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Diversity of Information Diffusion in Online Social Networks: A Comparative Study

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Abstract

Online social networks are being created for social interactions and those users that fulfill this paradigm are the real users of online social networks. As these interactions became diverse, the information that these diverse interactions were carrying also flood the online social networks, thereby creates the diffusions of this diverse information and which in turn creates the numerous phenomena among the users of online social networks. These phenomena are so diverse that as you will change the scale of your view, you will notice a different phenomenon that has been adopted by online social network under scanner, from macroscopic view to microscopic view you will notice this flip of phenomena. Keeping an eye on the already sorted out diversity of works, that are hidden or prevalent, we are going to lay a concrete survey to this diversity in this paper by keeping the motive that every existing attempt paves a way for the new one.

Keywords: Social networks, Online social networks, Social Network Analysis (SNA), Information diffusion, Influential user, Spam, Online social graph.

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1. Introduction:

The term “social networks” was coined by Barnes in the human relations Journal in 1954[1]. The social networks are the networks involving people and their interactions [2]. The social networks of the present era have made an elite formalization into the so called online social networks. Online social networks are the usage of the dedicated website to be interactive with other people[3][4]. The first step towards the online social networks was made by the creation of email, then with the evolution of human societies more and more online social network platforms were created. This evolution of online social networks can be traced as facebook and flicker in 2004, twitter in 2006 and sina microbloging in 2009. Every day a lot of information travels through online social networks and this huge amount of data serves as a base for the computational analysis and scientific work. Due to abundance of online social network data, this data fits in the category of big data [5]. The complexities of this data have made evolutions from fine grain to coarse grain [6] as web shifted from web1.0 to web 2.0 [7]. Since the creation of ARPANET [8] to the creation of complex networks, whether technological such as internet, world wide web etc. or online social networks such as Facebook, twitter etc. [9] content dissemination has been has been the implicit means for their creation. This content dissemination has now been formalized as information diffusion, particularly for the online social networks it is information diffusion in online social networks. This information diffusion in online social networks is a variant of an area of study in social sciences called “diffusion of innovation”, which seeks to explain how, why and at what rate new ideas and technology spread through cultures [47]. As human beings have an innate desire to share information with others [10], so the wide availability of online social network services have encouraged and engaged users to share information and increased the ability of individuals to share information [11]. Social networks are creating a complete virtual environment [12] clearly supports this challenging task of information diffusion [13], because of its diversity and usage;62% of adults worldwide use online social networks and spend 22% of their online time on online social networks on an average [14] and in India people spend one in four minutes online using online social networking sites; more than any other internet websites [15]. Thus, to mine knowledge and analyze this mined knowledge [16] from the data of information diffusion in online social networks is a need of an hour. The information diffusion over online social networks can be better understood as depicted in the figure Fig.1 below.

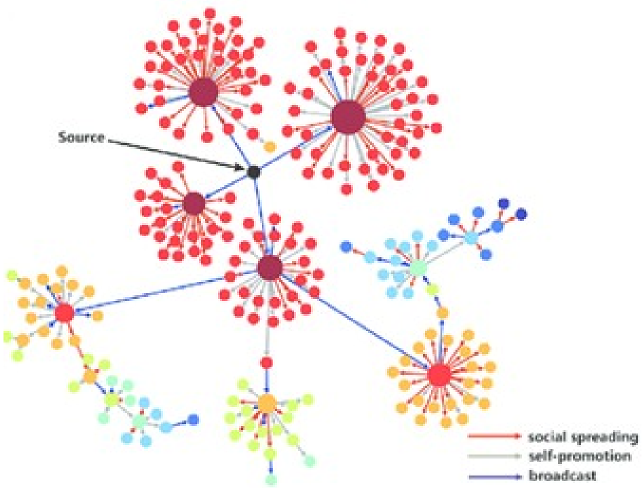


Fig. 1: Information Diffusion in Online Social Networks

OSNs and social media analysis are popular research areas in the contemporary network science [17]; particularly when we talk of information diffusion in OSNs, the diversity and prevalence is apparent almost everywhere; whether it is the case of epidemics in biology, viral marketing in economics, gossip and rumor mongering in sociology and heat diffusion in physics etc. [18]. Researchers have tried to analyze OSNs since the fundamental research discoveries by Girvan and Newman in 2002 [19] and researchers have unveiled this field of information in OSNs through varied dimensions.

