International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

Performance Analysis Of Various Community Detection Algorithms For Complex Networks

S. Nithyanantham [1], M. Sangeetha [2], Dr. T. Meeradevi [3]

[1,2] Department Of Computer Science And Engineering
[3] Department Of Electronics And Communication Engineering
[1] Bannari Amman Institute Of Technology,
[2,3] Kongu Engineering College

Email: [1]Nithyanantham@Bitsathy.Ac.In,
[2]sangeetham@Kongu.Ac.In,[3]meeradevi@Kongu.Ac.In

Abstract—Social Network Analysis Is An Important Research Area In Graph Data Analytics. Many Studies Were Made On The Empirical Study And Theoretical Modeling Of Complex Networks. Among Them, Community Detection May Be A Major Search Area In The Networks. The Complex Networks Have Densely Connected Nodes And Edges. There Exist A Number Of Connections Within The Group And Some Outside The Groups. Many Studies Were Proposed Based On The Types Of Network, Algorithms Or Scale Of A Network. There Is A Requirement For A Dynamic Method, Ready To Deal With Various Kinds Of Datasets And The Nuances Of Group Structure. Here We Focus On An In-Depth Comparative Review Which Includes All The Properties Of The Network. Since This Progression Is Essential In Social Data Mining.

Keywords— Community Detection, Complex Networks, Graph Clustering, Graph Mining, Network Study, Overlapping Community, Social Networks Analysis

1. INTRODUCTION

Complex Networks Have Several Characteristics To The Real-World Scenario In Diverse Domains Such As Sociology, Web Traffic, Financial Transactions, Sensor Networks, Anthropology, Biology, And Neuroscience. The Complex Networks Are Represented As Graphs G Which Contains Node V And Edge E, Where G = {V, E}. The Nodes Symbolize The Entities And The Edges In The Graph Show The Connection Among The Entities. Extracting Some Useful Information From This Complex Structure Is A Very Challenging Task. Identifying Communities Can Uncover The Structural Properties Of The Network. There Is A Need To Cluster Communities In These Complex Structures To Find Some Social – Aware Solution.

The Research Initiative Focuses On Detecting Communities Within A Network And Nowadays It Is Extended To Detect Touching Communities In Order To Find Communities Among The Multiple And Multi-Layer Graph. Many Extensive Works Have Been Proposed By The Researchers In The Past Decade. It Is Difficult To Choose The Best Approaches Based On The Real Scenario.

In This Paper, We Give A Huge Diversity Of Various Approaches To Make Better Diagnose And Evaluation Of The Community Detection Algorithms To Make It Easier For Further Improvement Of The Existing Approaches.

FUNDAMENTAL CONCEPTS

A. Complex Network

A Complex Network Is An Inheritably Interdisciplinary Field Includes Sociology, Statistics, And Graph Theory. It Is Characterized By A Group Of Entities And Their Relations. There Remain Many Forms Of Networks Such As Large-Scale Networks, Randomly Distributed Networks, And Scale-Free Networks Which Can Be Represented By Graphs [1]. Social Networking Analysis Is A Vast Domain Of Exploration Which Encircles The Complex Networks. Some Of The Real World Network Includes Facebook, Twitter, Renren, Co-Author Network.

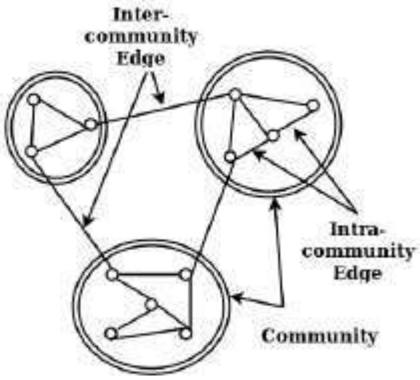

Fig-1: Basic Community Structure

B. Community

A Community Is Referred As Subset Of All Nodes With Similar Features. In A Graph Nodes Having Similar Characteristics Are Connected By The Edges And Form A Complete Graph.

