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MuICE: Mutual Influence and Citation Exclusivity Author Rank

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ABSTRACT

With constant growth in size of analyzable data, ranking of academic entities is becoming an attention grabbing task. For ranking of authors, this study considers the author's own contribution, as well as the impact of mutual influence of the co-authors, along with exclusivity in their received citations. The ranking of researchers is influenced by the ranking of their co-authors, more so if co-authors are seniors. Tracking the citations received by an author is also an important factor to measure standing of an author. This study proposes Mutual Influence and Citation Exclusivity Author Rank (MuICE) algorithm. We performed a sequence of experiments to calculate the MuICE Rank. First, we calculated Mutual Influence (MuInf) considering three different factors: the number of papers, the number of citations and the author's appearance as first author. Secondly, we computed MuICE incorporating all three factors of MuInf along with the exclusivity in citations received by an author. Empirically, it is shown that the proposed methods generate substantial results.

1. Introduction

Analysis of academic social networks has considerable applications in academic recommendation tasks. Citation, co-citation and co-authorship networks are formed when researchers cite each other's work and work in collaboration. Some general activities in academic social networks are ranking of authors (Ding, Yan, Frazho, & Caverlee, 2009; Liu, Bollen, Nelson, & Van de Sompel, 2005), expert finding (Daud, Li, Zhou, & Muhammad, 2010; Zhang, Tang, & Li, 2007), author interest finding (Daud, 2012) and author name disambiguation (Shu, Long, & Meng, 2009). This study calculates the rank of authors with respect to their mutual influence on each other and exclusivity in their received citations. A novice researcher who may get an opportunity to collaborate with a leading researcher can have more chances to prosper in the future. Considering author's own contribution in a work, as well as the impact of influence of his or her co-authors, gives a comprehensive representation of the position of an author in an academic networks.

Existing approaches find the rank of authors based on their in-links (number of nodes pointing to a node) information (Ding, 2011a; Ding et al., 2009; Gollapalli, Mitra, & Giles, 2011). The proposed method involves in-links information of a node, as well as it also considers out-links (number of nodes pointed to by) of an author. Co-author relationships from network are used to find the out-links information. This study considers a bibliographic network and presents three ways to find out the mutual influence of authors on each other, these are; with respect to the number of papers, the number of citations and the appearance of an author as first author. MuInf is based on PageRank (Brin & Page, 1998; Page, Brin, Motwani, & Winograd, 1999). We also

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tried to track the citations received by an author; i.e. Citations are received from how many exclusive sources. For this purpose, a bibliometric measure "f-index" (Katsaros, Akritidis, & Bozanis, 2009) is used. The term exclusivity here can be explained with the help of a simple example. Suppose there are two articles, if the first article receives three citations from three different authors and the second article receives three citations from the same author, then the first article must receive more weight as the citations received by it are from more exclusive authors. Due to the aforementioned reasons we are motivated to propose Mutual Influence and Citation Exclusivity (MuICE) Rank algorithm. Main contributions of this research are (1) finding the impact of authors based on their mutual influence on each other, with respect to the number of publications, the number of citations, the number of publications as first author and (2) ranking of authors by considering the exclusivity in their received citations along with their mutual influence.

The study conducts a detailed experimentation which shows that proposed MuICE method generates satisfying results when compared to existing methods. The rest of the paper is organized as follows: Section 2 provides a review of link analysis based ranking methods in academic social networks. Section 3 gives an overview of the existing methods used as baselines and the details of our proposed method. Section 4 describes the dataset, performance evaluation, parameter settings with results and discussions and at the end Section 5 concludes the study.

The following sets of terms are used interchangeably throughout the text, (academic social networks, bibliography network, co-author networks), (paper, article, publication) and (author, researcher) etc.

2. Related works

Author ranking methods based on analysis of link structure of a network can be classified into two groups: (1) Iterative methods and (2) Non iterative methods. This study includes the review of the former methods only.

Iterative link analysis methods execute a set of instructions iteratively for a decided number of times or until convergence of the algorithm. PageRank (Brin & Page, 1998; Page et al., 1999) is a state-of-the-art iterative link analysis algorithm and is the foundation of a large number of approaches that have been proposed for author ranking. These methods consider the authors or the publications of authors as vertices instead of pages while forming a graph. These graphs can represent co-authorship, citation or co-citation relationships. PageRank asserts a page to be significant if there are many other significant pages referencing it. The rank of a page is evenly dispersed among all the pages it is linking.

Another prevalent iterative technique based on link structure analysis is Hyperlink Induced Topic Search (HITS) which discriminates the pages as Hubs and Authorities (Kleinberg, 1999). The pages that function as directories by providing links to informative pages are known as Hubs. The pages that contain actual information and are pointed to by the hubs are called Authority pages. Fiala, Rousselot, and Ježek (2008) provided a modification of PageRank for ranking of authors in a bibliographic networks that considers the co-authorship graphs and citations. A variation of PageRank was proposed for finding experts from digital libraries to include various available facts from different objects and relations (Gollapalli et al., 2011). An alternative of centrality measure for analyzing the properties of academic networks was presented as Author-Rank algorithm (Liu et al., 2005). Author-Rank finds the impact of an author in an undirected co-authorship network contemplating collaboration frequency. Two variations of weighted PageRank were proposed for ranking of authors by Ding et al. (2009) and Yan and Ding (2011) where they studied a co-citation network and a co-authorship network respectively. Li and Tang (2008) explored the temporal dimension for the problem of expert finding. A generalization of PageRank for bibliographic networks was presented that included the time based statistics by exercising the forward and backward propagation process and combined the social networks with the random walk model. Fiala (2012) presented a method that weighs the citation between two authors on the basis that whether and when these authors have collaborated with each other. The time of publication and citation is also considered in this time-aware algorithm. Radicchi, Fortunato, Markines, and Vespignani (2009) proposed a new weighted version of PageRank, in which ranking was conducted by considering the diffusion of credits traded by the authors. Ding (2011a) measured the popularity and prestige of an author in a co-citation network. The primary focus of study was to assign high weight to the citations from prestigious authors as compared to the citations from less known authors. Wei, Barnaghi, and Bargiela (2011) semantically ranked documents and demonstrated the web surfing activities of a scholar instead of a random surfer. For this purpose, they introduced a knowledge base which contains a terminological topic ontology and academic research entities like authors, journals/conferences and papers. Ding (2011b) presented a topic sensitive extension of PageRank algorithm. The novelty was to enhance the semantics of authors ranking by introducing topic dependent weights in PageRank algorithm. Recently, a topic based model was presented for simultaneous modeling of academic entities including authors, papers and journals in a heterogeneous network (Amjad, Ding, Daud, Xu, & Malic, 2015).

