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ORIGINAL ARTICLE

Exploring the effect of reinvention on critical mass formation and the diffusion of information in a social network

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Abstract Widely used information diffusion models are based on the assumption that exposure to information, like exposure to a virus, is enough for it to spread. However, the diffusion of information is more complex and involves an array of decisions regarding whether to consume the information received, and upon consumption, whether to pass it on to others. Using an agent-based simulation run on an actual network graph, we model a realistic information consumption and transmission process. The model builds upon the combination of two prominent social theories: diffusion of innovations and critical mass theory. We introduce the concept of reinvention, the modification of information, and investigate its effect on both critical mass formation and on the overall diffusion of information in the social network. Results show that network topology is crucial while traditional concepts such as 'inflection point' or 'early adopters' are of secondary importance. Although reinvented information requires more nodes to reach critical mass, it prolongs the diffusion of information past the inflection point so that information reaches a larger final audience, while also exhibiting accelerated production functions. Reinvention is found to have a prominent effect when transmitted via weak ties, thus allowing information to undergo an evolutionary process that contributes to an overall higher value of information, collective outcome, in the network.

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1 Introduction

The challenge in achieving rapid diffusion, such as a power law or S-shape growth curves, when introducing new information to a social network is to pass the inflection point in the curve toward a positive trajectory. This paper studies the social dynamics leading up to and following the inflection point trying to understand what contributes to an upward trajectory and eventually to a large spread of information. Prior research comes initially from sociology with later applications in marketing and communications. The two leading theories are Oliver and Marwell's critical mass theory (CMT) and Rogers' diffusion of innovations (DOI). We combine insights from both theories in order to construct a model of critical mass formation and study its outcomes pertaining to the spread of information. Recent findings indicate that, possibly in contrast to common perceptions, rapid diffusion is a rare event occurring in 1 % or less of the potential cases (Goel et al. 2012). Understanding the underlying processes of diffusion of information in a social network is the goal of the present paper.

According to the DOI theory, diffusion of ideas and technology within a social system follows an S-shaped curve and critical mass is a point in time in which an inflection point occurs (Rogers 1995). At this point the rate of the adoption is fastest, i.e., the number of new adopters is increasing most rapidly. This point occurs when about 16 % of the individuals in the social system have adopted an innovation. CMT (Oliver et al. 1985), on the other hand, suggests that reaching the critical mass point does not necessarily imply vast diffusion. Rather, the dynamics leading towards this point influence the eventual outcome and thus affect overall diffusion.

In order to better understand the factors that contribute to critical mass formation and diffusion sustainability, we employ the process approach offered by CMT. We introduce the factor of reinvention from the DOI theory (Rogers 1962) as a contributor to critical mass formation and to the diffusion of information. Using MATLAB, we designed an agent-based model incorporating the theoretical constructs from both theories. The model was run on data from an actual network of Hollywood actors. This allowed us to test information flows in a realistic topology emanating from an actual network of people. Through the model we observe the potential of reinvention and its contribution to critical mass formation, the value of information in the network and to its final spread. Although the network analyzed describes a network of peers, following Dodds et al. (2003) we assume that our findings are of significance to both offline and online social networks.

The present results show that network topology is crucial while traditional concepts such as 'critical mass' or 'early adopters' are of secondary importance. Our findings indicate that although reinvention requires more nodes to reach the critical mass, it leads to acceleration of the diffusion of information past the inflection point. Reinvented information reaches a larger final audience and propagates in the network for a longer period of time. Weak ties are found to play a significant role not only in transmitting information, but also in innovative work. Furthermore, reinvention contributed to the overall value of information in the network, thus enhancing its spread.

In the following we provide the theoretical background leading up to our hypotheses.

2 Theoretical background

2.1 Critical mass theory and social dynamics

CMT aims to predict the probability, extent and effectiveness of group actions in pursuit of a collective good (Oliver et al. 1985). Critical mass formation is thus regarded as a process of building sustainability rather than a static point in the diffusion process. The theory outlines the conditions under which reciprocal behavior starts and becomes self-sustained. The critical mass is defined as a "small segment of the population that chooses to contribute to the collective action" thus creating conditions for the majority to join leading to the achievement of the collective good. The success of the critical mass in achieving the collective good depends on whether the group is heterogeneous in terms of *interest* and *resource* levels and the ability of the initial, critical, group of contributors to draw further participation by others. In social settings, the critical mass, as described in CMT, comprises the initial seed nodes that start the diffusion process.

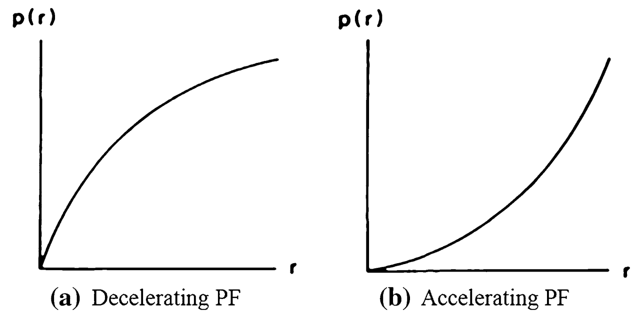

Fig. 1 **a** Decelerating PF. **b** Accelerating PF

In this research, relying on Kossinets and Watts (2006), tie strength between actors is considered a surrogate measure for *interest* level, as they indicate the frequency of interactions between them, and thus the interest they find in each other's work. Weak ties represent low mutual interest while strong ties are an expression of high joint interest.

According to CMT, resource is considered as the ability to contribute. In a network, one's connections are an asset which can be utilized to reach many others. In this sense, the ability to contribute to the realization of a public good is enhanced by the number of connections one has. Furthermore, according to Burt (1997), social capital is determined by the number of connections. Thus, we use node degree as a surrogate measure for *resource* level.

The ability to draw repeated participation is a consequence of two distinct dynamics described by production functions. By plotting the amount of resources contributed and the collective output of these contributions two types of production functions emerge: the first describes situations in which the earliest contributors have the greatest effect on achieving the public good, and subsequent contributors have progressively less effect. This situation is referred to as a *decelerating production function*. In the second situation, initial contributors have negligible effects on achieving the collective good, and subsequent contributors yield the greatest effect. This situation is referred to as an *accelerating production function*. In a decelerating production function, each contribution makes others' subsequent contributions less valuable, and thus less likely. For example, adding a book review to an existing review repository is expected to follow a decelerating function. In an accelerating production function, an early contribution makes subsequent ones more worthwhile and thus, more likely. For example, in petitions, early joiners are important for starting the process, and later joiners, having seen the first joiners, perceive the value of joining a growing group, and add value by joining (Fig. 1).

Differences in production functions are associated with distinct social dynamics. The decelerating function tends to be self-limiting. The accelerating production function tends to be self-reinforcing resulting in considerable diffusion. These differences have implications regarding the development that follows the critical mass point and thus affect the overall spread of the collective good.

