



Weighted P-Rank: a Weighted Article Ranking Algorithm Based on a Heterogeneous Scholarly Network

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Abstract. The evaluation and ranking of scientific article have always been a very challenging task because of the dynamic change of citation networks. Over the past decades, plenty of studies have been conducted on this topic. However, most of the current methods do not consider the link weightings between different networks, which might lead to biased article ranking results. To tackle this issue, we develop a weighted P-Rank algorithm based on a heterogeneous scholarly network for article ranking evaluation. In this study, the corresponding link weightings in heterogeneous scholarly network can be updated by calculating citation relevance, authors' contribution, and journals' impact. To further boost the performance, we also employ the time information of each article as a personalized PageRank vector to balance the bias to earlier publications in the dynamic citation network. The experiments are conducted on three public datasets (arXiv, Cora, and MAG). The experimental results demonstrated that weighted P-Rank algorithm significantly outperforms other ranking algorithms on arXiv and MAG datasets, while it achieves competitive performance on Cora dataset. Under different network configuration conditions, it can be found that the best ranking result can be obtained by jointly utilizing all kinds of weighted information.

Keywords: Article ranking · Link weighting · Heterogeneous scholarly network · Weighted P-Rank algorithm

1 Introduction

Academic impact assessment and ranking have always been a hot issue, which plays an important role in the process of the dissemination and development of

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academic research [1–3]. However, it is difficult to assess the real quality of academic articles due to the dynamic change of citation networks [4]. Furthermore, the evaluation result will be heavily influenced by utilizing different bibliometrics indicators or ranking methods [5]. As a traditional ranking method, PageRank [6] algorithm has already been widely and effectively used in various ranking tasks. Liu *et al.* [7], for instance, employed the PageRank algorithm to evaluate the academic influence of scientists in the co-authorship network. In [8], Bollen *et al.* utilized a weighted version of the PageRank to improve the calculation methodology of JIF. It is worth remarking that the vast majority of ranking algorithms such as PageRank and its variants deem the article (node) creation as a static citation network. In the real citation network, however, articles are published and cited in time sequence. Such approaches do not consider the dynamic nature of the network and are always biased to old publications. Therefore, the recent articles tend to be underestimated due to the lack of enough citations. To address this issue, Sayyadi and Getoor proposed a timeaware method, FutureRank [4], which calculates the future PageRank score of each article by jointly employing citation network, authorship network, and time information. In comparison to the other methods without time weight, FutureRank is practical and ranks academic articles more accurately. Furthermore, Walker *et al.* proposed a ranking model called CiteRank [9], which utilizes a simple network traffic model and calculates the future citations of each article by considering the publication time of articles. However, a main problem of the network traffic model is that it does not reveal the mechanism of how the article scores change. Moreover, although PageRank algorithm is advanced at exploring the global structure of the citation network, it neglects certain local factors that may influence the ranking results.

This paper aims to develop a weighted P-Rank algorithm based on a heterogeneous scholarly network and explore how the changes of the link weightings between different subnetworks influence the ranking result. To further boost the performance of weighted P-Rank algorithm, we utilize the time information of each article as a personalized PageRank vector to balance the bias to earlier publications in the dynamic citation network. The key contributions of this work can be summarized as follows:

- A weighted article ranking method based on P-Rank algorithm and heterogeneous graph is developed.
- The weighted P-Rank algorithm considers the influence of citation relevance, authors' contribution, journals' impact, and time information to the article ranking method comprehensively.
- We evaluate the performance of weighted P-Rank method under different conditions by manipulating the corresponding parameters that can be used to structure graph configurations and time settings.
- By introducing the corresponding link weightings in each heterogeneous graph, the performance of the weighted P-Rank algorithm significantly outperforms the original P-Rank algorithm on three public datasets.

2 Article Ranking Model

In this section, we introduce the proposed article ranking algorithm in detail. Specifically, we first define and describe a heterogeneous scholarly network that is composed of author layer, paper layer and journal layer, and how the different elements in the three layers are linked and interacted. Furthermore, a link weighting method based on P-Rank algorithm is developed to compute the article score in the heterogeneous scholarly network.