3. Mutual Influence and Citation Exclusivity Author Rank (MuICE)

The concept of mutual influence of authors was presented by Li, Foo, Tew, and Ng (2009). They introduced PubRank algorithm for finding the rising stars. Using the same concept of mutual influence Daud, Abbasi, and Muhammad (2013) proposed StarRank for finding the rising star in co-authors network. This study adopts the term, mutual influence, in an intuitive manner for ranking of authors. To identify the exclusivity in citations received by an author, we used f-index (Katsaros et al., 2009), which is a bibliometric measure to evaluate an author by considering the citations received by an author. The f-index introduced the concept of co-terminal citations. Co-terminal citations are a generalization of co-citations and are introduced as an attempt to find the trends that prevail among communication in scholarly networks. They gave fair credit to self-citations, instead of eliminating their effect, while keeping track of multiple author citations.

In literature, mutual influence and exclusivity in citations of an author are not being integrated for ranking of authors. This encourages us to propose Mutual Influence Rank (MuInf) and Mutual Influence and Citation Exclusivity Author Rank (MuICE).

Before giving the details of our proposed methods, a brief introduction of the baseline methods goes first. The first baseline method is weighted PageRank presented by Yan and Ding (2011), which considers the number of citations as weight.

$$W{-}PR(a_i) = (1-d)\frac{CC(a_i)}{\sum_{p_j \in M(a_i)} CC(a_j)} + d \sum_{a_j \in M(a_i)} \frac{W{-}PR\left(a_j\right)}{L\left(a_j\right)} \tag{1}$$

where $W\text{-}PR(a_i)$ is weighted PageRank of author a_i under consideration, $CC(a_i)$ is the number of citations pointing to the author a_i, $M(a_i)$ is the set of authors pointing to the author a_i, $\sum_{a_j \in M(a_i)} CC(a_j)$ is the citation count of all authors in the network, $L(a_j)$ is the number of outgoing links of author a_j and d is the damping factor.

The second baseline method is also a weighted PageRank presented by Yan and Ding (2011), which considers the number of publication as weight instead of citations count.

3.1. Construction of co-authorship network

This research considers a co-authorship network for evaluation of authors. We delineate a co-authorship network as a directed, weighted graph $G = (V, E)$, where V is a set of vertices representing authors in the graph and E is a set of edges which represent the co-author connections. Formally, $V = \{v_i | v_i$ is an author in considered dataset$\}$ and $E = \{(v_i, v_j) | co\text{-}auth\ (v_i, v_j) > 0, v_i, v_j \in V\}$, where *co-auth* (v_i, v_j) represents the papers in which authors v_i and v_j are co-authors. it should be noticed that in the proposed weighted directed graph the edge (v_i, v_j) and (v_j, v_i) are not the same. The weight of the edge (v_i, v_j) is the influence of author v_i on author v_j, while in edge (v_j, v_i) it is the influence of author v_j on author v_i.

3.2. Mutual influence based ranking algorithm (MuInf)

This section introduces the mutual influence based ranking of authors. It is believed that an author who co-authors with eminent authors, has more chances to become a renowned author. An extension of PageRank algorithm is proposed to find the mutual influence of authors on each other in three different ways. The proposed method integrates the mutual influence based weights in the original PageRank formula along with publications, citations and first author publication weights.

3.2.1. Mutual influence with respect to number of publications ($MuInf_P$)

This method studies the influence of co-authors on each other considering their number of publications. Senior researchers have more influence on their co-workers as compared to the junior because the senior researchers have more publications. Mutual influence method is inspired from PubRank (Li et al., 2009) and is based on PageRank. As mentioned in Section 3.1, we consider a graph in which nodes represent authors and edges represent the co-author relationship among them. When the authors A_x, A_y are co-authors of an article, weight (A_x, A_y) shows the influence of A_x on A_y and likewise (A_y, A_x) is the fraction with which A_y influences A_x.

This can be explained with in a simple example. Consider two researchers, A_x with 8 papers and A_y with 6 papers. If they are co-authors in 3 publications, their mutual influence based weight can be calculated as under:

$$W_P(A_x, A_y) = \frac{(A_{xy})}{TA_y} = \frac{3}{6} = 0.5 \text{ and } W_P(A_y, A_x) = \frac{(A_{yx})}{TA_x} = \frac{3}{8} = 0.37 \tag{2}$$

where sum of publications for authors A_x and A_y are given by TA_x and TA_y respectively, sum of publications co-authored by A_x and A_y is given by (A_{xy}) and (A_{yx}) and the weight with which author A_x influences author A_y is given by $W_P(A_x, A_y)$. It can be seen from Eq. (2) that author A_x influences author A_y more due to higher weight of $W_P(A_x, A_y)$. This shows seniority of author A_x over author A_y. Mutual influence with respect to number of papers can be calculated as follows.

The equation of the mutual influence method with respect to the number of papers is:

$$MuInf_P(A_i) = (1-d)\frac{WP(p_i)}{\sum_{p_j \in M(p_i)} WP(p_j)} + d \sum_{A_j \in M(A_i)} \frac{W_P(A_j, A_i) * MuInf_P(A_j)}{\sum_{A_k \in M(A_i)} W_P(A_k, A_i)} \tag{3}$$

where rank of author A_i is given by $MuInf_P(A_i)$, $M(A_i)$ represents a set of authors citing author A_i, the influence of A_j on A_i is given by $W_P(A_j, A_i)$, the sum of publications of author i is given by $WP(p_i)$, the total number of publications in dataset under consideration is given by $\sum_{p_j \in M(p_i)} WP(p_j)$ and d is the damping factor.

3.2.2. Mutual influence with respect to number of citations ($MuInf_C$)

In this section we calculate the influence of co-authors on work of each considering the number of citations received by their papers. Authors with a higher number of citations are believed to be more influential. Difference of $MuInf_C$ from $MuInf_P$ becomes

Table 1
Authors with their number of papers and number of citations received.

Authors	Scenario 1		Scenario 2	
	Number of papers	Number of citations	Number of papers	Number of citations
A_x	8	22	8	12
A_y	6	14	6	14

Table 2
Authors and their papers showing presence as first author or not.

Authors	Paper # (first author y/n)		
	Scenario 1	Scenario 2	Scenario 3
A_x	**1(y), 2(n)**, 3(y), 4(n)	**1(y), 2(n)**, 3(n), 4(n)	**1(y), 2(n)**, 3(y), 4(n)
A_y	**1(n), 2(y)**, 3(y)	**1(n), 2(y)**, 3(y)	**1(n), 2(y)**, 3(n)

more evident in situations when an author having a lower number of publications, yet receives a higher number of citations due to the high quality of work.

