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Higher Education Career Guidance through Social Network Analysis

Rohini A[1], SudalaiMuthu T[2] and *Tanupriya Choudhury[3]

[1] Research Scholar, School of Computing Science, Hindustan Institute of Technology and Science, Kelambakkam, Chennai, India.
rohinaruna@gmail.com

[2] Associate Professor, School of Computing Science, Hindustan Institute of Technology and Science, Kelambakkam, Chennai, India.
tsmuthu@gmail.com

[3] *Associate Professor, Dept. of Informatics, School of CS, University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, India.
*tanupriya1986@gmail.com**

***Abstract*: The career guidance in higher education is an increasing concern in student's needs. The purpose of the study is to analyze the links between source node (Guidance Experts) and the target Node (Students). This paper presents the proximity of a node has analyzed the influential link position between the vertices in the core-periphery structure. The use of fuzzy logic and graph metric properties of Nodes used to find the Node selection criterion in terms of influence propagation. The approach yielded results with good accuracy.**

Keywords: Social Network Analysis, Clustering, Information - Propagation, Community Detection

I. Introduction

Social media raised the students to discover key influences to chosen their higher education institution. The use of social media has been fit into the delivery of information to the nodes. The purposes which are: allow access to experience through learning and create understand their condition using online assessments. The raise of social network community analysis has brought challenges for career guidance experts. Wei Kuang et al. (2020) has been analyzed the social media technology and Kislev et al. (2020) approached the career guidance with various role of dimensions using machine learning techniques. The role of the career guidance experts to deliver the content, services and establishing method for explore careers and utilizing social network for career. The experts emphasize the real-time information and coming up with the pioneering ways to engage the nodes. The study originates that blogs of information to make the career decisions. A Career guidance in social media platform is defined as to analyze the topological properties of a higher educational institution and students' demands. The field of study deals with the unawareness to choose the higher education institutions are generally caused by student satisfaction to meet their demands, and sense of belonging. It has been referred to the part of campus community. A challenging problem which arise in the domain is the complexity of links between the nodes has more difficult to identify the target node. The enormous data have been generated by the rapid development of social networks of microblogs, the link has been increased in the structure, it's become more complicated to make the community and sub-community in the cluster when the number of nodes is a large, it's difficult to get valid results. Moreover, few studies have focused on the social patterns are represented mathematically to understand the dynamics of the links, topological properties and modularity. Graph Theory approach to resolve the problem to find the influential node, analyze the cluster, the centrality of the nodes, modularity, matrix representation of the adjacency matrix of the nodes, and visualizing the node-link diagrams in the topology. The influential link has been formed between the Guidance Experts (G_e) to the Students (S) by the characteristics of users' interest. For this study, investigates, to predict the performance of nodes by the graph metrics approach. One of the major aims of the study inferred to the users in an online microblog, the combination of nodes has mined to predict the target node properties in the spatial network, users have often to share the information by the post, tags, and comments from who share the same properties in the spatial structure. it has predicted the users link what they are interested to look on the online, and the natural way to leverage the user properties to predict the node links of what they were interested, it can predict the attributes of social networking analysis of the content propagation and scope of the sharing contents, it describes the demographic properties and the statistical analysis would bring to relate the attributes and predict the links in different phenomena. This gives a significant advantage of the feasibility of node-link has been monitored and significant sources have been retrieved by user interaction to understand and analyze the node. The contribution of this work has made in the 500 nodes and their attributes of information to answer the required forms for the career guidance advice, from each node gathered the higher secondary grades, year of passing, interest to study, location. financial aid and the demographic properties of the students. our second data covers the educational institution attributes whether their goals have related with the students and inferred the links to the students (target node), for each user information has been collected in the Facebook profile page by the tools and support of *fboauth* function, which gives the list of user-provided attributes.

In this paper, a study has been undertaken to predict the reliability of the links. Section 2 discusses the development of social network analysis has been focused on the social relationship of linking individuals and metrics used for analyzing and predicting the links in the related works. Section 3 defines the Career Guidance growth and effect of social media. In section 4, To Analyze the node and explorer design of the matrix. In section 5, Proposed research work tracking the accuracy of individual links and predict the trusted links on the secure conditions. It presents the steps to perform the experiment. Graph metrics approach for predicting the reliability is given. In Section 6, the results obtained during the experiment are discussed. Conclusion of the present study are given in section 7.

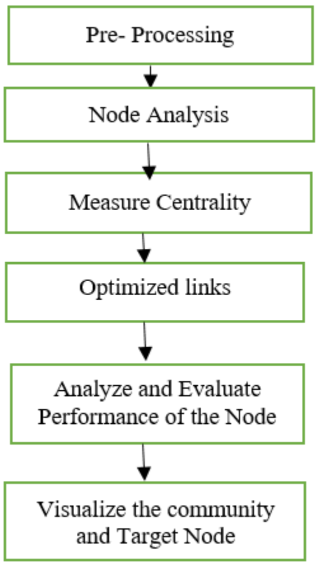

Figure 1: Framework of the proposed Study

II. Related Works

The development of social network analysis has been focused on the social relationship of linking individuals. It compares the relationship between the ego-centric nodes. This kind of study examines how various kinds of objects interact together to form various kinds of links to make the homogeneous community.

