International Journal of Computational Intelligence Systems
Vol. **13(1)**, 2020, *pp.* 1699–1713
DOI: https://doi.org/10.2991/ijcis.d.201015.002; ISSN: 1875-6891; eISSN: 1875-6883
https://www.atlantis-press.com/journals/ijcis/

Research Article

Link Prediction in Social Networks by Neutrosophic Graph

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ARTICLE INFO

Article History
Received 29 Jul 2020
Accepted 03 Oct 2020

Keywords
Social network
Neutrosophic graph
Link prediction
Modified RSM index

ABSTRACT

The computation of link prediction is one of the most important tasks on a social network. Several methods are available in the literature to predict links in networks and RSM index is one of them. The RSM index is applicable in the fuzzy environment and it does not incorporate the notion of falsity and indecency parameters which occur frequently in uncertain environments. In the present method, the behaviors of the common neighbor and the other parameters, like nature of job, location, etc., are considered. In this paper, more parameters are included in the RSM index for making it more flexible and realistic and it is best fitted in the neutrosophic environment. Many important properties are studied for this modified RSM index. A small network from Facebook is considered to illustrate the problem.

1. INTRODUCTION

Nowadays, the use of social networks [1] are progressing very fast. Social networks can be used for many purposes. Many types of social networks are available. These social networks are prepared to grow their business rapidly, and hence the providers of social networks try to increase their networks.

Over the past few years, online social networking has exploded in popularity as a means for people to share information and build connections with others. For communication, marketing, and spreading of news, etc., it becomes a vital instrument. In the social network market, there is a substantial competitive situation, so all social network organizations are trying to enhance their networks' popularity. So popularity directly depends on how many users and edges/relationship are there between users. In social networks, it is essential to know how to improve the number of edges.

A user of a social network wants to connect to another user by nature of the user, therefore, at first, he/she gathers some information like common friends, personality, age, sex, educational background, job and living area.

It is analyzed that the personalities of common friends are proportional to build a link between to unknown friends. There are lots of graph-theoretic measures for link prediction. However, the given data in social networks are not precise all the times. Fuzzy systems capture these uncertainties with a degree of memberships. So, the fuzzy graph gives a more effective result for this calculation. Samanta and Pal [2–5] introduced many types of fuzzy graphs. Mahapatra *et al.* [6–8] presented many applications of the fuzzy graph.

It is a common research topic in social networks on how to improve the number of edges in networks, and many types of methods are used to increase links. Nowell *et al.* [9] introduced common neighbor (CN) methods of link prediction and it is modified as Jaccard's coefficient [10]. Sorensen [11] introduced Sorensen Index. Adamic/Adar (AA) index was introduced by Adamic and Adar [12].

Almost all the link prediction methods are calculated on the basis of the neighbors. The prediction score for links is based on the number of neighbors. If the number of neighbors increases, the probability of predicting links will also increase. Yet neighbors' behavior is essential. But, in link prediction calculation nature of common neighbor plays a vital role. Mahapatra *et al.* [13] introduced RSM index for link prediction calculation depending on the nature of common neighbor in the fuzzy graph.

Though capturing false data is a research question, some times, data are displayed with falsity and indeterminacy. The number of friends of person may be assumed as true value. But the number of inactive or fake friends may be assumed as falsity. Sometimes data are not available or the data are contradicting the facts. In these cases, indeterminacy may be taken to capture the notions. All three values, true value, falsity, indeterminacy, are taken in neutrosophic graphs [14]. Manh Tuan *et al.* [15] proposed link prediction calculation by neutrosophic modelling. In these cases, too, the nature of common friends is ignored. Besides, there are some other realistic notions like locality, jobs, educations which have effect in link prediction calculation. In the proposed method, the RSM index has been updated with these notions in neutrosophic fuzzy

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environment. This article proposes an advanced idea of RSM index, modified RSM index.

Some Notations

All the basic notations are shown in Table 1.

2. PRELIMINARIES

A fuzzy graph $\xi = (V, \sigma, \mu)$ is complete if $\mu(u, v) = \min\{\sigma(u), \sigma(v)\}$ for all $u, v \in V$, where (u, v) denotes the edge between the vertices u and v.

A neutrosophic set A in X is characterized by a truth membership function $T_A(x)$, an indeterminacy membership function $I_A(x)$ and a falsity membership function $F_A(x)$. The functions $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or nonstandard subset of $]0^-, 1^+[$. That is, $T_A(x) : X \to]0^-, 1^+[$, $I_A(x) : X \to]0^-, 1^+[$ and $F_A(x) : X \to]0^-, 1^+[$ and $0^- \leq T_A(x) + I_A(x) + F_A(x) \leq 3^+$.

A neutrosophic graph is an order pair $\zeta = (A, B)$, where $A : V \to [0, 1]$ is a neutrosophic set in V (nonempty) and $B : V \times V \to [0, 1]$ is a neutrosophic relation on V such that

$$T_B(x, y) \leq min\{T_A(x), T_A(y)\},$$

$$I_B(x, y) \geq max\{I_A(x), I_A(y)\},$$

$$F_B(x, y) \geq max\{F_A(x), F_A(y)\}$$

for all $x, y \in V$.

2.1. Link Prediction Methods

In a social network, two unknown users may be connect in future. Suppose in Figure 1 consider a small networks, at time t the vertices c and d has no edge but in future at time t^* there may have some chance to connect each other. This type of chance is calculated by method of link prediction calculation.

Various types of link prediction methods are available, some of these are given below.

Table 1 Some basic notations.

Notation	Meaning
ξ	Fuzzy graph
ζ	Neutrosophic graph
V	Vertex set
E	Edge set
$T_A(x), I_A(x), F_A(x)$	True membership value, indeterminacy membership value, falsity membership value of the vertex x of ζ
$T_B(x,y), I_B(x,y), F_B(x,y)$	True membership value, indeterminacy membership value, falsity membership value of the edge (x, y) of ζ
$C(x)$	Set of neighbor of the vertex x
d_x	Degree of vertex x
$(T_{C_i}, I_{C_i}, F_{C_i})$	True value, indeterminacy value, falsity value of nature of common neighbors
S_{xy}	Link prediction value between the vertices x and y
$(T_{D_i}, I_{D_i}, F_{D_i})$	True value, indeterminacy value, falsity value of the other parameters
(T_L, I_L, F_L)	True value, indeterminacy value, falsity value of link prediction by modified RSM index
$\hat{S}_{xy}$	Score of link prediction between the vertices x and y by modified RSM index

2.1.1. Common neighbors (CN)

CNs [9] methods directly depend on number of common neighbors. Suppose, set of neighbor of a vertex x is $C(x)$ then link prediction value by this method is

$$S(a, b) = |C(a) \bigcap C(b)|.$$

2.1.2. Salton index

$C(x)$ is the set of neighbor and d_x is the degree of a vertex x then the link prediction value by Salton index [16] defined as

$$S(a, b) = \frac{|C(a) \bigcap C(b)|}{\sqrt{d_a * d_b}}.$$

2.1.3. Jaccard index

Suppose, set of neighbor of a vertex x is $C(x)$ then the link prediction value by Jaccard index [10] is

$$S(a, b) = \frac{|C(a) \bigcap C(b)|}{|C(a) \bigcup C(b)|}.$$

2.1.4. Sorensen index

Soresen index [11] of link prediction is defined as

$$S(a, b) = \frac{|C(a) \bigcap C(b)|}{d_a + d_b}.$$

2.1.5. Hub promoted index

The link prediction value by Hub Promoted index [17] is defined as

$$S(a, b) = \frac{|C(a) \bigcap C(b)|}{min(d_a, d_b)}.$$

2.1.6. Hub depressed index

The link prediction value by Hub Depressed index is defined as

$$S(a, b) = \frac{|C(a) \bigcap C(b)|}{max(d_a, d_b)}.$$

2.1.7. Leicht-Holme-Newman index

The link prediction value by Leicht-Holme-Newman index [18] is defined as

$$S(a, b) = \frac{|C(a) \bigcap C(b)|}{(d_a * d_b)}.$$

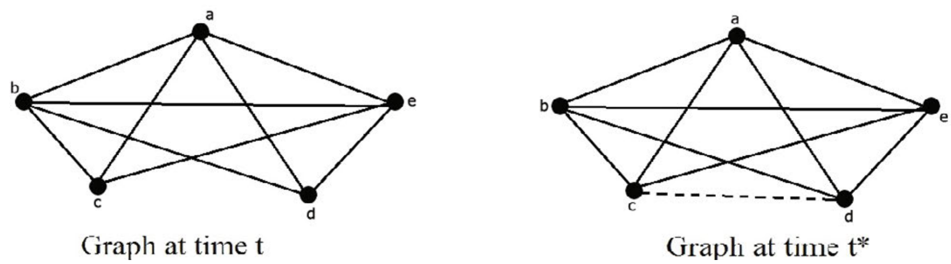

Figure 1 | Example of link prediction.

