Comprehensive Analysis Of Social Theories Based Community Detection Framework Over Social Media

Pranita Jain, Deepak Singh Tomar

Abstract: Community over social media is the communal group of globally spread user having similar interest regarding a communal topic or product. Community detection algorithm over social media, clustering the highly-dense social media user over resultant communal issue. Recently, researchers applying social media mining and clustering approach to detect community over social media. But due to lack of network information, the performance of this research does not get significant results. This paper presents a social theory based comparative analytical framework that tries to extract hidden information from the graphical representation of social media. Along with that, it compares the performance of the benchmark community detection algorithm, i.e. walk trap, edge betweenness, and fast greedy over six different social media data set. That yield intersecting facts about the capabilities and deficiency of community analysis methods.

Index Terms: Community Detection, Confounding, Edge Betweenness Algorithm, Fast Greedy Algorithm, Homophily, Influence, Social Media, Social Media Mining, Social Theory, Walk Trap Algorithm.

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1. INTRODUCTION

NOW, in the era of digital marketing, advertisement and publicity, the social media platforms offer a dynamic perspective to classify like-minded consumers as well as users through community detection. Graphically social media can be molded as a graph SNS(U, R), where U refers to a set of end-user as vertices, and R is used to indicate relationships among connecting users as edge, as shown in figure 1. For digital marketing welfare, social media lead to the formulation of a group of like-minded people as community having a unified preference towards any product, policy, and local or global issue [1-8]. Communities on social media are groups of users who post or like identical tweets, messages, video, and audio over any social [8], economic, political [1], educational, intellectual, national, and international terror [9] issues. Community detection algorithms over social media, identify implicit and explicit online communal relationships. Extract worthwhile structural and functional informational for business analytics, character assessment, political policy, product recommendations, and policy making for government and private organizations. The technical objective of community detection is to divide the network (social media) into denser areas of any graph and make it easier to make the community as an efficient manner. Such dense fields are called near-close relations, so it is easy to analyze them to belong them same community. The determination of such communities is useful in the context of various applications in social network analysis, including client segmentation, recommendations, link estimates, and vertex labeling and impact analysis. Recently, researchers identify graphical and communal similarities over social media through graph and member-based community detection algorithm. Graphical similarity includes modularity and density of communal node (end-user), whereas communal similarities encompass degree, similarity, and reachability of communal node. This paper presents a comparative analytical framework to analyze the impact of social balance, status, and correlation theories of social media mining over community detection.

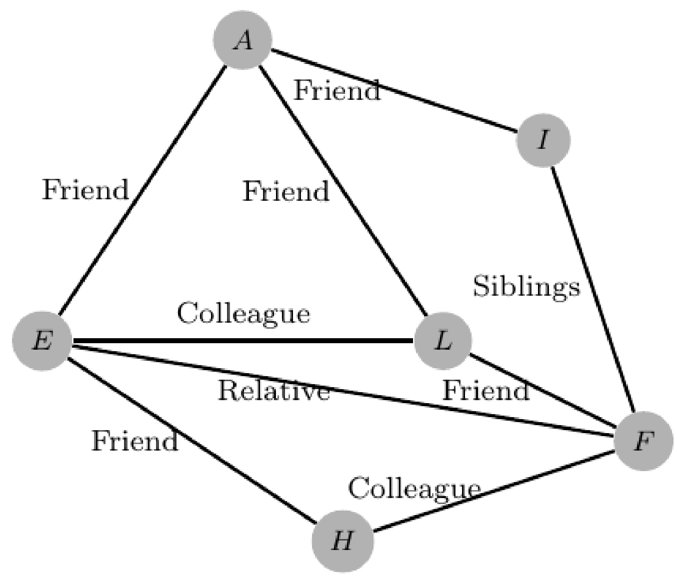

***Fig.**1 Social Media Network*

The rest of the paper is organized as follows: Section 2 covers recent research on community detection over social media. Section 3 present description of the proposed framework, and section 4 include performance evaluation and report of the data set, and finally, Section 5 concludes the paper, outlines the framework performance and research outcome.

