CCRec:Content of Publications and Collaboration Network Combined Academic Collaborators Recommendation

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Abstract

With the academic research filed expanding, the problem of finding proper potential collaborators is really cumbersome. In this paper, we proposed a content of publications and collaboration network combined academic collaborators recommendation model (CCRec). Compared to traditional approaches, CCRec is more effective because it recommends collaborators combining the content of publications and collaboration network in different topics. Experiments based on DBLP data sets show that CCRec significantly outperforms traditional approaches, with the topic drift problem well solved.

Author Keywords

Guides, instructions, author's kit, conference publications Mandatory section to be included in your final version.

ACM Classification Keywords

H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous. See: http://www.acm.org/about/class/1998/ for help using the ACM Classification system. Mandatory section to be included in your final version.

Introduction

Collaboration network is one kind of academic social networks formed by scholars and their collaborations. In the academic field, recommending collaborators to scholars or groups may help scholars build more collaborations and better communications.

Studies show that they often recommend academic collaborators by exploiting the collaborations network and the profiles of scholars such as affiliation. However, the fact is always ignored that collaborations among scholars largely depend on the research field reflected from their publications. Thus it may have a superior performance to combine the content of publications and collaboration network to compare the similarity of scholars.

This paper proposed a content of publications and collaboration network combined academic collaborators recommendation model (CCRec). CCRec first uses the topic clustering (sensitive) 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 scholar. Finally, DoI and SoI combine to form the feature vector for each scholar and comparing the similarity of feature vector can get the recommending list.

PROPOSED SCHEMA

Overview

The TSCRec academic collaborators recommendation model is inspired by the truth that scholars usually desire to co-operate with people who have high similarity with them. As mentioned above, scholars often behave differently across multiple domains of interest, which can denote scholars' academic features. In this work, TSCRec model contains a simple way to obtain these domains by a topic-clustering method. We define the DoI (degree of interest) and SoI (strength of influence) of scholars on different domains. Further more, we conduct vectors for every scholars based on these two metrics to measure the scholars academic feature.

Fig. 1 depicts the four components of TSCRec: *topic clustering and scholar partition*, *Topic-sensitive random walk*, *vector similarity calculation and TopN recommendation*. Topic clustering and scholar partition provide the distribution of scholars' interest in various domains and the DoIs of every scholar. Topic-sensitive random walk calculate scholars' influence in various domains and the SoIs of every scholar. Finally, The last component provide a TopN recommendation by the vectors similarity.

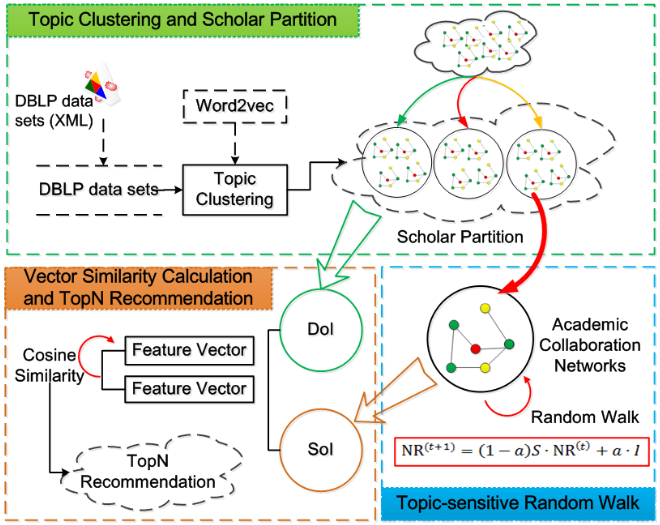

Topic Clustering and Scholar Partition
DBLP data sets (XML)
Word2vec
DBLP data sets
Topic Clustering
Scholar Partition
Vector Similarity Calculation and TopN Recommendation
Cosine Similarity
Feature Vector
Feature Vector
TopN Recommendation
DoI
SoI
Academic Collaboration Networks
Random Walk
$NR^{(t+1)} = (1-a)S \cdot NR^{(t)} + a \cdot I$
Topic-sensitive Random Walk

Figure 1: The architecture diagram of TSCRec model

Topic Clustering and Scholar Partition

In TSCRec, topic clustering and scholar partition conducted various domains and map all scholars to these domains. Initially, TSCRec extract and parser key words from titles of all the papers in academic area and filter out some unworthy grammatical particle, e.g. "of", "the", "and". As a text corpus, these set of preprocessed key words are rich in a variety of academic topics. The word2vec, a famous tool of NLP (Natural Language Processing), is utilized to cluster the key words into different topics which can denote various academic domains. Afterwards, TSCRec extract the key words from titles of scholars' papers, and partition these scholars into different domains by mapping every authors' key words into relevant topics obtained above. Assuming that, there are some keywords of one scholar belongs to a topic, we will partition this scholar into this topic. What we can come up with is that, one scholar can appear in different domains for its diversity of interest which can exactly represent its distribution of scholars. In general, there are also a great many scholars in each domains.