C. Community Detection

Community Detection Or Graph Clustering Extracts Useful Information And Finding Unknown Features Of Users And Entities In The Complex Networks. It Groups Nodes With Similar Features. Community Detection Has Applications In Various Fields Such As Ad-Hoc Networks, Cloud Based, Citation Networks, Social Networks.

D. Taxonomy Of Community Detection

1. Node Based

The Node Based Community Detection Algorithm Utilizes The Structure Information Of Nodes And Directly Identify The Community That The Node Belongs To. Every Node In The Group Need To Satisfy Some Set Of Properties Like Nodal Degrees, Members Reachability, Mutuality Completeness, And Relative Frequency Of In And Out Ties.

2. Component Based

Component Is A Portion Of The Network That Is Disconnected From Each Other. Component Deliberate The Acquaintances Surrounded By A Component Totally. The Component Has To Fulfill Some Set Of Properties Deprived Of Zooming Into The Nodal Level.

3. Network Based

Network Based Community Detection Partitioning The Complete Networks Into Many Disjoint Sets.

4. Hierarchy Based

Hierarchy Based Builds A Hierarchy Of Communities.

E. Factors For Community Detection

1. Vertex Similarity

Two Nodes Having The Same Equivalence Class Refers To Vertex Similarity.

2. Edge Density

The Total Numerals Of The Shortest Paths Which Go Through A Connected Edge In A Graph Or Network Represents Edge Density.

3. Distance Between Vertices

The Distance Among The Connected Two Vertices Of A Graph Is The Minimum Length Of The Paths Connecting Them.

F. Evaluation Criteria For Community Quality

1. Optimal Modularity

Optimal Modularity Is A Measure The Obtains The Strength Of Divided Network Into Some Modules. High Modularity Networks Has Dense Connections Among The Nodes Which Are Presented Within The Modules.

$$Q = \sum_{i-1}^{k} (e_{ii} - a_i^2)$$

Equation 1

Eii – Probability An Edge Is In Module I, Ai – Probability Of A Random Edge Would Come Under Module I When Q=1 Indicates Network Have Strong Community Structure [2][3][4]. The Average Range In Typical Networks Will Between
0.3 To 0.7

2. Normalized Mutual Information

NMI Determines The Quality Of Cluster By Measuring The Accuracy If The Actual Truth Community Shape Is Called In Prior And Requires Only Class Labels Of Instances [2][5]. It Can Be Compared With Different Number Of Clusters.

$$\mathrm{NMI}(Y, C) = \frac{2 \times I(Y; C)}{[H(Y) + H(C)]}$$

Equation 2

Y = Labels Of Class C = Labels Of Cluster
H(.) = Entropy Value
I(Y;C) = Shared Information Among Labels Of Class And Cluster

3. Multi-Criterion Score

It Divides The Graph Into Smaller Manageable Parts And Analyzes Each Part Then Integrates The Parts Into More Manageable Solutions. It Evaluates The Quality Of Clusters By Measuring Internal Density Value, Conductance, Expansion, Cut Ratio Value, Normalized-Cut Value, Greater-Out Degree Fraction, Average-Out Degree Fraction, Flake-Out Degree Fraction [6].

$Conductance: f(S) = \frac{c_S}{2m_S + c_S}$ $Expansion: f(S) = \frac{c_S}{n_S}$	Undirected Graph ->G(V,E) Nodes Available In Graph |V | ->N Edges Available In Graph |E|->M Nodes Cluster's Sets->S Nodes Available In S ->Ns ; Ns=|S| Edges Available In S ->Ms ; Ms = |{(U, V) : U ∈ S, V ∈ S}| Edges Present At The Boundary Of S = Cs Cs = |{(U, V) : U ∈ S, V _∈ S}|

$Internal\ density: f(S) = 1 - \frac{m_S}{n_S(n_S - 1)/2}$ $Cut\ Ratio: f(S) = \frac{c_S}{n_S(n - n_S)}$ $Normalized\ Cut: f(S) = \frac{c_S}{2m_S + c_S} + \frac{c_S}{2(m - m_S) + c_S}$	F(S) Quality Of Clusters. Lesser Value Of Score F(S) More Groups - Alike Group Of Nodes.

