Innovation Diffusion in Social Networks: A Survey

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Abstract. The innovations diffusion is a process of communication by which a new idea spreads among a population. A successful propagating leads researchers to seek the elements, which approve and consequently contribute to its spread, or otherwise, find the elements that prevent it. In fact, many efforts were made to models this social phenomenon; however, each one had its strengths and weaknesses. Therefore, this paper aims (1) to discuss and to analyze existing models showing their utility and limitation, (2) highlighting the detail of their applications, and (3) suggesting a taxonomy, which resumes the state of art. Then, to address the current social networks models, it seems necessary to begin by presenting the diffusion of innovation theory, then to detail models, which do not incorporate the social structure, more precisely the mathematical models.

Keywords: Diffusion of innovation · Mathematical models
Social networks models

1 Introduction

The advent of the Internet, and its universally emerging use, by its Democratic policy, allows any person to be connected to the network, and therefore anyone can benefit, distributes information, and proposes its own services or product as a marketing process. As a matter of fact, this free exchange of information involves unrestricted spread. It has also encouraged academics to reflect, what are the reasons that encourage the propagation or the diffusion, in a specific case, if it carries a certain innovation.

In any social system, the diffusion notion takes a chief place, as its influences the individuals' behavior [1]. Thus, this process is the heart of the society evolution. Studying the innovations diffusion is analyzing and identifying mechanisms that allow the social system to change [2]. It is also to recognize the way that encourages a population to adopt an innovation whose advantage is not immediately observable [3].

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In other words, the research in diffusion is mainly to provide more possibility to comprehend how and why this phenomenon do well [3–8]. The study of the innovation diffusion affords an insight to the adoption prediction. To expound and analyze this social phenomenon, the diffusion of innovation theory was introduced as a general framework. This theory is the ultimate prominent behavioral application of network investigation [7, 9].

Coming back in history, the psychologist used the mathematical models as a behavior quantitative theory [10]. After a duration, an answer is wanted, how much could mathematical models support social science? [11]. Epstein [12] maintains that these models may possibly explain the social phenomenon but have not the possibility to predict its future. Therefore, Silverman and Bryden [13] recommend simulation because it offers an optimistic solution to social science. The current development of technologies affords the simulation with more opening and capability to study complex systems comparing with mathematical models [14]. Axelrod [15] explains that the fact that in social science, the simulation helps to take into account the interaction and its influence. In other word, the simulation takes into account the social network structure. Models and simulation approaches provide a better understanding of this social process and give convincing answers to these questions [16]. Geroski submits "*We use models to help illuminate phenomena that we find difficult to understand or to solve problems which are too difficult to think through. These benefits come because models simplify reality*" [17, p. 621].

The richness of literature prompted the study to propose a taxonomy that summarizes the state of the art on this subject. The objective is to provide analysis around the social networks models. To correctly place this problem, some basic concepts will be first defined, then in Sect. 2; the mathematical models will be explained and analyzed. Moreover, Sect. 3 will dealt the social networks models by presenting the necessary details. Finally, Sect. 4 will conclude the work's findings.

2 The Diffusion of Innovation

Rogers [6] defines the innovation diffusion as "*the process by which an (1) innovation is communicated through certain (2) channels over (3) time among the members of (4) a social system*".

(1) **The innovation** is anything perceived as new by the potential adopters.
(2) **The communication channels** are the medium whereby the message is transferred and exchanged.
(3) **The time** is key factors, because whatever the innovation contribution, it diffuses slowly in the population. Thus, it requires time.
(4) **The social system** is a set of interdependent units that are got together to achieve a common objective.

The following definition and assumption are important to the understanding of the subsequent models.

2.1 Adoption Rate

It presents the level of innovation adoption by the population as a function of time. Initially, the diffusion rate goes up pretty much slowly. Then, rises over time, which leads to a period of rapid adoption from the first period, until saturation. It draws an "S" curve, which should be guaranteed by the diffusion models [18].

