A Social Network-based Approach to Expert Recommendation System

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Abstract. We present a hybrid method for an expert recommendation system that integrates the characteristics of content-based recommendation algorithms into a social network-based collaborative filtering system. Our method aims at improving the accuracy of the recommendation prediction by considering the social aspect of experts' behaviors. For this purpose, social communities of experts are first detected by applying social network analysis and using factors such as experience, background, knowledge level, and personal preferences of experts. Representative members of communities are then identified using a network centrality measure. Finally, a recommendation is made to relate an information item, for which a user is seeking for an expert, to the representatives of the most relevant community. Further from an expert's perspective, she/he has been suggested to work on relevant information items that fall under her/his expertise and interests.

Keywords: Recommendation Systems, Social Network Analysis, Clustering, Semantic-based Similarity, Information Retrieval, Knowledge Management.

1 Introduction

Identifying/classifying experts is an emerging research area that has been widely studied by many researchers in recent years. One objective in exploring the experts is to facilitate the process of finding the right people whom we may ask a specific question and who will answer that question for us. In the field of knowledge management, the concept of tacit knowledge refers to a type of knowledge possessed only by an individual. In general, it is difficult to communicate the tacit knowledge to others via words and symbols, or to codify it. One example of tacit knowledge is experience. Tacit knowledge usually resides in the expert's brain. Therefore finding relevant experts for a particular task is challenging.

Profiling the expert and constructing the expert directories and yellow pages is an efficient and effective way to manage the tacit knowledge [9]. However, with the increasing complexity of tasks and the need for narrowed expertise in some highly on-demand areas, it is becoming more difficult to passively find the appropriate experts through directories. As an alternative approach, recommendation systems have been adopted into knowledge management systems to provide active knowledge sharing. In these systems, recommendations are made to the users according to the users' needs and interests. Many efforts have been made to improve the accuracy of explicit recommendation algorithms. However, fewer researches have focused on tacit knowledge recommendation. Recommendation systems are classified into three groups based on the way that the user models are constructed, the employed prediction methods, and also the type of items to be recommended [2]. These three groups are content-based, collaborative filtering, and hybrid methods. One important aspect that has been ignored until recently is the social element of the user behavior in making recommendations. People communicate with their peers, whom they trust, to get advice. Therefore, it seems more rational to deliver recommendations within an informal community of users and a social context. An approach that has recently received much attention is to use the social structure of user community, in addition to the users' profiles and previous behaviors, as an additional source of information in building recommender systems.

Hybrid intelligent systems are becoming popular due to their capabilities of handling many real world complex problems. In a hybrid intelligence system, a synergistic combination of multiple techniques is used to build an efficient solution to deal with a particular problem. [1, 4, 5]. For instance, logic-oriented neural networks greatly benefits from synergistic links between the technology of fuzzy sets and neural networks [19]. In logic-oriented neural networks some prior domain knowledge is incorporated to improve the structure of the network and establish some interesting and meaningful connections. This unique feature is not available in case of standard neural networks as they do not come with any direct interpretability capabilities which could be instantaneously taken advantage of domain knowledge [19].

This research work presents a hybrid recommendation system which is indeed a social network-based collaborative strategy that it also maintains the content-based profiles for each user. In order to design such a hybrid system, we make use of artificial intelligence-based information retrial methods and unsupervised learning (clustering) techniques for analyzing the characteristics of a social network. One advantage of this approach is that users can be recommended an item not only when this item is rated highly by users with similar profiles, but also directly, i.e., when this item gets highly scored against the user's profile. In the domain of the expert recommendation system, our proposed system discovers communities of experts and accordingly assist users to effectively find groups of experts who have users' desired tacit knowledge. In this context, the social structure of the experts' relations, captured in a social network, is used as the social component of the recommendation system. The social network of experts is constructed based on factors such as experience, background, knowledge level, and personal preferences of experts.