2.1.8. Preferential attachment index

The link prediction value by Preferential Attachment index is defined as

$$S(a,b) = d_a * d_b.$$

2.1.9. AAdar index

The link prediction value by AA index [12] is defined as

$$S(a,b) = \sum_{P \in N(a) \bigcap N(b)} \frac{1}{(\log d_P)}.$$

2.1.10. Resource allocation index

The link prediction value by Resource Allocation index [19] is defined as

$$S(a,b) = \sum_{P \in N(a) \bigcap N(b)} \frac{1}{d_P}.$$

2.1.11. RSM index in fuzzy graph

The link prediction value by RSM index [13] in fuzzy graph is defined as

$$S_(a,b) = \sum_{i=1}^{r} \frac{N_i}{r}.$$

N_i is the nature of the common neighbors and it is calculated by $N_i = min\{\mu(a,x_i), \mu(b,x_i)\}$, x_i is the common neighbors between the vertices a, b where $\mu(a,x_i)$ is the edge membership value of edge (a,x_i) of a fuzzy graph and $i = 1,2,3,\ldots,r$.

3. MODIFIED RSM INDEX FOR LINK PREDICTION

All above methods except "RSM index" are based on the number of neighbors. As a result, link prediction value depends on the number of neighbors. The number of common neighbors increases, then the probability of link prediction will be increase. However, the nature of neighbors is significant for the calculation of link prediction in "RSM index." But, there are several other factors which are essential to predict the link between two unknown people. That is, despite no mutual friends, there are still chances to be linked between two unknown people based on other parameters like location, job, education, etc. In the proposed Modified RSM Index, link prediction value is calculated from nature of neighbor and a few other parameters in neutrosophic environment.

Now introduce the Modified RSM Index in neutrosophic environment-

Consider u and v be any two nonadjacent vertices of a neutrosophic graph ζ. Also, let u and v have n number of neighbors as $w_1, w_2, \ldots, w_n$. Then the link prediction between u and v depends on the nature of this common neighbor and some other associated parameters like (i) job, (ii) location, (iii) education, etc.

Now, true value, indeterminacy value, falsity value of nature of common neighbors are denoted by $(T_{C_i}, I_{C_i}, F_{C_i})$ defined by

$$T_{C_i} = min\{T_B(u,w_i), T_B(w_i,v)\}$$

$$I_{C_i} = max\{I_B(u,w_i), I_B(w_i,v)\}$$

$$F_{C_i} = max\{F_B(u,w_i), F_B(w_i,v)\},$$

where, $T_B(u,w_i), I_B(u,w_i), F_B(u,w_i)$ are the true membership value, indeterminacy membership value, falsity memberships value of the edge (u,w_i) and $i = 1,2,\ldots,n$.

Also, consider the $(T_{D_i}, I_{D_i}, F_{D_i})$ be the true membership value, indeterminacy membership value, falsity memberships value of the other m associated parameters.

Then the link prediction between u and v is denoted by (T_L, I_L, F_L) is defined by

$$T_L = \frac{\sum_{i=1}^{n} T_{C_i} + \sum_{j=1}^{m} T_{D_j}}{m+n}$$

$$I_L = \frac{\sum_{i=1}^{n} I_{C_i} + \sum_{j=1}^{m} I_{D_j}}{m+n}$$

$$F_L = \frac{\sum_{i=1}^{n} F_{C_i} + \sum_{j=1}^{m} F_{D_j}}{m+n}$$

Score of link prediction by Modified RSM Index

$$\hat{S}_{uv} = \frac{2 + T_L - I_L - F_L}{3}.$$

3.1. Algorithm to Calculate Score of Link Prediction by the Neutrosophic Graph

Input: $\zeta = (A, B)$ be a neutrosophic graph.

Output:- Score of link prediction between two vertices a and b of ζ.

Step 1: Calculate true value, indeterminacy value, falsity value of nature of common neighbors (direct) between a, b are $(T_{C_i}, I_{C_i}, F_{C_i})$, where $i = 1, 2, 3, \ldots, n$.

Step 2: Calculate $(T_{D_i}, I_{D_i}, F_{D_i})$ be true membership value, indeterminacy membership value, falsity memberships value of the other m associated parameters.

Step 3: Calculate true value, indeterminacy value, falsity value of link prediction between a and b is (T_L, I_l, F_L).

Step 4: Calculate the score of link prediction by Modified RSM Index is $\hat{S}_{ab} = \frac{2+T_L-I_L-F_L}{3}$.

Example 1. Consider in Figure 2, a neutrosophic graph with five vertices and the vertices membership value are consider as in Table 2. Edges membership values are consider as in Table 3. Here, we consider three others parameters like (i) job, (ii) location, (iii) education. The membership value between of three parameters between a and b are location $(0.7, 0.3, 0.5)$, job $(0.8, 0.2, 0.1)$, education $(0.5, 0.1, 0.2)$. Now, the nature of this common neighbor c is

$$T_{C_c} = min\{0.6, 0.6\} = 0.6$$

$$I_{C_c} = max\{0.6, 0.5\} = 0.6$$

$$F_{C_c} = max\{0.4, 0.3\} = 0.4.$$

Similarly, nature of d is $T_{C_d} = 0.5$, $I_{C_d} = 0.6$, $F_{C_d} = 0.5$ and for vertex e is $T_{C_e} = 0.2$, $I_{C_e} = 0.5$, $F_{C_e} = 0.5$. Then the link prediction between a and b is $L_{a,b} = (T_L, I_L, F_L)$ is

$$T_L = \frac{0.6 + 0.5 + 0.2 + 0.8 + 0.5 + 0.7}{6} = 3.3/6 = 0.55$$

$$I_L = \frac{0.6 + 0.6 + 0.5 + 0.2 + 0.1 + 0.3}{6} = 2.3/6 = 0.383$$

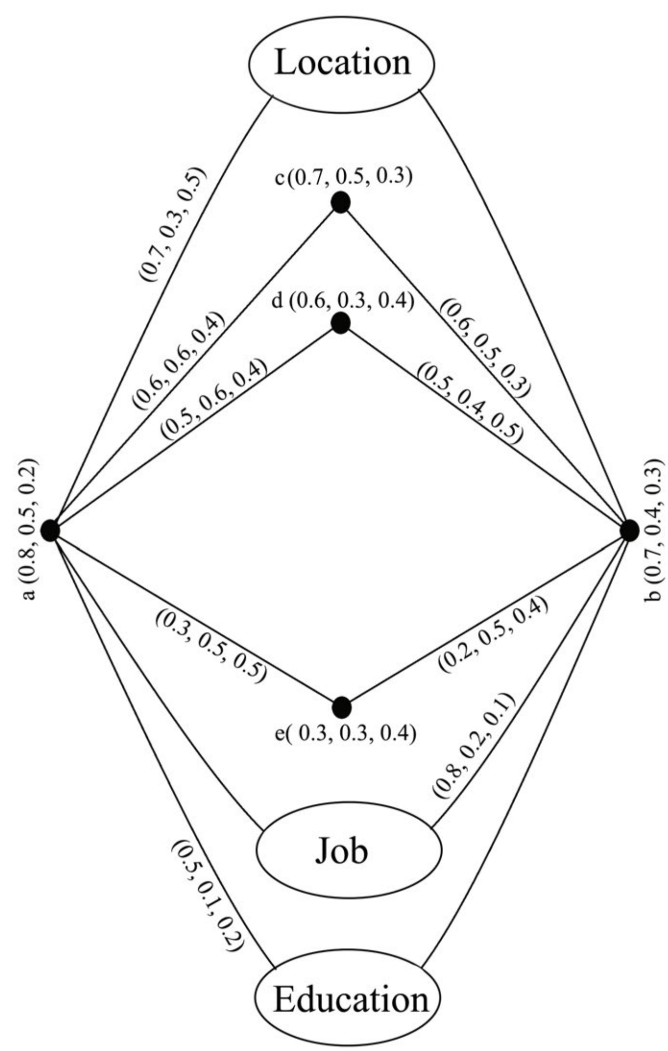

Figure 2 Link prediction by modified RSM index between the vertices a and b.