COMMUNITY DETECTION ALGORITHMS

A. Classical Methods For Community Detection

1. Partitioned Clustering

In This Algorithm The K Value Has To Be Fixed In Advance. The Goal Is To Cluster The Nodes In The Network To The Given K Clusters. The K-Means Clustering Is A Classic Example Of The Partitioned Clustering Algorithm [7][8]. A Major Drawback Is To Fix The K Clusters In Advance.

2. Hierarchical Clustering

Finding The Number Of Clusters In A Given Network In Advance Is A Difficult Task. So We Go With Hierarchical Clustering Algorithms. The Algorithm Can Be Agglomerative Algorithm Or Divisive Algorithm [9]. In Agglomerative Clustering Each Node Is Considered As A Cluster And If The Similarities Between Two Nodes Are High Then It Is Merged. It Is A Bottom Up Approach. In Divisive Clustering The Network Is Considered As A Whole And Nodes With Low Similarity Is Separated. It Is A Top Down Approach. A Major Drawback In This Approach Is Merging Point And Cutting Point. So We Get Communities With Low Quality.

3. Graph Partitioning

The Graph Partitioning Algorithm Divides The Graph Into Scheduled Dimensional Groups Which Gratifies The Objective Function By Eradicating The Edges In The Graph [10][11][12][13][14][15]. Each Node In The Graph Is Having A Possibility P Based On The Connection, Pin Is The Possibility That The Node Is Associated To Its Groups, Pout Is The Possibility That The Node Is Associated Outside The Group. If The Node Is Connected To Its Group, Then Pin
> Pout The Node Is Belonging To The Community.

4. Spectral Clustering

Spectral Clustering Is A Version Of Graph Clustering. The Objective Function Used In The Spectral Clustering Is Min-Cut, R-Cut (Ratio Cut) And N-Cut (Normalized Cut) [16][17][18]. In This The Numbers Of Clusters Have To Be Known In Progress And The Computational Time Is Also High. This Algorithm Is Inappropriate For Complex Networks Due To Its Computational Time.

5. Infomap

It Is Proposed For Multi Partite Graph. It Has A Quality Function And Searches The Graph Partition To Find The Partition That Optimizes The Quality Function [19].

B. Procedures For Overlapping Community Detection

Many Of The Classical Community Detection Algorithms Focus Only On The Disjoint Communities. But A Real World Social Network Is Having Nodes Belonging To More Than One Community. So, The Research Focus Is On Overlapping Community Detection Algorithms.

1. Clique Percolation Method

In CPM A Complete Sub-Graph In A Graph Is Termed As A Clique. K-Clique Is Summarized As The Graph Which Is Fully Complete With K-Vertices. Two K-Cliques Are Adjacent When They Get Segmented Into K-1 Nodes. Group Of All K-Cliques That Can Be Reached From Every Other Over A Series Of Adjacent K-Cliques Is Called K- Clique Communities. The Edges Of Community Likely To Form Cliques [20][21]. This Method Finds The Maximal Cliques And Then Converts The Groups To K-Group Communities. It Finds All Groups, And Then Reduces Size By 1 And Repeat. It Is Efficient On Real Networks. This Method Fails To Give Meaningful Results When Number Of Cliques Is Low. Cpmd And Cpmw Are Improvement Of CPM. It Is For Directed Networks And Weighted Networks.

2. Link Partition And Line Graph

In Link Partitioning A Graph Is Partitioned Based On The Link Instead Of Nodes In The Graph. The Links Are Partitioned Using Hierarchical Clustering Based On The Edge Similarity [22]. The Edge Similarity Is Computed Using The Jaccard Index

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

The Hierarchical Clustering Builds The Link Dendogram. The Link Is Dendogram Is Cut Based On Some Threshold Values And That Gives The Link Communities.

3. Local Expansion And Optimization Partition

In This Local Expansion Method, The Local Communities Are Detected By Using Rank Removal Method. In The Graph, Every Nodes Are Graded Based On Some Criteria And The Nodes With Highest Ranks Are Removed, Until A Small Disjoint Graph Is Obtained [23][24]. The Number Of Graphs Obtained After The Rank Removal Method Is Large And Size Of The Communities Obtained Is Very Small. So The Communities Have To Be Merged Based On Adjacency Community And Connectivity Community. Weighted Overlapping Scores Are Used To Overlap The Communities. Then The Last Step Is To Refine The Obtained Communities Based On Modularity.

