AN AGENT-BASED SIMULATION OF VIRAL MARKETING EFFECTS IN SOCIAL NETWORKS

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ABSTRACT

The social environment of a person has a high influence of his or her consumer behaviour. Social networks transfer these social environments to the online world and enable a targeted influence on the customers purchasing behaviour by word of mouth from their social contacts. With the rapid spread of social networks and the increasing resistance to conventional advertising, companies have to develop new marketing strategies for their online shops taking into account this new trend. Often the managers of an online shop cannot estimate the return on investment for engagements in social networks due to their lack of experience. In this paper, we present an agent-based simulation that enables the simulation of viral marketing effects in Facebook, the world's largest social network, in order to support the decision making process of shop managers. We validate the simulation model by using several Facebook-specific studies and discuss the simulation results in detail.

INTRODUCTION

The social environment of a person is one of the main factors influencing his or her consumer behaviour. Especially if we want to purchase new products or services we are unfamiliar with, we ask our friends and family for advice and mostly trust their recommendations (DiMaggio and Louch 1998). For instance, a survey by Lucid Marketing shows that 68% of the people consulted friends and relatives before purchasing home electronics (Burke 2003).
With the rapid spread of the social media applications and the increasing resistance to conventional advertising, the companies have to develop new marketing strategies. Especially social networks like Facebook, Twitter, XING, Google+, or LinkedIn provide new possibilities for the e-commerce domain. Social networks transfer real social environments to the online world and allow influencing the purchasing behaviour by word of mouth from social contacts. A study of the transaction data of one million users of the world's largest e-commerce website Taobao finds out that the social network of a user is the most relevant criterion in order to predict the purchasing behaviour (Stephen et al. 2011).
The world's largest social network with over 900 million active users[1] is Facebook. Companies can create fan pages in order to present itself within Facebook and to establish direct contact to the customers. Whereas most of the large scale enterprises have setup a fan page, small and medium-sized companies have only little experience with Facebook and other social networks. Often these companies cannot estimate what the benefits of a Facebook engagement are and which costs are incurred by the Facebook presence. An online survey within the research project SimProgno concluded that the decision uncertainty regarding the return on investment for social networks is one of the significant problems for managers of an online shop (Intershop Communications AG 2011).
In this paper we address this problem and describe an agent-based simulation in order to support the shop managers in their decision making process. The main questions that we want to answer are the following: (1) How many Facebook fans can I expect? (2) What are the benefits for the online shop? (3) What costs are incurred?
The paper is structured as follows. In the next section, we briefly introduce the agent-based simulation paradigm. Then we describe our simulation model in detail. In the fourth section, we run the simulation model, discuss, and validate the simulation results. After that, we give an overview of related simulation approaches. The paper finishes with a short summary of the findings and an outlook on future work.

AGENT-BASED SIMULATION PARADIGM

Nowadays, there are several established simulation techniques available. A relatively new approach is the agent-based simulation technique. This approach uses intelli-

[1]Number of users at the end of March 2012. Source: `https://newsroom.fb.com/content/default.aspx?NewsAreaId=22`.

gent agents as a key element for the modelling of complex systems. Agents are modular entities in a certain environment that have only a limited perception of their environment. They are capable of doing autonomous actions and interact with other agents in order to achieve their objectives (Wooldridge 2009).
By the specification of attributes and methods for each agent the agent-based paradigm provides a natural way for modelling the human behaviour in social networks. Especially, the heterogeneous online behaviour can easily be modelled. For example, we distinguish between different frequencies of use, ranging from the weekly usage of social networks through to daily usage. Moreover, the human behaviour in social networks is strongly influenced by the virtual social environment of the people. Due to the explicit representation of individuals in agent-based models, the individual circle of friends of a social network user can directly be modelled. This is a key benefit of the agent-based simulation technique in comparison with top-down approaches like System Dynamics (Sterman 2000) in which individual attributes have to be represented by aggregated values.
The implementation of multi-agent systems is usually done by means of specialized modelling platforms. Today, there is a large number of such toolkits available. We use the open source software Repast Simphony (North et al. 2007) to implement our agent-based model.

