https://doi.org/10.51408/issi2025_094

Research leadership recommendation in research leading-participating multiplex networks based on Wasserstein Distance

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Abstract

Research leadership has long been a central focus in research collaboration. Effective research leadership recommendation is critical for identifying suitable collaborators. However, existing studies predominantly focus on recommending co-author relationships, neglecting the dimension of research leadership. In the context of multiplex networks, existing literature measures interlayer similarity using centrality correlations, which capture only a limited aspect of node importance. To this end, we propose a RMNW model for research leadership recommendation. RMNW constructs a two-layer network: the target layer represents research leadership relationships, while the auxiliary layer captures research participation relationships. The model utilizes Wasserstein Distance to quantify interlayer similarity based on local and global neighborhoods. It integrates information from both layers for link prediction in the target layer, controlled by a tunable parameter λ to balance contributions from each layer. Extensive experiments validate the RMNW model, showing that it significantly outperforms state-of-the-art methods for link prediction in multiplex networks.

Introduction

Research collaboration has become essential due to the growing complexity and nonlinearity of contemporary scientific challenges (Schneider, Sogbanmu et al. 2024). It combines complementary knowledge and expertise from diverse sources to address problems and foster innovation (Gu, Pan et al. 2024). Collaborative efforts typically maintain higher standards of internal quality control compared to single-authored publications (de Frutos-Belizón, García-Carbonell et al. 2024). Collaborator recommendation has received increasing attention across various fields (Liu, Wu et al. 2023, Zhu, Quan et al. 2023).

Research leadership has always been a focal point of research collaboration. Leading authors (first and corresponding authors) play a critical role in securing the academic resources and expertise necessary to initiate and sustain these endeavors (Chinchilla-Rodríguez, Sugimoto et al. 2019). Leading authors primarily offer global, comprehensive and sustained contributions (Sekara, Deville et al. 2018, Xu, Liu et al. 2024). It is essential for researchers to identify suitable research leaders to initiate and advance collaborative teams for new projects. Similarly, it is crucial for research leaders to select appropriate participating authors (non-first or non-corresponding authors) who can provide local, specialized and staged contributions (He, Wu et al. 2022). Throughout the collaboration process, interactions between leading and participating authors are typically more frequent, closer, and more reciprocal than interactions between two participating authors (He, Liu et al. 2023). Therefore, a two-layer multiplex network, where one layer represents research leadership relationships and the other represents research participation relationships, provides a more effective framework for modeling the complex dynamics inherent in research collaboration.

The recommendation of research leadership (i.e., leading-participating relationships or leading-leading relationships) is critical for effective collaborator identification. However, existing studies face three major limitations. First, most studies focus on recommending relations among all co-authors within collaborations (Liu, Wu et al. 2023), while overlooking the crucial dimension of research leadership relations. Second, although some studies involve research leadership recommendation (He, Liu et al. 2023), they usually model collaboration dynamics using single-layer networks (He, Wu et al. 2021, Cai, Tian et al. 2024), thereby neglecting the interlayer interactions between leadership and participation relationships. Third, existing literature generally measures interlayer similarity by correlating node centralities, such as degree-degree correlation (Zhao, Li et al. 2014) and average similarity of neighbors (ASN) (Najari, Salehi et al. 2019). However, each of these centralities captures different dimensions of node importance, which can introduce bias into the prediction process.

To this end, we propose a novel two-layer Research Leading-Participating Multiplex Network (RLPMN). In the RLPMN, the first layer captures research leadership relations, while the second layer captures research participation relations. Second, we introduce a novel interlayer similarity measure between the target and auxiliary layers, based on the Wasserstein Distance between the local and global neighborhoods of nodes in each layer. In summary, the primary contributions of this study are as follows:

This is the first study to analyze research leadership and collaboration through the lens of a multiplex network.

It is the first to recommend research leadership relations by integrating both intralayer information from the research leadership layer and interlayer information from the research participation layer.

This study introduces a novel approach, namely, adopting Wasserstein Distance to accurately measure the distributional distance of node neighborhoods across layers, providing a precise measure of interlayer similarity.

The proposed framework

Figure 1 illustrates the proposed framework, RMNW (Research leadership recommendation in research leading-participating multiplex networks based on Wasserstein Distance). It is composed of four modules: (1) network construction, (2) interlayer similarity, (3) synthesizer, and (4) recommendation.

Network construction

Let $\mathcal{G} = (G_T, G_A)$ be our proposed Research Leading-Participating Multiplex Network (RLPMN), where $G_T = (V_T, E_T)$ represents the target layer, consisting of research leadership relations (link set E_T), including leading-participating connections and leading-leading connections, which are established between a leading author (either the first author or corresponding author) and a participating author (non-first and non-corresponding), or between two leading authors. And $G_A = (V_A, E_A)$ signifies the auxiliary layer, which comprises research participating relations (link set E_A), including the participating-participating connections between two participating authors (non-first and non-corresponding authors). The common node set $V_T = V_A$ contains N nodes ($|V_T| = N$). Regarding link weights, consistent with the approach of (Zeng, Shen et al. 2017), we assign equal credit to all leading authors (both the first author and corresponding author). In the target layer, the link weight between a leading author i and the $j-th$ author is as follows,

$$W_{ij} = \begin{cases} 2, & if\ j\ is\ also\ a\ leading\ author \\ 1 + \frac{1}{j}, & if\ j\ is\ a\ participating\ author \end{cases} \tag{1}$$

In the auxiliary layer, the weight of the link between i-th author and j-th author is as follows,

$$\mathrm{W}_{ij} = \frac{1}{i} + \frac{1}{j} \tag{2}$$

Figure 1 illustrates the construction of the RLPMN based on two co-authored publications.

