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Identifying Opinion Leaders with Improved Weighted LeaderRank in Online Learning Communities

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Abstract

Opinion leaders play a crucial role in closely interconnecting groups and help achieve better group performances in online learning communities. Weighted LeaderRank is superior to other methods in identifying opinion leaders, but there are some limitations in its weighted mechanism. This study further optimizes the weighted mechanism of weighted LeaderRank by introducing users' initial comprehensive influence and the number of user interactivity. Experimental results show that the improved weighted LeaderRank algorithm can improve the accuracy of opinion leader identification in online learning communities compared with the other two typical algorithms.

Keywords: opinion leaders; weighted LeaderRank; online learning communities

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1. Introduction

Nowadays there are ever-increasing learners in online learning. [6,20,25] demonstrate the importance of group learning to improve the learning achievement. The groups will obtain greater achievement if they have proper group leaders, who are also called opinion leaders and are generally more active in learning and discussing, and they conduct greater and positive effects on other learners [21,26]. However, identifying opinion leaders effectively and efficiently from enormous online learners is a big challenge [15]. Among the methods, such as degree centrality, k-shell decomposition, PageRank, LeaderRank etc., weighted LeaderRank is more accurate and effective for identifying opinion leaders. But, it also has some limitation in its weighted mechanism. Besides that, different kinds of users in social networks have different characteristics. So, by analyzing online learning user behaviors in online learning forums, which is a common platform for learners to communicate and discuss with each other, this study proposes an improved weighted LeaderRank algorithm by further optimizing the weighted mechanism of weighted LeaderRank. The results from experimenting on a famous Moocs forum show that the algorithm proposed in the paper can identify opinion leaders more accurately and effectively when compared with two other typical algorithms. The rest of this paper is organized as follows. Section 2 discusses the related works; Section 3 discusses the weighted LeaderRank algorithm; Section 4 proposes the improved weight LeaderRank algorithm; Section 5 introduces the experiment and compares the effect between proposed algorithm and other two kinds of typical algorithm. In the last section we emphasize the conclusion analysis.

2. Related Work

Opinion Leaders were firstly proposed by Lazarsfeld et al. in 1944 [14]. Opinion leaders, who have superior status, education, and social prestige, have significant influence over their followers, and they also encourage group information exchange and improve group performance [1,5,17]. Researchers have conducted plenty of studies in identifying opinion leaders. Previous studies mostly focus on identify the importance of nodes based on the amount and the distance of their neighbors, such as degree centrality [3], semi-local centrality [4], k-shell decomposition [12], eccentricity [10], closeness centrality [7],

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betweenness centrality [8] and flow betweenness centrality [2]. These methods consider the quantity, but ignore the influences of their neighbors. Eigenvector centrality [16] involves the importance of a node. The influence of node A with more neighbors may be lower than node B with few neighbors because the neighbors of node B have higher influence. Nevertheless, eigenvector centrality algorithm inevitable has a localization problem if there are many nodes with huge degrees in the network.

PageRank [22] extends eigenvector centrality, which is a classic algorithm of directed graph sorting and is used by Google to rank the importance of webpages in their search engine results. Now PageRank and some improved PageRank algorithms are extensively applied in many other areas. [23] applied PageRank to access user influence in social network. [24] proposes an improved PageRank algorithm based on the initial influence of users, which consists of the numbers of users posting, replying, being replied and being read. However, there are some other elements to construct a user's influence model that were not considered, such as being praised and being concerned. [11] applied PageRank to identify the measure author impact in co-authorship network. [19] applied PageRank to order scientific papers. However, there are some limitations with PageRank: (1) the probability that describes the random information is the same. It is not fit for real circumstances. For example, the ratio that people go to other webpages from a hot webpage is definitely lower than that of when people click other pages from a boring webpage; (2) the parameter C is usually acquired by experiences and the optimal parameter is not fit for all situations [13].