2.2 Cycle of Innovation Diffusion

Rogers [4] in the book of 1962 defined different types of attitudes towards the innovation. Its idea is to associate the different types corresponding adopters to the different phases of adoption of a novelty where some people are more open to newness than others do. These stages and rates draw a curve in "bell".

Innovators (2.5%). Courageous people, aim change. They are individuals with a strong ambition towards new ideas or technologies "the taste of adventure", they prefer to be the first to possess them. They present innovation to their social system, they have very significant communication mechanisms.

Early Adopters (13.5%). They follow very closely the innovators. They try new ideas, but in a careful way. They are educated and more integrated into the social system than innovators, their opinions matter and can facilitate the diffusion process. They are the opinion leaders and with whom other members get information and seek advice on innovation.

Early majority (34%). They are thoughtful, pragmatic and do not seek changes but developments that improve life. They have many social contacts. They accept change more quickly than others do. They adopt innovation as a group with the accumulation of positive opinions. It represent alone a third of individuals. The one by which the innovation can be considered to be in diffusion on a large scale. Because it serves as a transmission link between members who relatively adopted the innovation early, and those whose decision is tardy. Therefore, it is the privileged target of companies because of its quantity and its ease to convince.

Late Majority (34%). They are conservative skeptics; they accept it only when the majority has already adopted it. They are the ones who undergo social pressure before deciding. Indeed, the late majority adopts innovation more by social pressures than by actual predisposition. They also represent 1/3 of the members of the system. If it resembles the early majority, it differs from them in the motivations for its adoption of innovation.

Laggards (16%). They are traditional people, very skeptical, they like to be glued to "old ways", and will admit them only if the new idea has become the mainstream or even the tradition. Sometimes they are critical about new ideas and they expect a great reliability of innovation, they adopt only by constraint or absolute necessity. They are volunteers who refuse to innovate.

3 Mathematical Models

Several mathematical models have been suggested to model the spread of information among the population. In this section, three well-known models are detailed:

3.1 Logistic Model

It is based on the cumulative distribution patterns. It follows a growth model, which has proven to be a consistent pattern by empirical research on the diffusion of innovation [18]. It is approximated by a logistic function and described by the following equation

$$F(t) = P/r * e^{-st} \tag{1}$$

Where t is the time P and s are positive real numbers, r any real. This function was proved by Verhulst in 1845 [19]. He proposed as a model of evolution of the non-exponential population with s steepness and capacity P.

3.2 Gompertz Model

It is a mathematical model, where the development begins and finish slowly. This sigmoid function is come close gradually to α value. This function refers to Gompertz [20]. It is an exceptional case of the logistic function. Gompertz function is described by

$$F(t) = \alpha e^{-\beta e \lambda t} \tag{2}$$

Where α, β and λ are positive real numbers.

3.3 Bass Model

A remarkable expansion took place in the marketing literature on the diffusion 1970s and the largest enhancement to this scientific explosion is a model for predicting of the spread of new consumer products proposed by Bass [21] in 1969. Bass prediction model has become so important in the field of marketing because it offers some plausible answers to the uncertainty linked to the introduction of a new product in the market. Some of the largest US companies have used the Bass model [3].

To better describe the distribution, particularly to take into account the effect of social pressure Bass defines two main forces driving adoption: innovation and imitation. These explanatory factors reflect the fact that part of individuals adopts by social pressure of individuals who have already adopted, while some adopt by interpersonal persuasion. Diffusion speed is proportionate to (a) the population that has already adopted the service, denoted by f(t), and (b) the remaining market potential represented by M F(t).

From the 19th century, the sociologist Tarde [22] has well highlighted the importance of social influence and the way it is at the base of the formation of a value of the invention, based on its diffusion [2]. He used the word "imitation" to describe the adoption; in his book, he called "the laws of imitation" which published it in 1903.

