An Improved Genetics-based Model of Emotion Diffusion on Facebook based on Similarity, Interactivity and Connectivity Principles

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Abstract: *Today, as the age of social media continues to bloom and breed social networking sites like Facebook and Twitter, it is essential to note how these media are used to transmit information from each user to another user which gave birth to a variety of studies in the field of online information diffusion. Furthermore, humans are emotional creatures, people communicate with emotions, consciously or unconsciously there are displayed emotions on everything we do, thus, it is important to study not just the diffusion of information but also the diffusion of the emotion contained in a certain information in Social Networking Sites. Emotion diffusion in a very large and seemingly infinite network over time is indeed quite an attraction and must be studied in order to come up with mechanisms to prevent undesirable situations like suicide. Moreover, SIC Emotion Diffusion Model aims to consider the Similarity, Interactivity and Connectivity (SIC) of a Facebook user towards his/her Facebook friends as a factor of information diffusion, specifically emotion diffusion. Furthermore, though Genetics-based Diffusion Model was able to solve the problem of information lost faced by the Genetic Algorithm Diffusion Model (GADM), it didn't consider relationship among individuals like similarity, interactivity and connectivity on social networking sites as indicator on the propagation probability of information from a specific user to another user which his or her follower, friend or whatever terms the specific social networking site has. Based on the results of the experiments conducted, the mathematical experiment differed from the observational experiments' results by about 16.66%, which showed that based on the experiment the proposed model is 83.34% accurate, thus, it is notable to consider SIC Emotion Diffusion Model as basis for the emotion of a status' diffusion or propagation probability. For the next stage of this research, it is best to consider larger data sets with more factors or Facebook factors to be considered to yield more efficient and accurate results.*

1. Introduction

Various studies have been conducted seeking to quantify and describe how information diffusion takes place. However, what caught the attention of the researcher is the approach of those studies which models diffusion as a biological event, specifically in the field of genetics. These studies, that the researcher is aware of, are "The Genetic Algorithm as a General Diffusion Model for Social Networks" and "A new Genetics-based Diffusion Model for Social Networks". Genetic Algorithm Diffusion Model (GADM) was formulated by researchers Lahiri and Cebrian, how-ever according to the study conducted by Chen, et.al (2011), GADM has one major problem which deals with "information lost", and thus to overcome it, Genetics-based Diffusion Model is presented. However, Genetics-based Diffusion Model did not consider relationship among individuals like similarity, interactivity and connectivity on social networking sites as indicator on the propagation probability of information from a specific user to another user which his/her follower, friend or whatever terms the specific social networking site has. Furthermore, Apolloni et.al (2009) also stated in their paper that their study they observed two phenomena, (1) individuals are more comfortable talking to each other if they have similar interests and (2) individuals are more likely to talk when they are more familiar with each other. These two assumptions above are the fundamental assumptions in social science, they added.

Facebook being the top social networking site is deemed to be the social networking site to best fit the purpose of this study because of its features that are helpful as indicators of similarity, interactivity and connectivity like likes, wall posting and post commenting, photo sharing among the features. Furthermore, this study will use the Genetic-based Diffusion Model as inspiration and foundation into constructing a more comprehensive SIC Genetics-based Emotion Diffusion Model due to its characteristics that avoids information lost and the comprehensiveness of its diffusion process.

2. Review of Related Literature

Alvari, et.al. (2012) stated that "informative human-human social interactions motivated us to assign the community formation problem in social networks to a play of interactions between their constituents, i.e. people. In real life, it is necessary for everyone to make friendship with those who have something valuable to share with, since humans are all sociable", In addition, Apolloni, et.al. (2009), said that if sociological models help explain human behavior computer modeling simulates a wide variety of scenario and that with the advancement on computers and computing capabilities, diffusion process has become an emerging research. Tang, & Fong (2013) said that individuals nowadays value others' comments and opinions which they found mostly in social media.

