Exploiting Publication Contents and Collaboration Networks for Collaborator Recommendation

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ABSTRACT

Due to the expansion of academic research in diverse fields, the problem of finding relevant and potential collaborators has become cumbersome. In this work, we propose an academic collaboration recommendation model called C-CRec. CCRec combines publication contents with collaboration networks to effectively generate academic collaboration recommendation for researchers. Using the DBLP data sets, we conduct benchmarking experiments to examine the performance of CCRec. Our preliminary experimental results show that CCRec outperforms other state-of-the-art methods especially in addressing the topic drift problems.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

General Terms

Theory

Keywords

Collaboration recommendation, publication contents, collaboration networks, topic clustering, random walk.

*Dr. Trovato insisted his name be first.
†The secretary disavows any knowledge of this author's actions.
‡This author is the one who did all the really hard work.

1. INTRODUCTION

Nowadays, with rapid development of Internet technology, the scale of Internet is beyond the imagination of people and Internet gradually becomes the main carrier of sharing information. Thus, how to obtain the useful one from vast information has become a complex task with the problem of information overload phenomena occurring. Therefore, recommender systems and techniques immensely help people by providing easier access to the specific resources they really need.

In academia, cooperation among researchers is of vital necessary. Studies show that researchers are usually prolific by well collaboration with collaborators. This is to say, the collaborator is a considerable factor well connected with the productivity of a scholar. So scholars tend to get acquainted with potential collaborators, especially the most valuable collaborators. In academic social networks, there has been a variety of methods proposed recommending collaborators who they have ever collaborated with or never.

In this context, previous studies have exploited mainly two aspects for academic collaboration recommendation, that is content-based and collaboration network-based methods respectively. Plenty of researches show that the traditional content-based method mostly focuses on the tags made by people, which can not completely stand for the research topic of the scholar. Thus, it would be imperative taking research field into account when recommending collaborators, particularly the personalized recommendation on account of various research fields. For the collaboration network-based method, there has been a suite of methods such as Random Walk algorithm, but rarely methods have ever integrated the content-based and collaboration network-based method. What's more, in view of the burdensome and embarrassing initial collaboration with unconnected researchers ever and the less value of already known collaborators, the unconnected researchers are more deserve to be recommended to seek more potential and valuable collaborators.

In this paper, we propose a novel hybrid model exploit-

ing publication contents and collaboration networks for collaborator recommendation called CCRec. CCRec combines the content-based method and collaboration network-based method by synthesizing publication contents and collaboration networks. Because the publication contents are largely on behalf of the research field of a scholar, we can more precisely achieve the personalized recommendation according to their different kinds of research fields. We extract key words from publication contents of all researchers and divide these key words into several topics, then get a number of research fields corresponding to different researchers. For researchers tend to collaborate with those in the similar research field, thus in each topic there is a big collaboration network. Therefore, we explore all the collaboration networks in each research topic. With the publication contents and collaboration networks combined, CCRec greatly outperforms other traditional methods recommending totally new collaborators.

CCRec first uses topic clustering to partition the words from all the publications' titles into multiple domains. Then, CCRec computes the degree of interest (DoI) and the strength of influence (SoI) pertaining to each domain for each researcher. Finally, DoI and SoI are combined to form the feature vector for each researcher. By comparing the similarity of feature vector, CCRec provides a TopN collaboration recommendation list.

The remainder of the paper is structured as follows. Section 2 briefly presents the related work. We discuss the details of our model in section 3, which highlights the problem statement and the structure of the model. In section 4, we conduct a mass of experiments and analyzes the results. At last, section 5 concludes the paper.

2. RELATED WORK

Social networks have been researched for decades to exploit the relationships and interactions between people. There is also a sample system helping people find experts on a certain topic. While summarizing the preterit work, researches mainly focus on three parts including content-based method, social networks-based method and minority hybrid method. For the first two methods, many practical examples have confirmed it, but fewer researches have done for the hybrid method.