The rest of the paper is organized as follows. Section 2 presents several related works. Section 3 describes the proposed methodology. Section 4 demonstrates an example application of the proposed recommendation system. Finally, the paper is concluded in section 5.

2 Related Work and Our Contribution

With the rise of the eCommerce systems in the past decade, major internet retailers have begun to build recommender systems to personalize content to show to their users through an information filtering process. Recommendation systems were first employed by Amazon.com, which would show users personalized recommendations of items that the system thought they would like based on the items that they had bought or rated in the past [10]. Since then they have been widely and successfully used in the fields of movies such as the EachMovie database [3], music such as Last.fm website [8], books [17], and documents [11]. Since collaborative filtering recommendation systems carry the social characteristics of users, different concepts of social network analysis can be utilized to improve the accuracy and reliability of recommendations. Several studies have been conducted on the use of social networks in recommendation systems. For example, in [15] authors use two different social networks in a system to recommend possible collaborations for individuals. Ogata et al. [18] use social networks to facilitate finding a person to collaborate with. In [6], trust clusters are used to improve the recommendation in which clusters are based on trust rather than similarity. Further, several trust-aware recommendation methods have been proposed [12–14] in which it is shown that by using users' trust relations, the performance of the traditional recommender systems can be improved.

The main contribution of this paper is to design and develop a general framework that attempts to detect communities of experts in a social network and to build a recommendation system that utilizes the information extracted from expert communities to make predictions. The ultimate goal of this system is to recommend experts who carry the appropriate tacit knowledge with regards to the user information needs. To assess and evaluate the effectiveness and usability of the proposed expert recommendation system in the real world, an experiment with 315 researchers and 62 research topics (information items) has been conducted. Results have been evaluated against information collected from 23 subjects, who rated their research interests in a given list of research topics, through a questionnaire.

3 The Proposed Model

In the proposed framework, the expert recommendation system is built in four phases: 1) a profile is constructed for each individual expert by using the information collected from different online sources; 2) the semantic knowledge derived from *Wikipedia* is embedded into profiles; 3) a social network is constructed according to the similarities among the experts' profiles, communities of experts are detected in the social network, and representatives of communities are identified; and 4) a prediction is made to recommend representatives from an expert community that has required expertise to fulfill the user's specific information need. In the rest of this section, components of the proposed system will be described in more details.

3.1 Constructing Experts' Profiles

To build rich profiles for experts, different types of relevant information need to be collected. The manual entering mean for each expert is a very time consuming task and obviously is not feasible. Therefore, to create a textual profile for each individual, a crawler automatically extracts information from relevant web pages to individuals and collects them in the profiles. Profiles constructed in this manner contain relevant information such as work experience, educational history, social and political activities, abilities and specialties, interests, etc. to each individual.

3.2 Integrating Semantic Knowledge into Profiles

In traditional text clustering methods, text documents are represented as "Bag of Words" (BOW) without considering the semantic relationships among words. In BOW approach, each document is considered as a vector in which dimensions represent all words that appear in the corpus (dictionary). The value associated to a given term reflects its frequency of occurrence within the corresponding document (term frequency or *tf*) and within the entire corpus (inverse document frequency or *idf*). Apparently, the BOW approach is limited since it only uses the set of terms explicitly mentioned in the document and ignores relationships between important terms that do not co-occur literally. For example, if two documents are about automobile sale markets, but one of them uses car and the other one uses auto as a core word, they may be falsely assigned to different clusters in spite the fact that both of them share the same topic and use synonym core words. The most common way to solve this problem is to enrich document representation with the background knowledge. There exist several ontologies like *WordNet* [16] which have been used as external sources for embedding background knowledge to text documents [7], but these ontologies are manually built and their coverage are too restricted. Their maintenance requires extreme effort as well. For these reasons, *Wikipedia*, the world largest electronic encyclopedia to date, has been recently used for text representation enrichment [20] as a more feasible strategy. *Wikipedia* is a well-formed document repository in that each article only describes a single topic. The title of each article is a succinct phrase which is considered as a concept. Equivalent concepts are related to each other by redirected links and are referred to the same page on the *Wikipedia* directory. Meanwhile, each article (concept) belongs to at least one category, and categories are organized in a hierarchical structure. All these features make *Wikipedia* a proper ontology which excels other ontologies to be used for extracting semantic correlations among different concepts. In the context of our work, we take advantage of *Wikipedia* ontology to embed semantic information into profiles.