The Bass model is a predictive model of the future adoption of a product. To apply, you must first define the market size M, then the coefficients p innovation and imitation q, and it can estimate the number of adoptions f(t) in any specified time. The equation is

$$f(t) = M\,p + (q - p)\,F(t) - q/M\,F(t)^2 \tag{3}$$

3.4 Discussion

For the scientist who attempts to predict the future, there is always a need for simple models that describing events. Logistic and Gompertz models could be used to compare the growth rates for different innovations [23]. Each such model should be based upon easily understood assumptions; that support the forecaster in his efforts to make the future what he wants it to be. The models aforementioned are simply based on clearly coefficient. The best-known diffusion models used for technology diffusion purposes are the Bass model, the logistic family models [24], as well as the Gompertz model [20].

For several decades, great attention turned to the Bass diffusion model [3]. The estimation of accurate parameters was the most important point for getting a proximate forecasting [25]. To deal with this problem, the evolutionary approach is a practical solution. For example, Venkatesan and Kumar [26] joined the diffusion model of Bass with the evolutionary technique precisely the genetic algorithms (GA). They aim to predict future sales in the telecommunications sector. Three main genetic operations used: reproduction, crossover, and mutation. By using cellular phone adoption data, they found out that the integration of genetic algorithm gives more robustness and produces more consistency comparable to non-linear least squares(NLS), ordinary least squares(OLS), and time series model. A further illustration is a work of Wang et al. [25], where a hybrid approach that combines the genetic algorithms with the particle swarm optimization (PSO) were proposed. By comparison with NLS, GA and PSO, the consequence of this conjunction provides better predictions, and more accurate parameters for forecasting the notebook shipment.

A significant number of existing models based on the use of parameters that determine the process of adoption of innovation and simple mathematical functions concentrated on observation and description of patterns of diffusion. These models allow more explicit diffusion pattern, but require the estimation of diffusion coefficients, obtained from historical data or time series. This raises the problems of the application in contexts where there is no data or the data are insufficient [27].

The problem with these mathematical models that is impossible to reproduce the failure of the diffusion of innovation, except by artificially placing the potential adopters at 0, while potential adopters may exist but not be reached during the propagation. The aggregative approach itself does not take into account network effects, geographical boundaries, or the heterogeneity of people. Precisely, the difference between Rogers's categories of adopters is overlooked.

Modeling at this macro level, however, is imprecise because it assumes the high-connected social network, in which each person interacts with all world [23, 28]. Pelc [29] aimed at encouraging researchers to integrate the social network where interactivity level is so important. Epstein [12] addressed this issue, stating different reasons for building social models: mathematical models could explain (not predict) the emergence of collective phenomena, or capture qualitative behavior of phenomena. Such criticism strongly limits the description of the mathematical models. To take into account the heterogeneity of the population and the network effect, the models are moving towards approaches called individual-oriented models where the social structure and the communication channels are taken into account. The following section probes into the social networks models.

4 Social Networks Models

4.1 Threshold Model

The way that the social network influences the diffusion process, is the principal focus of threshold model [30]. This model has been assumed to understand the process of innovation diffusion [23]. The threshold is the fraction of adopters in a system needed for an individual to be an adopter. Valente [30] applied this concept as an extension of Granovetter's [28] work, where, the individual's decision depends on the behavior of others in the group or the system. For the reason that the individuals are more effected by facts received from personal network. Valente [30] proposes using the direct communication network rather than a system to which the individual belongs. The exposure E_i is the proportion of the adopters in the personal networks. It is measured by

$$E_i = \sum w_{ij} \times y_i / \sum w_i \tag{4}$$

The principle of threshold models is as follows: an individual changes its state if a sufficiently large proportion of his neighbors are in this state. This proportion constitutes the threshold of the individual. The diversity of these thresholds, as well as the position of the individual on the social network, create a heterogeneity in the population. The linear threshold model is derived from threshold model.

Linear Threshold Model. Suggested by Kempe et al. [31]. LTM works as follow: the individual is influenced by each neighbor according to a weight. A uniform random threshold from 0 to 1 are assigned to each individual I. This threshold is imperative to I to became an adopter. For each step of simulation, an activated sequence of individuals activate similarly their neighbors' and so on. The propagation ends when there are no further inactive person.