2.1 Heterogeneous Scholarly Network

A complete heterogeneous scholarly network consists of three subnetworks (i.e., author network, paper citation network, and journal network). There exist three types of edges in the network i.e., undirected edge between the authors and the papers, directed citation edge between the original paper and its citing papers, and undirected edge between the papers and the published journals. As stated in [10], the heterogeneous scholarly graph of papers, authors, and journals can be expressed as the following form:

$$G(V, E) = (V_P \cup V_A \cup V_J, E_P \cup E_{PA} \cup E_{PJ}) \tag{1}$$

where V_P , V_A , and V_J are the paper nodes, author nodes, and journal nodes in the three layers respectively. E_P denotes the citation link in the paper layer, E_{PA} denotes the link between paper and author, and E_{PJ} denotes the link between paper and journal.

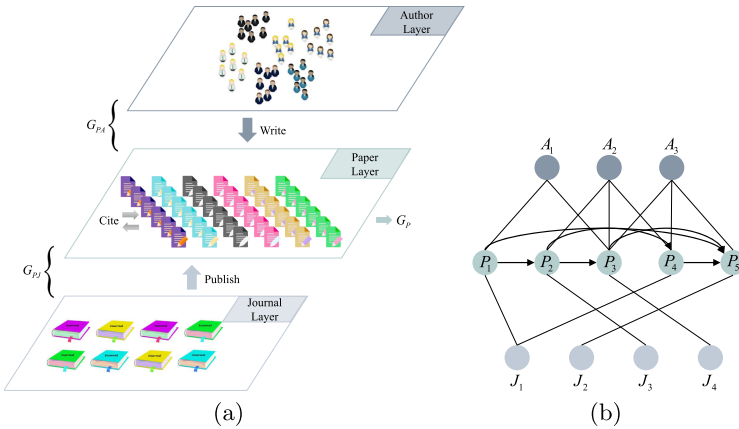


Fig. 1. Visualization of a heterogeneous scholarly network

As shown in Fig. 1a, the paper-author network and paper-journal network are two undirected graphs which can be represented as $G_{PA} = (V_P \cup V_A, E_{PA})$

and $G_{PJ} = (V_P \cup V_J, E_{PJ})$, respectively. In Fig. 1b, by contrast, the paper citation network is a directed graph $G_P = (V_P, E_P)$, the arrows point in the direction of paper citation: $P_4 \rightarrow P_5$ means P_4 cites P_5 . In this work, we assign link weights to the corresponding subnetworks such that the three unweighted graphs can be updated as $G_P = (V_P, E_P, W_P)$, $G_{PA} = (V_P \cup V_A, E_{PA}, W_{PA})$, and $G_{PJ} = (V_P \cup V_J, E_{PJ}, W_{PJ})$, in which W_P , W_{PA} , and W_{PJ} refer to the link weight in the three graphs, respectively. With link weightings (W_P , W_{PA} , and W_{PJ}) defined in the corresponding G_P , G_{PA} , and G_{PJ} , the unweighted heterogeneous scholarly graph $G(V, E)$ becomes

$$G(V, E, W) = (V_P \cup V_A \cup V_J, E_P \cup E_{PA} \cup E_{PJ}, W_P \cup W_{PA} \cup W_{PJ}) \quad (2)$$

2.2 Link Weighting in Paper Citation Graph (G_P)

In this study, we develop a link weighting to assign weight in the paper citation graph (G_P) based on the citation relevance between two papers, which can be utilized to improve the reasonability of the article ranking. To be specific, the citation relevance (link weighting) between two different papers is mainly influenced by two factors, namely, text similarity (semantic-based) and citation network structure (structure-based). Supposing that the citation relevance between two papers is higher if the two papers are more likely to be similar in semantic and share mutual links and common nodes in the citation network.

In our work, the “slide” weighted overlap approach improved by ADW [11] is employed, which can be used to compute the semantic similarity between the abstracts T_i and T_j from papers i and j . Let S be the intersection of overlapping senses with non-zero probability in both signatures and r_i^j be the rank of sense $s_i \in S$ in signature j , where rank 1 represents the highest rank. The slide overlap Similarity₁(P_i, P_j) can be computed using:

$$\text{Similarity}_1(P_i, P_j) = \tanh \left(\frac{\alpha \cdot \sum_{i=1}^{|S|} e^{(r_i^1 + r_i^2)^{-1}}}{\beta \cdot \sum_{i=1}^{|S|} e^{(2i)^{-1}}} \right) \quad (3)$$

where $\tanh(\cdot)$ is hyperbolic tangent function, and $\sum_{i=1}^{|S|} (2i)^{-1}$ is the maximum value to bound the similarity distributed over the interval [0,1]. Note that the maximum value would occur when each sense has the same rank in both signatures. Moreover, we normalize parameters α and β such that $\alpha + \beta = 1$.