Extracting semantic knowledge: To extract semantic knowledge from *Wikipedia*, a content-based method is applied to enable system find proximity between *Wikipedia* concepts, thus connections between concepts can be established. In this method, each *Wikipedia* article (*i.e.*, concept) is represented by a *tf-idf* vector. The similarity between concepts are measured by computing the cosine similarity of their corresponding vectors. Then, a symmetric concept-concept matrix, called semantic kernel S, is created to present similarities among all pairs of *Wikipedia* concepts. Each element $S_{i,j}$ of this matrix determines the cosine similarity between a pair of concepts with indexes i and j, respectively, where $i, j \in \{1, 2, \ldots, c\}$ and c is the total number of concepts considered. If a row and a column refer to the same concepts or two synonym concepts, the similarity value is 1. Note that queries on synonym concepts are redirected to the same page by *Wikipedia*. Further, the more similar two corresponding concepts are, the higher the value of the corresponding entry is. This kernel represents semantic relationships among all *Wikipedia* concepts according to similarities of their corresponding articles.

Integrating Background Knowledge into Experts' Profiles: To integrate the semantic knowledge represented in matrix S into profiles, first a type of relation needs to be defined that associates profiles to *Wikipedia* concepts. For this purpose, a scheme based on the concept match is adopted to map the text document profiles to the *Wikipedia* concepts directly. In this mapping scheme, profiles are scanned and similarity-based correlations between *Wikipedia* concepts and each profile are measured. To calculate the similarity between a profile and a concept, the *tf/idf* representation method is utilized. Profiles and concepts are presented in form of vectors in which dimensions are *Wikipedia* concepts. Expert profiles are considered as a collection of documents and each concept is considered as a phrase query which can be assumed a short text document. In addition, all operations that are applied to documents in *tf/idf* approach, like porter stemmer or removing stop words, now are applied to concepts that are considered as query phrases. Finally, the cosine similarity is used to measure the similarity between pairs of corresponding vectors of document profiles and *Wikipedia* concepts. The result is presented in a document-concept matrix D in which a row entry represents a profile, columns are *Wikipedia* concepts, and each element $D_{i,j}$ denotes the cosine similarity between a document i and a concept j of *Wikipedia*, where $i \in \{1, 2, 3, \ldots, n\}$, $j \in \{1, 2, \ldots, c\}$, n is the number of documents, and c is the number of concepts.

Once the document-concept similarity matrix is built, the semantic knowledge represented by the semantic kernel can be integrated into the profile representation. For this purpose, a linear combination of the document-concept matrix D and the semantic kernel S is applied and and a new semantic-based document-concept similarity matrix R is generated. The new matrix represents the semantic-based profiles. Each element $R_{i,j}$ is calculated as follows:

$$R_{i,j} = \sum\nolimits_{k=1}^{c} D_{i,k} \times S_{k,j} \tag{1}$$

, where k is the number of concepts, $1 \leq i \leq m$ is the row index and $1 \leq j \leq n$ is the column index. As the formula shows, the occurrences of all other concepts in i^{th} document affect the semantic relationship between j^{th} concept and i^{th} document as well by considering the weights of all concepts' similarities to the j^{th} concept. In other word, the weight of each concept's influence on the semantic relationship between a specific concept j and a document i is equal to the similarity of that concept to concept j. Figure 1 shows an example semantic-based document-concept similarity matrix resulted from the linear combination of a document-concept matrix D and a semantic kernel S. In this example, only three *Wikipedia* concepts are shown.