2. Related Work

Online social networks and social Media analysis are popular research areas in the contemporary network science [17];particularly when we talk of information diffusion in online social networks, whose diversity and prevalence is apparent almost everywhere; whether that can be the case of epidemics in biology ,viral marketing in economics, gossip and rumor in sociology and heat diffusion in physics etc.[18].researchers have tried to analyze the online social networks since the research discoveries by Girvan and Newman in 2002[19] and particularly to this subfield of information diffusion in online social networks; researchers have unveiled this field of information in online social networks through varied dimensions. Some of attempts related to this paper are:

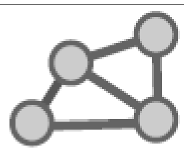
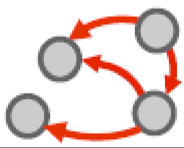
S. Wu et. al. classified users of online social networks [20], A. Guille et. al. used T-BASIC model to study information diffusion in online social networks [21], w. chengjun et.al. extended ABXC model to ABXCT model for online social networks [22], A. Das et. al. studied the effect of persuasion properties of messages in online social networks [23], A. Silva et. al. proposed profile rank method for finding relevant content and influential users in online social networks [24], Y.Matsubara et.al.

proposes a SPIKEM model for studying the rise and fall patterns of influence propagation in online social networks [25], Y.Yang et. al. uses RAIN model for modeling information diffusion in online social networks [26], L. Liu et.al. proposed a susceptible view forward removed (SVFR) model to describe the information diffusion in online social networks [27], X.Ren et. al. proposed a Role and Topic Aware Independent cascade (RIIC) model to uncover information diffusion in online social networks [28], A. Susarra et.al. analyzed channels that are central to the information diffusion in online social networks [29], L. Taxidou et. al. proposed Prov-SAID model to tackle diffusion and provenance in online social networks [30], M. Farajtabar et.al. Proposed a probabilistic model for finding out dynamics of information diffusion and network evolution in online social networks [31], S Dhamal et.al. used independent cascade to tackle the problem of finding K users in many phases [32], J.Ping Huang et. al. proposes a game theoretic approach to capture information diffusion in online social networks [33], L.Taxidou et. al. proposes an information cascade model to find the influence paths in online social networks [34], Y.jianget. et. al. proposed a multi agent perspective for information diffusion in online social networks [35], L.Weng proposed an agent-based model to demonstrate the role of finite individual attention to explain heterogeneity of global patterns [36], Y.Matsubara et. al.proposes SPIKEM model for uncovering information diffusion in online social networks [37], A.Kunle et. al. proposes a Multiplex Influence Maximization (MIM) approach to find influential users [14], F. Wang et. al. proposes a mathematical equation for modeling information diffusion in online social networks [38], V. Arnaboldi et. al. models information diffusion as ego networks [12], M.Farajtabar et.al. uses associative rule learning approach for finding influential users in online social networks [39], A.Guillie et. al. proposes a K core method to find influential spreaders [4], C.Yang et. al. proposes a Neural DiffusionModel(NDM) of deep learning for tackling the micro level independent cascade [40], C. Gatti et. al. proposes a multiagent social network simulation for tackling information diffusion in online social networks [41], H. Kim et. al. proposes a hydrodynamics prediction model for information diffusion in online social networks [42], A. Davoudi et. al. proposes a nonlinear differential equation to study information diffusion in online social networks [43], K. Saito et. al. proposes a model for hot span detection in online social networks [44], Z. Wang et. al. proposes a polling-based method to tackle the activity maximization problem [45], Q. Wang studies the problems associated with online social network data [46], E.Yoneki et. al. studies influence maximization problem [47], P.Sermpezis et. al. studies information diffusion in online social networks as epidemics [48], M.Farajtabar et. al. proposes a probabilistic generative model for information diffusion and network evolution [49], N.Diu et. al. proposes TOPICCASCADE for topic specific information cascade [50], E.Bakshy studies influence of users with each other [51],S.Jalali et.al. proposes a dynamic model to target petition diffusion in online social networks [52], C.Jiang et.al. a game theoretic formulization for information diffusion in online social networks [53], M.K. Mahdi et .al. Proposes SFA-ICBM model for modeling independent cascades and finding influentials [54], F. Wang et. al. proposes linear diffusive model for finding influence power of spreading and decaying of news stories [55], P. Tanwar et. al. studies spam detection using Latent Dirichlet Allocation model [56], J.Bright et. al. studies the sentimental analysis [57], J.Obregon et. al. proposes a process model based on extension of Flexible Heuristic Miner [58], L. Jain et. al. uses a Firefly algorithm to find global and local opinion leaders [59], J.Dai et. al. proposes LNC Local Neighbor Communication model to find influential users [60], D. Pothineni et al. attempts to measure different thermodynamic variables when taking online social networks as thermodynamic system [61], J. Alemany et. al. presents a new Risk model based on friend layers [62].