2 RELATED WORK

Now, these days Social Media has become a significant platform for message sharing globally without any geographical boundaries. Technically social media can be referred to as a graph, where nodes and links represent user and relationship among them, respectively. These Consequences lead to employed graph mining algorithms in social media mining for extracting useful patterns from social media. Obaida Hanteer et al. [1] present a hashtag-based topical audience model for multiplexing explicit interactions and conversations between

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end-users and identify politically influence community over Twitter. Noha Alduaiji et al. [2] present a clique structure and influence propagation-based temporal interaction biased model for community detection. This model grapes temporarily active user -over dense communities through density metric and influence of communal node with the frequency of their interactions with the sibling's node. Radhia Toujani et al. [4] present a genetic algorithm based hybrid hierarchical clustering approach for convergence of locally optimal community detection. Genetic hierarchical clustering algorithm build bottom-up cluster with higher objective function and decompose with lower quality function. Feng Wang et al. [5] present a homophily based twitter community topic modeling system, where LDA is used to capture the recent topics in the aggregated tweets. Clique algorithm used to verify internal and external topic similarity and extract common interests to build structure-based communities. Amin Salehi et al. [6] present a social interactions and user-generated content based framework to identify detect antagonistic and allied communities over social media. This framework based on a hypothesis that the inter-community perspective of end-user can contemplate inter-community relationships. Aftab Farooq et al. [7] present a graph-based community detection algorithm using influence node centralization. This paper visualizes and evaluates the correlation matrix to extract the most influential node over a communal desire group. Kantinee Katchapakirin et al. [8] present a natural language processing based behavioral information identification model for Thai social community detection over Facebook. Firas Saidi et al. [9] present an adequate evidential clustering method to identify cyber-terrorist subgroups as community over social media. This method employed probabilistic constrained evidential C-Means (CECM) algorithm to identify must-link and cannot-link constraints to magnify military, finance, and local leaders committees.

Xiaoming Li et al. [10] present a correlation theory-based multi-layer network to encapsulate direct and indirect influence relation and drive local community detection. Wathsala Anupama Mohotti et al. [11] present a density and content-based clustering approach for community detection over social media. Dimitrios Vogiatzis et al. [12] present a social tagging based density-based community detection algorithm for crisp and overlapping community over hyper-graphs. Shuai Zhao et al. [13] present a latent Dirichlet allocation-based probabilistic link partition (LBLP) model for overlapped community detection. This probabilistic model unified influence and content information of network structure. Xiaolong Deng et al. [14] present a probabilistic graph and vector Influence clustering-based community detection algorithm. This method use ITG (information transfer gain) to identify most influence node over communal desire group. Fang Hu et al. [15] present a Node2vec based spectral clustering algorithm for community detection. This algorithm extracts rich information from low dimension feature vector of identical phantom node. Antonella Tomasella et al. [16] present a heterogenous community detection algorithm through asymmetric relations, which extract by integrates social and contextual information of end-user over social media. Arie Croitoru et al. [17] present a spatiotemporal clustering-based community detection algorithm and perform geospatial analysis of spatial footprint over both physical and cyberspace for information propagation. Amritpal Singh et al. [18] present probabilistic Data structure and quotient filter based storage schema for Community Detection over social media. Whereas Jesus Sanchez-Oro et al. [19]present metaheuristic based Greedy algorithm for community detection over social media. Amreen Ahmad et al. [20] present a hybrid influence maximization approach based on dynamic Weighted Sum and multi-criteria decision-making methods for community detection over social media. Soumaya Guesmi et al. [21] present relational concept analysis based multi-relational community detection over heterogeneous social media. Youcef Abdelsadek et al. [22] present knowledge acquisition and interactive visualization dependent two complementary steps for community detection over twitter. Andreas Kanavos et al. [23] present an influence based graph mining approach for emotional community detection over social media. Vincenzo Moscato et al. [24] present a game theory-based logistics and information streams to identify most influence node on communal group over twitter Recently, researcher has done a remarkable job of improving the scalability and quality of the community detection algorithm. But unfortunately, due to lack of network information, resultant community structure having lower modularity and normalized mutual information

3 PROPOSED FRAMEWORK

This paper presents a comparative analytical framework to analyze the impact of social theories of social media mining over the performance of the benchmark community detection algorithm as shown in figure 2.