Lü et al. [15] in 2011 proposed LeaderRank based PageRank by adding a g node and bidirectional edges between the g node and other nodes to replace the parameter C of PageRank. So LeaderRank is more adaptive and parameter-free. Compared to PageRank, LeaderRank is more effective and has higher robustness against manipulations and noisy data. The value of the links between g node and other nodes are the same in the LeaderRank algorithm. But actually, some nodes with higher in-degrees have higher possibilities to be visited. Therefore, Li et al. [15] further improved this limitation by introducing a weighted mechanism and propose weighted LeaderRank. Regardless of the accuracy, the tolerance or the robustness, weighted LeaderRank is superior to LeaderRank.

Without a doubt, weighted LeaderRank is an effective and efficient algorithm. But, it also has limitations, such as its weighted mechanism just lets the in-degree of each node be the weight of the link, which does not completely express the user's features. So, this study tries to optimize the weighted mechanism according to online learning user behaviors in forums and further improves the accuracy of algorithm.

3. Weighted LeaderRank Algorithm

Pagebank is the basis of LeaderRank. PageRank is firstly proposed by L Page et al. in 1998 [22], which determines the importance of a web page by counting not only the number, but also the quality of links to the page. The basic idea is that if the page links to page u have higher "importance", web page A also has high PageRank value even though these links are few. In general, PageRank value of page p is calculated by the following Equation (1):

$$\mathrm{PR}_i(\mathrm{t}+1) = \frac{(1-c)}{N} + c\sum_{\mathrm{j}=1}^{n} \frac{PR_j(t)}{T(p_j)} \tag{1}$$

Where PRi(t) is the PageRank score of page i at time step t, the initial value is 1; c is damping factor, which is general 0.85; N is the number of webpages; T(pi) is the number of outlinks of page i. PRi(t) is computed iteratively until PRi(t) is stable.

LeaderRank was improved by introducing a ground node that connects to every node through bidirectional links. Thus, the network becomes strongly connected and the bidirectional links replace the damping factor C so that this algorithm is more effective. The equation of LeaderRank is expressed as Equation (2):

$$\mathrm{Q}_i(\mathrm{t}+1) = \sum_{j=1}^{m} \frac{a_{ji}}{T(p_j)} \mathrm{Q}_i(\mathrm{t}) \tag{2}$$

Where $Q_i(t)$ is the LeaderRank score of page i at time step t, the initial value is also 1 for all nodes except for the ground node, and $Q_g(0)$ is equal to 0 for the ground node; N is the number of webpages plus g node; a_{ji} is equal to 1 if there is a link from j to i, and 0 otherwise. $T(p_i)$) is the number of outlinks of page i. $Q_i(t)$ also will being computed iteratively until $PRi(t)$ is stable.

Weighted LeaderRank algorithm further improves Leader Rank by introducing a weighted mechanism [20]. Weighted LeaderRank considers if the in-degrees of nodes are different, so the scores from the ground node to these nodes are different. The nodes with high scores have high probabilities to be visited. The equation is listed as Equation (3):

$$Q_i(t+1) = \sum_{j=1}^{m} \frac{a_{ji}}{T(p_j)} Q_i(t) \tag{3}$$

Where v_{ij} is 0 just when $a_{ij}=0$; v_{ij} is 1 when $a_{ij} <> 0$; $v_{gi} = (T(pi))\ \alpha$ and $v_{ig} = 1$ for node i and the ground node g, α is free a factor.

4. Improved Weighted LeaderRank Algorithm

Forum is the main place for users in online learning communities to interact with each other. This research mainly identifies opinion leaders according to their behaviors in forum. Weighted LeaderRank algorithm improved LeaderRank algorithm by introducing a weight of any node i and the ground node, which is the in-degrees of this node. That means in-degrees of a node express the importance of the node. In forums, the in-degrees of users is not just the replying relationship, but consist of several interactive behaviors, such as posting, replying, be replied to, reading [24] etc. So, we further improve the weighted mechanism based weighted LeaderRank algorithm by introducing user comprehensive influence and the interacting number.

