Chapter 18
Social Networks and Recommender Systems: A World of Current and Future Synergies

Kanna Al Falahi, Nikolaos Mavridis, and Yacine Atif

Abstract Recently, there has been a significant growth in the science of networks, as well as a big boom in social networking sites (SNS), which has arguably had a great impact on multiple aspects of everyday life. Since the beginnings of the World Wide Web, another fast-growing field has been that of recommender systems (RS), which has furthermore had a proven record of immediate financial importance, given that a well-targeted online recommendation often translates into an actual purchase. Although in their beginnings, both SNSs as well as RSs had largely separate paths as well as communities of researchers dealing with them, recently the almost immediate synergies arising from bringing the two together have started to become apparent in a number of real-world systems. However, this is just the beginning; multiple potentially beneficial mutual synergies remain to be explored. In this chapter, after introducing the two fields, we will provide a survey of their existing interaction, as well as a forward-looking view on their potential future.

Introduction

Network science, arguably having its beginnings in the 1700s with Euler's Seven Bridges of Knigsberg [1], has passed through a number of important stages, including the creation of graph theory [2], the sociogram, and the advent of social network analysis [3], culminating in the recent boom and solidification as a discipline. Just a little after, some of the most important recent results, such as

K.A. Falahi (✉) • N. Mavridis • Y. Atif
UAE University, Al Ain, United Arab Emirates
e-mail: K.alfalahi@uaeu.ac.ae; NikolaosM@uaeu.ac.ae; Yacine.Atif@uaeu.ac.ae

A. Abraham and A.-E. Hassanien (eds.), *Computational Social Networks: Tools, Perspectives and Applications*, DOI 10.1007/978-1-4471-4048-1_18,

the development of scale-free networks [4], the first social networking sites (SNS), started to appear [5], and within less than a decade, Facebook has more than 6% of the world's population as active users.[1]

In parallel to these developments, since its early ARPAnet days (1969), the Internet, even more so after the creation of the World Wide Web (1991) and the wide-spread use of early graphical browsers (mosaic, 1993), has rapidly been utilized as an important platform for a host of activities that are essential to modern daily life: communication, information-seeking, education, as well as, quite importantly, business and e-commerce. One of the most important aspects implicated in successful e-commerce is the ability to identify products or services (items) in which people (users) might be interested in to estimate their interest ratings, and then to recommend such items to users, in order to have the users potentially purchase the items.

This is the central problem that recommender systems (RS) are targeting and it is quite an important problem, for users, merchants, as well as society at large. When it comes to merchants, the immediate and tangible economic benefits of a successful recommendation in terms of increasing sales and creating revenue are obvious. When it comes to users (potential buyers), nowadays, they are often overwhelmed with a multitude of choices and options in their online business experiences, while at the same time they have limited resources and free time to invest in the selection process. Hence, there is an increasing need for using recommendation support to overcome this problem and provide users with personalized recommendations on different items such as books, movies, music and news. Furthermore, the basic ideas behind recommender systems can be applied not only narrowly to purchasing and business, but can be extended to a wider context, for example within the social realm, in which such systems could recommend acquaintances for personal or professional relations, which could potentially increase collective social capital [6].

In terms of their underlying theory driving their implementation, Recommender Systems (RS), although having their roots in a number of disciplines, such as forecasting theories [7], information retrieval [8], approximation theory [9] and consumer choice modeling [10], started solidifying as an area in the 1990s, and today are at the heart of many multibillion dollar e-businesses, such as Amazon [11], Netflix and MovieLens [12]. At the heart of the problem of creating a successful recommendation is the ability to generalize from known or estimated attributes of items and users, and possibly also from existing ratings, in order to predict yet unknown ratings of items from users, towards the ultimate goal of a successful purchase. Thus, in order to create such a successful recommendation, one needs to possess information (data) as well as processes (algorithms): the required information usually consists of a database of users and items, together with adequate attributal information about them, and possibly similarity spaces for the two domains (users and items), as well as an algorithmic/mathematical means of creating and updating predictions on the basis of this information.

[1] http://www.facebook.com/press/info.php?statistics

And this is exactly the first obvious point of beneficial contact between social networking sites (SNS) and recommender systems (RS): there is a wealth of information about users, their attributes and preferences, as well as their relations, within social networking sites (Synergy I). Furthermore, a second easy observation that provides a strong basis for synergies has to do with social networking sites as a popular locus for online life: users spend an important percentage of their online time [13] in SNS. Thus, SNS are an ideal platform, not only for gathering information useful for creating recommendations, but for actually presenting these recommendations to users (Synergy II). Furthermore, in social networking sites, there is a need for recommendation not only of products and services but of individuals or groups, with which the user can potentially became related to, in a personal or professional fashion. And this creates the third domain of strong potential synergies (Synergy III) between RS and SNS, as we shall discuss, together with other potential synergies.

The rest of this chapter is organized as follows: The section "Social Networks" presents background on relevant research on social networks and sites, while sections "Recommendation Techniques" and "Recommender Systems Limitations" discusses recommender systems with their underlying techniques and algorithms as well as the limitations in these systems. In section "Recommender Systems in Social Networks", after talking about shortcomings of recommender systems, we discuss how these have been and can be potentially further addressed through their synergies with social networks, followed by sections on future work and conclusion.

Social Networks

In the traditional way, businesses use to reach consumers via advertisements through TV and radios cannot satisfy all users as they are generally broadcasted to all users regardless of their personal preferences. The online space provides more efficient approach by allowing users to view products based on their desires especially with the usage of social networks. The web has become more social and data is generated in real time. Famous social networks, such as Facebook and Twitter, are good examples for such evolving social web. These social network websites provide a rich environment for performing recommendations.

Social Networks Definition

Social networks are built from a group of people who share the same interests, backgrounds, and activities. In social networks, people can communicate with each other in many ways. They can socially share and upload files such as images, videos, and audios to their profiles. Social networks consist of nodes that are the actors in the network. These nodes might be a user, a company etc. The nodes are linked to each other through connections or ties. In social networks, these connections represents the relationships between nodes as friendship, partnership, kinship, etc. The number of nodes is changing and expanding specially on the web as new web pages and profiles created everyday [14].