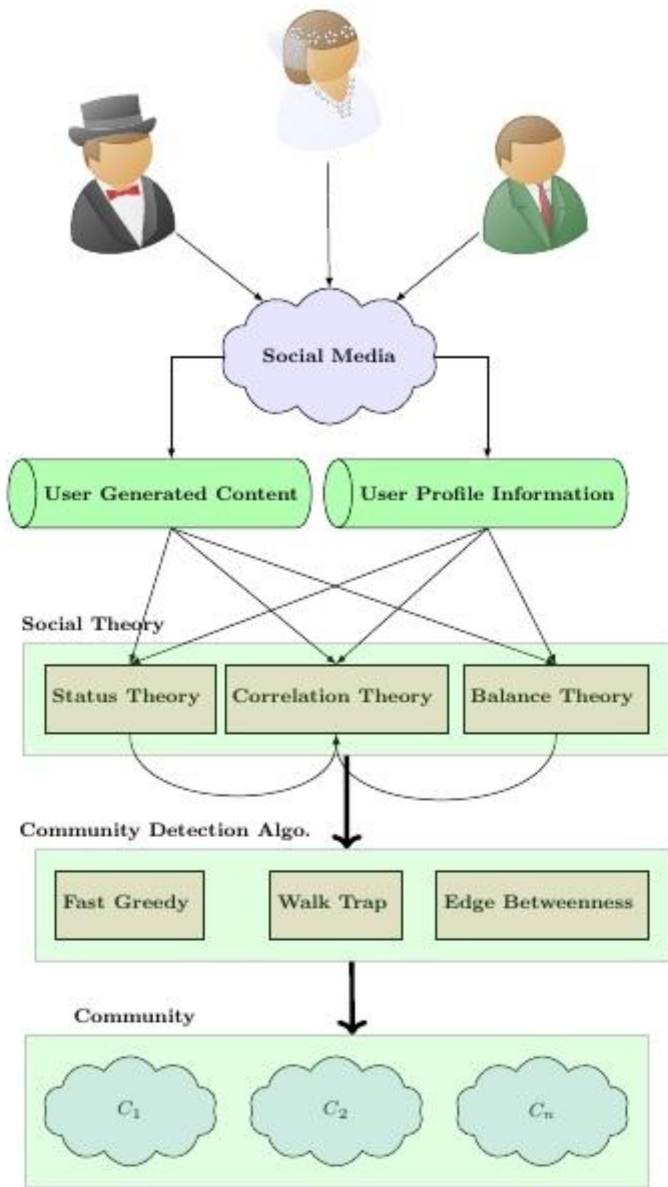

Fig.2 *Proposed Social Theory Based Community Detection Framework*

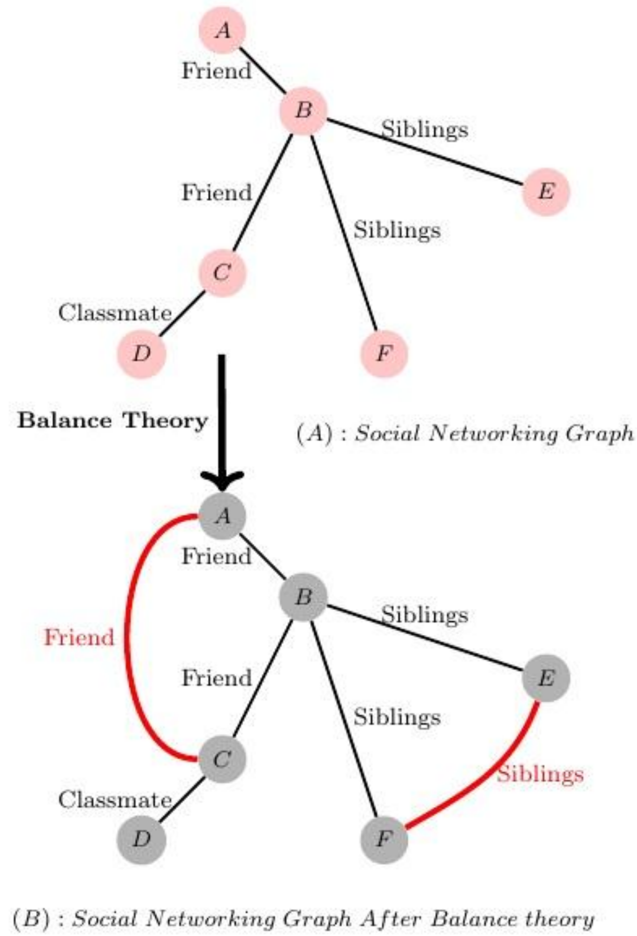

Fig.3 *Social Balance Theory*

3.1 Social Theories

Social theory in social media mining (SMM), analyze and extract useful pattern from user-generated and profile content of social media user. Recently researcher encapsulates SMM with data mining concepts, theories, and algorithms to build an effective approach for extracting communal intersection from user-generated and profile content of social media user. In this section, social theories of SMM are illustrated as follows.

3.2 Balance Theory

Balance theory in social media mining extract hidden relationship among communal node as an implicit relationship. For instance, consider G (U, R) as a social media graph having six user nodes (A, B, C, D, E, and F) and five relationship edges, as shown in figure 3(A). Then after applying the balance theory of SMM, two hidden implicit relationships are extracted over graph G (U, R), as shown in figure 3(B) by the red line.

3.3 Status Theory

Status theory in social media mining extract hidden hierarchical status communal node as an implicit consistency. For instance, consider X(Y, Z) as a social media graph having six user nodes (M, N, O, P, Q, and R) and five status edges, where head node having higher status then respective tailed node as shown in figure 4(A). Then after applying the Status theory of SMM, five hidden implicit status are extracted over graph X(Y, Z), as shown in figure 4(B) by the red line.