To explain the phenomena, consider a simple example with two different scenarios shown in Table 1. Consider scenario 1 in which there are two authors, A_x with 8 papers and A_y with 6 papers and they have co-authored 4 papers with each other. The citations obtained by their co-authored publications are 8. The author A_x has 22 citations (C_{ix}) and author A_y has 14 citations (C_{iy}). The citation weight W_C with which they influence each other is calculated as follows:

$$\begin{aligned} W_C(A_x, A_y) &= \frac{(C_{xy})}{TC_{iy}} = \frac{8}{14} = 0.57 \\ W_C(A_y, A_x) &= \frac{(C_{yx})}{TC_{ix}} = \frac{8}{22} = 0.36 \end{aligned} \tag{4}$$

where sum of citations for authors A_x and A_y are given by TC_{ix} and TC_{iy} respectively, sum of citations of their co-authored papers is given by (C_{xy}) and (C_{yx}) and the weight with which author A_x influences author A_y is given by $W_C(A_x, A_y)$. It can be seen from Eq. (4) that author A_x influences author A_y more due to higher weight of $W_C(A_x, A_y)$. This shows seniority of author A_x over author A_y. Substituting the values given in scenario 2 of Table 1 in Eq. (4) we get $W_C(A_x, A_y) = 0.57$ and $W_C(A_y, A_x) = 0.66$ which shows that when the citations of author A_x were lowered, the weight with which A_y influences A_x increases. It must be noticed here that only the number of citations is considered, the number of publications of both authors in two scenarios is the same.

Mutual influence with respect to number of citations can be calculated as follows:

$$MuInf_C(A_i) = (1-d)\frac{WC(p_i)}{\sum_{p_j \in M(p_i)} WC(p_j)} + d\sum\nolimits_{A_j \in M(A_i)} \frac{W_C\left(A_j,\ A_i\right) * MuInf_C\left(A_j\right)}{\sum_{A_k \in M(A_i)} W_C(A_k, A_i)} \tag{5}$$

where rank of author A_i is given by $MuInf_C(A_i)$, $M(A_i)$ represents a set of authors citing author A_i, the influence of A_j on A_i is given by $W_C(A_j, A_i)$, the sum of citations of author i is given by $WC(p_i)$, the total number of citations in dataset under consideration is given by $\sum\limits_{p_j \in M(p_i)} WC(p_j)$ and d is the damping factor.

3.2.3. Mutual influence with respect to author name position ($MuInf_{FA}$)

This section cogitates whether authors to be ranked appear as the first author in their publication or not. Author whose name appears as the first author of an article will be given more weight in this strategy. However, otherwise they will be given half weight assuming that normally the first author is the main contributor. A novel link weighting strategy is proposed to find the contribution of an author based on the author's position in list of co-authors of an article, along with their mutual influence. To demonstrate the phenomena an example is included here. Consider two researchers, A_x and A_y. Author A_x has 4 publications while A_y has 3 publications and they have 2 co-authored publications. Table 2 shows the author's name's position (y if its first author, n otherwise). The bold faced letters show the common/co-authored publications of A_x and A_y. Non bold letters show the publications of A_x and A_y with other authors. For example, A_x: **1(y), 2(n)**, 3(y), 4(n) means that A_x has four publications 1, 2, 3 and 4. Bold faced **1(y)** shows that paper 1 was co-authored by A_y, and (y) shows A_x was the first author. Non bold faced 4(n) shows that publication 4 was not co-authored by A_y and (n) shows A_x was not the first author. Authors who appear as the first author are given full credit while half credit is given to all other authors.