Apolloni, et.al.(2009) used a "probabilistic model to decide whether two people will converse about a particular topic based on their similarity and familiarity. Similarity is modeled by matching selected demographic characteristics, while familiarity is modeled by the amount of contact required to convey information. Today, Social Networking Sites like Facebook and Twitter in "exchanging information, opinions and emotions about events that are happening across the world" (Cao, et.al, 2012). Also, Chen et.al (2011), noted that the "amount of information of an individual increases with continuing interactions with other individuals, because one is always seeking new information from the other individuals". Thus, as long as there is interaction among individuals in social networking sites, information diffusion in social networks is infinite.

2.1 Previous studies of SNS Information Diffusion

As cited in Cao and company's work, information diffusion on Social Networking Sites has been a long term field of study among researchers who are in the field of sociology. One of the reasons is because users' sentiments in social networks spread quickly, thus, it is necessary to develop a mechanism to apprehend propagation of emotions (Tang & Fong, 2013). In the study of this field, Lahiri and Cebrian(2010) stated that quite a few phenomenon are used to model the process of Information Diffusion in Social Networking Sites like, "the spread of human or computer viruses, and the adoption of products in 'viral marketing' campaigns."

They further added that because it is hard to gather or have absolute and exact information on how information spreads actually occur and exist, "so a variety of stochastic models are used to simulate spreading processes in networks." Chen, et.al (2011), also pointed out the use of stochastic model in order to solve the difficulty of obtaining accuracy of the diffusion process, however he also pointed out that these models "focus on either one single object or exclusive objects spreading". The following are studies and researches according to their approaches:

• Biological Approach

Lahiri and Cebrian (2010), showed "that a form of the canonical genetic algorithm paired with Holland's hyperplane-defined functions can be used as a large, rich class of diffusion models for static and dynamic social networks." They also "presented a case study on the Enron e-mail dataset, modeling probabilistic information flow between people as they exchange e-mails". Lastly, GADM "utilizes a very basic form of the genetic algorithm“. Chen, et.al (2011), conducted a study which gave an improvement to the study conducted by Lahiri and Cebrian, which is the Genetic Algorithm Diffusion Model. They formulated a Genetics-based Diffusion Model which solves the problems and disadvantages of GADM. Furthermore GDM "can simulate multiple objects with different relationships spreading in social networks. To simulate information diffusion, GDM regards an individual in a network as a ‘chromosome’, and a message that spreads in as a ‘gene’.”

Guisheng, et.al (n.d.) tried to solve two problems in their model, one is “how to establish the diffusion model so as to simulate the diffusion process better and second, how to speed up the diffusion process so as to make for more scalable Viral Marketing”. Given these above problem, they “propose a Cellular Automaton based Network Diffusion (CAND) Model that takes all the nodes in the network as cells. Lastly, they recommended exploring “the relationship between the performance of a diffusion model and network structures” and “to study the seeds’ influence on diffusion process.”

Adullah and Wu (2011) conducted a study on Information Diffusion which “focused on building a mathematical model of news spreading on Twitter. To do so, they have shown that well-known deterministic compartmental epidemic models can be extended to explain dynamics of trend spreading for various types of trends including real-time news as well as social events. Furthermore, they recommended for future work “to build a real-time online system for early detection of attention gathering trends from streams of tweets” and “modeling the information spreading on Twitter as a stochastic epidemic model.”

• Competitive Diffusion

Broecheler, et.al (2010) studied Information Diffusion considering that “multiple phenomena often diffuse through a social network, sometimes in competition with one another. Product adoption and political elections are two examples where network diffusion is inherently competitive in nature. For example, individuals may choose to only select one product from a set of competing products (i.e. most people will need only one cell-phone provider) or can only vote for one person in a slate of political candidate (in most electoral systems).

• Real World Simulation

Apolloni, et,al. (2009), conducted a study entitled, “A Study of Information Diffusion over a Realistic Social Network Model” which introduced a “dynamic, interaction-based approach to describe the spread of information through conversations between pairs of individuals within a social network, capturing and utilizing the specific times of the interactions”. Furthermore, they “concentrate on information spread through conversation because of its importance in many human affairs. One-on-one conversations are examined here as a mechanism by which information is spread through the social network.”

