Entry Point Matters
Effective Introduction of Innovation in Social Networks

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Abstract: Social networks have grown massively in the last few years and have become a lot more than mere message exchange platforms. Apart from serving purposes such as linking friends and family, job linking or news feeding, their nearly pervasive nature and presence in day-to-day activities make them the biggest potential market and access platform to hundreds of millions of customers ever built. Faced with such a complex and challenging environment, we claim that introducing innovation in an efficient way in such networks is of extreme importance. In this paper, we put forward a mechanism to select suitable entry points in the network to introduce the innovation, so fostering its acceptance and enhancing its diffusion. To do this, we use the underlying structure of the network as well as the influencing power some users exercise over others. We present results of testing our approach with both a Facebook dataset and different examples of random networks.

1 INTRODUCTION

Social networks have grown to become very complex systems in which individual users, groups, companies and other organisations are represented as entities, and relationships among them denote a certain affinity, e.g. friendship, co-working, similar preferences and tastes, and so on. Hundreds of millions of people are involved in these networks and they probably form the largest potential market ever to have emerged. It is for this reason that introducing innovation in such networks turns out to be fundamental for boosting firms' income and profits or, at least, for maintaining them. Nevertheless, despite the potential to provide access to hundreds of millions of customers, due to their complex nature, social networks have not shown yet their full potential as a marketplace.

Innovation is considered as a key point for the establishment and growth of any firm (Calantone et al., 2002). However, the introduction of innovation in a market has typically been considered as a leap of faith, since no technique can guarantee its success. Although there exist different market techniques and models that help to shed light on the process, the majority of them are mostly ad-hoc solutions that may apply to particular types of products or specific markets. There is considerable literature on this topic, with most opinions agreeing on the two main characteristics that more significantly and effectively affect an innovation's success: *adoption* and *diffusion*. Seminal works by Bass (Bass, 1969) and Rogers (Rogers, 1995) have progressed on the field, but they are oriented towards traditional markets. The emphasis of these works is on what happens once innovation is introduced in a market, but they do not examine what could be the best entry points to initiate product adoption and diffusion or how a firm would be able to identify these and/or choose among them.

With the emergence of the Internet, the nature of markets has changed dramatically and new ways of introducing innovations in a market have been brought into play. In particular, introducing innovation through social networks requires a more effective way of introducing new products by identifying the best or more appropriate entry points for doing so. In this paper, we suggest that in addition to developing and analysing new techniques for innovation diffusion for different types of products and markets – which has been the subject of work over the last decades – it is also important to focus on identifying the best or key entry points from which the innovation adoption and diffusion processes can be initiated. For social networks, this means looking at their inherent

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structure and other characteristics that may enable us to identify key entry points that we would want to use to introduce the innovation into.

The aim of this paper is to provide a mechanism able to identify suitable entry points for the innovation in the social network in order to achieve *a more efficient early adoption of the innovation*, in terms of cost, rate of adoption and subsequent benefits to the firm introducing it. We claim that the network's underlying structure can be analysed in order to determine the most promising entry points for introducing an innovation; that is, which individuals would be the first ones in adopting the innovation and also which of them will contribute to its more effective and wide diffusion. Our mechanism relies on mining the underlying structure of the network, as well as on the power of influence some users have on others. We present a set of experiments based on a Facebook dataset (McAuley and Leskovec, 2012) that shows the effects of deploying our mechanism when applied to it. Moreover, we also present the results of applying the mechanism to different random networks with different properties.

The paper is structured as follows: Section 2 describes the model of the network. Then we present our mechanism in Section 3. In Section 4, we show an empirical evaluation of our approach. We review the work in the literature and compare to our approach in Section 5. Finally, we sum up our work and sketch different lines of future work in Section 6.

2 NETWORK AND INDIVIDUAL MODEL

This section presents a model for the social network, as well as a model for the innovation adoption of the user.

2.1 Social Network Model

A social network Ω can be modelled as a directed graph $G_\Omega = (V,E)$, in which V corresponds to a set of users and E is a set of edges representing relationships in Ω. Let $(v_i, v_j) \in E$, with $v_i, v_j \in V$, an edge in G_Ω representing a relationship from v_i to v_j. These relationships might denote, for example, follower-followee relations (e.g. Twitter), friendship (e.g. Facebook), job links (e.g. LinkedIn), and so on. The neighbourhood of a user is denoted as a function $neigh(v_i) = \{v_j\}$ iff. $\forall v_j \exists (v_i, v_j) \in E$.