$$\begin{aligned} W_{FA}(A_x, A_y) &= \frac{(\sum C_x + \sum C_y)}{\sum TC_y} = \frac{(1+0.5+1+0.5+0.5+1+1)}{(0.5+1+1)} = 2.2 \\ W_{FA}(A_y, A_x) &= \frac{(\sum C_y + \sum C_x)}{\sum TC_x} = \frac{(0.5+1+1+1+0.5+1+0.5)}{(1+0.5+1+0.5)} = 1.8 \end{aligned} \tag{6}$$

```
1.  Count the unique authors in the dataset
2.  Count the number of papers written by authors
3.  Calculate the number of citations of each author
4.  Calculate the respective method's weights for each author
5.  Calculate the contribution of the authors with respect to participation as first author or otherwise
6.  Find out list of co-authors of each author and his/her number of papers
7.  Create objects for all unique authors in the dataset
8.  While not end of file
        1.  Find Author name
        2.  Calculate Author Contribution based on publications
        3.  Find Coauthors
        4.  Calculate Paper Count
        5.  Calculate Citation Count
        6.  Calculate First Name Count
9.  End while
10. Set Initial Rank of each Author to a 1/Total number of authors
11. Set Damping factor (0.15, 0.5, 0.85)
12. For iteration 1 to 50
13.     For each author 1 to n
14.         For each coauthor of n
15.                 Calculate Sum of Weights
16.         For each coauthor of n
17.             Result+=  (Multiply Weight with Initial Rank of Coauthor and divide by Sum of Weights)
18. Set Next Rank of Each author (1-damping factor)*publication of author/total publications in network + Result
19. Set initial Rank as Next Rank
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Fig. 1. Pseudocode for $\mathrm{MuInf_P}$ method.

where $W_{FA}(A_x, A_y)$ is the contribution weight with which A_x influences A_y and vice versa for $W_{FA}(A_y, A_x)$. ΣC_x and ΣC_y is the contribution on the basis that they are first authors or not. ΣTC_x and ΣTC_y is the total contribution of authors A_x and A_y in all papers written by them. In scenario 1, both authors have 2 papers as the first author. In their co-authored papers they both appear as the first author once, but author A_x influences author A_y more because A_x has more number of papers overall.

In scenario 2, the author A_x having four papers, appears as the first author in only 1 paper. While author A_y having three papers, appears in two papers as the first author. Solving Eq. (6) for scenario 2 one can see that $W_{FA}(A_x, A_y)$ is 2 and $W_{FA}(A_y, A_x)$ is also 2. This shows that, although A_x has more number of publications, but A_y is equally influential. The reason behind this is that A_y appears in more publications as first author. In scenario 3, the author A_x having four papers, appears as the first author in 2 papers while author A_y having three papers, appears as the first author in only one paper. Solving Eq. (6) for scenario 3 we can see that $W_{FA}(A_x, A_y)$ is 2.5 and $W_{FA}(A_y, A_x)$ is 1.7. This demonstrates how the influence of authors on each other is changing with a changing number of papers as first author.

The equation of mutual influence with respect to author's name appearance as first author is:

$$MuInf_{FA} = (1-d)\frac{WFA(p_i)}{\sum_{p_j \in M(p_i)} WFA(p_j)} + d\sum_{A_j \in M(A_i)} \frac{W_{FA}\left(A_j,\ A_i\right) * MuInf_{FA}\left(A_j\right)}{\sum_{A_k \in M(A_i)} W_{FA}(A_k,\ A_i)} \tag{7}$$

where $MuInf_{FA}(A_i)$ is rank of the author A_i, $M(A_i)$ is set of authors pointing to the author A_i (authors who have cited A_i), $W_{FA}(A_j, A_i)$ is influence of A_j on A_i, $WFA(p_i)$ is the total number of publications of author i as the first author, $\sum_{p_j \in M(p_i)} WFA(p_j)$ is the total number of publications and d is the damping factor.

3.3. Mutual Influence and Citation Exclusivity Author Rank (MuICE)

All three mutual influence based formulas follow a similar sequence of steps in the main algorithm, while the calculation of weights is different. Fig. 1 gives a pseudocode for the main algorithm followed by the $\mathrm{MuInf_P}$ method.

The idea of exclusivity of citations articulates that if two papers of an author have the same number of citations, but with a different number of unique authors citing his or her work, then the paper with larger number of citations by different authors must be given more weight. Such as, if there are more unique authors in citing authors of paper A, as compared to paper B, paper A will be given more weight as it is read by more authors as compared to paper B.

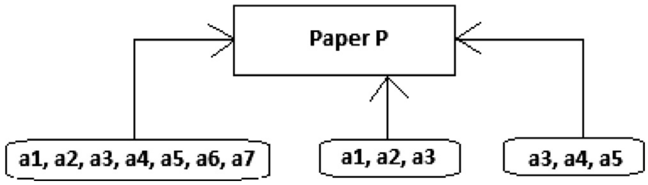


Fig. 2. Articles citing paper *P* with overlapping co-authors.

To further explain the concept of exclusivity of citations a simple example is given below. Suppose that paper P is cited by three different papers, of which paper one was co-authored by a1, a2, a3, a4, a5, a6 and a7, paper 2 was co-authored by a1, a2 and a3, while paper three was co-authored by a3, a4 and a5. The point to be noted here is the existence of author a3 all citing documents. This pattern of citations, where some author has cited one paper multiple times in different papers originated the term of co-terminal citations. The scenario is represented in Fig. 2.

Now let nca^P be the number of articles citing paper P. $F_i^P = \{aj$: author aj appears in exactly i articles citing $P\}$. According to this, for Fig. 2 we have $F_1^P = \{a6, a7\}$, $F_2^P = \{a1, a2, a4, a5\}$ and $F_3^P = \{a3\}$. Now let f_i^P be the ratio of cardinality of F_i^P to the total number of unique authors citing paper P. That is:

$$f_i^P = \frac{\left|F_i^P\right|}{total\ number\ of\ unique\ authors} \tag{8}$$

Now f^p is a nca^P-dimensional vector like $f^p = \{f_1^P,\ f_2^P,\ f_3^P, \ldots f_{nca^P}^P\}$ which is equal to $\sum_{i=1}^{nca^P} f_i^P = 1$. Now for paper P of Fig. 2 we have $f^p = \{\frac{2}{7} + \frac{4}{7} + \frac{1}{7}\}$. Now we will convert this vector into scalar through a dot product such as

$$\hat{f} = (f.s). \tag{9}$$

where the value of $S = \{nca, nca\text{-}1, nca\text{-}2, \ldots. 1\}$. Using these values we will calculate a decimal value that characterizes the rank of an author.

$$N_f^P = f^p \cdot s \tag{10}$$

Substitute values to get $N_f^P = (\frac{2}{7} * 3 + \frac{4}{7} * 2 + \frac{1}{7} * 1) = 2.14$. To find the f-index value of an author first find $N_f^{P_i}$ for all of his or her papers P_i. Thus, for calculating the f-index of an author, exclusivity in citations of an author are considered. The example calculates the f-index for one paper by an author. For experimentation, one has to calculate f-index values for all papers of an author and assign the average value to an author as f-index. The same process will be followed for all the authors in the dataset.

