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A STUDY ON SNA: MEASURE AVERAGE DEGREE AND AVERAGE WEIGHTED DEGREE OF KNOWLEDGE DIFFUSION IN GEPHI

Ayyappan.G[1], Dr.C.Nalini[2]
Research Scholar, Department of CSE, Bharath University, Chennai[1]
Professor, Department of Computer Science and Engineering, Bharath University, Chennai[2]
Email: ayyappan.it@bharathuniv.ac.in

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Abstract

Social Media is a term that covers the platforms Facebook, twitter, blogs and other things typically thought of as social networking. ONS's are primarily Internet based tools for sharing and discussing information among human beings. In this paper focuses mainly to study social network parameters commonly used to explain social structures.

In this paper, we extract academic researcher data from an academic social network, analyze and evaluate network parameters on some widely recognized graph topology using GEPHI social network tool. Using these parameters we find out the strength of research spectrum, authors contribution in academic knowledge diffusion.

In this research work we have collected this data set from ArnetMiner (http://www.arnetminer.org). In this massive real time dataset we have taken co-author training set randomly it contains 100 records from the 4258615 records. We measure average degree and average weighted degree of research community.

This research community we identified collaborations of authors and co authors published in research article using gephi tool we find out the maximum and minimum research community groups in the academic knowledge diffusion.

Keywords: Graphs, edges, lines, arcs, Average Degree, Average Weighted Degree.

1. Introduction

A graph is *vertices*, *nodes*, or *points* which are connected by *edges*, *arcs*, or *lines*. Simple graph - does not have loops (self-edges) and does not have multiple identical edges. Simply we define graphs are connections of vertices and edges.

We don't consider graph shape, we consider only nodes are connected or not. An edges connected two vertices.

Two types of edges :

1. Symmetrical,

2. Arcs (Directed).

Two types of graph frameworks:

1. Graph,

2. Digraph.

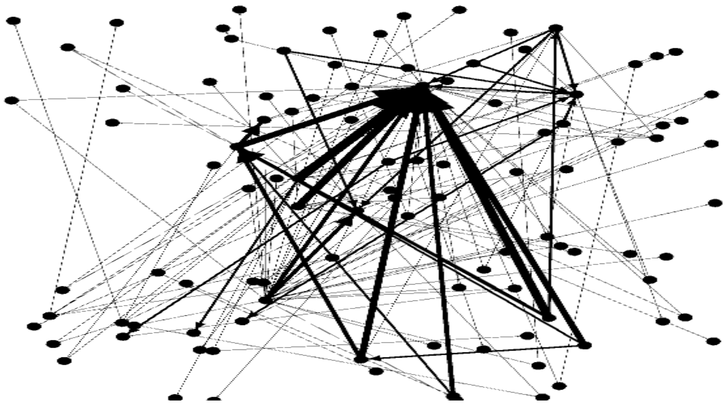

Fig1: Cluster of Research community without Label Representation.

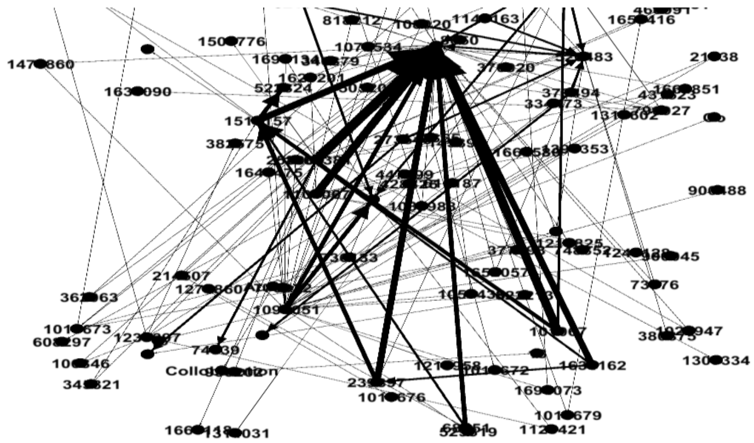

Fig2: Cluster of Research community With Label Representation.

II. Related Work

Dynamic network analysis can provide an aid to longitudinal SNA research. However, as a relatively young field, many aspects have not been explored and there are few standards that have been established.