We assume that neighbours can communicate with each other if there exists a link between them. As we are dealing with directed graphs to represent the network structure, if user v_i wants to communicate with v_j then there must exist a link $(v_i, v_j) \in E$. Users communicate the innovations they adopt to the users they are connected to, that is, to their neighbours. We call this communication a *signal*. Users communicate signals right after they have adopted an innovation. A signal sent by user v_i - right after adopting a certain innovation k - to another user v_j is denoted by $\sigma^k_{v_i \to v_j}$. We assume a signal σ^k is broadcasted by the user to all its neighbours when adopting the innovation k.

There are concrete examples of this direction in real world networks. For instance, in Twitter, when users tweet messages, these are broadcasted to every follower the user has, while in Facebook, messages left by a user on his/her wall are typically visible, at least, to his/her friends. Figure 1 depicts this process. Thus, signals may cover a wide range of types of information, from text messages to videos, SMS messages, and so on, depending on the social network under study.

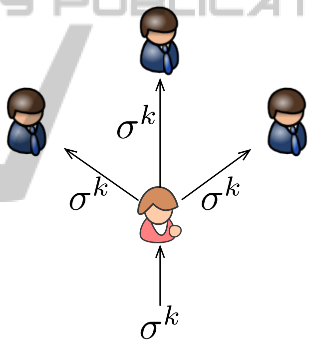


Figure 1: Signal propagation after innovation adoption.

2.2 Agents in Play

There are three different types of stakeholders in our model.

- **Users** (S): are typical agents in a social network that may or may not adopt an innovation and, if so, spread it through to their neighbours.
- **Innovation creators** (IC): are agents that create innovation (e.g. companies).
- **Network explorers** (NE): these agents are managed and deployed by the ICs and they are responsible for exploring the network to identify promising users through which to introduce the innovation into the network.

2.3 User behavioural Model

When a user receives a signal about an innovation, it reasons about the opportunity of adopting it and eventually has to come to a decision: *adopt* or *not adopt*. We consider users as rational entities. In order to model this reasoning process of adoption, we adapt the model proposed by Bass (Bass, 1969). In the Bass Model (BM), the probability of innovation adoption of a user is calculated as follows:

$$A_k(t) = p + \frac{q}{N} \cdot N^k(t) \quad (1)$$

where, p is the *coefficient of innovation* or how innovative the user is, q stands for the *coefficient of imitation* or how the user is affected by others' adoptions, $N^k(t)$ is the total number of adopters up to time t, and N is the total number of potential product buyers.

In our case, we regard users as only having a partial view of the network, i.e. they only have knowledge about their neighbours. Note that since we consider that different innovations may take place at the same time, A_k denotes the probability of adopting innovation k, while N^k is the number of neighbours that have already adopted the specific innovation k.

We assume that any link in the social network entails some sort of influencing power among the users. For instance, in Twitter, the action of following someone means the followed has power over the follower, the former is somehow appealing to or influential on the latter. However, there exist other types of social networks in which this is not so clear. An example of this is Facebook, in which friendship acceptance brings about two new links in the network (recall that links are unidirectional). Although, in this case, it is a bit blurrier what type of power holds behind a virtual friendship, it must exist in both directions, otherwise the friendship link would not have been established. In some social networks, users may be analysed in terms of profile features. For example, in Facebook, there is a check list of different preferences, regarding sentimental status, political view, religion, and so on, that users fill in to complete their profiles.

Besides the inherent relation given by the link between two users in the social network, profiles could be utilised to obtain similarity measures among individuals since common interests usually foster the innovation adoption. In order to include similarity between users into the model, we extend equation 1 to represent the probability of adoption. Given a received signal $\sigma^k_{v_i \rightarrow \cdot}$ the resulting function is presented in equation 2.

$$A_k(t) = \alpha \cdot p + \beta \cdot \left[\frac{q}{|neigh(\cdot)|} \cdot N^k_{neigh(\cdot)}(t) \right] + \gamma \cdot sim(\cdot, v_i) \quad (2)$$

where $N^k_{neigh(\cdot)}(t)$ is the number of neighbours that already adopted the innovation up to time t[1]. Parameter α determines the sensitivity of the user to internal forces (coefficient of innovation) versus external forces (coefficient of imitation) to adopt the innovation (parameter β). γ represents the degree of belief the user has on the importance of the similarity regarding his/her neighbours. Note that $\alpha + \beta + \gamma = 1$ is a requirement of the model.