Communication scholars have adopted and applied CMT, recognizing information as a type of collective good (Markus 1987; Fulk et al. 2004; Monge et al. 1998; Peddibhotla and Subramani 2007; Rafaeli and Larose 1993). According to Oliver and Marwell (2001) various information sharing patterns have properties that affect people's willingness to participate in information sharing, thus affecting its diffusion. CMT has been criticized in two main points: the simulations it is built upon addressed situations mainly with an accelerating production function, with "one step mobilization" meaning that organizers mobilize their direct ties only and in which individual's possess perfect information regarding others' doings (Marwell et al. 1988). This simulation may not capture the complexity and variety of situations in everyday life such as those entailing decelerating production functions and those involving "two steps" of mobilization that are described extensively in the diffusion literature (Lazarsfeld 1944; Lazarsfeld and Menzel 1961; Rogers 2003).

Furthermore, CMT has been criticized by Monge et al. (1998) regarding its form of production functions treatment of individual contributors as substitutional, i.e., that production functions combine participant contributions into the sum R. Therefore, CMT discriminates between contributions on the basis of their magnitude, assuming that one contribution of a given magnitude, R, can be substituted for any other. But, in cases where the relative importance of contributions varies significantly in ways that their relative size does not capture, the relative weight associated with each contribution should be taken into account.

To address CMT limitations the present research implements the variance in participant contributions by accounting for the varying resource and interest levels, represented by number of ties and tie strength. This is done in a simulation model that runs on an actual network graph and incorporates multiple steps of mobilization. Yet, in order to better describe the complexity inherent in the subjective process of the diffusion of information we turn to the DOI theory and to models of information diffusion. Tying them back with CMT enables the development of the model presented in Sect. 3.2.

2.2 Diffusion of innovations theory

The DOI theory seeks to explain how innovations, ideas and technologies, are taken up in a population. Diffusion is the process by which an innovation is communicated through certain channels over time among members of a social system. As such, diffusion is a special type of communication concerned with the spread of messages that are perceived as new ideas. Social change occurs when new ideas are invented, diffused, adopted or rejected, leading to certain consequences (Rogers 1962). An innovation, according to Singhal and Dearing (2006), can be an idea, knowledge, belief or social norm, product or service, technology or process, even culture, as long as it is perceived to be new.

According to the DOI theory, individuals in a social system are divided into five adopter categories according to their innovativeness level, i.e., the degree to which they are relatively earlier in adopting new ideas than other members of a social system. Each of these categories has distinguished characterizations in term of personality traits, communication behavior and socioeconomic status. According to innovativeness levels, the five categories are: innovators, which comprise 2.5 % of the social system, followed by early adopters (13.5 %), early majority (34 %), late majority (34 %) and finally, the laggards comprising 16 % of the social system (Rogers 1995). The diffusion process within a social system follows an S-shaped curve indicating progressive diffusion through these categories. Critical mass occurs at a point in time in which the rate of the adoption is fastest, i.e., the number of new adopters is increasing most rapidly. This point, referred to as the inflection point, occurs when about 16 % of the individuals in the social system have adopted an innovation. According to the DOI theory, once the adoption of an innovation reaches an inflection point, further diffusion becomes self-sustained (Rogers 1995). We argue that reaching the inflection point does not necessarily imply vast diffusion. Rather, the dynamics taking place up to that point, as described in CMT, will determine the extent and sustainability of the diffusion process. Next, we focus on the specific case of information diffusion.

2.3 Diffusion of information

Widely used information diffusion models such as independent cascade model (Goldenberg and Efroni 2001; Kempe et al. 2003); continuous time independent cascade model (Gruhl et al. 2004); susceptible infected recovered model (Kermark and Mckendrick 1927); susceptible infected susceptible model (Pastor-Satorras and Vespignani, 2001) and rumor spreading model (Zhao et al. 2012) are built on the assumption that *exposure* to information, like exposure to a virus, is enough for it to spread. But, the diffusion of information, especially digital information, is more complex and involves more than just exposure.

Literature attributes diffusion of information to either structural properties of the network (Barrot and Albers 2008; Kitsak et al. 2010; Canright and Engø-Monsen 2006; Watts 2002; Watts and Dodds 2007; Valente 1996) or to factors embedded in the information itself (Berger and Milkman 2009; Romero et al. 2011; Wojnicki and Godes 2008; Berger and Heath 2005). Those studies focused on network-related factors that are associated with the transmitter of information (Stephen et al. 2010; Kempe et al. 2003). The present research combines structural and social factors associated with the diffusion of information and, importantly, focuses on the receiver of information as an active decision-maker.

Information diffuses by explicit retransmissions that involve a decision of the receiving node whether to consume the information received and, upon consumption, whether to pass it on to others. Throughout the diffusion process, consumers of information are able not only to retransmit information but also to annotate, appropriate, and recirculate content (Jenkins 2009). In light of these possibilities, we suggest reinvention as a new variable to explain the diffusion of information and thus contribute to critical mass formation in the diffusion of information in a network.

2.4 Reinvention

In the first several decades of diffusion research, innovation was assumed to be an invariant quality that did not change as it diffused (Rogers 1995). In the 1970s diffusion scholars began to study the concept of *reinvention*, defined as the act of changing or modifying an innovation by a user in the process of adoption and implementation.

Reinvention was found to enhance the overall adoption in areas such as products (Von Hippel 1976), management programs (Mamman 2002), and educational programs (Blakely et al. 1987; Berman and Mclaughlin 1975). In digital information, reinvention is manifested, for example, in web mash-ups where existing data sources are reused from heterogeneous sources (Abiteboul et al. 2008) or in remixes of music where familiar vocal and musical tracks are blended together to create something new and unexpected (Howard-Spink 2005).

Havelock (1974) identified that reinvention activity is motivated by enhancing the sense of pride, displaying ownership over the innovation and gaining status and recognition. Yew (2009) found that reinvention of information online is mostly facilitated by the opportunity to express creativity, self-identity and building social relationships through the creative process.

Reinvention is measured by the degree to which elements of the innovation are similar to, or different from the "core" elements of the innovation (Kelly et al. 2000). Reinvention implies modifying the information in the process of its spread. This modification affects the eventual value of information in a positive or negative manner, thus capturing the subjective nature of reinvention. In both cases, the change is either constant or relational with respect to the original value of information received. In this research reinvention is operationalized as a positive or negative change to the original value of information. The starting node is endowed with a unit of information with a value of one. The value changes based on the probability of performing reinvention and based on the change trajectory as described in more detail in Sects. 3.1.2 and 3.2. The actual content of information is of secondary importance as information transmission is studied from a probabilistic perspective.