Many approaches have been presented to formalize academic collaboration recommendation as a link prediction problem. Link prediction is to predict new links that might be added to the social networks, which is useful for collaborator recommendation, but differs from it in that the latter is context-based. David et al. first defined link prediction: to predict the edges that will be added to the network in the future time t' at the time of t in a social network. Some of these approaches have been applied to large social networks and results show a good performance. Lichtenwalter et al. examined some important factors for link prediction and proposed a general framework.

For content-based method, the CollabSeer system recommends collaborators for a researcher, which a an open system introduced by Chen et al. considering research interests for collaborators recommendation. Lopes et al. considered researchers' publications area and the vector space model to make collaboration recommendation. Pavlov and Ichise extracted structural attributes from graph of past collaborations and uses them to train a set of predictors using supervised learning algorithms, then these predictors can be used to predict links between existing nodes in the graph. Tin Huynh et al. proposed a new approach that uses additional information as new features to make recommendations, i.e., the strength of the relationship between organizations, the importance rating, and the activity scores of researchers. We also propose a new method for evaluating the quality of collaborator recommendations.

Ma et al. analysed how social networks information can benefit recommender systems and proposed a method improving the performance of recommender systems by incorporating social network information. In addition, Lopes et al. present a novel method for recommending new collaborators and identifying existing collaborations. They took the semantic issues involved in the relationships among researchers in different areas. Barabasi et al. analysed the basic network properties of academic social networks in terms of degree distribution, average separation, clustering coefficient, average degree and so on. In another study, Newman researched a number of statistical properties of scientific collaboration networks like the number of papers, numbers of collaborators and degree of clustering in the networks, etc.

Lee et al. studied how well content-based, social networks-based and hybrid recommendation algorithms predicted coauthor relationship, and the result show that a hybrid algorithm combining content and social networks information outperformed better.

3. DESIGN OF CCREC

Our proposed design scheme for CCRec is inspired by the reality and truth that a researcher usually desires to know other researchers who have similar research interests and strong influence in academia. As mentioned above, researchers often behave differently across multiple domains of interests. Such behaviors usually reveal academic features of different researchers in different domains. Besides, as a social-based model, the RWR model has been proved to be competent for calculating the rank score of node in social networks derived from the co-authorship [2], researchers' strength of influence in specific domains can be well reflected by RWR. In this work, we adopt a content-based method to acquire multiple domains of interests. and use RWR to measure the researchers' strength of influence in different domains. After that, We use the feature vector to evaluate the similarity of researchers and then obtain the recommendation list. The detailed process is described bellow and the corresponding pseudo-code is illustrated in Algorithm 1. Figure 1 depicts the three components of CCRec.

3.1 Topic Clustering and Researcher Partition

It is a content-based method for topic clustering and researcher partition, which generates various domains and maps all researchers into these domains. In this work, we use a famous tool of NLP (Natural Language Processing), word2vec, which provides an efficient implementation of the continuous of *bag-of-words* and *skip-gram* architectures for computing vector representations of words. It takes a text corpus as

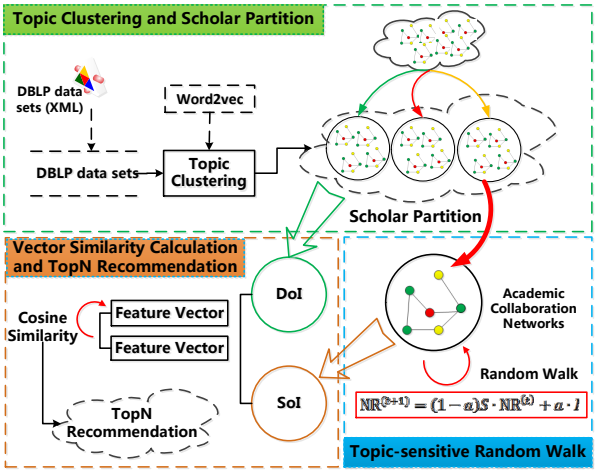


Figure 1: The architecture diagram of CCRec model

input and produces the word vectors as output. The resulting word vector file can be used as features in many natural language processing and machine learning applications. The word vectors can be also used for deriving word classes from huge data sets. This is achieved by performing K-means clustering on top of the word vectors. The output is a vocabulary file with words and their corresponding class IDs. In case of CCRec model, the input data is a set of titles from all the papers created by each researcher. The titles are split in many sequential words. In addition, there is a necessary to filter out some irrelevant words, e.g. "of","the", "and", etc. For extracting from titles, this set of preprocessed words can outline the core contents of papers, which are signified as valuable and reliable corpus to denote a variety of academic topics. With this English corpus,word2vec obtains various domains and cluster the word into the domains.

