Academic Paper Recommendation Based on Heterogeneous Graph *

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Abstract. Digital libraries suffer from the overload problem, which makes the researchers have to spend much time to find relevant papers. Fortunately, recommender system can help to find some relevant papers for researchers automatically according to their browsed papers. Previous paper recommendation methods are either citation-based or content-based. In this paper, we propose a novel recommendation method with a heterogeneous graph in which both citation and content knowledge are included. In detail, a heterogeneous graph is constructed to represent both citation and content information within papers. Then, we apply a graph-based similarity learning algorithm to perform our paper recommendation task. Finally, we evaluate our proposed approach on the ACL Anthology Network data set and conduct an extensive comparison with other recommender approaches. The experimental results demonstrate that our approach outperforms traditional methods.

Keywords: Academic Paper Recommendation, Heterogeneous Graph, Citation Information, Content Information, Similarity Learning.

1 Introduction

Recommender system is a hot research topic in the age of big data, and has a wild range of applications. For instance, Amazon recommender system recommends some similar products that you may be interested in according to your browsing record and your registration information. As for the academic area, more and more academic papers are coming out from a lot of conferences and journals [1]. As the number of papers increased dramatically, the existing academic papers retrieval tools cannot satisfy researcher's needs. As a consequence, researchers would like to have other tools which can help to find out relevant papers to their current work. So, in order to help researchers find relevant papers quickly and precisely, paper recommender system arises at this time.

For paper recommendation, there are a variety of forms. The definition of academic paper recommendation in our work can be described as: given a paper

* This work was supported by the National Natural Science Foundation of China (No. 61472183, 61333014)

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(target paper), the recommendation system finds out some papers related to target papers. For this task, most of the existing related works recommend papers by calculating the smilarities between papers with certain information, such as citation, content, and so on. So the approaches for paper recommendation include citation-based methods [2–5], content-based methods [6] and hybrid methods [7].

In this paper, to make use of both citation information and content knowledge, we propose a new approach to perform paper recommendations. The main idea of our approach is to design a similarity learning method based on a heterogeneous graph that contains different kinds of features. We firstly present how to construct a heterogeneous graph with citation and content features in papers. Then we introduce a heterogeneous graph-based similarity learning algorithm. The similarities between target paper and candidate papers can help perform the paper recommendation task.

This paper is organized as follows: In section 2, we briefly review three approaches of paper recommendation. In section 3, we introduce the structure of a heterogeneous graph to represent papers and their relations. And then we present a heterogeneous graph-based similarity learning algorithm which is further applied for recommendation. In section 4, the experimental results are shown to evaluate our method. We conclude the paper and give the future work in section 5.

2 Related Work

Co-coupling was the first citation-based method proposed by Kessler for paper recommendation [3]. Citations were analyzed to establish the similarities between papers. Co-coupling occurred when two papers referred a common third paper, then that two papers were Co-coupling. It was an indication to say that the two papers were related to the same topic. The Co-coupling strength of two given papers was higher if they referred more common papers. Kessler [3] considered that the larger the value of Co-coupling strength of the two papers, the larger the probability of the two paper shared a common topic.

Co-citation, like Co-coupling, was also a paper recommendation approach that makes use of the citation information [5]. Co-citation was defined as the frequency with which two papers were cited together by other papers. If two given papers were both cited by many other papers, that two given papers must be highly relevant.

Lawrence proposed an approach called CCIDF (Common Citation Inverse Document Frequency) [4]. The algorithm calculated the CCIDF value of all papers in the database to a given paper A. The CCIDF was calculated according to the following three steps:

1. Use the Identical Citation Group algorithm to get a count (c_i) of how frequently each cited paper i occurs in the database. Take the inverse of these frequencies as a weight for that citation ($w_i = \frac{1}{c_i}$).
2. Find the set of n papers B_j which share at least one common citation with A.

3. Compute the CCIDF score between paper A and $B_j (j = 1, ..., n)$, the function is defined as follow:

$$CCIDF_j = \sum_{(i \in A) \bigcap (i \in B_j)} w_i \tag{1}$$

Finally, choose the N-best papers with high CCIDF values for researchers as recommendation.