The contribution of reinvention to critical mass formation in information diffusion has not been studied. The aim of this study is to better understand the contribution of reinvention to attaining critical mass not only as an inflection point, but also the dynamics leading towards this point and how they affect the subsequent sustainability of diffusion. Through a series of exploratory questions we gradually examine the relationship between reinvention of information and the spread of information accounting for the socio-structural characteristics of interest and resource levels.

Our research questions are concerned with comparing the spread of information without and with reinvention, before and after the appearance of the inflection point. The spread of information is modeled assuming either weak or strong ties. The trajectory of reinvention is either accelerating or decelerating.

We start by studying the process leading up to the inflection point. We are interested to learn whether reinvention, which is a concept we adopt from DOI theory, influences the dynamics leading up to the diffusion of information inflection point, as described in CMT. The two main influences on critical mass attainment, resource and interest levels and the production function change regime, are implemented in the research design in order to observe the interplay between these known factors and the new factor of reinvention. The first set of research questions is:

RQ1: Events leading to the inflection point in the diffusion process. Does reinvention contribute to the process of critical mass formation in information diffusion? Does the contribution of reinvention change based on tie strength (interest), degree (resource) and acceleration or deceleration (production function trajectory) of the introduction of reinvention? How fast does the inflection point appear and does reinvention promote or delay its appearance?

Past the inflection point the focus is on the propagation and termination of the diffusion process as well as on the process outcome. Recall that CMT studies the development of collective outcomes and DOI theory deals with broad diffusion of new ideas and technologies. In this context, the next set of research questions tease out the events taking place past the inflection point, again accounting for the tie strength, number of links per node and production function trajectory. We account for the termination of diffusion by exploring questions relating to duration of the process and to the collective outcome, i.e., the spread and reach of information in the network, and the value of the information at the end of the diffusion process.

RQ2: *Events occurring past the inflection point.* Does reinvention affect the diffusion of information beyond the inflection point? How is the collective outcome affected? Does reinvented information propagate in the network for a longer time? Does it reach a larger number of final consumers? Does reinvention of information affect the collective outcome, namely, the value of information generated at the end of the diffusion process?

3 Method

Using MATLAB, a probabilistic mathematical model was developed and run on a social graph of Hollywood actors. The model incorporated variables from CM and DOI theories with the aim of simulating information diffusion in a complex network. The following sections describe the variables, data source, model and procedure.

3.1 Variables

3.1.1 Dependent variables

Critical mass The average number of nodes sharing information until an inflection point appeared.

Spread of information The average number of nodes the information has reached.

Super spread when at least 20 % of the nodes in the network consumed the information.

Collective outcome The overall value of information as a function of the number of nodes who consumed it.

Sustainable diffusion The number of iterations needed for the propagation of information in the network following the inflection point.

3.1.2 Independent variables

Reinvention A positive or negative modification of original information.

Relative reinvention (*RRI*) Adding or subtracting 20 % from the value of information with each reinvention. Simulates situations in which initial reinvention may have a small effect on the value of information and subsequent reinvention an increasing effect (accelerating production function).

Absolute reinvention (*ARI*) Adding or subtracting a constant value set to 20 % of the initial value of information at the starting point. This simulates situations in which initial reinvention has the greatest effect on the value of information and subsequent reinvention a decreasing effect (decelerating production function).

Resource level Represented by node degree: the number of direct links between a given node and other nodes.

Interest level Represented by tie strength inferred from joint activity, the number of joint movies.

In this research, the probability for consuming information by a node is determined by the tie strength involved. We chose the basic probability of consumption in the weakest tie (one joint movie) to be 5 % in the first set of experiments, and 40 % in the second set of experiments where strong ties were transmitters of the information.

For example, when two actors in our first set of experiments had only one joint movie, the probability that one consumed information sent by the other was 5 %. When two actors had two joint movies, the probability of acceptance was 10 %, when they had three joint movies it was 15 %, and so on. In the second set of experiments, one joint movie implied a 40 % probability of consumption, and co-acting in three movies raised the consumption probability to 100 %. In this way, the stronger the tie, the higher the probability of consuming the information transmitted via the tie.

3.2 Model development

An agent-based mathematical simulation model was developed using MATLAB (version 7.12). The model is based on discrete step iterations to demonstrate the influence of reinvention on the process of critical mass formation and the overall diffusion of information. The model incorporates theoretical constructs, based on prior literature (Oliver et al. 1985; Moldovan and Goldenberg 2004; Rogers 1962), where variables in the model are given a certain value or probability.

Each starting node received a standard assignment of value of information set to 1 at the beginning of the experiment. Information that underwent reinvention was described by a change in value that was either constant or relative (ARI, RRI as described in Sect. 3.1.2). Each reinvention occurred independently and cumulatively at the individual node level, yet the simulation allowed the study of the collective outcome.

Nodes in the network were assigned various probabilities for each of the following states:

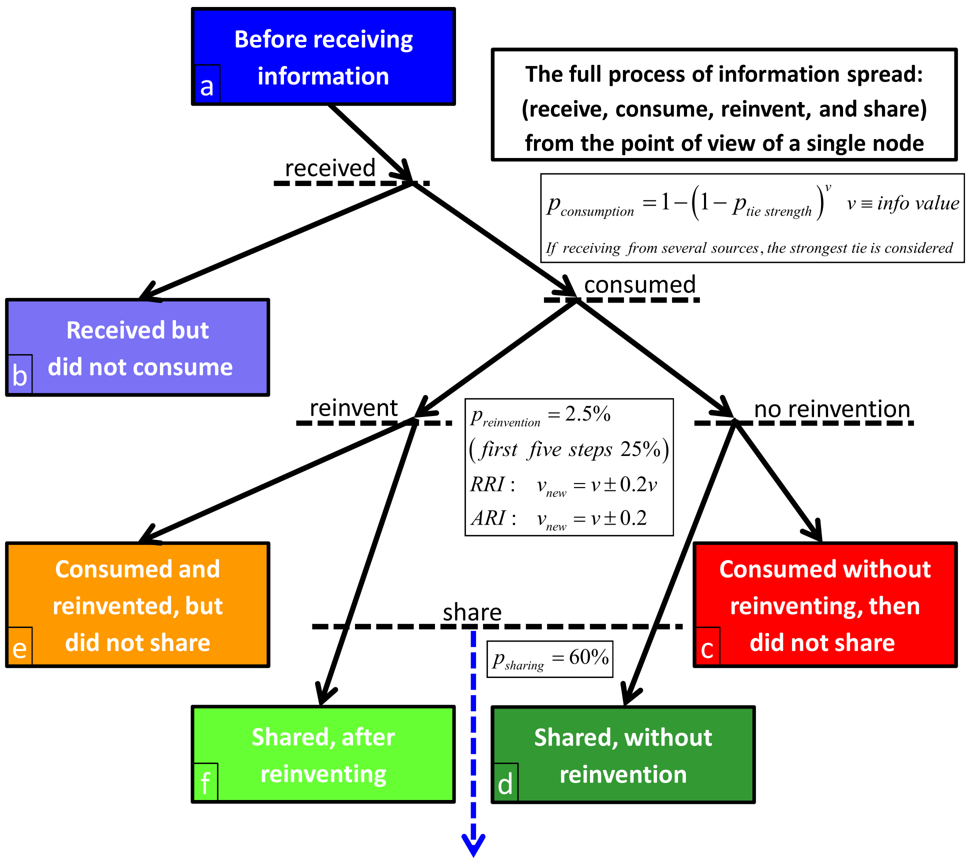

Fig. 2 Model of information flow with assigned probabilities

(a) before receiving information
(b) received information but did not consume
(c) consumed without reinventing, then did not share
(d) consumed and shared without reinvention
(e) consumed and reinvented but did not share
(f) consumed, reinvented, and shared.