4.1. Weight Improvement Based on Users Initial Comprehensive Influence

Initial comprehensive influence is superior to in-degrees in being used as a weight to calculate a user's final influence. Every user has a different initial comprehensive influence. The total number of posting, replying, reading and so on of every leaner is not the same. One who has higher initial comprehensive influence definitely has a stronger final influence. Therefore, we allow the initial comprehensive influence as a weights of ground g to any node i and set wgi= (fiin)α, and fi is the initial comprehensive influence. We propose a learner influence model to get users' initial comprehensive influences, and propose a learner influence model. The construction of the model is mainly according to users' behaviors in the forum. We divide the initial comprehensive influence into two parts: positive influence and indirect influence.

- Positive influence: this kind of influence, which consists of the total number of posting and replying, shows how positive the user is in the forum. Posting indicates that users are willing to propose and share their opinion, questions and ideas. Replying points out that these users are ready to discuss or answer questions other users proposed. The higher the total number of posting and replying is, the higher the user's positive influence is and also the more active the use is.

- Indirect influence: This kind of influence mainly consists of the total number of being read, being replied to, being praised and being concerned, which indicates how deeply concerned this user is by other users. The higher number of being replied to shows that the post is deeply concerned by most users, which also indicates that the post impacts more users. Besides being replied to, being read, being praised and being concerned also show the popularity of the post. The higher the indirect influence is, the more users are affected.

Figure 1 indicates the users initial comprehensive influence model.

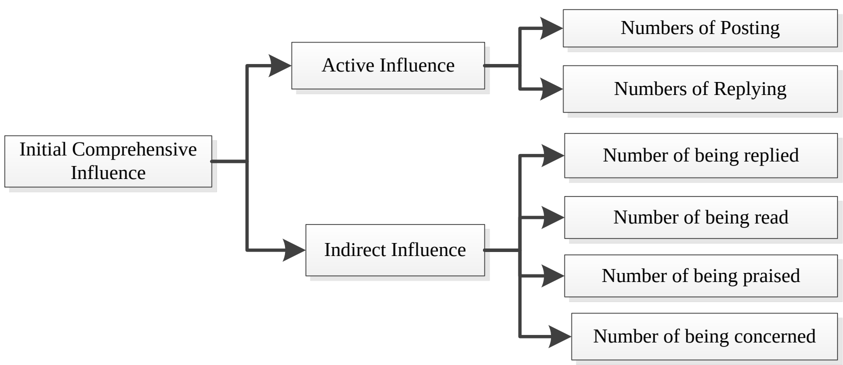

Figure 1. Users initial comprehensive influence model

According to the analysis above, we propose Equation (4) to calculate users initial comprehensive influence:

$$f = \sum_{i=1}^{2} w_i * a_i + \sum_{i=1}^{4} v_i * b_i \tag{4}$$

Where f is initial comprehensive influence; w_i and v_i are weight; a_1 is the number of posting, a_2 is the number of replying; b_1 is the number of being replied, b_2 is the number of being read, b_3 is the number of being praised, b_4 is the number of being concerned.

We apply the Entropy Weight method to obtain appropriate weight w_i and v_i. Entropy concept was proposed by Shannon in 1948 [18]. It has been widely employed in social and physical sciences. The basic idea of Entropy weight method is to determine the weight of individual indicators by calculating the entropy and entropy weight. The less the entropy is, the greater the amount of useful information. So, the corresponding entropy weight is also greater, and vice versa [9]. There are three steps to get the entropy weight [25]:

Step 1: Normalization of the arrays of decision matrix

Suppose there are a series of data T_1, T_2, …, T_k, $T_i=\{t_1, t_2, …, t_n\}$, use the below equation to obtain the normalized outcome k_{ij}.

$$k_{ij} = \frac{t_{ij}\text{-min}(t_i)}{\max(t_i) - \min(t_i)}$$

Step 2: Calculate entropy:

Set $G_j = \text{-ln}(n)^{-1} \sum_{i=1}^{n} v_{ij} \ln v_{ij}$, $v_{ij} = \frac{k_{ij}}{\sum_{i=1}^{n} k_{ij}}$ If $v_{ij} = 0$, $\lim_{v_{ij} - 0} v_{ij} \ln v_{ij} = 0$

