Many-to-Many Collaborator Recommendation Based on Matching Markets Theory

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***Abstract*—As the academic data developing rapidly, it is crucially important to obtain more scientific achievements by helping scholars to make the right choices of potential collaborators among the big data. The conventional methods are to provide each scholar with a Top N recommendation list of candidates, in which some scholars are recommended to overmany collaborators and only guarantee the optimal results of them. To bridge this gap, in this work-in-progress, we present an academic collaborator recommendation method based on matching theory from the perspectives of maximizing preference and minimizing cost. The method adopts the multiple indicators extracted from the papers published by scholars to integrate the preference matrix among scholars. which applies matching theory to achieve a stable many-to-many matching of recommendation. It aims that each scholar can choose the collaborators they are keen on. After conducting abundant experiments on Microsoft Academic Graph, we demonstrate that this approach is definitely effective in improving recommendation accuracy and coverage.**

***Index Terms*—many-to-many, matching markets theory, collaborator recommendation**

I. Introduction

The multi-disciplinary and interdisciplinary researches have grown rapidly in the past decades. Meanwhile, the scientific collaboration among scholars has become increasingly important [1]. Researchers have found that the scholars published a large amount of papers tend to be more cooperative, and scientific collaboration is crucial to improve researchers' productivity as well as trigger innovation [2]. However, it is a great challenge to find valuable collaborators from the huge academic data. The recommendation systems and technologies greatly help people by providing easier access to the resources needed by them [3].

Traditionally, the essence of scholarly collaborator recommendation is to create a rank of potential collaborators, which relies on the correlation among scholars. Most of the methods can only give a list of static candidate collaborators, a text or graphical scholar profile [4]. These methods are one-way recommendations, regardless of the two-way choices between scholars. The focus is to provide a rank list based on some similarity among scholars, which would result in the condition where the one has been recommended to many scholars simultaneously. Because of the limit of time, the scholar cannot accept overmany collaborators. Therefore, only a small part of recommendation results have been implemented successfully. These methods can only guarantee the optimal results of the small amount of scholars, which we called the local optimal results.

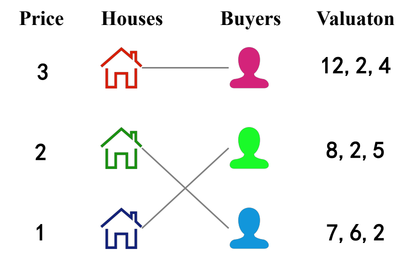


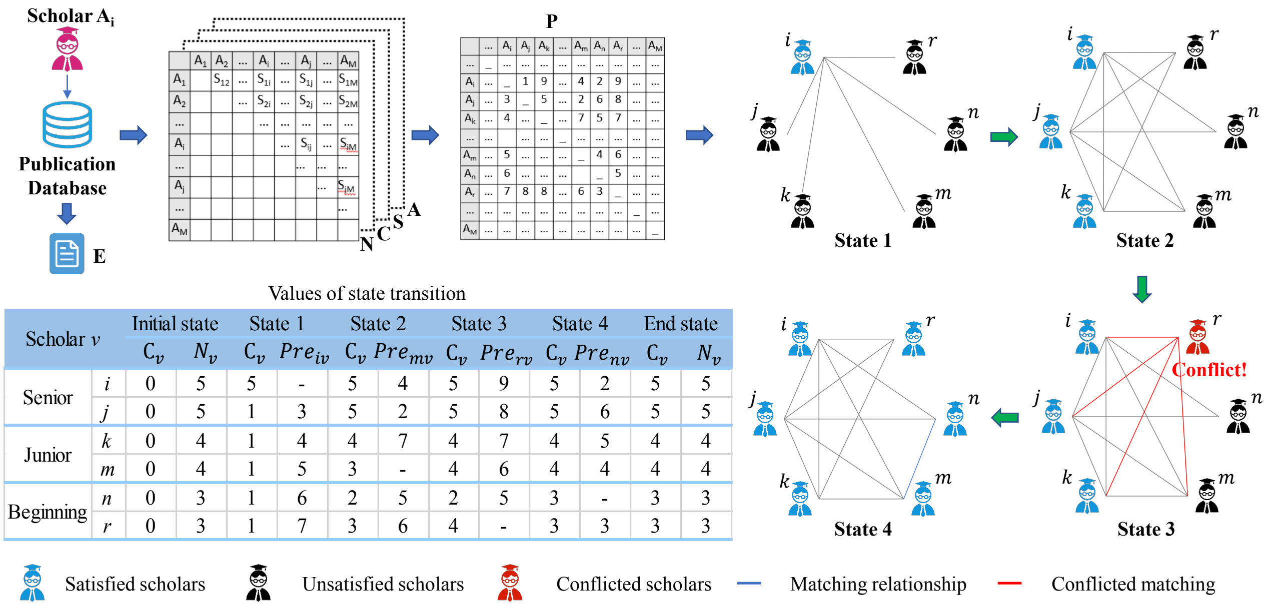
Fig. 1. Toy Example of House Allocation in Housing Market.