Figure 2 depicts the application of the formulas to the various states of the nodes.

The simulation ran by performing a large number of repetitive experiments until convergence was observed. Each experiment included a large number of random events, therefore, any experiment might include a low-probability event misleading into incorrect conclusions. An experiment was initiated by the selection of one node as the first to share new information.

3.3 Data

The data source is an actual collaboration network of movie actors that contains all Hollywood movies and their casts since the 1890s and up to 2001. Data were retrieved from http://nd.edu/~networks/resources.htm. This is an undirected network in which nodes are actors. Edges form between actors who acted in movies together. Tie strength is indicated by the number of films they co-acted in. The dataset covers more than 110 years, so some links could not have been created due to the time gap. Similar limitations are found in most complex networks where nodes are aging (e.g., abandoned web pages or Facebook profiles). Nevertheless, the actors' network is scale-free and in this respect it is similar to many social and other networks on and off-line (Barabási and Albert 1999). This network configuration was used to research statistical mechanisms of complex networks (Albert and Barabási 2002) and hierarchical organization (Barabási et al. 2001). Table 1 contains a summary of the main descriptive statistics for the actors' network.

Table 1 Hollywood actors network descriptive

Nodes (actors)	Links (co-acting)	Mean degree	Density	Clustering coefficient	Mean tie strength
374,511	15,014,839	80.183	0.00021	0.16601	1.1012

The degree distribution is typical of a power law curve, and the clustering coefficient implies that low degree nodes belong to very dense sub-graphs and those sub-graphs are connected to each other through hubs. The network density indicates that the Hollywood actors network is sparse; the majority of actors co-acted in one movie and each node (actor) co-acted, on average, with 80 other nodes.

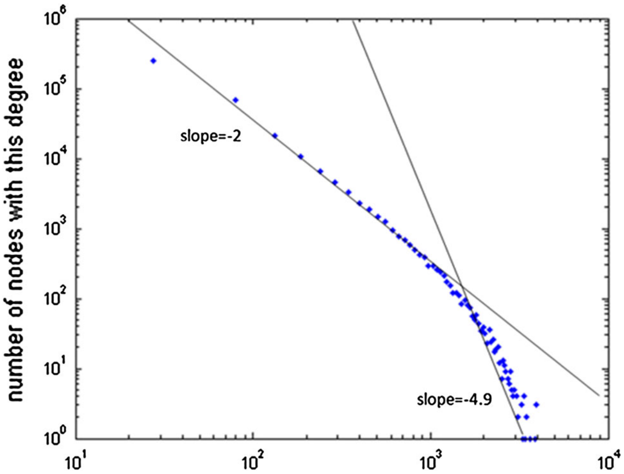

Fig. 3 Degree distribution

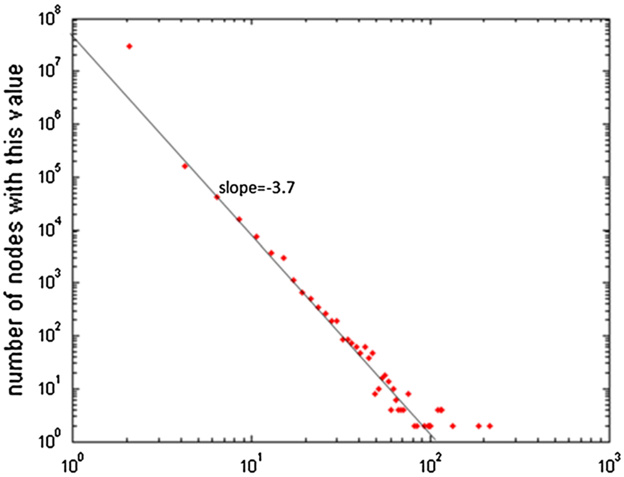

Fig. 4 Tie strength distribution

The success of the critical mass of actors in achieving the collective good depends on whether the group is heterogeneous in terms of interest and resource levels (Oliver et al. 1985). Figures 3 and 4 describe the distribution of degree (resource level) and tie strength (interest level) in the Hollywood actors network.

Figures 3 and 4 indicate heterogeneity which is a prominent necessary condition for the occurrence of the critical mass (Oliver et al. 1985).

3.4 Procedure

The model was run on the flow of information without reinvention and then with reinvention, in order to isolate reinvention's unique effect. After simulating different starting points, peripheral and central nodes, we chose the option that showed the greatest variance in results: the weakest neighbor of the biggest hub.

We chose a conservative starting point in which our initial transmitter of information is connected to seven nodes only, of various degrees, four of which are considered hubs (hubs are nodes with a degree of at least 10 times the mean degree). The basic parameter describing the flow of information in the network is the probability of consuming information, which depends on the individual tie strength between two actors, and is proportional to the number of co-acted movies. In terms of tie strength, the network is heterogeneous, with connections varying from 5 to 100 %, which is based on a conservative assumption that the lowest probability of consuming information is 5 %, corresponding to a connection of two actors who co-acted in just a single movie.

The dynamics start to evolve by the starting node's neighbors who are the new receivers of information. Information arrives with a certain value assignment according to the node state detailed above. Each new receiver node "decides" what to do with incoming information based on the probabilities assigned to various possible actions. In particular, each node decides whether to reinvent, and then whether to share the information with its neighbors. Each decision phase is one experiment iteration. The new state obtained leads to continuing the sharing of information according to the model rules. Reinvention occurs upon consumption of information before the decision to share. It can have a positive or negative value. The type or reinvention, RRI or ARI, is determined by the experimenter before the experiment begins.

The process is repeated by finding the new receivers. On the whole, a single iteration consists of marking the new receivers, the receivers deciding about reinvention and sharing the information with new receivers for the next iteration. Iterations are repeated until final resolution when information cannot continue to flow between nodes. At this point, we assess whether critical mass was reached, the magnitude of collective outcome, and the spread of information. The number of iterations needed before convergence depends on the network diameter.