4. Fuzzy Partition

In Fuzzy Partitioning Overlapping Community Detection Method Each Node In The Graph Belongs To Each Community In Different Aspects. The Local Random Walk Method And Distance Metric Is Used To Find The Community Structure. The Unsupervised Fuzzy C-Means Clustering Is Used To Cluster The Nodes In N- Dimensional Space [25] [26]. Each Node Has A Certain Membership Degrees Of Nodes Belonging To Different Clusters. The Membership Degrees Are Between 0 And 1 Indicates The Strength Of Association With Different Communities.

5. Agent Based Partition

The Swarm Of Agents Is Used For Detecting Overlapping Community. The Neighbor Of The Nodes And Their Acquaintance Are Found By Using Link Weightage Computation Using Jaccard Co-Efficient. The Judging Agent Examines All The Nodes In Random Manner And Mark Closeness Between Each Nodes During Random Investigation [27]. The Result Of Team Of Agents Results Are Aggregated. This Founds The Intrinsic Community Structure And A Global Community Structures.

C. Algorithms For Local Community Detection

In Real-World Networks The Size Is Huge. So It Is Difficult To Analyze The Network As A Whole. So The Local Community Detection Algorithms Are Proposed[41]. In A Undirected Graph G = {V,E} If The Connection Information Is Partially Known. The Local Community Starts From Pre-Selected Source Node.

1. Clause's Algorithm

The Clauset Algorithm Of Local Community Detection Is Related To Web Crawler Procedure [28]. The Source Node S Is Chosen And It Follows A Greedy Approach To Add The Neighbor Nodes And The Acquaintance Till The Size Of The Community Is Reached. The Community Highly Depends On The Source Node S.

2. Label Propagation Algorithm

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

This LPA Does Not Require A Predefined Objective Function Or A Community Size. Each Node Starts With A Unique Identifier Termed As A Label [29] [30]. Initially Each Node In The Graph Has Its Own Label. The Labels Are Then Updated Based On Its Neighbor Nodes[42]. At Every Step The Labels Are Updated Based On The Neighbor's Label. The Graph With Dense Structure For A Community. Similarly, Many Communities Are Formed Based On The Idenfiers.

3. Local Node Expansion

The Nodes Centrality Is Found Using Some Similarity Measures Such As Jaccard Similarity. The Nodes With Highest Centrality And Embeddedness Is Considered To Be A Central Node [31][32][33]. Because The Community Structure In The Local Community Detection Highly Depends On The Central Node Otherwise Termed As A Seed Node. Each Node Will Join The Community Which Is Having Maximum Neighbors.

4. Local Optimization

The PSO LDA Algorithm Is Used To Find The Local Community Structure. Compared To Other Optimization Procedures This PSO LDA Have Two Smart Features [34]. PSO Enhances From The Local Optimum And Runs Fast. Particles In The PSO [40] Can Be Mapped To The Nodes In The Graph.

D. Algorithms For Multi Graph Community Detection

1. Matrix Factorization

The Multi Graph Community Detection Algorithm Evolves With Three Phases. The First Phase Is The Construction Of The Graph With Prior Available Information. The Second Phase Is The Matrix Factorization (NMF) And The Third Phase Is Community Discovery With Multi Graphs [35][36][37][38].

2. Pattern Mining

The Community In Multi Graphs Is Found By Performing Frequent Pattern Mining On The Set Of Nodes And Edge Link Between Those Nodes [39]. This Method Can Be Widely Used On Social Network Sites[40]. The Community Is First Started With Small Number Of Homogeneous Pattern Nodes In The Graph And It Can Be Increased In Further Iterations Based On The Concept Of Leader And Follower In The Network.

COMMONLY USED DATASETS IN COMMUNITY DETECTION

Table 1 Represents Most Commonly Used Datasets For Community Detection With Their Nodes, Edges, Average Degree And Clustering Co-Efficient Of The Dataset.