Zhu et al. [1] proved by the NP-hard and the diffusion models of linear threshold and cascade models in the inactive and active links in the group. The influence diffusion and the detailed study of the critical links were analyzed and yielded the good accuracy level of participation of links in the community [2]. The information diffusion model algorithm has put into the maximization of the influence propagation between the vertices [3]. The influential node in the community and the content of information has spread over the links for optimized solution of information diffusion in career planning in the secondary education. The conflict of opinion in the network, the spread of information has approximately estimated by the calculation of (1- (1/e)) it has achieved the good simulation results. Greedy algorithm for the influence spread of information and proved the high rate of computational complexity when it has dealt with the dense social networks [4]. The diffusion also speeds up in the process in the range of time scale series have been reviewed in the cost-effective evaluations of influence spread [5]. Network centrality methods were contributed to the new greedy, degree of discount, and mixed greedy of algorithms that were used to evaluate the problem of analysis and influence maximization [6]. A systematic literature review for big data analytics to predict the reliability of the neuro-fuzzy model educational framework explained the forecasting features in social media [7].

Heterogeneous graph network analysis framework has designed in the community structure for spreading the influence of nodes in directed and undirected links in the whole network [8]. Maximizing the influence propagation, the researcher has used the simulated annealing method to solve the computational complexity expenses in the signed social network structure and analysis of the adaptive weighted network in the community and designed with a two-phase competitive influence algorithm to reduce the accuracy realistically, the static part of the nodes and links were not changed in the role of time consideration [9-14]. Social interaction between the students for active construction and encourage the meaningful interaction and collaboration between the nodes and contribute their ideas in mean change point analysis [15-17]. The collected information has discussed the concepts of opinion mining, analysis and solutions to the problem-based learning method. Ego-Centric nodes with interpersonal relations with collaborators, the goal of the content propagation has been understanding the concepts of influence diffusion [18 -21]. The team-based learning and promote the learning ideas to facilitate in the complex network, this approach has given a structured way to help to guide the strong and weak students. Structured the problem-based learning method to engage the students in active conditions and create the interaction in the content space of acquired the understanding the domain knowledge.

Data Analytics presents to educational institutions give a framework for a vast array of data efficiently in the learning environment, it is a relevant significant number of issues in the learning system and skill to the students to enhance the future [22 - 28]. Used the Naive Bayes algorithm and the poison distribution model in the large training sample set to the student’s guidance for optimizing the links, community analysis and routing evaluation [29-33]. Discretization and structural improvement, to deal with the independent and relevant attributes based on the mutual and conditional set for the integrity of social links [34-38]. Authors have focused on improving machine learning classifiers for loss detection their related experiments were proved and but it is widely used in the academic performance of students to progress the clustering techniques. [39-41] Metrics for the data evaluation by three different parameters for access the data Frequency, Quantity, and recent access used the weight-based algorithm, yielded values had given better hit rates in various link weight

[42]. Gathered sources from the learning management system, social network blogs, and student's information system.this analysis gives timely information for decision making [43]. Author discussed the systematic analytics to predict the reliability of the neuro-fuzzy model educational framework explained the forecasting features in social media. Moreover, [45-55] described the analytical scope, list of theories related to that social network analysis using fuzzy logic techniques has more supported to analyse the problem.

III. Exponential Growth

The demand of students to choosing the institution for higher education still has become well-versed with the e-awareness which is coming up. The education industry still proves its worth in terms of the web-enabled era of 2.0. In our study has focused the *career guidance disinclination* towards the latest technologies led to a major hurdle in choosing institutions as well as rather than go to and collect feedback from the institution. The maximum number of students wanted to integrate studies with technology [25].

Nowadays web-enabled technologies are commonly and popularly used the younger people, particularly experts and students. The acceptance rates are higher in social networking platforms such as Facebook. The distinctive features of the social networking sites are (a) sharing content tools (b) interaction with students (c) to develop collaboration links (d) Facts about valuable information to enhance the social bonding with the communities.

It connects the friends, friend-of-a-friend of social relationships between the nodes shown to develop the career guidance to aspirant nodes in the E-Learning environment. This sort of social networking modeling system gives us the realistic solution for whoever is looking for career guidance to higher education institutions or influence propagation to keep up-to-date with the career guidance influential experts to have positive links with the nodes.

Proposed work has analyzed Facebook – Social Networks in detail. In the networks consist of nodes (individuals, Higher Education Institution or any entity, etc.) who are linked with one-to-one or one to many relationships It is an interdisciplinary process to determine, observe, and discover (i) the structural properties of the real-world network, (ii) configuration of connections, (iii) to understand network members, (iv) in-degree (incoming connections) and out-degree (outgoing connections), (v) isolated members, (vi) frequency of connections (density), (vii) average shortest path length and (viii) to identify communities (more often interacting) to which the explore the patterns of social network links and their structural properties concerning the synthetic networks

IV. Analysis of Node Degree

Users are connected with the social groups. It is used to represent Sociograms and started to explore the social relations, the metrics and analysis are described below:

Graphs consist of vertices and edges in that form of discrete structures that connect the vertices in the structural network. It has been depending on the type and number of edges connected to the nodes, to arrange the discrete of objects and concerned with their structural properties and with them In-Degree and Out-Degree of links.