In order to get representative results for the model, we simulated the full process of information flow and repeated the full experiment about 900 times for each set of parameters (with and without reinvention). Such a large number is needed in order to allow a high-resolution histogram since many "decisions" of nodes in the model are probabilistic.

4 Results and analysis

This section answers the research questions by addressing several comparisons:

Table 2 Model summary results

Measuring	No RI		Relative RI		Absolute RI	
	Weak ties	Strong ties	Weak ties	Strong ties	Weak ties	Strong ties
# of iterations to inflection point	7.75	5.15	8.1	5.17	7.9	5.15
# of nodes in inflection point	30,362	132,220	38,855	130,610	38,049	130,270
Nodes to IP as % of total network nodes	8.10	35.3	10.37	34.87	10.15	34.78
# of iteration to reach final spread following inflection point	75.2	17.9	142.7	18.4	105.6	18.3
# of iteration to reach 90 % of final spread following inflection point[a]	28.9	8.2	60.9	8.2	35.5	8.2
Chance of super-spread (%)	17	85	20	84	20	86
Percentage of network reached (%)	39.4	85.5	67.5	86.4	55	86.2

[a] Following the inflection point we observed a "subnetwork effect" in which the spread of information, after reaching 90 % of the network, kept on spreading in small subnetworks. This additional spread, although adding only a small number of consumers, increased the number of steps. In order to overcome this "subnetwork effect", we distinguished between the spread of information up to and after reaching 90 % of the network

- The effects obtained from weak and strong ties.
- Without and with reinvention.
- In the reinvention experiments two trajectories are compared: absolute (ARI) and relative (RRI) reinvention as explained in Sect. 3.1.2.

Table 2 summarizes the average results for hundreds of experiment iterations. Cells highlighted by light gray refer to the diffusion process prior to the inflection point (RQ1), and those highlighted by dark gray—to the diffusion process following inflection point (RQ2).

As seen in Table 2, before the inflection point reinvention has a negligible effect on the spread of information which implies that the short answer to RQ1 is negative. Reinvention becomes influential after the inflection point as evidenced by the longer duration of information diffusion (# iterations) and the overall percentage of network reached. The answer to RQ2, then, is positive. In the following we provide the detailed results and analysis.

The first part of the analysis relates to the events leading up to the inflection point (RQ1) as seen in the light grey cells of Table 2.

When comparing the number of nodes involved in transferring information until the inflection point appears, with and without reinvention, the findings indicate that in the case of weak ties, reinvented information needed a larger group of initial adopters and required slightly more iteration steps to reach the inflection point, in comparison to situations when no reinvention took place. When strong ties were used to transmit information, reinvention had no effect.

The most striking observation is that the conditions sufficient to attain vast diffusion are different than the traditional inflection point. At the initial stages of the diffusion process, regardless of reinvention, the spread of information becomes self-sustained as soon as a hub consumes and shares information. We refer to this as the "point of no return", which occurs earlier in the process than reaching an inflection point. This, in fact, may be the defining point for the continuation of the diffusion process. This finding is in accordance with Dezső and Barabási's (2002) observation that in scale-free networks epidemic thresholds vanish as a consequence of the existence of hubs, and Shakarian et al.'s (2013) finding that seed sets of nodes that guarantee spreading to the entire network are several orders of magnitude smaller than the population size.

Up to the point-of-no-return in 71 % of the cases, information is not consumed by any of the neighboring nodes. In 10 % of the cases, information is consumed, but is not shared. Of the 19 % remaining cases in which one node consumed and shared the information, only 6 % of information consumers reinvented the information. These 6 % are divided equally between cases in which reinvention had a negative value, i.e., lowered the value of information, and cases in which reinvention had a positive value, thus enhancing value. The relative rarity of the reinvention activity emphasizes its unique contribution when it occurs.

Figures 5 and 6 illustrate the diffusion and occurrence of the "point of no return".

In summary of RQ1, the contribution of reinvention up to inflection point depends on tie strength. While reinvention does not affect the realization of the inflection point when strong ties are involved in the diffusion process, it postpones the appearance of the inflection point when information passes through weak ties. However, the defining step for subsequent diffusion is the occurrence of the point-of-no-return, a hub, before the inflection point.

Next we analyze the events occurring past the inflection point (RQ2) as seen in the dark grey cells of Table 2.

In terms of sustainability of the information diffusion process in the network, comparing the number of iterations

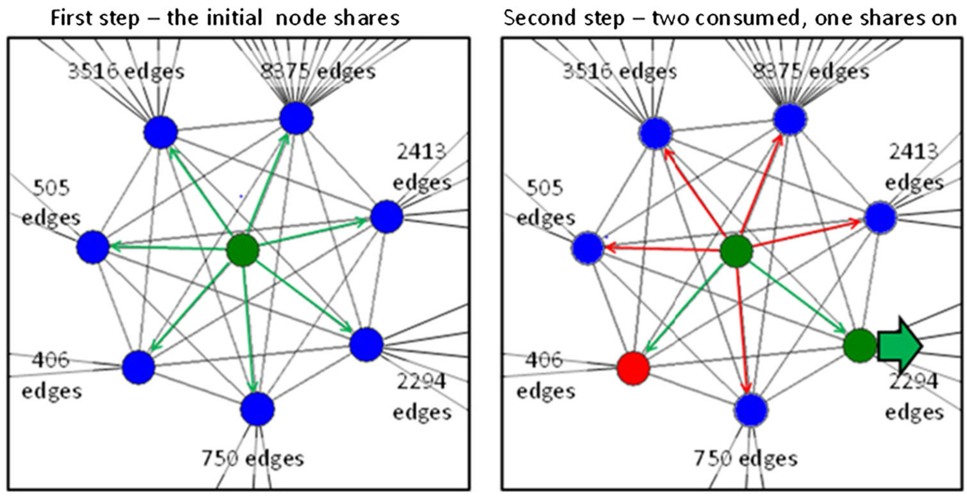

Fig. 5 Two neighbors consume and one (*green*) shares (color figure online)