3.4 Social Correlation

Correlation theory in social media mining extracts transmit effect via Influence, Homophily, and Confounding parameters among communal nodes as explicit characteristics. Higher status communal node changes the belongingness of its lower status node into their respective community through Influence theory. Whereas, homophily builds the belongingness of similar characteristics node over the same community. However, any online forum creates an environment to make individuals similar, as confounding.

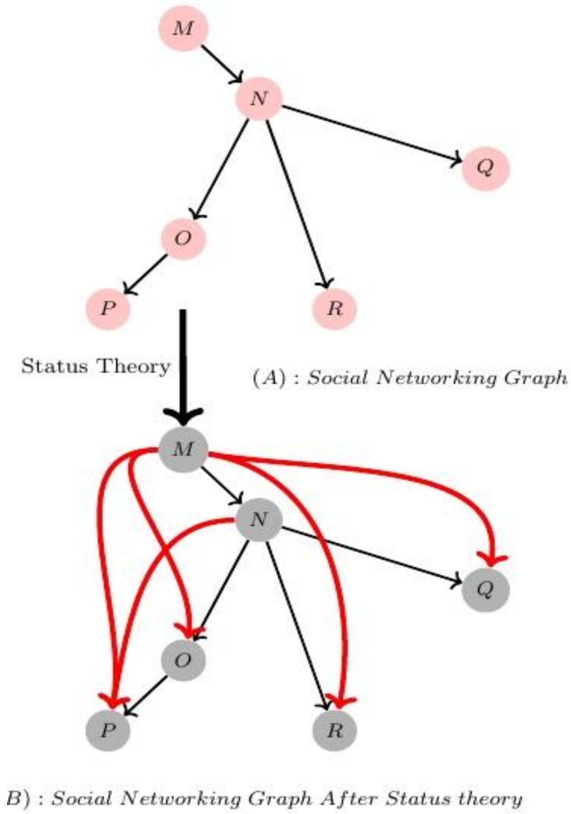

Fig.4 *Social Status Theory*

3.5 Walk trap Algorithm

Walk trap community detection algorithm follow random walk theory, build by Pascal Pons and Matthieu Latapy. Walk trap algorithm trapped casual walker in the dense communal part of the social media graph G (U, R). Evaluate the information spreading probability P_x form user U_a to U_b, then calculate distance measure between communities and finally by applying hierarchical clustering detect desire community. Walk trap algorithm calculates the distance measure among communal node in O (U^2 Log U) average case, O(R U^2) worst-case time complexity with O (V^2) space complexity.

3.6 Edge-Betweenness Algorithm

Edge-betweenness community detection algorithm, identify communities by progressively removing relationship edges from social media graph, and after removing lower weight relationship edge, resultant sub graph consider as community. The edge-betweenness algorithm initially calculate the betweenness parameter of all existing relationship edges. Then after progressively remove relationship edges highest value of betweenness and finally dendrogram sub graph is identified as community structure.

3.7 Fast Greedy Algorithm

Fast Greedy community detection algorithm applied a greedy approach to optimize the modularity score. Initially, the fast greedy algorithm starts with a non-cluster element and form a single tone community. Then progressively, every pair of users compute their current modularity score and merge with similar modularity score subgroup and form resultant community structure having higher modularity.

4 ENVIRONMENT SETUP RESULT ANALYSIS

For performance evaluation of benchmark community detection algorithm has been carried out over six different graphical social media data set, namely Word adjacencies, Zachary karate club, Dolphin social network, Les Miserables, Books about US politics and American College football club data set. The detail network information of data set is illustrated in table 1, where 'V', 'E', 'CC', 'AD', and 'MD' represent the number of Vertex, Edge, cluster coefficient, average degree, and Maximum degree respectively.

Table 1: *Social Media data sets for Community Detection*

Data Set	Network Information				
	V	E	CC	AD	MD
Zachary's karate club (ZKC)	34	78	25.6.	4.5882	17
American College football (ACF)	115	615	5.73	10.71	13
Dolphin social network (DCN)	62	159	30.9	5.1290	12
Books about US politics (BUP)	105	441	-	-	-
Les Miserables (LM)	77	254	49.9	6.5974	36
Word adjacencies (WA)	112	425	15.7	7.5893	49