Another citation-based method was proposed by Yicong Liang [2], Which performed recommendation from an citation network. Firstly, they used a new metric called Local Relation Strength to measure the relatedness between cited and citing papers. Secondly, they used a Global Relation Strength model to compute the relatedness between two papers in the entire citation network. Nevertheless, these citation-based methods disregarded other useful information.

Almost all citation-based methods have the risk of that if a candidate paper has no citation relation to the target paper, the candidate paper will never be recommended even they share many common contents, like keywords or topic words. So, citation-based methods obviously disregarded some other useful information, such as content of papers.

Ohta et al. [1] proposed a content-based method to recommend relevant papers to support online-browsing of research papers. They generated a bipartite graph which consists of two kinds of nodes to represent the papers and the terms respectively. Then, they applied the HITS algorithm to assign each candidate paper a hub score, And finally according to the hub scores, the top-N papers would be recommended.

Hassan and Radev [7] firstly used both citations information and content knowledge to compute the similarity between two papers. They used the cosine measure to compute the content similarity. And if one paper had citation relation to another paper, the two papers were also considered similar. And they simply define a linear combination of the two similarities as follow:

$$s(x, y) = \omega * content(x, y) + (1 - \omega) * citation(x, y) \tag{2}$$

Where $\omega \leq 1, s(x, y)$ is the mixture similarity between paper x and paper y, $context(x, y)$ is the content similarity, and $citation(x, y)$ is the citation similarity. This formulation clearly did not take into account any dependency between content and citation.

3 Our approach: Paper Recommendation with Heterogeneous Graph

In this section, we will introduce our approach which can jointly make use of both citation and content knowledge for paper recommendation with a heterogeneous graph. In section 3.1, we propose the construction of a heterogeneous graph to represent the citation information and the text content knowledge simultaneously. In section 3.2, we introduce a heterogeneous graph-based similarity learning algorithm which is further applied to recommend papers. Finally, we present a simple introduction of the solution of the similarity learning algorithm.

3.1 Construction of the Heterogeneous Graphs

Both citation information and content knowledge are valuable for papers recommendation. In detail, the references and citations between papers and the words in papers are key clues for papers recommendation. And there are also dependencies between the words in papers. The heterogeneous graph is a natural representation for the data with different kinds of features. A heterogeneous graph also can be called as a multi-layer graph for more clearly presented.

As for our paper recommendation task, we can construct a multi-layer graph with nodes of papers and nodes of words. We now formally present the definitions of the multi-layer graph as follows.

Definition 1: Papers Citation Graph The paper citation graph describes the relationship between the citation papers. For simplicity, the citation graph is an undirected graph, which can be represented by a two tuple, $G_p = \{V_p, E_p\}$. Each node represents a paper, and each edge represents citation or reference between two papers. If paper p_i cites paper p_j, the initial weight of edge w_{ij} equals to $context(p_i, p_j)$. The context function is as follow:

$$context(p_i, p_j) = cosine(p_i, p_j) = \frac{||p_i \cdot p_j||}{||p_i|| \times ||p_j||} \tag{3}$$

Where p_i and p_j are vectors, which represent the content of paper p_i and p_j respectively. The key-terms are extracted based on the $tfidf$ score, the weights of these key-terms are computed by wordnet, and if key-terms t_j appears in paper p_i.

Definition 2: Key-Terms Graph Contents, like words or terms, are another kind of key features. So, we will construct a words graph, $G_t = \{V_t, E_t\}$. Considering the scale of the graph, we extract some key-terms as nodes with the following three main steps:

1. We remove the stop words from these papers.
2. We use TF-IDF [8] to score all the candidate key terms, and all the candidate key-terms are ranked according to the TF-IDF score, then we select the K top ranked terms from each paper as the nodes in the key-terms graph. The $tfidf_i$ of the term t_i is defined as follow:

$$tfidf_i = tf_i \times \log\left(\frac{N}{m}\right) \tag{4}$$

Where tf_i is the frequent count of the term t_i in a document, N is the total number of the documents, and m is the number of documents which contain the term t_i. At the same time, we regularize the $tfidf$ score for each word in the same paper, then, the $tfidf$ score is regarded as the initial score of the importance the key-term to the paper.