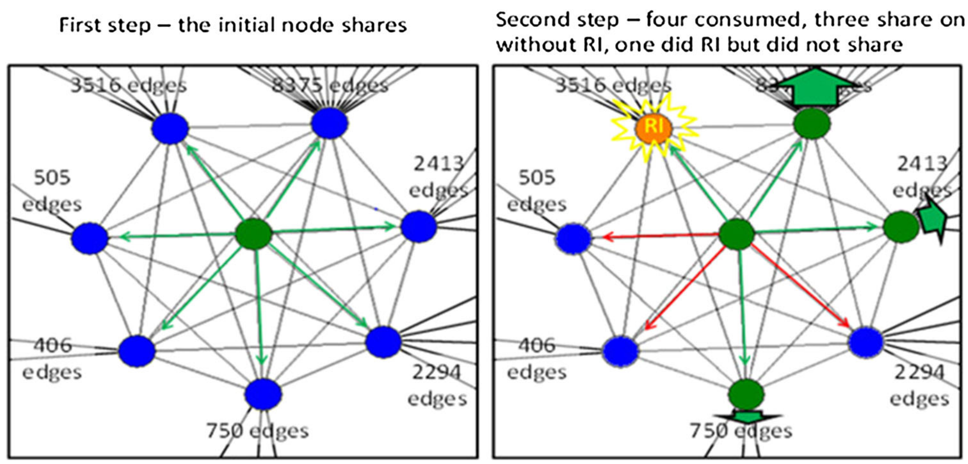

Fig. 6 Four neighbors consume, one reinvents without sharing (*orange*) (color figure online)

needed for information to reach 90 % of the network with and without reinvention indicates the duration information propagated in the network. According to the results, when reinvention of information was relative (RRI) information propagated in the network for about double the time as information that has not been reinvented (60.9 vs. 28.9 iterations). Absolute reinvention had a smaller effect (35.5 iterations).

Table 2 indicates that following the inflection point, reinvented information significantly increased the percentage of the network reached when compared to situations in which no reinvention occurred (RRI-67.5 %, ARI-55 vs. 39.4 %).

Figure 7 illustrates the abrupt diffusion when information is transmitted via strong ties. Weak ties, on the other hand, moderate burstiness. When information is assigned a relative value the effect is stronger compared to reinvention with absolute value; information peaks later than for absolute reinvention in terms of number of new consumers,

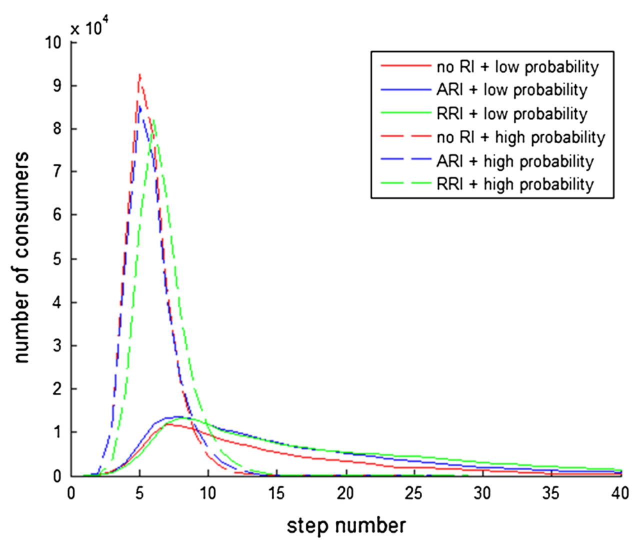

Fig. 7 Diffusion of information considering prob. of acceptance (tie strength) (color figure online)

Table 3 Decrease in consumer group size with an increase of 1 in the average degree of all consuming nodes, in weak and strong ties

Tie strength	Weak	Strong
No RI	−30,000 (−20.3 %)	−10,000 (−3.1 %)
Absolute RI	−40,000 (−19.4 %)	−11,000 (−3.4 %)
Relative RI	−60,000 (−23.7 %)	−11,000 (−3.4 %)

but although delayed, it propagates in the network for a considerably longer time period thus reaching a larger number of final consumers than information with absolute value reinvention.

As reinvented information reached a considerably larger percentage of the network than information that has not been modified, we were interested in discovering the type of nodes reached—were they central or peripheral? Peripheral nodes have lower degree than central nodes; therefore, we calculated the average degree of the final consumer group in each experiment and found the average node degree was lower when information was reinvented. The average degree without reinvention was 8.2. With reinvention, the average degree was lower: 6.8 for absolute reinvention, and 6.0 when reinvention was relative. Thus, reinvented information not only reached a higher percentage of nodes in the network, it reached more remote and peripheral nodes than information that has not been modified.

Furthermore, when simulating an increase in node degree, we found that the size of the final consumer group decreases as the average resource level of that group increases: when the average degree increases by 1, the number of consumers drops as described in Table 3.

For example, in the case of absolute RI transmitted via weak ties, when the average degree increased by 1, the number of consumers dropped by 40,000, a 19.4 % decline in spread. The average resource of the final consumer group is lower when the group is larger. Moreover, the negative correlation is even stronger when reinvention occurs, especially RRI. We address possible explanations to these findings in the Sect. 5.

Next, we address the issue of collective outcome by plotting the number of consumers vs. the cumulative value of information spread in the network when no reinvention takes place, in comparison to relative and absolute reinvention added to information.

Relying on the results regarding the effect of tie strength in the diffusion process, the model ran in two settings: transmission via weak (Fig. 8) or strong (Fig. 9) ties.

When information was shared via weak ties, reinvented information manifested a curve, as opposed to information that had not been reinvented. This "reinvention curve" indicates that reinvention happened repeatedly throughout

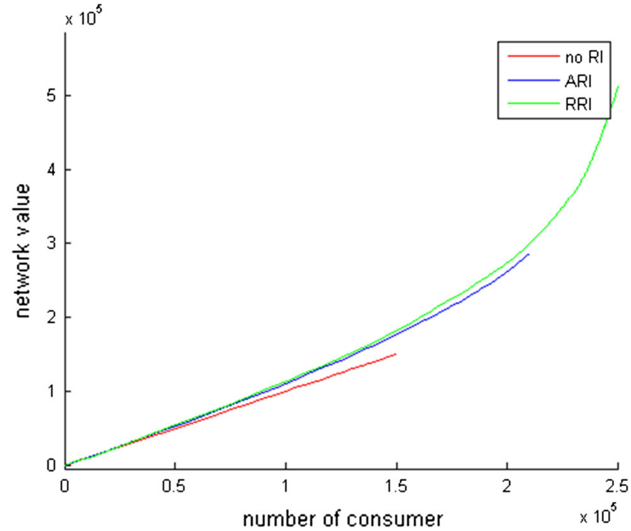

Fig. 8 Weak tie scenario with no, relative and absolute reinvention (color figure online)

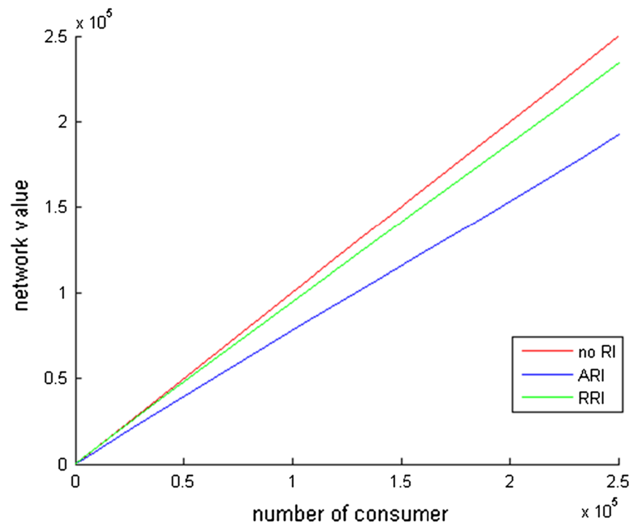

Fig. 9 Strong tie scenario with no, relative and absolute RI (color figure online)

its spread. This repetition of reinvention enhanced the value of information. Relative value assigned to reinvention shows the longest curve, indicating that the value of information grew with the number of consumers and that subsequent reinvention had the greatest effect on the collective outcome. This acceleration, which is self-reinforcing, suggests that reinvention transmitted via weak ties contributes to the overall diffusion of information in social networks.