Feature Vector Calculation
To measure the distribution of scholars' interest, we proposed DoI to define the scholar's proportion of interest in one domains:

$$DoI_{s,d} = \frac{N_d}{\sum_{k=1}^{n} N_k} \tag{1}$$

It is a content-based method by utilizing the information on the titles of scholars publications. Where N_d is the number of key words of scholar s in domains d.

We proposed SoI to define the scholar's strength of influence in one domains, which is measured by a random walk method based on co-authorship networks.

$$R_d^{(t+1)} = \alpha \mathbf{S} R_d^{(t)} + (1-\alpha) q \tag{2}$$

It is a graph-based method by utilizing the information of co-authorship networks. Where R_d represent the rank score vector of all scholars in domain d, q is the initial vector of R, α denotes the damping coefficient. Random walk is a iterative process. After limited iterations, the vector R will be convergent. We can get $SoI_s = R_{d,s}$.

To be more accurate, We define feature vector F by combining DoI and SoI, which measure the academic feature of scholar on various domains.

$$F_{s,d} = DoI_s * SoI_s \tag{3}$$

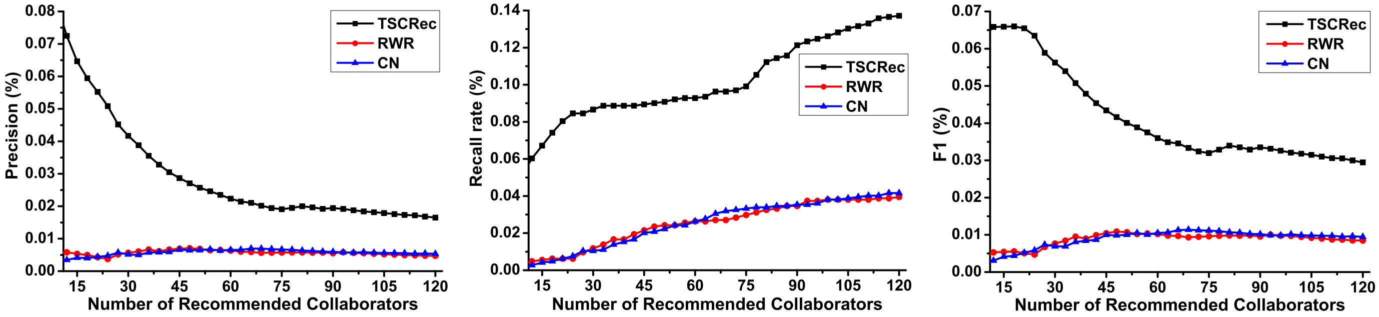
Collaborator Recommendation by Feature Vector Similarity
In C2Rec, The academic feature of scholars is measured by the feature vector F. We use a *cosine similarity* method to computing the similarity of these feature vectors, and further denoting the similarity between scholars.

$$SimCos(s_1, s_2) = \frac{\sum_{i=1}^{n} (F_{s_1,i} * F_{s_2,i})}{\sqrt{\sum_{i=1}^{n} F_{s_1,i}^2} * \sqrt{\sum_{i=1}^{n} F_{s_2,i}^2}} \tag{4}$$

Finally, C2Rec recommend to scholars those potential collaborators who have high similarity with them, and provide a TopN collaborators recommendation list.

Evaluation and Analysis

We have conducted experiments with data sets of all Data Mining on DBLP. We take the year 2011 as the partition of training set and testing set. To better evaluate our model, we compared CCRec with two traditional approaches Random Walk with Restart (RWR) [1] and Common Neighbors (CN) [2]. And the metrics to evaluate the performance are precision, recall rate and F1. What we should illustrate is that we just recommend the new collaborators who never cooperated with the scholar,



(a) Precision

(b) Recall Rate

(c) Coverage Rate

Figure 2: Performance of TSCRec, RWR and FOF

because the new collaborators are more meaningful and practical in real academic filed.

Figures above show the performance comparison of CCRec, RWR and CN in precision, recall rate and F1. From the experimental results, it can be observed that CCRec significantly outperforms RWR and CN. Figure 1 reveals that the precision of CCRec is always higher than that of RWR and CN. It shows an upward tendency for the recall rate of CCRec, which is obviously superior to RWR and CN. For the F1, CCRec exceeds RWR and CN all the time, and it reaches the peak 6.598% when recommending 18 scholars.

In short, CCRec outperforms RWR and CN with higher precision, recall rate and F1. This is because CCRec with content of publications and collaboration network combined has a distinct advantage in recommending new collaborators.

Concluding Remarks

The conclusions we reach are: 1) CCRec outperforms RWR and CN in precision, recall rate and F1 integrating the content of publications with academic collaboration network. 2) With topic clustering, the problem of topic drift has been well solved.

Our research on CCRec reveals the combination of research field and his academic collaboration network can not be ignored when recommending collaborators. With the two taken into account, the results of collaborators recommendation are more specific and effective. While we need to explore more on how to enhance the performance better and take more comparison experiments.