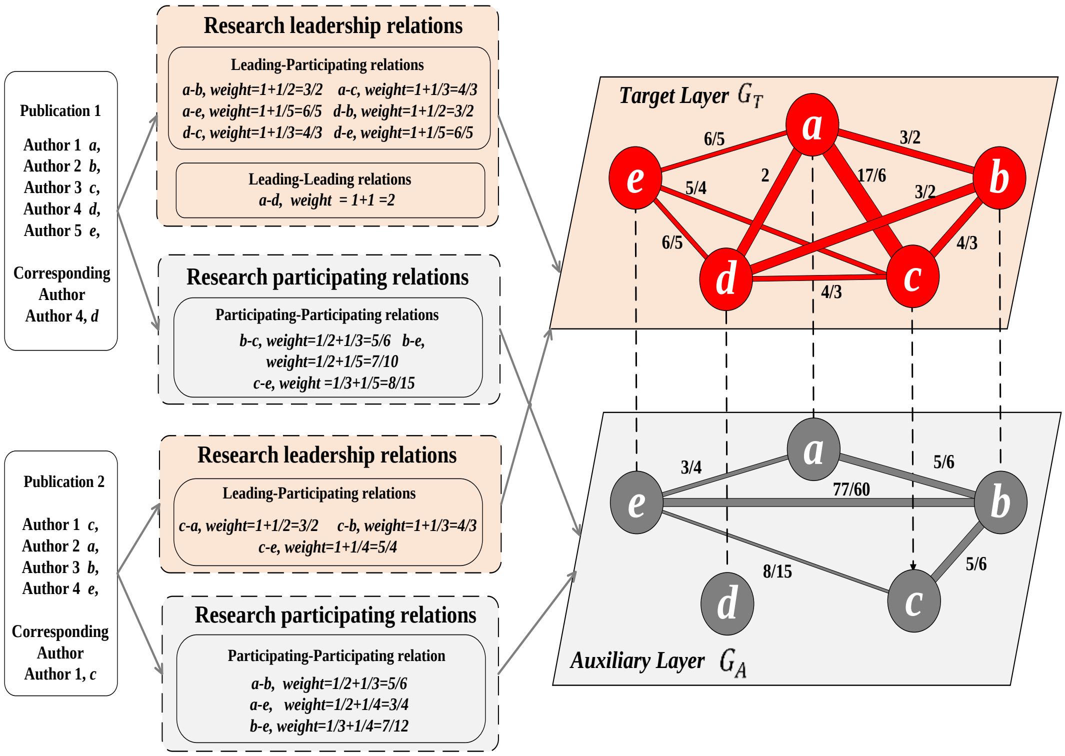

Figure 1. An illustration of Research leading-participating multiplex network (RLPMN) based on two co-authored publications.

Interlayer similarity

To calculate the internal node distance, we embed each node into a low dimensional space. Specifically, as illustrated in Figure 2, the calculation process is divided into three sub-modules: Neighborhood Sampling by 2nd Order Biased Random Walk (NSBRW), Node2Vec embedding, and Interlayer Similarity based on Wasserstein Distance of interlayer neighborhood distribution (ISWN).

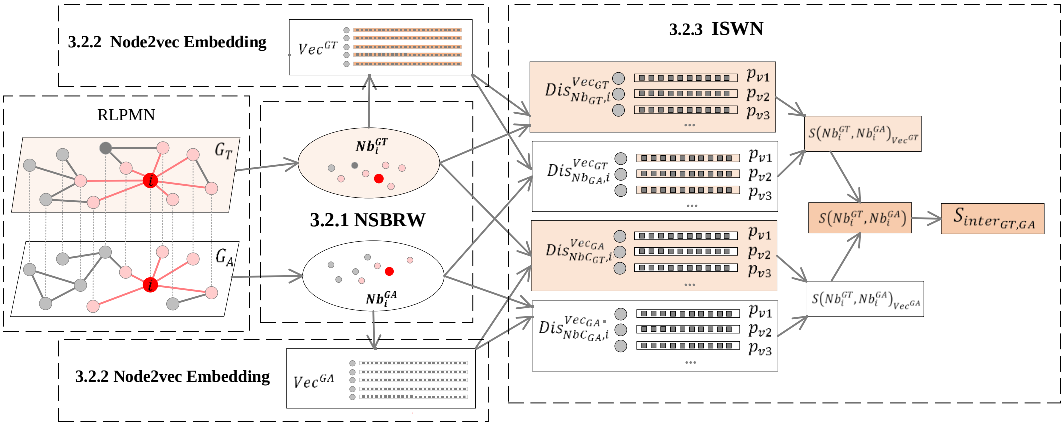

Figure 2. The proposed framework of calculating interlayer similarity.

NSBRW

Following the work of Grover and Leskovec (2016), we employ a 2^{nd} order biased random walk characterized by two parameters p and q. This approach allows for a smooth interpolation between breadth-first sampling (BFS) and depth-first sampling (DFS), enabling the sampling of both immediate and high-order neighborhoods for each node in both the target and auxiliary layers. Figure 3 illustrates the sampling process for the focal node i. From the target layer G_T, we generate Nb_i^{GT}, the neighborhoods of node i, and from the auxiliary layer G_A, we generate the neighborhoods of node i, Nb_i^{GA}.

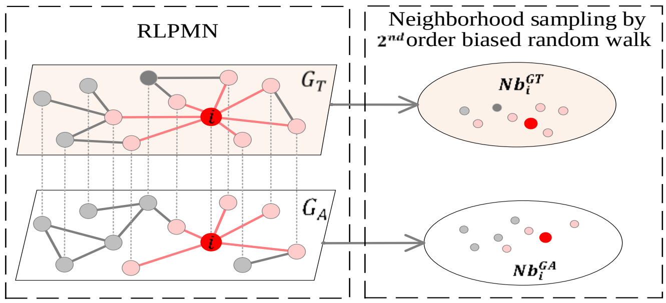

Figure 3. An illustration of neighborhood sampling by 2nd order biased random walk.

Node2vec embedding

With the neighborhoods of each node sampled from both the target and auxiliary layers, we can embed each node into a $d-dimensional$ vector following the node2vec algorithm (Grover and Leskovec 2016), by extending the Skpi-gram architecture to networks. Figure 4 illustrates the Node2vec embedding process for the focal node i. We can embed node i into a d-dimensional vector Vec_i^{GT} based on the neighborhoods sampled from the target layer G_T, and the a d-dimensional vector Vec_i^{GA} based on the neighborhoods sampled from the auxiliary layer G_A.

