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Abstract

Recommender agents are being widely used by E-commerce business to help customers make decisions from a large amount of choices. To improve the performance of recommendation agents, three main approaches (content-based approaches, collaborative approaches and hybrid approaches) have been proposed to address recommendation problem whose basic idea is to discover similarity of items[1] *and users and predicate users' preference toward a set of items. This provides potential for using social network analysis to make recommendations since social network analysis can be used to investigate the relationships of customers. In this research, we illustrate the concepts of social network analysis and how it can be employed to make better recommendations in E-commerce context. Application and research opportunities are presented.*

Keywords: Recommender agents, social network analysis, E-commerce recommendation

[1] "Items" refer to products or services, like books, movies, restaurants etc.

1 INTRODUCTION

The growth of E-commerce business is promising. According to JupiterResearch, online retail sales in US will continue to grow at double-digit rates for the next several years[2]. As forecasted by JupiterResearch analyst Patti Freeman Evans, the online sales will reach $166 billion in 2009 and $215 billion by 2012, growing at an 11 percent compound annual growth rate. According to *Development Report on China Online Shopping Market* conducted by Iresearch and the largest Chinese auction website *Taobao.com*, the annual turnover in China's online shopping market reached RMB 120 Billion Yuan in 2008, with a growth rate of 120% over the previous year.[3]

With the rapid development of E-commerce business, large amount of information available on the Web presents great challenges to customers finding what they are interested in (Huang et al. 2004). For example, there are millions of books available at *Amazon,* and millions of items for sale at *eBay*. Searching from numerous choices and making final decision is a tough task. Recommendation agents help customers reduce information overload and provide them with customized information in target domains. Moreover, providing value-added services such as recommending personalized products can build good customer relationship to retain customers (Mirza et al. 2003). Recommender agents are being widely used by large amount of E-commerce sites as a business tool to help consumers easily find products they are interested in and make customized recommendations (Montaner et al. 2003). Companies like *Amazon* (Linden et al. 2003), *Netflix* and *eBbay* have implemented recommendation technologies to improve customer loyalty (Schafer et al. 2001).

To provide more effective and accurate recommendations, various recommendation methods are proposed in the literature (Deshpande et al. 2004; Sarwar et al. 2000). Most of these methods take customer attribute, item attribute and interactions between customers and items as input and predict future interactions between customers and items as output (Schafer et al. 2001). Most recommendations are made based on item-to-item similarity (in terms of characteristics) and user-to-user similarity (in terms of interests or preferences).

Recommender agents have an inherently social element and ultimately bring people together (Perugini et al. 2004). And their basic principles are to discover similarity of users and items. This enables social network analysis as a tool to enhance the performance recommender agents.

Social network analysis (SNA) has attracted a lot of attention in recent years (Jennifer et al. 2005; Ortega et al. 2008; Otte et al. 2002). Different from variable analysis and topological analysis, which focus on the concepts and attributes of objects, SNA addresses the structure and relationships of objects. SNA sheds light on discovering underlying relationships of people. Take two unknown people and two friends for example. There may be no significant differences in their attributes. However, the relationships between two unknown people and a pair of friends are much different. In recommendation context, the interests of two friends tend to be related to some extent. This kind of information can be used to improve the recommendation results.

The focus of social network analysis is relationships. Much information about network relations has been learned and many constructs have been created to capture different perspectives of the relationships. Therefore, SNA can be used to discover relationships of users to aid making recommendations.

In this paper, we will study social network analysis and investigate how this approach can be used to make better recommendations.

2 http://news.cnet.com/8301-10784_3-9888859-7.html
3 http://www.webprochina.com/?tag=china-online-retail-sales

2 LITERATURE REVIEW OF E-COMMERCE RECOMMENDATION

2.1 Overview and development of recommender agents

Traditional approach to make recommendations is based on manually analyzing the features of customers, their historical transactions and characteristics of items, and identifies a list of potential items for each user which she might be interested in (Yang et al. 2008). This approach has been employed in many face-to-face shopping contexts, like shopping mall. However, it is inappropriate for E-commerce sites where there are large amounts of choices available.

The roots of recommender agents can be traced back to information retrieval and information filtering research. Information retrieval returns users relevant information in response to their short-term queries. Information filtering works by filtering out irrelevant information to users. Recommender agents moves further to "elicit the interests or preferences of consumers for products, either explicitly or implicitly, and make recommendations accordingly" (Xiao et al. 2007). Recommender agents enable customized recommendations and creation of a new online store personally designed for each customer (Schafer et al. 2001).