• Conjoined Social-Physical interaction

Cochran, et.al (2013) studied “the diffusion of information in an overlaying social-physical network. Specifically, we consider the following set-up: There is a physical information network where information spreads amongst people through conventional communication media (e.g., face-to-face communication, phone calls), and conjoint to this physical network, there are online social networks where information spreads via web sites such as Facebook, Twitter, FriendFeed, YouTube, etc.

• Visualization of Information Diffusion Patterns

Cao et.al (2012) also conducted a study called “Whisper: Tracing the Spatiotemporal Process of Information Diffusion in Real Time” that proposed a “novel design termed ‘Whisper’ to fulfill the need for tracing infor-mation diffusion processes in social media, in real time manner.” This study aimed to answer the questions “when, where and how an idea is dispersed” and emphasizes three major aspects of Information Diffusion namely: “temporal trend, social spatial extent and community response to a topic of interest.

• Logistic Model

Wang, et.al (2012) proposed “a Partial Differential Equation (PDE), specifically, a Diffusive Logistic (DL) equation to model the temporal and spatial characteristics of information diffusion.”

2.2. Emotion as an Information Contagion

Humans are emotional creatures, people communicate with emotions consciously or unconsciously there are displayed emotions on everything we do. In an article at Stresshacker.com (2010), it is stated that Emotion as Information is portrayed in the way how positive or negative values or feelings are conveyed in one’s self after an interaction with an individual or individuals. “Additionally, emotional appraisal is generally much more immediate, i.e. faster, than cognitive (reasoned) appraisal. In other words, we are capable of "feeling" positive or negative about something or someone much faster and earlier than we can "understand" or "evaluate cognitively" their real worth" The immediacy, strength and unfailing manifestation of this emotional information is one of the principal reasons that people find the information from feelings to be especially credible. Very often we discover that we should have listened to that gut feeling, or can congratulate ourselves on having followed our good hunch.

In addition, there is also a study conducted that focuses on the concept of Emotion as Information, entitled "Feeling-as-Information Theory" by Schwarz (2010). Feeling-as-Information Theory conceptualizes the role of subjective experiences –including moods, emotions, metacognitive experiences, and bodily sensations – in judgment. It assumes that people attend to their feelings as a source of information, with different feelings providing different types of information. Whereas feelings elicited by the target of judgment provide valid information, feelings that are due to an unrelated influence can lead us astray. The use of feelings as a source of information follows the same principles as the use of any other information"

Thus, it is important to study not just the diffusion of information but also the diffusion of the emotion contained in a certain information in Social Networking Sites. Emotions if not controlled maybe fatal because it leads to violence, like suicide and crimes.

The following are studies conducted on Emotion Diffusion to the best of the researcher's knowledge:

• Hogendoorn, et.al (2010) in a study they conducted introduced "an agent-based model that simulates the spread of information and emotion among a group of agents." Furthermore the model "incorporates the effect of emotions upon the spreading of information as well as the effect of information upon emotions."

• In addition to the study mentioned above, Christakis, et.al (2010) evaluated the "spread of long-term emotional states across a social network". Furthermore, they introduced "a novel form of the classical susceptible–infected–susceptible disease model which includes the possibility for 'spontaneous' (or 'automatic') infection, in addition to disease transmission (the SISa model). Using this framework and data from the Framingham Heart Study," they "provide formal evidence that positive and negative emotional states behave like infectious diseases spread-ing across social networks over long periods of time."

• Lastly, the world's top social networking site, Facebook, with its data scientist Adam Kramer has conducted a study on spread of emotions in the network. Kramer (as cited in dl.acm.org, 2012 concluded that emotions flow even on text-only communities found on social networking sites.

3. Study Framework

Facebook SIC Emotion Diffusion Model aims to consider the Similarity, Interactivity and Connectivity of a Face-book user towards his/her Facebook friends as a factor of Information Diffusion, specifically Emotion Diffusion.

