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Analyzing the Impact of Information Diffusion Models on Social Networks

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Abstract

Today, personal life has been induced by online informal communities all over the world with the increase of social networks. They expect to move more personal information to online communities. Hence, online social systems can mirror the structure of human culture. A snippet of data can be traded or diffused between people in informal communities. From this dissemination procedure, bunches of dormant data can be mined. It very well may be utilized for showcase anticipating, gossip controlling, and sentiment checking in addition to other things. Nonetheless, the exploration of these applications relies upon the dispersion models furthermore, techniques. Hence, we review different data dissemination models from late decades. From an examination procedure see, we isolate the dispersion models into two classes—informative models and prescient models—in which the previous incorporates plagues and impact models and the last incorporates free course, direct limit, and game hypothesis models. The motivation behind this paper is to explore the examination strategies and methods, and contrast them agreeing with the above classes. The entire examination structure of the data dissemination models dependent on our view is given. There is a discussion towards the each segment, enumerating related models that are referenced in the writing. We presume that these two models are not autonomous, they generally supplement each other. At long last, the issues of the informal organizations research are analyzed, and future investigations are proposed. In this paper we proposed Profile Based Equal Responsibility Rumor Diffusion Game Model (PERRDGM) which is compared with Equal Responsibility Rumor Diffusion Game Model (ERRDGM) and we observed that cover degree is improved by 6% and precision by 1% using proposed model.

Keywords: Profile Based Equal Responsibility Rumor Diffusion Game Model (PERRDGM), Game theory model, past rumor diffusion experience, user profile.

I. Introduction

With the development of social networks, there are an ever increasing number of new platforms, e.g., Facebook and Flickr in 2004, YouTube in 2005, Twitter in 2006, and Sina Micro-blog in 2009. The ways by which individuals get data have changed. Previously, people were passive receivers of information yet now they are its active publishers and communicators. If data streams starting with one individual or network then onto the next in a system, at that point a data dispersion process—otherwise called data proliferation, data spread, or on the other hand data scattering—has happened.

Much research is done to analyse the breaking down of data diffusion, with most analysis researching which variables influence data dissemination, which data diffuses most rapidly, and how data is scattered [2,3]. These inquiries are addressed utilizing data dissemination models and different strategies, which assume a significant job in understanding the

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dissemination. We don't have the foggiest idea why the data streams to this heading in interpersonal organizations, in spite of the fact that we have seen the upsides of an informal organization in data dispersion. In the event that, utilizing data diffusion models, we can work out who the significant clients are, and which factors are impacting the data dissemination process, at that point we can understand better.

A decent performance model is significant for seeing how to anticipate furthermore, impact data dispersion, and has noteworthy reference an incentive to different applications, e.g., rumor controlling [4–6], conduct investigation [7], checking popular feeling, the investigation of psychological phenomena [8], and for asset allocation in general public health frameworks [9]. Without a doubt, the coming of OSNs likewise drove us to a huge progression in the investigation of human online conduct.

Truth be told, large information originating from OSNs speak to an important wellspring of data to depict the elements of complex social phenomena (e.g., the dissemination of data in the system, the arrangement of social connections and networks), which are hard to examine with customary examination strategies regularly dependent on reviews and interviews.

A ton of exertion has been placed in the most recent years to portray OSNs by considering their charts, since this is the characteristic approach to examine basic properties of human social connections in OSNs. The greater part of the writing has concentrated on plainly visible properties of OSN charts, i.e., the basic qualities of the worldwide system framed by all clients and their associations.

A comparatively less investigated but significantly important subject of investigation are the microscopic properties of OSNs, and primarily the basic qualities of our personal social networks, also called ego networks. In the human sciences literature, it is notable (e.g., [2]) that the qualities of inner self systems are major to decide key aspects of human conduct, for example, trust, sharing of resorces, and arrangement of networks.

From reference works in psychology and anthropology (e.g., [3–6]), we realize that the properties of offline ego networks are obliged by a progression of psychological and time limits, which bound the measure of connections that every individual can effectively keep up because of their characteristic expense regarding 'computational resources' for the mind. In particular, psychological requirements limit the complete number of dynamic connections people can keep up at a non-unimportant degree of closeness. This breaking point is on normal around 150 connections, which is known as the Dunbar's number [3].