Table 2 Vertex membership value of Figure 2.

Vertex	Membership Value
a	$(0.8, 0.5, 0.2)$
b	$(0.7, 0.4, 0.3)$
c	$(0.7, 0.5, 0.3)$
d	$(0.6, 0.3, 0.4)$
e	$(0.3, 0.3, 0.4)$

Table 3 Edges membership value of Figure 2.

Edge	Membership Value	Edge	Membership Value
(a, c)	$(0.6, 0.6, 0.4)$	(c, b)	$(0.6, 0.5, 0.3)$
(a, d)	$(0.5, 0.6, 0.4)$	(d, b)	$(0.5, 0.4, 0.5)$
(a, e)	$(0.3, 0.5, 0.5)$	(e, b)	$(0.2, 0.5, 0.4)$

$$F_L = \frac{0.4 + 0.5 + 0.5 + 0.5 + 0.1 + 0.2}{6} = 2.2/6 = 0.367.$$

Score of link prediction by modified RSM is $\hat{S}_{ab} = \frac{2+T_L-I_L-F_L}{3} = \frac{2+0.55-0.383-0.367}{3} = 1.8/3 = 0.6$

Lemma 1. The value of nature of a vertex is not fixed.

Proof. In Figure 3 a neutrosophic graph shown here Q is the common neighbor between the vertices P and R. So, the nature of Q is $(0.4, 0.5, 0.6)$. Also, Q is the common neighbor between the vertices R and S. In this case nature of Q is $(0.3, 0.5, 0.6)$. So,the nature of Q is not fixed. Therefore, the nature of a vertex is not fixed.

Theorem 1. *Score of link prediction between u and v in a neutrosophic graph ζ by Modified RSM Index is $\hat{S}_{uv}$ then $0 \le \hat{S}_{uv} \le 1$.*

Proof. $\hat{S}_{uv}$ is the Score of link prediction between u and v in a neutrosophic graph ζ. Then, $\hat{S}_{uv} = \frac{2+T_L-I_L-F_L}{3}$ and $0 \le T_L \le 1$, $0 \le I_L \le 1$ and $0 \le F_L \le 1$ are true.

The value of $\hat{S}_{uv}$ will maximum if the value of T_L is maximum and I_L, F_L are minimum value.

So, the maximum value of $\hat{S}_{uv}$ is $\hat{S}_{uv} = \frac{2+1-0-0}{3} = 1$.

Also, the value of $\hat{S}_{uv}$ will minimum if the value of T_L is minimum and I_L, F_L are maximum value. So, the minimum value of $\hat{S}_{uv}$ is $\hat{S}_{uv} = \frac{2+0-1-1}{3} = 0$.

Then $0 \le \hat{S}_{uv} \le 1$.

In the modified RSM index ignore the other parameter then following theorems hold.

Lemma 2. Let ζ_n $(n \ge 4)$ be a neutrosophic cycle graph then link prediction by the modified RSM index and nature of neighbor are equal.

Proof. In the Figure 4, consider ζ_5 is a neutrosophic cycle graph with 5 vertices. Now link prediction between B and E (having common neighbor A) is equal to nature of A. In the cycle neutrosophic graph, there is only one common neighbor and cycle graph less than three vertices is a complete graph. Therefore, link prediction by the modified RSM index in neutrosophic cycle graph is equal to nature of the neighbor.

Theorem 2. *Let ζ be a star neutrosophic graph then the link prediction by modified RSM index between any two vertices is equal to the nature of center against those vertices.*

Proof. In Figure 5, consider a star neutrosophic graph with the vertices A, B, D, E, F, G, H, I and C is the center vertex. In this case link prediction between A and B is equal to the nature of the center vertex C against the vertices A and B (Lemma 1, it is proved that nature of a vertex is not fixed). So, in star neutrosophic graph there is a only

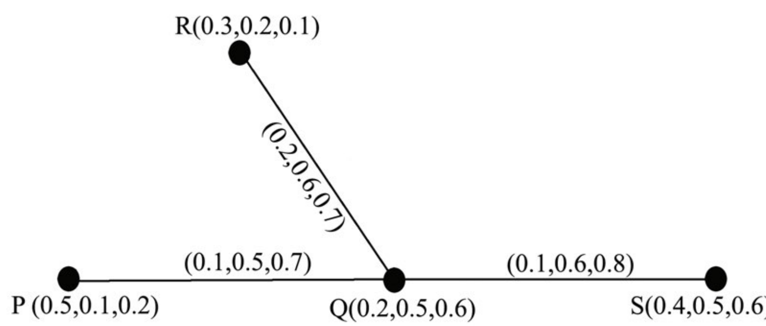

Figure 3 A neutrosophic graph.

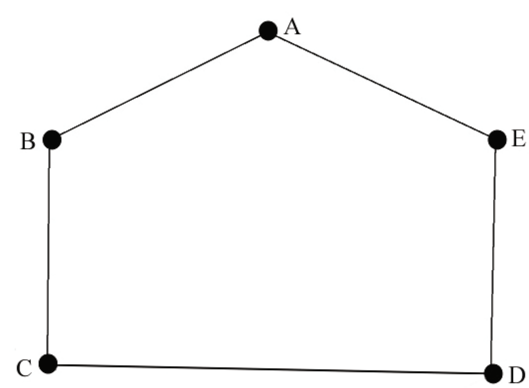

Figure 4 The link prediction for the neutrosophic cyclic graph.

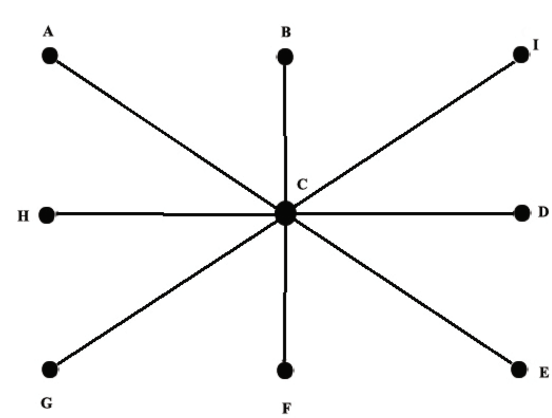

Figure 5 The link prediction for the neutrosophic star graph.

one neighbor C. So, the link prediction between any two vertices is equal to the nature of center vertex against those vertices.

4. VERIFICATION OF MODIFIED RSM INDEX IN A SMALL NETWORK FROM FACEBOOK

Few data have been collected from Facebook, which is reflected in Figure 6. A small network of Facebook friends has been considered for the analysis of modified RSM index. All the users of Facebook have been considered as vertices of this network and there exists an edge between two vertices if they are friends in Facebook. Based on these data, a small network has been considered (see Figure 7). Figure 8 shows the mutual friend between two friends. In the considered network, few link-predicted measures have been shown by Modified RSM index. For the considered graph, vertex have true membership value, falsity and indeterminacy membership value. A total number of Facebook friends of a node are assumed as the indicator of true membership value. The normalized value is taken as true membership value of a vertex. Among Facebook friends, few friends are inactive. These friends indicate the falsity membership value of a vertex. The ratio of inactive friends to the total number of friends is assumed as falsity. The number of inactive friends is considered by calculating the "likes/comments" in the last five posts. Now, indeterminacy membership value of a vertex is taken as $1 - (\textit{number of active friends/total number of friends})^2$. This is taken as when the number of active friends increases, the indeterminacy value decreases. All the calculation of vertex membership value have been shown in Figure 9.