Step 3: calculate each entropy weight W_i.

$$w_i = \frac{1 - G_i}{x - \sum G_i} \, (i = i, 2, ..., k) \, .$$

4.2. Weight Improvement Based on Users Initial Comprehensive Influence

The weighted LeaderRank mainly considers the weight of nodes from the ground node. As for the weight between any normal nodes, the weight is 1. Actually, the relationship of different users is different. Learner A replied learner B many times but just replied to learner C only one time, which means the relationship between A and B is stronger than it is between A and C. So, in this paper, we introduce the time of being replied to of each node as another weight. The improved weighted LeaderRank algorithm is shown in Figure 2: if a_{ij}<>0, $w_{ij}=n_{ij}$, n_{ij} is the total times that i replied j.

The structure of improve weighted LeaderRank is shown in Figure 2.

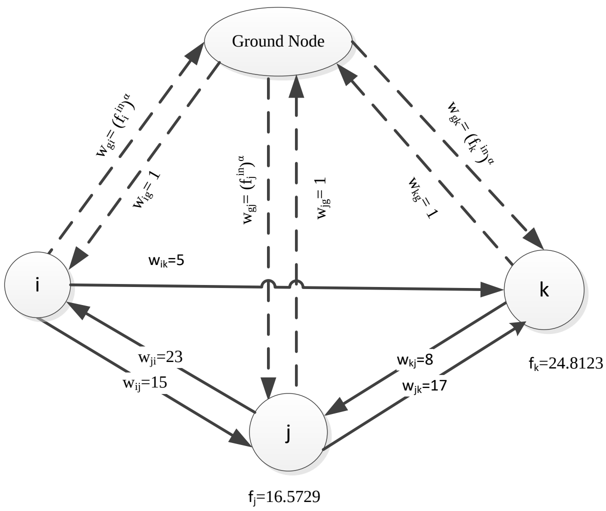

Figure 2. Structure of improved weighted LeaderRank

5. Experiment and Result Discussion

5.1. Data Collection

In the last four years, an increasing number of people around the world have enrolled in Massive Open Online Courses (MOOCs). Nowadays, Coursera, Edex and Udacity, which have the largest catalogs of courses in the world, are definitely the "top-three" MOOCs platforms. As of January 2016, Udacity, Edx, and Coursera separately offer more than 120, 820 and 1,563 courses, respectively, and the online learners come from 28 countries. MOOCs not only provides common learning materials such as course slides, lecture videos, assignments, quizzes, and so on, but also supply forums, which are interactive platforms among learners, teachers and teaching assistants. Coursera's forums are clearly separated from the course materials, so learners can communicate with others before or after studying. Learners can post and answer questions, offer advice and so on. The machine learning course at Coursera is one of the most welcomed courses. Over 100,000 students of different counties joined the class. Machine learning is taught by Andrew Ng, who is one of the founders of Coursera. We chose this course as our experiment object and crawl data from the forum of this course was obtained between April 18 and June 3, 2016. The amount of the dataset includes 1723 posts, which consist of the author, the amount of be read, be praised, be concerned, as well as all of the users who reply to the posters. We further discard some duplicate posts and some posts that are not closely tied to the course. Finally, we get 1215 records and 302 users. Among the users, there are 221 users who participate in posting, 147 users who participate in replying, and only 66 users who participate in both posting and replying activities. It means there are just 22.5% users who really actively participate in the forum discussion. The percentage of different kinds of users is shown in Figure 3.

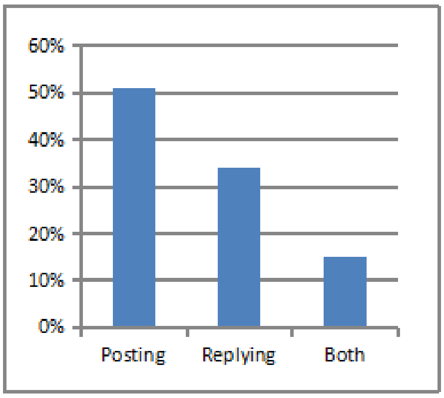

Figure 3. Percentage of different kinds of users

According to the dataset, we obtain two matrices; one is users' mutual replying relationships. If user i replied to user j, the link that i points to j will be created and the edge weight is the number of replies. If one user replied to oneself, there is not an edge link to the node itself. The mutual replying relationship is shown in Table 1.