In this work, we employ cosine similarity to measure the citation relevance of two papers in terms of network structure. The cosine similarity between two paper nodes in the citation network can be calculated by:

$$\text{Similarity}_2(P_i, P_j) = \cos(P_i, P_j) = \frac{|N_{P_i} \cap N_{P_j}|}{\sqrt{|N_{P_i}| \times |N_{P_j}|}} \quad (4)$$

where N_{P_i} denotes the neighborhood of node P_i , and $|N_{P_i} \cap N_{P_j}|$ denotes the number of nodes that link to both P_i and P_j .

Based on the Similarity₁ (semantic-based) and Similarity₂ (structure-based), the link weight between two paper nodes in the paper citation graph (G_P) can be represented as follows:

$$W_{i,j} = \lambda_1 \cdot \text{Similarity}_1(P_i, P_j) + \lambda_2 \cdot \text{Similarity}_2(P_i, P_j) \quad (5)$$

where $W_{i,j}$ is the weight from paper i to paper j in G_P , Similarity₁ and Similarity₂ are the semantic-based and structure-based similarities between two papers respectively. Parameters λ_1 and λ_2 are two corresponding coefficients, which can be defined as the following form:

$$\lambda_1 = e^{\mu[\text{Similarity}_1(P_i, P_j) - \varepsilon_1]} \quad (6)$$

$$\lambda_2 = e^{\mu[\text{Similarity}_2(P_i, P_j) - \varepsilon_2]} \quad (7)$$

with μ being a parameter shaping the exponential function, and ε_1 and ε_2 being the media values of Similarity₁ and Similarity₂ respectively. Here let $\mu = 6$ so that those similarity values that exceed the threshold can be constrained by the exponential curve. Parameters λ_1 and λ_2 are normalized as $\lambda_1 + \lambda_2 = 1$.

For a G_P with n papers, the adjacency matrix of the citation network can be denoted as an $n \times n$ matrix, where the link weight between two paper nodes can be calculated by:

$$M_{i,j} = \begin{cases} W_{i,j} & \text{if paper } i \text{ cites paper } j \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Let \overline{M} be the fractionalized citation matrix where $\overline{M}_{i,j} = \frac{M_{i,j}}{\sum_{i=1}^n M_{i,j}}$. Let e be the n -dimensional vector whose elements are all 1 and v be an n -dimensional vector which can be viewed as a personalized vector [12]. Next let $x(v)_{\text{paper}}$ denote the PageRank vector corresponding to the vector $x(v)_{\text{paper}}$, and $x(v)$ can be calculated from $x = \overline{M}x$ where $\overline{M} = d\overline{M} + (1-d)ve^T$. Thus, PageRank vector x can be computed using:

$$x(v)_{\text{paper}} = (1-d)(I - d\overline{M})^{-1}v \quad (9)$$

where d (set at 0.85) is a damping factor. Let $Q = (1-d)(I - d\overline{M})^{-1}$, then $x = Qv$. For any given v , PageRank vector $x(v)$ can be obtained from Qv .

2.3 Link Weighting in Paper-Author Graph (G_{PA})

In the paper-author graph (G_{PA}), let $P = \{p_1, p_2, \dots, p_n\}$ denote the set of n papers and $A = \{a_1, a_2, \dots, a_m\}$ denote the set of m authors, then G_{PA} can be represented as an $n \times m$ adjacency matrix, where the link weight $A_{\text{author } i, j}$ from author j to paper i is:

$$A_{\text{author}}(i, j) = \begin{cases} 1 & \text{if author } j \text{ writes paper } i \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

In this study, the link weights in G_{PA} can be deemed as the level of authors' contributions to their articles. Modified Raw Weight ($W_{R,j}$) [13] is adopted to assess the authors' contributions according to the relative rankings of authors in co-authored publications. For the author of rank j the Modified Raw Weight is:

$$W_{R,j} = \frac{n - \frac{j}{2} + 1}{\sum_{j=1}^n n_j} = \frac{2n - j + 2}{n \cdot (n + 1)} \cdot \frac{2}{3} \tag{11}$$

where $W_{R,j}$ is the Modified Raw Weight of author j , j is the position of author j in the author list, n is the total number of authors in the paper, and $\sum_{j=1}^n n_j$ is the sum of author positions. Hence, the unweighted G_{PA} can be updated by:

$$A_{\text{author}}(i, j) = \begin{cases} W_{R,j} & \text{if author } j \text{ writes paper } i \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

