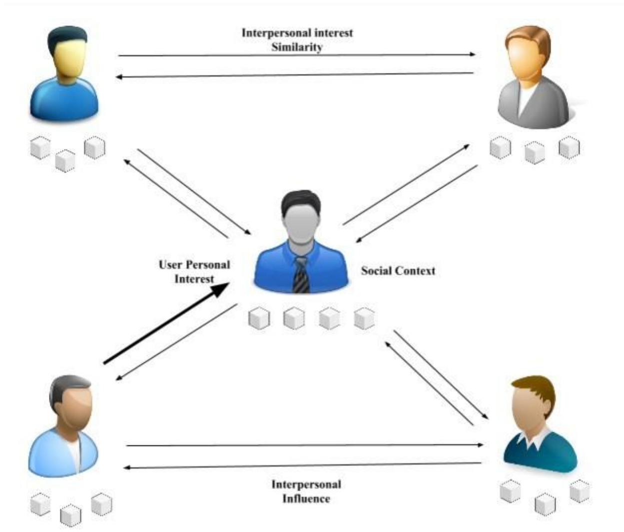

Fig 1. Four main social factors in our recommendation model, including user personal interest, interpersonal interest similarity, interpersonal influence and user context. The items under users are historical rating records, which can be used to mine users' personal interest. The category icon on line between two users denotes their interest similarity. And the boldness of the line between users indicates the strength of interpersonal influence.

A.Interpersonal Influence

A social recommendation can be represented as a triple (sender, receiver, item), while the traditional recommendation focuses on the pair of (receiver, item). The involvement of sender and receiver brings interpersonal influence into a social recommendation, which makes it largely different from a traditional recommendation. Interpersonal influence actually plays a critical role. For example. A professor recommends a reference book to his student

B.Personal Interest

Due to the individuality, especially users with many rating records, users usually choose items all by themselves with little influence by their friends. However, many previous works took the circles of friends in social networks to solve the cold start problem. It did work for the cold start users with a few records, but ignored the individuality for experienced users. For that we are considering personal interest to recommend for the experienced users

C.Interpersonal Interest Similarity

Interpersonal interest similarity is also plays important role in recommendation system, let's consider a scenario as shown in figure 2. User 1 likes apple, mango, grapes and pomegranate, user 2 likes only orange and mango, user 3 likes grapes, mango and pomegranate. By their interest we can say that user 1 and user 3 have similar interests so we can recommend mango to user 3.Interpersonal interest similarity is also plays important role in recommendation system, let's consider a scenario as shown in figure 2. User 1 likes apple, mango, grapes and pomegranate, user 2 likes only orange and mango, user 3 likes grapes, mango and pomegranate. By their interest we can say that user 1 and user 3 have similar interests so we can recommend mango to user 3.

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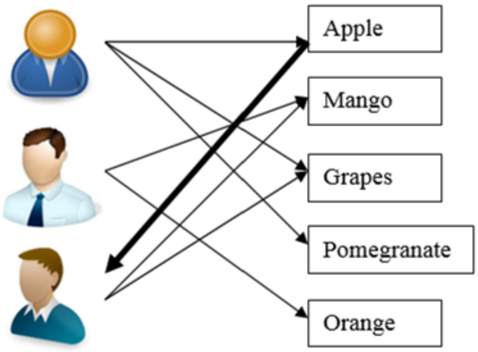

Fig 2: Interpersonal Interest Similarity
Bold line indicate the recommendation to the user.

D.Social Context

Context has rarely been incorporated into recommender systems so far, but physical (e.g. a user's location) or social (e.g. the social network of a user) context can be useful sources for improving recommender systems.

Fig 3: User Context

For example is a restaurant guide running on a mobile device such as PDA in the recommendation process, it is important to take the current context into account, because in a mobile scenario, nearby restaurants are preferable and a restaurant that is not open on the given day, should not be considered at all, even if it matches the user preferences very well

IV. Conclusion

In this paper, a personalized recommendation approach was proposed by combining social factors personal interest, interpersonal interest similarity, social context and interpersonal influence. In particular, the personal interest denotes user's individuality of rating items, especially for the experienced users. To solve cold start problem we considered the interpersonal interest similarity and interpersonal influences, and we are considering social context into consideration so that we can providing location specific recommendation to the users. So that User can get search results according to his interest, he can get the search results with respect to user current context. The can get better influenced search results and lastly it will reduce the bandwidth of the network.

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