In addition, CCRec partitions researchers to particular domains with follows method. 1, Extract mesh terms from a researcher's publications. 2, Traverse all the terms and check the word vector. The model will tag the researcher to the particular domains which contains these domains. It should be emphasized that one researcher always belongs to several domains and there are also many researchers in one domain.

3.2 Feature Vector Calculation

As mentioned in section 2, in general, researchers devote to several adjacent domains. But in the case of attention and strength of influence in various domains, they are offering some biases. To measure the distribution of researchers' interest, we define the *SoI* (Strength of Influence) to denote the academic values (Rank Score) of researchers in different domains, which can be regarded as the elements of feature vector of researchers. In case of one of the domains, there are numerous researchers with similar research interest. Their co-author relationships can be modeled by a network. Thus, there are many co-author networks corresponding to different domains. The *SoI* is measured by RWR model based on the co-author networks. The core equation of the RWR model is shown below:

$$R_d^{(t+1)} = \alpha \mathbf{S} R_d^{(t)} + (1-\alpha)q \tag{1}$$

where R_d represents the rank score vector of all researchers in domain d, q is the initial vector R^0, and α denotes the damping coefficient. RWR is an iterative process. After limited iterations, the vector R will be convergent. In this scenario, $SoI_s = R_{d,s}$. That is, the final value of the vector item $R_{d,s}$ is the SoI of researcher s.

In addition, with the help of RWR, The SoIs in various domains are quantified for each researcher. To measure researchers academic feature, we define the vector F with SoI.

3.3 Collaboration Recommendation by Feature Vector Similarity

CCRec recommend collaborators for researchers based on their similarities. To measure the academic features similarity of researchers, we borrow a standard method, *cosine similarity* (CS). CS is employed to define the similarity between two users s_1 and s_2 based on their feature vectors F_{s_1} and F_{s_2}.

$$Sim(s_1, s_2) = \frac{\sum_{i=1}^{n}(F_{s_1,i} * F_{s_2,i})}{\sqrt{\sum_{i=1}^{n} F_{s_1,i}^2} * \sqrt{\sum_{i=1}^{n} F_{s_2,i}^2}} \tag{2}$$

Finally, we consider that researchers with high similarities have common interest, they should be recommended to each other as potential academic collaborators. Hence, CCRec provide a TopN recommendation list for each researcher.

4. EVALUATION AND ANALYSIS

We conduct various experiments using data from DBLP [1], a computer science bibliography website hosted at University Trier. We extracted the subsets of the entire data using the required information, which are all in the field of data mining involving 34 journals and 49 conferences. The data was modeled by an academic social network, which contains 59659 nodes (authors) and 90282 edges (coauthor relations). We divided the data set into two parts: the data before year 2011 as a training set, and others as a testing set.

We embarked on benchmarking experiments on CCRec. To evaluate the performance of CCRec model in a better way, we use three metrics which are widely used in the recommender systems, *Precision*, *Recall* and *F1* [4]. We compared CCRec with the two following approaches. ACRec: a random walk recommendation model based on collaboration networks [2]. CNRec: a common neighbors based recommendation model [3]. Four groups of experiments were conducted. 1, Find the most valuable collaborators, who may have known each other before, or active in adjacent circles. 2, Recommend most potential collaborators, who have never cooperated with the target researcher before. 3, Evaluate how domains clustering impact the performance of CCRec. 4, Exploit the impact of clustered domains number on CCRec. For each experiments, we randomly chose 100 constant researchers which are at least somewhat active in academic activity, say have coauthored more than 30 person-time with others. We make collaborators recommendation for these 100 researchers, moreover compute the average of precision, recall and $F1$.