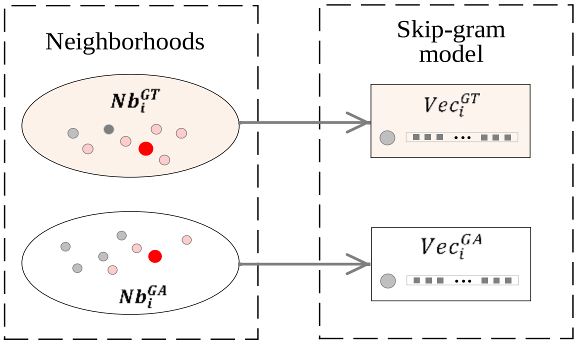

Figure 4. An illustration of Node2vec embedding.

ISWN

In Section 2.2.1, for a focal node i, we have obtained the neighborhoods Nb_i^{GT} sampled from the target layer G_T, and the neighborhoods Nb_i^{GA} sampled from the auxiliary layer G_A. In Section 2.2.2, we have embedded each node into a d-dimensional vector Vec^{GT} based on the target layer G_T, and a d-dimensional vector Vec^{GA} based on the auxiliary layer G_A. Therefore, we can represent neighborhoods Nb_i^{GT} into a d-dimensional space distribution based on the node vector Vec^{GT} as $Dis_{Nb_{GT}}^{Vec^{GT}}$, and into a d-dimensional space distribution based on the node vector Vec^{GA} as $Dis_{Nb_{GT}}^{Vec^{GA}}$. Similarly, we can represent neighborhoods Nb_i^{GA} into a d-dimensional space distribution based on the node vector Vec^{GT} as $Dis_{Nb_{GA}}^{Vec^{GT}}$, and into a d-dimensional space distribution based on the node vector Vec^{GA} as $Dis_{Nb_{GA}}^{Vec^{GA}}$.

Consequently, we can obtain the distance between Nb_i^{GT} (the focal node i's neighborhoods from the target layer G_T) and Nb_i^{GA} (i's neighborhoods from the auxiliary layer G_A) via the node embedding vector based on the target layer vector Vec^{GT} by the Wasserstein Distance as follows,

$$Distance\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GT}} = WassersteinD\left(Dis_{Nb_{GT},i}^{Vec^{GT}}, Dis_{Nb_{GA},i}^{Vec^{GT}}\right) \qquad (3)$$

The similarity of the focal node i's neighborhoods in the target layer G_T and the auxiliary layer G_A based on the target layer on the target layer vector Vec^{GT} is calculated as follows,

$$S\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GT}} = \frac{1}{1 + Distance\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GT}}} \qquad (4)$$

Similarly, we can obtain the distance between Nb_i^{GT} and Nb_i^{GA} via the node embedding vector based on the target layer Vec^{GA} by the Wasserstein Distance as follows,

$$Distance\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GA}} = WassersteinD\left(Dis_{Nb_{GT},i}^{Vec^{GA}}, Dis_{Nb_{GA},i}^{Vec^{GA}}\right) \quad (5)$$

The similarity of the focal node i's neighborhoods in the target layer G_T and the auxiliary layer G_A based on the target layer on the auxiliary layer vector Vec^{GA} is calculated as follows (Segaran 2007),

$$S\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GA}} = \frac{1}{1 + Distance\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GA}}} \quad (6)$$

As shown in Figure 5, the symmetric similarity of the focal node i's neighborhoods in the target layer G_T and the auxiliary layer G_A is calculated as follows,

$$S\left(Nb_i^{GT}, Nb_i^{GA}\right) = \frac{1}{2}\left(S\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GT}} + S\left(Nb_i^{GT}, Nb_i^{GA}\right)_{Vec^{GA}}\right) \quad (7)$$

Finally, the interlayer similarity of the target layer and the auxiliary layer is the mean of similarity of all nodes' neighborhoods in G_T and G_A,

$$S_{inter_{GT,GA}} = \frac{1}{N}\sum_{i=1}^{N} S\left(Nb_i^{GT}, Nb_i^{GA}\right) \quad (8)$$

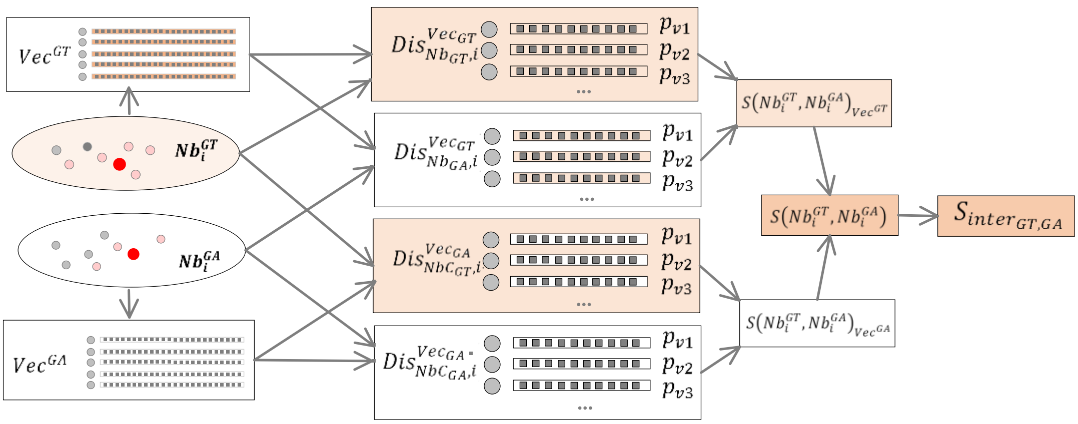

Figure 5. An illustration of Interlayer Similarity based on Wasserstein Distance of interlayer neighborhood distribution.

Synthesizer

For the node pair (u, v) in the target layer G_T, the synthesized index for link possibility is defined as follows (Wu, Ji et al. 2023),

$$P_{u,v} = (1 - \lambda) \times P_{u,v}^{GT} + \lambda \times S_{inter_{GT,GA}} \times P_{u,v}^{GA} \quad (9)$$

Here, $P_{u,v}^{GT}$ represents the existence likelihood of the link (u, v) in the target layer G_T based on traditional methods, solely adopting the intralayer information of G_T. Leveraging the node vectors based on each layer in Section 2.2.2, we adopt the cosine similarity of Vec_u^{GT} (the vector representation of node u based on the target layer G_T) and Vec_v^{GT} (the vector representation of node v based on the target layer G_T) to measure the intralayer similarity of the node u and v in the target layer G_T. Similarly, $P_{u,v}^{G_A}$ denotes the existence likelihood of the link (u, v) in the auxiliary layer G_A, solely based on the intralayer information of G_A. The parameter λ is the tunable variable that determines the weight of information provided by the auxiliary layer G_A for the link prediction in the target layer G_T.