The true membership value of an edge is calculated from the number of common friends. True membership value of an edge is "Normalized value of mutual friends × minimum true membership value of end vertices," i.e., $\mu_T(x, y) = \{\text{Normalized value of mutual friends}\} \times \{\sigma_T(x) \wedge \sigma_T(y)\}$. For the simplification we assumed the indeterminacy membership of an edge is the maximum indeterminacy membership value of end vertices, i.e.,$\mu_I(x, y) = \sigma_I(x) \vee \sigma_I(y)$. Also, same condition applies for the falsity membership value of an edge, i.e., $\mu_F(x, y) = \sigma_F(x) \vee \sigma_F(y)$. The membership values of all edges are shown in Figure 8. Also, the neutrosophic graph

Vertex	Location	Number of Friends	Distinct Like count from Last 5 post
JS	Ramchak, Moyna,	1157	15+30+19+3+18 = 85
DD	Durgapur, Burdwan	1034	7+1+5+21+186 = 220
MS	Panchberia, Ghatal	874	10+155+13+2+9 = 189
JM	contai	416	2+12+7+10+28 = 59
DK	Tamluk	428	1+1+1+3+2 =8
PP1	Barpeta	961	6+0+30+10+2 =48
DP	Khukurdha	233	37+50+1+3+1 =92
SKS	Khukurdha	526	4+2+6+4+3=19
AM	Khukurdha	946	3+153+4+51+8 =219
PP2	Jhargram	1000	11+1+4+1+7 = 24
RD	Khukurdha	1200	30+10+12+18+2=72

Figure 6 Source data, data taken from Facebook.

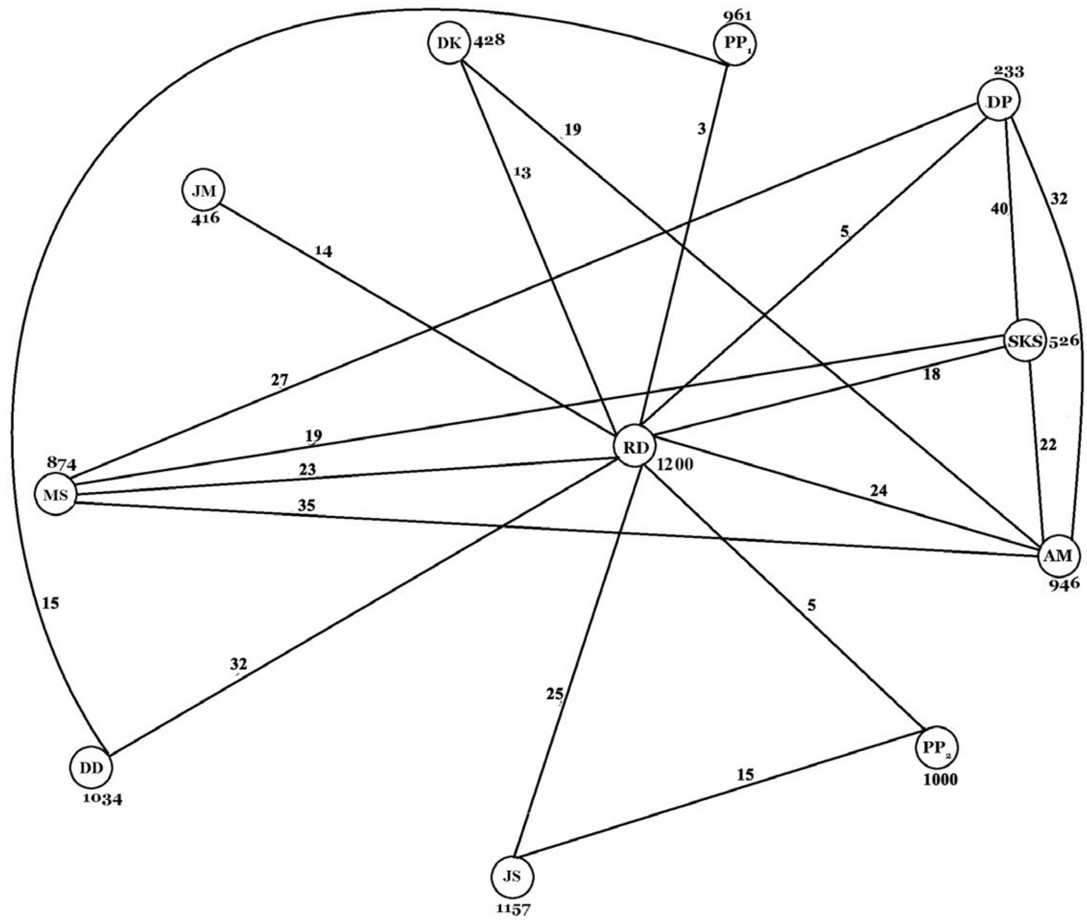

Figure 7 Source graph, data taken from Facebook.

of this source graph has been shown in Figure 10. The location membership value of all predicted edges is shown in Figure 11. Here, the distance between their (predicted vertex) home address is shown in Figure 11 and the normalized score of this distance taken as true membership value of location. Also, the distance between their (predicted vertex) Facebook address is shown in Figure 11. The calculation of falsity membership value and indeterminacy membership value of location has been shown in Figure 11. Then, the calculation of the link prediction by modified RSM index of all the thirty-six predicted edges is shown in Figure 12. Also, calculation of the value of link prediction by first five methods of the Subsection 3 of all thirty-six predicted edges is shown in Figure 13 and the normalized score of link prediction by first five methods and modified RSM index is shown in Figure 14. Also, a comparison graph with the RSM index and the first five methods is shown in Figure 15.

Also, calculation of the value of link prediction by another five methods of the Subsection 3 of all thirty-six predicted edges is shown in Figure 16 and the normalized score of link prediction by another five methods and modified RSM index is shown in Figure 17. Also, a comparison graph with the RSM index and another five methods is shown in Figure 10.

Here, the common neighbor method gives the same value for maximum prediction links. However, the modified RSM index gives the different value of predictions links compare to the common neighbor method. For example, consider a link in serial number 6 of Figure 14. It is the link between JM and AM. The common neighbor method only counts the number of common neighbors. However, our method modified RSM index checks the nature of common neighbors and other parameters. Also, this value considers the neutrosophic environment. Thus the results of our proposed methods depend on the human behaviors and other parameters like the location. HUB Promoted index gives high value for the prediction links compare to modified RSM index. The score of link prediction of the links of serial numbers 6, 7, 17, 28, 34 of Figure 14 is different from our proposed method. Jaccard method gives the score proportional to our proposed method except for some links. Few results are upper than the modified RSM index, and some are lower than abovementioned links.

The almost similar score is given for HUB depressed and modified RSM index except for some links. Leicht-Holme-Newman index gives identical results with modified RSM index except for that specific links of serial numbers of Figure 16 are 3, 4, 5, 18, 22, 34. The almost same scores are given for the methods AA and Preferential

EDGE	EDGE MEMBERSHIP VALUE				
	MUTUAL FRIEND	NORMALIZED VALUE	TRUE VALUE = NORMALIZED VALUE X MINIMUN TRUE VERTEX MEMBERSHIP VALUE OF END VERTICES	INDETERMENSITY VALUE	FALSITY VALUE
JM-RD	14	0.35	0.12	1.00	0.94
RD-DK	13	0.33	0.12	1.00	0.98
DK-AM	19	0.48	0.17	1.00	0.98
PP_1-RD	3	0.08	0.06	1.00	0.95
PP_1-DD	15	0.38	0.30	1.00	0.95
DP-MS	27	0.68	0.13	0.95	0.78
DP-RD	5	0.13	0.02	1.00	0.94
DP-SKS	40	1.00	0.19	1.00	0.96
DP-AM	32	0.80	0.15	0.95	0.77
SKS-MS	19	0.48	0.21	1.00	0.96
SKS-RD	18	0.45	0.20	1.00	0.96
SKS-AM	22	0.55	0.24	1.00	0.96
AM-RD	24	0.60	0.47	1.00	0.94
AM-MS	35	0.88	0.64	0.95	0.78
PP_2-RD	5	0.13	0.10	1.00	0.98
PP_2-JS	15	0.38	0.31	1.00	0.98
JS-RD	25	0.63	0.60	1.00	0.94
DD-RD	32	0.80	0.69	1.00	0.94
MS-RD	23	0.58	0.42	1.00	0.94

Figure 8 Calculation of edge membership value.