Table 1 - Network Datasets

Network	Nodes	Edges	Average Degree	Average Clustering Coefficient
Zachary Karate Club (1)	**34**	**78**	**4.59**	**0.57**
American College Football Network (1)	**115**	**613**	**10.66**	**0.40**
Polbooks (1)	**105**	**441**	**7.59**	**0.49**
Lusseau's Dolphins' Network	**62**	**159**	**5.13**	**0.26**

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

(1)				
JAZZ Musician Network (1)	**198**	**2,742**	**27.70**	**0.62**
C. Metabolic Network (2)	**453**	**2040**	**9.01**	**0.65**
Com-Youtube (3)	**1134890**	**2987624**	**5.26**	**0.40**
Com-Amazon (3)	**334836**	**925872**	**5.53**	**0.40**
DBLP (3)	**26,956**	**88,742**	**6.80**	**0.42**

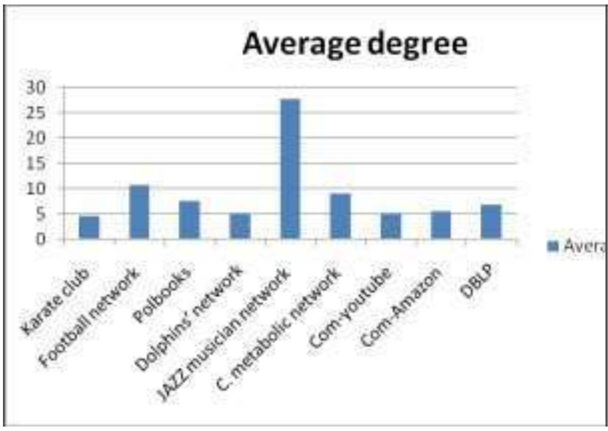

Fig 2: Average Degree Of Graph

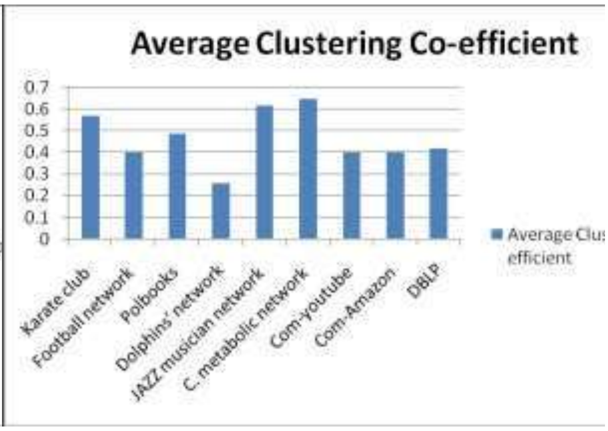

Fig 3: Average Clustering Co-Efficient

Fig 2 Shows The Average Degree Of Various Real World Datasets. The JAZZ Musician Network Have The Maximum Average Degree Of 27.70 Whereas Karate Club Dataset Has Minimum Average Degree Of 4.59.

Fig 3 Shows The Average Clustering Co-Efficient Of Various Real World Datasets. The C. Metabolic Network Have The Maximum Average Clustering Co-Efficient Of
0.65 Whereas Lusseau's Dolphins' Network Have Minimum Average Clustering Co-Efficient Of 0.26.

I. PERFORMANCE EVALUATIONS

The Community Quality Of The Above Mentioned Datasets Are Evaluated Based On Optimal Modularity.

Table 2 Shows The Modularity Of Various Real-World Datasets.