The same imperatives likewise direct explicit structures as indicated by which social connections are sorted out inside the sense of self system, as clarified in detail in Section 2. Ongoing examinations of the basic properties of well known OSNs (i.e., Facebook and Twitter) uncovered that online sense of self systems have similar properties of disconnected inner self systems, with comparative size also, the equivalent progressive structure [7–9]. This affirms ego network properties rely principally upon psychological imperatives of the human mind, and are not affected by the utilization of explicit correspondence equipment, for example, cell phones [10] and furthermore Online Social Networks.

In such manner, Facebook and Twitter do not appear to improve human social limit, however they just speak to extra social channel we can utilize as shown in figure 1. Additionally, notwithstanding affirming that notable highlights of human inner self systems too show in OSNs, these investigations have uncovered extra properties [7], which had been estimated [11], yet never saw due to absence of large information sources. This exhibits OSNs can be utilized likewise as a 'social magnifying instrument' to explore novel key properties of our social conduct.

Ongoing outcomes introduced, e.g., in [12–14] show that the examples of data dispersion we see in OSNs firmly rely upon the structure of the clients' inner self systems. In this way, by understanding the last it is additionally conceivable to structure OSN administrations where the highlights of sense of self system structures (and the clients' conduct they decide) are abused to streamline information the board. For instance, as showed by Lerman [15], models of data dispersal in OSNs that consider the compelled idea of human online social conduct defeat some inborn confinements of past cutting edge models [16].

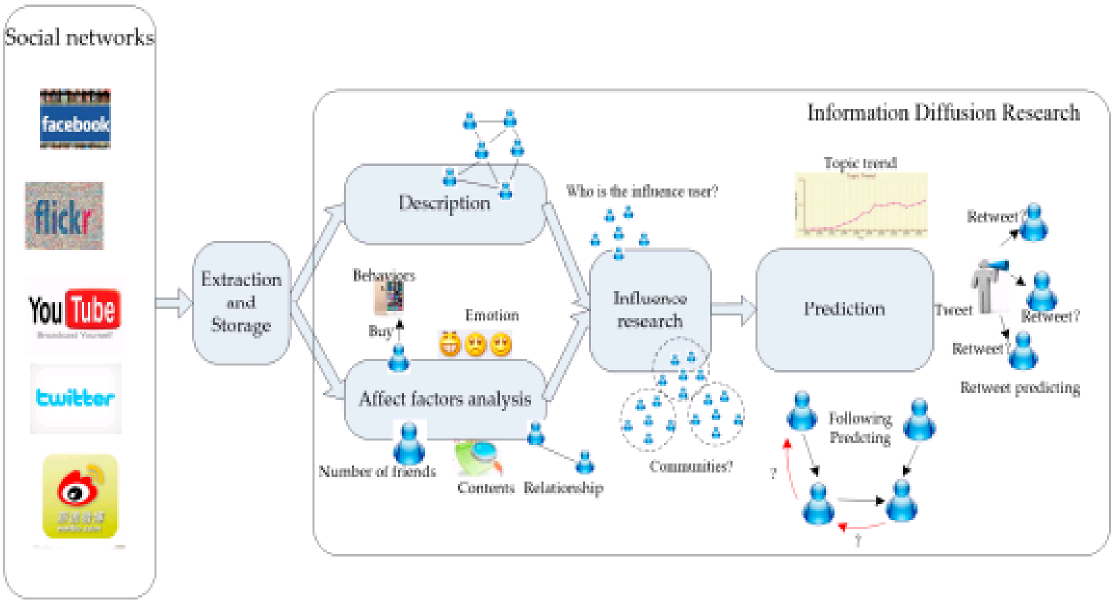


Fig 1: Information Diffusion Research

II. Related Work

Researchers and academicians had proposed many diffusion models [24] [29]. Some of them are one-way information diffusion in a star-shaped social network [28], susceptible-infected-removed (SIR) model [25], SPNR (Social Network Rumor Diffusion Predication**)** Model [26], HISB(Human Individual and Social Behaviors) Model[12].

III. Proposed Method

There are two diffusion models based on game theory. They are Basic Rumor Diffusion Game Model (BRDGM), Equal Responsibility Rumor Diffusion Game Model (ERRDGM). We propose Profile Based Equal Responsibility Rumor Diffusion Game Model (PERRDGM) in this section.

For this model, we are considering the task of spreading a gossip shared by two game players, the current user and his / her neighbors. In other words, if the rumor is transmitted by more neighbors, the weakening of the existing consumer reduction. The Process involved in the proposed system is described using the Figure 2.

