Advertising and word of mouth in tourism, a simulation study

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Abstract

This paper seeks to model the effect of word of mouth (WOM) on travel behavior. In particular it seeks to examine the effect of social networks on WOM amongst a population in the origin prior to travel. In this paper the effect of WOM is compared to that of paid advertising (ADV).

In other words we simulate a situation in which a tourism operator (a hotel manager for example) wishes to understand the possible effectiveness of traditional advertising as compared to word-of-mouth for promoting the services offered to a particular target market. By comparing the two situations (ADV and WOM) we can better understand the relative effect of these two methods and the higher effectiveness, at least in the short term, of WOM. For ADV, a more intense advertising effort is needed to reach the same level of informed people than for WOM. The findings show that for WOM, this level of effort is dependent on a moderate cohesion of the group. However, if the cohesion is either very low or very high, this proportion is attained only with a much higher expenditure of resources.

Keywords: networks, cohesion, advertising, word of mouth, modeling, simulation

Introduction and background

The nature of tourism is that the potential visitor lives at a distance from the place where the consumption of the experience will occur, the destination. This distance may increase the perceived psychological risk of travel due to the cost of the trip and the lack of familiarity with the destination (Law, 2006; Roehl & Fesenmaier, 1992). On the other hand, distance may increase the attractiveness of the destination making it exotic and appealing. These factors have emphasized the importance of marketing as a fundamental activity for a tourism operator (or destination) and an important determinant of success (Govers et al., 2007) as marketing is considered a key variable that managers can influence in their search for customers. In order to better market a tourism destination or resort, marketers study consumer behavior and develop models such as those examining consumer decision making and information search (Moutinho, 1987). A variety of previous studies have used such models to examine how to influence the consumer to travel to particular places.

A number of prior studies have examined the way potential travelers obtain information on which to base travel decisions (Fodness & Murray, 1999; Gitelson & Crompton, 1983; Lee & Sparks, 2007; Rasinger et al., 2007; Zins, 2007). The main approach used is based on individual psychology where visitors are considered active and purposeful agents who seek information useful for their trip. The effect of others is recognized through discussion of social influences on decision making or more specifically the effect of word-of mouth (WOM) (passing information from person to person) but somewhat surprisingly there has been little study of the specific effect of such influences (Murphy, 2001). Recently studies have examined at the effect of a number of individual traveler characteristics that encourage WOM (Simpson & Siguaw, 2008) and have also noted the strong effect of WOM on travel patterns, particularly for the backpacker market (Hanlan & Kelly, 2005). Other studies, have suggested the effectiveness of WOM but always from an individual perspective (Kim et al., 2005; Stokes & Lomax, 2002; Sweeney et al., 2008). WOM is considered to be growing in importance due to the increase in digital social networking. This digital version of WOM is considered to provide a wealth of new opportunities and possibilities to reach market segments that would have been hard to access otherwise (Dellarocas, 2003; Litvin et al., 2008).

This paper seeks to examine the effect of WOM compared to advertising on travel using a modeling approach. In particular it seeks to examine the effect of social networks on WOM amongst a population in the origin prior to travel. In this paper the effect of WOM is compared to paid advertising (ADV).

Modeling advertising and word of mouth

There is a long history in marketing of developing models to help address marketing problems with early investigations in the 1950s characterized by use of existing operations research and management science methods (Leeflang & Wittink, 2000). In general two types of marketing models may be discussed, market response models which try to model market reaction as a function of marketing activities without consideration of intermediate variables and intermediate effects models which consider a consumer decision or aggregate market outcome as the result of a series of, often sequential, processes.

Many authors have studied the effects and the impact of advertising and WOM activities, and numerous models for the process have been proposed (Vakratsas & Ambler, 1999). Formal models regard the process as an information diffusion process, whereby an organization sends consumers advertising messages containing explicit (Goldenberg et al., 2001; Stigler, 1961) or implicit (Milgrom & Roberts, 1986; Nelson, 1974) information about itself or its products. The process is initiated by sending a message to a number of potential customers over an appropriate communication channel (Nelson, 1974; Stigler, 1961). A certain fraction of the potential consumers will acquire the advertising information. After a period of time some of them will have ‘disposed of’ the piece of information received (because they have forgotten or they are not interested or convinced) and in this case, the customers are considered independent of one another.

Most of the models used to explain the effects and the general behavior of ADV campaigns have attempted to provide analytical expressions for the phenomenon (Bass et al., 2007; Doraszelski & Markovich, 2007). In these studies, the intensity and duration of the campaign memory effects and number of concurrently broadcasted messages are considered as parameters. Recently, simulation models based on techniques derived from different fields (physics, for example) have been used and have provided interesting outcomes (Sznajd-Weron and Weron, 2003). These interdisciplinary works mostly derive from the research on opinion formation models (Castellano et al., 2007) and many also take into account the peculiarities of the distribution of the relationships among the target population.