Table 2 Optimal Modularity

Table 3

Normalized Mutual Information

Network	Modularity (Q)
Zachary karate club	0.419
American college football network	0.6035
Polbooks	0.5246
Lusseau's dolphins' network	0.5143
JAZZ musician network	0.4422
C. metabolic network	0.4233
Com-youtube	0.6930
Com-Amazon	0.8739
DBLP	0.8486

Network	NMI
Zachary karate club	0.419
American college football network	0.6035
Polbooks	0.5246
Lusseau's dolphins' network	0.5143

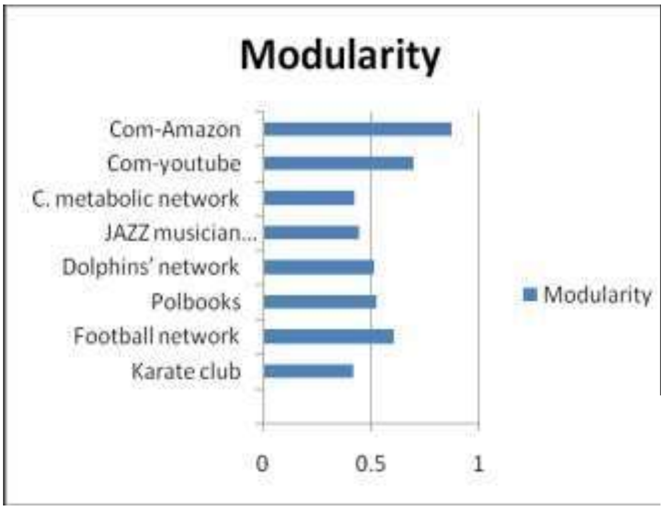

Fig 4 : Modularity
Figure 11 Shows The Optimal Modularity Values Of Various
Networks Using Louvian Community Method.

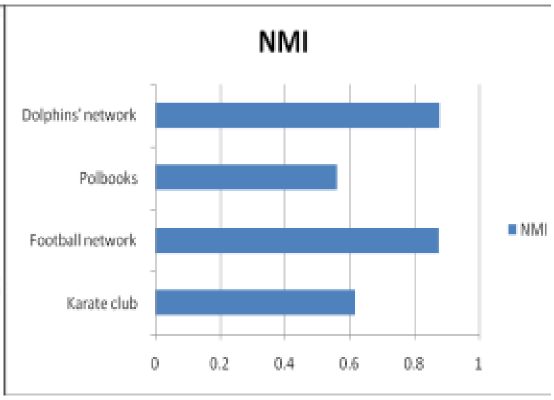

Fig 5: NMI
Figure 5 Shows The Normalized Mutual Information Of Various Networks Using Louvian Community Method.

2. CONCLUSION AND FUTURE WORK

In This Paper We Introduce Various Types Of Graphs And Need For Community Detection. Besides We Review Lot Of Community Detection Methods On These Various Networks. In Some Traditional Methods Community Was Easily Detected But The Number Of Clusters Has To Be Predetermined In Other Traditional Methods The Cut Section Of Dendrogram Tree Has To Be Determined, It Makes The Algorithm Slower. Overlapping Community Detection Predicts The Overlapping Community But Sometimes Needs Fully Connected Graph Structure. In Local Community The Community Size Has To Be Known In Advance. In Multi-Graph Community Detection With The Increase In Size Of The Graph Pattern Mining Is Difficult. The Research Of Community Detection Techniques Lies In

Deciding The Suitable Community Detection Algorithm For The Underlying Networks. Future Research Direction Lies In Improving Speed And Accuracy With Increase In Size Of The Network.