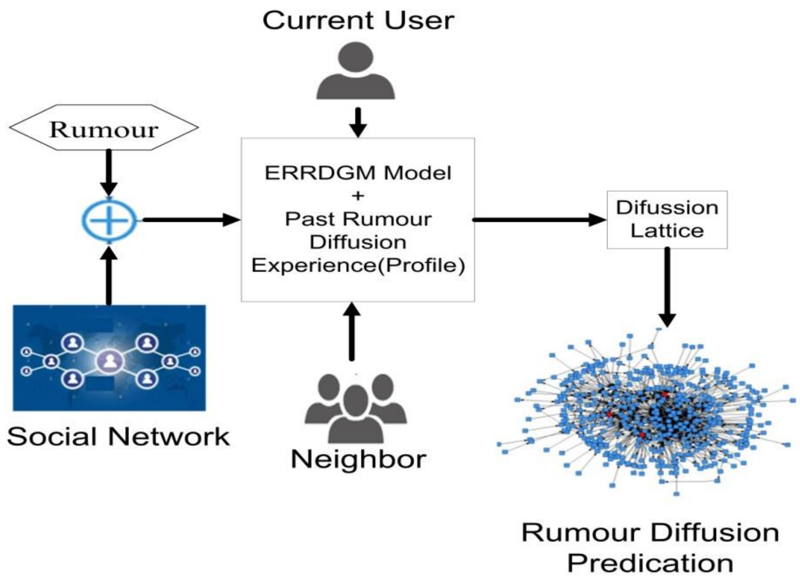


Fig 2: Process of Predicting Rumor diffusion by considering user profile.

The game process is defined as follows:

(1) Game players are defined as GP = {k, neighbor(k)} which includes the $node_k$ and its neighbors neighbor(k).

(2) Game strategy is denoted as GS = {GS_c, GS_n}, where GS_c is the game strategy for $node_k$, GS_n is the game strategy for neighbors. GS_c = {retweet, non-retweet} GS_n = {0, 1,….,*l*} where *l* is the number of neighbor who doesn't diffuse the rumor.

(3) Game revenue function is denoted as GRF = {F_C , F_N }. Where F_C defines revenue function of $node_k$ and F_N defines Revenue function of neighbors.

According to the game process, we have a game revenue matrix, which is shown in Table 1.

We carry out the game cycle between the players after receiving the game revenue matrix. Finally, the game reaches the balance state of Nash that is treated as a constant rumor spreading state and the nodes are selected in the Strategy chosen for each nash equilibrium node as diffusion nodes and non-diffusion nodes. We divide the diffusion process into the game and diffusion process to get a diffusion network. In the game, we use the approach proposed for calculating the diffusion nodes. We use a grid structure to record the diffusion path in the diffusion process.

Table 1: The revenue matrix of PERRDGM model.

Current/Neighbor	0	1	….	n-1	n
Retweet	$F_C(0)$, $F_N(0)$	$F_C(1)$, $F_N(1)$	…	$F_C(n-1)$, $F_N(n-1)$	$F_C(n)$, $F_N(n)$
Non-retweet	0, $F_N(0)$	0, $F_N(1)$	…	0, $F_N(n-1)$	0, $F_N(n)$

IV. Experimental Setup

We scampered four rumors with diffusion networks to reinforce our model's performance. The What's app, one of the biggest social media, was a crawler for our experimental data set. We have collected all the information, including contact ties, social networks, user information, etc. They have been transformed into a structured data set. In the different fields, four rumors are chosen.

Rumor 1 is part of the financial problem. Rumor 2 is part of the topic of social events. Rumor 3 is part of the topic of health. Rumor 4 is related to promotion offer.In addition we crawled around all nodes relating to rumor diffusion, four rumors and nodes of non-diffusion connecting socially linked diffusion nodes. Table 2 outlines the status of four rumors.

The four rumors were widely spread in whatsapp, which is one of India's largest social networks. We only crawled a sub-set of diffusion network due to the limitation of the What s device. While the network of diffusion has just 415 nodes included in rumor 2, the diffusion cycle can be seen.

Table 2: The details of rumor diffusion networks in dataset.