2.2 Application examples

Recommender agents enhance E-commerce sales in three ways: converting browsers into buyers, increasing cross-sell and building loyalty (Schafer et al. 2001). There is a lock-in effect between E-commerce websites and customers. Websites use recommender agents to learn customers, obtain their preferences and provide them with products fit their needs. Once a customer accepts the recommendation services provided by a particular website and benefits from these kinds of service, the customer's switching cost to other competing websites increases over time. This can greatly improve customer loyalty.

Many E-commerce businesses use recommender agents embedded in their web sites to recommend customized products to customers. *Amazon* employs recommendation algorithms to personalize its websites to each user (Linden et al. 2003). *eBay* invested a recommender agent that offered new content to recommend items to users based upon their preferences and how they rated pages they have previously seen through the engine[4].

2.3 Extant recommendation approaches and their limitations

The heart of recommender agents are recommendation approaches. Based on the source of recommendation data, those recommendation techniques can be classified into three types (Adomavicius et al. 2005; Balabanovic et al. 1997): (a) content based recommendation techniques, which are based on similarity of the items to user's preferences (Mooney et al. 2000), (b) collaborative based recommendation techniques (Cheung et al. 2004; Huang et al. 2007), which are based on the tastes or similarity of users, (c) hybrid recommendation techniques, which combines the former two approaches (Salter et al. 2006).

Content based approaches employ similarity function and classification methods to analyze and cluster items with similar characteristics, and recommendations are generated based on matching

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[4] Darryl K. Taft (2007, May). eBay Acquires Social Search Engine StumbleUpon; eBay will likely use its $75 million acquisition to surface and recommend its vast inventory of auction and sale items. eWeek,1. Retrieved December 12, 2008, from Academic Research Library database.

between characteristics of items and user profiles (Mooney et al. 2000; Pazzani et al. 2007). The underlying principle is that if particular users are interested in some items, then items with similar characteristics will also attract their interests. Items are recommended based on the information of items themselves rather than preferences of other users. The advantage of this approach is that new items are able to be recommended to users with unique interests based on discovering relations or similarities between new items and old items. Since a customer's preferences are inferred from items in which she has shown an interest, the content-based approach is not appropriate for new customer whose preference is not clear.

Collaborative approach mines relevance of users by investigating their behaviours. Recommendations are made by finding correlations among users (Lin et al. 2000; Schafer et al. 2007). The basic idea is that if customers show shared interests before, they tend to have common interests in future. Those users whose interests are similar are called recommendation partners. Recommendation partners are found by using similarity functions such as cosine-based similarity approach, correlation-based similarity function and clustering methods (Huang et al. 2004). Collaborative approaches recommend items to target customers that appear in their recommendation partners' profiles but not in their profiles (Yang et al. 2008). This approach maintains preferences of individual users, and finds other users whose known preferences significantly correlate with a given user, and recommends to this user other items enjoyed by her recommendation partners.

Since content based and collaborative approaches mainly focus on one aspect of recommendation element, which are other item-centric or customer-centric, some useful information is missing in the recommendation process. To improve the quality of recommendations and make use of advantages of both content based and collaborative approaches, many efforts have been made to combine the former two approaches to implement a hybrid approach (Burke 2002; Salter et al. 2006).

Among these three methods, collaborative approach is the most widely used and successful one which attracts considerable concentration both in academia and actual E-commerce business. In spite of its success, this approach has several limitations: 1) Its inability to recommend new items to users. When a new item is introduced, it is unlikely to recommend it to appropriate users using this approach since no user express their preference for this item. 2) The sparse transaction (or rating) data condition makes predicting accurate recommendations difficult. Usually, similarity of customers' preference is measured using transaction data, which is represented by a customer-item matrix. Due to sparse data problem, most elements in this matrix are zero, which makes it difficult to measure the similarity between two users. One solution is to combine content based approach. An alterative approach is resorting to social network analysis to discover similarity of customers. Social network analysis can conquer the weaknesses of the collaborative approach from two perspectives. The first is that it can investigate not only the direct transaction relationships of customers but also their indirect relationships. The second is that it provides mechanism to discover the similarity of customers from their social communications, include transactions, purchasing behaviour, etc.

From the principles of the three recommendation approaches, we know that one of the most important issues for making recommendations is to mine or model the similarity among customers and items. Moreover, recommendations are not delivered in vacuum, but rather cast within an informal community of users (Perugini et al. 2004). Analyzing users' links in such community can shed light on discovering their similarity from other perspectives. In reality, a customer's decision to buy a product is influenced by her friends, acquaintances, etc. Thus, social network analysis as a powerful tool to analyze relationships of people provides great potential in making recommendations.