3. REFERENCES

[1] X. F. Wang, “Complex Networks: Topology, Dynamics And Synchronization”, International Journal Of Bifurcation And Chaos, Vol. 12,No. 05,Pp. 885- 916,2002.
[2] Tanmoy Chakraborty, Ayushi Dalmia , Animesh Mukherjee , Niloy Ganguly, “Metrics For Community Analysis: A Survey”, Journal Of ACM Computing Surveys (CSUR), Volume 50 Issue 4, November 2017
[3] Article No. 54.
[4] Shang, Keke & Small, Michael & Wang, Yan & Yin, Di & Li, Shua, “Novel Metric For Community Detection”. (2019).
[5] M.EJ. Newman, M. Girvan, “Finding And Evaluating Community Structure In Networks”, Phys. Rev. E 69 (2) (2004) 026113.
[6] Danon L, Diaz-Guilera A, Duch J Et Al. “Comparing Community Structure Identification”. J Stat Mech-Theory E, 2005.
[7] Jure Leskovec, Kevin .T. Lang, Michael W. Mahoney. “Empirical Comparison Of Algorithms For Network Community Detection”. WWW. 2010.
[8] Papadopoulos S, Kompatsiaris Y, Vakali A Et Al. “Community Detection In Social Media”. Data Mining And Knowledge Discovery, 2011, 24 (3) : 515-54.
[9] T. B. Macqueen. “Some Methods For Classification And Analysis Of Multivariate Observations”. In: L. M. L. Cam, J. Neyman, (Eds.). 1967. 281-297.
[10] T. Hastie, R. Tibshirani, J .H. Friedman, T”He Elements Of Statisticalmlearning”, Springer, Berlin, Germany, 200I.
[11] Pothen, A., “Graph Partitioning Algorithms With Applications To Scientific Computing”, Technical Report, Norfolk,VA, USA, 1997.
[12] Sima, J., And S. E. Schaeffer, 2006, In Proceedings Of The Thirty-Second International Conference On Current Trends In Theory And Practice Of Computer Science (Sofsem 06), Edited By J. Wiedermann, G. Tel, J. Pokorny, M. Bielikova, And J.Stuller (Springer-Verlag, Berlin=Heidelberg, Germany), Volume 3831 Of Lecture Notes In Computer Science, Pp. 530-537.
[13] W. Donath, A. Hoffman, “Lower Bounds For The Partitioning Of Graphs”, IBM J. Res. Dev. 17 (5) (1973) 420 - 425.
[14] Mu Zhu.” Research On The Key Technologies Of Community Detection In Complex Networks”. 2014(35).
[15] Kernighan B W, Lin S. “An Efficient Heuristic Procedure For Partitioning Graphs”[J]. Bell System Technical Journal, 1970,49(2): 291-307.
[16] Lin Yuan. “Research On Community Detection And Graph Partitioning”. 2014(17)
[17] Jeffrey Q.Jiang, Andreas W.M.Dress, Genkeyang, “A Spectral Clustering-Based Framework For Detecting Community Structures In Complex Networks”,Applied Mathematics Lettersvolume 22, Issue 9, September 2009, Pages 1479-1482
[18] Zhou, Zhixin And Arash A. Amini. “Analysis Of Spectral Clustering Algorithms For Community Detection: The General Bipartite Setting.” J. Mach. Learn. Res. 20 (2018): 47:1-47:47.