3. Components of Information Diffusion and Models for their handlings

In this research area of information diffusion in online social networks, we are always revolving around the four components: (1) People (2) Content (3) Network and (4) Diffusion [20][36] as depicted in the Table. 1 below:

Table1: Components of Information Diffusion

Component	Representation	Function
People		These are the actors of seen who produce information(content) for diffusion in OSN's
Content		This is the element that people create for diffusions in OSN's
Network		This is the output that people with diffusing contents create in OSN's
Information Diffusion		This is process that can reveal varied pattern formations that have led to network formations in OSN's

Each of these components acts a full-fledged dimension for researchers of information diffusion in online social networks, to tackle the problems intrinsic in these components, so we are going to take each component as dimension of information diffusion in online social networks and the popular problems associated with each component.

3.1 People:

People are the real physical entities that are apparent on online social networks. Their reflections on online social networks are felt as user accounts, pages, handles etc., when online social networks are represented by underlying online social graphs, they are modeled as nodes of the given graph.

The most popular problem that is studied in the study of information diffusion under this domain is influential user detection in online social networks. Much research has been done in this problem area of information diffusion in online social networks, so we are going to explore some of the good attempts that have been made to tackle this problem of finding influential users in online social networks.

3.1.1 Influential User Detection:

There is no concrete definition of influence and so influential user in online social networks [35], each researcher takes it according to implicit character of users in datasets of online social networks under scanner [59].Influence may be loosely defined as the capacity of effecting the character, development, growth, popularity and behavior of others in online social networks [61] and the people that show this character at the peak scale are referred to as influential users. To detect these influential users is a young problem in the domain of information diffusion in online social networks. Some of the works that have taken the cognizance of finding influential users in online social networks are:

a) Profile Rank

Profile rank is similar to the idea of Page Rank Algorithm. This method finds influential users; Measures Profile Rank using random walks in user content graph. This method can also work for the content relevance [24].

b) Multiplex Influence Maximization (MIM):

Multiples Influence Maximization (MIM) method finds influential users that are acting asseeds. Most users are overlapping [14].

c) Associative Rule:

This method finds influential users and belongs to the machine learning domain of studies. Uses support, confidence, and lift parameters to learn influential Users. This method is faster, but its application for bigger pages/contents is not natural [39].

d) K Core Approach

K core approach finds influential users. Uses graph structure of the given network for finding core K and uses minimum degree concept to tackle problem. This approach uses maximal connected sub graph concept to uncover k-Core of given online social graph [4].

e) SFA-ICDBM:

This method finds most Influential users in the given Network and Uses extended CPM to find initial communities. Makes use of belonging coefficient to find influentials. Takes the cognizance of overlapped nodes while considering the solution [54].

f) Modified firefly Algorithm:

This Approach finds local and global influential users (opinion leaders). Opinion leaders are found in inter-class community and intra-class community that have been found by modified Louvain method earlier. This Algorithm Ranks users based on attractiveness score to find opinion leaders. Results show that the method performs best when operated by different SNA measures [59].

g) Interest Group based influential user detection:

This Approach finds influential users in each Interest Group. Model is based on local graphical traversal in each Group. Model works well for finding observer nodes in each Interest Group [63].

These are some of the problem solutions that are considered by different Researchers and every solution creates new window for making the solutions possible for finding the people (users), whom we call as influentials.

3.2 Content:

It is this content that brings people to online social networks; some to view the content, some to share the content and some to comment on content. Content takes many forms depending on the online social network platform under usage; twittes on twitter and messages on Facebook etc. [36]. Content of online social networks are mostly modeled as weights of links when represented in graphical form and the movements of contents depicted as directed links when represented by online social network graphs. One of most difficulties that have posed the hurdles to research on information diffusion in online social networks is the lack of sufficient and complete communication content (data) of online social networks [47]. The problem that is related to this content in the area of information diffusion in online social networks is Spam detection, so we are going to address the same problem and the associated solutions here:

3.2.1 Spam detection and its solutions:

Cyber criminals are generating the attacks using a growing arsenal of weapons such as spam [64]. Spam was first invented by Monty Python in year 1970[56].It is possible for attackers to use unwanted data to be send as content called spam over Online Social Networks[65],so our problem in hand is to detect this spam as a content under the of information diffusion in online social networks; some of the attempts are:

a) Latent Dirichilet Allocation (LDA):

This Method Detects spam and no spam data.Uses a corpus and Dictionary built on twitter data sets and Uses LDA as classifier that classifies matrix (corpus) into two matrices Document-topics matrix and Topics-term matrix.LDA detects spam data mostly up to thirty characters [56].