2.4 Link Weighting in Paper-Journal Graph (G_{PJ})

In the initial P-Rank algorithm, the paper-journal graph (G_{PJ}) can be represented as an $n \times q$ adjacency matrix, where n and q are the number of papers and journals, respectively:

$$A_{\text{journal}}(i, j) = \begin{cases} 1 & \text{if paper } i \text{ is published on journal } j \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

Here we develop a weighted G_{PJ} in which the corresponding link weight can be updated by the journal impact factors [14,15]. Similar to G_{PA} , the link weights in G_{PJ} can be regarded as the level of journals' impact to the published articles. Here, the "mapminmax" function defined in MATLAB R2018b version is used to normalize the JIF list, the range distributed over the interval [0,1,1]. The formula 13 can thus be rewritten as below:

$$A_{\text{journal}}(i, j) = \begin{cases} \text{Normalize}[\text{JIF}_j] & \text{if paper } i \text{ is published on } j \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

2.5 Weighted P-Rank Algorithm

The weighted P-Rank score of papers can be expressed as $x(v)_{\text{paper}}$ in Eq. 9, where the personalized vector is

$$v = (\varphi_1((\frac{x(v)_{\text{author}}}{n_{\text{p_author}}})^T \times A_{\text{author}}^T) + \varphi_2((\frac{x(v)_{\text{journal}}}{n_{\text{p_journal}}})^T \times A_{\text{journal}}^T))^T \tag{15}$$

where $n_{\text{p_author}}$ represents a vector with the number of publications for each author, and $n_{\text{p_journal}}$ represents a vector with the number of publications for each journal. The mutual dependence (intra-class and inter-class walks) of papers, authors, and journals is coupled by the parameters φ_1 and φ_2 , which are

set at 0.5 as default. The weighted P-Rank scores of author and journal can be expressed as:

$$x(v)_{\text{author}} = A_{\text{author}}^T \times x(v)_{\text{paper}} \quad (16)$$

$$x(v)_{\text{journal}} = A_{\text{journal}}^T \times x(v)_{\text{paper}} \quad (17)$$

In this study, we adopt a time weight T_i to eliminate the bias to earlier publications, which can be regarded as a personalized PageRank vector. Here according to the time-aware method proposed in FutureRank [4], the function T_i is defined as:

$$T_i = e^{-\rho \times (T_{\text{current}} - T_{\text{publish}})} \quad (18)$$

where T_{publish} denotes the publication time of paper i , and $T_{\text{current}} - T_{\text{publish}}$ denotes the number of years since the paper i was published. ρ is a constant value set to be 0.62 based on FutureRank [4]. The sum of T_i for all the articles is normalized to 1.

Taken together, the weighted P-Rank score of a paper can be calculated by:

$$x(v)_{\text{paper}} = \gamma \cdot \text{Pagerank}(\overline{M}, v) + \delta \cdot T + (1 - \gamma - \delta) \cdot \frac{1}{n_p} \quad (19)$$

with parameters γ and δ being constants of the algorithm. $(1 - \gamma - \delta) \cdot \frac{1}{n_p}$ represents the probability of random jump, where n_p is the number of paper samples.

In the proposed algorithm, the initial score of each paper is set to be $\frac{1}{n_p}$. For articles which do not cite any other papers, we suppose that they hold links to all the other papers. Hence, the sum of $x(v)_{\text{paper}}$ for all the papers will keep to be 1 in each iteration. The steps above are recursively conducted until convergence (threshold is set at 0.0001). The pseudocode of the weighted P-Rank algorithm is given in Algorithm 1.

3 Experiments

3.1 Datasets and Experimental Settings

Three public datasets are used in this study, i.e. arXiv (hep-th), Cora, and MAG. The summary statistics of three datasets are listed in Table 1. It is worth remarking that the A_{journal} values of all conference articles were sampled from the average JIF of all journals calculated in the corresponding dataset.