4.2 Epidemic Approach

It is easy to observe the relation between epidemic disease and the diffusion of information. The Influenza for example, is a contagious disease that spread from person to person. Epidemics can pass through a population, or they can persist over long time periods at low levels. As epidemics can spread between people, ideas and information can also spread from person to person, across similar kinds of networks that connect people. The Diffusion of innovation is usually treated as social contagion [32]. Similar to the spread of disease, as a reaction chain phenomenon. First there are some adopters, while members of their networks adopt, then they move on to their own networks and so on. First slowly, then faster and faster and then slows down again because potential adopters are reduced.

This approach assumes that exposure to information enough to become informed, and potentially transmit the information to someone else. However, we know that all individuals do not have the same propensity to adopt and transmit the information immediately after its receipt. Mathematically, this phenomenon is best described by an S curve, it can be easily constructed from an array of single frequency of adoption time. The epidemic approach assumes that meetings between individuals can appear randomly in the population. To simulate the diffusion of innovation, where the main channel of communication is the word-of-mouth, this approach is the most appropriate for this case [17]. Indeed, it is generally used to describe the transmission of innovations [33].

The SIR Epidemic Model. The state of individuals changes through three possible stages:

Susceptible. The individual is suspected to catch the disease from its neighbors.

Infectious. If the individual catch the disease, he became infectious and has some probability to infect his neighbors.

Removed. After some period of infection, the individual became removed from consideration.

Ba et al. [34] have designed a model that is based on the epidemic approach. To take into account the heterogeneity of the population, which is a real fact, they inspired by the Granovetter threshold models. They simulated the innovation diffusion in Senegalese rural environment by using Netlogo development software. The simulation was done using multi-agent systems. The network on which the diffusion took place was generated using an interaction network generator. This simulation has led to some interesting conclusions: on the first part, the geographical disparity that separates individuals does not in itself constitute a barrier to the wide dissemination of information; on the other part, an important factor is the social structure of the environment. The social network and links on through which the influence of external sources happens is the central interesting for Myers et al. [35]. They investigate how information spread in the network from node to node. They apply the contagion and exposure models. The results confirms that the effects of external sources on the information diffusion. Namely, by quantifying this degree of influence over time, they argue that the information is likely to "jump" across the network.

4.3 Evolutionary Model

Despite the promising outcomes and recent interest in modeling social systems, it was pointed out that in many cases; models lack realism and do not take the realities of the field into account [11]. In recent years, numerous publications have appeared dealing with the incorporation of the evolutionary perspective to the social science, this integration known as evolutionary psychology. This combination gets a chief place within psychological science [36]. The evolutionary psychology is a field that apply the evolutionary concepts in psychology arena. Buss et al. [36] highlight the importance of incorporating the evolutionary perspective to social science. The evolutionary principal base on the notion that the individuals with more effective characteristics have more probability to replicate and live [36]. The evolutionary computation need only a little specific problem knowledge. Thus, they can be applied to deal with a varied range of problems [37].

Nevertheless, a little available literature on innovation diffusion that applies techniques based on evolutionary computation [27]. An example of the evolutionary algorithm is the paper of Sampaio et al. [27]. They recommend the evolutionary algorithm to simulate the diffusion of innovation process. The evolutionary computation is suitable to model the progress of adoption decision process. Their central support is Rogers' innovation diffusion theory and the threshold approach. Another important factor that was taken into account, is the knowledge function of Verhulst [19]. This function is used to simulate the evolution accumulation acquaintance by time. The result was compared to Logistic, Gompertz, and Bass models. The effect of first adopters and the social structure are studied.

In a previous work [38], we proposed a novel evolutionary model based on the human interactions as an evolutionary learning process, because the decision does not occur directly from the first exposition to the innovation, but it follows an evolutionary process affected by the other neighbors already been adopters. We used three social networks type: regular ring network, lattice network on a torus and random network. The simulation proved the capability of the model to produce the S-shaped diffusion pattern, it is built on two associated factors: the individual decision process and the social learning influence. Consequently, the paper may offer a significant outline to better understand the subject of human behavior.