Recommendation

We can conduct research leadership recommendation based on the RLPMN in Section 2.1, interlayer similarity $S_{inter_{GT,GA}}$ in Section 2.2, and the intralayer information $P_{u,v}^{G_T}$, $P_{u,v}^{G_A}$ and synthesizer $P_{u,v}$ in Section 2.3. According to the Equation (9), we can obtain the link possibility of all node pair (u, v), and by sorting, we can obtain the top *N* recommendations with the highest $P_{u,v}$.

Table 1. The RMNW model.

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Algorithm 1: Pseudo-code fo the proposed method: RMNW
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Input: Multiplex network $\mathcal{G} = (G_T = (V, E_T), G_A = (V, E_A))$, embedding dimensions d, walk length l, number of walks r, window size k, target nodes $Node_t$,

Output: the top-N recommended nodes list for each target node.

Nb^{GT} = GenerateNeighbors(G_T)
Nb^{GA} = GenerateNeighbors(G_A)
Vec^{GT} = Node2VecEmbedding(k, Nb^{GT})
Vec^{GA} = Node2VecEmbedding(k, Nb^{GA})
$S_{inter_{GT,GA}}$ = InterlayerSimilarity(Nb^{GT}, Nb^{GA}, Vec^{GT}, Vec^{GA})
RecommendedList = Recommend(taregtNode)

GenerateNeighbors(G)
Initialize Nb^{G} to Empty
for $w = 0 -> W - 1$ do
for $v \in V$ do
Nb_v^{GT} = BiasedRandomWalk(G, v, l)
Append Nb to Nb^{G}
Return Nb^{G}

InterlayerSimilarity(Nb^{GT}, Nb^{GA}, Vec^{GT}, Vec^{GA})
Initialize $S_{inter_{GT,GA}} = 0$
for $v \in V$ do
$Dis_{Nb_{GT},v}^{Vec^{GT}}$ = NeighborDistri(v, Nb_{GT}, Vec^{GT})
$Dis_{Nb_{GA},v}^{Vec^{GT}}$ = NeighborDistri(v, Nb_{GA}, Vec^{GT})
$S(Nb_v^{GT}, Nb_v^{GA})_{Vec^{GT}} = \frac{1}{1 + WassersteinD\left(Dis_{Nb_{GT},v}^{Vec^{GT}}, Dis_{Nb_{GA},v}^{Vec^{GT}}\right)}$
$Dis_{Nb_{GT},v}^{Vec^{GA}}$ = NeighborDistri(v, Nb_{GT}, Vec^{GA})
$Dis_{Nb_{GA},v}^{Vec^{GA}}$ = NeighborDistri(v, Nb_{GA}, Vec^{GA})
$S(Nb_v^{GT}, Nb_v^{GA})_{Vec^{GA}} = \frac{1}{1 + WassersteinD\left(Dis_{Nb_{GT},v}^{Vec^{GA}}, Dis_{Nb_{GA},v}^{Vec^{GA}}\right)}$
$S_{inter_{GT,GA}} += \frac{1}{2}(S(Nb_v^{GT}, Nb_v^{GA})_{Vec^{GA}} + S(Nb_v^{GT}, Nb_v^{GA})_{Vec^{GT}})$
$Return \frac{1}{|V|} \times S_{inter_{GT,GA}}$
Recommend(t)
Initialize $RecommendedList$ to Empty
for $v \in V$ do
$P_{t,v}^{G_T}$= cosine(Vec_v^{GT}, Vec_t^{GT})
$P_{t,v}^{G_A}$= cosine(Vec_v^{GA}, Vec_t^{GA})
$P_{t,v} = (1 - \lambda) \times P_{u,v}^{G_T} + \lambda \times S_{inter_{GT,GA}} \times P_{u,v}^{G_A}$
Append $P_{t,v}$ to $RecommendedList$
$Return$ Sort($RecommendedList$)

Experiments

In this section, we validate the effectiveness of our proposed model RMNW. Specifically, we present the datasets, baseline methods, evaluation metrics, and implementation details from Section 3.1 to Section 3.4. The research leadership recommendation results are analyzed in Section 3.5.

Dataset

Experiments are conducted on publications the field of "Pharmaceutical Sciences". Publications are retrieved from the Web of Science Core Citation Database, a widely accepted source for studying scientific publications (Yoo, Jung et al. 2024). An advanced search query, "WC = A AND PY = B" is employed, where A is the above Web of Science categories, and B is the publication year "2014-2023". In total, 426708 publications were retrieved. Single-authored publications are excluded. We conduct author name disambiguation following (Sinatra, Wang et al. 2016). Authors with over ten publications are selected (Zhang 2017), resulting in 30286 authors. The dataset is divided into two subset based on publication year: works published before 2022 serve as the training set, while those from 2022 onward form the testing set (Pradhan and Pal 2020, He, Wu et al. 2022).

Evaluation metrics

We employ widely adopted metrics in recommending systems to evaluate the proposed model, namely $F1\ Score$, $nDCG$, and MRR.

(1) $F1\ Score$: $F1\ Score$ is a popular metric to evaluate the performance of a binary classifier. We can divide all the results into four categories: TP (true positive), FP (false positive), TN (true negative), and FN (false negative).

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F1 = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{12}$$

As shown in Equation 12, the $F1\ Score$ only cares the proportion of true results and false results, ignoring the ranking of the recommended results. Therefore, two more metrics are adopted.