Table 1. Mutual replying relationship

Users name	Adhi Narayanan	Akash Gupta	aldo	Aleksei Solovev	Alex Camargo	Alexandru Coca	Amr Mohamed Kayid	…
Abhilash R	4	0	0	0	0	0	0	
Adrian Edlund	0	0	0	5	0	0	1	
Ajay Chauhan	1	0	3	0	0	0	0	
Alexander ossmanith	0	0	0	0	1	0	1	
Ameya Shanbhag	0	1	0	0	0	0	0	
…								

Another is the number of each learner posting, reading, being read, being replied, and being praised being concerned, which is shown in Table 2.

According to Table 2 and Entropy Weight method introduced in section 4.1, we can obtain the weights of posting, replying, being read, being replied, being praised, and being concerned. The results are shown in Table 3.

Table 2. Users activities

ID	Name	Posting	Replying	Being Read	Being replied	Being praised	Being concerned
1	Bryn Baritompa	1	0	35	3	0	3
2	Chiao Mei LIM	2	0	40	4	0	6
3	Eduardo Diaz Real	1	0	38	4	0	3
4	Zahir Alward	3	0	116	4	0	7
5	Eleazar Gallegos	1	4	290	41	95	53
6	vignajeth	5	0	66	5	0	10
7	Imasaki Kenjiro	1	1	41	8	0	8
8	Jeremy Andrew Russell	4	2	291	44	6	30
9	Tony Go	17	0	186	33	2	48
10	Andrew Albers	1	1	304	5	12	4
…							
162	Huy D. Tran	2	0	86	9	1	7

Table 3. Entropy Weight

Elements	Posting	Replying	Being read	Being replied	Being praised	Being concerned
Weight	0.3978	0.2056	0.0994	0.1767	0.0713	0.0492

5.2. Experiment Result and Discussion

We develop a program with C# according to the algorithm we proposed to obtain the users' finial influences. The top 20 user influences are shown in Table 4.

Table 4. Top 20 users influence

Rank	Name	Posting	Replying	Being Read	Being replied	Being praised	Being concerned	Influence
1	Tom Mosher	176	74	3222	346	42	421	151.7358
2	Chirag Uttamsingh	27	11	4784	67	134	535	94.34717
3	Tony Go	22	9	186	21	78	66	70.71908
4	Abhilash R	13	7	357	36	33	7	65.23145
5	Vinyas Malagaudanavar	11	11	160	33	15	19	53.71908
6	Jeremy Andrew Russell	9	2	291	44	6	30	52.34528
7	Jacques Joubert	10	0	166	17	18	12	46.34717
8	vignajeth	10	7	66	5	36	10	42.38029
9	Rodrigo Alonso	8	4	169	17	15	18	40.97526
10	Zoltan Halasz	7	5	78	9	7	14	40.23145
11	Ashish Nair	6	10	50	7	9	7	37.09098
12	Saul	8	3	39	4	12	7	34.34717
13	Patrick Choi	4	3	195	11	36	13	34.23145

Table 4 (Continued). Top 20 users influence

14	Zahir Alward	5	8	116	4	16	7	33.97526
15	Rhum Whysky	7	2	74	5	22	4	32.34717
16	Chiao Mei LIM	3	6	156	9	19	6	32.23145
17	Huy D. Tran	6	2	86	9	6	7	31.97526
18	Glen Turner	2	4	18	8	5	4	31.34717
19	Tim Yagan	3	3	25	4	10	5	30.34717
20	Huang Yu Ku	2	1	72	4	12	4	29.34717

In order to illustrate the accuracy of our algorithm, we also obtain the influence with PageRank and LeaderRank. The top 20 users of these three kinds of algorithms are shown in Table 5.

