Social Network Based Recommendation Systems: A Short Survey

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***Abstract*—This paper examines the background of the recommender systems and the state-of-art technologies in this current research area. We examined the needs for recommendation systems and the enhanced performance by using the additional social network information. We compared different types of social network information and how they are used to improve the recommendation systems with a few examples. We also discussed different evaluation methods that are important to measure the performances of a recommendation system. We concluded that the recommendation system is a very important research area and could be applied in many domains. We summarized different measures towards evaluating a recommendation system especially those incorporating the social network information.**

Keywords: Artificial Intelligence, Recommendation Systems, Algorithms.

I. Introduction

In human history, people have always been trying to make predictions and forecasts for a range of issues. There are different kinds of predictions. Some are based on past experience, for example, weather forecasting [1]. Some are based on the understandings of the underlying mechanisms, for example, the election results. Some researchers also tried to differentiate between prediction and forecast such as in [2]. In this paper, we consider both predictions and forecasts are the same as recommendations.

Although the recommendation or prediction practices have existed for a long time, with the development of modern technologies and knowledge accumulated over time, it becomes a popular research area since mid-1990 [3]. The social network data have proven to be able to improve the performances of recommendation systems.

There have been many work done in the industry and academic areas on developing new recommendation approaches. Examples of such applications include Amazon.com's item recommendations, movie recommendations (MovieLens), webpage recommendations (Google). Facebook provides features to recommend a list of people you may know. Potter developed a recommendation system to suggest the possible substitute words based on misspelled words [4] which was succesfully implemented in Microsoft Word. Research community's interests reached another level when Netflix issued one-million-dollars prize for the best movie recommendation algorithms in 2009.

Different from the traditional research, the current researches focus on the recommendation problems that can provide ratings or rankings of items or services. A recommendation system will be able to estimate the ratings or rankings from the user's past experience or similar users' preferences. If we can obtain these ratings, it will have many real life implications.

A recommendation system helps the seller to sell more diverse items and enables the user to select items that might be hard to find without a recommendation. A well designed recommendation system can also improve the experience of the users of websites or other services.

[2] illustrates some popular tasks that a recommendation system can assist. A recommendation system can also assist in roles such as recommendation of a sequence, recommendation of a bundle of items, finding credible recommender, helping others and/or influencing others.

Users need recommendations because they do not have enough knowledge to make autonomous decisions. Various researchers have tried to understand the factors that lead to the acceptance of a recommendation by a given user. The social network data provides an important source of information to help improve such tasks.

II. RELATED LITERATURE AND CHALLENGES

Many current literatures evaluate different types of recommendation system technologies, and their real life applications. [5] introduces and classifies recommendation system into six main techniques. In *content based recommendation system techniques*, a recommendation system learns to recommend items that are similar to the ones that the users liked in the past. A recommendation could be based on specific domain knowledge about how certain item features meet users' needs and preferences. In a *knowledge based systems*, a similarity function is used to estimate how much the users' needs match the recommendations. But *community based recommendation system* recommends items based on the preferences of the users friends. Here, the recommendation system recommends items based on the preferences of the users' friends or social contacts. This technique becomes more useful especially in the social network based recommendation system. Because each of these recommendation techniques has its shortcomings, hybrid recommendation systems have been developed to combine two

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or more techniques so that the advantages of a system fix the problems of the other recommendation systems.

Privacy preserving in recommendation system has been a challenge in recent times. Recommendation systems exploit users' data to generate personalized recommendations. This clearly has negative impacts on the privacy of the users.

Diversity of the items recommended to a target user is another issue to discuss. In a recommended list, it is more likely that the user will find a suitable item if there is a certain degree of diversity among the items. There are many situations, especially in the early stage of a recommendation process, in which the users want to explore new and diverse directions. In such cases, the user is using the recommender as a knowledge discovery tool [6]. This is an issue that needs to be incorporated into the evaluation of system.

III. SOCIAL NETWORK BASED RECOMMENDATION SYSTEM

Although many researchers have discussed the usefulness of social network based predictions, recommendation system in social networking area is still in its early phase. [5] describes non-social network based recommendation system such as Collaborative Filtering as traditional methodology, and discussed its flaws and weaknesses.

The solutions to the problem identified in the traditional recommendation systems could be developed by applying social network data in recommendation systems. Integration of social networks can theoretically improve the performance of current recommender systems. First, in terms of the prediction accuracy. Second, with friends' information in social networks, it is no longer necessary to find similar users by measuring their rating similarities. When people are friends, there are certain things in common among them. Therefore the social network based recommendation system makes the community based recommendation technique more powerful and useful.