3 SOCIAL NETWORK ANALYSIS AND ITS POTENTIAL APPLICATIONS

3.1 Overview

SNA was initially developed and practiced by social scientists to investigate the interaction among the members of a community to understand complex phenomena and structure of social worlds. Social network theory views social relationships in terms of nodes and links, where nodes represent individuals or organizations and links can be a single or multiple types of relationships or shared characteristics among people (Freeman 1979), such as friendships, coworking or information exchange etc. Interests in SNA has grown among researchers from different fields, like Physics, information sciences etc (Fortunato et al. 2004; Leicht et al. 2006; Otte et al. 2002). And its application can be found in many areas, such as research on organizational knowledge sharing (Tsai 2002), identifying subgroup structure and working relationships in organization (Cross et al. 2001), investigating the structures and interactions within criminal network (Jennifer et al. 2005).

Social network analysis can investigate structure and properties of a network from three different levels, individual node level (the focus is a target node), subgroup level (addressing a set of nodes with common characteristics) and the entire network level. Thus, it can be used to investigate the relationships of customers from these three levels to discover their preferences.

A great deal of concepts and constructs have been developed through decades of accumulated research in social network analysis research. Some important concepts and their potential applications in E-commerce recommendations will be introduced in the following subsections.

3.2 Some important concepts and their potential applications

3.2.1 Categories of networks

Criteria	Network type
Types of relations	Simplex/Multiplex
Direction of relations	Directed/Undirected
Strength of relations	Binary/Signed/Ordinal/Valued

Table 1 Categories of networks based on different criteria

Social networks can be classified into different categories based on criteria as shown in Table 1. According to the types of relations among nodes within networks, there are two categories of networks: simplex and multiplex. There is only one kind of relation in simplex networks. While for multiplex networks, there exist at least two types of relationships. Based on the direction of relations, networks can be divided into directed where the relations originates with a source node and reaches a target node or undirected where a link represents bonded-tie between a pair of nodes. The strength of links of nodes can be binary (the value of the links are 0 and 1 where 0 means no link and 1 denotes link); signed (the value of the links can be positive, negative or zero); ordinal (represents whether the link is the strongest, next strongest, etc.); or valued (measured on an interval or ratio level) (Hanneman et al. 2005). The direction and strength information can be represented using an adjacency matrix.

3.2.2 Centrality

Centrality reveals how influential and powerful a node is, which reflects the roles of individuals in a network. There are three most important centrality measures: degree centrality, closeness centrality and betweenness centrality.

3.2.2.1 Degree centrality

Nodes which have more links to others tend to be at advantaged positions. Thus, a node's degree can be used to measure its centrality and power. For an undirected network, degree centrality of a particular node is defined as the number of links this node has (Jennifer et al. 2005). A node i's degree centrality $d(i)$ can be formulated as

$$d(i) = \sum_j m_{ij}$$

where $m_{ij} = 1$ if there is a link between nodes i and j, and $m_{ij} = 0$ if there is no such link. For a directed network, it is necessary to distinguish the in-degree centrality and out-degree centrality.

3.2.2.2 Closeness centrality

Degree centrality reflects the power of a node through its immediate links that this modes has while ignore the indirect links of this node. This kind of information can be captured by closeness centrality because it emphasizes the distance of a node to all other nodes (Freeman 1979).

As a mathematical formula of node i's closeness centrality, $c(i)$ can be represented as:

$$c(i) = \sum_j d_{ij}$$

where d_{ij} is geodesic distance from node i to node j (which is the number of links in a shortest path from node i to node j). Since closeness centrality is based on distance between nodes, it is an inverse measure of centrality in that a larger value indicates a less central node while a smaller value indicates a more central node.

3.2.2.3 Betweenness centrality

Betweenness centrality of a node i is defined as the number of shortest paths between pairs of other nodes that run through i (Girvan et al. 2002). In order to alleviate the effects of number of paths going through i, it is standardized by dividing the number of paths going through i. The betweenness centrality $b(i)$ of nodes i can be obtained through the following formula:

$$b(i) = \sum_{j,k} \frac{g_{jik}}{g_{jk}}$$

where g_{jk} is the number of shortest paths from node j to node k ($j,k \neq i$), and g_{jik} is the number of shortest paths from node j to node k passing through node i (Otte et al. 2002).