Performance evaluation of benchmark community detection algorithm with and without social theories are described in tables 2 and 3 as Modulaities and Normalized Mutual information, respectively. Both the evaluation parameter are significantly improved after incorporating social theories with community detection algorithm. The benchmark algorithm, Walk trap, Fast greedy and Edge-betweenness gain approximate 0.3162131 - 0.6029143, 0.334662 - 0.597407 and 0.3505370 - 0.599629 modularity and 0.32965 - 0.73202, 0.34967 - 0.83651 and 0.39254 - 0.84178 NMI over social media data set respectively, as shown figure 5 and 10. Walk trap algorithm leads the modularity and gains the

Table 2: *Comparative Analysis of Modularity on Community Detection algorithms*

Classification Technique	Modularity					
	ZKC	ACF	DCN	BUP	LM	WA
Walk Trap	0.3532216	0.6029143	0.4888454	0.5069724	0.5214055	0.3162131
Fast Greedy	0.3806706	0.5497407	0.4954907	0.5019745	0.5005968	0.3346962
Edge Betweenness	0.4012985	0.599629	0.5193821	0.5168011	0.5380681	0.3505370
Walk Trap + Balance Theory	0.4233015	0.7127023	0.5878464	0.6172628	0.6404769	0.3752342
Fast Greedy + Balance Theory	0.4934114	0.6507124	0.5968565	0.6012507	0.6101731	0.4512847
Edge Betweenness + Balance Theory	0.5539103	0.6917027	0.6268160	0.6219581	0.6811231	0.4912148
Walk Trap + Status Theory	0.4734012	0.7327121	0.6218719	0.6572124	0.6614262	0.4612942
Fast Greedy + Status Theory	0.5214317	0.6629024	0.6418916	0.7212129	0.6324167	0.5012043
Edge Betweenness + Status Theory	0.6011392	0.7223028	0.6928913	0.7515161	0.712459	0.5512948
Walk Trap + Correlation Theory	0.4932419	0.7417523	0.6628837	0.6772124	0.7014293	0.4897948
Fast Greedy + Correlation Theory	0.5332918	0.6814591	0.6521635	0.7572428	0.6515269	0.5227149
Edge Betweenness + Correlation Theory	0.6412528	0.7714569	0.7251691	0.7971421	0.7413228	0.5724142
Walk Trap + Social Theories	0.7112922	0.9124576	0.7751387	0.8892411	0.9318223	0.6214943
Fast Greedy + Social Theories	0.7912729	0.8514971	0.8457421	0.9242465	0.9014257	0.7240406
Edge Betweenness + Social Theories	0.8215723	0.897265	0.9152629	0.9417468	0.9572254	0.7910678

Table 3: *Comparative Analysis of Normalized Mutual Information on Community Detection algorithms*

Classification Technique	Normalized Mutual Information					
	ZKC	ACF	DCN	BUP	LM	WA
Walk Trap	0.73202	0.53045	0.50365	0.48215	0.34197	0.32965
Fast Greedy	0.83651	0.69147	0.65287	0.53249	0.39274	0.34967
Edge Betweenness	0.84178	0.82658	0.71987	0.55241	0.41235	0.39254
Walk Trap + Balance Theory	0.79173	0.64231	0.54735	0.51283	0.44196	0.47572
Fast Greedy + Balance Theory	0.85253	0.77421	0.72981	0.59163	0.47183	0.48351
Edge Betweenness + Balance Theory	0.86192	0.85273	0.76152	0.62975	0.50273	0.52872
Walk Trap + Status Theory	0.82631	0.67354	0.57831	0.53762	0.46198	0.49218
Fast Greedy + Status Theory	0.87164	0.79843	0.73162	0.55241	0.48432	0.52172
Edge Betweenness + Status Theory	0.89175	0.86162	0.78423	0.59083	0.52741	0.54283
Walk Trap + Correlation Theory	0.86109	0.71523	0.62098	0.54721	0.49816	0.52821
Fast Greedy + Correlation Theory	0.89012	0.82316	0.79648	0.63108	0.53192	0.55106
Edge Betweenness + Correlation Theory	0.88102	0.89321	0.81035	0.71054	0.57076	0.59185
Walk Trap + Social Theories	0.95013	0.81034	0.85182	0.77109	0.72513	0.69804
Fast Greedy + Social Theories	0.90172	0.90187	0.83106	0.84329	0.79064	0.81841
Edge Betweenness + Social Theories	0.91109	0.92081	0.89372	0.87105	0.83103	0.85274