In recent times, there have been opportunities for novel recommender applications on the social web that directly involve humans in a recommendation process, in which users make recommendations to other users. This is called crowd-recommendations.

IV. RECOMMENDATION SYSTEMS AS A RESEARCH PROBLEM

One of earliest research in the *Social-Network Based Recommendation* is documented in [7], in which it describes recommendations can be influenced by many factors and how they can be modeled in a recommendation system.

Recommendation systems are tranditionally classified into three areas [3]:

1) *Content-Based Recommendations*: It uses information describing the nature of an item and based on a sample of the users preferences, to predict which items the user will like.
2) *Collaborative Recommendations*: It uses a large amount of information on users' behaviors, activities or preferences and predicts what users will like based on their similarities to other users.
3) *Hybrid Recommendations*. This is an approach combining collaborative filtering and content-based filtering.

To improve the recommendation performances, we can use the additional relationships from the users social contexts. There are explicit user-provided annotations and the implicit aggregated feedbacks describing the personal preferences n the social network data.

With the advances of technologies, there is emerging presence of social media and social networking systems. [8] introduced a Random Walk approach using social tagging information. [9] explored the PageRank algorithm and proposed a FolkRank algorithm to provide ranking and recommendations for the folksonomy structure that exists in a social system.

There are some common limitations and problems with these recommendation systems and they could be summarized in several general categories:

1) *New User problem*: A recommendation system has no information to make recommendations about a new user. This is also called *cold start* problem.
2) *Sparsity Problem*: Due to the large amount of items and users, it is natural that users will only have ratings on a few items that are most relevant to themselves. This leaves a large amount other items not rated or not having social contacts by the users.
3) *Over-Specialization*: This is a problem when the system can only recommend the items that the user already saw or those with high scores and the user is limited to being recommended to the items that are similar to those already rated [3].
4) *Limited Content Analysis*: This is similar to the *New User Problem* and many times we dont have enough information regarding the items.

From the literatures we have reviewed, we summarized a comparison grid in Table I as a overview of different recommendation techniques. More details could be found in [3] .

TABLE I. SUMMARY OF TECHNIQUES

Recommendation Systems		
Approaches	Heuristic-Based	Model-based
Content-based	*TF-IDF (information retrieval) *Clustering	*Bayesian classifiers *Clustering *Decision trees *Artificial neural networks
Collaborative	*Nearest neighbor (cosine, correlation) *Clustering *Graph theory	*Bayesian networks *Clustering *Artificial neural networks *Probablistic models *Linear regression
Hybrid	*Linear combination of predicted ratings *Various voting schemes *Incorporating one component as a part of the heuristic for the other	*Incorporating one component as a part of the model for the other *Building one unifying model

V. SOCIAL NETWORK FACTORS USED IN RECOMMENDATION SYSTEM

Social influence plays an important role in consumer behaviors. Through social networks, we are able to discover additional information to predict the user preferences and enhance the traditional ranking algorithms. Traditional recommender systems do not take into consideration explicit social relations among users, yet the importance of social influences in marketing has long been recognized [10].

In exploring the social networks to aid recommendations, we need first understand what information exists and what are helpful in making recommendations. [11] discussed some current research using social embedding to improve the recommendations. It recognizes the lack of considerations on the friends' advice and user's mental model mismatches with the system models.

A Bayesian-inference based recommendation is applied to the online social network [12], in which users share content ratings with friends and the unrated items' rating could be inferred based on a Bayesian network. The *cold start*(new user problem) and *sparsity problems* are also discussed in this paper.

Not only recommendations for an individual are necessary, sometimes, the recommendations for a group of users are desired as well. [13] introduced three categories of recommendation systems for group recommendations.

1) Merging sets of recommendations
2) Aggregations of individuals' ratings for particular items
3) Constructions of group preference models

There are other types of information that can utilize the social networks to improve the recommendations. [14], [15] researched the methods for using social network to improve tag recommendations. [16] introduced how to use social trust data to improve the movie recommendations. The results show that these recommendations are more accurate than other techniques when the user's opinions about a film are divergent from the average.

The top-k recommendations have been studied in [17], in which the social network information is explored to improve the top-k recommendations. The top-k recommendations recommend to the users a small number of items rather than one single item. In [18], it proposed *Matrix Factorization models* and *Nearest Neighbor algorithms* to improve the accuracy.