(2) $nDCG$: Let $rel_{R,i}$ represent the graded relevance of the recommended researcher R at position i based on the ground truth data. Discounted cumulative gain (DCG) penalizes highly relevant researchers that appear lower in the recommendation list. The DCG accumulated at a particular rank position p for a recommendation list R is computed as follows:

$$DCG_{R,p} = rel_{R,1} + \sum_{j=2}^{p} \frac{rel_{R,j}}{\log_2(j+1)} \tag{13}$$

The Ideal Discounted Cumulative Gain (IDCG) arranges the results in descending order by relevance and then calculates DCG:

$$IDCG_{I,p} = rel_{I,1} + \sum_{j=2}^{p} \frac{rel_{I,j}}{log_2(j+1)} \quad (14)$$

The normalized DCG ($nDCG$) for a recommendation result R at a specific rank position p is given by the ratio of $DCG_{R,p}$ to $IDCG_{I,p}$ as follows (Järvelin and Kekäläinen 2002),

$$nDCG_{R,p} = \frac{DCG_{R,p}}{IDCG_{I,p}} \quad (15)$$

(3) MRR: Reciprocal Rank (RR) is a metric used in ranking systems to measure how quickly the first relevant item appears in a list of ranked results. Let $rank_i$ be the first relevant result appears at position i in the ranked result list Q. The RR is calculated as

$$RR = \frac{1}{rank_i} \quad (16)$$

If there is no relevant result in Q, the RR is 0. And MRR (Mean Reciprocal Rank) is the mean of RR,

$$MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{rank_i} \quad (17)$$

Baselines

We compare the proposed model with the following state-of-art methods for link prediction in multiplex networks. We also tune the baselines to their best performance for comparison.

(1) LPGRI (Wang, Tang et al. 2023): The model proposes a interlayer similarity, "Global Relevance", using the average Pearson correlation of all node representation vectors from different layers to leverage the information from the auxiliary layer.

(2) MLRW (Nasiri, Berahmand et al. 2021): The model extends the local random walk by leveraging the interlayer and intralayer information, and defines a biased random walk to find the potential link probability in the target layer.

(3) LPIS (Najari, Salehi et al. 2019): The model adopts the AASN-based (asymmetric average similarity of neighbors) correlation $LPIS/AASN$ as interlayer similarity to leverage the information from the auxiliary layer.

(4) MNE (Zhang, Qiu et al. 2018): The model proposes a network embedding approach to jointly represent information of all layers in the multiplex network. But for the task of link prediction, it simply takes the average probability in all

layers as the final probability of a potential link.

(5) RMNW variants: $RMNW_{DDC}$ is a variant of RMNW which uses the degree-degree correlation (Zhao, Li et al. 2014) as the interlayer similarity measure. $RMNW_{ASSN}$ is another variant, which adopts the asymmetric average similarity of neighbors (AASN) to measure the overlap of common neighbors between node pairs across layers, serving as the interlayer similarity (Najari, Salehi et al. 2019). $RMNW_{LO}$ is yet another variant that employs link overlap to quantify the common edges across layers, which serves as an indicator of interlayer similarity (Najari, Salehi et al. 2019).

Implementation details

The parameter settings used for random walk in 2.2.1 NSBRW, and 2.2.2 Node2vec Embedding follow the typical values adopted in (Grover and Leskovec 2016). Specifically, we set vector dimension $d = 128$, and simulate $r = 10$ random walks of fixed length $l = 80$, starting from each node. The window size is set to k=10, and the return parameter $p = 1$ and in-out parameter $q = 1$. As for the tunable parameter λ, we follow the approach outlined in (Jafari, Abdolhosseini-Qomi et al. 2021), and set $\lambda = 0.5$. For the recommendation task, we randomly select 500 authors as the target authors (Pradhan and Pal 2020, He, Wu et al. 2022) and evaluate the performance of our $RMNW$ model alongside other baseline models.

1.1 *Performance comparison*

We compare our proposed $RMNW$ with various baselines. Table 2 reports the $F1$-score and MRR of recommendation performance. Table 3 presents the performance in terms of $nDCG$. Overall, the proposed $RMNW$ model outperforms all.

Regarding the $F1$-score, as shown in Table 2, $RMNW$ achieves the highest $F1$-score for all recommending number N ($F1@5, F1@7, \ldots, F1@30$), except for $F1@3$. Notably, $RMNW$ performs the best when $N = 7$ ($F1@7 = 0.1609$), representing an increase of 0.0072 (4.68%) compared to the highest $F1@7$ among the baselines. As N increases, the $F1$-score of $RMNW$ exhibits a gradual downward trend, a pattern also observed among the baselines. Among the baselines, the $MLRW$ generally achieves the highest $F1$-score, followed by $LPGRI$ and $LPIS$. In particular, when $N = 3$, the $F1@3$ of $MLRW$ exceeds that of $RMNW$. Conversely, $RMNW_{DDC}$ and MNE yield the lowest $F1$-score.

Regarding MRR, as shown in Table 2, the $RMNW$ outperforms all baselines. Specifically, it achieves an increase of 0.0383 (7.03%), compared to the highest $F1@7$ among the baselines. $MLRW$ and $LPGRI$ also exhibit high MRR, while $RMNW_{DDC}$ and MNE perform poorly.

In terms of $nDCG$, as shown in Table 3, $RMNW$ achieves the best performance compared to other baselines. It attains the highest $nDCG$ of 0.3329 for the top 3 recommendation. Among the baseline models, $MLRW$ achieves the highest $nDCG$, followed by $LPGRI$ and $LPIS$. Consistent with the performance in terms of $F1$-score and MRR, MNE and $RMNW_{DDC}$ yield the lowest $nDCG$.

Table 2. $F1$ and MRR of $RMNW$ and baseline methods.

Method	$F1@3$	$F1@5$	$F1@7$	$F1@10$	$F1@15$	$F1@20$	$F1@25$	$F1@30$	MRR
$LPGRI$	0.0929	0.1472	0.1526	0.1472	0.1386	0.1187	0.1032	0.0759	0.5349
$MLRW$	**0.0962**	0.1497	0.1537	0.1488	0.1403	0.1221	0.1058	0.0793	0.5448
$LPIS$	0.0910	0.1419	0.1463	0.1417	0.1343	0.1152	0.1009	0.0746	0.5102
MNE	0.0878	0.1307	0.1332	0.1297	0.1225	0.1032	0.0931	0.0695	0.4445
$RMNW$	0.0933	**0.1584**	**0.1609**	**0.1557**	**0.1468**	**0.1246**	**0.1098**	**0.0812**	**0.5831**
$RMNW_{DDC}$	0.0859	0.1292	0.1311	0.1284	0.1217	0.1028	0.0914	0.0660	0.4401
$RMNW_{ASSN}$	0.0896	0.1365	0.1414	0.1372	0.1301	0.1112	0.0969	0.0712	0.4865
$RMNW_{LO}$	0.0881	0.1334	0.1385	0.1329	0.1270	0.1083	0.0936	0.0697	0.4692

Table 3. $nDCG$ of $RMNW$ and baseline methods.