3.3. Network:

The online social networks which involves social interactions can be modeled as graphic networks; graphs with adopted weights as communication contents[66],so online social networks can be represented by a graph G(V,E) with V as a set of nodes as people(users) and E as set of edges representing communication n contents[28][2].these online social graphs can be directed or undirected based on the character of underlying online social network[36].these online social graphs can be represented by adjacency list,adjancey matrix[3][67],incidence lists, incidence matrix[5];use list representation when complexity of online social network under scanner is small and uses matrices when network is dense [67].the best problem that is being studied with related to structure of a social graph of underlying online social network in the field of information diffusion in online social networks is network evolution; which captures how network evolve during diffusions of interactions in online social networks. Many researchers have opted to go for the discourse of this problem and solve it as:

3.3.1 Probabilistic model:

This Model tackles the problem of network evolution in online social networks; Models network link creation as “information driven” survival process and couples the intensity of survival process with retweeting events. This Model Uncovers the joint dynamics of information diffusion and network evolution and develops a convex optimization frame work to learn the parameters of the model from the network evolution traces. This Model performs best on real and synthetic data [31][49].

The network evolution is still emergent problem and needs ocean of ventures to solve the real social evolutions in online social networks.

3.4 Information Diffusion:

when apiece of content(information) flows from one individual to another or from one community to another in an online social network ,an act of information diffusion is said to have occurred in that online social network[1][68].when this act of information diffusion in online social networks is studied under the broad domain of information diffusion of SNA,we often encounter the “3 w issue”, the three W’s are ”what”, ”why” and ”where”. the first w “what” refers to the question “what information is there to be found in online social networks", the second w is "why" refers to the question "why has the information propagated this way", the third w is "where" refers to the question "where will the information be diffused in the future" [1][48].this 3W issue has been best studied under the broad spectrum of two information diffusion process models:-

Explanatory models and prediction models.

3.4.1 Explanatory Models:

Such models explain the process of information diffusion that has been adopted by the given online socialnetwork under scanner. These models reflect the real human behavior. The best example of these models is epidemic models such as SIS, SIRetc. Models [7]. Parameters of these models are easily available and are little complexin case of modeling complexities [12][3].

3.4.2 Prediction Models:

Such models long for tackling the decision problem [66] which can take yes or no states for deciding whether diffusion will usher or not from current known state to unknown state; unknown state belongs to future.

These models do not reflect the true nature of human socialism.

Parameters of models are hard to model, so these models are highly complex in nature.

The best examples of these models are independent cascade model, linear threshold model etc…, [12][3][46][7][69][70].

Keeping these two models of information in eye, we can look at these two models with respect to the "3W issue" and their capabilities of modeling real human behavior; this is shown below in the Table 2:

Table 2. Comparative Analysis of Information Diffusion Models

Model of Information Diffusion	Tackle W1 of 3W Issue	Tackle W2 of 3W Issue	Tackle W3 of 3W Issue	Reflect True Human Behavior
Explanatory model	Yes	Yes	No	Yes
Prediction model	Yes	Yes	Yes	No

This table reflects the real functionalities of the two-process models of information diffusion in online social networks.

Researchers have used both the models to put their efforts on information diffusion in online social networks keeping the two model paradigms as base, so we are going to uncover some of the efforts that have been made for each of the models here.

The components of information diffusion in collective and comparative way can be shown as depicted in the table Table3.

Table 3. Research Components of Information Diffusion in Online Social Networks

Research Component of Information Diffusion	Modes of Handling	Purpose of Component in the Light of Handling Mode
Information Dissemination	Independent Cascade Model	Studies the information cascades by identifying the transmission of activeness from active node at time t to inactive node at time t+1 depending on the weight of connecting edge.
	Linear Threshold Model	Studies the information cascades by identifying the transmission of activeness by simply using the threshold function at an inactive node by taking the input from previous active nodes.
	Epidemic model	Studies the information cascades by identifying the transmission of activeness based on epidemiology of medical science.
Community Detection	Disjoint Community Detection	Finds the community structure in OSNs but node belongs to a single community.
	Overlapping Community Detection	Finds the community structure in OSNs but node may belong to multiple communities.
Influence Maximization	Influential Users as Seeds	Finds the limited influential users by selecting them in such a way that they increase the influence dissemination in the given OSN.
Influential User Detection	Global and Local Influential Users	Finds the influential users that are unlimited in nature depending on the given OSN, but those users are global or local to the network of the given OSN.

4. Conclusion

We have taken a focusable view on the exiting windows that have been projected by different researchers in the field of information diffusion in online social networks. We should bring this legacy of work into vigil and should transform our new ideas into the real models of this day in the light of already existing work that has been made.

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