VERTEX MEMBERSHIP VALUE

Vertex	Number of friends (B)	True Value (Normalized value of B)	Number of inactive friends (D)	Number of Active Friends (A)	Indeterminacy 1-(A/B)^2	Falsity (D/B)
JS	1157	0.96	1072	85	0.99	0.93
DD	1034	0.86	814	220	0.95	0.79
MS	874	0.73	685	189	0.95	0.78
JM	416	0.35	357	59	0.98	0.86
DK	428	0.36	420	8	1.00	0.98
PP1	961	0.80	913	48	1.00	0.95
DP	233	0.19	141	92	0.84	0.61
SKS	526	0.44	507	19	1.00	0.96
AM	946	0.79	727	219	0.95	0.77
PP2	1000	0.83	976	24	1.00	0.98
RD	1200	1.00	1128	72	1.00	0.94

Figure 9 Calculation of vertex membership value.

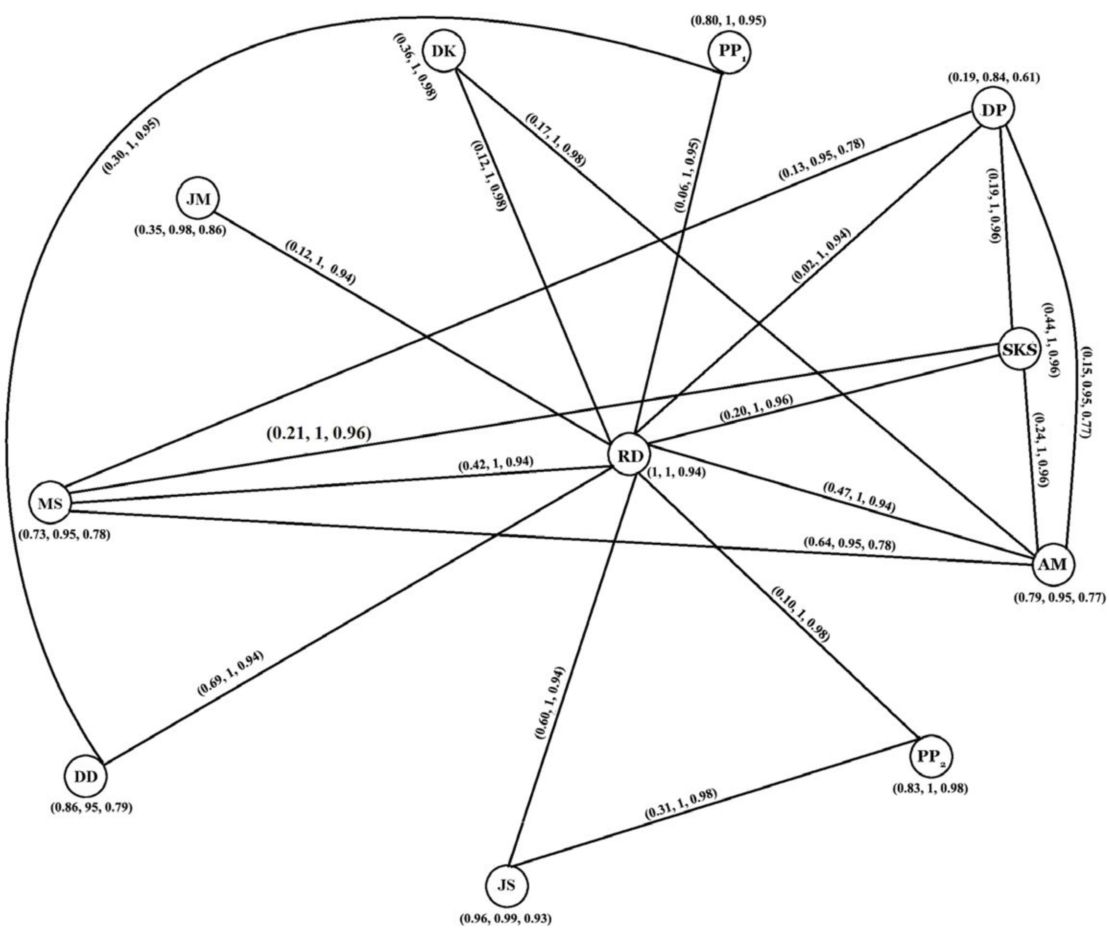

Figure 10 | Neutrosophic graph of the source graph.

attachment. Thus it can be decided that the modified RSM index is the considerable expected result for link prediction than other existing methods.

5. CONCLUSION

In the modified RSM index, few limitations are there. Calculation of true value, falsity and indeterminacy from crisp data is not easy to capture. There are no available methods to find such data. In this study, some parameters which display the results are assumed for true value, some parameters which are taken wrongly in the displayed results are assumed as falsity, and the parameters which are neutral for showing the results are indeterminacy. Otherwise, this method captures all the notions of link prediction. This link prediction captures the nature of common neighbors as well as jobs, education and living places are assumed in the calculations.

CONFLICTS OF INTEREST

The authors do not have any kinds of conflicts of interests.

AUTHORS' CONTRIBUTIONS

Mr. Rupkumar Mahapatra, Dr. Sovan Samanta and Prof. (Dr.) Madhumangal Pal equally contributed to preparing the article. Prof.(Dr.) Qin Xin verified the results and statements and guided the work.

ACKNOWLEDGMENTS

The authors are highly thankful to the Editor-in-Chief, guest editor of the special issue and reviewers of the paper. The authors are also grateful to Mr Rajib Dolai, Assistant Professor, Economics, Tamralipta Mahavidyalaya for helping in data collection.