There are different properties that social networks provide here we will define two main concepts:

1. Profiling where each user has his own profile, which represents the user's preferences and interests
2. Linking between users, which make it easier to analyze relationships among users
3. The ease of data extraction from social network sites

User Profile

Usually individual corporations such as Google and Yahoo! moderate online social networks sites. Most of social networks provide their functionalities for free to the users. Though some social networks need the users to register in order to gain access to the full facilities of the website. Personal information about each user is stored in his/her profile. A profile is a collection of user information that shapes the user identity on the Internet [15]. These profiles contain information about the user as well as his/her interests.

User Connections

The main goal of social networks it to connect people, thus each user in a social network can establish a link with other users in the network. Figure 18.1 shows the different relationships that occur in social networks. An example would be the concept of following in Twitter where a user (creator) can follow other users (targets). A full connection between the creator and the target is established if both are following each other. In the case of Twitter example, the full connection will allow additional functionalities such as the ability of sending private messages between users. Users create these connections in order to follow each others' contributions, especially if they are of the same interest.

Data Extraction

Data extraction from social network sites is easy, as many studies done in the field of data collection and extraction from social network have shown is done through introduction of datasets. One dataset is presented in [16] where the researchers introduced a social network dataset based on Facebook. They studied the users, interest as well as the relationships between them.

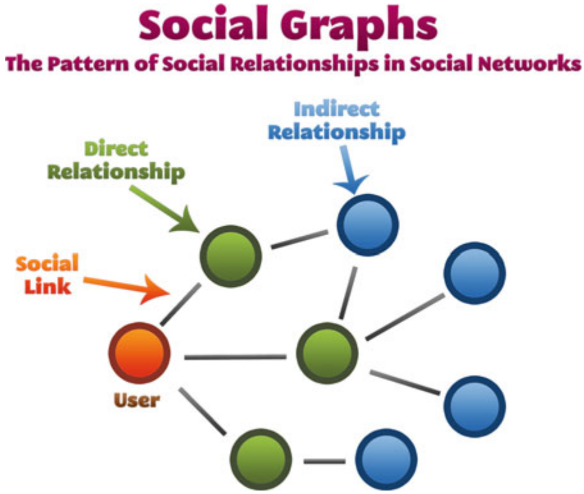

Fig. 18.1 Social graph: the pattern of social relationships in social networks

Understanding the structure of social networks will help evaluating the strength, weaknesses, opportunities and threats associated with them. Many such works have been done in the field of social networks analytics. One of the most popular papers is Milgram's "The Small-World Problem" [17] where the earliest experiment about the six degrees of separation was investigated. Milgram studied the average path length for social networks in the United States and suggested that we live in a small world. Watts also studied the mathematical analyses of the small world structure [18] as he examined the small world systems and discussed the problem of measuring the distances in social world and he studied examples of real small-world networks.

Recommendation Techniques

In mid-1990s recommender systems started to evolve as an independent research area as researchers started to focus on business ratings [19–22]. The problem with recommender systems is related to rating items that have not been seen by the user. When the recommender can estimate the rating for these unrated items, then it can recommend new and varied items to the users [19]. Different algorithms have been introduced over the last decade, both in academia and industry. Online vendors such as Amazon and Netflix used some of these recommender systems for commercial purposes. These systems are used to predict user interest in a new item based on his previous ratings on other items. Customers become more satisfied when the system predicts more.

These companies invest in improving such systems to have accurate items recommendations. For example, Netflix announced an open competition in 2006 with a prize of US $1,000,000 for the best algorithm that predicts user interests in a movie.[2] Recommender systems have attracted much attention since the publication of the first papers in collaborative filtering [20–22], but they still need further improvement in order to produce more effective results [19]. These improvements include better methods to represent user behavior and improve the prediction accuracy. Recommender systems are now an important part of many e-commerce sites and in this chapter we will study the current methods of recommender systems for social networks with their different limitations.

In general, recommendation environment can be represented as follows [19]: Let U be the set of all users and let I be the set of all items that can be recommended. The spaces U and I can be very large as the number of users and items respectively might be over a million in some cases [19]. u is the user for whom recommendation needs to be generated and i is some item for which we would like to predict u's preferences. And let f be the utility function that measures the importance of item i to user u (f: $U \times I \Rightarrow R$), where R is a set of nonnegative ordered values within a specific range, where the utility function for a specific item is represented by ratings. We need to select the item $i' \in I$ that maximizes each user $u \in U$ utility. This can be represented through the following formula.

$$\forall u \in U, i'_u = \text{argmax}_{ei \in I} f(u, i) \tag{18.1}$$

There are different ways to calculate the utility function. It can be defined by the user or calculated by an application [19]. User ratings are triplets *(u,i,r)* where r is the value assigned by the user u, to a particular item i. Usually this value is a fixed subset of the real numbers or a binary variable. In the user's space U, each user is represented by a profile that includes different attributes such as the user ID, age, gender, income, etc. a simple profile could contain the user ID only. Also each item in the items space I is represented by a set of characteristics. For example when recommending books each book can be represented by its ID, title, author, etc. Fig. 18.2 shows the users and items in the $U \times I$ space.

The problem with recommender systems is that the utility function f is not defined on the whole space $U \times I$ but on a part of it [19]. When the utility function is represented by ratings generated by the users, then the users will rate items that they previously seen while the other set of items is still unexplored and unrated. An example of user-item rating matrix is represented in Table 18.1 for a book recommendation application as on Amazon. Ratings are scaled from 1 to 5. The symbol ϕ indicates that the user did not rate the corresponding book. Therefore, the recommender system must predict the missing ratings for each user-book combination and perform an appropriate recommendation based on that.