THE AGENT-BASED SIMULATION MODEL

Facebook Domain Analysis

The main actors of a social network are the registered members of the social network. In Facebook, it is differentiated between individuals and companies. Individuals create public profile pages containing personal information such as age, gender, or interests and hobbies. Furthermore, the individuals can become friends with other individuals in order to communicate with each other, share photos, etc. This results in a complex friendship network that evolves over time. We use the term *Facebook user* to denote an individual member of Facebook and the term *Facebook friends* or shortly *friends* to denote the friends of a Facebook user.
The communication in Facebook is based on messages. The core element for every Facebook user is the news feed. It is integrated into the main page of every profile page and displays new messages from the user's Facebook friends. The news feed is generated by a Facebook-specific algorithm that is called the EdgeRank Algorithm. This algorithm structures the news feed and determines what is shown, the position of a feed item and how long this feed item is shown. The objective of this algorithm is the generation of an individual news feed which contains only the most relevant messages for every Facebook user. As a consequence, not all received messages are displayed to the Facebook users.
Companies can create so called fan pages in Facebook which differ from individual profile pages. By means of fan pages it is possible for a company to present itself within Facebook and to establish direct contact to the company's customers in order to get their feedback or to inform them about new products or services. Facebook users can become friends of a company if they use the famous like button on the fan page. All friends of the Facebook user are informed in their news feeds about this event. The Facebook friends of a company are called *fans*. They are informed in their news feeds if the company publishes a new message on the fan page. The fans of a company are therefore the Facebook users who can be reached directly with fan page updates. The fans are able to respond to a message by commenting it, saying that they like the information by clicking the like button, or they can use the share button to save the message in their own profile pages. The consequence of all these interactions is a message to all friends of the fan who responds to the fan page update. The friends are therefore informed about the interaction with the company and it is possible that they become fans of the company too. Alternatively, the friends can also respond to the message. In both cases, the information of the company are spread among their friends and a viral effect is started.
In summary, we focus on two aspects: (1) the communication process between a company and its fans as well as between the friends themselves and (2) the individual circle of friends of each Facebook user.

Model Structure and Agent Classes

In this section we introduce the static structure of the simulation model, that is, we define the agent types and its attributes as well as other fundamental concepts. The structure of the model is illustrated as a UML class diagram in Figure 1 and will be described in detail in the following paragraph.
As a consequence of the domain analysis we distinguish between the two agent types *user* and *company*. The users represent the Facebook users. Every user has an individual circle of friends consisting of other user agents. Furthermore, a user can become a fan of the company agent. The online behaviour of a user agent is characterized by its online activity and its interaction level. The online activity specifies how often a user agent logs in to Facebook. We differentiate between users which are daily online, users which are online several times a week, and users which are online only once a week. The user type describes the interaction level of a user agent. Here, we distinguish between users which behave exclusively passive, so called lurkers, and active user agents, that use the interaction concepts of Facebook. The attribute *isRegularCustomer* specifies, whether a user agent is a regular customer or not. Regular customers play an important role for the growth of the fan base because

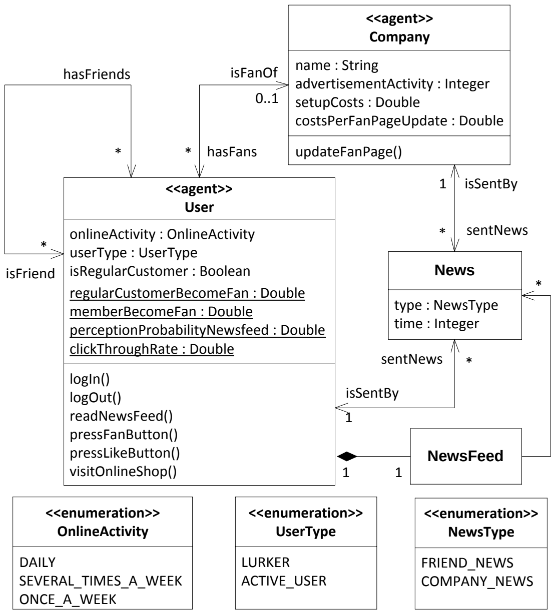

Figure 1: Static Structure of the Model

these users identify themselves with the company and therefore it is highly probable that regular customers can be acquire as fans.

In addition to the individual attributes of every user agent, there are some global Facebook-specific parameters which are identical for all user agents and therefore modelled as class variables. These variables are underlined in the class diagram and are briefly described in the subsequent section. The decision if a user agent becomes a friend of the company or not is modelled by a specific probability and mainly depends on whether the user is a regular customer of the company or not. The probability of regular customers is specified by the variable *regularCustomerBecomeFan* and the probability of the other agents is defined by the parameter *memberBecomeFan*. The variable *perceptionProbabilityNewsfeed* describes the perception probability of an individual message in Facebook and is used to model the EdgeRank Algorithm. Finally, the clickthrough rate specifies the probability that a user agent visits the company's online shop if it perceives a message with information of the online shop.