When WOM is considered, the main communication channel becomes the set of relationships among the potential market actors. Described in this way, the WOM communication process has a striking analogy with an epidemiological infection process (Bettencourt et al., 2006). A population of actors is considered to be susceptible to an ‘advertising infection’. During the unfolding of the process, a certain number of actors become infected while some recover and become immune by forgetting the information received (or discarding the information because they are not interested in it). The mathematical models describing an epidemiological infection process are well known (Bailey, 1975; Hethcote, 2000). When we introduce the underlying social network for modeling a WOM phenomenon, these models need to be amended in order to consider the topology of the communication network which has been shown to have a great impact on the whole dynamic of the diffusion (Barthélemy et al., 2005; Iribarren & Moro, 2007; López-Pintado, 2004).

Complex networks have been extensively studied in the last decade. The availability of large samples of data on networked systems (natural or artificial) and the advances in information technology have made possible the rapid development of a whole new discipline which may be termed ‘network science’ and the discovery of a whole range of models for these systems. A network is described by a number of metrics able to synthesize its topological (structural) features. These have also been found to be important determinants for the behavior of many dynamic processes. The main metrics used to characterize a network are: the statistical distribution of the connections (degree distribution); the density and the pattern local groups assume (clustering); the average number of connections between any two nodes (path length); the possibility to identify dense subgroups (modularity); the efficiency (at a local or global level) with which a process can develop; and the correlation between the number of connection a node and its neighbors have (Boccaletti et al., 2006; da Fontoura Costa et al., 2008; Watts, 2004). It has been found that besides networks with a purely random distribution of links (RN), networked systems exhibit peculiar forms, called small-world (SW) networks where clustering is higher and path length lower than in a random case or scale-free (SF) network where the degree distribution follows a power-law relationship.

Methods

Numerical simulations are used in this paper as a means to derive insight into phenomena that are difficult to study for theoretical or practical reasons (Inbar & Stoll, 1972). While the outcomes of a simulation are only one possible representation of the phenomenon under study, researchers consider them as good approximations provided that a reliable conceptual model and good implementation practices are used. No absolute value can be given to such processes, as their value depends on the specific situation or the specific purpose (Küppers & Lenhard, 2005; Law & Kelton, 2000; Schmid, 2005). Nonetheless, even with these limitations, simulation models are considered effective in reproducing different types of complex systems and represent a valuable support to decision making (Tesfatsion & Judd, 2006; Toroczkai & Eubank, 2005).

Advertising (ADV) and WOM are, as described above, different processes and are simulated here using two different models. ADV, in essence, can be described as follows. A message is broadcast to a target population of individuals. The targets receive the message and form an opinion: they can either accept the information content or ignore it (or refuse). Since the work of Weidlich (1971), a number of models have been proposed to explain or simulate the process of opinion formation in a group of individuals. Most of these have been devised by using simplified versions of well known physical models used to describe magnetic properties in a material. The analogy is due to the similarity of the situations: a magnetic material can be seen, in a rough approximation, as an ensemble of elementary magnets, each one having one of the two possible magnetizations (also called spins): positive or negative. The number and the distribution of the spins is influenced by the temperature T of the material and can be influenced by the strength of an external magnetic field H (Feynman et al., 1963: chap. 37).

Among the many possible models (Castellano et al., 2007; Stauffer, 2003) the 'Magnetic Eden Model' (MEM) was chosen for use here. Originally proposed by Eden (1961) to describe the growth of bacterial colonies, it has been generalized by Ausloos et al. (1993) and adapted by Candia and Albano (2008) to a stochastic situation. The model is as follows. Let us assume that a certain number N of elements in a material can be magnetized by assuming a spin ± 1. A randomly chosen element starts the process. At each point in time all the neighbors (elements directly connected to a magnetized one) can be magnetized. The global energy E of a configuration of spins is given by:

$$E = -J\sum_{\langle ij \rangle} S_i S_j - H\sum_i S_i$$

where Si = ±1 indicates the orientation of the spin for magnetized element, J > 0 is a coupling constant (representing the strength of the interaction between neighbors), H > 0 is the external magnetic field, and ⟨ij⟩ indicates that the sum is taken over all pairs of magnetized elements. The probability for a new spin to be added to the set of magnetized elements is proportional to exp(−ΔE/T), where ΔE is the total energy change involved and T is the absolute temperature of the material. At each step, all perimeter elements are considered and the probabilities of adding a new spin (either up or down) to each site must be evaluated. This is done by employing a Monte Carlo simulation method: all probabilities are first computed and normalized then the new element and the orientation of the new spin determined. The process ends when all the elements of the material have been magnetized. A characteristic of this model is that once a spin is set, it is 'frozen' and cannot change.

Applying this model to an advertising process it is relatively straightforward to interpret the whole process as a single campaign (at the end a certain number of target individuals will have 'absorbed' the message), the magnetic field H is a measure of the intensity of the campaign, and the temperature T is a measure of the social cohesion of the target group (or responsiveness to advertising messages), a spin S = +1 means an individual has accepted the advertising message, S = -1 means that the message was ignored (or refused). Once the campaign is ended, the opinions of the target population are set and we may assume that they remain stable until the next campaign.