3.2.2.4 Potential application

Nodes with high centrality mean that they have more influence on other nodes. In recommendation context, customers tend to see what products other influential customers buy and then make their decisions. Customers can benefit from the buying list of other influential users and their comments. Future research may use social network analysis to identify influential customers and take into consideration this influence factor.

3.2.3 Vertex similarity

Similarity of nodes in a network is based on the structure of a network. There are two different ways to measure the similarity of vertices. The first is based on the idea that similar nodes tend to have common neighbors. Under this basic idea, there are three measures to describe the similarity between a pair of nodes in a network as shown in the following: σ_{Jacard} . $\sigma_{\cos ine}$ and $\sigma_{\min}$. Let Γ_i be the neighborhood of node i (the set of nodes that directly connected to i via an edge), Γ_j be the neighborhood of node j, then the similarity of vertices i and j σ can be formulated as:

$$\sigma_{Jacard} = \frac{|\Gamma_i \cap \Gamma_j|}{|\Gamma_i \cup \Gamma_j|}$$

$$\sigma_{\cos ine} = \frac{|\Gamma_i \cap \Gamma_j|}{\sqrt{|\Gamma_i||\Gamma_j|}}$$

$$\sigma_{\min} = \frac{|\Gamma_i \cap \Gamma_j|}{\min(|\Gamma_i|,|\Gamma_j|)}$$

Another way is based on the premise that two vertices are similar if they are connected to other vertices that are themselves similar (Leicht et al. 2006) This kind of similarity considers not only direct neighbors but also neighbors' neighbors.

Potential application Vertex similarity can be used to explore other customers whose interests and preferences are similar to a particular customer in terms of the measure of their neighbours (direct or indirect). Take a shopping network for example where nodes represent customers and links represent a pair of customers ever bought a same item. Then customers with high vertex similarity to a target customer can be considered as this customer's recommendation partners. Personalized items can be recommended to the target customer based on her recommendation partners' preference.

3.2.4 Cohesive subgroups

A subgroup is any collection of nodes selected from the nodes of the whole graph, together with corresponding edges that links these nodes. A cohesive subgroup is a subset of nodes whose ties are relatively strong and intense (Fortunato et al. 2004). The aim of finding cohesive subgroups is to define a meaningful division of network based on the structural properties of the whole network.

According to literature, there are four main ways to find cohesive subgroups based on four structural properties: the mutuality of the ties, the closeness or reachability of the members of the subgroup, the frequency of ties among members and the relative frequency of ties among subgroup members compared to nonmembers (Wasserman et al. 1994). Cohesive subgroups based on the mutuality of ties require that all pairs of subgroup members choose each other. In other words, this kind of subgroup is a complete sub-network where any two nodes are directly connected. Cohesive subgroups based on reachability require that all members of a particular subgroup are reachable from each other.

Cohesive subgroups based on frequency of members require that members in a subgroup have minimum number of nodes adjacent to each other. Cohesive subgroups based on the relative frequency of ties among members can be considered as part of the previous subgroup with relatively high density in the network.

Based on the requirement of strength of links of members from the strongest to weakest, subgroups have several types: cliques, *N*-cliques, *k*-plexes, *k*-cores and communities (Girvan et al. 2002; Han et al. 2008; Newman 2006). A clique is a maximal fully connected sub-network where every node is directly connected to all other nodes. An *N*-clique is a maximal sub-network where the largest geodesic distance between any pair of nodes is less than *N*. A *k*-plex is a maximal sub-network with *N* nodes and each node is directly connected to at least *N*-*k* other nodes. A *k*-core is a maximal group of nodes, all of which are directly connected to at least *k* other members of the group. The concept of community is an extension for finding cohesive groups based on the relative frequency of links. Community is a group of vertices within which connections are dense while between which are sparser (Xiang et al. 2008).

Potential application Cohesive subgroup concept can be used to group or cluster customers with same interests or characteristics. For example, a transaction network where nodes represent customers and links represent two customers purchase a common product is divided into several subgroups, customers in same group tend to exhibit similar interests. This kind of information can be used to provide personalized recommendation to customers.

4 SOME REPRESENTATIVE EXAMPLES

Social network analysis presents great potential in E-commerce recommendation as discussed in previous section. In this section, some examples will be given to illustrate how to incorporate social network analysis into E-commerce recommendation.

Using distance

SNACK incorporates social network information in automated collaborative filtering to mine the similarity of users (Lam 2004), where social network is generated artificially. The social network is constructed in the way that two users are linked if one has the other user as one of her 3 most similar users. And similarity of other users to an active user is measured by Pearson correlation and modified by their closeness in the network. Others being equal, two users are more similar if they are closer in the network.