highest value over ACF, whereas Edge betweenness algorithm achieves highest NMI information. The performance of the baseline community detection algorithm is significantly boosted up after rectifying network information by incorporating social theories. The community detection algorithm, Walk trap, Fast greedy and Edge-betweenness gain approximate 0.3752342 - 0.712703, 0.4512847 - 0.6101731 and 0.4912148 - 0.6917027 modularity and 0.44196-0.79173, 0.47183 - 0.85253 and 0.50273 - 0.86192 NMI with balance theories over social media data set respectively, as shown in table 2 and figure 6 and 11. In the case of status theory, the community detection algorithm Walk trap, Fast greedy and Edge-betweenness gain approximate 0.4612942 - 0.7327121, 0.5012043 - 0.7212129 and 0.5512948 - 0.7515161 modularity and 0.46198 - 0.82631, 0.48432 - 0.87164 and 0.52741 - 0.89175 NMI over social media data set respectively, as shown in table 2 and figure 7 and 12. Whereas in the case of correlation theory, the community detection algorithm Walk trap, Fast greedy and Edge-betweenness gain approximate 0.4897948 - 0.7417523, 0.5227149 - 0.7572428 and 0.5724142 - 0.7971421 modularity and 0.49816 - 0.86109, 053192 - 0.89012, and 0.57076 - 0.89312 NMI over social media data set respectively, as shown in table 2 and figure 8 and 13.

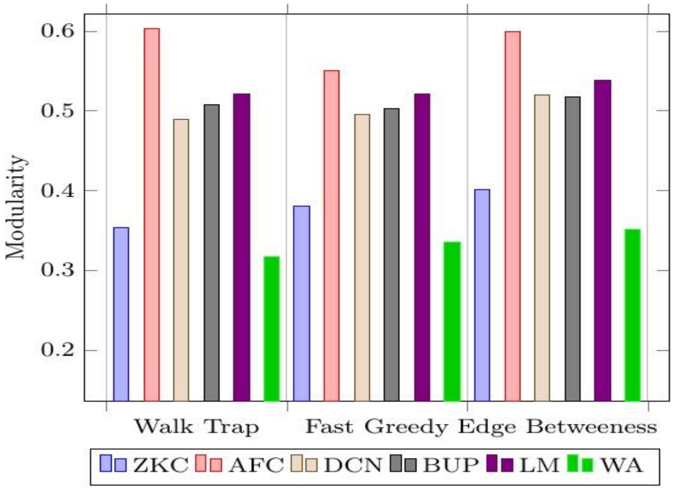

Fig. 5 *Modularity of Community Detection with benchmark algorithm*

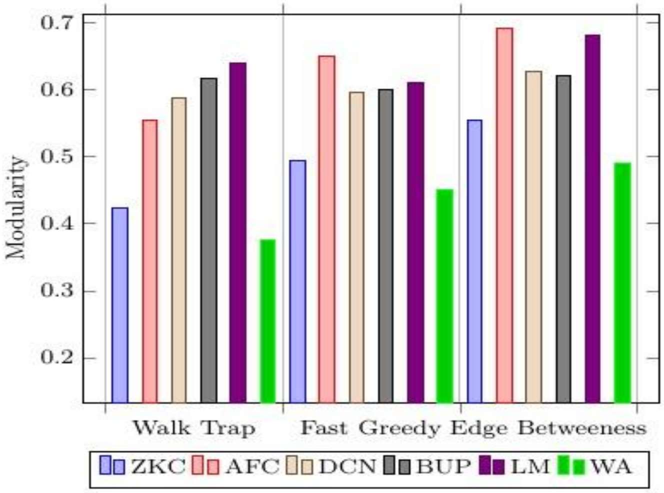

Fig. 6 *Modularity of Community Detection with benchmark algorithm and Balance theory*

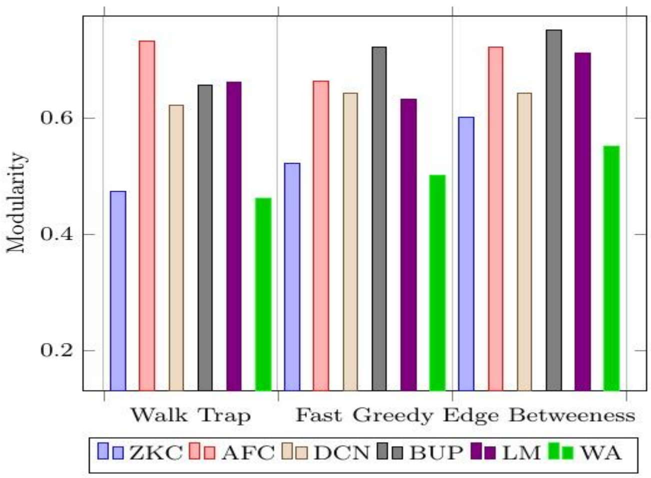

Fig. 7 *Modularity of Community Detection with benchmark algorithm and Status theory*