Method	$nDCG@3$	$nDCG@5$	$nDCG@7$	$nDCG@10$	$nDCG@15$	$nDCG@20$	$nDCG@25$	$nDCG@30$
$LPGRI$	0.2889	0.2832	0.2787	0.2718	0.2684	0.2653	0.2607	0.2617
$MLRW$	0.3068	0.2999	0.2953	0.2894	0.2830	0.2762	0.2715	0.2664
$LPIS$	0.2798	0.2724	0.2679	0.2634	0.2588	0.2533	0.2488	0.2465
MNE	0.2552	0.2526	0.2506	0.2477	0.2452	0.2421	0.2365	0.2329
$RMNW$	**0.3329**	**0.3266**	**0.3228**	**0.3183**	**0.3132**	**0.3089**	**0.3037**	**0.3001**
$RMNW_{DDC}$	0.2546	0.2493	0.2455	0.2425	0.2394	0.2355	0.2303	0.2261
$RMNW_{ASSN}$	0.2713	0.2643	0.2610	0.2564	0.2517	0.2486	0.2434	0.2409
$RMNW_{LO}$	0.2606	0.2568	0.2540	0.2519	0.2479	0.2458	0.2420	0.2396

Sensitivity analysis

In this section, we implement the sensitivity analysis of the parameter λ on the performance of RMNW. We adopt $F1@7$, MRR, and $nDCG@7$ as evaluation metrics with $\lambda \in \{0.1, 0.2, \ldots, 0.9\}$. Figure 6-8 report the results in terms of $F1@7$, MRR, and $nDCG@7$, respectively. Regarding $F1@7$, as shown in Figure 6, $\lambda \in \{0.3, 0.4, 0.5, 0.6\}$ leads to good performance. Conversely, excessively small or large λ would degrade the performance in all three research fields. For MRR, as shown in Figure 7, $\lambda \in \{0.3, 0.4, 0.5, 0.6, 0.7\}$ yields better recommending performance. On the one hand, a small λ fails to capture sufficient information from the auxiliary layer. On the other hand, a large λ can also overlook critical information from the target layer. In terms of $nDCG@7$, as shown in Figure 8, $\lambda \in \{0.3, 0.4, 0.5, 0.6\}$ can achieve better recommending performance. Similar to the other metrics, both small and large λ can degrade the performance.

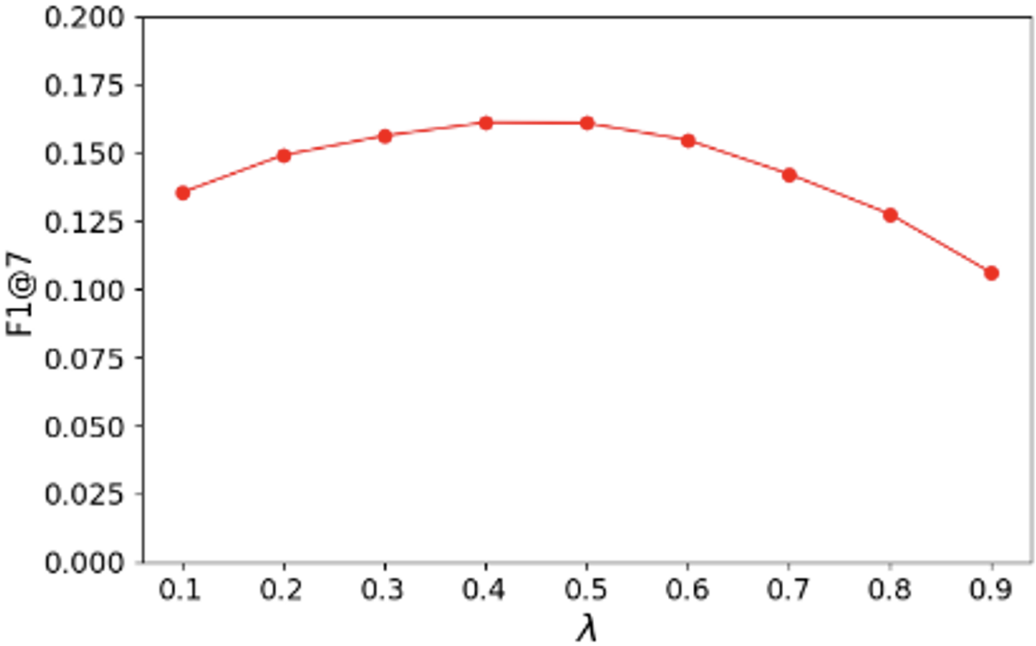

Figure 6. Sensitivity of the parameter λ on the $F1@7$ of RMNW.

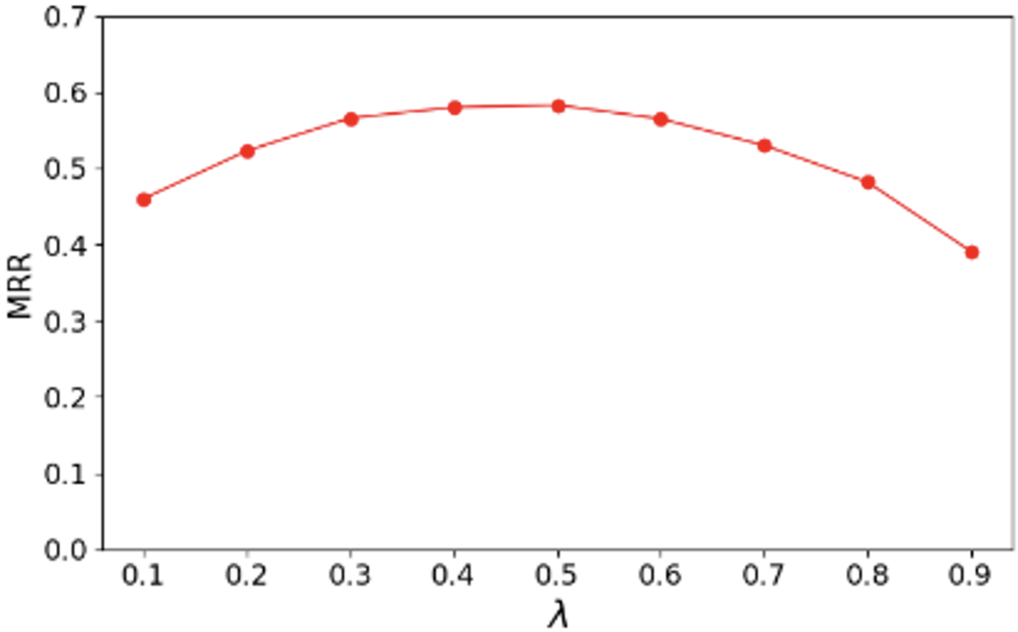

Figure 7. Sensitivity of the parameter λ on the MRR of RMNW.