We call this the Adapted Bass Model (A-BM) which attempts to add similarity between users into the probability of adopting the innovation. Note that this function can cover different types of social networks. While in Facebook similarity is easily obtained if we have access to the users' profiles, in Twitter there is no such notion of profile features ($\gamma = 0$).

User profiles can be represented as an n-dimensional preference vector $\rho^{v_i} = (\rho^{v_i}_1, \rho^{v_i}_2, ..., \rho^{v_i}_n)$ with $\rho^{v_i}_j \in \{0, 1\}$ denoting the user v_i presents this feature (with 1) or it does not (with 0). We calculate similarity (*sim* function in eq. 2) by using the Tanimoto similarity index (Tanimoto, 1958). This function is typically used to compare chemical molecules that can be represented with an array of binary elements in chemical processes. Since ρ^{v_i} profiles are binary arrays, this index appears to be an efficient way to calculate similarity, but other methods could be potentially used here depending on the complexity and representation of the profile. Let users u and v be represented by bitmaps ρ^u and ρ^v, ρ^u_i and ρ^v_i be the i-th bit of ρ^u and ρ^v, respectively. Let $\wedge$, $\vee$ be bitwise *and* and *or* operators respectively. Thus the Tanimoto similarity index is given by equation 3.

$$sim(u, v) = \frac{\sum_i \rho^u_i \wedge \rho^v_i}{\sum_i \rho^u_i \vee \rho^v_i} \quad (3)$$

We assume that the contact between an IC and a user to introduce a certain innovation k into the network has an associated cost for the IC given by equation 4:

$$c(k) = c_1 + c_2 \quad (4)$$

$c_1 \in \mathbb{R}$ represents the cost for advertising the innovation (send the signal to a user) and c_2 is the cost associated with the consumed resources, i.e. the cost of the incentive, used by the IC to persuade a user to adopt the innovation. $c_2 = 0$ represents no need for incentives. c_2 may be obtained with a function taking into account the relative importance of the user in the network. We define an example of this type of function in Section 4 when setting up a test scenario for empirical evaluation. Note that the cost is only applicable when there exists any sort of communication between the IC and a user selected as entry point; the diffusion phase does not have any cost for the IC.

[1]The notation $(\cdot)$ refers to the user doing the calculation.

3 SISM MECHANISM

This section presents a novel mechanism that aims to identify and choose suitable entry points for innovation in a social network. Given an innovation issued by an IC, the mechanism will address the problem of how to identify promising entry points for the innovation into the network, in order to achieve an as wide as possible diffusion of it. To this end, the mechanism relies on the identification of well positioned users in the network (from a structural perspective), as well as on the power that users exhibit when influencing others. The former is related to the position a user has in the network (from a structural point of view) (Goldenberg et al., 2009), while the latter is related to the ability a user has to exercise influence over another user to make her adopt an innovation (Fasli, 2006). Since diffusion depends on the users' acceptance of the innovation, in this paper we focus on the innovation seeding, which is the only process the IC has control over. We call our approach Social Innovation Seeding Mechanism (from now on SISM).

3.1 Identifying Hubs

We use different measures from social networks to infer which are the most promising users to introduce the innovation into the network. These measures are related to the well-studied property of centrality in the literature. The concept of centrality encapsulates "micro" measures that allow us to compare nodes and to say something about how a given node relates to the overall network (Jackson, 2008). The centrality of a node gives us information about the position an individual holds in the network. Many different measures of centrality have been developed, and they each tend to capture different aspects of the position that a node has, which can be useful when working with information flows, bargaining power, infection transmission, influence and other important behaviours in a network. We use the following centrality measures to identify hubs:

Degree: it represents the number of links that a node has. Equation 5 defines this function.

$$DC^{v_i} = \frac{d(v_i)}{|V|-1} \tag{5}$$

where $d(v_i)$ denotes the out-degree of node v_i in the network.

Closeness: it is defined as how close a given node is to any other node in the network. Mathematically it is represented as the inverse of the average distance between a user $v_i \in V$ and any other user $v_j \in V$. It is formally defined in equation 6.

$$CC^{v_i} = \frac{|V|-1}{\sum\limits_{v_i \neq v_j} sp(v_i, v_j)} \tag{6}$$

where $sp(v_i, v_j)$ is the shortest path between node v_i and v_j.