3. We compute the initial similarity between the key-terms.

Now, each node represents a key-term and each edge represents the similarity score of two terms. In this paper, we use a knowledge-based approach to compute the similarity between two terms. WordNet is a lexical database for English. This database links English nouns, verbs, adjectives, and adverbs to sets of synonyms that are in turn linked through semantic relations that determine word definitions. We use the Leacock-Chodorow which relies on the shortest path between two terms in WordNet [9, 10]. First, the method finds the Least Common Subsumer (LCS) [11], and gets the shortest path between the two terms. The Leacock-Chodorow method is defined as follow:

$$sim_{LC} = -\log\left(\frac{shortest\_path(t_i, t_j)}{2W}\right) \tag{5}$$

Where $W = 16$ and $shortest\_path$ represents the distance of term t_i to term t_j through the LCS of term t_i and t_j.

Definition 3: Connectivity between Paper Citation Graph and Key-Terms Graph The two graphs, G_p and G_t, are connected as follows. There exists an edge between paper p_i and key-term t_j if t_j appears in paper p_i.

The layer connectivity function is as below:

$$Z_{p_i t_j} = \begin{cases} 1 \text{ or } tfidf_j, & \text{if } t_j \in p_i \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

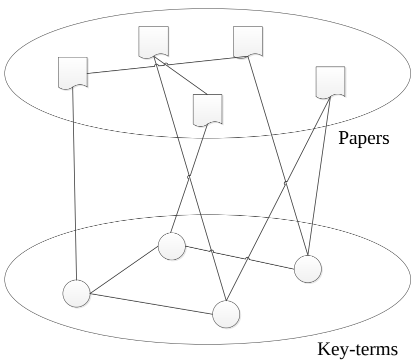

Fig. 1. An example of heterogeneous graph

Fig.1 shows the construction of a heterogeneous graph to represent the citation information and the text content knowledge simultaneously.

3.2 Similarity Learning on Graph for Paper Recommendation

The approach for incorporating information from different heterogeneous features is inspired by the graph-based framework in a semi-supervised manner [12]. Given a dataset $\{(x_1, y_1), ..., (x_L, y_L), x_{(L+1)}, ..., x_n\}$, which contained n instances, and L instances whose labels were given by $y(x)$. The method defined a single graph $G(V, E, w)$. The set of nodes was represented as $V = \{(x_1, x_2, ..., x_n)\}$. The edge weights w_{ij} represented similarity between instance x_i and x_j. The problem was to classify all other nodes using a discriminant function f. The main idea of graph-based semi-supervised classification was that similar instances tended to have similar categories. The definition of the objective function was as follow:

$$F = u \sum_{x \in L} (f(x) - y(x))^2 + \frac{1}{2} \sum_{i,j=1}^{n} w_{ij} (f(x_i) - f(x_j))^2 \tag{7}$$

Where u is a hyperparameter, and $0 \leq u \leq 1$. The objective function contains two terms. The former term aims at minimizing the difference between the ground truth labels and the predicted ones while the latter one attempts to regularize the node labeling over the network such that similar instances share similar labels.