All experiments are conducted on a computer with 3.30 GHz Intel i9-7900X processor and 64GB RAM under Linux 4.15.0 operating system. The program codes of data preprocessing and graphs modeling are written by Python 3.6.9, which is available on <https://github.com/pjzj/Weighted-P-Rank>.

Algorithm 1: Weighted P-Rank Algorithm Based on Heterogeneous Network

Input : G_P, G_{PA}, G_{PJ} , JIF list of all journals, and time list of all papers
Output : Weighted P-Rank score of paper $x(v)_{\text{paper}}$
Parameters: $\alpha, \beta, \gamma, \delta, \rho, \lambda_1, \lambda_2, \mu, \epsilon_1, \epsilon_2, d, \varphi_1, \varphi_2$
Steps :
1 Initialize all the scores of papers: $x(v)_{\text{paper}} = \frac{\text{ones}(n_p, 1)}{n_p}$, where n_p is the number of paper samples
2 Normalize JIF of each journal in dataset: $\text{mapminmax}[J] \leftarrow$ JIF list (J)
3 Compute and normalize time score of each paper based on Eq. 18:
 $T_i = \text{Normalize}[e^{-\rho \times (T_{\text{current}} - T_{\text{publish}})}]$
4 Update G_P by Eqs. 5 and 8: $C_w \leftarrow C$
5 Update G_{PA} by Eqs. 11 and 12: $A_w \leftarrow A$
6 Update G_{PJ} with Eq. 14: $J_w \leftarrow J$
7 **while not converging do**
8 Eq. 17: $x(v)_{\text{journal}} = A_{\text{journal}}^T \times x(v)_{\text{paper}}$
9 Eq. 16: $x(v)_{\text{author}} = A_{\text{author}}^T \times x(v)_{\text{paper}}$
10 Eq. 15: $v = (\varphi_1((\frac{x(v)_{\text{author}}}{n_{\text{p-author}}})^T \times A_{\text{author}}^T) + \varphi_2((\frac{x(v)_{\text{journal}}}{n_{\text{p-journal}}})^T \times A_{\text{journal}}^T))^T$
11 Calculate $\text{Pagerank}(\bar{M}, v)$
12 Update the score of each paper based on time information (Eq. 19):
 $x(v)_{\text{paper}} = \gamma \cdot \text{Pagerank}(\bar{M}, v) + \delta \cdot T + (1 - \gamma - \delta) \cdot \frac{1}{n_p}$
13 **end**
14 **return** $x(v)_{\text{paper}}, x(v)_{\text{author}},$ and $x(v)_{\text{journal}}$

Table 1. The datasets utilized in experiments

Dataset	Articles	Citations	Authors	Journals
arXiv	28,500	350,000	14,500	410
Cora	16,252	43,850	12,348	8156
MAG	15,640	200,483	26,430	9575

3.2 Evaluation Metrics

Spearman’s Rank Correlation

In this paper, Spearman’s rank correlation coefficient is used to assess the performance of proposed algorithm under different conditions. For a dataset $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N] \in \mathbb{R}^{D \times N}$ with N samples, N original data are converted into grade data, and the correlation coefficient ρ can be calculated by:

$$\rho = \frac{\sum_{i=1}^n (R_1(P_i) - \bar{R}_1)(R_2(P_i) - \bar{R}_2)}{\sqrt{\sum_{i=1}^n (R_1(P_i) - \bar{R}_1)^2 \sum_{i=1}^n (R_2(P_i) - \bar{R}_2)^2}} \tag{20}$$

where $R_1(P_i)$ denotes the position of paper P_i in the first rank list, $R_2(P_i)$ denotes the position of paper P_i in the second rank list, and \bar{R}_1 and \bar{R}_2 denote the average rank positions of all papers in the two rank lists respectively.

Robustness

Here according to the corresponding historical time point on three datasets, the whole time on each dataset can be divided into two periods. The time period

before the historical time point can be denoted as T_1 , while the whole period can be denoted as T_2 . The robustness of algorithm can thus be measured by calculating the correlation of ranking scores in T_1 and T_2 .