Betweenness: it is a measure based on how well a user is situated on the paths it lies on (Freeman, 1977). Let $np(v_j, v_k)$ be the number of paths between $v_j \in V$ and $v_k \in V$ and $np_{v_i}(v_j, v_k)$ the number of paths between v_j and v_k on which $v_i \in V$ lies on. Then we obtain the centrality of node v_i in terms of connecting v_j and v_k as the ratio

$$\frac{np_{v_i}(v_j, v_k)}{np(v_j, v_k)}$$

Generalising to obtain the betweenness centrality of node v_i we obtain equation 7.

$$BC^{v_i} = \sum_{v_j \neq v_k \neq v_i} \frac{np_{v_i}(v_j, n_k)/np(v_j, v_k)}{(|V|-1)\cdot(|V|-2)/2} \tag{7}$$

The mechanism will use one of these measures in order to identify a ranking of "central" users that essentially comprise hubs in the network. The IC will then decide which users in the top ranking to approach in order to introduce the innovation.

3.2 Identifying Power

Now we put forward a method to investigate the power that a subset of selected hubs (typically the top ones in the aforementioned ranking) exercise on others. In this approach, we adhere to the notion of *referent* power (Fasli, 2006), as power deriving from identification. We say a user v_i has power[2] on user v_j iff. there exists a connection $(v_i, v_j) \in E$ and, when v_i sends a signal $\sigma^k_{v_i \to v_j}$ user v_j subsequently always adopts innovation k. Then, we can say user v_i somehow influences v_j to adopt k.

In order to calculate the power of a user in the network, we will use the so-called *network explorers* (NEs). As we pointed out in Section 2.1, this type of agent is deployed by innovation creators (ICs) with the aim of assessing the power that users have on others. The IC will add an NE in the network connecting it to a relevant user in order to monitor and calculate an estimate of the latter's power. Note that in some types of networks this process may be more complex,

[2]For clarity we use power to refer to referent power.

since the connection to the network requires the approval from the other side, i.e. an acceptance from a user already in the network (e.g. LinkedIn). We assume NEs can always connect to a selected user or, at least can monitor her signals. Algorithms 1 and 2 provide the steps for the power estimation. In Algorithm 1, in order to examine the power user v_i has in the network we add an NE v_{exp} and connect it to v_i (line 1). Once this initial connection is made, our algorithm also connects v_{exp} to all of v_i's neighbours (lines 2–4). Our intention with this step is for v_{exp} to be aware of the signals sent by v_i when adopting an innovation but also the signals emanating from its neighbours so that we can track the power of influence on them. Algorithm 2 presents a method to calculate the power of a user v_i by taking advantage of the connections made in Algorithm 1 (line 1).

Algorithm 1: $connectExplorer(\cdot)$ algorithm that introduces the explorer into the network.

Require: $v_{exp} \in NE$, $v_i \in V$ the user whose power is estimated
1: $E \leftarrow E \cup (v_i, v_{exp})$
2: **for each** v_j in $neigh(v_i)$ **do**
3: $\quad E \leftarrow E \cup (v_j, v_{exp})$
4: **end for**

Firstly, the explorer v_{exp} waits to listen for any signal (line 2). When v_{exp} receives a signal from v_i (line 5), that necessarily implies that neighbours received it as well. Therefore, each neighbour, as explained in Section 2.3, must decide if it accepts or not the innovation signalled by v_i. If the innovation is accepted, a new signal will be forwarded, and so received by v_{exp} (line 7). Explorer v_{exp} will annotate different signals received from v_i's neighbours (line 8). We then calculate the ratio of adopted innovations after v_i's signal (line 10). Finally the algorithm returns a value of power as a linear combination of past influence calculated for v_i and the influence ratio calculated (line 15). Parameter δ represents sensitivity of past influence in contrast to new one. At this point, an important feature to remark in the approach is that influence assessment is very much dependent on the position of the user in the network. That is, the same user in another location may result in exercising very different influence on its neighbours. This occurs because it is the recipient user the one that decides whether to adopt or not the innovation. In other words, the *influencer*'s power arises from the neighbours around it, which are biased to be influenced, rather than by a pro-active attitude of the *influencer* to exert that power. Once v_{exp} has accomplished its task, it returns the calculated influence to the IC it belongs to. The IC may repeat the process with some

Algorithm 2: Power estimation using NEs.