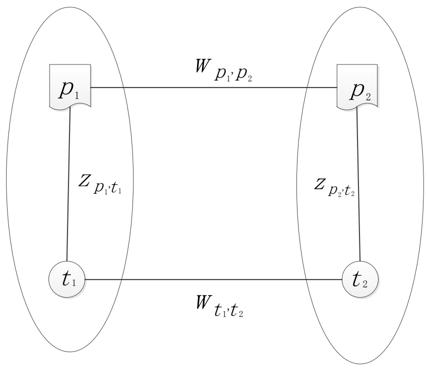

Fig. 2. Some part of the heterogeneous graph

According to the idea of graph-based framework in a semi-supervised manner, we apply the idea on our heterogeneous graph. In our method, according to the citation relationship between papers, we could compute the content similarity between papers which are the labeled instances. Fig.2 shows the main structure of the heterogeneous graph. We consider node p_1 and node t_1 as a whole, and simultaneously we consider node p_2 and node t_2 as another whole, then we consider $w_{p_1,p_2} * w_{t_1,t_2}$ as the similarity of the two parts. Similarly, we also could consider node p_1 and node p_2 as a whole, and consider node t_1 and node t_2 as another whole, then consider $z_{p_1,t_1} * z_{p_2,t_2}$ as the similarity of the two parts. So far, we transform the heterogeneous graph into a single graph, so that we extend the idea of graph-based framework in a semi-supervised manner into our task paper recommendation.

The algorithm is called heterogeneous graph-based learning algorithm which was firstly introduced by Pradeep [13]. According to the definition of paper recommendation, given a node of paper, we could recommend the top N papers according to the ranking of similarities between the target paper and the candidate papers. We can transfer our paper recommendation task to similarity learning problem.

We defined an objective function to learn the edges weight iteratively. The edges include the edges in the same layer and the connective edges between the different layers. The objective function is defined as follow:

$$\begin{aligned} F(W,Z) = \alpha_0 * \sum_{p_1,p_2 \in G_p} (w_{p_1,p_2} - w^*_{p_1,p_2})^2 + \alpha_1 * \sum_{p \in G_p, t \in G_t} (z_{p,t} - z^*_{p,t})^2 \\ + \alpha_2 * \sum_{p_1,p_2 \in G_p} \sum_{t_1,t_2 \in G_t} z_{p_1,t_1} z_{p_2,t_2} (w_{p_1,p_2} - w_{t_1,t_2})^2 \\ + \alpha_3 * \sum_{p_1,p_2 \in G_p} \sum_{t_1,t_2 \in G_t} w_{p_1,p_2} w_{t_1,t_2} (z_{p_1,t_1} - z_{p_2,t_2})^2 \end{aligned} \tag{8}$$

Where $\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3 = 1$. $w^*_{p_1,p_2}$ represents the initial similarity between papers, and $z^*_{p,t}$ represents the initial importance of key-terms to the papers, w_{p_1,p_2} and $z_{p,t}$ are the updated values.

The objective function contains four terms. The first and the second terms try to minimize the difference between the updated similarity and the initial similarity. And the third and the fourth terms try to regularize the similarity between nodes such that similar parts achieve similar weights. Given a heterogeneous graph, we will apply a graph-based similarity learning algorithm to update the similarities between two nodes iteratively.

3.3 The Solution of Objective Function

We minimize the objective function in section 3.2 using Alternating Optimization, an approximate optimization method. The partial derivative of the objective function is given as follows:

$$\begin{aligned} \frac{\partial F(W,Z)}{\partial w_{p_1,p_2}} = 2\alpha_0 * (w_{p_1,p_2} - w^*_{p_1,p_2}) \\ + 2\alpha_2 * \sum_{t_1,t_2 \in G_t} z_{p_1,t_1} z_{p_2,t_2} (w_{p_1,p_2} - w_{t_1,t_2}) \\ + \alpha_3 * \sum_{t_1,t_2 \in G_t} w_{p_1,p_2} w_{t_1,t_2} (z_{p_1,t_1} - z_{p_2,t_2})^2 \end{aligned} \tag{9}$$

To minimize the above function, we set the function to zero, then the solution is achieved as follows:

$$w_{p_1,p_2} = \frac{1}{C_1}(\alpha_0 w^*_{p_1,p_2} + \alpha_2 \sum_{t_1,t_2 \in G_t} z_{p_1,t_1} w_{t_1,t_2} z_{p_2,t_2}) \tag{10}$$

Where

$$C_1 = \alpha_0 + \alpha_2 \sum_{t_1,t_2 \in G_t} z_{p_1,t_1} z_{p_2,t_2} + \frac{\alpha_3}{2} \sum_{t_1,t_2 \in G_t} w_{t_1,t_2}(z_{p_1,t_1} - z_{p_2,t_2})^2 \tag{11}$$

Similarly, we can also update the importance score, z_{p_1,t_1}. Since objective function needs to update multiple iterations, here we stop iterating when,

$$|w^t_{p_1,p_2} - w^{t-1}_{p_1,p_2}| \leq \tau, \forall (p_1, p_2 \in G_p) \tag{12}$$

Finally, we would achieve the final similarity score between two papers according to the final graph, and according to the rank of similarities between candidate papers and target paper, we would recommend the top n papers.