The problem of unrated has been approached in two different ways: (1) specifying heuristics that define the utility function and empirically validating its performance and (2) estimating the utility function that optimizes certain performance criterion, such as the mean square error. Recommender systems are classified

[2] http://www.netflixprize.com

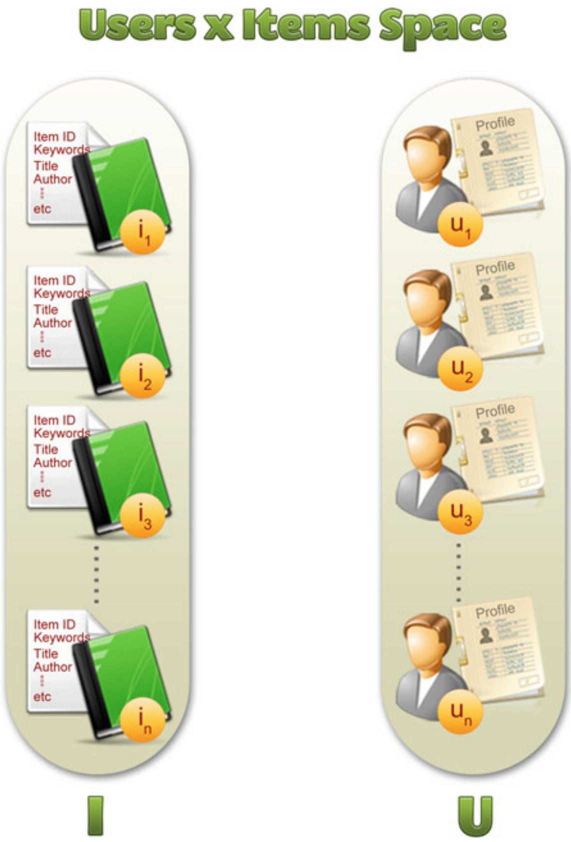

Fig. 18.2 Users and items in the $U \times I$ space

Table 18.1 A fragment of a rating matrix for a book recommender system

User	Freedom	The warmth of other suns	Unbroken	Matterhorn
John	1	5	4	ϕ
Alice	3	3	5	2
Mark	ϕ	4	ϕ	4
Bill	4	5	1	3

according to their way of estimating unrated ratings. Next we will present the different classifications and will survey these different techniques used to perform recommendations. Table 18.2 summarizes the recommendation techniques used in content-based recommendation and collaborative recommendation . Recommender systems are classified into the following types [9]:

1. Content-based recommendations
2. Collaborative recommendations
3. Hybrid approaches

Table 18.2 Recommendation techniques

Technique	Background	User input	Process
Content-based	Features on items in I	U's ratings of items in I	Generate a classifier that fits u's ratings behavior and use it on i
Collaborative	Ratings from U on items in I	Ratings from u on items in I	Identify users in U similar to u, and extrapolate from their ratings on i

Content-Based Recommendation

In content-based recommendation, users are recommended items based on their previous preferences [23–25]. In another way, the utility function $f(u, i)$ of an item i for a user u can be estimated based on the ratings assigned by the user u to all the items $i_n \in I$ that are similar to item i. For example, to recommend a book i to user u, the content-based recommender system will get the previously rated books by user u and then the books with highest similarity to the user preferences are recommended. In content-based recommenders the recommendation is based on the item itself rather than the preferences of other users [23, 24, 26]. Moreover, in this approach, users can help the system in providing initial ratings and the system can build a unique characteristic for the user preferences without matching them with someone else's interests [24]. Figure 18.3 represents the content-based recommendation approach.

A typical system would show a summary of items to the user and allow the user to click on an item to get detailed information. For example, Amazon would present a page with books summary and then the user would select one book to read the details and purchase the book if interested. As websites represent the items in a graphical way, but in the server these items are stored in databases. As we said earlier, there could be millions of items in the database, so we need to find a way to show a part of them to the user [27].

Content-based systems are based on previous researches done in the field of information retrieval, so they focus on recommending items that contain textual information as in documents and websites (URLs) [19]. They improved over the traditional information retrieval approaches by using user profiles [19], which contain information about the user tastes and preferences. These profiles can be generated using implicit (learning from users behaviors) or explicit (through questionnaires) approaches. Items are stored usually in databases. Each item is represented by a set of variables, attributes or characteristics. And each record will contain a value for each attribute. The table uses a unique identifier for each item to distinguish items that have common values such as title. The data is called structured if the items are described by the same set of attributes and the value range of these attributes is known [27]. The data is unstructured if there is no attribute names with well-defined values. Instead, they contain a paragraph or a text that describes the

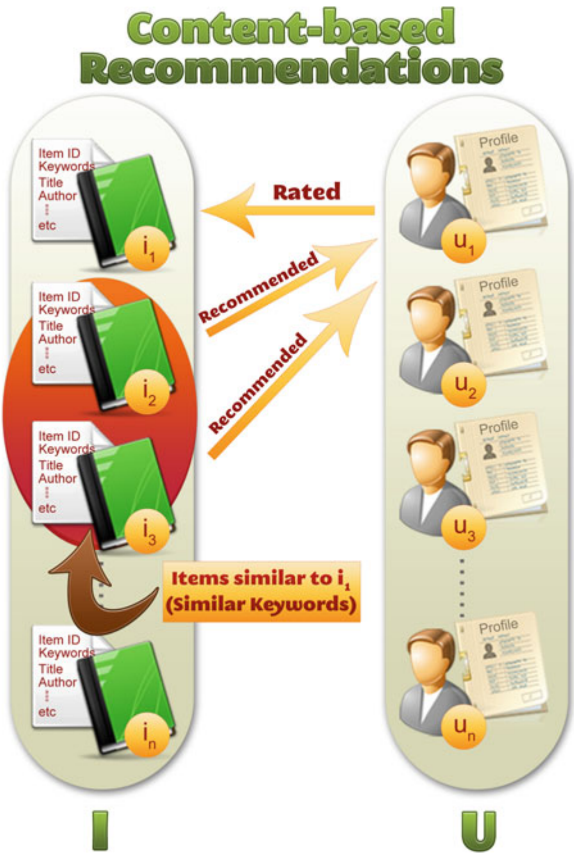

Fig. 18.3 Content-based recommendations

item, such as news articles. Analyzing natural language is very complex as the same word could have many meanings. For example, Grey would represent a color and a name, and power and electricity would refer to the same thing. Some data is represented in a semistructured way as they have some attributes with defined values and free text fields [27].