Fig. 1. Linear combination of D and S that produces R

3.3 Construction the Social Network of Experts

In order to build the social network of experts, a relationship between experts should be defined. For this purpose, expert profiles are considered as nodes of the network and semantic-based similarities among all pairs of profiles are considered as edges. In order to compute the semantic proximity of profiles to each other, an operation widely used in social network analysis, namely folding, is applied. Assume the semantic-based document-concept similarity matrix R, in which rows represent documents and columns represent concepts. Multiplying the similarity matrix R, by its transpose R', will produce a new symmetric matrix in which rows and columns both represent profiles and elements quantify the semantic relationship between pairs of expert profiles. This recently generated similarity matrix is used to construct the links in the social network of experts. For each pair of profiles, if their corresponding similarity in the similarity matrix is a none zero value, then a link is established between the corresponding experts in the network.

Detecting Expert Communities: A community is typically thought of as a group of nodes with more interaction amongst its members than between its members and the remainder of the network. Different clustering algorithms can be applied for this purpose. In this study, the aim is to detect communities of experts such that there are stronger similarities between cluster members, in terms of expertise, knowledge, and experience, than between cluster members and other members of network. We have chosen k-means clustering algorithm to detect the communities of experts. Further, two measures, homogeneity and separateness, are used to evaluate clustering solutions. Since these objectives are conflicting, k-means algorithm is applied with various numbers of clusters (k) until an acceptable compromise is achieved. In other words, we have to trade off between maximizing homogeneity and minimizing separation. In order to apply k-means algorithm to cluster the social network, each node (expert) is represented by a vector whose features are the semantic-based similarities to all other actors in the network. Clearly, the recentley generated similarity matrix can be used for the clustering purpose as each row of the matrix presents the similarity of an expert to all other experts.

Finding Communities Representatives: Usually clustering solution can be summarized by introducing a representative member for each cluster. In our work, since each cluster represents an expert community, the representative member of a cluster is in fact an expert who summarizes that community in terms of the knowledge, experience, and expertise carried by its members. To find a cluster representative, we have decided to use a centrality measure, called *eigenvector centrality*, which is widely used in social network analysis. According to the *eigenvector centrality*, a node is central to the extent that its neighbors are central. In other words, in a clique the individual most connected to others within the cluster and other clusters, is the leader of the cluster. Members who are connected to many otherwise isolated individuals will have a much lower score in this measure then those that are connected to groups that have many connections themselves. In our domain, the *eigenvector centrality* follows that an expert well-connected to well-connected experts can carry on valuable types of knowledge and experience much more widely than one who only has connections to lesser important experts in a community. Experts with higher scores of *eigenvector centrality* are more favorable when it is needed to find the right people whom we may ask a specific question and who will answer that question for us.

3.4 Building the Expert Recommendation System

In this work a hybrid approach, that integrates the content-based characteristics into a social network-based collaborative filtering system, is proposed to recommend the most appropriate information items to communities of experts. Information items are specified in forms of user's questions for which a user is seeking for the right experts. By applying similarity measures commonly used in information retrieval approaches, in particular cosine similarity measure, information items are recommended to members of a community if they highly match with the knowledge taste and preferences of that community members. The social network component of the proposed system captures the social aspect of the experts' behaviors. Experts collaborate with their peers on different knowledge areas to obtain new expertise and improve their own knowledge and experience. For a user who is looking for an expert for her/his information needs, our system recommends a representative of a social community whose members have the relevant knowledge. We argue that a representative will be a better choice than an individual expert who has been recommended only based on the expert's individual profile regardless of her social relations. If more than one expert is required, more members of the same expert community are recommended. Experts in a social community are more similar to their community members than the other experts in terms of knowledge, experience, and expertise. In other words, all members of a community are experts in almost same topics. Thus, in a collaborative filtering recommendation system, to recommend information items to more than one expert, community members are better choices.