Require: $v_{exp} \in NE$, $v_i \in V$ the user whose power is estimated
Require: $pastInfluence \leftarrow 0$
1: $connectExplorer(v_{exp}, v_i)$
2: **while** true **do**
3: $\quad positive \leftarrow 0$
4: $\quad newInfluence \leftarrow 0$
5: $\quad$ **if** $signalReceived$ **then**
6: $\quad\quad$ **for each** j in $neigh(v_i)$ **do**
7: $\quad\quad\quad$ **if** $signalReceived$ **then**
8: $\quad\quad\quad\quad positive++$
9: $\quad\quad\quad$ **end if**
10: $\quad\quad\quad newInfluence \leftarrow possitive/|neigh(v_i)|$
11: $\quad\quad$ **end for**
12: $\quad\quad$ **if** $pastInfluence == 0$ **then**
13: $\quad\quad\quad$ **return** $newInfluence$
14: $\quad\quad$ **else**
15: $\quad\quad\quad$ **return** $\delta \cdot pastInfluence + (1 - \delta) \cdot newInfluence$
16: $\quad\quad$ **end if**
17: $\quad$ **end if**
18: **end while**

other users it may consider as being promising entry points for introducing the innovation. The IC will eventually decide on the best entry points and send a signal to the selected user(s).

4 EMPIRICAL EVALUATION

4.1 Basic Workings

We are interested in exploring whether SISM helps the IC identify the best entry point for its innovation and also the potential impact that the underlying structure of the network may have on the performance of the algorithm. In the experiments that follow, and for simplicity and clarity, we only follow through and show in action one IC trying to introduce sequentially multiple innovations. Moreover we assume an IC typically deploys one NE per hub to be studied, in our case the top 10% of ranked users returned from the hub identification phase.

In the first time step, the IC uses one of the methods to select an entry point in the network. It then sends a signal to the selected user with the new innovation. The signalled user decides to accept the innovation or not. If it accepts it (following the adoption function in eq. 2), the user will send a signal to its neighbours (to be considered at the next time step). If the entry point user does not accept the innovation, then it will be incentivized by the IC. The incentive the IC will be willing to pay is calculated following equation $c_2 = \frac{C}{pos(\cdot)}$, where $pos(\cdot)$ is the position of the user in the ranking of hubs calculated by the system, and C is a constant that may vary in different domains. We set $C = 1000$ for this set of experiments. So better connected users (how well-connected a user appears to be depends on the measure used to calculate this – see Section 3) will have to be paid more since they are supposed to be more effective entry points.The next time step starts with users processing the received signals. This is repeated every time step until no new signals are sent out, at which point the diffusion converges.

We use two different measures in order to evaluate our approach. Firstly, we are interested in measuring the number of users adopting the innovation. Secondly, we attempt to measure the associated benefit of introducing the innovation into the network following $B(k) = r \times |adopters| - c(k)$. The r value stands for the reward obtained by the IC after every adoption. Although the value of r is domain dependent, as this scenario is generic we set $r = 10$ for all experiments; any other constant would have been valid as well. In eq. 4, c_1 is a domain-dependent constant. As innovations in our experiments are generic, we decided not to include this value in the cost function ($c_1 = 0$). In each experiment, we show average results from 10 executions using different random seeds.

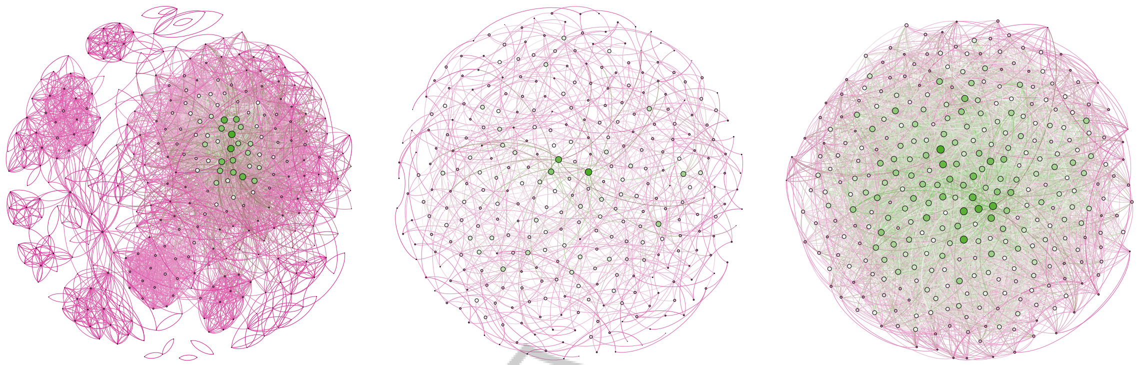
We assume that it would be of interest to apply the algorithm for power estimation (Alg. 2) only to a few of the hubs obtained using the policies presented in Section 3. In this set of experiments, we will use the best 10% of hubs to calculate their power. We will connect a NE to each one of these hubs and also to their neighbours, as explained in Alg. 1 and then SISM will apply Alg. 2. δ is set to 0.8.