Now we are going to introduce the formula for Mutual Influence and Citation Exclusivity (MuICE) Rank. We combined the weight factors of mutual influence that were introduced in Eqs. (3), (5) and (7) along with f-index as follows:

$$\begin{aligned} MuICE(A_i) = {} & (1-d)\left(\frac{WP(p_i)}{\sum_{p_j \in M(p_i)} WP(p_j)} + \frac{WC(p_i)}{\sum_{p_j \in M(p_i)} WC(p_j)} + \frac{WFA(p_i)}{\sum_{p_j \in M(p_i)} WFA(p_j)}\right) \\ & + d \sum_{A_j \in M(A_i)} \frac{W_P(A_i, A_j) W_C(A_i, A_j) W_{FA}(A_i, A_j) * F_{A_i} * MuICE(A_j)}{\sum_{A_k \in M(A_i)} W_P(A_k, A_i) * \sum_{A_k \in M(A_i)} W_C(A_k, A_i) * \sum_{A_k \in M(A_i)} W_{FA}(A_k, A_i)} \end{aligned} \tag{11}$$

where n is the total number of authors, and F_{A_i} is the f-index score for that author.

The results are discussed in Section 4.5 which demonstrate that considering only the number of papers or the number of citations for ranking of an authors is not a sufficient criteria. Assimilation of exclusivity of citations along with mutual influence of authors will produce effective and dependable results.

4. Experiments

4.1. Dataset

In this study, we considered a co-authorship graph which was extracted from version 5 of datasets available at AMiner[1] website (Tang et al., 2008). It entails all papers from DBLP and the citation relationship between these papers in the form of references. Author name disambiguation has also been considered while making this dataset. In this dataset the total number of papers are 1,572,277 and 2,084,019 citation relationships in the form of references. The set of references was incomplete for some papers present in this dataset. We extracted a component from available references information in such

[1] https://aminer.org/billboard/citation, Version 5 named as DBLP-Citation-network V5.

Table 3
Statistics of subset retrieved from the dataset.

	Statistics
Time period	1960–2011
Number of publications	117,676
Number of citation relationships	988,030
Number of authors	128,778

a way that citations of papers in our dataset can be calculated. The statistics of retrieved dataset component are given in Table 3.

4.2. Performance measurement

Performance measurement normally requires the ground truth values, which are absent in case of ranking of authors. For assessing our proposed methods we evaluated the results of MuInf and MuICE with two different weighted PageRank algorithms proposed by Yan and Ding (2011). We implemented these baseline methods on selected dataset using the same parameter settings as for proposed methods to ensure impartial assessment. We will discuss the impact of the factors like the number of publications of an author, the total number of citations received by an author, the number of co-authors an author has worked with, the number of papers in which author appears as first author in the results and discussion section. For the purpose of evaluation a brief list of profiles of the top ranked authors is compiled in order to see whether they are prestigious authors or not, as in this field ground truth values are not available for purpose of comparison.

4.3. Parameter setting

To conduct experimentation, the proposed method is tested on three different values of the damping factor 'd', i.e. 0.15, 0.5 and 0.85. The standard PageRank algorithm uses 0.85 as default value of the d, which means that there is 85 % chance that an individual will follow one of the links given by a page and 15% chance that he or she will open a totally new page. We tested our proposed method on $d = 0.85$, $d = 0.5$ and $d = 0.15$. First two values of d are based on the discussion by Maslov and Redner (2008). In the event of citations, they suggested that the most suitable choice of d is ½ i.e. 0.5 because for citations, it is more likely to follow a chain up to two links. When the value of d is lowered (as 0.15) as per analysis by Yan and Ding (2011) emphasis on co-authorship topology is reduced and citation count become more prominent.

4.4. Baseline methods

For the purpose of comparison and evaluation, two methods are implemented as baseline: weighted PageRank with respect to the number of citations (W-PR$_C$), and weighted PageRank with respect to the number of publications (W-PR$_P$) (Yan & Ding, 2011). The original W-PR (Yan & Ding, 2011) considered the citation count as the weight. They calculated the total number of citations/publications of the author to be ranked, and it is divided by the total number of citations/publications in the whole network and this value is multiplied by $(1 - d)$, the rest of the formula is the same as PageRank formula. We computed 200 iterations of each method and selected the top 25 authors ranked by each method.

4.5. Results and discussion

We proposed three variations of MuInf and final formula of MuICE. This section includes the comparison and discussion about proposed and baseline methods. We also include the results with respect to different values of d. The number of publications, citations and ranks of authors discussed in this section are subject to the selection of dataset. The tables are calculated with $d = 0.5$. The averages are rounded to the nearest decimal places in all tables. "Cit" stands for the number of citations, "Pub" denotes the number of publications, "NoCA" symbolizes the number of Co-Authors and "AFA" stands for As First Author, "Avg" represents Average or mean value and "Stdev" shows standard deviation in all tables.

4.5.1. Comparison of MuInf with baseline methods

As discussed in Section 3, we considered the co-authors network and calculated the influence of all pairs of co-authors in our dataset. Due to the resemblance of weights, we compared MuInf$_P$ with W-PR$_P$ and MuInf$_C$ with W-PR$_C$. In MuInf$_P$ the publications count is considered as ranking parameter. Table 4 shows top 25 authors ranked by W-PR$_P$ and MuInf$_P$. Apart from the factor of mutual influence of co-authors, MuInf$_P$ and W-PR$_P$ used similar weights in the formula. The average number of publications of top 25 authors (Table 4) by W-PR$_P$ method is 91, the average number of publications of MuInf$_P$, is 114. Both methods have ranked the same authors on first two positions. Jiawei Han was ranked on position 3 with 150 co-authors and 152 publications, while Alberto L. Sangiovanni-V position 3 of W-PR$_P$ has moved to position 15. Luca Benini was ranked on next position