3.3 Experimental Results

Graph Configurations

Two parameters can be set in graph configurations: φ_1 and φ_2 . By using various combinations of graphs, we compare and assess four different cases of P-Rank algorithm with previous works. The cases and the associated parameters are listed below:

- G_P ($\varphi_1 = 0, \varphi_2 = 0$): which is the traditional PageRank algorithm for rank calculation.
- $G_P + G_{PA}$ ($\varphi_1 = 1, \varphi_2 = 0$): A new graph (G_{PA}) is introduced into the heterogeneous network which only utilizes citation and authorship.
- $G_P + G_{PJ}$ ($\varphi_1 = 0, \varphi_2 = 1$): A new graph (G_{PJ}) is introduced into the heterogeneous network which only utilizes citation and journal information.
- $G_P + G_{PA} + G_{PJ}$ ($\varphi_1 = 0.5, \varphi_2 = 0.5$): Two new graphs (G_{PA} and G_{PJ}) are introduced into the heterogeneous network which uses citation, authorship, and journal information simultaneously.

Time Settings

Based on whether to use time information, there exist two kinds of settings:

- No-Time ($\delta = 0$): which does not utilize article time information to enhance the effect of the recent published articles.
- Time-Weighted (see Eq. 19): which can be used to balance the bias to earlier published articles in the citation network.

With these assumptions, we are now ready to verify Spearman's ranking correlation of different cases on three datasets, as shown in Tables 2, 3, 4 and 5. From an analysis of Table 2, it can be found that the best performance (arXiv: 0.5449; Cora: 0.3352; MAG: 0.4994) of proposed algorithm is all achieved from the weighted graph configurations as follows: $G_P + G_{PA} + G_{PJ}$. In addition, we note that under the four graph configuration conditions (G_P ; $G_P + G_{PA}$; $G_P + G_{PJ}$; $G_P + G_{PA} + G_{PJ}$), an important observation from the experimental results is that weighted graphs significantly outperform unweighted graphs.

Table 2. Spearman's ranking correlation of different graph configurations on three datasets.

Graph configurations	arXiv		Cora		MAG	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
G_P	0.4153	0.4339	0.2607	0.2793	0.3521	0.3764
$G_P + G_{PA}$	0.4133	0.4490	0.2879	0.3096	0.4125	0.4530
$G_P + G_{PJ}$	0.4082	0.4273	0.2730	0.2894	0.4049	0.4254
$G_P + G_{PA} + G_{PJ}$	0.4915	0.5449	0.3135	0.3352	0.4748	0.4994

Table 3. Spearman’s ranking correlation of two time settings on arXiv dataset.

Time settings	G_P		$G_P + G_{PA}$		$G_P + G_{PJ}$		$G_P + G_{PA} + G_{PJ}$	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
No-time	0.4153	0.4339	0.4133	0.4490	0.4082	0.4273	0.4915	0.5449
Time-weighted	0.5880	0.6228	0.5616	0.6496	0.5800	0.6574	0.6753	0.7115

Table 4. Spearman’s ranking correlation of two time settings on Cora dataset.

Time settings	G_P		$G_P + G_{PA}$		$G_P + G_{PJ}$		$G_P + G_{PA} + G_{PJ}$	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
No-time	0.2607	0.2793	0.2879	0.3096	0.2730	0.2894	0.3135	0.3352
Time-weighted	0.3120	0.3490	0.3593	0.3848	0.3116	0.3729	0.3772	0.3962

Table 5. Spearman’s ranking correlation of two time settings on MAG dataset.

Time settings	G_P		$G_P + G_{PA}$		$G_P + G_{PJ}$		$G_P + G_{PA} + G_{PJ}$	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
No-time	0.3521	0.3764	0.4125	0.4530	0.4049	0.4254	0.4778	0.4994
Time-weighted	0.4245	0.5051	0.4693	0.5474	0.4500	0.5139	0.5548	0.5933

The best performance is highlighted in bold.

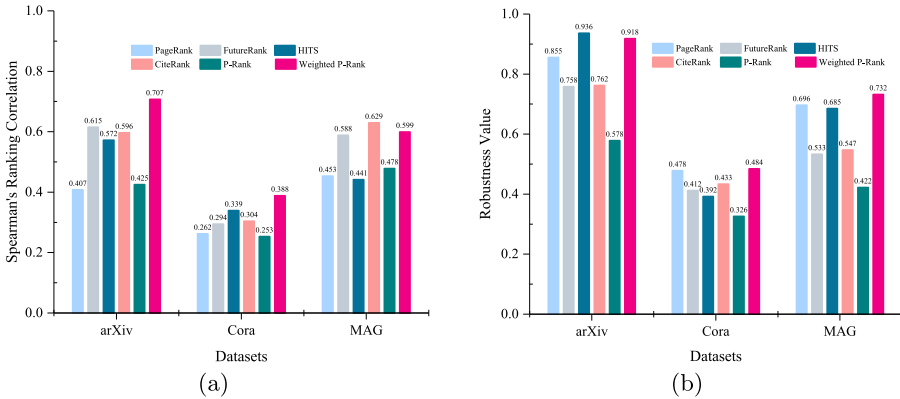


Fig. 2. Spearman’s ranking correlation and robustness of six algorithms on three datasets.