4.2 Experiment 1. SISM Performance

First, we put forward how the social network for this block of experiments is generated. We have used a dataset based on Facebook (McAuley and Leskovec, 2012) which consists of 'circles' (or 'friends lists'). The data was collected from survey participants using a Facebook application. This network contains 333 users and 5038 links among them denoting reciprocal friendship (all edges in the graph are bi-directional). The dataset also includes node features (profiles) that allow SISM to work with similarities (as explained in Section 2.3). Figure 2(a) shows the graph of the initial network. The node size represents the degree of users' connectivity (bigger representation means a higher degree). Here we intend to compare the SISM approach with a traditional broadcasting approach for innovation introduction, in which the network is flooded with attempts to introduce the innovation. As far as we know, this is the most common manner of deploying marketing campaigns, especially the ones based on press ads or TV commercials. For the sake of simplicity, we simplify the problem comparing the consequences of selecting a single entry point using SISM against the selection of an entry point randomly. Furthermore, we test SISM with different features: varying parameters for α, β and γ in the A-BM probability of adoption function and also the different policies to identify hubs, namely *degree centrality* (SISM-DC), *closeness centrality* (SISM-CC) and *betweenness centrality* (SISM-BC). The initial population is generated from the dataset, endowing each user with random coefficients of innovation and imitation, respectively. In Figures 3(a), 3(b) and 3(c), the SISM mechanism (fixed to SISM-DC) outperforms a random policy for selecting entry points (RandomEP). However, different populations generated with variations in the function for the innovation adoption bring about different results. When α is set to a high value (3(a)), denoting a tendency to follow internal forces to accept the innovation, a wide coverage in adoption is achieved (around 94% of the users).

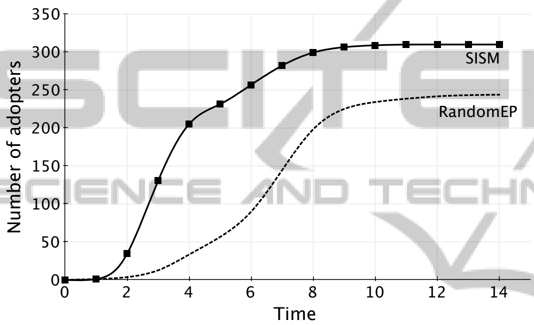
Even when the coefficients of innovation are relatively low (as in Figure 3(c)), the repetitiveness/accumulation of the signal increases the chances for adopting the innovation due to the longer period that one can be influenced by neighbours' adoption (as it occurs in Figure 3(c)). Here we observe a poor performance for the random entry point selection policy, since isolated and with low influence users do not have enough power to influence their neighbours to adopt the innovation. Note that in the case of a neutral population – 3(b) – users are sensitive to different forces: internal, external and profile similarity.

Figure 4 presents the benefit – calculated as explained in Section 4.1 – obtained by both approaches in the latter experiments. It is worth noting that SISM achieves high benefits regardless the type of population in the network. This is a consequence of the wider spread that the innovation reaches. Even when the use of the SISM mechanism results in higher incentive costs – on average – when the entry point user does not accept the innovation for free, this payment entails an innovation introduction at a suitable point to foster the diffusion. An approach is said to converge when there are no more signals to be processed by the users; i.e., the innovation reaches its maximum in terms of adoption. In the case of the RandomEP, low performance consequently means a low convergence rate, since diffusion gets easily *trapped*. However, convergence in SISM is not affected by the type of