Social networks of customers are employed to provide better recommendations for users (Ben-Shimon et al. 2007), where the links of the network is constructed by one user sending an invitation and initiating friendship and other users accepting the invitation (they also can reject the invitation, then there is no link between the users). Each user's personal social network is a snapshot of the social network of all users, up to level 6 (which means in a user's personal social network, the distance between this user and other users is less than 6). The items recommended to a user are based on the preferences of the members in her personal social network.

Using *k*-core subgroup

Social network analysis is used to recommending trusted online auction sellers based on the "closeness of reputation relationship" index(Wang et al. 2008). Accounts of *2*-core subgroup which have transactions with at least two fraudulent accounts are identified to aid predicting potentially fraudulent accounts.

Using cohesive subgroup

Cohesive subgroups obtained from customers' social networks are used to infer their preferences over items and then recommend corresponding products to them (Yang et al. 2008). The customers' social networks are derived from their interaction data. The underlying principle is that the subgroups are composed of customers with strong ties, therefore, interests of users in a cohesive subgroup are similar to some extent.

The above examples show how social network analysis can be incorporated in recommender approaches to fully grasp the customer information and mine their relationships to improve the performances of the recommendation approaches. New concepts and constructs can be employed to improve the performance recommendation approaches. However, using social network analysis in E-commerce recommendation is still in primitive stages and the construction of social network is mainly based on transaction data, rating data and browsing data. Other kinds of data like friendship and trust can also be used to construct social network.

5 DISCUSSION AND DIRECTIONS FOR FUTURE RESEARCH

Social network analysis provides a means to mine customers' relationships. Based on our previous presentation, social network analysis can have important implications for making E-commerce recommendations.

Some customers have more influence on other customers, they are known as "leader" or "pioneer". Their positive attitudes may affect other customers' responses. New products tend to be known by more customers through influential ones. Providing customers with what other influential customer purchase can help them make decisions. Social network analysis can be used to mine users' interests from two perspectives, individual customer perspective and subgroup perspective. Vertex similarity (from individual customer perspective) enables discovering whose preferences are similar to a targeted customer in terms of their common neighbourhood. Cohesive subgroup (from subgroup perspective) can be used to divide the whole network into several subgroups and customers in the same subgroup share similar preferences. E-commerce companies can borrow these ideas directly to learn customers' preferences to improve the recommendation results.

This research also opens new directions for future research.

- How to extract social network data
  - Extraction of social network data internally. Transaction and rating information can be recorded and obtained from database of E-commerce companies. Some E-commerce sites provide users services that connect people with similar shopping tastes and enable their communication, like *Kaboodle*[5] and *ThisNext*[6]. The social network can be implicitly inferred from their interaction logs.
  - Extraction of social network data externally. Many social network sites enable us to discover various kinds of relationships of people, like weblogs, *Facebook*[7], *Xiaonei*[8], etc. But using personal information may raise privacy concerns, which needs careful considerations. Even the relationships of people can be extracted from social network sites, whether the data reflects customer's preferences or interests and to what extent still needs to be considered.
- How to integrate with other recommendation approaches, like content-based approach and collaborative approach. The hybridization approaches which combine content based approach and collaborative approach may provide some guidelines (Burke 2002), for example, weighted approach (the scores of each recommendation results are combined to make final recommendation), switching approach (different approaches will be used in correspondence with the users' states), cascade approach (using one approach to refine other approaches' results).
- Social network analysis can be combined with other techniques like ontology to capture complete information of the recommendation domain. Ontology can be used to represent the concepts and their relationships to provide a rich conceptualization of the recommendation domain, which can complement social network analysis approach.
- New advances in social network analysis can provide insights in mining relationships of customers.

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[5] http://www.kaboodle.com
[6] http://www.thisnext.com
[7] http://wwww.facebook.com
[8] http://www.xiaonei.com/

6 CONCLUSIONS

Recommendation approaches have been widely applied in E-commerce domain to deal with information overloading and to provide customers personalized products. Typically, these approaches fall into three categories: content-based approaches, which are item-centric, collaborative approaches, which are user-centric and hybrid approaches. The basic idea of recommendation approaches is to discover items with similar characteristics and customers with similar tastes and then predict the preferences of customers for items. Social network analysis which focuses on relationships of individuals provides potential for making recommendations under E-commerce context. This paper presents some examples to show how social network analysis has been used for providing personalized recommendations to customers and suggests opportunities for future research.

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