Company is the second agent type representing a company that creates a new fan page in Facebook. As simplification we assume that the behaviour of the user agents with respect to a company is not influenced by other companies. Hence, we assume that in every simulation scenario there is exactly one company agent. The attribute *advertisementActivity* specifies how often a company update its fan page. There are two additional attributes which are necessary for the cost calculation. On the one hand, the setup costs denote the costs resulting from the initial setup of the fan page. On the other hand, the costs per fan page update specify the average costs for publishing a new message on the fan page.

In addition to the two agent types, *news* are another basic concept of the model. The news represent the Facebook messages and are shown in the news feeds of the Facebook users. We distinguish between news that are generated by the friends of a user, called *FRIEND_NEWS*, and messages that are generated as a result of a fan page update. The latter ones are called *COMPANY_NEWS*. Furthermore, every news has a *time* specifying the creation date of the news. The time is especially relevant for the occasional users of Facebook because in most cases the news feed contains only the messages of the last few days.

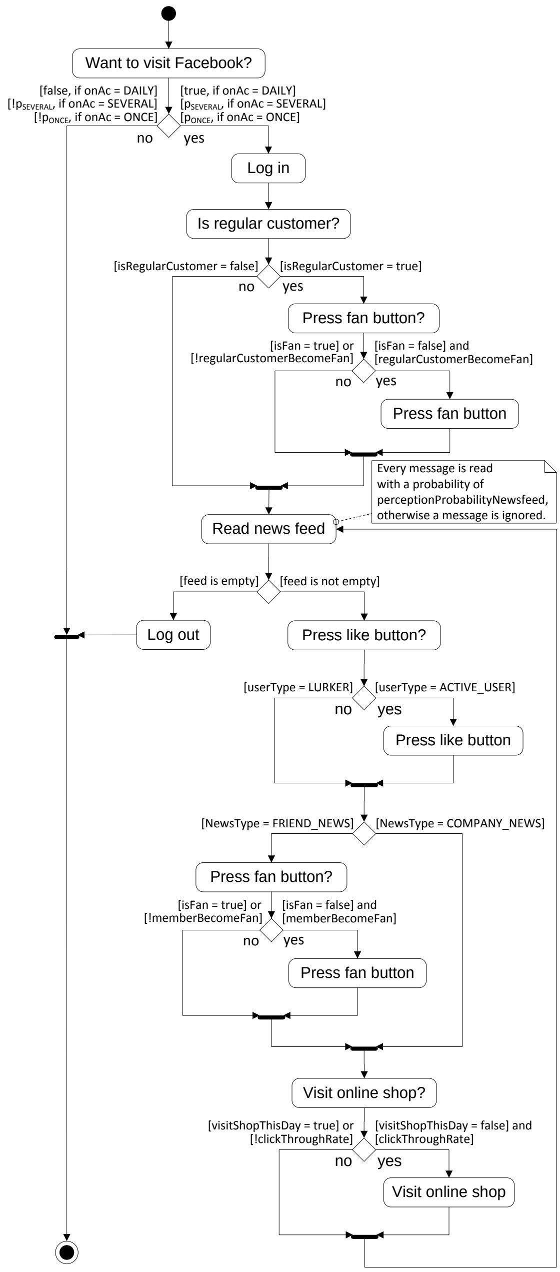

Figure 2: Activity Diagram of the User Agent (onAc: onlineActivity; ONCE: ONCE_A_WEEK; SEVERAL: SEVERAL_TIMES_A_WEEK)