Matching theory [5] is a part of economics, focusing on who gets something, especially when the scarce commodities are heterogeneous and inseparable [6]. A matching is usually defined as a series of non-conflicting one-to-one matching pairs. Matching theory is widely used in resource allocation scenarios, such as labor market, organ transplant matching and so on. There are lots of well-written surveys on matching markets [7] such as the reseach by Roth and Sotomayor [8], [9], which explicitly demonstrates two-sided matching markets. The Fig. I shows a simple example of house allocation matching matket. In this survey we pay particular attention to construct a matching market in which all the participants are scholars.

Currently, there is no application of matching theory to academic collaborator recommendation system, and there is no an effective method to achieve many-to-many collaboration matching [10]. We employ matching markets theory to build a new collaborator recommendation system, which tries to achieve the maximum preference valuation.

In this paper, we aim to apply matching theory to a scholarly collaborator recommendation system, and achieve stable many-to-many matching of recommendation to solve the problem of time limit. Besides, it can find a global optimal matching in the recommendation which means scholars can match with preferred collaborators. In our study, we propose a new model for collaborator recommendation by adopting matching theory. We conduct four experiments to verify the rationality and effectiveness of each indicator so that we can determine the weight of each indicator. We integrate the four indicators on the basis of their weights, marking it as the precision of the recommendation. Moreover, we generate a preference sequence for each scholar as well as we can acquire a stable optimal matching through it.

Overall our paper makes the following contributions:



Scholar v		Initial state		State 1		State 2		State 3		State 4		End state	
		C_v	N_v	C_v	Pre_{iv}	C_v	Pre_{mv}	C_v	Pre_{rv}	C_v	Pre_{nv}	C_v	N_v
Senior	i	0	5	5	-	5	4	5	9	5	2	5	5
	j	0	5	1	3	5	2	5	8	5	6	5	5
Junior	k	0	4	1	4	4	7	4	7	4	5	4	4
	m	0	4	1	5	3	-	4	6	4	4	4	4
Beginning	n	0	3	1	6	2	5	2	5	3	-	3	3
	r	0	3	1	7	3	6	4	-	3	3	3	3

Fig. 2. Toy Example of Whole Process from the Perspective of PPG.

- We find the expected collaborator number by using academic age aiming to solve the problem that some scholars are recommended to overmany collaborators.
- We creatively employ matching theory to build a new collaborator recommendation system, which pays more attention to satisfy all the scholars rather than the given one.
- We propose a method, from the perspectives of $Priority$ to $Popular$ $Groups$ (PPG) and $Minimum$ $Cost$ in $Step$ (MCS) to achieve the global optimal results.

Experiments based on Microsoft Academic Graph (MAG) [11] prove that our method outperforms conventional methods in collaborator recommendation.

II. Design of Algorithm

A stable matching has two conditions. The one is that each individual matches with an acceptable object. And the other is that there are not two heterogeneous individuals to match and you can achieve better results than the current matching [5]. We set up the matching market to achieve a stable many-to-many matching, in which all th participants are scholars.

In this paper, $Priority$ to $Popular$ $Groups$ (PPG) and $Minimum$ $Cost$ in $Step$ (MCS), are proposed to achieve a stable collaborator matching. When the given scholar is matched collaborators more than the expected number, PPG aims to satisfy the most popular scholars while MCS aims to minimize the cost of each choice. A loss function is defined to describe the state of global optimal matching. The basic framework of our method is shown in Fig. 2. The main symbols are shown in Table I, especially in which S is not a upper triangular matrix. In this section, we will give a detailed description of the method.