As we mentioned before, content-based recommender uses text-based items. The content of these items is represented through keywords. One example is LIBRA, which is a content-based book recommender proposed by Mooney and Roy[24] that uses information extraction techniques in order to extract information from Amazon for each title. Also in Fab System, the content is represented by the most 100 major words in order to recommend web pages to users. Similarly, Items are represented through keywords in [28] and the Syskill and Webert system [23] represents documents with the 128 most informative words. The importance of a keyword in a document can be measured by using some weighting measures such as term frequency/inverse document frequency (TF-IDF) measure [8, 30]. The TF-IDF value for a keyword k in a document d is defined as follows:

$$w_{k,d} = tf_{k,d} * \log\left(\frac{n}{df_i}\right) \tag{18.2}$$

where $tf_{k,d}$ is the number of occurrences of k in d, N is the total number of documents and df_i is the number of documents containing k. of the other methods presented in [31], they represent each term t by a distribution of terms (vector) that is typical of the documents in which t occurs. The limitation of the content-based recommender will be described in the discussion section.

Collaborative Recommendations

In collaborative recommendations, the user is recommended items that people with similar tastes and preferences liked in the past [21, 32]. In other words, the utility $f(u,i)$ of item i for user u can be estimated based on the ratings assigned to item i by users $u_n \in U$ who are similar to u. For example, to recommend a book i to user u, the collaborative recommender system will find the set of users who share the same interest in books with user u then the books that are most liked by the similar users is recommended to user u. Figure 18.4 shows the collaborative recommendation approach. The first collaborative recommender system is Grundy [14], which uses stereotypes to build models for users by building the individual user models and then use them to recommend books to each user. Another system is Tapestry that uses individual users to identify other similar users manually [15]. GroupLens [33] is also one of the first groups to use collaborative filtering for Usenet news. Other early collaborative filtering recommender systems are Video Recommender [20] and Ringo [22]. Other recommender systems proposed such as Amazon book recommendation systems, PHOAKS that is used to help people find information on the WWW [34] and the joke recommender system Jester [35].

Collaborative recommendation can be divided into two categories: (1) memory-based and (2) model-based. In memory-based algorithms [21, 22, 32, 36, 37] the unknown rating of an item i for a user u is calculated based on the ratings of other users, who are similar to user u, for the same item i. The similarity between users is calculated as a distance measure. Different user similarity measures could be used as long as the result is normalized with a normalization factor [19]. One of the similarity measures that could be used is the correlation where Pearson correlation coefficient is used to measure similarity [21, 22]. Another similarity measure is cosine-based [25, 32] where the two users are represented as two vector in m-dimensional space and the similarity is measured by computing the cosine angle between them [19]. Model-based algorithms [32,35,38–43] use ratings to build a model, which is used then in predictions [19]. Different approaches

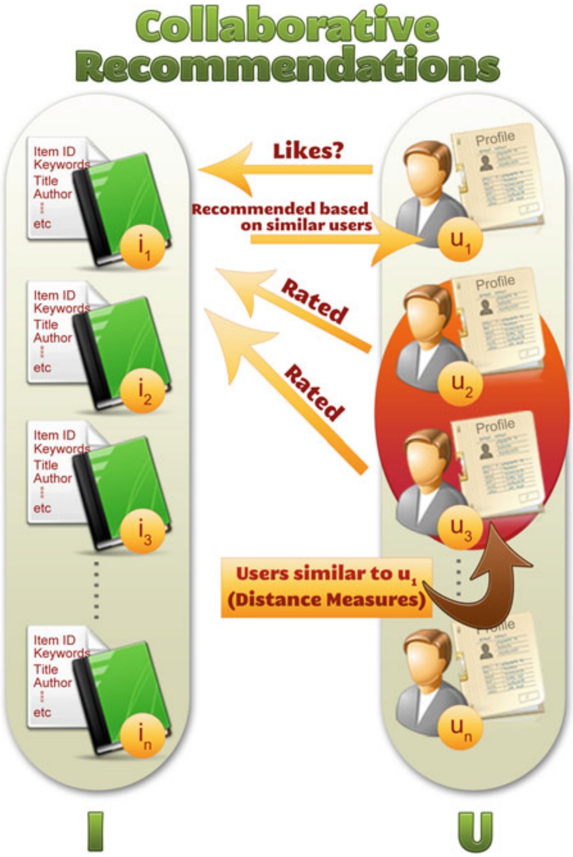

Fig. 18.4 Collaborative recommendations

are introduced to learn the model such as [32] that proposed two probabilistic models: cluster model (where similar users are clustered into classes) and Bayesian network, where the rating value of each item is determined through the states of each node. Statistical model is proposed in [43] where they compared different algorithms such as K-means and Gibbs sampling that are used to predict the model parameters. Other collaborative filtering techniques are proposed such as Bayesian model [44], probabilistic relational model [39], linear regression [25] and maximum entropy model [42]. The main difference between memory-based and model-based algorithms is that model-based algorithms estimate the ratings through using statistical and machine learning approaches to learn a model from the underlying data, while the former use some heuristic rules to predict the ratings. It is possible to combine both techniques [45] (memory-based and model-based), which will result in more reliable recommendations than using one technique alone. Collaborative recommendation systems also suffers from limitations as mentioned in [28] and [46]. We will describe these limitations in the discussion section.

Hybrid Recommendations

In hybrid recommendations, the systems use a combination of collaborative and content-based methods that tries to get over the limitations of both the systems by combining them [28]. These systems can be classified according to the following list [19]:

1. Implementing collaborative and content-based methods separately and then combining their predictions
2. Integrate some of the content-based features into a collaborative approach
3. Integrate some of the collaborative features into a content-based approach
4. Combines both collaborative and content-based methods