Behaviour of the Agents

A simulation run is executed as a sequence of discrete time steps representing a sequence of days, whereas one time step stands for one single day. In every time step, all agents are active only once and act in random order. Beginning with the user agent, we describe the behaviour of the different agent types in this section. The behaviour of the agents for each time step is specified by activity cycles which are performed for all existing agents in every time step during a simulation run.
The user agent's activity cycle is illustrated as an activity diagram in Figure 2. The activity cycle starts with the decision whether the agent wants to visit Facebook or not. The decision depends on the online activity of the agent. For example, if $onlineActivity = DAILY$, the agent visits Facebook in every day. If the user do not log in, then the activity cycle is finished and the agent becomes inactive until the next activity cycle begins. Otherwise the user logs in to Facebook. If the user is a regular customer, then it maybe visits the fan page of the company and becomes a fan of the company's fan page with a probability of *regularCustomerBecomeFan* because we assume that the regular customers are informed about the new fan page through other marketing channels like email. Then, the user reads its news feed. Every message is perceived with a probability of *perceptionProbabilityNewsfeed*, otherwise the message is ignored. If the news feed is empty, the user logs out and finishes its activity cycle. Otherwise the user reads the perceived messages. If the user is an active user ($userType = ACTIVE\_USER$), then the user interacts with the message by clicking the like button. The like button represents all Facebook-specific interaction possibilities, namely to like, comment, or share a message. If the message was sent by a friend of the user and the user is not a fan of the company's fan page, then the user become a fan with a probability of *memberBecomeFan*. Regardless of the message type and the user type the user visits the online shop of the company with a probability specified by the variable *clickThroughRate* because the user is interested in the described products. We assume that a user agent visits the online shop only maximal once in the activity cycle. Then the procedure repeats with the next message until the news feed is empty.
Next, we describe the behaviour of the company agent. The corresponding activity diagram is presented in Figure 3. The company agent decides in every time step if a new message is published on the Facebook fan page. The decision depends on the promotion strategy of the company specified by the variable *advertisementActivity*, abbreviated with "*ad*". For example, if the attribute $ad = 1$, then the company updates the fan page every day, if $ad = 2$ the fan page is updated every two days and so on. If the variable $ad = 0$, then the company never updates the Facebook fan page and the company agent is inactive during the whole simulation run.

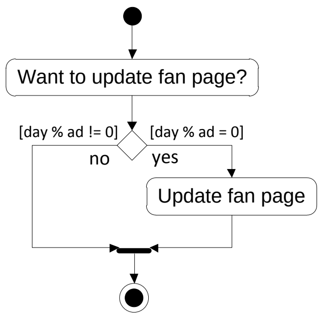

Figure 3: Activity Diagram of the Company Agent (day: current day of the simulation run; %: binary modulo operation; ad: advertisementActivity)

The Communication Process

The communication process emulates the Facebook-specific process as described in the domain analysis. In this section we illustrate the communication procedure by an example consisting of four agents. The example is shown in Figure 4 using a sequence diagram.

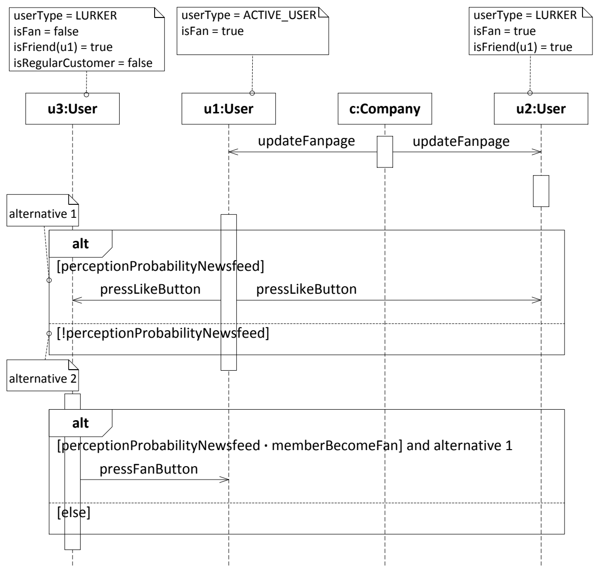

Figure 4: Sequence Diagram of the Communication Process

Assuming there are three user agents u_1, u_2, u_3 and one company agent c. Furthermore, we assume the following properties of the agents: (1) u_1 and u_2 are fans of c, and u_3 is not a fan of c, (2) u_1 is an active user and u_2, u_3 are lurkers, (3) both u_2 and u_3 are Facebook friends of u_1 and (4) u_3 is not a regular customer of c.
Firstly, agent c is active denoted by the activation box in the diagram. The company agent publishes a new fan page update. As a result, all fans, that is, u_1 and u_2 are informed about the update. Then, agent u_2 is active. Maybe agent u_2 perceives the message and visits the online shop, but u_2 never spreads the content among

its friends because it is a lurker. After that, agent u_1 is active. If the agent perceives the message, then it will interact with the message using the like button because it is an active user. The agents u_2 and u_3 are informed about the interaction because they are the Facebook friends of u_1. In this case the company message is sent to agents which are not fans of c. Finally, agent u_3 is active. If the agent perceives the message, it will become a fan of c with the probability *memberBecomeFan*. As a results, the friends of u_3 are informed about this event (u_1 in our scenario) and the general visibility of the company's fan page is further increased.