	Rumor Content	Diffusion nodes	Total nodes
Rumor 1	The Government of India is giving Rs. 10,000 per month for the families who lost their jobs during Covid-19 pandemic.	1543	37,102
Rumor 2	More than thousand people were infected with corona virus after attending to an event organized by jewelry shop owner in Haryana.	415	743
Rumor 3	Drinking alcohol can boost immunity levels in an individual, thus resist and combat with corona virus.	3532	13,213
Rumor 4	Whats app is straight away crediting $1000 in the individual accounts who are downloading its app before 5.00 pm today. You can only claim and get credited once and it’s also limited. Get your offer instantly.	32,154	12,365

Two measures are used in our experiment to confirm the performance of our ERRDGM model. First of all, we test the similarity of the simulated rumor diffusion network with the real rumor distribution network using the cover grade. Secondly, to measure the degree of prediction we use precision for broadcast nodes and nodes for non-diffusion. The degree of cover and accuracy calculation are as follows:

$$D_0 = X_{pd} / X_{td}$$

$$P = X_r / X_t$$

Where X_{pd} is the number of real nodes found in prediction to rumor diffusion, X_{td} is the number of distribution nodes within true network diffusion, X_r is the number of correct prediction nodes, including diffusion nodes and non-diffusion nodes, X_t is the number of full nodes.

In this game we just spread rumors and simulate the rumor diffusion cycle using the rumor sources node. The parameters are set as follows: u=10, α= 0.4 β=0.6 γ=0.5 and *v* obeys a normal distribution of (0; 200). To effectively show the performance of PERRDGM model, we use ERRDGM model as our baseline.

V. Results

We perform the process of equal responsibility on an iterative basis and simulate the diffusion of social networks to determine the diffusion scale of the rumor diffusion. Since many nodes are available in social networks and a 2D social network graph is hard to draw, we only display nodes contained in a simulated diffusion network as diffusion nodes by the PERRDGM model.

The following are the conclusions from the experimental results:

(1) The PERRDGM model is better than the ERRDGM model. Compared with the ERRDGM model, the cover degrees of rumor diffusion predication are improved 6%, 6%, 6% and 6% for rumor 1, 2, 3 and 4 respectively as shown in Table 3 and Table 4.

(2) The PERRDGM model is better than the ERRDGM model. Compared with the ERRDGM model, the precision of rumor diffusion predication are improved 1%, 1%, 1% and 1% for rumor 1, 2, 3 and 4 respectively as shown in Table 3 and Table 4.
(3) The comparison of rumor diffusion network and simulated rumor diffusion network of PERRDGM and ERRDGM is shown in the figure 4.
(4) The comparison of cover degree and precision with the increasing network scale is shown in Figure 3.

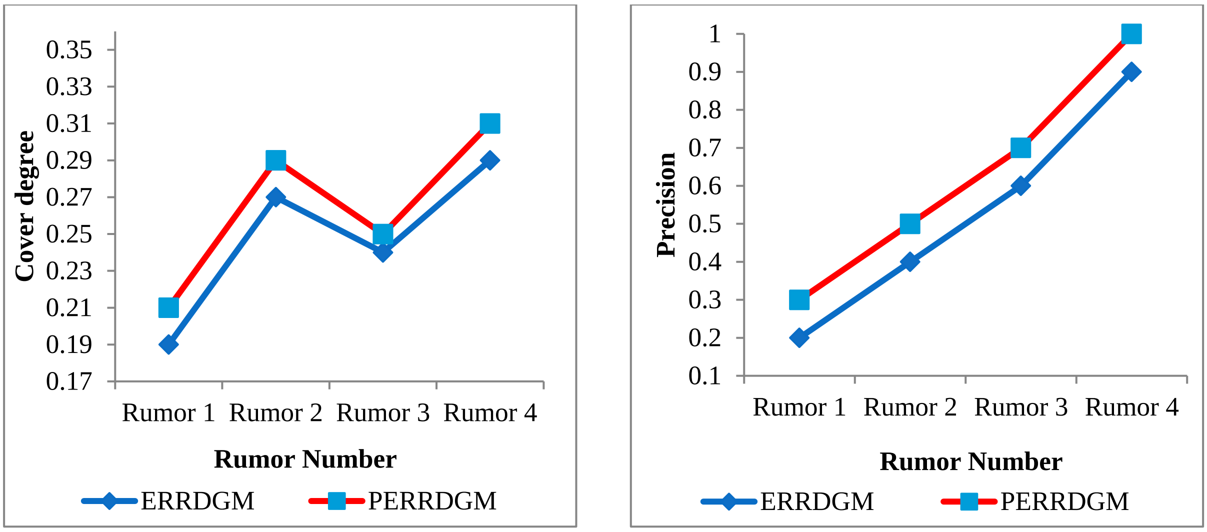
Table 3: The performance of ERRDGM model.