All experiments were performed on a 64-bit Linux-based operation system, Ubuntu 12.04 with a 4-duo and 32GHz Intel CPU, 4-G Bytes memory. All the programs are implemented with Python.

4.1 Most Valuable Collaborators Recommendation

In our previous work [2], We proposed the ACRec model to make the most valuable collaborators for researchers. In this section, we explored the performance of CCRec and ACRec on making most valuable collaborators recommendation. The comparative results are shown in Fig. 2.

As shown in Fig. 2, The number of recommended collaborators have an obvious influence on the metrics with a clear trend. In the case of CCRec, as shown in Fig. 2(a), the precision drops when the number of recommended collaborators is increasing. At the same time, the recall in Fig. 2(b) rise with the growth of recommendation list, which approximate to 20% in the end. As for ACRec, it has the same trend with CCRec on precision and recall. Thus it can be seen, the precision and recall is a pair of contradictory metrics. Weighing the two metrics to maximum the profit, G. Shani et al. [4] adopt the metric $F1$. Fig. 2(c) describes the performance of CCRec and ACRec on $F1$. In case of CCRec model, the $F1$ generally increase until the number of recommended collaborators is over 15, and then decrease gradually. Since the point 15 is exactly the peak of $F1$. We can see that, CCRec performs best when recommend 15 collaborators to each researchers, and the $F1$ can reach to 6.13%. However, in this scenario, ACRec get its' highest $F1$ score 11.01% at point 30.

In terms of Fig. 2, It is much in evidence that ACRec model outperforms CCRec model on making most valuable collaborators recommendation. This is because, ACRec base on a link-importance guiding random walk, considering the walk distance and rank score, find the most valuable collaborators who may have known each other before, or active in adjacent circles. Thus, comparing with ACRec, there is no obvious advantage for CCRec to find the most valuable collaborators in adjacent circles.

4.2 Most Potential Collaborators Recommendation

We define the Most Potential Collaborators as some collaborators who are worthy enough to be recommended and have never cooperated with the target researcher. Making the most potential collaborators recommendation is of great significance as the new collaborators are more meaningful and practical in academia. In this section, we explored the performance of CCRec, ACRec and CCRec on making most valuable collaborators recommendation.

Figure 3 shows the performance of CCRec, ACRec and CNRec in terms of precision, recall and $F1$ with the number of recommended collaborators increasing. It can be observed that CCRec significantly outperforms ACRec and CNRec all the time on these three metrics. CCRec shows a downtrend for precision and an uptrend for recall rate. In the case of $F1$, it reaches the peak 4.18% when recommending 21 researchers. We also see the evidence of this, when making most potential collaborators recommendation, ACRec performs similarly to CNRec.

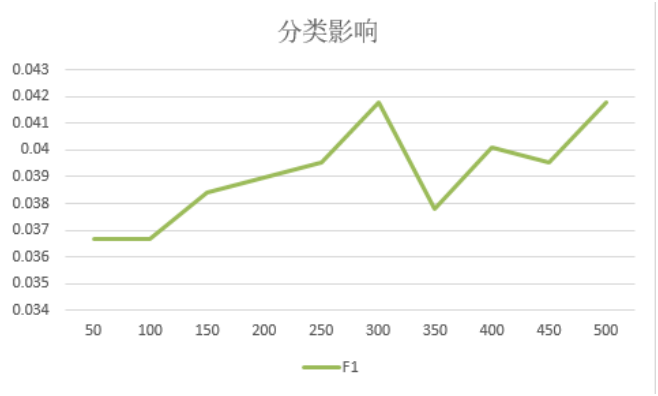


Figure 4: The impact of clustered domains number on CCRec

In a nutshell, CCRec outperforms ACRec and CNRec with higher precision, recall and $F1$ on making the most potential collaborators. We analyzed the theory. Each researcher is represented by the feature vector, as well as CCRec model combines publications contents and collaboration networks to define the vector, which has distinct advantages (e.g. rich information, more accurately to represent researchers' feature) in recommending new collaborators.