MODEL VALIDATION AND DISCUSSION

Configuration

In order to run and validate the simulation, we have to specify the values of the input parameters. We distinguish between two groups of input parameters: company-specific input parameters and Facebook-specific input parameters. The first group represents the relevant key performance indicators of the company. The values of these parameters are shown in Table 1. The parameters are based on a case study. Hereby, it is assumed that the conception and implementation of the fan page is realized in-house by trainees who are supported by a freelancer. The fan page updates are also performed by trainees. Hence, the estimated costs represent a low-priced scenario. If a specialized social media agency is requested, then the costs are considerably higher.

Table 1: Company-Specific Parameters

Input Parameter	Value
number of regular customers	40,000
advertisement activity	1
setup costs	3,000 €
costs per fan page update	75 €

The Facebook-specific parameters are used to characterise the general behaviour of the Facebook users. These values are presented in Table 2. Some of the input parameters are based on studies about Facebook. The most relevant references are described in the following list.

- In (Carter 2011) it is analysed how many fans see the posts of a fan page in their news feed. The author determines a surprisingly low value of approximately 10% caused by the EdgeRank algorithm.

- The Facebook online activity is investigated in (Crowd Science 2009). The study states that 50% of all Facebook users visit Facebook every day and 26% of the users visit Facebook several times a week. We assume that the remaining 24% of the users connect to Facebook once a week.

- The participation in online social networks follows a 90-9-1 rule, meaning that only a very small number of users contribute to the community (Nielsen 2006). Most of the users are passive and do not interact with the company's fan page. We assume a lurker rate of 97%.

Table 2: Facebook-Specific Parameters
(* denotes values which are derived from studies.)

Input Parameter	Value
regular customer become fan	0.1
member become fan	0.02
perception probability news feed	0.1 *
clickthrough rate	0.015
daily online rate	0.5 *
several times a week online rate	0.26 *
lurker rate	0.97 *
p_{SEVERAL}	0.4
p_{ONCE}	0.14

Finally, we have to specify the structure of the social network, that is, the overall number of user agents and the friendship relations between the agents. We use the complete Facebook subnetwork of the University of Pennsylvania published by (Traud et al. 2011). The network consists of 41,554 Facebook users who are connected by 1,362,229 friendship relations. We assume, that ten percent of the regular customers have a Facebook profile page, that is, 4,000 of the 41,554 Facebook users are chosen randomly and set as regular customers.

Simulation Run and Results

We run the simulation experiment ten times with the input parameters described in the section above. The simulation period is set to 365 days. Due to the lack of space, Table 3 shows only the arithmetic mean values of the simulation results.

Table 3: Simulation Results with a Simulation Period of 365 Days (* mean value of the last 150 days; + advertisement activity = 7)

Output Parameter	Value
number of fans	6050
number of online shop visits	6397
overall costs	30375 €
monthly fan growth	0.021427 *
clickthrough rate	0.003009 *
interaction rate	0.002405 *
weekly fan reach	0.0785 *,+

The first parameter (number of fans) describes the number of Facebook fans at the end of the simulation run.

The next two parameters denote the overall number of online shop visits caused by the Facebook users and the overall costs during the whole simulation period. The other output parameters are time-related or message-related key performance indicators that are used in the next section to validate the simulation model. We consider only the last 150 days of the simulation period for the calculation of these values to eliminate the influences of the abnormal fan growth at the beginning of the simulation run. The monthly fan growth (m_{growth}) denotes the relative growth of the Facebook fans within a month. The value within a time interval $\left[d, \bar{d}\right]$ is calculated as follows: $m_{growth}\left(d, \bar{d}\right) = \frac{fans_d - fans_{\bar{d}}}{fans_d}$; $fans_d$ denotes the number of fans at day d, $\bar{d}$ the number of fans at day $\bar{d}$, $\bar{d} = d + 30$. The last three output parameters refer to the fan page posts of the company. The clickthrough rate is defined as the quotient of the number of shop visits caused by a fan page post and the number of fans on the post's publication day. The interaction rate denotes the number of post's interactions in relation to the number of fans on the post's publication day. Finally, the weekly fan reach is the proportion of fans that are reached by one fan page post within one week, in other words, if the company publishes one fan page post per week, the weekly fan reach is 7.85%. In order to calculate this value, we have to set the advertisement activity to seven.