4 An Example Application

In this section, we present an example for an interesting application of our proposed expert recommendation system. We have chosen the problem of a conference chair assigning papers to be reviewed by the most relevant members of the program committee. For this purpose, 315 program committee members of the 16th *ACM SIGKDD*[4] conference have been selected as the system input. In addition, 62 keywords listed under the "conference topics" have been used as information items for which the program chair is seeking for relevant researchers. This set of keywords covers a wide range of scientific topics in the field of knowledge discovery and data mining. The main goal of this experiment is to recommend a subset of keywords to the most relevant research community with respect to the type of knowledge, expertise, and experience represented by that community.

A crawler, implemented for this work, extracts relevant information from online sources, and a profile is automatically constructed for each researcher by the system. For our experiment, the *DBLP*[5] bibliography has been crawled to collect the list of publications corresponding to each researcher. Information such as list of keywords and abstracts are retrieved for publications from digital libraries and *Google Scholar*. A profile that contains this information indicates a researcher's interests, experiences, and specialties, etc. Further, in order to build the semantic kernel S, we have to extract contents of *Wikipedia* concepts (articles). For this purpose, we automatically construct a tree structure, for a specific domain, e.g. *compute science*, which contains both category and concept pages. The tree structure will help us extract all pages related to that specific topic that appears in the root of the tree. For clustering analysis, *Weka*[6], an open source data mining tool was used. In addition, *ORA*[7], a social network analysis tool, was utilized for identifying representatives of expert communities. *ORA* calculates the eigenvector centrality of all members of a community and the member with the highest eigenvalue is reported as the representative of that community.

[4] http://www.kdd.org/kdd2010
[5] http://www.informatik.uni-trier.de/~ley/db/
[6] http://www.cs.waikato.ac.nz/ml/weka/
[7] http://www.casos.cs.cmu.edu/projects/ora/

4.1 Clustering Experiments

In the community detection phase, two criteria are used to find the best clustering solution: homogeneity and separation. Indeed, the semantic-based similarities (relationships) between researchers in the social network are treated as features to describe corresponding nodes. The k-means algorithm clusters social network nodes in different groups based on values of these features. We examine various clustering solutions, generated by the algorithm using different values of k in the range of 10 to 40. Then we choose a clustering solution which is an acceptable trade off between maximizing homogeneity and minimizing separation as the best solution among others. The range of k is chosen based on the number of researchers as well as the number of information items such that the average number of researchers in each cluster varies in a reasonable range. In our experiment, the best clustering solution for the expert social network is the solution with 12 clusters. In Figure 2, the number of clusters for different clustering solutions is plotted on the horizontal axis against the values of homogeneity and separateness on vertical axes.

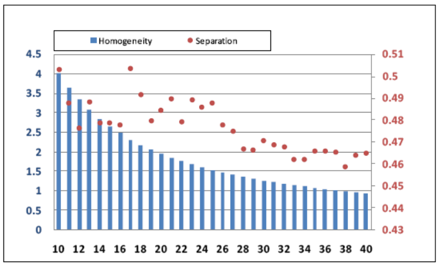

Fig. 2. Results of homogeneity and separateness for different clustering solutions

4.2 Recommendation Experiments

We have conducted two sets of experiments in order to investigate the performance accuracy of the recommendation system with and without the social network component. When the social network is not used, recommendations are made based on the similarity between researchers' profile and information items. In the other words, the importance of individuals in their community is neglected. In the second set of experiments, the system utilizes the social network of experts through the process. Recommendations are made based on the similarity between communities' representatives and information items. In this approach, the most appropriate experts are selected from a community whose representative has more expertise and knowledge about the requested item based on his/her profile information. In both approaches, if more than one expert is required, the system automatically suggests the second most relevant expert.