Table 5. Top 20 users of three kinds of algorithms

Rank	PageRank	Weighted LeaderRank	Improved weighted LeaderRank
1	Tom Mosher	Tom Mosher	Tom Mosher
2	Chirag Uttamsingh	Chirag Uttamsingh	Chirag Uttamsingh
3	vignajeth	vignajeth	Tony Go (Anton Gorodenskyi)
4	Glen Turner	Glen Turner	Abhilash R
5	Eduardo Diaz Real	Amr Mohamed Kayid	Vinyas Malagaudanavar
6	Daniel Mejia	Eduardo Diaz Real	Jeremy Andrew Russell
7	Huy D. Tran	Lebedinskiy Artem	Jacques Joubert
8	Liv Boeree	Daniel Mejia	vignajeth
9	Lebedinskiy Artem	Joel M. Villanueva L.	Rodrigo Alonso
10	Amr Mohamed Kayid	Huy D. Tran	Zoltan Halasz
11	Jordan Sorensen	Susa Na	Ashish Nair
12	Joel M. Villanueva L.	Jp Lou	Saul
13	Ángel Luis Quesada	Ángel Luis Quesada	Patrick Choi
14	Jp Lou	RaviKiran Gopalan	Zahir Alward
15	Laura Richter	yeepom	Rhum Whysky
16	Loong Chek Jen	Loong Chek Jen	Chiao Mei LIM
17	Lou Marvin Caraig	Huang Yu Ku	Huy D. Tran
18	Huang Yu Ku	XinluXiao	Glen Turner
19	Zoltan Halasz	Laura Richter	Tim Yagan
20	Rhum Whysky	Liv Boeree	Huang Yu Ku

The first and second ranks of the three algorithms are the same. The first one is Tom Mosher, and the second one is Chirag Uttamsingh. The number of posting, replying, being read, being replied, being praise, being concerned of the two users are beyond the other users. But, the third one of the algorithm we proposed is Tony Go. The third one of the Weighted LeaderRank and PageRank are both Vignajeth. Weighted LeaderRank and PageRank address the interaction among users, especially the relationship of replying and be replied to. As for the algorithm we proposed, it more so considers posting, being read, being praised, and being concerned on top of replying and being replied to. Although the number of replying and being replied to of Tony Go is a little bit lower than Vignajeth, the number of posting, replying, being praised and being concerned are higher than that of Vignajeth. This means Tony Go actively participated in the forum and his posts are widely concerned. The fifth one of the algorithm we proposed is Vinyas Malagaudanavar, who is 8th in the Weighted LeaderRank and 11th in the PageRank. Why are there great differences? Although the amount number of being replied to of Vinyas Malagaudanavar's posts is not very high, the influences of these replying users are relatively higher, which correspondingly improves the influence of Vinyas Malagaudanavar. Besides, there are some users, such as Abhilash R, Jacques Joubert and Rodrigo Alonso, who are identified by improved algorithm and cannot be found by Weighted LeaderRank and PageRank. Although the amount of posts the three users post is a little bit less, the amount of being replied to, being praised and being concerned are more. Furthermore, the three users reply posts in time and discuss the contents of these posts many times. All of these indicate that the qualities of these posts are higher and these posts also got much more concern and discussion. Based on the analysis above, the algorithm we propose, which consider a user's comprehensive activity and indirect influences and interactivities, is more accurate than PageRank and Weighted LeaderRank.

$$E(i) = w1E1(i) + w2E2(i) \tag{5}$$

$$E1(i) = \frac{\sum_{i=1}^{N} T(i)}{N} \tag{6}$$

$$E2(i) = \frac{\sum_{i=1}^{n} F(i)}{n} \tag{7}$$

In Equation (5), *E(i)* indicates the evaluation value of the top i users; *w1* and *w2* are weight, which are both 0.5; *E1*(*i*) indicates the ratio of the number of affected users by the top i users; *E2*(*i*) is the ratio of influence of affected users by the top i users; $T(i)$ is the number of users who are affected by user i. $F(i)$ is the influence of users who are affected by user i, M is the total influence of all users. This formula not only considers the number of users who are infected directly and indirectly, but also considers the influence of these affected users. The higher the $E(i)$ is, the greater the influence these top i users have.