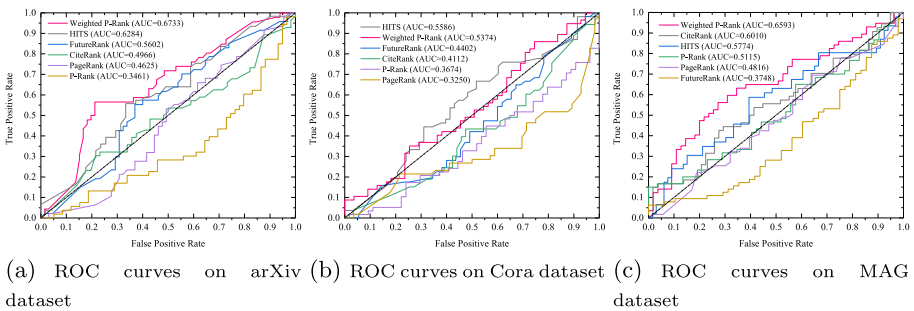


Fig. 3. ROC curves obtained by 6 ranking algorithms (Weighted P-Rank, P-Rank, PageRank, FutureRank, HITS, and CiteRank) on three different datasets.

By comparing and analyzing the data from Tables 3, 4 and 5, under the conditions of two time settings (No-Time and Time-Weighted), it can be seen that the performance of Time-Weighted configurations always outperform the results of corresponding No-Time configurations, and the best performance (arXiv: 0.7115; Cora: 0.3962; MAG: 0.5933) is obtained by jointly utilizing all kinds of configurations as follows: $G_P + G_{PA} + G_{PJ}$ +Time-Weighted.

For better comparison, we also measure the performance of the weighted P-Rank and five famous algorithms (PageRank, FutureRank, HITS, CiteRank, and P-Rank) on three datasets by using Spearman's rank correlation and robustness. We see from Fig. 2 that weighted P-Rank achieved superior rank correlation (arXiv: 0.707; Cora: 0.388; MAG: 0.599) and robustness performance (arXiv: 0.918; Cora: 0.484; MAG: 0.732), in particular compared to the initial P-Rank algorithm.

It can be seen from Fig. 3 that weighted P-Rank algorithm (as plotted by red curve) significantly outperforms other ranking algorithms on arXiv and MAG datasets, while it achieves competitive performance on Cora dataset. The AUC vales obtained by weighted P-Rank on arXiv, Cora, and MAG datasets are 0.6733, 0.5586, and 0.6593 respectively. By a sharp contrast, the AUC values achieved by initial P-Rank algorithm are unsatisfactory, especially on arXiv dataset (only 0.3461). This result indicates that link weighting plays an important role in heterogeneous graphs, which will be very helpful to improve the performance of the article ranking algorithm.

4 Conclusion

This paper developed a weighted P-Rank algorithm based on a heterogeneous scholarly network for article ranking evaluation. The study is dedicated to assigning weight to the corresponding links in G_P , G_{PA} , and G_{PJ} by calculating citation relevance (G_P), authors' contribution (G_{PA}), and journals' contribution (G_{PJ}). Under conditions of two weighting combinations (Unweighted and Weighted) and four graph configurations (G_P , $G_P + G_{PA}$, $G_P + G_{PJ}$, and $G_P + G_{PA} + G_{PJ}$), the performance of weighted P-Rank algorithm is further evaluated and analyzed. The experimental results showed that the weighted P-Rank method achieved promising performance on three different datasets, and the best ranking result can be achieved by jointly employing all kinds of weighting information. Additionally, we note that the article ranking result can be further improved by utilizing time-weighting information.

In the future, a series of meaningful studies can be conducted subsequently, combining network topology and link weighting. For instance, we would test the effect of link weighting on more ranking methods and verify how the parameters influence the performance of the algorithms.

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