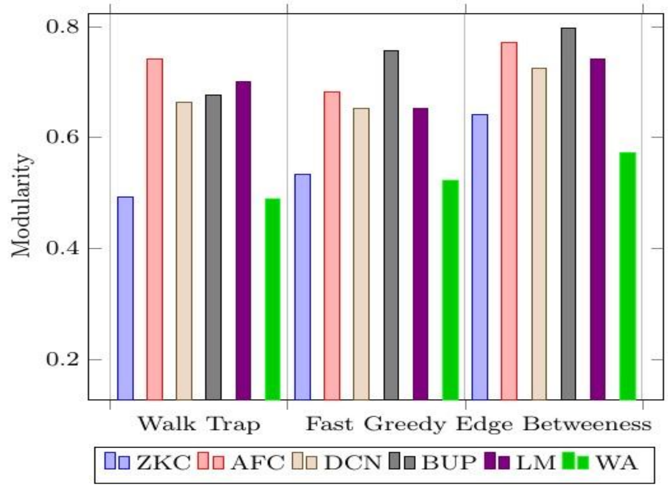

Fig. 8 *Modularity of Community Detection with benchmark algorithm and Co-relation theory*

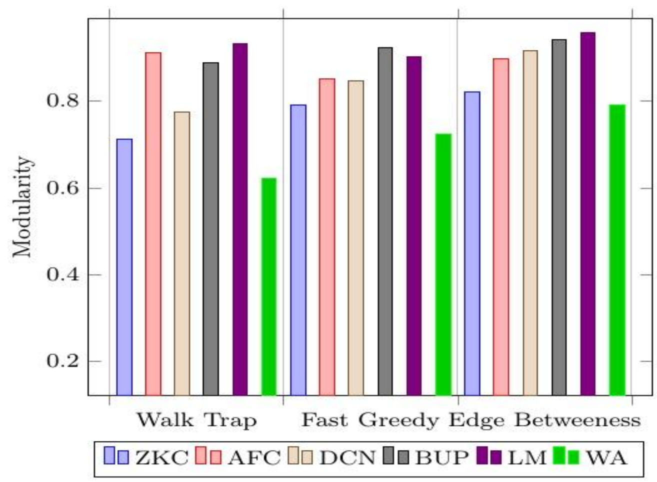

Fig. 9 *Modularity of Community Detection with benchmark algorithm and Social theory*

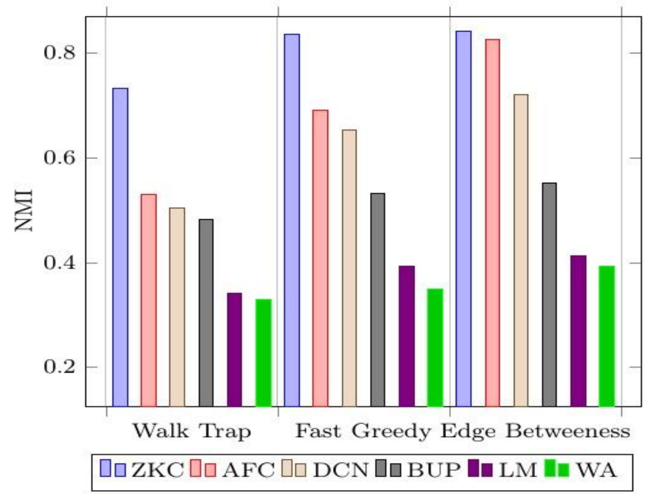

Fig. 10 *NMI of Community Detection with benchmark algorithm*

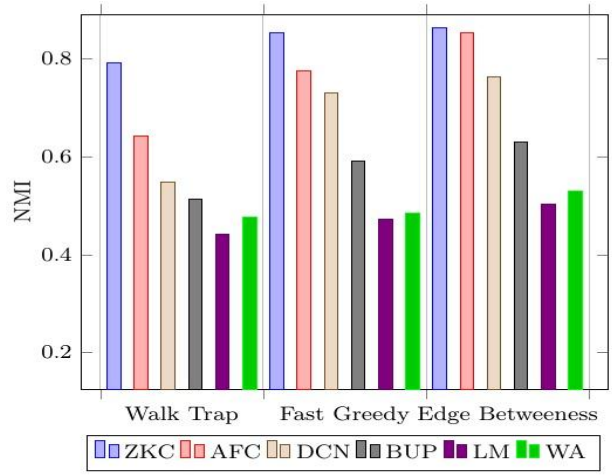

Fig. 11 *NMI of Community Detection with benchmark algorithm with Balance Theory*