1. Implementing collaborative and content-based methods separately and then combining their predictions: In this type of hybrid recommendation, content-based and collaborative systems are implemented separately and then the recommendation results are combined using linear combination, ratings [47] or voting scheme [48]. Some quality metrics could be applied to choose the best way that gives recommendation with quality.
2. Integrate some of the content-based features into a collaborative approach: Many hybrid recommender systems such as Fab [28] and collaboration via content [48] are using the traditional collaboration with the aid of content-based approach for maintaining user profiles. These profiles are used then to measure similarity between users. This will solve different problems as when not many users have enough number of commonly rated items [48]. Also users will be recommended items directly when the items have high score against the user profile [28].
3. Integrate some of the collaborative features into a content-based approach: The dimensionality reduction technique on content-based profiles is the most used approach in this kind of recommendations. User profiles are represented as vectors and some normalization techniques is used to reduce the dimensionality as in [49] that uses latent semantic indexing (LSI) to create a collaborative view of a collection of user profiles which results in improving the performance that using only content-based approach.
4. Combines both collaborative and content-based methods: Many researchers use this approach as they propose to combine collaborative and content-based approaches as in [50, 51] where a combined probabilistic method is proposed to combine collaborative and content-based recommendations. Knowledge-based techniques [52] could be used in hybrid recommendation to address some of the limitations such as new user and new item problems [19]. One example of knowledge-based recommender systems is Entre [53] that uses the knowledge cuisines and food to recommend restaurants to the users. Just these types suffer from the need for knowledge acquisition [19].

Different researchers [28, 48, 49] and [54] compared the performance of hybrid recommendations against the collaborative and content-based approaches. They found that hybrid approaches can provide more accurate recommendations than using just collaborative or content-based methods [19].

Recommender Systems Limitations

There are different limitations for using recommender systems. The most two distinct but related well problems are new user and new item problems. A new user with few ratings becomes hard to recognize in recommender systems. Similarly a new item with few ratings cannot be easily recognized by the recommendation system, so there is a need to encourage users to rate items in such systems [53]. In this section, we will discuss these limitations for each recommendation technique and we discuss how to extend these systems.

Content-Based Recommendation

Content and Keywords Limitations

To perform content-based recommendation, the system needs the list of important keywords associated to an item. To find this list, item contents need to be represented in a format that is automatically parsed by computers as in texts or assign the keywords manually to the items [19]. Keyword extraction techniques such as information retrieval are used in recommender systems. But these techniques cannot be applied on data types other than texts such as video, audio or graphics, which lead to a limitation on content-based recommender systems. Another problem occurs when two items are assigned the same set of keywords, which makes them indistinguishable since the content-based systems uses these keywords to predict recommendations. Using the same set of keywords will lead to inaccurate results as the systems will not be able to distinguish between well-written book for example and badly written book [22].

Insufficient Recommendations for New Users

To have accurate a reliable recommendation, the user needs to rate sufficient number of items, as this is the base for content-based recommendations. The system will not be able to predict good recommendations if the user is new in the system and he rated only a few items.

Collaborative Recommendation

Insufficient Recommendations for New Users

As with the content-based recommendation, in order for the system to predict accurate recommendations, it needs first to understand the user's preferences based on the ratings he gave. Researchers used different ways to solve this problem, such as using hybrid recommendation approaches through combining content-based and collaborative techniques as discussed in the sections "Social Networks" and "Recommendation Techniques."

Insufficient Ratings for New Users

Collaborative recommender systems perform recommendation based on user preferences; so for a new item to be seen and recommended by the system a sustainable number of users must rate it. Hybrid recommendation approaches are also used to solve this problem as discussed in the sections "Social Networks" and "Recommendation Techniques".

Recommender Systems in Social Networks

What Can Social Networks Provide to Recommender Systems?

In our daily life, we rely on recommendations from other acquaintances to choose the best products to buy. Nowadays people are depending on the Internet to make their decisions. The Internet alone could not provide the users with sufficient suggestions for their needs as it contains many products and services. So social networks become pivotal for generating recommendations, as integrating recommender systems in social networks will add new intuitions and observation that cannot be achieved through using traditional recommenders. Which produces more accurate and efficient recommendations results? We will summarize these intuitions in the following points: (1) relations between users; (2) improve performance; (3) better recommendation for unrated items; (4) user content-based as recommendation source.

Relations Between Users (Social Influences)

Traditional recommender systems do not take the social relationships between users into consideration [55] even though the studies of measuring the importance of social influence [56, 57] has been performed long time ago. When friends tend to recommend products, other friends will accept these recommendations most of the times, as they trust each other. Businesses that adopted in their recommender systems the relation between humans have achieved a huge success. For example, Hotmail used social influence to reach 12 million subscribers just in 18 months with a marketing budget of US $50,000. Hotmail spread all over the world even in countries they did not make any advertisements such as Sweden and India [58]. This shows that people relations are powerful when making decisions on buying products [55].

Improve Performance

Integrating social networks will improve the performance of recommender systems on different levels as (1) prediction accuracy and (2) similarity between friends [55].

Prediction Accuracy

Understanding the relations between users and their friends as well as the information obtained about them can improve the knowledge about user behaviors and ratings [55]. As a result, predicting user preferences will become easier to infer, which will improve the prediction accuracy.

Similarity Between Friends

Through using social networks, recommender systems will no longer need to use similarity measures in order to measure the similarity between users [55]. When two people are friends, in social networks, we can infer that they share the same interest.

Better Recommendation for Unrated Items

When integrating recommender systems with social networks, the recommender system will be able to recommend items to users even if they have not rated them. This happens based on the preferences of the user's friends [55].

User Content-Based as Recommendation Source

There are two main sources for traditional recommender systems, which are the free text fields and the ratings [59]. Comments are used in e-commerce websites to increase the revenue [60, 61]; they allows users to get the experience of other users with a certain product [62], which makes this method very popular to be integrated in e-commerce websites. But those customer reviews are not accurate as a study showed that the ratings are either of extremely high or extremely low [63]. For that, some studies proposed to use social networks as a data source [59]. They used different text mining techniques, as well as web logs and trustful social networks for allowing the customers to get accurate and satisfaction reviews.

How Can Recommender Systems Use Social Networks to Perform Recommendations?

The different properties of social networks encourage the research in the field recommender systems integration with social networks. These studies are varied and spread over wide areas such as, network value, trust, social tagging, etc.

There are different studies [64, 65] for measuring the network value from analyzing the ability of the customers to influence their friends to buy new products. According to [64], the customers with high influence could leverage the profit of the company.