Thus, it is needed to use some theories of Social Psychology to be able to show a valid framework for this study's assumption or claim. Furthermore, the concepts and theories to be used are: the concept of Observational Learning of Albert Bandura's Social Learning Theory, Similarity and Familiarity Principle and will be incorporated with the

Genetics-based Diffusion Model to meet this study's aim.

3.1. Observational Learning

Observational Learning is a core concept in Albert Bandura's Social Learning Theory. Observational Learning, according to Princeton.edu (n.d.) "is a type of learning that occurs as a function of observing, retaining and replicating novel behavior executed by others. It is argued that reinforcement has the effect of influencing which responses one will partake in, more than it influences the actual acquisition of the new response."

3.2. Similarity

Similarity is a factor in Interpersonal Attraction which, according to sparknotes.com (n.d.), "refers to positive feel-ings about another person. It can take many forms, including liking, love, friendship, lust, and admiration" Furthermore, the Law of Similarity states that "If two things are similar, the thought of one will tend to trigger the thought of the other. If you think of one twin, it is hard not to think of the other."(Boeree, 2010)

3.3. Familiarity Principle

Familiarity principle or the mere exposure effect "describes a phenomenon that causes humans to rate or feel positively about things to which they are frequently and consistently exposed, including other people. All else equal, you will buy products, invest in stocks, frequent establishments, and engage in behaviors that are familiar to you based on past exposure. This can lead to suboptimal decisions and results and has no basis in rationality."

3.4 Genetics-based Diffusion Model

The Genetics-based Diffusion Model will need a propagation probability of a diffusing gene (message) in order to determine if it will cause influence to others upon diffusion. Thus, by calculating the propagation probability based on the theories and concept above, propagation probability will be almost accurate if it is not accurate.

4. The Facebook SIC-based Emotion Diffusion Model

In order to have a greater accuracy in analyzing data, data collected such as posts or comments in Facebook will be annotated as carrying positive or negative emotions. Moreover, the receivers of diffused emotion will not be every-one in one's friend's list, but rather only those users who liked and commented that certain post in order to eliminate doubts if a user really saw that status or did not and just showed that it is seemingly influenced by coincidence. Furthermore, using the Genetics-based Diffusion Model (GDM) as basis, this research considered GDM's concept which is having the 'chromosomes' as individuals in the social network and 'genes' as the message/information an individual has. However, given that this study does not focus on the information an individual contains, but on the emotion behind it, 'genes' will now be redefined as the message/information with corresponding emotion (positive or negative).

Moreover, the propagation probability of a gene in GDM's interaction rule was not clearly specified. With this, the idea of having its propagation probability as the total of all indicating factors of Similarity, Interactivity and Connectivity (SIC) came up. These indicators are as follows according to category:

• Similarity:
— Basic Profile
— Interests (i.e. hobbies)

Factors under this category are computed one by one by getting the percentage of similarity among users A and B, where A is the donor and B is the receptor. Similarity of factor F, denoted by SF, is derived by getting the number of similarities of users A and B on a specific factor listed above over the total of the elements contained on users A and B, denoted by A_E and B_E, respectively, of a specific factor F, under this category, which is simply denoted by,

$$S_f = (A_e \cap B_e) / (A_e \cup B_e) \quad (1)$$

Furthermore, the average percentage of similarity among users is derived by the equation

$$S = (\textstyle\sum_0^n S_f)/n \qquad (2)$$

where n is the number of factors under the Similarity category.

• Interactivity:
— Liked Posts
— Comments on Posts
— Wall Posts

Factors under this category are computed one by one by getting the percentage of Interactivity among users A and B, where A is the donor and B is the receptor. Interactivity of factor F, denoted by IF, is derived by getting the number of interactions of users B towards A on a specific factor listed above, denoted by BA, over number of interactions of users A towards B on a specific factor, AB of the said factor F, under this category, which is simply denoted by:

$$I_{f} = B_a / A_b \qquad (3)$$

Furthermore, the average percentage of interactivity among users is derived by,

$$I = (\sum_0^n I_f)/n \qquad (4)$$

where n is the number of factors under the Interactivity category.