When information was shared via strong ties, two interesting phenomena occurred. First, reinvention took place at the beginning of the diffusion process and then ceased. Reinvented information, although diffusing widely, is of a lower final value as can be seen in Fig. 9, where the green and blue lines indicate that with a similar number of consumers, the network value is lower than when no reinvention occurred. When transmitted via strong ties, reinvention is found to have a negative effect on the collective outcome of the network.

5 Discussion

This research puts forth questions regarding the diffusion of information in social networks: do existing models for the diffusion of information account for the interplay between social theory and network structure? Does the diffusion of information behave differently than diffusion of other innovations? Does reaching an inflection point promise sustainable diffusion? And finally, does reinvention, the modification of information, a prominent cultural feature, contribute to the diffusion of information via networks?

5.1 Information diffusion model

As outlined in the introduction, widely used information diffusion models are built on the assumption that *exposure* to information, like exposure to a virus, is enough for it to spread. The present finding that in 71 % of the cases, information is not consumed by any of the neighboring nodes implies that mere exposure is not enough for information to diffuse and that the diffusion of information, especially digital information, is more complex. Wu et al. (2004) point out the differences between information flows and the spread of viruses: while viruses tend to be indiscriminate, infecting any susceptible individual, information is selective and passed by its host only to individuals the host thinks would be interested in it. Furthermore, receivers of new information are faced with the decision whether to consume the information and upon consumption they choose whether to pass it on to others. Explicit retransmissions of information are key for information to spread and reach critical mass of exposure.

The model introduced in this research incorporates some of the complexity involved in information transmission in social networks: the decisions to consume, share, and reinvent information while considering tie strength throughout the diffusion process. The three cases studied were: information diffusion when no reinvention occurs, with accelerating or decelerating reinvention applied by nodes. In order to relate to reinvention in a realistic and balanced manner, reinvention was equally assigned either positive or negative value, meaning that a modification of information could increase or diminish the original value of information. Comparison between the two value change regimes (accelerating RRI, decelerating ARI) allows to learn the dynamics involved in critical mass formation when reinvention of information takes place. Reinvention is not influential in the pre-critical mass stage and goes into effect following the critical mass formation process, leading to a longer information diffusion process, a bigger final audience, and a higher value of the collective outcome.

As we assigned decelerating and accelerating value to reinvented information on a single node basis throughout the simulation process, we were interested to see whether these different values on a single node basis will manifest a similar overall effect in the network. We expected to see a decelerating production function for absolute reinvention, and an accelerating production function for relative reinvention. Surprisingly, we found that assigning relative or absolute values to single nodes did not result in the expected production functions. The production functions were linear or accelerating, depending on the tie strength involved. This finding is in accordance with Schelling's (1978) observation that micro-motives aggregate to unpredictable macro-behaviors.

5.2 Inflection point vs. the point of no return

The present findings show that the conditions sufficient to attain vast diffusion of information are different than the traditional inflection point that involves both innovators and early adopters (Rogers 1962). The initial stages of the diffusion process, as shown in Figs. 5 and 6, indicate that regardless of reinvention, the spread of information becomes self-sustained as soon as a hub consumes and shares information implying that innovators alone can comprise the critical mass needed for attaining vast diffusion, as long as they are friends of hubs. We refer to this as the "point of no return", which occurs earlier in the process than reaching an inflection point. This finding is in accordance with Dezső and Barabási's (2002) observation that in scale-free networks epidemic thresholds vanish as a consequence of the existence of hubs. In other words, the presence of neighboring hubs, rather than the number of nodes, is crucial for diffusion. So, *who* is the initial transmitter of information is more influential in the diffusion process than "*how many*".

Furthermore, Rogers elaborated that an inflection point occurs when 16 % of the individuals in the social system adopted an innovation. The current findings indicate that when no reinvention takes place—only 8 % of the social system are needed to reach the inflection point. When reinvention occurs—10 % of adopters are sufficient to reach the inflection point. This finding suggests that the spread of information "behaves" differently than tangible innovations.

Rogers' (1995) observation that once the adoption of an innovation reaches an inflection point, further diffusion becomes self-sustained is challenged by CMT which argues that the dynamics leading to the inflection point influence the sustainability of the diffusion process. Our results indicate that in the case of information, diffusion is so abrupt that processes occurring after the inflection point are of larger significance than anticipated.

5.3 Segmenting the diffusion process before and after the inflection point

In the process of attaining critical mass, reinvention was found to have a different effect prior to, and following the inflection point. While reinvention had a small effect on the diffusion of information prior to inflection point (required more nodes and more iterations), it had a prominent effect on the overall diffusion process following the inflection point.

When looking at the overall diffusion process following the inflection point, reinvention is found to contribute to the sustainability of the diffusion process in terms of the number of consumers and the duration of propagation in the network: information that has been reinvented reached a higher percentage of nodes in the network compared to information that was shared without modifications. In cases of relative value change, information reached a larger percentage of the network and propagated in the network twice as long as in the absence of reinvention. This implies that reinvention allows information to undergo an evolutionary process, in which information of lower value was not retransmitted, and only information with higher value diffused. Positive reinvention enhanced the value of information and thus propelled further reinvention which in turn, contributed to the spread of information. Moreover, while most research focuses on getting processes started and obtaining a critical mass, the present research reveals the importance of the prolonged effect of processes occurring post the critical mass point.

5.4 The importance of tie strength

The current findings indicate an interesting interplay between tie strength and the value of information regarding the inflection point, the sustainability of the diffusion process and the dynamics involved in critical mass formation.

When information is transmitted via strong ties, in all three settings, there is an average of 85 % chances to reach a super-spread (Table 2), as opposed to 19 % average chance in weak ties. Although weak ties have a lower probability to spread widely, when a super-spread occurs, it requires fewer nodes to reach the inflection point and the effect of reinvention stands out clearly when examining the percentage of the network the information has reached. Reinvention is found to have the strongest effect when transmitted via weak ties. In these cases, information reached a larger final audience (67.5 vs. 39.4 %) and propagated in the network for the longest period of time (60.9 vs. 28.9 iterations).