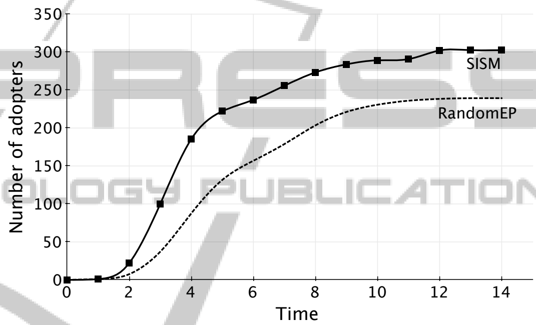


(a) Facebook dataset (b) Poor-connected network (c) Well-connected network

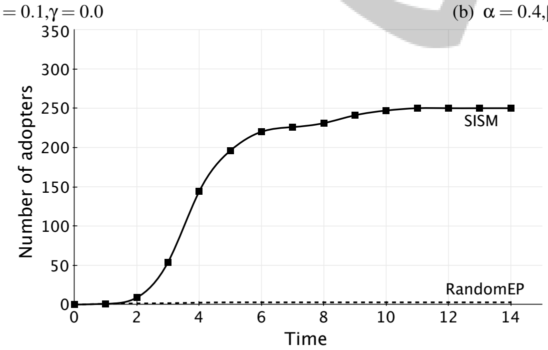
Figure 2: Different networks used in the experiments.



(a) $\alpha = 0.9, \beta = 0.1, \gamma = 0.0$



(b) $\alpha = 0.4, \beta = 0.3, \gamma = 0.3$



(c) $\alpha = 0.1, \beta = 0.9, \gamma = 0.0$

Figure 3: Number of adopters for different values of α, β and γ.

population, it always outperforms RandomEP, since it chooses a suitable entry point and so spreads the innovation in a shorter time.

4.3 Experiment 2. Network Topology Effect

We created two different networks with different topologies with the same size as in the previous block. The first instance, represents a poor-connected random network (Fig. 2(b)) while the second one stands for a well-connected random network (Fig. 2(c)). We intend to benchmark the effectiveness and suitability (in terms of the number of adopters) of SISM on them. We assume that in such networks there are no publicly available profiles from which we can draw on similarity measures, hence profile vectors cannot be calculated ($\gamma = 0$ in eq. 2). We set up $\alpha = \beta = 0.5$. From the study of the results of the poor-connected network (Fig. 5) we conclude that SISM-BC outperforms the other mechanisms. This is explained by the fact that SISM-BC estimates how *present* a user is in any possible path between two different users. This information is then used by SISM as a relevant heuristic

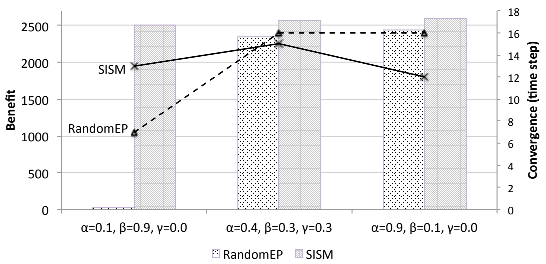


Figure 4: Average benefit and convergence.

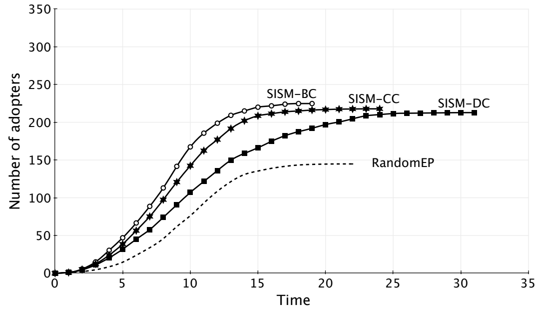


Figure 5: Number of adopters for the poor-connected network.