Model Validation

At first, we analyse the development of the Facebook fans. This issue is also addressed in (Kroleski 2011). The author analysed the data of nearly 1,000 companies that created a new Facebook fan page over the first 60 days. He found that the fan growth is very high during the first days but with increasing of time the fan growth decelerates strongly. Furthermore, Kroleski figured out that the composition of the fan group changes over time. Friends and regular customers are mostly fans of the first days. People, who are unfamiliar with a company, can mainly be acquired as fans after the first 45 days.

Figure 5 shows the fan growth of three simulation runs. The solid black line shows the results of the simulation run which is closest to the average number of fans and represents therefore the average case of the simulation study. The dashed line shows the proportion of the regular customers for this simulation run. In accordance with the findings of Kroleski the number of fans is growing very strong during the first days and the fan growth decreases more and more over time. Furthermore, the fans are primarily regular customers at the beginning. New people become fans at later times. The lower dotted line shows the results of the simulation run with the lowest number of fans and the upper dotted line the simulation run with the highest number of fans. These two extremes follow also the characteristics described by Kroleski.

In addition to the development of the Facebook fans,

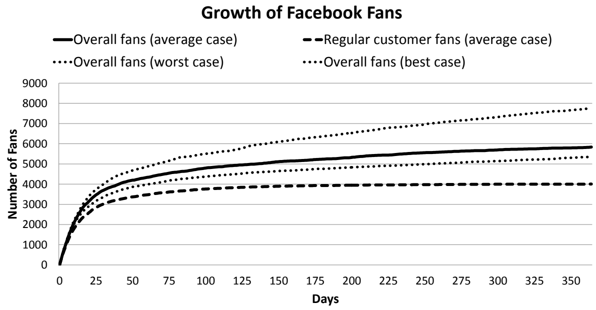

Figure 5: Growth of Facebook Fans of Three Simulation Runs Representing the Worst Case, Average Case, and Best Case of the Simulation Study

there are further model characteristics that should be validated. We found reference values for four additional key performance indicators that are mainly based on published surveys. A comparison of the simulation results and the reference values is shown in Table 4. The reference value for the interaction rate is based on our own data set. For this, we analysed the Facebook interactions, that is, the likes, shares, and comments of company's fan page posts over a period of three month for two companies in the fashion industry.

In conclusion, the simulation results have a high conformity with the specified reference values. Therefore, we conclude that our simulation model is correct.

Table 4: Comparison of Simulation Results and Reference Values

Parameter	Simulated Value	Ref. Value	Reference of the Reference Value
monthly fan growth	0.021	0.02	(Drake Direct 2012)
clickthrough rate	0.003	0.003	(Constine 2011)
interaction rate	0.0024	0.0023	own data
weekly fan reach	0.0785	0.08	(Lipsman et al. 2011)

Discussion of the Simulation Results

In this section, we will apply the simulation model to answer the questions of Section 1. We consider the additional visitors of the online shop as the key performance indicator in order to respond to the second question, that is, we assume that Facebook is primarily used for marketing purposes. We simulate five different scenarios of advertisement activity because this parameter essentially determines the costs of the Facebook presence. The other input parameters are set as described in Table 1 and Table 2. Every scenario is run ten times with a simulation period of 365 days. The arithmetic mean values of the output parameters number of fans, number of online shop visits, and overall costs are shown in Table 5.

Table 5: Simulation Results for Different Advertisement Activities (KPI: key performance indicators, ad: advertisementActivity, fans: number of fans, visits: number of online shop visits, costs: overall costs, c. p. f.: costs per fan, c. p. v.: costs per online shop visit)

KPI	ad=1	ad=3	ad=7	ad=14	ad=0
fans	6050	5390	5070	4956	4727
visits	6397	2631	1490	1099	635
costs (€)	30375	12075	6900	4950	3000
c. p. f. (€)	5.02	2.24	1.36	1.00	0.63
c. p. v. (€)	4.75	4.59	4.63	4.50	4.72

If $ad = 1$, then the number of acquired fans is 28% higher in comparision with the number of fans for $ad = 0$. The effects on the shop visits are much greater. The number of shop visits has increased tenfold if the advertisement activity is changed from zero to one.