TABLE I
Description of Key Symbol

Symbol	Definiton
N	co-author network similarity matrix
C	content similarity matrix
S	scholar attraction matrix
A	co-attendance similarity matrix
P	preference matrix
E	the file of expected collaborator numbers
v	the given scholar(i, j, k, m, n, r)
C_v	the number of matched collaborators of scholar v
N_v	expected collaborator number of scholar v
Pre_{iv}	the preference of scholar i to scholar v for i to make choices

A. Preference Calculation

For all the target scholars, we calculate the preferences between each other adopting the following formula:

$$Pre_{mn} = \sum_{i=1}^{4} P_i \times S_{mn}^{i} \tag{1}$$

Where Pre_{mn} denotes the preference of scholar m to scholar n, P_i denotes the precision of the indicator i, and S_{mn}^{i} denotes the similarity of scholar m to scholar n of the indicator i. There are four indicators, co-author network, content, scholar attraction and co-attendance network. So i ranges from 1 to 4. From the preference matrix, we generate a preference partial sequence for each scholar relative to all other scholars.

B. Expected Collaborator Number

Scholars are divided into three groups on the basis of academic age [12]: beginning academic age $<$ 12, junior

TABLE II
THE RESULT OF EXPECTED COLLABORATOR NUMBER

Expected number	N_b	N_j	N_s
Calculated result	3.47	3.58	4.91
Experiment value	3	4	5

academic age $\geq$ 12 and $\leq$ 24, and senior academic age $>$ 24. Wang et al. split scholars into 3 groups of different academic ages by calculating the average annual productivity, i.e., number of publications per year, of scholars at each academic age. They found that the annual productivity of scholars at different ages was consistent.

We analyze the average number of collaborators per year of all scholars from 2009 to 2013, to obtain the average number of collaborators in each group as the number of recommended candidates (N_b, N_j, N_s) for the many-to-many matching experiment. Expected Collaborator Number is marked as N. Through the experiment, we get the results in Table II.

C. Method Process

The process of PPG is similar to the process of MCS. When the conflicted pair occurs, the difference appears.

1) One-to-One Matching: We verify the convergence and feasibility of the algorithm in one-to-one matching. The process of experiment contains 3 steps described as follows:

- Step 1: If all the scholars are successfully matched, that is, if there is a matching pair (i, j), there is no possibility: there is (i, k) that scholar j and scholar k are not the same one. Then the current state has reached the stable matching.
- Step 2: To find the most popular scholar i (In the initial state, scholar v is recommended to R_v scholars at the same time, and $R_i = max(R_v)$). We firstly meet the choice of scholar i. For all current recommended matching pairs (k, i) $(i = 1, 2, 3, ...R_i)$.
  - In PPG, k corresponding to $max(Pre_{ik})$.
  - In MCS, k corresponding to $max(Pre_{ik} - Pre_{i(k+1)})$.
- Step 3: Then (k, i) is marked as successful pair , and we delete scholar i and scholar k from the recommendation list. Then return step 1.

Two experiments, named experiment 1-1 and experiment 2-1, are set up for the one-to-one matching from the perspectives of PPG and MCS. The loss function of the 2 experiments is defined as follow:

$$S_1 = \sum_{i=1}^{M} |Pre_{ik} - Pre_{i1}| \quad (2)$$

Where Pre_{ik} denotes the preference of scholar i to scholar k, and Pre_{i1} denotes the maximal preference of scholar i. And M is the count of the scholars involved in the matching experiment, which equals 1810 in this paper.

2) Many-to-Many Matching: Then we extend the one-to-one matching to many-to-many matching process, adding the factor of academic age. The process contains 3 parts, data initialization, matching process and end state.

a) Data Initialization: In the initial state, the number of matched collaborators for each scholar, marked as C, equals 0. Then we rank all scholars by their popularities for position partial list, marked L. Meanwhile, the priority of each group orders by senior $>$ junior $>$ beginning. The level of popularity is determined by the position of the one in the initial preference partial sequences of all other scholars.