[19] Von Luxburg U. “A Tutorial On Spectral Clustering” [J]. Statistics And Computing, 2007, 17 (4):395-416.
[20] Rosvall, M., Bergstrom, C.T.: “Maps Of Random Walks On Complex Networks Reveal Community Structure”. Proceedings Of The National Academy Of Sciences 105(4) (2008) 1118 – 1123
[21] I. Derenyi, G. Palla, T. Vicsek, Clique Percolation In Random Networks, Phys. Rev. Lett. 94 (16) (2005) 160202.
[22] G. Palla, I. Derenyi, I. Farkas, T. Vicsek, “Uncovering The Overlapping Community Structure Of Complex Networks In Nature And Society”, Nature 435(2005) 814 - 818.
[23] Ahn Y Y, Bagrow J P, Lehmann S. “Link Communities Reveal Multi Scale Complexity In Networks”. Nature, 2010, 466 (7307): 761-764.
[24] Jiajing Zhu, Yongguo Liu , Changhong Yang, Wen Yang , Zhi Chen, Yun Zhang, Shangming Yang, Xindong Wu , “A Degree-Based Block Model And A Local Expansion Optimization Algorithm For Anti-Community Detection In Networks”, PLOS-ONE, April 18, 2018
[25] Xing, Yan & Fanrong, M. & Yong, Zhou & Ranran, Z., “Overlapping Community Detection By Local Community Expansion”, Journal Of Information Science And Engineering, (2015), 31. 1213-1232.
[26] He X., Guo K., Liao Q., Yan Q., “Overlapping Community Detection Algorithm Based On Spectral And Fuzzy C-Means Clustering”. In: Sun Y., Lu T., Xie X., Gao L., Fan H. (Eds) Computer Supported Cooperative Work And Social Computing. Chinesecscw 2018. Communications In Computer And Information Science, Vol 917. Springer, Singapore, (2019).
[27] Zhang, Shihua & Wang, Rui-Sheng & Zhang, Xiang.,” Identification Of Overlapping Community Structure In Complex Networks Using Fuzzy C-Means Clustering”, Physica A: Statistical Mechanics And Its Applications. 374. 483-490. 10.1016/J.Physa.2006.07.023. (2007)
[28] Xuzhou,Xiaohuizhao,Yanhengliu,Gengsun, “A Game Theoretic Algorithm To Detect Overlapping Community Structure In Networks”, Physics Letters A
[29] Volume 382, Issue 13, 5 April 2018, Pages 872-879 Clauset A. “Finding Local Community Structure In Networks “[J]. Physical Review E, 2005,72(2): 026132.
[30] Xuegang, Hu & He, Wei & Li, Huizong & Pan, Jianhan, “Role-Based Label Propagation Algorithm For Community Detection”, (2016).
[31] Raghavan U N, Albert R, Kumara S,”Near Linear Time Algorithm To Detect Community Structures In Large-Scale Networks”. Physical Review E, Statistical, Nonlinear, And Soft Matter Physics, 2007, 76 (3 Pt 2) :036106.
[32] Joyce Jiyoung Whang, David F. Gleich, Inderjit S. Dhillon, “Overlapping Community Detection Using Seed Set Expansion”, CIKM' 13.2013(2099- 2108).
[33] Isabel M. Kloumann,.Ton M. Kleinberg. “Community Membership Identification From Small Seed Sets”. KDD'14. 2014(1366-1375).
[34] Sorn Jarukasemratana, Murata, Xin Liu. “Community Detection Algorithm Based On Centrality And Node Distance In Scale-Free Networks”.24th ACM Conference On Hypertext And Social Media. 2013.
[35] Lancichinetti, A., Radicchi, F., Ramasco, Lj., Fortunato, S.: Finding Statistically Significant Communities In Networks. Plos ONE 6(4) (April 2011) E 18961
[36] Kamuhanda, Dany & He, Kun, “A Nonnegative Matrix Factorization Approach For

Multiple Local Community Detection”, 10.1109/ASONAM.2018.8508796, (2018).
[37] Vladimir Gligorijevic , Yannis Panagakis, Stefanos Zafeiriou,” Non-Negative Matrix Factorizations For Multiplex Network Analysis”, IEEE Transactions On Pattern Analysis And Machine Intelligence , Volume 41 Issue 4, April 2019 Page 928-940.
[38] Santra, Abhishek Et Al. “Structure-Preserving Community In A Multilayer Network: Definition, Detection, And Analysis.” Arxiv Abs/1903.02641 (2019).
[39] Roberto Interdonato, Andrea Tagarelli, Dino Ienco, Arnaud Sallaberry, Pascal Poncelet. “Local Community Detection In Multilayer Networks. Data Mining And Knowledge Discovery”, Springer, 2017, 31 (5), Pp.1444-1479.
[40] Xiaoming Li,Guagquan Xu,Litao Jiao,Yinan Zhou,Wei Yu, Multi-Layer Network Community Detection Model Based On Attributes And Social Interaction Intensity, Elsevier Computers & Electrical Engineering, July 2019.
[41] Nithyanantham, S., Singaravel, G. Resource And Cost Aware Glowworm Mapreduce Optimization Based Big Data Processing In Geo Distributed Data Center. Wireless Personal Communication (2020). Https://Doi.Or/10.1007/S11277-020-07050-6
[42] Sujatha, K & Shalini Punithavathani, D, ‘Optimized Ensemble Decision-Based Multi-Focus Image Fusion Using Binary Genetic Grey-Wolf Optimizer In Camera Sensor Networks”, Spinger, DOI: 10.1007/S11042-016-4312-3, Multimedia Tools And Applications
[43] Viji, C., Rajkumar, N., Suganthi, S.T. Et Al. An Improved Approach For Automatic Spine Canal Segmentation Using Probabilistic Boosting Tree (PBT) With Fuzzy Support Vector Machine. J Ambient Intell Human Comput (2020).