One path taken was to treat network edges as probabilistic, and use multi agent systems to study network evolution (Carley 2003). Carley redefined the traditional sociogram by adding probabilistic parameters on the edges, providing a quantification of the likelihood they will form. Individual nodes were also given more emphasis; they are treated as agents, and can potentially impact how a network will develop. Terroist networks are a good example where prediction is vital (Krebs 2002), and one in which link prediction has important applications(Carley, Dombroski, Tsvetovat, Reminga and Kamneve 2003; Liben-Nowell and Kleinberg 2006).

Another visualization method is to explicitly use the time and order of social interactions to build the network (Berger-Wolf and Saia 2006). Researchers have also appliedDNA methods to studyother forms oflongitudinal networks. Kossinetts and Watts(2006)examinedthe stability of bridges, defined asconnections outside one's circle of acquaintances, and measuredhow social ties werecreated and dissolved over time.Barabasi and colleagues (2002)appliedDNA methods to findunique properties in an evolving citation network that differedfrom classic models. Indeed, various forms of citation and co-authorship networks offer a wealth of reliable data with which to study the evolution of networks. New layouts and metric computations are constantly being developedfrom these dynamic network studies (Brandes and Pich 2012).

The study of dynamic networks greatly benefits from visualizations that can illustrate ideas and concepts not immediately visible in a static sociogram. In fact, "The ability to see data clearly creates a capacity for building intuition that is unsurpassed by summary statistics" (Moody, McFarland and Bender-deMoll 2005). Moody and others'research emphasizes how the ability to see data can be superior to summary statistics, and illustrates the need to visualize hownetworks develop and change over time.Additionally, they lay the foundation of how dynamic network visualizations should be presented (e.g. differentiating between discrete and continuous time), and recommend visualization and analysis be interactive. These theoretical ideas were developed in parallel with SoNIA, a software package forvisualizing dynamic network data (Bender-deMoll and McFarland 2006).Other researchers have continued to focus on studying different properties of dynamic networks, e.g. the evolution of subgroups(Falkowski, Bartelheimer and Spiliopoulou 2006), effects of network topology and organizational structure over time (Kossinets and Watts 2006), detecting and predicting statistically significant changes in a network over time (McCulloh and Carley 2011), and new visualization methods using shortest-path computations (Brandes and Pich 2012).

III. Materials and Methods

Gephi is an interactive visualization and exploration platform for all kinds of networks and complex systems, dynamic and hierarchial graphs. Gephi is a tool for people that have to explore and understand graphs. Like Photoshop but for data, the user interacts with the representation, manipulate the structures, shapes and colors to reveal hidden properties. The goal is to help data analysts to make hypothesis, intuitively discover patterns, isolate structure singularities or faults during data sourcing. It is a complementary tool to traditional statistics.

This is a software for Exploratory Data Analysis. Gephi tool provides an fastest graph visualization engine to speed-up understanding and pattern discovery in large graphs. Gephi is powered by ad-hoc OpenGL engine, it is pushing the envelope on how interactive and efficient network exploration can be.

- Networks up to 50,000 nodes and 1,000,000 edges
- Iterate through visualization using dynamic filtering
- Rich tools for meaningful graph manipulation Gephi is a modular software and can be extended with plugins. Plugins can add new features like layout, filters, metrics, data sources, etc. or modify existing features. Gephi is written in Java so anything that can be used in Java can be packaged as a Gephi plug-in.

1. Average Degree:

Average Degree is the sum of edges of a vertex. In **graph** theory, the **degree** (or valency) of a vertex of a **graph** is the number of edges incident to the vertex with loops counted twice. The **degree** of a vertex is denoted deg(v)

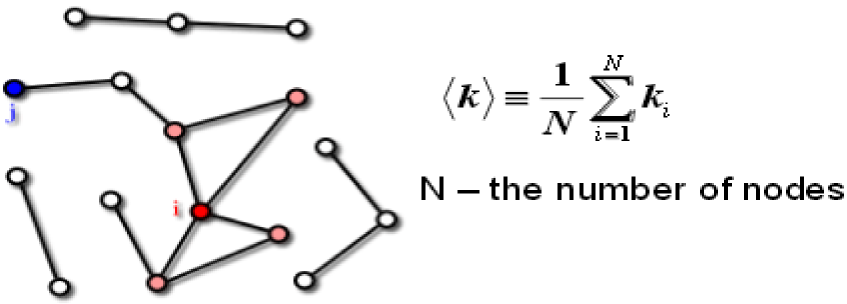

Fig :3 Nodes Representation.