The requirements of each scholar are satisfied in turn according to L. The scholar is removed from L after being completely matched, then we update the matched collaborators number, marked as C, of each scholar.

b) Matching Process: Matching process, shown in Algorithm 1, contains 4 steps with detailed description as below.

- Step 1: For scholar s in L, check whether $Cs < Ns$ is true or not, if not, we recommend for the next one in L. If true, return to step 2.
- Step 2: When a new pair (s, i) is generated, we detect whether $C_i < N_i$ is established or not. If the inequality is established, the pair (s, i) is marked as a successful matching pair. Then $C_i = C_i + 1$, $C_s = C_s + 1$, and return to step 1. If not, return to step 3.
- Step 3: When $C_i = N_i$, (s, i) is marked as a successful pair. For all successfully matching pairs (k, i).
  - In PPG, k corresponding to $min(Pre_{ik})$.
  - In MCS, k corresponding to $min(Pre_{ik} - Pre_{i(k+1)})$.

  If $k = s$, (s, i) is marked as failed pair. We recommend the scholar after i in the preference sequence of s to make a new pair, then return to step 2. If $k \neq s$, (k, i) is marked as failed pair. Then $C_s = C_s + 1$, $C_k = C_k - 1$, and return to step 4.
- Step 4: If there is $C_m = N_m$ for any scholar m, the end state has reached. Otherwise we recommend for the next one in L, and return to step 1.

Algorithm 1 Framework of Matching Process

Input: List L, Matrix P, Table E, Set D
Output: Set D

for v in L **do**
  descend the perference list of scholar v
  get the preference partial sequence of scholar v
  $C_v = 0$
  $N_v = N$
  // N is the value of v in Table E
end for
for s in L **do**
  if $C_s < N_s$ **then**
    MatchingPeocess(s)
  end if
end for

Algorithm 2 Matching Process for Scholar s

Input: List L, Matrix P, Table E, Set D

Output: Set D // successful matching pairs

for i in the perference list of s **do**
  if $C_i < N_i$ **then**
    mark (s, i) as successful pair
    add (s, i) into D
    $C_i = C_i + 1$
    $C_s = C_s + 1$
  else
    add (s, i) into D
    select all (k, i) in D
    $k = argmin(Pre_{ik} - Pre_{i(k+1)})$ in MCS
   // while $k = argmin(Pre_{ik})$ in PPG
   if $k = s$ **then**
     mark (s, i) as failed pair
     remove (s, i) from D
     $continue$
   else
     mark (k, i) as failed pair
     remove (k, i) from D
     $C_s = C_s + 1$
     $C_k = C_k - 1$
   end if
  end if
end for

c) End State: The condition means the matching reaches stable state, in which all the scholars are matched successfully is spotted on, namely, no any new pair exists to break the current matching state.

Two experiments for the many-to-many matching from the perspectives of PPG and MCS are named experiment 1-2 and experiment 2-2, with the loss function defined as follow:

$$S_2 = \sum_{i=1}^{M} \sum_{j=1}^{N_i} |Pre_{ik_j} - Pre_{ij}| \tag{3}$$

Where Pre_{ik_j} means the preference of scholar i to the first j of scholars who matched to i. Pre_{ij} means the top j in the preference list of scholar i, in which the preference valuations of matched scholars are deleted from the sequence. M is the count of the scholars involved in the matching experiment, which equals 1810 in this paper. And N_i is the expected collaborator number of scholar i.

III. Experiment

To investigate the effectiveness of PPG and MCS on collaborator recommendation, we conducted experiments and analyzed the effect of our algorithm on different dimensions by the evaluation metrics of precision, duration of collaboration, and collaboration index [12].

In particular, we added the scholars themselves to the end of the preference partial sequence of their own. It indicated that the scholar chose to be single when there was no suitable scholar for matching.