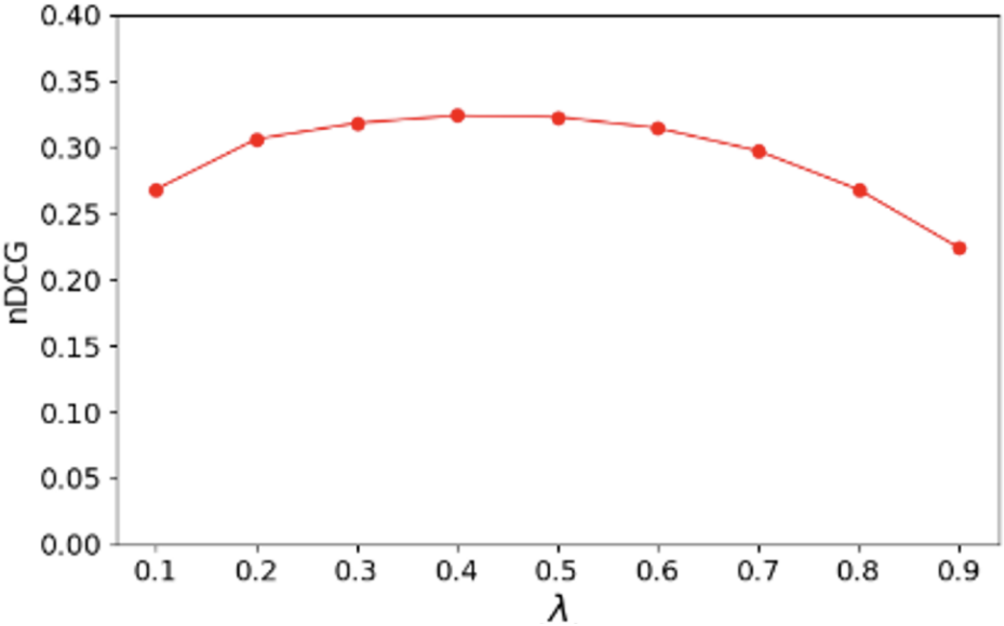

Figure 8. Sensitivity of the parameter λ on the $nDCG@7$ of RMNW.

Ablation studies

We conduct ablation studies to understand the impact of information from the target layer G_T and auxiliary layer G_A on the recommendation performance. The results are presented in Table 4. Model 1 utilizes the information entirely from the target layer G_T ($\lambda = 0$). Model 2 integrates the information from both target layer G_T and auxiliary layer G_A ($\lambda = 0.5$). Model 3 utilizes the information entirely from the auxiliary layer G_A ($\lambda = 1$). From Table 4, we observe that Model 3 consistently yields the lowest $F1@7$, MRR, and $nDCG@7$ across all fields. While Model 2 achieves the best performance. These findings indicate that integrating the information from both layers significantly improves recommendation performance in the target layer G_T.

Table 4. Research leadership recommendation with information from different layers.

Model	λ	Information from the target layer G_T	Information from the auxiliary layer G_A	$F1@7$	MRR	$nDCG@7$
1	0	√	×	0.1182	0.4070	0.2210
2	1	×	√	0.0791	0.2933	0.1513
3	0.5	√	√	0.1609	0.5831	0.3228

Discussion

Our proposed RMNW model significantly improves overall recommendation performance across various metrics, including $F1, MRR, and\ nDCG$. As shown in Tables 2, the $RMNW$ model outperforms baseline models in all evaluation metrics.

Second, integrating information from the research participation layer (auxiliary layer) notably enhances research leadership recommendation performance in the research leading-participating multiplex networks. For example, as highlighted in Tables 3 of the Ablation studies Section, combining information from both the target layer and auxiliary layer ($\lambda = 0.5$) yields improvements of 36.1%, 43.2%, and 46.1% in $F1, MRR, and\ nDCG$, respectively, compared to solely using information from the target layer. Furthermore, even using the degree-degree correlation as interlayer similarity metric, the $RMNW_{DDC}$ achieves better performance than Model 1 ($\lambda = 0$, single-layer network link prediction).

Third, the Wasserstsin Distance effectively captures the interlayer similarity between the target and auxiliary layer. As detailed in Table 2-3, the $RMNW$ consistently achieves the highest $F1, MRR\ and\ nDCG$ compared to other variants such as $RMNW_{DDC}$ (degree-degree correlation), $RMNW_{ASSN}$ (overlap of common neighbors), and $RMNW_{LO}$ (overlap of the common edges).

We also implement the sensitivity analysis of the parameter λ on the recommendation performance ($F1@7, MRR\ and\ nDCG@7$). As depicted in Figure 6, generally, $\lambda \in \{0.3, 0.4, 0.5, 0.6\}$ leads to good performance. And these results confirm the robustness and effectiveness of the proposed RMNW model.