4 Experiments

4.1 Dataset

We use an open dataset to evaluate our proposed approach. The dataset is a subset of ACL Anthology Network (ANN) [2]. ANN is a collection of journal, conference and workshop papers. The ANN dataset consists of 18572 papers and 70756 citation links where these papers are published between 1965 and 2011. The subset consists of two parts, one part contains 15 target papers published in 2008 or 2009 from 15 junior researchers, and the other part contains 597 full papers published from 2000 to 2006 as the candidate papers. Each target paper has a list of related papers which is manually labelled.

4.2 Evaluation Measures

For the information retrieval (IR), the results which are more relevant with the query will be at the top. Our paper recommendation is similar to IR. In order to properly evaluate the effect of paper recommendation approach, we apply IR evaluation measures: (1) Normalized Discounted Cumulative Gain (NDCG) (2) Mean Reciprocal Rank (MRR) (3) F1-Score [14, 15].

Normalized Discounted Cumulative Gain (NDCG). Discounted Cumulative Gain gives more weight to highly relevant documents , while the highly relevant documents appearing lower in a search result list should be penalized as the graded relevance value is reduced logarithmically proportional to the position of the result. The DCG is defined as:

$$DCG_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{log_2 i} \tag{13}$$

Where p is document rank position, i denotes the i^{th} ranked position, and rel_i is the weight of the document which in the i^{th} ranked position. In our work, if the document is relevant to the query document, then $rel = 1$ and $rel = 0$ for the irrelevant document.

$$nDCG_p = \frac{DCG_p}{IDCG_p} \tag{14}$$

Where $IDCG_p$ is called Ideal DCG till position p, which represents the best result score.

The average normalized DCG over all target set is selected to show the accuracy of recommendation. General recommendation system will recommend some items for the user. In our work, we use $NDCG@N(N = 5, 10)$ for evaluation where N is the number of top-N papers recommended by our approach.

Mean Reciprocal Rank (MRR). Mean Reciprocal Rank is only concerned about the ranking of the first relevant term which is returned by the system, average over all target papers. The MRR is defined as:

$$MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{rank_i} \tag{15}$$

Where $|Q|$ represents the number of the target papers, and the $rank_i$ represents the rank of the i^{th} target paper.

F1-Score. F1-Score is an oft-used measure in the information retrieval and natural language processing communities. This measure was first introduced by C. J. van Rijsbergen. F1-Score combines recall (r) and precision (p) with an equal weight in the following form:

$$F_1(r, p) = \frac{2rp}{r + p} \tag{16}$$

4.3 Results

We evaluate the performance of the our method compared with citation-based methods, Co-citation [5], Co-coupling [3], CCIDF [4], GRS [2], content-based method, HITS [6], and the citation and content linear combination method called Linear Combination [7]. In the following experiments, $K = 50$ which means we select the top 50 ranked terms from each paper as the nodes in the key-terms graph, and the method parameters are solely tuned based on the test set, among them $\alpha_0 = 0.35, \alpha_1 = 0.35, \alpha_2 = 0.15$ and $\alpha_3 = 0.15$.