A graph G = (V, E) consists the set of vertices (V) (nodes and links) and E the set of ordered and unordered pair of entities of (V) called the links, such that there is a mapping from the set E to set V. If an edge e € E is associated with the (x, y) of an ordered and unordered pair, where (x, y) € V, the connector or joining node is said to be ‘e’, The ‘e’ connects the (x, y) is said to be an incident of each vertex. The dyads are adjacent nodes in the structural network. e€E is associated with the vertices is said to be digraph, if it is not associated with the dyadic of the vertex is called the undirected graph of the network.

Case 1:

In the Undirected Graph G = (V, E) with ‘n’ vertices $v1, v2, v3 \ldots..Vn \text{ and } m$ and edges $e_1, e_2, e_3, \ldots, e_m$, then the matrix A = $[a_{ij}]$,

Where a_{ij} = {1, where edge e_j is incident on v_i

0, otherwise.

It is called the incident matrix of G.

The explorer design of the matrix has represented to support the visualization of nodes and links.

a. Initiate the probe.
b. Explore the request and response.
c. To find the harmony data.
d. Visualize the harmony data.

$$\begin{bmatrix} 10011 \\ 11000 \\ 01101 \\ 00110 \end{bmatrix}$$

The incidence matrix basic properties are:

1. Each column of A contains the minimum two-unit in-Degree or Out-Degree of links in the community.
2. Row with null values corresponds to the isolated vertex.
3. Degree (V_i) = 1’s in the I row.

Case 2: Degree of nodes

The group G1 In-Degree and Out-Degree of links for each node of the undirected graphs in the structural network has found by verifying the sum of in and out Degree of links is equal to the number of links in the cohesive subgroups.

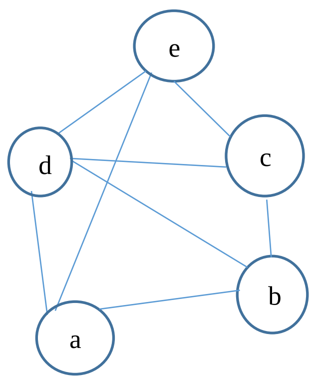

Figure 2. Degree of Nodes

Several methods are suggested and analysed the node degree to address the links, computing time and centrality measures in the edges [14], [16], [18 -19], [21], [33-34], [46] some researchers are focused on theories and some of them has been used to analyse the Graph metric properties.

{Degree(-a) = 2, Degree (-b) =1, Degree (-c) =2, Degree(-d) =3 and Degree(-e) =0} and

{Degree(+a) =1, Degree(+b) =2, Degree(+c) =1, Degree(+d) =1, Degree(+e) =3}

Result of Node 'a'

= Σ Degree (-a) = Σ Degree(+a) = 8

as same as calculation for remained edges.

Eq (1) gives, If all the nodes of an undirected graph in the odd Degree of each link show that multiple numbers of edges in the structural network. From the Eq (2), If it is in an undirected graph, even the number of links will be considered by 2n, let several links in the structure are in 'n'.

$$\sum_{k=1}^{2n} degree(V) = n \qquad \text{Eq (1)}$$

$$= \sum_{k=1}^{2n} \mathrm{k} = 2\mathrm{n} \qquad \text{Eq (2)}$$

By the Eq (1) and Eq (2) graph properties were verified and get the results below show

(i) 'n' is even the Degree of each 'n' vertex is (n-1),
(ii) 'n' is odd, the Degree of each vertex is even, the total number of odd Degree links is null, that is even.

A. *The mixing parameter on accuracy and computing time*

The accuracy of the mixing parameter function of μ has measured the normalized mutual information, this information has been used in detecting the communities.

'N' has defined by the rows corresponding rows in the community and the columns referred to the originate of the nodes in the community, the nodes of **N**, N_{ij}, is the whole number of the nodes on the community, in the detected group j, *i* node has appeared in the group, the normal mutuality of content is

$$I(\rho,\overline{\rho}) = \frac{-2\sum_{i=1} C \sum_{j=1} \overline{C} Nij \log(Nij * N / Ni * Nj)}{\sum_{i=1} CNi * \log(Ni/N) + \sum_{J=1} \overline{CNj * \log(Nj/N)}} \quad \text{Eq (3)}$$

The communities denoted by C, by algorithm detected communities is denoted by $\overline{C}$, by the row *i* of N is said to be N_i and j is said to be N_{ij} .estimated communities are $I(\rho,\overline{\rho})$ equals to 1 in algorithm partition has found it is independent of the real groups.