Table 4
Top 25 authors ranked by weighted PageRank (W-PRp) and $MuInf_P$.

Rank	W-PRp			Muinf-p		
	Authors	**Pub**	**NoCA**	**Authors**	**Pub**	**NoCA**
1	Philip S. Yu	205	160	Philip S. Yu	205	160
2	Mahmut T. Kandemir	165	117	Mahmut T. Kandemir	165	117
3	Alberto L. Sangiovanni-V	116	146	Jiawei Han	152	150
4	W. Bruce Croft	93	108	Luca Benini	145	160
5	Nicholas R. Jennings	107	106	Kang G. Shin	143	109
6	Qiang Yang	78	116	Hector Garcia-Molina	139	155
7	Lei Zhang	56	109	Elisa Bertino	137	126
8	Micha Sharir	81	80	Jason Cong	127	104
9	Jason Cong	127	104	Massoud Pedram	125	68
10	Andrew B. Kahng	102	106	David Blaauw	117	110
11	Ming Li	54	83	Ming-Syan Chen	84	42
12	Kaushik Roy	110	95	Christos Faloutsos	116	145
13	C. Lee Giles	85	101	Giovanni De Micheli	94	85
14	Wolfgang Nejdl	42	82	Nicholas R. Jennings	107	106
15	Massoud Pedram	125	68	Alberto L. Sangiovanni-V	116	146
16	Brad A. Myers	96	103	Mary Jane Irwin	94	92
17	Divesh Srivastava	81	110	Francky Catthoor	113	164
18	Scott Shenker	79	148	Donald F. Towsley	109	133
19	Peter Stone	52	52	Kaushik Roy	110	95
20	Elke A. Rundensteiner	80	84	M. Frans Kaashoek	60	80
21	Pankaj K. Agarwal	65	81	David R. Karger	53	78
22	Ravin Balakrishnan	88	69	Andrew B. Kahng	102	106
23	Christos H. Papadimitriou	63	79	Hari Balakrishnan	62	102
24	Moshe Y. Vardi	53	57	Narayanan Vijaykrishnan	81	89
25	Tuomas Sandholm	76	44	Hans-Peter Seidel	98	132
Average		**91**	**96**		**114**	**114**
Stdev		**37**	**29**		**34**	**32**

Number of publications and citations of authors in all tables are subject to selection of papers in our dataset.

with 160 co-authors and 145 publications. It is observed that not only the number of co-authors is influencing the ranking of an author, but co-authorship with a prestigious author is making a great impact as well. This observation is based on traversal of co-authors list of authors ranked by $MuInf_P$. Philip S. Yu is present among co-authors list of Jiawei Han, Ming-Syan Chen, and Christos Faloutsos in top 25. Mahmut T. Kandemir appears among co-authors list of Luca Benini, David Blaauw, Mary Jane Irwin and Francky Catthoor. Similarly, Jiawei Han appears among co-authors list of Ming-Syan Chen. From Table 4 we noticed that Ming-Syan Chen has the least number of co-authors (42) but, amongst these 42, two researchers are substantially prominent, causing him to appear among top 25 authors. To have an insight about the strength of proposed method we calculated the standard deviation along with the mean values. We noticed that proposed method yields greater average and smaller standard deviation for number of publications, showing the strength and stability of proposed method as compared to baseline method.

In $MuInf_C$ and W-PR_c used the number of citations as ranking parameter. In addition, $MuInf_C$ also involves the mutual influence based citations weights. Table 5 shows top 25 authors ranked by W-PR_c and $MuInf_C$. We realize that the mean of citations count of the top 25 authors of W-PR_c is 2525, while the mean of citations of $MuInf_C$ is 2535. We noticed that the top 25 authors of these two approaches are coinciding, with some variation in positions. David E. Culler is ranked on top by both approaches. Rakesh Agrawal and Hector Garcia-Molina are replacing positions (2 and 3) with each other in two methods and they are co-authors of each other as well, hence they influence each other.

Hari Balakrishnan secured 4th position making Deborah Estrin and Philip S. Yu go down one position respectively, due to high influence of his greater number of citations, hence more impact of mutual citations weight as well. Analogous examples are spotted all through Table 5. The rationale behind this patterns is that $Muinf_C$ and W-PR_c are based on PageRank which is highly influenced by citations. Once again like $MuInf_P$, $Muinf_C$ method appears to be stable as the standard deviation value for citations of this method is comparatively smaller than baseline method.

4.5.2. Discussion about $MuInf_{FA}$ and MuICE methods

The ranking criterion of the proposed method is quite different from the existing and baseline methods and it offers a different perspective for ranking authors. Hence, $MuInf_{FA}$ and MuICE cannot be compared with any existing method as they incorporate entirely new features which have not been used before.

Some reservations are observed from literature regarding use of these indices to determine ranking because papers are referred for reasons which can be discrete from quality or effectiveness of a study (Kelly & Jennions, 2006; Leimu & Koricheva, 2005). Costas and Bordons (2007) emphasize that h-index is heavily subjective towards the number of publications and

Table 5
Top 25 authors ranked by weighted PageRank (W-PR$_c$) and MuInf$_C$.

Rank	W-PRc			Muinf-c		
	Authors	**Cit**	**NoCA**	**Authors**	**Cit**	**NoCA**
1	David E. Culler	3798	110	David E. Culler	3798	110
2	Hector Garcia-Molina	3187	155	Rakesh Agrawal	3554	102
3	Rakesh Agrawal	3554	102	Hector Garcia-Molina	3187	155
4	Deborah Estrin	3163	138	Hari Balakrishnan	3181	102
5	Philip S. Yu	3154	160	Deborah Estrin	3163	138
6	Hari Balakrishnan	3181	102	Philip S. Yu	3154	160
7	Scott Shenker	2701	148	Jiawei Han	3046	150
8	Jiawei Han	3046	150	M. Frans Kaashoek	2867	80
9	Christos Faloutsos	2655	145	Scott Shenker	2701	148
10	M. Frans Kaashoek	2867	80	Christos Faloutsos	2655	145
11	Anoop Gupta	2422	95	David R. Karger	2585	78
12	Joseph M. Hellerstein	2180	133	Rajeev Motwani	2447	83
13	David R. Karger	2585	78	Ion Stoica	2429	89
14	Ion Stoica	2429	89	Anoop Gupta	2422	95
15	Rajeev Motwani	2447	83	Ramesh Govindan	2250	85
16	Pat Hanrahan	2091	104	Joseph M. Hellerstein	2180	133
17	David J. DeWitt	2065	134	Jennifer Widom	2094	90
18	Ramesh Govindan	2250	85	Pat Hanrahan	2091	104
19	Jennifer Widom	2094	90	Randy H. Katz	2088	88
20	W. Bruce Croft	1861	108	David J. DeWitt	2065	134
21	Michael J. Franklin	1886	20	Hans-Peter Kriegel	1982	48
22	Jeffrey D. Ullman	1841	117	Michael J. Franklin	1886	117
23	Randy H. Katz	2088	77	W. Bruce Croft	1861	108
24	Raghu Ramakrishnan	1596	88	Surajit Chaudhuri	1854	75
25	Hans-Peter Kriegel	1982	48	Jeffrey D. Ullman	1841	77
Average		**2525**	**106**		**2535**	**108**