The key performance indicators costs per fan and costs per online shop visit provide a first hint towards an optimized activity level in Facebook. The number of fans is growing slowly if the level of activity is increased. Therefore, the high costs cannot be amortized and the costs per fan increase if the advertisement activity is raised. If the number of Facebook fans is the relevant parameter for a shop manager, then a medium or low level of activity is recommended.

The situation is different, if the number of shop visits should be optimized regarding the costs of the Facebook engagement. Only if the Facebook users are informed permanently about new products, special offers, prize competitions, and so on, it is possible to generate a continuously high traffic from Facebook to the online shop. The costs of a high activity level in Facebook are amortized through the visitor traffic, therefore the costs per visit remain almost constant in the different levels of activity.

RELATED WORK

One of the most widely used simulation models in marketing is the Bass diffusion model (Bass 1969). The model forecasts the adoption of new products differentiating the adopters in innovators and imitators. The imitators are stimulated by the word of mouth of the innovators, that is, this model considers also the social influence of the purchasing behaviour. The recommendation effects are modelled in a very general way by using aggregated coefficients representing the contact rate with innovators and the adoption probability of the imitators. The social environment of individuals is not modelled in detail. In the meantime, numerous extensions of the Bass diffusion model are developed. In (Bass et al. 1994) the model is extended with additional variables for pricing, etc. The word of mouth modelling, however, remained unchanged.

An agent-based model to simulate promotional strategies for new products is described in (Delre et al. 2007). The customers are modelled as agents and are connected by a Strogatz and Watts network with additional random links representing the social environment of each customer. The decision whether the new product is adopted or not depends on the customer's individual preference and a social influence. The decision making process is triggered if at least one of the customer's social contacts has adopted the new product. The social influence depends on the number of adopters in the social environment. In contrast to our model Delre et al. consider the adoption of new products and not only the spread of marketing information. Furthermore, the authors do not analyse the costs of the promotional activities.

An example for the successful application of the agent-based paradigm in the social network domain can be found in (Menges et al. 2008). The authors present an agent-based model simulating the dynamic evolution of email social networks. The social environment of the individuals is modelled with a modified version of the Barabási-Albert model, a well-known algorithm for generating random networks which are similar to the network structure of Facebook (Catanese et al. 2012). However, the model focuses only on the development of the network structure, the information flow, especially for marketing information, is outside the scope of the model.

CONCLUSION AND FUTURE WORK

In this paper, we present an agent-based model simulating the fan growth of new Facebook fan pages and the spread of marketing information within Facebook. We focus on the additional visitors that can be acquired by the fan page marketing and the costs arising from such an engagement to simulate the effects on online shops.

On the basis of a thorough analysis of the Facebook domain, we describe our simulation model in detail. The model is calibrated by real data of the social structure of Facebook and the outcome of several surveys. We show that this calibration reproduces the results of other Facebook studies. Finally, the effect of different levels of marketing activity is presented and discussed. The simulation model is calibrated with Facebook-specific data, but the high numbers of parameters allow the calibration for other social networks which are based on similar assumptions.

The current version of the simulation model does not include special marketing events increasing the Facebook fans such as advertisements or prize competitions within Facebook. Moreover, it is impossible to forecast the effects on the fan growth if the fan page is linked on the company's homepage. The model simulates therefore the so called organic growth of a Facebook fan page. We intend to realize the additional marketing instruments in the future.

The user agents are modelled without the possibility to cancel their friendship relation with the company, that is, if an agent becomes a fan of the company, then the agent remains a fan until the end of the simulation run. In a later release, we want to eliminate this limitation in order to simulate also the decrease of the fans caused by bad experiences of the users or bad publicity.

Furthermore, we plan to implement a trust model that enables a more precise description of the relationships in a social network and their influence on the behaviour of the user agents.

Our simulation model considers the additional visitors of the online shop, but the shopping behaviour of Facebook users differs from the behaviour of other customers, for example the conversion rate and the average shopping cart value are different. Therefore, we plan to model the whole shopping process for Facebook users in the future. Moreover, we model the visibility of a certain message in Facebook with a global parameter, which is equal for all user agents and constant during the whole simulation run. This is a very simple representation of the EdgeRank Algorithm. We want to refine the message visibility by an individual parameter for each user agent depending on the agent's interactions with the fan page.

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