The mutual information has normalized by the partition of association of student requirement results to get better accuracy; the normalized procedures have qualitatively found the similarities of behavior. Many algorithms are not supported the mixing parameters(μ) of fewer values, as it is I is superior from the larger values in the ($\mu \rightarrow 0$), accuracy values have decreased, size and mixing parameters have increased.

V. Materials and Methods

The data are authenticated and taken permission from the nodes of Facebook users by the *fboauth file* access permission token in R Programming. The queries were extracted from the user interaction data along with the properties of attributes which as node id, time, post the content, whom to share the content, forum, and thread of node ID's, comments from the friends, like, unlike, share the data were extracted confidentially and protectively in the online social network.

The Extracted data has analyzed and tested by R-Programming for statistical analysis and visualizing by I-Graph Package. It is used to provide functions and data types for the implementation of a graph algorithm and fast handling of large graphs with vertices and edges.

Interactivity analysis of nodes is the important aspects to analyze the exchange of information, the interaction has categorized into three levels (i) source node to target node (experts to students), (ii) target node to source node (students to experts), (iii) source node to source node (students to students) and (iv) groups, these are all the important factors of the proposed work has analyzed the knowledge learning process.

Exploratory analysis of seeking guidance to the students for higher education from different perspectives of career guidance. It has analyzed. 200 nodes were taken and 15 career guidance experts, 2019 year passed out of the students were selected by the analysis, the career guidance experts have advised the development of educational learning has propagated in different aspects based on the student's traits including grades, location, recognition of the university, awards of the university and students, and financial aid. the nodes should have acquired fair advice from to choose the educational institution on the influence propagation and influence diffusion of the social network links, the duration for collecting the information five weeks of mining the student's links in the online microblogs such as Facebook. The targeted nodes were approached to join the institution by their perspectives are green environment learning, the location has probably chosen high rise building in the urban areas, among 200 nodes, 45 nodes were interested to take the scholarship,55 nodes are aided funds, remained nodes are as per the educational fee, students preferred to attend the classes on morning sessions physically and continue to interact the sessions by posting and learning by online microblogs. The educational institution has encouraged the students to discuss the learning, by sharing the contents, post, tag, comments, and collaboratively work towards to achieve the objective of the nodes and goals of the educational institution requirement based learning facilitated by the G_e.

For predicting the student's traits is the significant part, Scholarship and Grade is the key of evidence about academic potential of the node applicants to consider the conditions as a minimum and maximum level of approaches, Aspirational offers has been encouraging the nodes to choose the institutions.it has to be challenged to take the offer conditions to understand the nodes. The study challenges the career guidance experts and the students can face in setting to predict the links will be realistic and optimistic. Proposed research work tracking the accuracy of individual links and predict the trusted links on the secure conditional offer of the nodes in the structural network of the detection of communities in online microblogs of Facebook.

A. *Centrality Analysis*

Each node has accessed the following parameters: what type of influence and interaction made in the cohesive subgroup of the core-periphery structure and the triads of distinct subgroups. The pattern of node-link position has to be provided in terms of accessing the benefits to the sparse nodes in the structural dimension of the network. Our proposed method has analyzed the influential link position to propagate the content of information to the expert node to target node, it measures the interaction between the dyadic pair of vertices and triads of vertices in the core-periphery structure. The theoretical measures have applied in the centrality of the influential position of the node.

In degree centrality – the number of nodes has communicated with the source code.

Out-degree Centrality – The source node has interacted with the other nodes in the network.

Closeness centrality- It calculated the geodesic path of a node to other nodes of the network.

Local closeness centrality – interact with the most influential node in the community. It has been measured by the power influence through the broken position of links and the week ties in the cluster of the network.

Betweenness Centrality- It defined the proportion of path between the geodesic distance.

Co-occurrence of the links – It is the evidential relationship of the frequent interaction in the network.

The interactions in the forum of students have extracted by *fboauth* techniques in Facebook application, it extracts the data of the students and career guidance expert's interaction in the form of queries. The four useful metrics are found the core and densely connected pair of nodes in the cluster in the core and cohesive subgroup of the structural dimension, the metrics supported to find the core-periphery structure which is:

(a) *Diameter* - The diameter is defined as the number of nodes has traversed in the sequential path from one node to other nodes.

(b) *Density* - The number of In-Degree of links within the structure has compared to the maximum possible links in the community.

(c) *Reciprocity* - It defined by the triads of the links the actual link has triggered to another node and creates the reverse link from the actual node in the linkage structure, and it is also defined the co-occurrence of the node links in the dyadic pair of vertices interaction.

(d) *Split* – It shares the content with the multiple groups in the periphery structure.