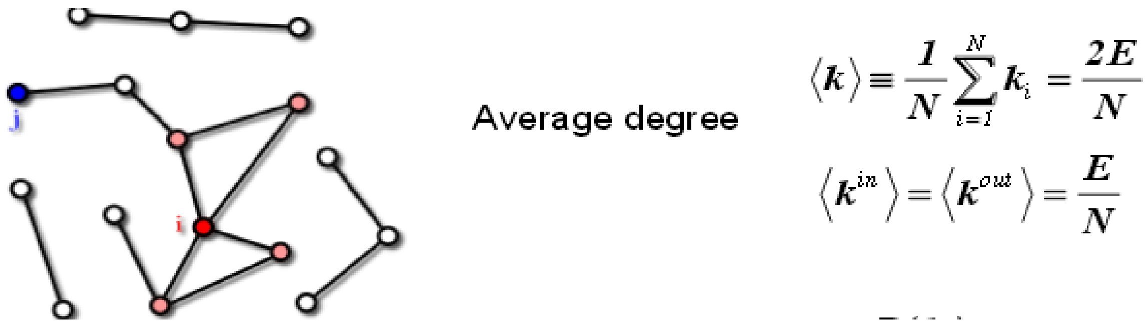

Fig:4 Average Degree Representation.

2. Average Weighted Degree:

Average of sum of weights of the edges of nodes. The graph is designed in such a way that, weight of an edges represents, how many times that edges is traversed between a pair of nodes.

If weight of node is higher, it means it has been visited many times than any other low weight degree node.

The weighted degree of a node is like the degree. It's based on the number of edge for a node, but ponderated by the weigtht of each edge. It's doing the sum of the weight of the edges.

For example, a node with 4 edges that weight 1 (1+1+1+1=4) is equivalent to:

- a node with 2 edges that weight 2 (2+2=4) or
- a node with 2 edges that weight 1 and 1 edge that weight 2 (1+1+2=4) or
- a node with 1 edge that weight 4 etc…

IV. Implementation and Result

a) **Average Degree:** Average degree of this work may consider In Degree distribution, Out Degree Distribution and Degree Distribution it may produce in Average Degree of this dataset is2.865.Itisrepresentingclearlyingraphical diagram.

Each red plots represents in degree. These red plots are plotted in between value plotted above 42 and the count goes above 40.

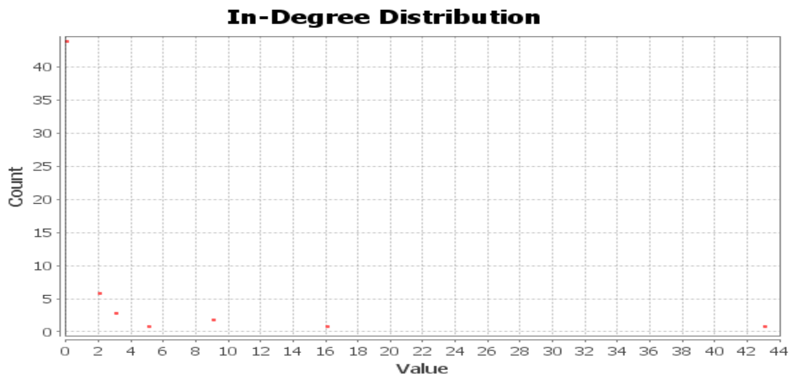

Fig 5: In Degree Distribution.

Each red plots represents out degree. These red plots are plotted in between value below 12 and the count goes to above 40.