We compare the influence of the top 10% of users by PageRank, Weighted LeaderRank and Improved Weighted LeaderRank according to Equation (6) and Equation (7) during the whole online learning. Figure 4(a) shows that the evaluation value of the top 10% users by improved LeaderRank is better than that by PageRank and LeaderRrank. In order to further demonstrate the effectiveness of Improved Weighted LeaderRank, we also execute experiments for the top 15%, 20%, 30% users separately by PageRank, Weighted LeaderRank and Improved Weighted LeaderRank. The results are shown in Figure 4(b) to 4(d).

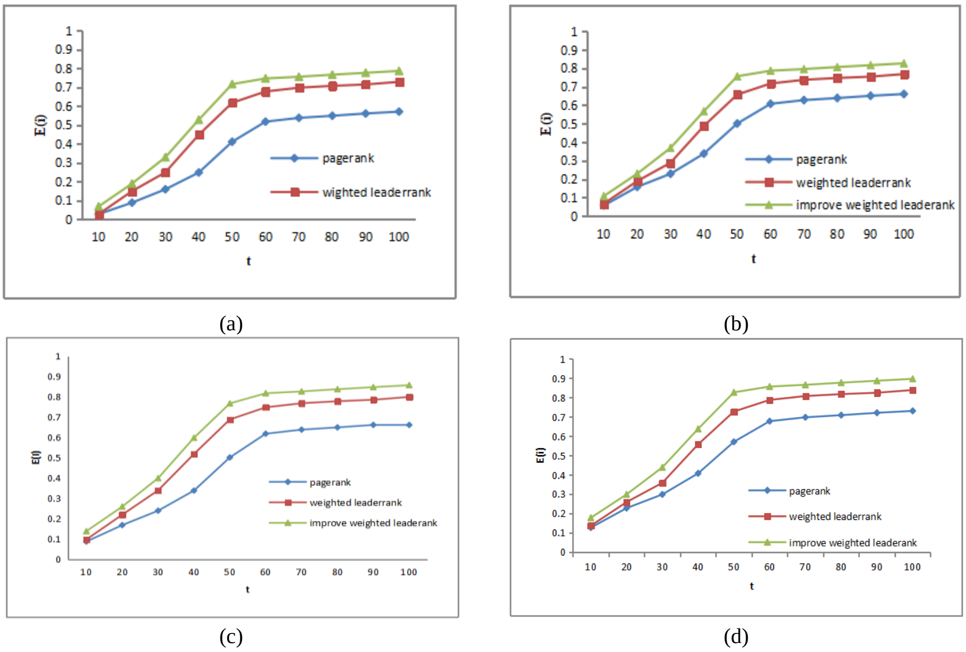

Figure 4. (a) evaluation value of the top 10% users by improved weighted LeaderRank, PageRank and LeaderRank
(b) evaluation value of the top 20% users by improved weighted LeaderRank, PageRank and LeaderRank
(c) evaluation value of the top 30% users by improved weighted LeaderRank, PageRank and LeaderRank
(d) evaluation value of the top 40% users by improved weighted LeaderRank, PageRank and LeaderRank

The results are also the similar. Therefore, the number of affected users and the total influence of the affected users show that the Improved Weighted LeaderRank is better than PageRank and Weighted LeaderRank.

6. Experiment and Result Discussion

Opinion leaders can be seen as the leaders of each online learning group, as they can help further improve the learning achievement of the whole group. Weighted LeaderRank is a great algorithm to identify opinion leaders. Based on this algorithm, we improve the weighted mechanism by importing users' initial comprehensive influence and inter-activities according to their activities in online learning forums. The algorithm we proposed has higher accuracy and much more fit for the identification of opinion leaders of online learning communities.

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