VI. MEASUREMENTS AND EVALUATIONS OF RECOMMENDATION SYSTEMS

It is important to use the correct measurements to evaluate if a recommendation system is good or poor. However, there is no single good evaluation method that has been used universally due to the complex nature of recommendation problems. A good evaluation measurement depends on the user tasks, types of analysis and datasets being used.

The evaluation of a recommendation system is difficult because of the diversity of the problems and the datasets. The different purposes of recommendations really determine how the systems are going to be implemented.

Here, we introduce a few common evaluation methods and discuss their advantages and disadvantages. More details of evaluations and comparisons of the following algorithms with experiments are given in [19].

1) Accuracy of recommendation systems:
   a) *Mean Absolute Error (MAE)*: It measures the average absolute deviation between a predicted rating and the user's true rating. Some related measures include *Mean Squared Error*, *Root Mean Squared Error*, and *Normalized Mean Absolute Error*. The equation below is used in [20], [21].

$$MAE = \frac{\sum_{i=1}^{N}(p_i - r_i)}{N} \tag{1}$$

   where N is the total number of predictions. p_i is the predicted value and r_i is the true value.
   b) *Classification Accuracy Metrics*: It measures the frequency with which a recommender system makes correct or incorrect decisions about whether an item is good.
   c) *Precision and Recall*: They are the most popular metrics for evaluating information retrieval systems.

$$Precision(P) = \frac{N_{rs}}{N_s} \tag{2}$$

$$Recall(R) = \frac{N_{rs}}{N_r} \tag{3}$$

   Where N_{rs} is number of accurate predictions. N_s is the number of predictions. N_r is the number of possible accurate predictions.

   Several ways have been taken to combine precisions and recalls. One of them is called *MAP (Mean Average Precision)*:

$$MAP(F) = \frac{2PR}{P+R} \tag{4}$$

   where P is Precision measure and R is Recall measure.
   d) *ROC Curves*: It is the acronym for *Receiver Operating Characteristic*, which is evolved from the use of *ROC Curves* in signal detection theory.
   e) *Rank Accuracy Metrics*. It measures the ability of a recommendation algorithm to produce a recommended ordering of items that matches how the users would have ordered the same items.
   f) *Prediction-Rating Correlation*. Two variables are correlated if the variance in one variable can be explained by the variance in the second. Three of the most well known correlation measures are *Pearsons productmoment correlation*, *Spearmans* and *Kendalls Tau*.
   g) *Half-life Utility Metric*: [21] presented a new evaluation metric for recommender systems

that are designed for tasks where the user is presented with a ranked list of results, and is unlikely to browse very deeply into the ranked list.

h) *The NDPM Measure*: It stands for "*Normalized Distance-Based Performance Measure*. NDPM only evaluates ordering and not prediction values.

2) Coverage of an evaluation system: This is the domain of items in the system over which the system can form predictions or make recommendations. Coverage must be measured in combination with accuracy, so recommenders are not tempted to raise coverage by making bogus predictions for every item.
3) Learning Rate: There are per-item learning rate and per-user learning rate. The overall learning rate is to measure this system over all the users and items.
4) Novelty and Serendipity: The general consideration is that a system may want to try to estimate the probabilities that a user will be familiar with an item. The dimension to measure the non-obviousness of the recommendation is novelty. A serendipitous recommendation helps the user find a surprisingly interesting item he might not have otherwise discovered.
5) Confidence: Researchers often faced challenges in deciding how to interpret the recommendation results along two often conflicting dimensions. One is the strength of the recommendation: how much does the recommender system think this user will like this item. Another one is the confidence of the recommendation: how sure is the recommender system that its recommendation is accurate.
6) User Evaluation: This answers the question of how to directly evaluate user reactions to a recommender system. This is more direct but yet important aspect of the evaluations.

VII. DISCUSSIONS

Social Network Based Recommendation Systems use the additional information from the social network structures to improve the performance and accuracy of recommendations. With the growing number of internet social networks, there are great potential to utilize this information to help with improving the recommendation systems. Good recommendation systems can not only improve the business outcomes but also help with reducing the information barriers for regular users.

New technologies are transforming the user behaviors and new types social network of information may become available in the future for improving recommendations. There are more research papers not covered in this paper, but it doesnt mean they are not important.

It is and will still be a challenge to preserve the user's privacy and at the same time utilize the user information for knowledge and recommendation systems. Many network sites have explored the use of user's network information, such as Google, Facebook and LinkedIn. However these usages are limited to their own applications and couldn't be publicly available for broader applications. There is a need for establishing a industry stardard for utilizing network information while protecting user privacy.

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