A. Dataset and Setup

a) Publication Database: We set up the publication database from MAG in the following steps:

- Step 1: Achieving the experimental target scholars. In order to ensure the experimental results, we set the following screening conditions:
  - The number of papers published by scholars before 2013 is ≥ 10 to ensure that researchers have relatively abundant research data for subsequent experiments
  - Scholars' collaborators after 2014 are more than 10 to ensure that TopN experiments have complete validation data.
  - Scholars from the top papers in the computer field from 2010 to 2013 in the ESI database to ensure that researchers are valuable scholars.
- Step 2: Finding the annual papers published by the target scholars in 2009-2018. The details of dataset are shown in Table III, and explained as below.
  - The data of 2009-2013 as the dataset of valuation calculation.
  - The data of 2012-2013 as the training set.
  - The data of 2014-2018 as the validating set.

TABLE III
THE DETAILS OF THE EXPERIMENT DATASET

Data	Count
Target scholars	1810
Papers in training set	19226
Papers in testing set	10768
Co-author network degree	6.8
Citation network degree	2.67
Co-attendance network degree	1.18

In the experiment of co-author network analysis, we ensure that each scholar has more than 10 co-authors, to obtain a network with highly analytical value. In the experiment of scholar attraction, we added the citation data of the publications of target scholars to expand the experiment data and get more convincing results.

b) Valuation Calculation: We calculated the four indicators of scholars and conducted collaboration recommendation experiments respectively.

- **Co-author network analysis** [13]: The co-authorship of scholars in the experimental dataset is analyzed. We establish the co-author network and obtain the vector representation of each node by Node2vec. Then we calculate the similarity of scholars by cosine similarity.
- **Content analysis** [14]: Using Word2vec and Doc2vec to calculate the similarity of scholars' content of publicatios.
- **Scholar attraction analysis**: Based on our previous work, we use citation network to analyze the attraction of scholars, which can be divided into self-attraction and attraction to other scholars.
- **Co-attendance network** [15]: Using the corresponding relationship between papers and meetings to calculate the

TABLE IV
PERFORMANCES BY THE EVALUATION METRIC OF PRECISION

	Experiment Top1		Experiment Top10	
	precision@1	precision@10	precision@1	precision@10
Content based	44.70%	23.48%	34.70%	16.29%
Co-author network based	49.28%	21.61%	32.28%	17.41%
Scholar attraction based	7.71%	4.42%	7.71%	3.34%
Co-attendance network based	10.38%	5.77%	10.38%	7.15%
Matching experiment 1-1	33.15%	-	33.15%	-
Matching experiment 2-1	38.45%	-	31.16%	-
Matching experiment 1-2	-	23.78%	-	19.52%
Matching experiment 2-2	-	24.63%	-	19.97%

similarity of scholars in co-attendance network. In the co-attendance network, each node represents a scholar, edges mean the co-attendance in conferences, and the weight of the given edge means the number of co-attendance conferences.

The results are shown in the Table IV. Top1 means the experiment that use the precision of the experiment recommended the top one to calculate the preference matrix, while Top10 use the precision of the experiment recommended the top ten.

B. Baseline Methods

We compare our algorithm with several collaborator recommendation approaches including:

- **Co-author network based** [16]: This method obtains the similarity based on co-author network established by the co-authorship in publications.
- **Content-based** [14]: This method calculates the similarity based on the content of scholars' publications.
- **Scholar attraction based** : Based on our previous work, we utilize citation network to analyze the attraction of scholars.
- **Co-attendance network based** [15]: Using the corresponding relationship between conferences to calculate the similarity between scholars.

C. Results

We made the experiments of precision@1 and precision@10 respectively, and analyzed the performance of PPG and MCS by experimental comparison. The results are shown in the Table IV. Through the experimental results, we can see that our proposed algorithm has obvious advantages in the experiments for precision@10, and disadvantages in the experiments for precision@1. The best result of our algorithm performs the precision of 38.45%, which is from the perspective of MCS in the experiment by the evaluation metric of precision@1. We can see that our algorithm is efficient both from the perspectives of MCS and PPG, and MCS performs better than PPG.

Meanwhile, our algorithm shows a good performance in time complexity. It spends several seconds to get the matching results and the sum of preference losses.