Conclusion and future work

Our work focuses on leveraging research participation relationships to enhance research leadership recommendations. We propose the RMNW model, which consists of four interconnected modules: (1) Network construction. This module distinguishes between research leadership and research participation relationships. It constructs a two-layer network, where the target layer represents research leadership relationships, and the auxiliary layer captures research participation relationships. (2) Interlayer similarity. This module employs the Wasserstein Distance to measure the interlayer similarity based on local and global neighborhoods of nodes in each layer. (3) Synthesizer. This module integrates information from both the target and auxiliary layers for link prediction in the target layer, controlled by a tunable parameter λ. (4) Recommendation. This module identifies potential research leadership partners by ranking the link probabilities of all node pairs and generating the top N recommendations. Extensive experimental results demonstrate that the

RMNW model significantly outperforms state-of-the-art multiplex network link prediction models. Sensitivity analysis further confirms the robustness and effectiveness of the proposed model. Moreover, ablation studies reveal that incorporating information from the research participation layer (auxiliary layer) substantially enhances the performance of research leadership recommendations.

This study has certain limitations that warrant further investigation. In constructing the research leading-participating multiplex network, we do not account for the temporal attribute of the collaboration relationships. However, recent collaborations are more likely to influence future collaboration and should ideally be given greater weight. In subsequent research, we aim to incorporate temporal attributes of collaboration relationships to further improve recommendation performance.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (72204189), Guangdong Basic and Applied Basic Research Foundation (2022A1515110972) and Digital Intelligence Humanities Fundation of Wuhan University (2024SZWK023)

References

Cai, R., W. Tian, R. Luo and Z. Hu (2024). "The generation mechanism of research leadership in international collaboration based on GERGM: a case from the field of artificial intelligence." Scientometrics: 1-19.

Chinchilla-Rodríguez, Z., C. R. Sugimoto and V. Larivière (2019). "Follow the leader: On the relationship between leadership and scholarly impact in international collaborations." Plos one 14(6): e0218309.

de Frutos-Belizón, J., N. García-Carbonell, F. Guerrero-Alba and G. Sánchez-Gardey (2024). "An empirical analysis of individual and collective determinants of international research collaboration." Scientometrics 129(5): 2749-2770.

Grover, A. and J. Leskovec (2016). node2vec: Scalable feature learning for networks. Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining.

Gu, J., X. Pan, S. Zhang and J. Chen (2024). "International mobility matters: Research collaboration and scientific productivity." Journal of Informetrics 18(2): 101522.

He, C., F. Liu, K. Dong, J. Wu and Q. Zhang (2023). "Research on the formation mechanism of research leadership relations: An exponential random graph model analysis approach." Journal of Informetrics 17(2): 101401.

He, C., J. Wu and Q. Zhang (2021). "Characterizing research leadership on

geographically weighted collaboration network." Scientometrics 126: 4005-4037.
He, C., J. Wu and Q. Zhang (2022). "Proximity-aware research leadership recommendation in research collaboration via deep neural networks." Journal of the Association for Information Science and Technology 73(1): 70-89.
Jafari, S. H., A. M. Abdolhosseini-Qomi, M. Asadpour, M. Rahgozar and N. Yazdani (2021). "An information theoretic approach to link prediction in multiplex networks." Scientific Reports 11(1): 13242.
Järvelin, K. and J. Kekäläinen (2002). "Cumulated gain-based evaluation of IR techniques." ACM Transactions on Information Systems (TOIS) 20(4): 422-446.
Liu, X., K. Wu, B. Liu and R. Qian (2023). "HNERec: Scientific collaborator recommendation model based on heterogeneous network embedding." Information Processing & Management 60(2): 103253.
Najari, S., M. Salehi, V. Ranjbar and M. Jalili (2019). "Link prediction in multiplex networks based on interlayer similarity." Physica A: Statistical Mechanics and its Applications 536: 120978.
Nasiri, E., K. Berahmand and Y. Li (2021). "A new link prediction in multiplex networks using topologically biased random walks." Chaos, Solitons & Fractals 151: 111230.
Pradhan, T. and S. Pal (2020). "A multi-level fusion based decision support system for academic collaborator recommendation." Knowledge-Based Systems 197: 105784.
Schneider, M. D., T. O. Sogbanmu, H. Rubin, A. Bortolus, E. E. Chukwu, R. Heesen, C. L. Hewitt, R. Kaufer, H. Metzen and V. Mitova (2024). "Science–policy research collaborations need philosophers." Nature human behaviour: 1-2.
Segaran, T. (2007). Programming collective intelligence: building smart web 2.0 applications, " O'Reilly Media, Inc.".
Sekara, V., P. Deville, S. E. Ahnert, A.-L. Barabási, R. Sinatra and S. Lehmann (2018). "The chaperone effect in scientific publishing." Proceedings of the National Academy of Sciences 115(50): 12603-12607.
Sinatra, R., D. Wang, P. Deville, C. Song and A.-L. Barabási (2016). "Quantifying the evolution of individual scientific impact." Science 354(6312): aaf5239.
Wang, C., F. Tang and X. Zhao (2023). "LPGRI: a global relevance-based link prediction approach for multiplex networks." Mathematics 11(14): 3256.
Wu, Y., Y. Ji and F. Gu (2023). "Identifying firm-specific technology opportunities in a supply chain: Link prediction analysis in multilayer networks." Expert Systems with Applications 213: 119053.
Xu, H., M. Liu, Y. Bu, S. Sun, Y. Zhang, C. Zhang, D. E. Acuna, S. Gray, E. Meyer and Y. Ding (2024). "The impact of heterogeneous shared leadership in scientific teams." Information Processing & Management 61(1): 103542.

Yoo, H. S., Y. L. Jung, J. Y. Lee and C. Lee (2024). "The interaction of inter-organizational diversity and team size, and the scientific impact of papers." Information Processing & Management 61(6): 103851.

Zeng, A., Z. Shen, J. Zhou, J. Wu, Y. Fan, Y. Wang and H. E. Stanley (2017). "The science of science: From the perspective of complex systems." Physics Reports 714: 1-73.

Zhang, H., L. Qiu, L. Yi and Y. Song (2018). Scalable multiplex network embedding. IJCAI.

Zhang, J. (2017). "Uncovering mechanisms of co-authorship evolution by multirelations-based link prediction." Information Processing & Management 53(1): 42-51.

Zhao, D., L. Li, H. Peng, Q. Luo and Y. Yang (2014). "Multiple routes transmitted epidemics on multiplex networks." Physics Letters A 378(10): 770-776.

Zhu, Y., L. Quan, P. Y. Chen, M. C. Kim and C. Che (2023). "Predicting coauthorship using bibliographic network embedding." Journal of the Association for Information Science and Technology 74(4): 388-401.