SL NO	PREDICTED EDGE	MEMBERSHIP VALUE (LOCATION)						
		HOME ADRESS DISTANCE IN K. M. (B)	DISTANCE BETWEEN FACEBOOK ADRESS IN K. M. (A)	HOME ADRESS DISTANCE IN UNIT(20 K. M.= 1 UNIT) (E)	TRUE MEMBERSHIP VALUE (1/E)	INDETERMINCY MEMBERSHIP VALUE (RADIUS OF HOME CITY + RADIUS OF FACEBOOK CITY/MAX{A,B})	ERROR (GIVEN LOCATION & ORIGINAL LOCATION) (D)	FALSITY MEMBERSHIP VALUE (D/B)
1	JM-DK	63	56	3.15	0.32	0.07	7	0.11
2	JM-MS	109	119	5.45	0.18	0.10	10	0.09
3	JM-DD	53	50	2.65	0.38	0.03	3	0.06
4	JM-JS	55	70.5	2.75	0.36	0.15	15.5	0.28
5	JM-PP_2	102.3	100.1	5.12	0.20	0.02	2.2	0.02
6	JM- AM	19	23	0.95	1.05	0.04	4	0.21
7	JM-SKS	22.5	21	1.13	0.88	0.01	1.5	0.07
8	JM-DP	56	60	2.8	0.36	0.04	4	0.07
9	JM-PP_1	103	117.3	5.15	0.19	0.14	14.3	0.14
10	DK-PP_1	96	60	4.8	0.21	0.36	36	0.38
11	DK-DP	104	115.3	5.2	0.19	0.11	11.3	0.11
12	DK-SKS	90	117	4.5	0.22	0.27	27	0.30
13	DK-PP_2	75	80	3.75	0.27	0.05	5	0.07
14	DK-JS	35	55	1.75	0.57	0.20	20	0.57
15	DK-DD	45	65	2.25	0.44	0.20	20	0.44
16	DK-MS	35	25	1.75	0.57	0.10	10	0.29
17	DP-PP_1	45	95.5	2.25	0.44	0.50	50.5	1.12
18	SKS-PP_1	55	65.3	2.75	0.36	0.10	10.3	0.19
19	AM-PP_1	65	70.3	3.25	0.31	0.05	5.3	0.08
20	PP_2-PP_1	75	110	3.75	0.27	0.35	35	0.47
21	JS-PP_1	77	70.12	3.85	0.26	0.07	6.88	0.09
22	MS-PP_1	85	80.1	4.25	0.24	0.05	4.9	0.06
23	DP-PP_2	99	90.6	4.95	0.20	0.08	8.4	0.08
24	DP-JS	89	88	4.45	0.22	0.01	1	0.01
25	DP-DD	87	85	4.35	0.23	0.02	2	0.02
26	SKS-PP_2	88	83.1	4.4	0.23	0.05	4.9	0.06
27	SKS-JS	104	100.3	5.2	0.19	0.04	3.7	0.04
28	SKS-DD	78	77.3	3.9	0.26	0.01	0.7	0.01
29	AM-PP_2	304	291.3	15.2	0.07	0.13	12.7	0.04
30	AM-JS	566	560	28.3	0.04	0.06	6	0.01
31	AM-DD	455	430.2	22.75	0.04	0.25	24.8	0.05
32	PP_2-DD	409	510	20.45	0.05	1.00	101	0.25
33	PP_2-MS	102	110.5	5.1	0.20	0.08	8.5	0.08
34	JS-DD	78	75.3	3.9	0.26	0.03	2.7	0.03
35	JS-MS	89	80.3	4.45	0.22	0.09	8.7	0.10
36	DD-MS	107	105.3	5.35	0.19	0.02	1.7	0.02

Figure 11 Calculation of location membership value.

SL NO.	PREDICTED LINK	NATURE OF NEIGHBOURS						OTHER PARAMETER (LOCATION) (T_D, I_D, F_D)			LINK PREDICTION BY MODIFIED RSM INDEX (T_L, I_L, F_L)			SCORE OF LINK PREDICTION BY MODIFIED RSM INDEX
		NEIGHBOUR1 (T_C_i, I_C_i, F_C_i)			NEIGHBOUR2 (T_C_i, I_C_i, F_C_i)									
1	JM-DK	0.12	1	0.98				0.32	0.07	0.11	0.22	0.53	0.55	0.38
2	JM-MS	0.12	1	0.94				0.18	0.10	0.09	0.15	0.55	0.52	0.36
3	JM-DD	0.12	1	0.94				0.38	0.03	0.06	0.25	0.51	0.50	0.41
4	JM-JS	0.12	1	0.94				0.36	0.15	0.28	0.24	0.58	0.61	0.35
5	JM-PP_2	0.12	1	0.98				0.20	0.02	0.02	0.16	0.51	0.50	0.38
6	JM- AM	0.12	1	0.94				1.05	0.04	0.21	0.59	0.52	0.58	0.50
7	JM-SKS	0.12	1	0.96				0.88	0.01	0.07	0.50	0.51	0.51	0.49
8	JM-DP	0.02	1	0.96				0.36	0.04	0.07	0.19	0.52	0.52	0.38
9	JM-PP_1	0.12	1	0.95				0.19	0.14	0.14	0.16	0.57	0.54	0.35
10	DK-PP_1	0.06	1	0.95				0.21	0.36	0.38	0.14	0.68	0.66	0.26
11	DK-DP	0.02	1	0.98	0.15	0.98	1	0.19	0.11	0.11	0.12	0.70	0.70	0.24
12	DK-SKS	0.12	1	0.98	0.17	0.98	1	0.22	0.27	0.30	0.17	0.75	0.76	0.22
13	DK-PP_2	0.1	1	0.98				0.27	0.05	0.07	0.19	0.52	0.52	0.38
14	DK-JS	0.12	1	0.98				0.57	0.20	0.57	0.35	0.60	0.78	0.32
15	DK-DD	0.12	1	0.98				0.44	0.20	0.44	0.28	0.60	0.71	0.32
16	DK-MS	0.12	1	0.98				0.57	0.10	0.29	0.35	0.55	0.63	0.39
17	DP-PP_1	0.02	1	0.95				0.44	0.50	1.12	0.23	0.75	1.04	0.15
18	SKS-PP_1	0.06	1	0.95				0.36	0.10	0.19	0.21	0.55	0.57	0.36
19	AM-PP_1	0.06	1	0.95				0.31	0.05	0.08	0.19	0.53	0.52	0.38
20	PP_2-PP_1	0.06	1	0.98				0.27	0.35	0.47	0.17	0.67	0.72	0.26
21	JS-PP_1	0.06	1	0.98				0.26	0.07	0.09	0.16	0.53	0.53	0.36
22	MS-PP_1	0.06	1	0.98				0.24	0.05	0.06	0.15	0.52	0.52	0.37
23	DP-PP_2	0.02	1	0.98				0.20	0.08	0.08	0.11	0.54	0.53	0.35
24	DP-JS	0.02	1	0.94				0.22	0.01	0.01	0.12	0.50	0.48	0.38
25	DP-DD	0.02	1	0.94				0.23	0.02	0.02	0.13	0.51	0.48	0.38
26	SKS-PP_2	0.1	1	0.98				0.23	0.05	0.06	0.17	0.52	0.52	0.37
27	SKS-JS	0.2	1	0.96				0.19	0.04	0.04	0.20	0.52	0.50	0.39
28	SKS-DD	0.2	1	0.96				0.26	0.01	0.01	0.23	0.50	0.48	0.41
29	AM-PP_2	0.1	1	0.98				0.07	0.13	0.04	0.09	0.56	0.51	0.34
30	AM-JS	0.47	1	0.94				0.04	0.06	0.01	0.26	0.53	0.48	0.42
31	AM-DD	0.47	1	0.94				0.04	0.25	0.05	0.26	0.62	0.50	0.38
32	PP_2-DD	0.69	1	0.98				0.05	1.00	0.25	0.37	1.00	0.61	0.25
33	PP_2-MS	0.1	1	0.98				0.20	0.08	0.08	0.15	0.54	0.53	0.36
34	JS-DD	0.6	1	0.94				0.26	0.03	0.03	0.43	0.51	0.49	0.48
35	JS-MS	0.42	1	0.94				0.22	0.09	0.10	0.32	0.54	0.52	0.42
36	DD-MS	0.42	1	0.94				0.19	0.02	0.02	0.31	0.51	0.48	0.44

Figure 12 Calculation of link prediction by modified RSM index.