In addition, we use the measurement of collaboration output proposed by Wang et al. [12] to measure our collaboration effectiveness. The results of the experiment group with N=10 are shown as Table V:

TABLE V
PERFORMANCES BY THE EVALUATION METHICS OF CD AND C-INDEX

	Mean CD	Mean C-index
Content based	2.479	3.727
Co-author network based	2.597	3.938
Scholar attraction based	1.973	3.438
Co-attendance network based	2.448	3.675
Matching experiment 1-1	2.907	3.847
Matching experiment 2-1	2.929	3.525
Matching experiment 1-2	2.689	3.221
Matching experiment 2-2	2.752	3.433

CO means the $Collaboration\ Duration$, which reflect how long two scholars have collaborated with each other. C-index means the $Collaboration\ Index$, which is proposed to better quantify the collaboration sustainability and inspired by the idea of h-index.

From the experimental results, we can see that our algorithm outperforms in the $Collaboration\ Duration$, but not obviously in the $Collaboration\ Index$. It means that the quantification of collaboration output is lower than those of baseline mathods. It shows that the idea of matching can promote the construction of a stable collaboration environment.

IV. DISCUSSION

In order to find the reason why our algorithm poorly performs to co-author network based method ans content based method in the experiments for precision@1. We analyzed the intermediate datas of this group of experiments and found that in this group of experiments, the repetition of recommendation results in co-author-network-based and content-based recommendation processs were low. It means that fewer one-to-many cases, and the average recommendation times of scholars were nearly 2. For more details, we added two experiments to ensure that the recommendation times was more than 5. In addition, we set up some rules, namely, when the repetitive recommendation is made, only the scholars with the maximum preference are selected for recommendation, and the others are regarded as recommendation failures. Results are as shown in Table VI.

V. RELATED WORK

Generally, the collaboration recommendation can be divided into two categories. The one is to recommend the

TABLE VI
PRECISION@1 IN THE VALIDATION EXPERIMENTS

	Experiment1	Experiment2	
Content based	29.70%	19.70%	
Co-author network based	25.28%	25.28%	
Matching experiment 1-1	30.55%	23.92%	-
Matching experiment 2-1	28.65%	28.30%	-

most potential partners (MPCs) that have never collaborated with the target scholars (i.e., to establish new partnerships). And the other is to recommend the most valuable partners (MVCs) that have collaborated with them (i.e., to strengthen old collaboration). In academia, the academic collaboration relationship is modeled so that we can obtain corresponding network [17]. The nodes represent scholars and the links (edges) represent collaboration relationships. The fundamental purpose of collaborator recommendation is to predict possible future links (MPCs) or to recommend links (MVCs) that may benefit academic social networks [4]. Mainstream collaborator recommendation models mainly include the following.

- Based on content [14] and popularity [18], the similarity is calculated by specific rules, and then the partial sequence is obtained for recommendation.
- Graph-based collaborator recommendation [13] is more about mining hidden information in academic networks to predict possible new connections on graphs.

Matching markets embody a number of basic principles: the way in which people may have different preferences for different kinds of goods, the way in which prices can decentralize the allocation of goods to people, and the way in which such prices can in fact lead to allocations that are socially optimal [5]. A matching is usually defined as a series of non-conflicting one-to-one matching pairs. Delayed acceptance algorithm (DA) [9] is widely used in bilateral matching. This kind of matching is biased and advantageous. Top-level Transaction Cycle algorithm (TTC) [7] is widely used in unilateral matching. According to the price, the agent chooses a preferred house to achieve a stable matching state.

VI. CONCLUSION

This paper proposes an academic collaborator method based on matching theory, which uses the multiple indicators extracted from the papers published by scholars to integrate the preference valuation between the two scholars. The method combines matching theory to achieve a stable many-to-many matching of recommendation. Through experiments based on MAG, we demonstrate the effectiveness of this approach in improving recommendation accuracy and coverage. The results of this paper indicates that when doing collaborator recommendations, we should not only consider the most excellent scholars, but also all of the academic network. The outcomes have significant implications for understanding matching theory in collaborator recommendation.

Despite its exploratory nature, this paper makes some attempt on scientific collaborator recommendation from the perspective of matching theory. In the future, we will take more efforts to improve the efficiency of the algorithm by using matching theory. Meanwhile, with the help of PPG and MCS model, we will try to provide a more credible recommendation system for collaborator recommendations to overcome the problems of the excessive information and the condition that one scholar is recommended to plenty of collaborators.

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