When comparing between the value change schemes assigned to reinvented information, the largest effect of reinvention is found in the *relative value* change when weak ties were involved in transmitting information. This finding implies that when transmitted via a weak tie, subsequent reinvention has the biggest effect on the diffusion of information in the network, thus producing an accelerating production function which in turn, manifests sustainability of the diffusion process. Weak ties are found to play a significant role not only in transmitting information, but also in innovative work.

5.5 Node degree as an indication of information reach in the network

Average node degree suggests that reinvention contributes to the diffusion of information to remote areas of the network. When no reinvention took place, average node degree was higher than when reinvention occurred; the higher the average degree, the lower the number of final consumers. Degree is associated with location; peripheral nodes are less connected and naturally, have a lower degree than central nodes in the network. These findings imply that information that was not modified diffused to high degree nodes, which are centrally located in the network. The lower average degree found in the diffusion process when reinvention took place and the negative correlation between average node degree and the number of final consumers, which became stronger when reinvention took place, implies that reinvented information reached more weak ties and remote clusters and nodes. A possible explanation is that reinvention "helped" information to reach remote areas of the network by tailoring the information to the tastes of a larger variety of nodes which are found in small groups in remote areas of the network.

Table 3 reveals that the decrease in the final number of consumers in the case of strong ties is fairly constant, while for weak ties, the change varies. This pattern of the effect of reinvention on the spread and persistence of information is consistent with our earlier analysis. When reinvention took place, information reached 10,000–30,000 more consumers per average node degree decrease in the case of weak ties (comparing to the change when no reinvention took place). This is an example of the self-reinforcing nature of relative reinvention—it reached more people than absolute reinvention. Eventually, relative reinvention led to a higher overall value of information (collective outcome) as discussed next.

5.6 Reinvention's contribution to the value of information

The large spread of valuable information in a network is a desirable collective outcome for members of the network. Collective outcome is measured by the overall value of information in the network as a function of the number of nodes who consumed it. Figures 8 and 9 depict the total value of information vs. the number of consumers in the network focusing on strong and weak tie scenarios in order to determine the effect of reinvention on the production functions and the collective outcome.

The negative effect of reinvention when transmitted via strong ties (Fig. 9) can be explained from structural or social points of view. From a structural perspective, the spread of information via strong ties is abrupt and terminates in fewer iterations than in the weak tie scenario, thus, allowing less opportunities for reinvention. This amount of reinvention is not sufficient for it to undergo an evolutionary process which would result in value enhancement. An opposite effect emerged in the case of weak ties. Figure 8 shows that reinvention happened repeatedly, enhancing the value of information. The slower and longer propagation allowed the repetition of reinvention and reach of nodes in the network that would not have been reached otherwise. From a social perspective; reinvention is mostly facilitated by the opportunity to express creativity, self identity and building of social relationships (Yew 2009). According to Havelock (1974), reinvention is motivated by gaining status and recognition. When communicating with strong ties, these motivations are less evident, as one's identity and status are already known and accomplished. The act of reinvention serves one's desire to gain status, recognition and build new relationships when communicating with weak ties.

6 Summary

In summary, critical mass in social sciences is a socio-dynamic term used to describe the existence of sufficient momentum in a social system such that it becomes self-sustaining and fuels further growth (Ball 2004). By combining theoretical constructs from two prominent theories we are able to better understand the dynamics involved in building this sufficient momentum that contributes to the vast diffusion of information in a social network.

We found the contribution of reinvention to the overall diffusion of information in the network prominent across all variables: the lower average node degree when reinvention takes place, the higher percentage of the network reached by reinvented information, the longer propagation in the network, the higher value of reinvented information in the network—all imply that reinvention contributes to the diffusion of information in the network in both reach and sustainability. The diffusion of information in a social network requires 8–10 % of individuals to adopt the information in order to reach an inflection point as compared to 16 % by the DOI theory. Importantly, information must pass through a hub in order to gain momentum.

The practical significance of the present research is that in order to attain vast diffusion via social networks, information should be in "free form", i.e., using a format that allows changes to information will lead to more sharing than closed formats. Think, for example, about sharing a document in a popular word processing format as compared to sharing the same document as an image. Another example may be that implementing Creative Commons publication rights is more aligned with network culture than "All Rights Reserved". Empowering people with the ability to modify information appears as a significant driver of the spread of information.

7 Limitations and further research

The model presented here was designed with best intentions to simulate real-world decision-making regarding the spread of information in a network. Still, the model suffers from some limitations. The data set of Hollywood actors' network comprises hundreds of thousands of nodes and millions of links. As such, it provides an excellent opportunity to explore critical mass formation and diffusion on a real complex scale-free network, a social graph. However, the dataset covers a long period, spanning from 1890 to 2001, so some links could not have been created due to the time gap. This limitation is found in most complex networks where nodes are aging (e.g., abandoned webpages and Facebook profiles) that narrow the range of actual vs. potential interactions. Nevertheless, preferential attachment is demonstrated in the actors' network as evidenced by the topology and in this respect it is similar to many social networks on and off-line. While the actors' network represents offline ties, following Dodds et al. (2003), we assume that our findings are of significance to both offline and online social networks.

Another limitation of our model is simplification: by synthesizing the variables into a single numeric value our results point out general directions or trends and not absolute values. In addition, we followed Roger's observation of innovators comprising 2.5 % of the network and assigned innovators randomly, not by their structural properties in the network. In further research we intend to incorporate into the model not only additional and varied starting points, but also multiple starting points simultaneously to further understand the effect of network structure on the diffusion process. Our model allowed nodes to receive information once. Further research may incorporate the opportunity of multiple possibilities to receive and consume information. This research focused on one undirected network. Further research may focus on additional networks, with special interest to distinguish differences in diffusion dynamics between directed and undirected networks. The advantage of the data source used here is that it represents a full social graph in order to see the full process of diffusion—we did not select part of the network. In this respect, the current findings represent other scale-free networks with similar attributes.

8 Conclusion

This research offers a new approach to studying the diffusion of information in social networks by combining social theories with network structure. Structure interacts with behavior to produce the current observations regarding the point of no return, the modest effect of reinvention prior to the inflection point and its pronounced effect afterwards. Critical mass attainment is faster for the spread of information than for other innovations since network structure is dominant. Vast diffusion is a rare event, especially when weak ties are at work, but when information is modified/reinvented, the duration of diffusion increases, the final spread is larger, information eventually reaches remote nodes in the network and the overall value of information becomes high. The present research offers quantitative observations that extend knowledge of DOI as it pertains to the spread of information, or dare we say, the spread of knowledge.

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