Score & Link Prediction calculation

SL. NO	Predicted Edges	COMMON NEIGHBORS: COMMON NEIGHBORS	COMMON NEIGHBORS: LINK PREDICTION OF COMMON NEIGHBORS	SALTON INDEX: DEGREE OF EDGE 1	SALTON INDEX: DEGREE OF EDGE 2	SALTON INDEX: LINK PREDICTION OF SALTON INDEX	JACCARD INDEX: INTERSECTION OF NODE NEIGHBORS	JACCARD INDEX: UNION OF NODE NEIGHBORS	JACCARD INDEX: LINK PREDICTION OF JACCARD INDEX	SORENSEN INDEX: LINK PREDICTION SORENSEN INDEX	HUB PROMOTED INDEX: LINK PREDICTION OF HUB PROMOTED INDEX	HUB DEPRESSED INDEX: LINK PREDICTION OF HUB DERESSED INDEX	LEICHT HOLME NEWMAN INDEX: LINK PREDICTION OF LEICHT HOLME INDEX	ADAMIC ADAR INDEX: DEGREE OF COMMON NEIGHBORS		ADAMIC ADAR INDEX: SCORE OF ADMIC ADAR INDEX	Preferential Attachment Index: Preferential Attachment Index	Preferential Attachment Index: Link Prediction of Preferential Attachment Index	Resource Allocation Index: Link Prediction of Resource Allocation Index
1	JM-DK	1	0.50	1	2	0.71	1	2	0.50	0.67	1.00	0.50	0.50	10		0.50	2	0.20	0.10
2	JM-MS	1	0.50	1	4	0.50	1	4	0.25	0.40	1.00	0.25	0.25	10		0.50	4	0.40	0.10
3	JM-DD	1	0.50	1	2	0.71	1	2	0.50	0.67	1.00	0.50	0.50	10		0.50	2	0.20	0.10
4	JM-JS	1	0.50	1	2	0.71	1	2	0.50	0.67	1.00	0.50	0.50	10		0.50	2	0.20	0.10
5	JM-PP_2	1	0.50	1	2	0.71	1	2	0.50	0.67	1.00	0.50	0.50	10		0.50	2	0.20	0.10
6	JM- AM	1	0.50	1	5	0.45	1	5	0.20	0.33	1.00	0.20	0.20	10		0.50	5	0.50	0.10
7	JM-SKS	1	0.50	1	4	0.50	1	4	0.25	0.40	1.00	0.25	0.25	10		0.50	4	0.40	0.10
8	JM-DP	1	0.50	1	4	0.50	1	4	0.25	0.40	1.00	0.25	0.25	10		0.50	4	0.40	0.10
9	JM-PP_1	1	0.50	1	2	0.71	1	2	0.50	0.67	1.00	0.50	0.50	10		0.50	2	0.20	0.10
10	DK-PP_1	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
11	DK-DP	2	1.00	2	4	0.71	2	4	0.50	0.67	1.00	0.50	0.25	10	5	1.21	8	0.80	0.30
12	DK-SKS	2	1.00	2	4	0.71	2	4	0.50	0.67	1.00	0.50	0.25	10	5	1.21	8	0.80	0.30
13	DK-PP_2	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
14	DK-JS	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
15	DK-DD	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
16	DK-MS	1	0.50	2	4	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
17	DP-PP_1	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
18	SKS-PP_1	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
19	AM-PP_1	1	0.50	5	2	0.32	1	6	0.17	0.29	0.50	0.20	0.10	10		0.50	10	1.00	0.10
20	PP_2-PP_1	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
21	JS-PP_1	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
22	MS-PP_1	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
23	DP-PP_2	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
24	DP-JS	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
25	DP-DD	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
26	SKS-PP_2	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
27	SKS-JS	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
28	SKS-DD	1	0.50	4	2	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
29	AM-PP_2	1	0.50	5	2	0.32	1	6	0.17	0.29	0.50	0.20	0.10	10		0.50	10	1.00	0.10
30	AM-JS	1	0.50	5	2	0.32	1	6	0.17	0.29	0.50	0.20	0.10	10		0.50	10	1.00	0.10
31	AM-DD	1	0.50	5	2	0.32	1	6	0.17	0.29	0.50	0.20	0.10	10		0.50	10	1.00	0.10
32	PP_2-DD	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
33	PP_2-MS	1	0.50	2	4	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
34	JS-DD	1	0.50	2	2	0.50	1	3	0.33	0.50	0.50	0.50	0.25	10		0.50	4	0.40	0.10
35	JS-MS	1	0.50	2	4	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10
36	DD-MS	1	0.50	2	4	0.35	1	5	0.20	0.33	0.50	0.25	0.13	10		0.50	8	0.80	0.10

Link prediction in verious methods

Figure 13 | Calculation of link prediction by common neighbors, Salton Jaccard, Sorensen, Hub Promoted, Hub Depressed, Newman, Adamic-Adar, Preferential and Resource Allocation.

Normalize score of Link Prediction													
SL. NO	Predicted Edges	Link prediction in verious methods											
		MODIFIED RSM INDEX		COMMON NEIGHBORS		SALTON INDEX		JACCARD INDEX		SORENSEN INDEX		HUB PROMOTED INDEX	
		LINK PREDICTION OF MODIFIED RSM INDEX	LINK PREDICTION OF MODIFIED RSM INDEX (N)	LINK PREDICTION OF COMMON NEIGHBORS	LINK PREDICTION OF COMMON NEIGHBORS (N)	LINK PREDICTION OF SALTON INDEX	LINK PREDICTION OF SALTON INDEX (N)	LINK PREDICTION OF JACCARD INDEX	LINK PREDICTION OF JACCARD INDEX (N)	LINK PREDICTION SORENSEN INDEX	LINK PREDICTION SORENSEN INDEX (N)	LINK PREDICTION OF HUB PROMOTED INDEX	LINK PREDICTION OF HUB PROMOTED INDEX(N)
1	JM-DK	0.38	0.76	0.50	0.50	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
2	JM-MS	0.36	0.72	0.50	0.50	0.50	0.70	0.25	0.50	0.40	0.60	1.00	1.00
3	JM-DD	0.41	0.82	0.50	0.50	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
4	JM-JS	0.35	0.70	0.50	0.50	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
5	JM-PP$_2$	0.38	0.76	0.50	0.50	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
6	JM- AM	0.50	1.00	0.50	0.50	0.45	0.63	0.20	0.40	0.33	0.50	1.00	1.00
7	JM-SKS	0.49	0.98	0.50	0.50	0.50	0.70	0.25	0.50	0.40	0.60	1.00	1.00
8	JM-DP	0.38	0.76	0.50	0.50	0.50	0.70	0.25	0.50	0.40	0.60	1.00	1.00
9	JM-PP$_1$	0.35	0.70	0.50	0.50	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
10	DK-PP$_1$	0.26	0.52	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
11	DK-DP	0.24	0.48	1.00	1.00	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
12	DK-SKS	0.22	0.44	1.00	1.00	0.71	1.00	0.50	1.00	0.67	1.00	1.00	1.00
13	DK-PP$_2$	0.38	0.76	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
14	DK-JS	0.32	0.64	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
15	DK-DD	0.32	0.64	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
16	DK-MS	0.39	0.78	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
17	DP-PP$_1$	0.15	0.30	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
18	SKS-PP$_1$	0.36	0.72	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
19	AM-PP$_1$	0.38	0.76	0.50	0.50	0.32	0.45	0.17	0.33	0.29	0.43	0.50	0.50
20	PP$_2$-PP$_1$	0.26	0.52	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
21	JS-PP$_1$	0.36	0.72	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
22	MS-PP$_1$	0.37	0.74	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
23	DP-PP$_2$	0.35	0.70	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
24	DP-JS	0.38	0.76	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
25	DP-DD	0.38	0.76	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
26	SKS-PP$_2$	0.37	0.74	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
27	SKS-JS	0.39	0.78	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
28	SKS-DD	0.41	0.82	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
29	AM-PP$_2$	0.34	0.68	0.50	0.50	0.32	0.45	0.17	0.33	0.29	0.43	0.50	0.50
30	AM-JS	0.42	0.84	0.50	0.50	0.32	0.45	0.17	0.33	0.29	0.43	0.50	0.50
31	AM-DD	0.38	0.76	0.50	0.50	0.32	0.45	0.17	0.33	0.29	0.43	0.50	0.50
32	PP$_2$-DD	0.25	0.50	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
33	PP$_2$-MS	0.36	0.72	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
34	JS-DD	0.48	0.96	0.50	0.50	0.50	0.70	0.33	0.67	0.50	0.75	0.50	0.50
35	JS-MS	0.42	0.84	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50
36	DD-MS	0.44	0.88	0.50	0.50	0.35	0.50	0.20	0.40	0.33	0.50	0.50	0.50

Figure 14 Normalized scores of modified RSM index along with common neighbors, Salton, Jaccard, Sorensen and HUB methods.