Yavaş and Yücel [39] addressed the way the homophily in the social network can affect the diffusion process. An agent-based simulation implemented model demonstrates that the homophily is self-reinforcing especially in its early increases. It is, in other words, more supporting at the beginning of the diffusion rather than being so later. In addition, by applying the evolutionary homophilous network, the extent of macro high homophily degree gets more influence than the one of individual's local neighborhood preference. Furthermore, Cowana and Jonard [40] focused on the relationship between the network topology and the diffusion process. They examined the effects of incremental innovations diffusion by means of three different network architectures. Additionally, they implemented heterogeneous agents connected exchanging information over time. This interaction involves the knowledge, which is represented as an evolutionary vector.

4.4 Discussion

The elements of the innovation diffusion are differently considered in the process of modeling. Rogers [3] mentioned four important elements that are: (1) the innovation,

(2) the time, (3) the social system and (4) the communication channels. The threshold models showed particular interest on the social structure, making distributed probability to create the social heterogeneity. The question is what about a personal network with a minimum of communication? However, the impact of communication channels was the focus of epidemiology approach and the evolutionary models. Another problem, is our choices depend only on the social pressure? While all the mentioned models ignored the various innovations characteristics, the need of a model that take into account the innovation features' is vital.

5 Summary

The innovation diffusion models converge to similar findings that are the "S" diffusion curve. Figure 1 illustrates a taxonomy that resumes the state of art in the subject of innovation diffusion.

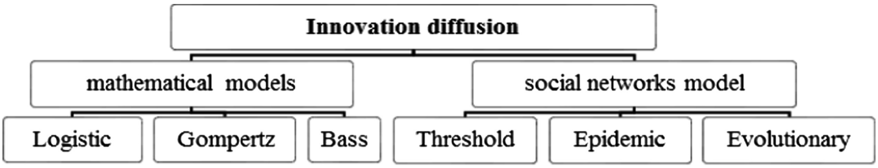

Fig. 1. Represent a taxonomy of the innovation diffusion models.

Table 1 gives a summary of the innovation diffusion elements more or less considered by the abovementioned models.

Table 1. The elements of innovation diffusion theory considered by the mentioned models.

Models	Innovation	Social network	Communication	Time
Logistic	✗	✗	✗	✓
Gompertz	✗	✗	✗	✓
Bass	✗	✗	✗	✓
Threshold	✗	✓	✗	✓
Epidemic	✗	✓	✓	✓
Evolutionary	✗	✓	✓	✓

6 Conclusion

When new idea, activity or object are invented, diffused, adopted or rejected, social changes occur. Research in this field has produced various theoretical models. A survey of mathematical models and social networks models for innovation diffusion was presented. Rogers's theory suggests that the adopters of any innovation can be classified into five categories: innovators, early adopters, the early majority, the late majority, and laggards. This theory describes the mechanisms that drive the diffusion of innovation [41]. The diffusion of innovation leads to the S-shaped curves representations, this object is guaranteed by the most of the models, the logistic and Gompertz models are good examples, which is much more used to demonstrate the cumulative effect. In 1969, inspired by Rogers and other theorists of the domain, Frank Bass developed a quantitative model that was as a reference to quantify the rate of adoption of an innovation in a population [3]. The mathematical models concentrate on the rate of adopters. A time ago, the innovation diffusion was only measured by the rate of adoption.

However, taking into account the interactions between individuals is critical [29], because, they are the main driver of the evolution of individuals [3], which the mathematical models do not take into account. The individual-oriented approach was a solution to integrate the social network. Later, several models have been introduced, in order to better comprehend the process and to incorporate the essential elements. These social network models confirm hypotheses about the causes of success or failure. The designed models still need some improvements like the integration of the innovation characteristics in the process of conceptualization. A taxonomy of models discussed and analyzed in this paper. These existing models greatly differ in their goals, as well as in their approach. The paper aims to offer some advance on this area and helps the novel researchers to understand the field of the innovation diffusion models.

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