Trust is also another field related to integrating recommender systems with social networks. It is defined by [66] as the level of subjective probability where each agent helps another agent to accomplish a future behavior. And in social networks the users prefer to get recommendations from their friends. The social relations between users in social networks infer new studies in the field of recommending with trust. People prefer to get recommendations from their friends rather than from a general recommender system [67]; moreover, users prefer to get recommendations from trusted systems [68] and there is a strong relationship between user similarity and trust [69]. In [70] they proposed a distributed trust-based recommendation system on a social network. In their method, the social network needs to have friendship-trust values associated with each field. Then they used a model to compute the trust values between nonadjacent nodes. Each node is assigned a knowledge base to list the vendor preferences (assigned with rating) that the node has for various products and services.

Recommending Users and Groups

In social networking sites, there is a need for recommending users or groups with which the user can potentially became related to, in a personal or professional fashion. There are many researches related to recommending users. Most of these researches build their models based on Facebook and Twitter as they are the most well-known social networks nowadays. One research [71] proposed Twittomender that recommends Twitter users to each other. They used content-based search to check the content of the tweets and collaborative filtering to check the followees and followers of users as well as some hybrid strategies to perform the recommendation. In [72] the authors implemented a system to recommend friends on MySpace. They address issues related to the size of the graph, as it was very huge, keeping the graph up to date and producing friends recommendations using the graph. The system consists of the friend graph manager that manages corresponding portion of the friend graph, the recommendation generator, the recommendation repository manager, and the feedback manager. The challenge with recommending users is how to preserve the privacy of those users specially with the increasing identity theft and web crimes. If the users do not trust the systems, there will be missing attributes that will weaken the generated recommendations.

Future Works

Recommender systems have bright future especially when they combined with social networks. These social networks can provide real time information, relations and connections between different users in the network. Moreover, social networks improved the recommender systems and leveraged them to a new level. So there is a need to study these social networks to understand more the different relations between users. Recommender systems are used now in many businesses to allow businesses to increase traffic, have greater engagement with users, customize the user experience and gain financial benefits [73]. These recommender systems will have potential importance in the future and would be used in (1) engines that identify content on the Internet, (2) the entertainment industry where everything will move to on demand, and (3) advertisement industry [73]. Moreover, adding recommender systems to search engines will generate a new area in which recommender systems would grow. In our future work, we will extend the chapter to cover more issues in recommender systems such as social tagging, scalability, and privacy as these are important issues that need to be addressed and studied extensively.

Conclusion

Much research has been done in the field of recommender systems that helped in improving such systems to produce accurate recommendation results. Social networks and virtual communities with their capabilities of providing user profiles and relations between users added a new way of performing recommendations. In this chapter, we presented social networks and recommender systems. Recommender systems are used in many applications and industrial companies such as Amazon [11] and MovieLens [12]. We discussed the different techniques used for recommendations and categorized them as follows: (1) content-based recommendations, (2) collaborative recommendations and (3) hybrid recommendations. There are limitations in content-based and collaborative recommendations. Hybrid recommendations are used to address the problems of collaborative and content-based approaches such as new user and new item problems. We also discussed the importance of integrating recommender systems in social networks and the different researches done in that field. Real-life recommender systems are very complex and therefore need advanced techniques that can consider many factors during the recommendation process. This leads to the need for developing more advanced recommender systems that can satisfy the customers by providing accurate recommendation based on the different preferences of these users.

References

1. Alexanderson, G.: Euler and königsberg's bridges: a historical view. Bull. Am. Math. Soc. **43**(4), 567–573 (2006)
2. West, D.B.: Introduction to Graph Theory, 2nd edn. Prentice Hall, Upper Saddle River (2000)
3. Wasserman, S., Faust, K.: Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge/New York (1994)
4. Pastor-Satorras, R., Vespignani, A.: Epidemic spreading in scale-free networks. Phys. Rev. Lett. **86**(14), 3200–3203 (2001)
5. Boyd, D., Ellison, N.: Social network sites: definition, history, and scholarship. J. Comput. Mediat. Commun. **13**(1), 210–230 (2007)
6. Chen, J., Geyer, W., Dugan, C., Muller, M., Guy, I.: Make new friends, but keep the old: recommending people on social networking sites. In: Proceedings of the 27th International Conference on Human Factors in Computing Systems. CHI '09, pp. 201–210. ACM Press, Boston (2009)
7. Armstrong, J.S.: Principles of Forecasting: A Handbook for Researchers and Practitioners. Kluwer Academic Publishers, Boston (2001)
8. Salton, G.: Automatic Text Processing: the Transformation, Analysis and Retrieval of Information by Computer. Addison-Wesley Publishing, Reading (1989)
9. Powell, M.J.D.: Approximation Theory and Methods. Cambridge University Press, Cambridge/New York (1981)
10. Thaler, R.: Toward a positive theory of consumer choice. J. Econ. Behav. Organ. **1**(1), 39–60 (1980)
11. Linden, G., Smith, B., York, J.: Amazon.com recommendations: item-to-item collaborative filtering. IEEE Internet Comput. **7**(1), 76–80 (2003)
12. Miller, B.N., Albert, I., Lam, S.K., Konstan, J.A., Riedl, J.: Movielens unplugged: experiences with an occasionally connected recommender system. In: Proceedings of the 8th International Conference on Intelligent User Interfaces. IUI '03, pp. 263–266. ACM Press, New York (2003)
13. Bellman, S., Lohse, G.H., Johnson, E.J.: Predictors of online buying behavior. Commun. ACM. **42**(12), 32–38 (1999)
14. Rich, E.: User modeling via stereotypes. Cogn. Sci. **3**(4), 329–354 (1979)
15. Goldberg, D., Nichols, D., Oki, B. M., Terry, D.: Using collaborative filtering to weave an information tapestry. Commun. ACM. **35**(12), 61–70 (1992)
16. Lewis, K., Kaufman, J., Gonzalez, M., Wimmer, A., Christakis, N.: Tastes, ties, and time: a new social network dataset using facebook.com. Soc. Netw. **30**(4), 330–342 (2008)
17. Milgram, S.: The small-world problem. Psychol. Today **2**, 60–67 (1967)
18. Watts, D.J.: Small Worlds: the Dynamics of Networks Between Order and Randomness, illustrated edn. Princeton University Press, Princeton (1999)
19. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng. **17**(6), 734–749 (2005)