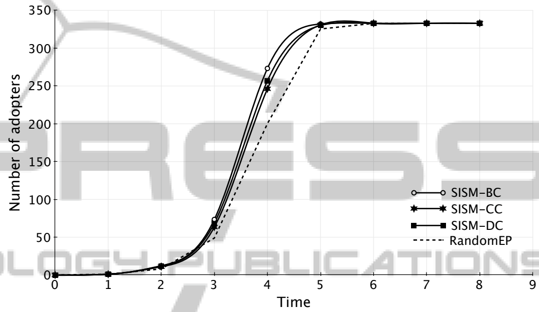


Figure 6: Number of adopters for the well-connected network.

to start the innovation diffusion. Similarly, in SISM-CC the closeness centrality is used also as a suitable heuristic. However, in the latter, this measure only focuses on how close a user is from any other user, but does not take into account the number of paths between any pair of users. This is rather more relevant since once the innovation is introduced, the path that it follows in the network depends on the adoption of every individual user. In the case of the SISM-DC, as one might expect, this reaches a lower number of adopters. Note that the number of users that adopt the innovation is around the 65% mark of the whole population in the best case (220/333). This is a consequence of the limitations in the connectivity of the network and in the users' adoption as well. Regarding the convergence of the different approaches, we conclude that SISM-BC converges first, as a consequence of the suitability of the entry point found by the mechanism, facilitating innovations reaching any potential adopter in a shorter time.

Figure 6 puts forward the results of the experiments carried out with the well-connected random network. From those results we must conclude that there is no significant difference among the various mechanisms. They all converge to the same performance level in a similar period of time. This is due to the nature of the network, as input signals for accepting the innovation are sent to the same user repeatedly, given the high average degree of any node in the network. The convergence rate in this case is (approximately) the same for any mechanism. We have also performed experiments with random networks of 10k users (with different average degree) and the results remain the same.

5 RELATED WORK

Little attention has been paid to the problem of innovation seeding in social networks. A new work in this area is (Seeman and Singer, 2013), in which the authors present an algorithm which provides a constant factor approximation to the optimal adaptive policy for any influence function in the triggering model. In (Luu et al., 2012), a probabilistic model for the diffusion process is presented and the authors conclude the degree distribution may dynamically change.

Another relevant approach is the one by Deroïan (Deroïan, 2002), in which the author explains how the formation of the network affects the diffusion process of the innovations. Although in this paper we do not cover the dynamics of the social network, this is a necessary and natural step for our future research. Another trend in the research on diffusion in social networks is to investigate when innovations become persistent in the population. Several threshold-based approaches can be found in the literature. For example, (López-Pintado, 2008) presents a method to find the threshold for the spreading rate above which a behaviour spreads and becomes persistent in a certain population. The paper concludes that this threshold depends on the connectivity distribution of the social network; this is what we have shown in our experimental section as well. Similarly, Valente (Valente, 1996) is focused on threshold models of collective behaviour which explain how users can eventually have different rates of adoption. This work also postulates that there exist two levels of innovation rates for a user: one *macro*, relative to the system, and one *micro*, relative to her personal network. In (Kempe et al., 2003)(Bakshy et al., 2011), the authors conclude that there exist some influential nodes that foster diffusion of innovation throughout the network. They show this by presenting different probabilistic models that allow estimating the node activation from the signals received by other users. In (Aral and Walker, 2012), the authors show that influential individuals tend not to be susceptible to influence from others, while susceptible individuals tend not to be influential.

Our work is different and adds to the works above. Our interests are not in studying the adoption or diffusion processes *per se* in social networks. The focus of our work is on identifying the most appropriate entry points to deploy in order to initiate product adoption and diffusion. In particular, in social networks, we aim to mine the underlying network structure and utilise characteristics of individual nodes such as influencing (referent) power to determine the most promising entry points for seeding the innovation. The contribution of this work is in providing a mechanism able to identify suitable entry points for the innovation in the social network in order to achieve *a more efficient early adoption*, in terms of cost, rate of adoption and subsequent benefits to the firm introducing it. Moreover, since the mechanism needs a global view of the social network it must be deployed by the network owner; that is, social network firms (Facebook Inc., Twitter Inc, etc.) might offer the use of the mechanism as a service for other companies interested in advertising and spreading their services and products.

6 CONCLUSIONS

In this paper, we have presented a mechanism to select suitable entry points in a social network to introduce innovation, so fostering its acceptance and its diffusion. For that purpose we have used the underlying structure of the network, as well as the power some users exercise on others. We have empirically validated the theoretical approach with a set of experiments over a Facebook dataset and two examples of random networks. As future work we intend to study an extension of the mechanism in order to deal with dynamic social networks, in which structural properties change quickly due to the evolution of the links in the network. Another interesting avenue for future work is to build a *macro* model for using the mechanism in an inter-network environment; i.e. to be able to use the mechanism to estimate the centrality and the power of users in different networks. This may be of relevance especially when new users connect to a network.

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