• Connectivity:
– Family Members
– Date joined Facebook
– Date of adding friends or accepting friend requests

This category is computed by getting the percentage of Connectivity or Relation among users A and B, where A is the donor and B is the receptor. Connectivity denoted by C, equal to the percentage of the time users A and B are friends in Facebook (A_B), over the time user B has joined Facebook (BFB), denoted by:

$$C = \frac{A\_B}{B_{fb}} \qquad (5)$$

Thus, Propagation Probability (P), is denoted by:

$$\mathrm{P} = (\mathrm{S} + \mathrm{I} + \mathrm{C})/3 \qquad (6)$$

Genetics-based Diffusion Model used the chromosome to represent a user, which can be a donor or a receptor, upon interaction of these chromosomes, insertion mutation may occur depending on the given diffusion probability, the Genetics-based Diffusion Model's equation or method of determining the probability will then be replaced by the SIC-based probability. Moreover, genes of the chromosome will now represent the user's Facebook data (basic info, likes, posts, photos, etc…) as determinants of his/her posts' diffusibility to his/her Facebook friends.

5. Experiments

This chapter shows an instance wherein the assumption that Similarity, Interactivity and Connectivity among users affect Emotion Diffusion holds.

5.1 Experimental Set-up

This study's experiment was conducted by gathering manually (*using See friendship feature and Graph Explorer*), data from a sample user, storing his/her Facebook data containing his/her profile, likes, posts and photos. The experiment focused on a status of the user containing an emotion and observed if those who have interacted to it (liked, commented) were affected by the diffused emotion of the status. The receptors' statuses immediately after the status was posted is scanned and identified as carrying the diffused emotions or did not. Furthermore, data from the users who interacted to it were also collected to be able to use the SIC principles in measuring diffusibility from the donor (sender) to the receptor (receiver). Moreover, Observational and Mathematical Experiments are being conducted in order to contrast Actual and Theoretical prediction on the number of diffused individuals or users, the next section presents the result of the experiment.

5.2 SIC-based Propagation Probability

Table 1. SIC-based Propagation Probability

SIC-based Propagation Probability				
FB UserID	**Simi-larity**	**Inter-activity**	**Connectivity**	**P=(S+I+C)/3 (in percent)**
1815710309	0.3271	33.3333	5.7143	13.1249
100001898866591	0.0823	100.0000	7.3171	35.80
100001042032796	1.2844	108.5535	10.0840	39.97396
100001561674190	0.5675	133.3333	100.0000	77.9669
100000104864617	0.1256	0.0000	5.7143	1.9466
100000222612978	0.3547	33.3333	0.0533	11.2471

Based on the computations conducted with the initial data gathered, Table 1 of the previous page shows that the SIC-based Propagation Probability predicts that one out of six users who were reached by the emotion being diffused by the user will be affected and contain the emotion diffused. Furthermore this conclusion is drawn from the assumption that users with propagation probability of more than the level of neutrality which is 50% will be affected.

6. Findings and Conclusion (Actual vs. Prediction)

Based on the results of conducted experiments, both Observational and Mathematical, the SIC-based Propagation Probability of the source to each of the receptors concluded that there will be one out of six receptors affected, which is 16.67% of the total number of diffused users. However, the Observational

Experiment which showed the actual number of users affected concluded that there are only two out of six that are affected, which is 33.33% of the number of diffused users. Thus, this shows a difference of 16.66% which implies that SIC-based propagation probability is 83.34% accurate. Moreover, this accuracy rate will increase as soon as more and more factors will be considered compared to this experiment with minimal factors considered due to data and time constraints. Improvements of this study is currently on going focusing on increasing the data set by developing a Facebook application that would make data fetching easier and choosing weights on SIC instead of giving them equal weights.

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