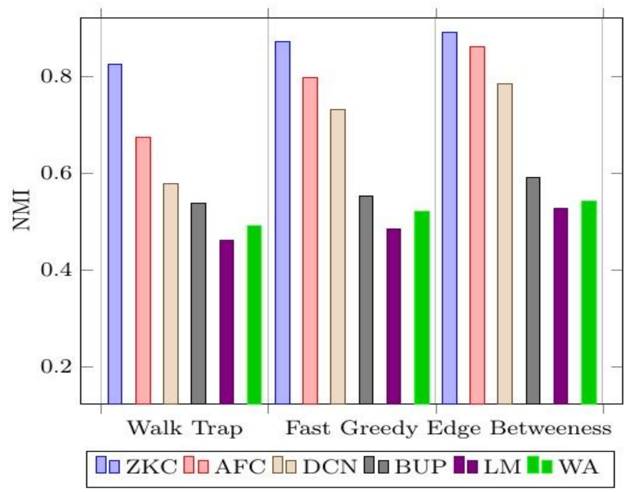

Fig. 12 NMI *of Community Detection with benchmark algorithm with Status Theory*

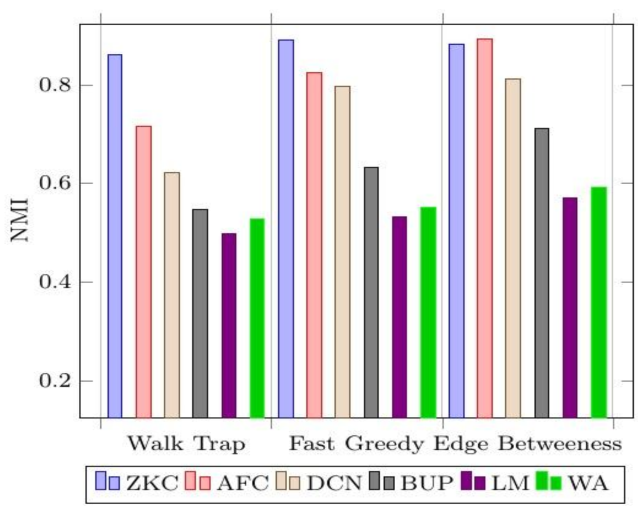

Fig. 13 *NMI of Community Detection with benchmark algorithm with Co-relation theory*

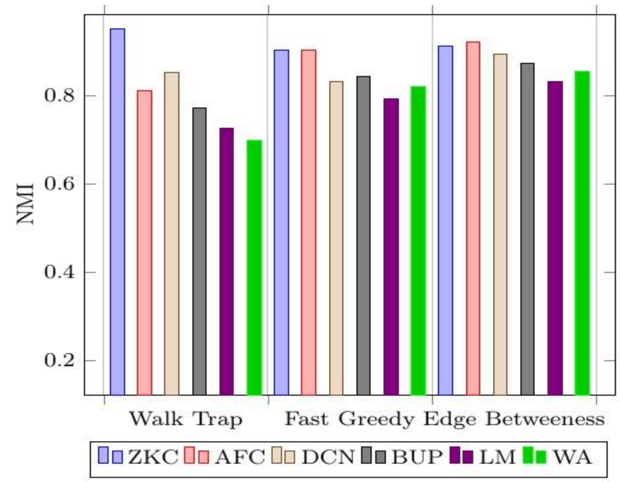

Fig. 14 NMI *of Community Detection with benchmark algorithm with Social theory*

However, after merging all these theories the community detection algorithm Walk trap, Fast greedy and Edge-betweenness gain approximate 0.6214943 - 0.9318223, 0.7240406 - 0.9014257 and 0.7910678 -0.9572254 modularity and 0.69804 - 0.95013, 0.79064 - 0.90172 and 0.83103 - 0.92081 NMI over social media data set respectively, as shown in table 2 and figure 9 and 14. After incorporating social theory with a community detection algorithm, it is observed that the proposed framework gains the highest modularity and NMI over highly dense network as AFC and LM data set.

4 CONCLUSION

Community detection over social media is identified, like-minded people having similar interests. Recently, researcher has done a remarkable job of improving the scalability and quality of the community detection algorithm. But unfortunately, due to lack of network information, resultant community structure having lower modularity and normalized mutual information. This paper proposed a comparative analytical framework that incorporates social theories to extract hidden network information form social media data set. This framework analysis the performance of benchmark community detection algorithm such as Walktrap, Fast-Greedy, and Edge Betweenness over six different data sets. The performance of benchmark community detection algorithms are significantly boosted up after incorporating social theories. Walktrap, fast greedy, and edge betweenness algorithm gain approximate 79%, 80%, and 78% improvement over different variants of data set. After incorporating social theory with a community detection algorithm, it is observed that the proposed framework gains the highest modularity and NMI over highly dense network as AFC and LM data set.

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