Stdev		**587**	**34**		**572**	**30**

citations and that it cannot recognize the scholars who are very careful about choosing a journal for publication of their manuscript and who do not have high levels of productivity, but have a high level of international impact. Moreover, Bartneck and Kokkelmans (2010) and Ferrara and Romero (2013) pointed towards the effect of self-citations that can be used to manipulate h-index and simple measures like this. On the other hand, the main strength of the proposed method is that it cannot be tempered or manipulated easily, as it does not only involve the number of publications or citations. It integrates a combination of weighing parameters along with mutual influence of co-authors and exclusivity of citations. The results of MuInf$_{FA}$ and MuICE are shown in Table 6. In MuInf$_{FA}$ we used the number of first author publications by an author as ranking parameter. However, the effect of link structure in PageRank and the effect of co-authors is still in the formula, with the help of which Philip S. Yu managed to gain the first position in these results as well with 11 publications as first author. A very interesting thing to note is that Jason Cong is on 2nd position with 88 publications as first author out of total 127. He was ranked on 8th position by W-PR$_p$, and MuInf$_P$. However, he was not among top 25 in W-PR$_c$ and MuInf$_C$ (65 in W-PR$_c$ and 45 in MuInf$_C$). We google scholar and DBLP to verify that Jason Cong has a prestigious profile. As generally it is assumed that first author has most of the contribution. MuInf$_{FA}$ method can give the reward to such authors who write most of the papers as first author.

MuICE method incorporates the exclusivity of citations received by an author in a combination of MuInf methods. For this purpose, we calculated the f-index (Katsaros et al., 2009) values of authors. From Table 6, we see that average citations of the top 25 authors of MuICE method is 2008. It can be noticed that receiving a very high number of citations is not the only criteria sufficient enough to rank the authors. From Table 6, we can also notice the effect of more number of co-authors on rank of an author. For confirmation of our results, we visited profiles of the authors to identify whether they are among prestigious award winners (e.g. ACM SIGMOD E. F. Codd Innovations Award), prestigious journal's editorial board members and leading conferences program committee members in the selected research field. The profiles of authors also confirms the strength of our proposed methods. Table 7 shows the statistics of authors ranked by MuICE method from the AMiner website.[2]

Table 8 shows a change of position of ranks of the top 25 authors of MuICE as compared to their positions in W-PR$_p$ and W-PR$_c$. In this table an up arrow '↑' means increase in rank, a down arrow '↓' represents decrease in rank, '≡' no change in rank and ∗ represents author's name was not in top 200 authors. This implies that ↑↑ means rank in MuICE is increased with respect to WPRc as well as WPRp, for example, researcher Jiawei Han shows ↑↑. Similarly, ↑↓ means rank in MuICE is increased with respect to WPRc and decreased with respect to WPRp for example, researcher Mahmut T. Kandemir shows this pattern. Likewise, ↑≡ shows rank in MuICE is increased with respect to WPRc and was not changed with respect to WPRp for example,

[2] http://aminer.org/.

Table 6
Top 25 authors ranked by $MuInf_{FA}$ and MuICE.

Rank	MuInfFA					MuICE				
	Authors	**Cit**	**Pub**	**AFA**	**NoCA**	**Authors**	**Cit**	**Pub**	**NoCA**	**f-index**
1	Philip S. Yu	3154	205	11	160	Philip S. Yu	3154	205	160	2.3519
2	Jason Cong	1428	127	88	104	Jiawei Han	3046	152	150	2.5264
3	Mahmut T. Kandemir	1355	165	37	117	Hector Garcia-Molina	3187	139	155	2.6268
4	Elisa Bertino	1469	137	53	126	Mahmut T. Kandemir	1355	165	117	1.9196
5	Luca Benini	1609	145	39	160	Christos Faloutsos	2655	116	145	2.6616
6	Jiawei Han	3046	152	23	150	Luca Benini	1609	145	160	2.2837
7	Andrew B. Kahng	950	102	48	106	Jason Cong	1428	127	104	2.6022
8	Kang G. Shin	1390	143	12	109	Elisa Bertino	1469	137	126	2.1338
9	Hector Garcia-Molina	3187	139	8	155	Kang G. Shin	1390	143	109	1.8251
10	Christos Faloutsos	2655	116	22	145	David E. Culler	3798	77	110	3.3751
11	Brad A. Myers	1259	96	30	103	David Blaauw	1581	117	110	2.4521
12	Massoud Pedram	872	125	4	68	Rakesh Agrawal	3554	59	102	3.1867
13	Pankaj K. Agarwal	488	65	58	81	W. Bruce Croft	1861	93	108	2.5015
14	David Blaauw	1581	117	7	110	Donald F. Towsley	1576	109	133	2.0934
15	Surajit Chaudhuri	1854	72	48	75	Scott Shenker	2701	79	148	2.9069
16	H. V. Jagadish	1572	83	31	84	Brad A. Myers	1259	96	103	2.3886
17	Wei Wang	786	95	25	171	Surajit Chaudhuri	1854	72	75	2.9321
18	Alberto L. Sangiovanni-V	1114	116	4	146	David J. DeWitt	2065	80	134	2.7595
19	Francky Catthoor	666	113	4	164	Nicholas R. Jennings	1364	107	106	1.9809
20	Azzedine Boukerche	235	63	52	55	H. V. Jagadish	1572	83	84	2.6243
21	W. Bruce Croft	1861	93	15	108	Alberto L. Sangiovanni-V	1114	116	146	2.129
22	Kaushik Roy	824	110	4	95	Giovanni De Micheli	1629	94	85	2.7771
23	Donald F. Towsley	1576	109	2	133	Andrew B. Kahng	950	102	106	2.2298
24	Nicholas R. Jennings	1364	107	2	106	Deborah Estrin	3163	67	138	3.1284
25	Ming-Syan Chen	1028	84	23	42	Massoud Pedram	872	125	68	1.9662
Avg		**1493**	**115**	**26**	**115**		**2008**	**112**	**119**	**2**
Stdev		**792**	**33**	**22**	**36**		**869**	**35**	**27**	**0**

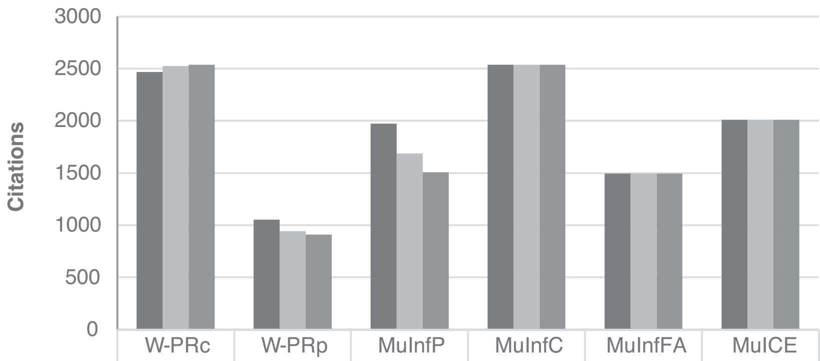
Table 7
Statistics of top 25 authors ranked by MuICE from aminer.org.

	Name	h-index	Publications	Citations
1	Philip S. Yu	117	813	64,373
2	Jiawei Han	111	781	81,075
3	Hector Garcia-Molina	114	495	57,524
4	Mahmut T. Kandemir	33	223	4570
5	Christos Faloutsos	85	512	38,220
6	Luca Benini	62	552	17,670
7	Jason Cong	23	36	2690
8	Elisa Bertino	66	810	18,706
9	Kang G. Shin	71	600	20,157
10	David E. Culler	59	177	30,963
11	David Blaauw	59	317	11,920
12	Rakesh Agrawal	86	266	53,984
13	W. Bruce Croft	44	135	8348
14	Donald F. Towsley	60	176	14,112
15	Scott Shenker	112	368	71,112
16	Brad A. Myers	66	334	17,296
17	Surajit Chaudhuri	61	213	16,526
18	David J. DeWitt	73	221	25,460
19	Nicholas R. Jennings	76	516	35,317
20	H. V. Jagadish	31	82	4319
21	Alberto L. Sangiovanni-Vincentelli	50	285	10,364
22	Giovanni De Micheli	63	385	17,047
23	Andrew B. Kahng	53	388	10,266
24	Deborah Estrin	85	291	59,570