Table 1. Top-10 Results of NDCG and MRR

Approach	NDCG@10	MRR	F@10
Co-coupling	0.070	0.084	0.023
Co-citaiton	0.085	0.120	0.028
CCIDF	0.087	0.098	0.027
GRS	0.257	0.193	0.101
HITS	0.106	0.093	0.030
Linear Combination	0.223	0.174	0.087
Multi-layer Graph	**0.324**	**0.267**	**0.185**

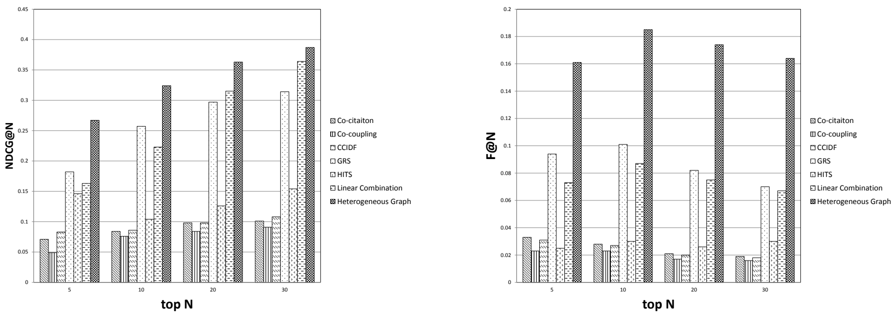

Fig. 3. NDCG@NResults

The result of our methods and other related work are shown in Table 1. From Table 1, we can see that Linear Combination and Multi-layer graph methods which use citation information and content knowledge perform better than most of the methods which just use one type of information. Compared with other methods, the our heterogeneous graph method improves the results significantly.

We further validate our method on the evaluation criterion of NDCG. Fig.3 shows the results of NDCG@N (N = 5, 10, 20, 30) from all the methods. The figure shows that our method gets the best performance.

According to the definitions of heterogeneous graph, the weights of edges have multiple initialization methods. In the paper citation graph, the weights of edges can be computed by three methods: (a1) Citation-based. If p_i and p_j exist citation relationship, then $w_{ij} = 1$. (a2) Content-based. $w_{ij} = Context(i, j)$. (a3) Citation, Content-based. If p_i and p_j exist citation relationship, then $w_{ij} = Context(i, j)$. Likewise, the weights of edges have three methods in the key-terms graph: (b1) Knowledge-based. the weight can be calculated using the above method WordNet. (b2) Co occurrence-based. If two terms appeared in the same paper, the weight equals to 1. (b3) Co occurrence, WordNet-based. If two terms appeared in the same paper, then the weight can be calculated using the above method WordNet.

In order to examine the sensitive of the initial weights of the edges, we do the other experiment. Table 2 is the results of five different weights of edges combinations in the heterogeneous graph. From table 2, we can find that no matter

Table 2. The results of different initial weights of edges combination graph

Settings	Combinations	NDCG@10	MRR
Linear Combination		0.223	0.174
Graph-1	a1+b1	0.223	0.174
graph-2	a2+b1	0.287	0.236
graph-3	a3+b1	**0.324**	**0.267**
graph-4	a3+b2	0.253	0.215
graph-5	a3+b3	0.272	0.226

what settings, our method is better than the Linear Combination method, and the graph-3 which combine citation, content-based and knowledge-based together performs better than other graph settings. Therefore, for the paper citation graph need to combine citation information and content knowledge together, and for the key-terms graph, the similarity between them only need to consider their actual similarity, don't have to consider their relationships in the data set.

5 Conclusion and the Future Work

Finding papers related to the target paper is becoming increasingly important especially when information overload. In this paper, we introduce a heterogeneous graph-based approach to find some papers related to the target paper which the researcher has browsed. Firstly, we use a multi-layer graph to represent the citation information and the text content knowledge of these papers. In the first layer, each node represents a paper, and in the second layer, each node represents a key-term. Secondly, we use a multi-layer graph-based similarity learning algorithm to compute the similarity score between papers. The relevance between the target papers and the candidate papers could be affected by the relationships of features with the same type and the importance of features to the paper. Finally, we do some experiments on the real database, and the experimental results showed that this method performs more effective than the state-of-the-art methods for recommending relevant papers for the researchers.

But there are still some disadvantages of our method. For example, due to the large number of key-terms, the number of nodes in the multi-layer graph is also large so that the speed of convergence is slow.

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