20. Hill, W., Stead, L., Rosenstein, M., Furnas, G.: Recommending and evaluating choices in a virtual community of use. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 194–201. ACM Press/Addison-Wesley Publishing Co., New York/Wokingham (1995)
21. Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., Riedl, J.: Grouplens: an open architecture for collaborative filtering of netnews. In: Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work. CSCW '94, pp. 175–186. ACM Press, New York (1994)
22. Shardanand, U., Maes, P.: Social information filtering: algorithms for automating 'word of mouth'. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 210–217. ACM Press, Addison-Wesley Publishing Co., New York/Wokingham (1995)
23. Pazzani, M., Billsus, D.: Learning and revising user profiles: the identification of interesting web sites. Mach. Learn. **27**(3), 313–331 (1997)
24. Mooney, R.J., Roy, L.: Content-based book recommending using learning for text categorization. In: Proceedings of the 5th ACM Conference on Digital Libraries. DL '00, pp. 195–204. ACM Press, New York (2000)
25. Sarwar, B., Karypis, G., Konstan, J., Reidl, J.: Item-based collaborative feeiltering recommendation algorithms. In: Proceedings of the 10th International Conference on World Wide Web. WWW '01, pp. 285–295, ACM Press, New York (2001)
26. Lang, K.: Newsweeder: learning to filter netnews. In: Proceedings of the 12th International Conference on Machine Learning, pp. 331–339. Morgan Kaufmann Publishers Inc., San Francisco (1995)
27. Pazzani, M., Billsus, D.: Content-based recommendation systems. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.) The Adaptive Web Methods and Strategies of Web Personalization, vol. 4321, pp. 325–341. Springer, Berlin/Heidelberg (2007)
28. Balabanovi, M., Shoham, Y.: Fab: content-based, collaborative recommendation. Commun. ACM. **40**(3), 66–72 (1997)
29. Cai, Y., Leung, H.-F., Li, Q., Tang, J., Li, J.: Recommendation based on object typicality. In: Proceedings of the 19th ACM International Conference on Information and Knowledge Management. CIKM '10, pp. 1529–1532, ACM Press, New York (2010)
30. Cantador, I., Bellogín, A., Vallet, D.: Content-based recommendation in social tagging systems. In: Proceedings of the 4th ACM Conference on Recommender Systems. RecSys '10, pp. 237–240, ACM Press, New York (2010)
31. Wartena, C., Slakhorst, W., Wibbels, M.: Selecting keywords for content-based recommendation. In: Proceedings of the 19th ACM International Conference on Information and Knowledge Management. CIKM '10, pp. 1533–1536. ACM Press, New York (2010)
32. Breese, J.S. Heckerman, D., Kadie, C.: Empirical analysis of predictive algorithms for collaborative filtering. In: Cooper, G.F., Moral, S. (eds.) Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence. UAI-98, University of Wisconsin, Madison, pp. 43–52 (1998)
33. Konstan, J.A., Miller, B.N., Maltz, D., Herlocker, J.L., Gordon, L.R., Riedl, J.: Grouplens: applying collaborative filtering to usenet news. Commun. ACM. **40**(3), 77–87 (1997)
34. Terveen, L., Hill, W., Amento, B., McDonald, D., Creter, J.: Phoaks: a system for sharing recommendations. Commun. ACM. **40**(3), 59–62 (1997)
35. Goldberg, K., Roeder, T., Gupta, D., Perkins, C.: Eigentaste: a constant time collaborative filtering algorithm. Inf. Retr. J. **4**(2), 133–151 (2001)
36. Delgado, J., Ishii, N.: Memory-based weighted majority prediction for recommender systems. In: ACM SIGIR'99 Workshop on Recommender Systems: Algorithms and Evaluation. ACM, New York (1999)
37. Nakamura, A., Abe, N.: Collaborative filtering using weighted majority prediction algorithms. In: Proceedings of the 15th International Conference on Machine Learning. ICML '98, pp. 395–403. Morgan Kaufmann Publishers Inc., San Francisco (1998)
38. Billsus, D., Pazzani, M.J.: Learning collaborative information filters. In: Proceedings of the 15th International Conference on Machine Learning. ICML '98, pp. 46–54. Morgan Kaufmann Publishers Inc., San Francisco (1998)