Metrics	Values
Accounts created	500
Active Nodes	200
No of Edges Weighed	800
Average Distance	2.63
Maximum Degree	50
Average Degree	4.65
Goodness for fit (k≥1) Exponent	1.625
P-value	0.26
Shapiro-Wilk test	0.941035

Table 1: Interaction of the nodes in the networks

The power-law distribution has applied in the communities, proposed work tested the hypothesis of in-degree of links followed as a power law and it has been calculated and shown in the table1. 500 nodes were created to propagate the content of information, the frequency of interaction has made in the 500 node, due to the influence diffusion the information has spread over the 500 nodes and FOAF also. It has to target the influential nodes in the structural dimension. By the chain of reaction, 200 nodes were actively participated by the continuous frequency of interaction and it had spread over the large portion of the sparse graph, those links were closed to the minimal number of edges. the computational complexity of content is to be reached lesser than the global information in the sparse graph. Geodesic of the pair of vertices has calculated by the co-occurrences of the nodes in the network. From this dispersed links of the node, weights are 800. It gives the strength of the formation of sub-communities to access the reliable links of choosing the properties of scholarship. detecting the communities by measuring the connection and interconnection between the nodes.

The Goodness metric of a node has captured to intuited the better partition of the cluster in the structural network. By the influence maximization the average distance of each node is 2.63 from the maximum degree of 50 and the average degree of 4.65, thus calculated degrees of the node have eventually influenced the sparse network and a large number of nodes in the social network analysis. This influence maximization of dyadic and triads pair of nodes has 2.63 geodesics has calculated in the social network metrics, the influence diffusion has easily propagated to 200 active link nodes in the community.

From the validation of power law, the exponent value has 1.625 and P-value has 0.26, By analyse the P-Value the correlation of source node and target node has the goodness of fit in the interaction between the active nodes of users, these active node has categorized into four levels of career guidance experts and target of the students to whom seeking the higher education institution for higher studies. The goodness of fit of the correlation has 0.26 of the positive correlation of the power-law distribution in the analysis of the social network. *Figure 2* depicts the Average in the degree of the node links density function has fitted to the distribution of the in-degree links, it specifies the individual node has focused to the focal point of the in-degree of the links in the cohesive subgroups.

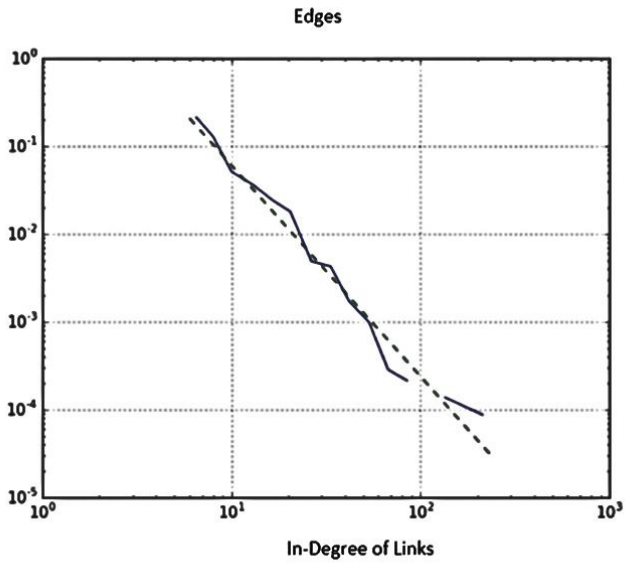

Figure 3. Average In-degree of links from the target node to the source node.

The interactions of the nodes have a continuous level of frequency in the network metrics, the results indicate the node has a fixed distance to interact with the other nodes in the group, through the multidimensionality search gap has regulated and the frequency of interaction has increased through the trained nodes and it reaches with the optimum solution, this approach has fixed geodesic of the nodes in the sparse graph and the fitness value of each node has given the maximum influential node of the core-periphery structure, there is no structural holes between the group of nodes, the strong linkage has made in the multiple access of folds in different dimensions.

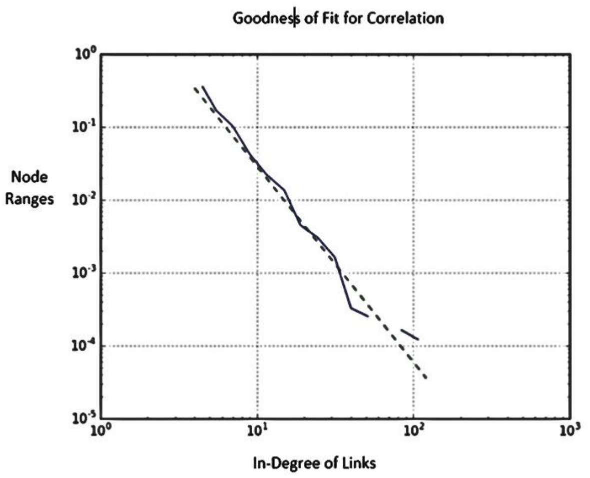

Figure 4. The density of the nodes in the distribution of good fit in the focal line

Figure 3 shows the in-degree of the links according to the node distance of 0.26 the information has propagated to the communities and several folds have taken to measure and enable us to link the strong positive influential nodes forum active users of 200 nodes, and notably, the normalized mutual information and P-score has mentioned the good correlation between the student-student, student to guidance expert nodes, expert to student node and a group of nodes in the temporal links of the cohesive sub-groups in the periphery structure. In particular, all nodes have a maximum degree of 50 and generate the community and dependency of computational capacities of a densely connected graph.