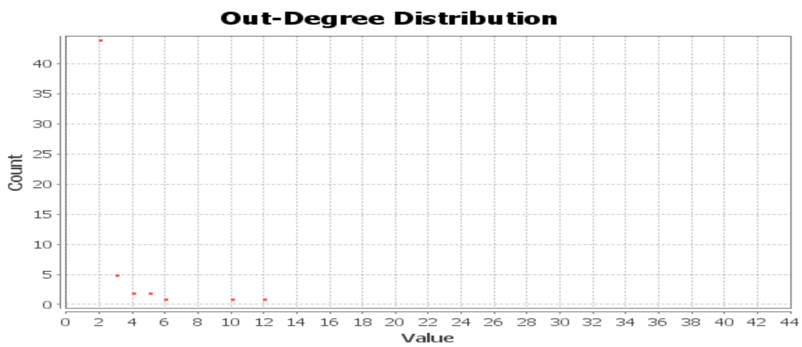

Fig 6: Out Degree Distribution.

Each red plots represents degree. These red plots are plotted in between value goes above 40 and the count it goes to above 44.

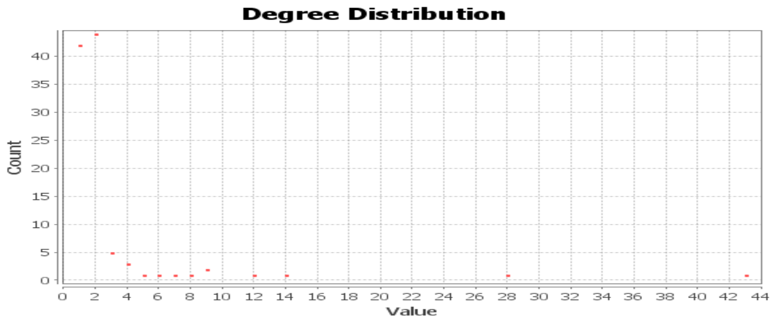

Fig 6: Degree Distribution.

b) Average Weighted Degree: Average degree of this work may consider In Degree distribution, Out Degree Distribution and Degree Distribution it may produce in Average Weighted Degree of this dataset is 1.933.It is representing clearly in graphical diagram. Each red plots represents in degree. These red plots are plotted in between value below 20 and the countable is below 7.

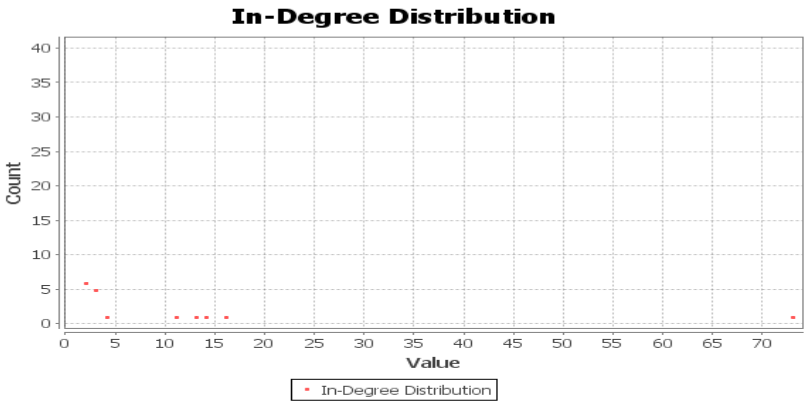

Fig 8: In Degree Distribution.

Each red plots represents out degree. These red plots are plotted in between value below 20 and the count it goes to upto 40.

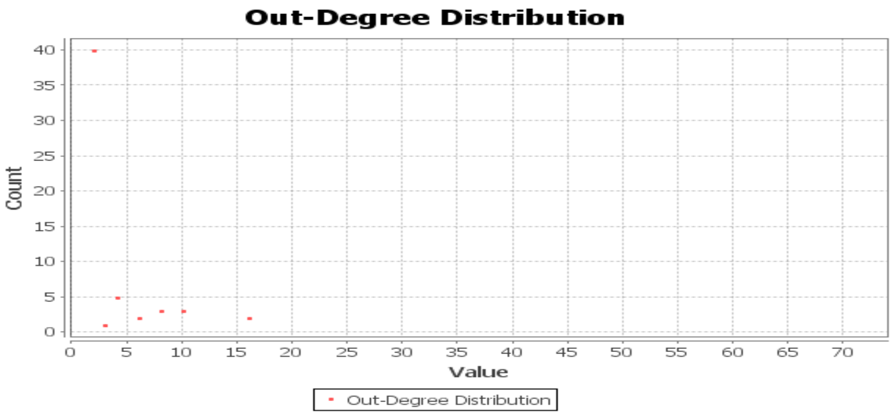

Fig 9: In Degree Distribution.