39. Getoor, L., Sahami, M.: Using probabilistic relational models for collaborative filtering. In: Proceedings Workshop on Web Usage Analysis and User Profiling. WEBKDD '99. Springer, Berlin/New York (1999)
40. Hofmann, T.: Collaborative filtering via gaussian probabilistic latent semantic analysis. In: Proceedings of the 26th Annual International ACM SIGIR Conference on Research and Development in Informaion Retrieval. SIGIR '03, pp. 259–266. ACM Press, New York (2003)
41. Marlin, B.: Modeling user rating profiles for collaborative filtering. In: Proceedings of the 17th Annual Conference of Neural Information Processing Systems. NIPS '03. MIT Press, Cambridge (2003)
42. Pavlov, D., Pennock, D.M.: A maximum entropy approach to collaborative filtering in dynamic, sparse, high-dimensional domains. In: Becker, S., Thrun, S., Obermayer, K. (eds.) NIPS, pp. 1441–1448. MIT Press, Cambridge, MA, USA (2002)
43. Ungar, L., Foster, D., Clustering methods for collaborative filtering. In: Proceedings of the Workshop on Recommender Systems at the 15th National Conference on Artificial Intelligence. AAAI'98. AAAI Press, Menlo Park (1998)
44. Chien, Y.H., George, E.I.: A bayesian model for collaborative filtering. In: Proceedings of the 7th International Workshop Artificial Intelligence and Statistics, Fort Lauderdale. Morgan Kaufmann, San Francisco (1999)
45. Pennock, D., Horvitz, E., Lawrence, S., Giles, L.C.: Collaborative filtering by personality diagnosis: a hybrid memory- and model-based approach. In: Proceedings of the 16th Conference on Uncertainty in Artificial Intelligence. UAI 2000, pp. 473–480, Stanford University, Stanford (2000)
46. Lee, W.S.: Collaborative learning for recommender systems. In: Proceedings of the 18th International Conference on Machine Learning. ICML-2001, vol. 2001, pp. 314–321. McGraw-Hill, Williamstown, MA, USA (2001)
47. Claypool, M., Gokhale, A., Miranda, T., Murnikov, P., Netes, D., Sartin, M.: Combining content-based and collaborative filters in an online newspaper. In: Proceedings of ACM SIGIR Workshop on Recommender Systems. SIGIR '99, Berkeley, CA, USA (1999)
48. Pazzani, M.: A framework for collaborative, content-based and demographic filtering. Artif. Intell. Rev. **13**(5/6), 393–408 (1999)
49. Soboroff, I., Nicholas, C.: Combining content and collaboration in text filtering. In: Proceedings of the IJCAI-99 Workshop on Machine Learning for Information Filtering, Stockholm, Sweden (1999)
50. Popescul, A., Ungar, L.H., Pennock, D.M., Lawrence, S.: Probabilistic models for unified collaborative and content-based recommendation in sparse-data environments. In: Proceedings of the 17th Conference in Uncertainty in Artificial Intelligence. UAI '01, pp. 437–444. Morgan Kaufmann Publishers Inc., San Francisco (2001)
51. Schein, A.I., Popescul, A., Ungar, L.H., Pennock, D.M.: Methods and metrics for cold-start recommendations. In: Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval. SIGIR '02, pp. 253–260, ACM Press, New York (2002)
52. Burke, R.: Knowledge-based recommender systems. In: Encyclopedia of Library and Information Systems, vol. 69. Marcel Dekker Inc., New York (2000)
53. Burke, R.: Hybrid recommender systems: survey and experiments. User Model. User-Adapt. Interact. **12**(4), 331–370 (2002)
54. Melville, P., Mooney, R.J., Nagarajan, R.: Content-boosted collaborative filtering for improved recommendations. In: Proceedings of the 18th National Conference on Artificial Intelligence. AAAI2002, pp. 187–192. AAAI Press, Menlo Park (2002)
55. He, J., Chu, W.W.: A social network-based recommender system (snrs). Ann. Inf. Syst. Spec. Issue Data Min. Soc. Netw. Data. **12**, 47–74 (2010)
56. Subramani, M.R., Rajagopalan, B.: Knowledge-sharing and influence in online social networks via viral marketing. Commun. ACM. **46**(12), 300–307 (2003)
57. Yang, S., Allenby, G.M.: Modeling interdependent consumer preferences. J. Mark. Res. **40**(3), 282–294 (2003)

58. Jurvetson, S.: What exactly is viral marketing? Red Herring **78**, 110–112 (2000)
59. Bank, M., Franke, J.: Social networks as data source for recommendation systems in: E-commerce and web technologies. Lect. Notes Bus. Inf. Process. **61**, 49–60 (2010)
60. Hu, N., Liu, L., Zhang, J.J.: Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. Inf. Technol. Manag. **9**(3), 201–214 (2008)
61. Ghose, A., Ipeirotis, P.G.: Designing novel review ranking systems: predicting the usefulness and impact of reviews. In: Proceedings of the 9th International Conference on Electronic Commerce. ICEC '07, pp. 303–310. ACM Press, New York (2007)
62. David, S., Pinch, T.J.: Six degrees of reputation: the use and abuse of online review and recommendation systems. First Monday **11**(3) (2005). http://firstmonday.org/htbin/cgiwrap/bin/ojs/index.php/fm/article/view/1590/1505
63. Hu, N., Pavlou, P.A., Zhang, J.: Can online reviews reveal a product's true quality?: empirical findings and analytical modeling of online word-of-mouth communication. In: Proceedings of the 7th ACM Conference on Electronic Commerce. EC '06, pp. 324–330. ACM Press, New York (2006)
64. Domingos, P., Richardson, M.: Mining the network value of customers. In: Proceedings of the 7th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '01, pp. 57–66. ACM Press, New York (2001)
65. Richardson, M., Domingos, P.: Mining knowledge-sharing sites for viral marketing. In: Proceedings of the 8th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '02, pp. 61–70. ACM Press, New York (2002)
66. Gambetta, D.: Can we trust? In: Trust: Making and Breaking Cooperative Relations, pp. 213–237. Basil Blackwell Publishers, New York (1988)
67. Sinha, R., Swearingen, K.: Comparing recommendations made by online systems and friends. In: Proceedings of the DELOS-NSF Workshop on Personalization and Recommender Systems in Digital Libraries, Dublin (2001)
68. Swearingen, K., Sinha, R.: Beyond algorithms: an hci perspective on recommender systems. In: Proceedings of the ACM SIGIR 2001 Workshop on Recommender Systems, New Orleans. ACM Press, New Orleans, Louisiana, USA (2001)
69. Ziegler, C.N., Lausen, G., Analyzing correlation between trust and user similarity in online communities. In: Proceeding of the 2nd International Conference on Trust Management, vol. 2995, pp. 251–265. Springer, Berlin/Heidelberg (2004)
70. Sarda, K., Gupta, P., Mukherjee, D., Padhy, S., Saran, H.: A distributed trust-based recommendation system on social networks. In: Proceedings of the 2nd IEEE Workshop on Hot Topics in Web Systems and Technologies (2008)
71. Hannon, J., Bennett, M., Smyth, B.: Recommending twitter users to follow using content and collaborative filtering approaches. In: Proceedings of the 4th ACM Conference on Recommender Systems. RecSys'10, pp. 199–206. ACM Press, New York (2010)
72. Moricz, M., Dosbayev, Y., Berlyant, M.: Pymk: friend recommendation at myspace. In: Proceedings of the 2010 International Conference on Management of Data. SIGMOD '10, pp. 999–1002, ACM Press, New York (2010)
73. Guy, I., Jaimes, A., Agulló, P., Moore, P., Nandy, P., Nastar, C., Schinzel, H.: Will recommenders kill search?: recommender systems – an industry perspective. In: Proceedings of the 4th ACM Conference on Recommender Systems. RecSys '10, pp. 7–12. ACM Press, New York (2010)