B. Shapiro-Wilk Test

P-value is 0.26 it is the chance of Type 1 error its more support to H1, the test data is statistically significant for the normal distribution. By the other performance test of the Shapiro-Wilk test (W) for validation. W value gives 0.941035 its acceptance rate of 94 % of the critical value shown in Figure 4. From the analysis, the average value of the sample size as 4.1212, Sum of Square Value as 299.515, skewness as 0.895 the shape showed the asymmetrical right positive, potentially normal tails with the P-value of 0.26. After that is done preprocessing methods applied to design and enhancing accuracy.

Further Analysis by using the Fruchterman-Reingold algorithm to find the combination of adjacent vertices and create the layout of the correlation. This algorithm has intuitively able to yield the solutions of graph metrics.

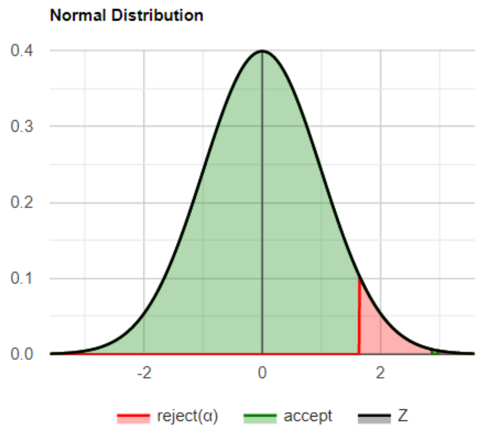

Figure 5. Shapiro-Wilk test to enhance the performance of acceptance.

The association of the links sparsification between the career G_e and S in table 2. The maximum requirement of comments, the post has belonged to the availability of Scholarship of Education Institution based on the Grades.

The gathered data in the form of conversation among preferred ego nodes in the network. The collected data has two phases:

Pre-processing: Collected data has represented in the form of matrix to enable the quantitative analysis. By modelling these matrices said to be social network graph.

Node analysis: In-degree, Out-degree, and Betweenness has measured to find the most influential Node in the graph.

Node id	Students to Guidance Experts S_l to G_e		Students to Students S_l to S_l		Guidance Experts to Students G_e to S_l		Group
	N	%	N	%	N	%	
1	55	82.3	86	32	1	56	123
2	54	56.3	125	52	2	25	156
3	24	54.8	186	55	3	34	187
4	15	46.2	456	94	4	25	195
5	65	89	54	23	5	23	154
6	66	85	123	56	1	35	65
7	84	83	156	58	2	16	48
8	41	25	186	61	3	45	124
9	19	13	158	58	4	29	186
10	7	10	187	64	5	17	456
11	46	56	547	86	1	23	54
12	23	68	641	94	2	25	123
13	89	91	321	78	3	18	156
14	45	56	157	22	4	16	186
15	17	23	196	35	5	54	16
16	15	28	354	67	1	19	7
17	25	38	387	68	2	12	187
18	24	46	345	61	3	10	106
19	29	49	324	58	4	6	95
20	34	59	574	54	5	9	90
21	42	65	554	52	4	13	123
22	38	54	453	45	3	18	43
23	29	76	214	43	2	20	79
24	37	56	785	56	1	46	85
25	45	84	346	78	5	67	104

*Table 2***:** Interaction of links between the Students to Guidance expert's node

• *Rule1*: Absence of interaction amongst two nodes (Neutral interaction) => No links p=> No Influence (Neutral).

• *Rule 2:* Direct influential link and positive content exchanged from both the Nodes, => Positive Influence.

• *Rule 3:* Negative influence propagation from one Node and positive/ neutral interaction from other => Influence is motivating negative as the negative, Influential node can motivate the positive influence node thus can change.

• *Rule 4*: Neutral interaction from one Node and positive/ neutral interaction from others then Influence is Neutral.

• *Rule5:* Negative interaction from both the Nodes =>Negative Influence. A high negative influence from the node has required to be taken by the immediate remedial measures

User 1	**User 2**	**Influence Result**
Neutral	Neutral, Positive	Neutral
Positive	Positive	Positive
Negative	Neutral, Positive	Motivating Negative
Negative	Negative	Negative

Table 3: Influential rules based on content and direction

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C. Identify Communities

The Influential node has been identified by two aspects provide a place to handle both aspects in the structural network. One which is dissemination of positive information and another is deterioration of influence information.

The first phase of the model shows understanding the links between the nodes during the discussion of G_e to S, and S to G_e. The level of participation has represented in the form of adjacency matrix by information exchanges, polarity exchanges of influence to allow the link analysis. The adjacency matrix denotes a specific propagation of nodes shown in *Table 4.* It shows the frequencies of Node A interacted 3 times with Node B, 2 times with Node C, 2, and 3 times with Node J and E individually. The blank diagonal represents no interaction of the node to himself or others.