25	Massoud Pedram	54	475	10,596

researcher Philip S. Yu shows this pattern. Out of 25, 11 authors show increasing pattern '↑↑' and none of them show complete decreasing pattern '↓↓'. This represents that effect of mutual influence along with criterions like number of publications, citations, first author publications and exclusivity of citation resulted in bringing forward successful authors to top, which baseline methods were not capturing. On the other hand absence of '↓↓' shows that there were no such authors who were ranked among top positions but were ignored by proposed method. A mixture of increase and decrease patterns like '↓↑' and '↑↓'

Table 8
Positions of top 25 authors ranked by MuICE in WPRc and WPRp.

Authors	MuICE	WPRc	WPRp	Change
Philip S. Yu	1	5	1	↑≡
Jiawei Han	2	8	*	↑↑
Hector Garcia-Molina	3	2	*	↓↑
Mahmut T. Kandemir	4	79	2	↑↓
Christos Faloutsos	5	10	*	↑↑
Luca Benini	6	49	*	↑↑
Jason Cong	7	65	8	↑↑
Elisa Bertino	8	52	*	↑↑
Kang G. Shin	9	72	*	↑↑
David E. Culler	10	1	*	↓↑
David Blaauw	11	53	*	↑↑
Rakesh Agrawal	12	3	73	↓↑
W. Bruce Croft	13	21	3	↑↓
Donald F. Towsley	14	41	*	↑↑
Scott Shenker	15	7	17	↓↑
Brad A. Myers	16	94	15	↑↓
Surajit Chaudhuri	17	29	75	↑↑
David J. DeWitt	18	18	35	≡↑
Nicholas R. Jennings	19	93	4	↑↓
H. V. Jagadish	20	47	*	↑↑
Alberto L. Sangiovanni-Vincentelli	21	103	2	↑↓
Giovanni De Micheli	22	62	77	↑↑
Andrew B. Kahng	23	163	9	↑↓
Deborah Estrin	24	4	*	↓↑
Massoud Pedram	25	*	14	↑↓



	W-PRc	W-PRp	MuInfP	MuInfC	MuInfFA	MuICE
d= 0.85	2466	1054	1973	2535	1493	2008
d= 0.5	2525	941	1687	2535	1493	2008
d= 0.15	2535	910	1507	2535	1493	2008

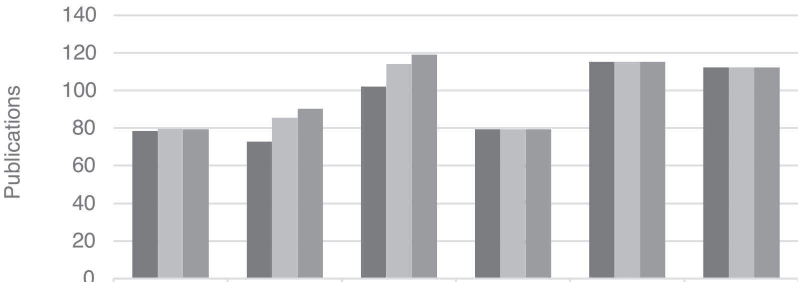
Fig. 3. Average citations of top 25 authors for baseline and proposed methods with different damping factors.

show that authors have changed positions in listing with respect to impact of their weighting factors in proposed and baseline schemes.

4.5.3. Effect of damping factor 'd'

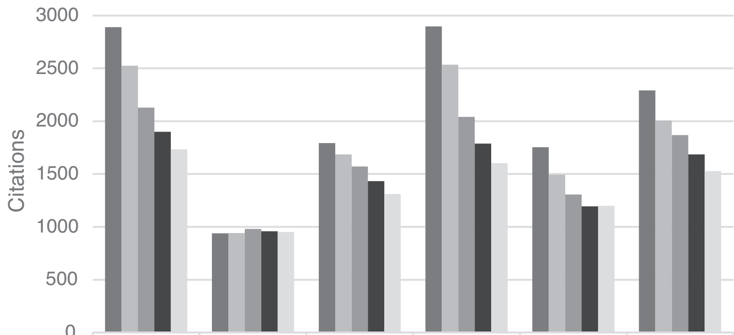
Empirical evaluation was performed using three different values of *d*, these are 0.85, 0.5 and 0.15. We establish from Figs. 3 and 4 that impact of *d* is present only in $MuInf_P$. This shows that MuICE Rank is independent of value *d* and we can attain uniform results with any value of *d*. We performed 200 iterations for all proposed schemes and witnessed that the process converges more quickly with $d = 0.15$.

Figs. 3 and 4 show the results of top 25 authors. To verify that the proposed method shows persistent results for an increasing number of top authors, we have calculated the mean of citations and publications for top 15, 25, 50, 75 and 100 authors. This is shown in Figs. 5 and 6 respectively for citations and publications. These figures show that the results of proposed methods are intuitive and promising.



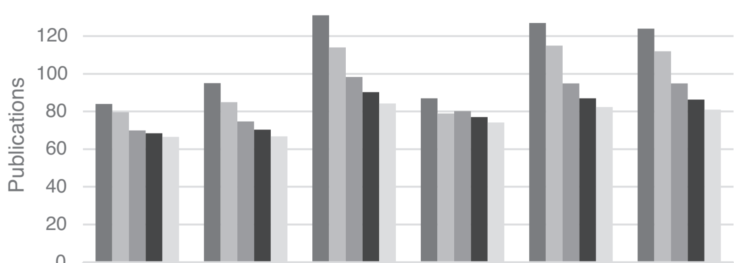
	W-PRc	W-PRp	MuInfP	MuInfC	MuInfFA	MuICE
d= 0.85	78	73	102	79	115	112
d= 0.5	80	85	114	79	115	112
d= 0.15	79	90	119	79	115	112

Fig. 4. Average publications of top 25 authors for baseline and proposed methods with different damping factors.



	W-PRc	W-PRp	MuInfP	MuInfC	MuInfFA	MuICE
15	2890	939	1792	2897	1753	2291
25	2525	941	1687	2535	1493	2008
50	2129	980	1572	2040	1307	1867
75	1901	959	1432	1787	1195	1685
100	1734	952	1312	1604	1199	1528

Fig. 5. Average citations of top 15, 25, 50, 75 and 100 authors for baseline and proposed methods ($d = 0.5$).



	W-PRc	W-PRp	MuInfP	MuInfC	MuInfFA	MuICE
15	84	95	131	87	127	124
25	80	85	114	79	115	112
50	70	75	98	80	95	95
75	68	70	90	77	87	86
100	67	67	84	74	82	81

Fig. 6. Average publications of top 15, 25, 50, 75 and 100 authors for baseline and proposed methods ($d = 0.5$).

5. Conclusions and future work

This research evaluates the influence of authors when they work in collaboration. We presented three different variations of Mutual influence method. These are: (1) $MuInf_P$, which finds the mutual influence of authors with respect to their number of publications and ranks them accordingly. (2) $MuInf_C$, which ranks the authors after finding their mutual influence with respect to their number of citations. (3) $MuInf_{FA}$, which finds the mutual influence of authors on each other by considering the number of publications in which they appeared as first authors. Afterwards, we presented MuICE method to evaluate the effect of exclusivity of citations received by authors along with mutual influence. For finding the exclusivity in citations received by an author we used f-index (Katsaros et al., 2009). The results depict the authors are substantially influenced by the work of their co-workers, especially in the case if the collaborators are senior researchers.

We computed all the methods with three different damping factors ($d = 0.85$, 0.5 and 0.15). For purpose of assessment, the ground truth is unavailable; thus, we computed the mean and standard deviation of publications as well as received citations of the top 25 authors for all approaches. We conclude that the proposed $MuInf_P$ method provides satisfying results when compared with baseline method $W\text{-}PR_p$ which uses the paper count as a weighting criteria. Analogously, when considering citations, results of $MuInf_c$ method are also substantial. The ranking criterion of the proposed MuICE is quite different from the existing methods and it involves a unique combination of different parameters instead of publication and citations count based weights. Hence, instead of comparing it with any existing method, we gathered the statistics of top authors of MuICE method from AMiner website and establish the fact that selected authors are the prestigious ones. These statistics make us conclude that only the number of publications or citations is not a sufficient criteria to rank authors. It is further concluded that collaboration has great impact on standing of an author and number of collaborators makes a difference. We also observed that MuICE produce the same results with all three values of the damping factor, however, the algorithm converges more quickly when damping factor is 0.15.

In the future, we are planning to extend our work to incorporate the ranking of papers, along with the impact of time dimension. We are also interested in applying this method for topic specific author ranking. The dataset must be divided into topic specific clusters before applying these methods.

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