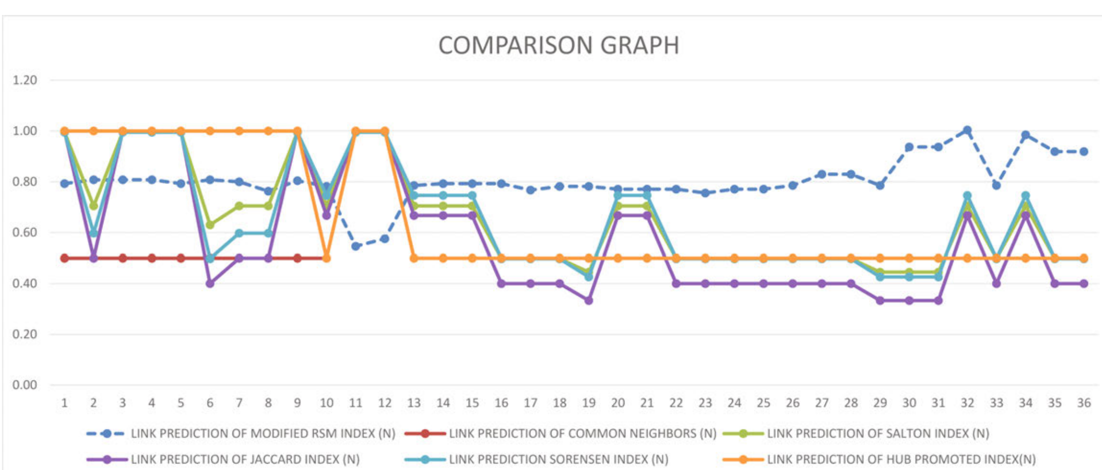

Figure 15 Comparison graph with common neighbors, Salton, Jaccard, Sorensen and HUB methods.

Normalize score of Link Prediction

SL. NO	Predicted Edges	Link prediction in verious methods: MODIFIED RSM INDEX		HUB DEPRESSED INDEX		LEICHT HOLME NEWMAN INDEX		ADAMIC ADAR INDEX		Preferential Attachment Index		Resource Allocation Index	
		LINK PREDICTION OF MODIFIED RSM INDEX	LINK PREDICTION OF MODIFIED RSM INDEX (N)	LINK PREDICTION OF HUB DERESSED INDEX	LINK PREDICTION OF HUB DERESSED INDEX (N)	LINK PREDICTION OF LEICHT HOLME INDEX	LINK PREDICTION OF LEICHT HOLME INDEX (N)	SCORE OF ADMIC ADAR INDEX	SCORE OF ADMIC ADAR INDEX (N)	Preferential Attachment Index	Preferential Attachment Index (N)	Link Prediction of Resource Allocation Index	Link Prediction of Resource Allocation Index (N)
1	JM-DK	0.38	0.76	0.50	1.00	0.50	1.00	0.50	0.41	0.20	0.20	0.10	0.25
2	JM-MS	0.36	0.72	0.25	0.50	0.25	0.50	0.50	0.41	0.40	0.40	0.33	0.82
3	JM-DD	0.41	0.82	0.50	1.00	0.50	1.00	0.50	0.41	0.20	0.20	0.33	0.82
4	JM-JS	0.35	0.70	0.50	1.00	0.50	1.00	0.50	0.41	0.20	0.20	0.20	0.50
5	JM-PP_2	0.38	0.76	0.50	1.00	0.50	1.00	0.50	0.41	0.20	0.20	0.08	0.19
6	JM- AM	0.50	1.00	0.20	0.40	0.20	0.40	0.50	0.41	0.50	0.50	0.20	0.50
7	JM-SKS	0.49	0.98	0.25	0.50	0.25	0.50	0.50	0.41	0.40	0.40	0.08	0.19
8	JM-DP	0.38	0.76	0.25	0.50	0.25	0.50	0.50	0.41	0.40	0.40	0.08	0.19
9	JM-PP_1	0.35	0.70	0.50	1.00	0.50	1.00	0.50	0.41	0.20	0.20	0.08	0.19
10	DK-PP_1	0.26	0.52	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.33	0.82
11	DK-DP	0.24	0.48	0.50	1.00	0.25	0.50	1.21	1.00	0.80	0.80	0.40	1.00
12	DK-SKS	0.22	0.44	0.50	1.00	0.25	0.50	1.21	1.00	0.80	0.80	0.40	1.00
13	DK-PP_2	0.38	0.76	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.28	0.69
14	DK-JS	0.32	0.64	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.08	0.19
15	DK-DD	0.32	0.64	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.28	0.69
16	DK-MS	0.39	0.78	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.20	0.50
17	DP-PP_1	0.15	0.30	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.20	0.50
18	SKS-PP_1	0.36	0.72	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.08	0.19
19	AM-PP_1	0.38	0.76	0.20	0.40	0.10	0.20	0.50	0.41	1.00	1.00	0.08	0.19
20	PP_2-PP_1	0.26	0.52	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.28	0.69
21	JS-PP_1	0.36	0.72	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.08	0.19
22	MS-PP_1	0.37	0.74	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.08	0.19
23	DP-PP_2	0.35	0.70	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.20	0.50
24	DP-JS	0.38	0.76	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.33	0.82
25	DP-DD	0.38	0.76	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.20	0.50
26	SKS-PP_2	0.37	0.74	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.20	0.50
27	SKS-JS	0.39	0.78	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.28	0.69
28	SKS-DD	0.41	0.82	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.08	0.19
29	AM-PP_2	0.34	0.68	0.20	0.40	0.10	0.20	0.50	0.41	1.00	1.00	0.08	0.19
30	AM-JS	0.42	0.84	0.20	0.40	0.10	0.20	0.50	0.41	1.00	1.00	0.33	0.82
31	AM-DD	0.38	0.76	0.20	0.40	0.10	0.20	0.50	0.41	1.00	1.00	0.28	0.69
32	PP_2-DD	0.25	0.50	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.08	0.19
33	PP_2-MS	0.36	0.72	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.08	0.19
34	JS-DD	0.48	0.96	0.50	1.00	0.25	0.50	0.50	0.41	0.40	0.40	0.40	1.00
35	JS-MS	0.42	0.84	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.20	0.50
36	DD-MS	0.44	0.88	0.25	0.50	0.13	0.25	0.50	0.41	0.80	0.80	0.08	0.19

Figure 16 | Normalized scores of modified RSM index along with HUB Depressed, Newman, Adamic-Adar, Preferential and Resource Allocation indexes.

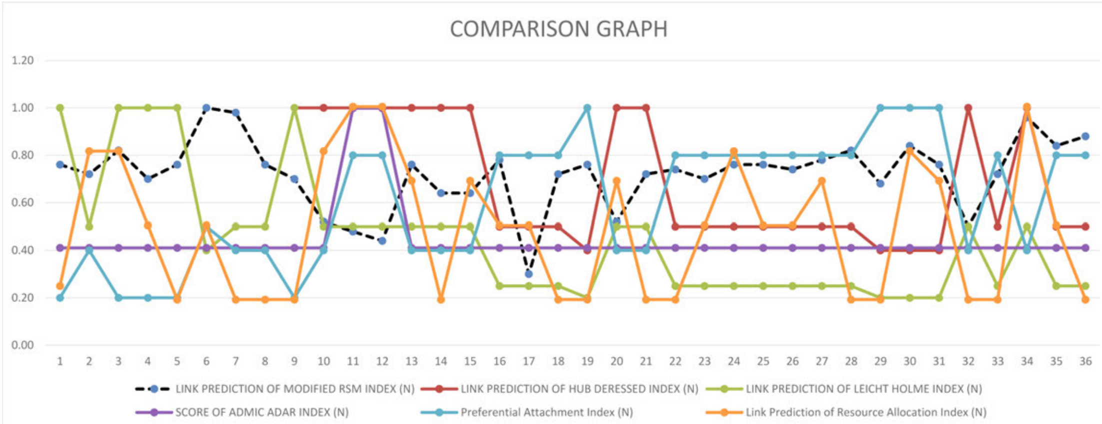

Figure 17 Comparison graph with HUB Depressed, Newman, Adamic-Adar, Preferential and Resource Allocation.

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