To measure the accuracy of our system, a set of 23 researchers is chosen to form a test set. Then, a questionnaire, for each researcher in the test set, is designed to discover preferred information items that a researcher is interested in. The questionnaires would contain 15 items from relevant to irrelevant. Questionnaires designed for different researchers were different from each other because we prepared them based on recommended items by our system to researchers. Researchers were asked to score information items based on their relevancy to researchers' interests. To evaluate the accuracy of the recommended items, a metric called precision at n or $P@n$ was used. This precision is defined as the fraction of retrieved instances that are relevant. Precision takes all retrieved items into account, but it can also be evaluated at a given cut-off rank, considering only the topmost results returned by the system. We consider k-top most relevant items that the system recommends to researchers and investigate how many of them are actually relevant considering the researchers real interests given in the questionnaire. In using of $P@n$, we set n to 1, 3 and 5. For example, $P@1$ indicates the percentage of researchers who are recommended relevant information when only one information item is considered. The same method is applied to evaluate the accuracy of the prediction when information items are recommended to members of communities whose representatives have expertise and knowledge relevant to information items for which we are looking for experts.

Type of Measure	Result (%)	
	Recommendation without Social Network Component	Recommendation with Social Network Component
P@1	82.6	83.4
P@3	78.2	75.0
P@5	75.6	78.4

(a)

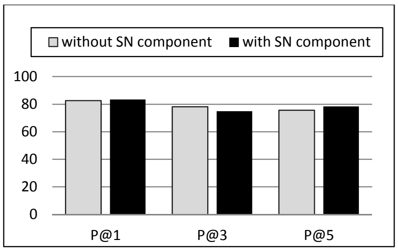

Fig. 3. The prediction accuracy of two recommendation models

Figure 3.(a) demonstrates the precision values achieved when the above experiments were conducted. A $P@1$ value of 82.6%, appeared in the first column of the Table shown in Figure 3.(a) indicates that 19 out of 23 researchers in the test set, are recommended with relevant information item when only one information item is considered. In addition, the $P@1$ value of 83.4%, shown in the second column of the table, means that the first recommended information item to 83.4% of representatives are relevant. In other words, 10 out of 12 (12 is the number of communities achieved in the precious experiment) representatives are recommended with relevant item when only one information item is considered.

As described earlier, the proposed recommendation system helps users, who are looking for the most appropriate expert in a specific domain, choose representative member of each community to fulfill their information needs. In fact, a representative member can represent the knowledge and expertise of all members within the same community better than any other member in his/her community since his/her similarity to mate elements is the highest among all other mates. Thus, whenever a user searches for an expert who has relevant expertise to a specific information domain, a reliable choice is to trust to a community representative who is recommended by the system. In addition, if more than one expert is needed, other community members can be recommended according to their importance indicated by eigenvector centrality measure; community members with higher eigenvector centrality are more reliable in that specific domain. Figure 3.(b) summarizes the performance results shown in the result Table in Figure 3.(a). As can be seen, the performance of recommendations with the social network component slightly outperforms the performance of recommendation system without the social network component. Indeed, considering three types of precisions that were calculated in each experiment, only $P@3$ value for recommendation system without the social network component is higher than its corresponding value in the second experiment. Therefore, based on the comparison made between the results, the use of social network seems to be reasonable in that it improves the prediction accuracy of the recommendation model.

5 Conclusion

We presented a hybrid expert recommendation system which is indeed a social network-based collaborative strategy that it also maintains the content-based profiles for each expert. These content-based profiles, once enriched with the semantic knowledge, are used to calculate the similarity between pairs of experts. Our system captures the social structure of the experts' relations by constructing a social network and utilizes the social characteristics of individuals while making recommendation. The proposed system employs a clustering analysis approach to discover expert communities. Representatives are identified by their centrality measures within their communities. Recommendations are made based on the relevancy of an information item, for which a user is looking for experts, to the knowledge carried by representatives of groups. The proposed framework was tested in a typical application domain with a real data set. Experimental results show that in the presence of the social network component, recommendations made by our system on average have higher accuracy than the recommendation predictions when the system neglects the social structure of individuals.

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