It estimates a regularized partial correlation network where the edges between nodes are akin to correlate the nodes. using the Fruchterman-Reingold algorithm to create a layout for the nodes: nodes with the lowest interaction / highest number of interactions are analyzed in the correlation matrix, of the 10 Nodes.

	A	B	C	D	E	F	G	H	I	J
A		3	2		3				1	2
B	1			1	2		1	4	1	1
C	1				2					3
D		1				1				
E	5	1	3			4		1		2
F	2	4	1	2	2					2
G	2	3								
H	2	2			1	3				3
I			1					1		2

Table 4: Correlation Matrix for Interaction among the Nodes

For the Second stage, Data has collected from Phase I and calculated the weighted interaction graph shown in Figure 4. Edges signifies the strength and week interaction of link pattern.

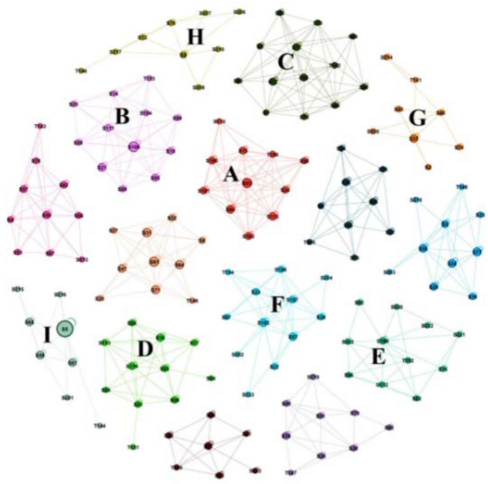

Figure 6. Grouping of nodes based on the student traits.

Social network analysis gives to mapping the user interaction and dynamics of relations in the user group. In Figure 2 rendered each node-link has mined the knowledge-based requirements and has to be identified the similarity-based characteristic links. It has grouped and it finds the communities in the peripheral structure. This similarity-based structural property has useful to find the vertices or nodes who has frequently interacted with the source nodes, from the target node the information diffusion process has taken place and spread it over the friend-of-a-friend (FOAF) interactions, followee-of -a- friend interaction, so the content has propagated through the structural network. the network centrality metrics of closeness, betweenness, the local closeness of the degree have found the degree of each node to make the similarity level of the individual node. From the interaction of the 500 nodes, 200 nodes are in Active state of the frequency of interaction has much faster than the rest of the nodes in the structure, computational complexity and timestamp also more than the active links, thus 200 nodes have grouped and can be recognized as the name of 'A', ’B’, ’C’, ’D’, ’E’, ’F’, ’G’, ’H’, and ’I’. The lower complexity of the groups is 'D', 'E', and 'I’. Densely connected groups are ‘A’, ‘B’, and ‘C’ the frequency of interactions, in-degree, and out-degree of links are more in that three groups, the nodes have actively participated among the few other nodes. These groups are partitioned by the association between the nodes and social objects (Educational Institution) and it has clustered by the contents of the social objects. The topics were shared by the nodes of the cluster.

VI. Results and Discussion

Figure 3 depicts, Group ‘A’, interaction has configured with the centrality degree of the out-degree of the active participant nodes. More frequency of interaction has made in the S107, in group ‘A’, has shown in figure 5. To observe the nodes fruitful interactions between the nodes are thicker in line, the intensity of the lines also thicker edges in the group. The node size has configured with a degree of centrality to the reciprocal of the nodes, the intensity of colour and thickness has shown to the nodes, which nodes are influential and non-influential of interactions in the community. S107 has a more influential node in the community, in the betweenness and closeness of a connected node centrality of vertices has been calculated by the geodesic between all pair of nodes in the community, by measuring the all nodes has highly influential and it has measured in the group A S107 has random walk closeness centrality of other nodes, in which the content has reached to other nodes speedy with a random walk of information propagation, the hierarchical closeness of node has extended to S97, the centralities have been categorized into their approach of cohesiveness, it has to be count the node has walked randomly from the initial node. The S97 has interpreted with S105, the in-degree of links has often interpreted in the form of the popularity of the content of information in the communities, the out-degree of links has direct to the other nodes.

Geodesic between the pairs of nodes S105 and S107, when it has spoken the closeness of centrality, the out-degree of the links has walked to the multiple numbers of nodes and compared the weightage in different sizes, if the distances are irrelevant to the information propagation, it can be produced the results differently.

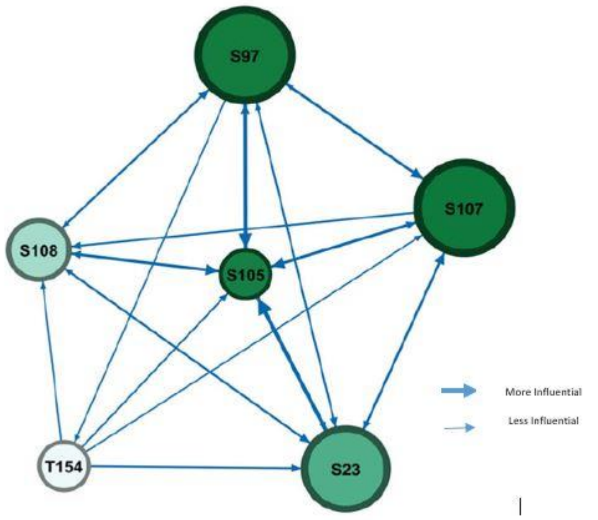

Figure 7. The source node has interacted with the less number of target nodes in the group.