Each red plots represents degree. These red plots are plotted in between value below 20 and the count it goes to above 40.

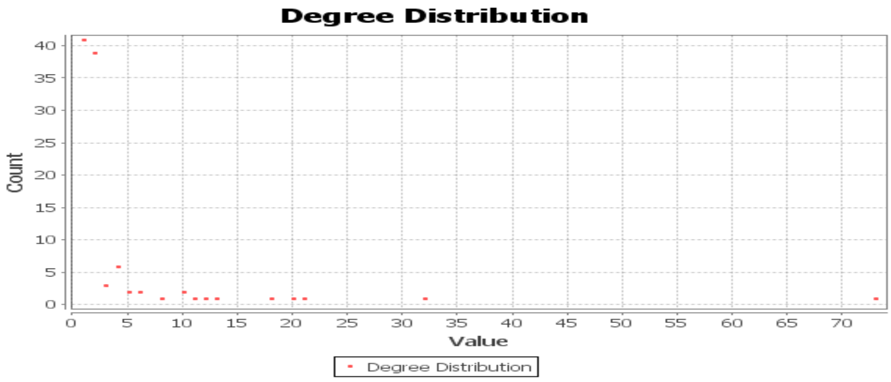

Fig 10: In Degree Distribution.

V. Conclusion

Commonly online social networking systems have become popular because they allow users to share content like as picture ,text, videos ,photos, audios and expand their social circle, by making new research circle. This paper introduced a framework to provide research work communities in SNA. This result define a new node similarity measure that exploits local and global characteristics of a academic social network. The average degree and average weighted degree show that a significant accuracy improvement can be gained by using information about both positive and negative edges of the research spectrum.

VI. References

1. http://matthieu-totet.fr/Koumin/2013/12/16/understand-degree-weighted-degree-betweeness-centrality/
2. http://users.phys.psu.edu/~ralbert/phys597_09/c02_graph_conc.pdf
3. Jie Tang, Jing Zhang, Ruoming Jin, Zi Yang, Keke Cai, Li Zhang, and Zhong Su. Topic Level Expertise Search over Heterogeneous Networks. Machine Learning Journal, Volume 82, Issue 2 (2011), Pages 211-237.
4. Kar-Hai Chu,Heather Wipfli,Thomas W. Valente,Using Visualizations to Explore Network Dynamics , Journal of Social Structure,Volume 14,
5. https://sites.google.com/site/ucinetsoftware/home
6. http://www.r-project.org/
7. Wipfli, H., K. Fujimoto and T. W. Valente (2010). "Global Tobacco Control Diffusion: The Case of the Framework Convention on Tobacco Control." American Journal of Public Health100(7): 1260.

8. Suh, B., L. Hong, P. Pirolli and E. Chi (2010). Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. 2010 IEEE Second International Conference on Social Computing (SocialCom), IEEE.
9. Correa, C. D. and K.L. Ma (2011). Visualizing Social Networks. Social Network Data Analytics, Springer: 307-326.
10. Kairam, S., D. J. Wang and J. Leskovec (2012). The Life and Death of Online Groups: Predicting Group Growth and Longevity. In Proceedings of the fifth ACM International Conference on Web Search and Data Mining, ACM.
11. McCulloh, I. and K. Carley (2011). "Detecting Change in Longitudinal Social Networks." Journal of Social Structure12(3).
12. Suh, B., L. Hong, P. Pirolli and E. Chi (2010).Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. 2010 IEEE Second International Conference on Social Computing (SocialCom), IEEE.
13. http://www.academia.edu/16776131/GEPHI_Introduction_to_Network_Analysis_and_Visualization
14. http://www.slideshare.net/digitalmethods/gephi-rieder-23834788
15. http://www.ijera.com/papers/Vol2_issue6/DB26703707.pdf