	Diffusion nodes	Total nodes	Diffusion nodes in the model	Cover Degree	Precision
Rumor 1	1543	37,102	3,453	23%	87%
Rumor 2	415	743	200	26%	43%
Rumor 3	3532	13,213	2,543	29%	72%
Rumor 4	32,154	12,365	5,654	26%	68%

Table 4: The performance of PERRDGM model.

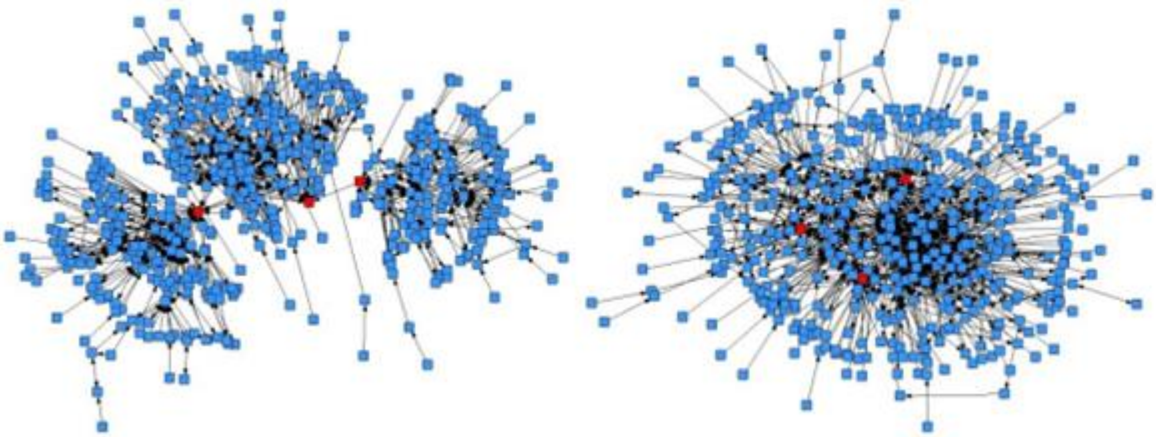
	Diffusion nodes	Total nodes	Diffusion nodes in the model	Cover Degree	Precision
Rumor 1	1543	37,102	3,453	29%	88%
Rumor 2	415	743	200	32%	44%
Rumor 3	3532	13,213	2,543	35%	73%
Rumor 4	32,154	12,365	5,654	32%	69%

The diffusion networks simulated are similar to the actual broadcasting networks. These results show that the rumor diffusion scale and network structure can be effectively predicted by our approach. The diffusion scale is specifically correlated with the diffusion series as this cover degree is increased; it is more related to the user's attribute and circumstances. The PERRDGM model further shows a major change in the delivery networks of small rumors. We think it is important because at the beginning of rumor spreading it can simulate the rumor-dissemination process and save plenty of time to choose the right rumor strategy.



(a) Cover Degree (b) Precision

Fig 3: The comparison of cover degree and precision with the increasing network scale.



(a) PERRDGM (b) ERRDGM

Fig 4: The comparison of rumor diffusion network and simulated rumor diffusion network

VI. Conclusion

Over years, a variety of social networks have emerged for people to stay in touch with others advantageously. A lot of data can in this way be created inside these networks that can reveal to us who the most notable individual is, who a point chief will be, why a situation will develop with a particular goal in mind, and other significant things. To tackle these issues requires multidisciplinary research that draws on the fields of software engineering, yet additionally humanism, brain science, financial matters, and others. Scientists have manufactured certain models to clarify the dissemination marvel, and others to anticipate future dispersion, which are all founded on AI. The essential objective of data dissemination examination is to outline the dispersion procedure. The pandemic model is the principal decision for this examination . It uses a model to reproduce data dissemination yet isn't exact. In this way, more statuses are added to the fundamental plague model, and despite the fact that the subsequent models are progressively exact, they are as yet not fit for genuine informal communities while thinking about clients' various practices, as a person's conduct can influence data dissemination. Such factors are significant when fabricating a dispersion model. Numerous extra factors could be engaged with data dispersion models, for example, organize structure, shared data, furthermore, client practices. In impact research particularly, more than one factor is constantly joined in request to augment the informal community's impact. In singular impact research, the center is consistently on one kind of data in particular. There are various kinds of data to be considered for examination into serious impact. As a rule, serious examination is regularly utilized in network impact we can infer that this kind of exploration is exceptionally important and its future applications might be capable to give choice help to general feeling observing, advertising, and so forth.

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