S23, S97, and S107 are adjusted to the nodes in the graph size, it's taking the shortest distance to propagates the information and highly influential when compared to among the group has shown in Figure 7, the highly influential link has propagated the content in shortest and different ways to reach the node links.

Metrics	After Centrality	Before Centrality
In-Degree	**37**	**30**
Out-Degree	**65**	**52**
Closeness	**0.92**	**0.78**
Betweenness	**30**	**24**

Table 5: Measurements of Influential node before and after centrality values in the community

When paired with metric analysis of active nodes in Group 'A', S97 and S107 give the dynamic interaction between all the users, their accuracy level of the link has measured and shown the results in Table 5. in-degree of the links has 37, other nodes are frequently interacted in different dimensions and effectively bring a better result in centrality, out-degree of the links has measured 65 before it was 52, it could support the learning analysis and exchanged the information. the geodesics path of the distance has 0.92 and 30, it brings the shortest path between all pairs of nodes in the synthetic structural network. while the study leads to the better interaction between all the links in the social network community, Educational Data Mining has designed to capture the academic perspective and gives a reliable insight into the interaction.

VII. Conclusion

The insight of study focused on career guidance to higher education with active users, the association of matrix produced the actionable information of nodes concerning the scholarship, each interaction of nodes yielded the goodness of fit k≥1 and P-value has 0.26 given the good correlation between the student-experts, experts-students, and students-students. Shapiro-Wilk test to improve the performance has yielded 94% accuracy**.** Mapping of Highest and lowest number of interaction between the nodes has visualized by Fruchterman-Reingold algorithm, the interaction of Group A-S97 and S107 have yielded the performance value of 95.3% has a highly influential node and dynamic interaction among the others in the Group A and it brings the shortest path between all pair of nodes. Correlation among nodes was performed using the Pearson rank correlation, the yielded results were students to students 78%, students to experts 15%, and experts to students 7% of interactions were identified Analysis emphasizing the capable of students searching for higher studies is helpful for review for various advanced global institution chosen his/her higher studies for getting the Institution advancement, moreover my study shows the learning analysis and visualize the pattern of links.

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Author Biographies

Ms. Rohini A received her Bachelor's degree in CSE from Anna University and a Master's Degree in CSE from Dr. M.G.R University, Chennai, India. She has ten years of experience in Computer Science and Engineering in the National and International Universities and she has published more than 10 publications in reputed International Conferences (Indexed by IEEE, Scopus, WoS, and Google Scholar). Currently, she is doing Ph.D. in the Hindustan Institute of Technology and Science, Chennai, India. Her area of research is Social Network Analysis.

Dr. SudalaiMuthu T is working as an Associate Professor in the Department of Computer Science and Engineering, Hindustan Institute of Technology and Science, Chennai, India. He received his Ph.D. degree from Hindustan University, Chennai. India. He is an ETH Certified Ethical Hacker. He has more than 30 publications in the reputed International Conferences and Indexed Journals. He delivered more than 30 keynote speeches in International Conferences, Seminars, and Workshops. He is received many awards and accolades in his career includes Best Teacher Award, Best Innovator Award. His research areas are Network Security, Advanced Computing. He is a lifetime member of CSI, ISTE, ACM, and IEEE.

Dr. Tanupriya Choudhury received his bachelor’s degree in CSE from West Bengal University of Technology, Kolkata, India, and master’s Degree in CSE from Dr. M.G.R University, Chennai, India. He has received his PhD degree in the year 2016. He has Ten years of experience in teaching as well as in Research. Currently he is working as an Associate Professor in Dept. of Informatics, School of CS at UPES Dehradun India. Recently he has received Global Outreach Education Award for Excellence in best Young Researcher Award in GOECA 2018. His areas of interests include Human computing, Soft computing, Cloud computing, Data Mining etc. He has filed 24 patents till date and received 16 copyrights from MHRD for his own softwares. He has been associated with many conferences in India and abroad. He has authored more than 210 research papers till date. He has delivered invited talk and guest lecture in Jamia Millia Islamia University. Maharaja Agrasen college of Delhi University, Duy Tan University Vietnam etc. He has been associated with many conferences throughout India as TPC member and session chair etc. He is a lifetime member of IETA, member of IEEE, and member of IET(UK) and other renowned technical societies. He is associated with Corporate and he is Technical Adviser of Deetya Soft Pvt. Ltd. Noida, IVRGURU, and Mydigital360 etc. He is holding the post of Secretary in IETA (Indian Engineering Teacher’s Association-India), He is also holding the Advisor Position in International Association of Professional and Fellow Engineers-Delaware-USA.