4.3 Impact of clustered Domains number

In this section, we exploit the impact of clustered domains number on the performance of CCRec. We adopted the following experiment settings. 1, Evaluating how the $F1$ change with the number of collaborators recommended. 2, Make the most potential collaborators recommendation for those 100 researchers selected above. 3, Recommend 21 candidate collaborators for each researcher. Fig. 4 shows the experimental results.

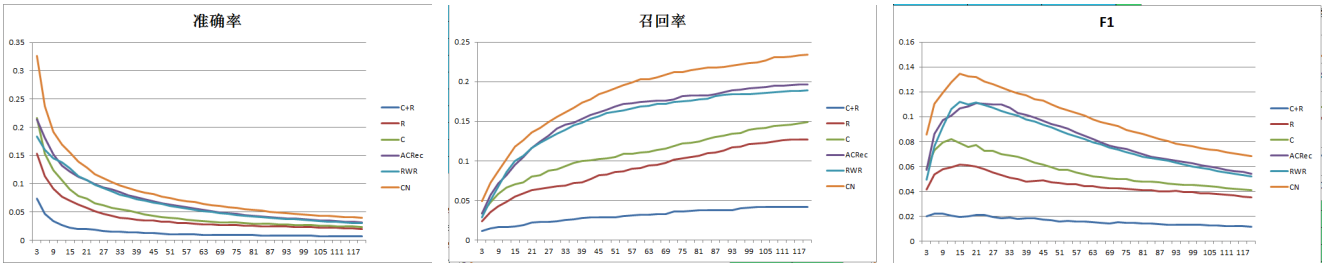
In terms of Fig. 4, the number of clustered domains does have certain effect on the performance of CCRec. If the number of clustered domains is appropriate, the $F1$ score can get some enhancement. In this scenario, when cluster the data mining academia into 300 or 500 domains, CCRec performs best on $F1$, which reach to 4.18%.

In summary, we can still claim that the works on combining the content and networks is really effective. Moreover, our approaches works well. In terms of precision, recall and $F1$, CCRec outperforms ACRec and CNRec on making most potential collaborators recommendation for academic researchers.

5. CONCLUSIONS

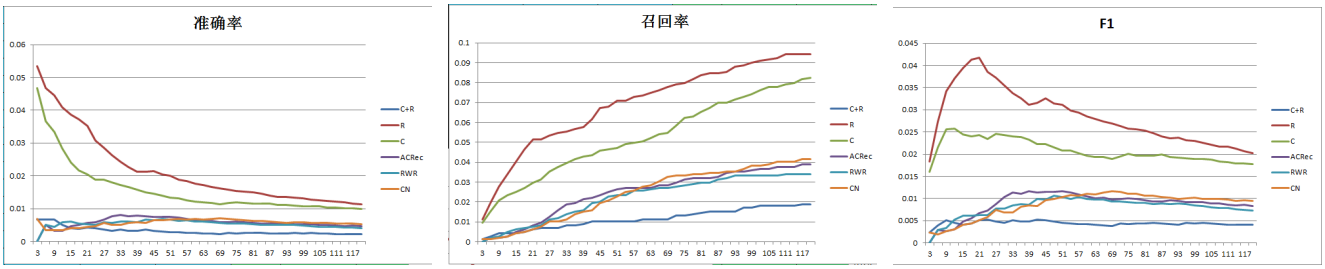
The conclusions we reach are: 1) CCRec outperforms RWRec and CNRec in precision, recall rate and F1 integrating publication contents with academic collaboration networks. 2) With topic clustering, the problem of topic drift has been well solved.

Our research on CCRec reveals that the combination of in-



(a) Precision (b) Recall (c) F1

Figure 2: Performance of CCRec and ACRec on most valuable collaborators recommendation



(a) Precision (b) Recall (c) F1

Figure 3: Performance of CCRec, ACRec and CNRec on most potential collaborators recommendation

formation regarding publication contents and collaboration networks of researchers can improve the generation of effective academic collaborations.

6. ACKNOWLEDGMENTS

7. ADDITIONAL AUTHORS

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