A population of 500 individuals was used for the simulations and were considered to interact in a random network (in the case of a 'traditional' advertising process links between target individuals are ignored) with 1000 links. The simulation were performed by using a modified version of the software implemented by Candia and Albano (2008). Several measurements can be used to represent the effectiveness of an ADV process. In what follows, the fraction of spins up (individuals accepting the advertising message) is used.

WOM was studied by using an epidemiological diffusion model (Hethcote, 2000). This was built by considering the infection cycle in an individual (actor). The actor is first considered susceptible (S), i.e. able and ready to receive a piece of information. Then, if reached by a message it becomes 'infected' (I) and is considered as such for a certain period of time. Finally, the individual can recover (R) by forgetting what he received (or discarding the information). The mathematical treatment is well known and consists of a system of differential equations that can be solved and produce curves describing the results of the infection. These are mostly s-shaped curves belonging to the family of logistic curves. Traditionally a perfect mixing is assumed: i.e., all individuals are equally able to infect all others, the contacts between them are ignored or, better, considered as having a random distribution. When dealing with WOM, however, the diffusion process develops by using the relationships among the social network formed by the individuals (potential tourists in our case) as infection channels.

Recent advances in the study of complex networks have allowed a reconsideration of epidemic diffusion models to take into account the effects of non-homogeneous network topologies (Balázs et al., 2005; López-Pintado, 2004; Watts & Dodds, 2007). These effects are quite important. For example, 'standard' epidemiological diffusion models show a clearly defined threshold condition for the spread of an infection which depends on the density of the linkages between the different elements of the network (Kermack & McKendrick, 1927). If the distribution of connections is not of a random nature, but has some structured, non-homogeneous characteristics, this threshold may disappear. The diffusion process, once started, unfolds over the whole network (Pastor-Satorras & Vespignani, 2001). The formulation of an epidemiological model leads to the layout of a system of differential equations which can be solved in standard way. In this paper we approach the problem by using computerized numerical simulations (Castellano et al., 2007; Stauffer, 2003).

As a substrate for the simulation, we should use a real social network, formed by a population of potential tourists. Classic ways for obtaining it are surveys among people which ask them how many and what relationships they have with other individuals. The construction of such a network, however, can be quite difficult and resource intensive, with a number of well known issues associated with the reliability of the answers and the size of the sample used (Killworth & Bernard, 1976; Kossinets, 2006; Lee et al., 2006; Marsden, 1990).

An interesting and useful suggestion to overcome these problems comes from a recent paper by Ormerod (2007). The author provides a method to simulate the topology of the social network in a specific country or geographical area by using available empirical evidence on the behavior of the members of the community. Knowing that that evidence is heavily influenced by the social connections among the individuals he builds a series of synthetic networks with different topologies and uses an agent-based model to derive a distribution of the characteristics. These are then compared with the empirical data. This allows the author to choose the topology that better reproduces the observed patterns.

The country used in Ormerod's paper is the United Kingdom for which he shows that a SW network with an average clustering coefficient $C \approx 0.26$ is the best approximation. "We can think of it as implying that people are mainly influenced by those closest to them, such as family members, but with a number of more long range connections, as it were, across their network of friends" (Ormerod, 2007: 51). For the sake of brevity and simplicity we use his results and consider this layout for the simulation of a WOM process. In other words we simulate a situation in which a tourism operator (a hotel, for example) wishes to understand the possible effectiveness of traditional advertising as compared to word-of-mouth for promoting the services offered to a UK market.

The network used has 500 nodes and 1000 links (density = 0.008), and a small-world structure (by construction) with a clustering coefficient = 0.25 and an average path length = 5.9. The algorithm employed is the following:

- a single node is initially infected;
- at each time step, with probability p_I each of the infected nodes, transmits the infection to its first neighbors;
- at each time step a fraction p_R of infected nodes recovers 'forgetting' the infection;
- the simulation is run until a stable configuration is reached, i.e. a situation in which no more changes in the number of infected or recovered nodes are recorded; and
- at the end, the peak number of infected nodes is used as a measure of the effectiveness of the process.

In both cases (ADV and WOM), the size of the network used is non influential for the aims of the simulations, the actual size used here was chosen for the capability of providing meaningful statistical outcomes while minimizing computational efforts. All simulations were run by using 10 different seeds and run 100 times each. The results presented are the average values. We assume that the proportion of people forgetting or refusing to accept the piece of information (the fraction of recovered actors in the epidemic process) is 10%. All simulations were implemented as Matlab (2004) scripts.

Results and discussion

The results for the ADV process simulation are shown in Figure 1. For different values of H (ADV campaign intensity) the fraction F_{UP} of individuals who accepted the message is shown. Different temperatures T corresponding to different levels of cohesion in the social group (or responsiveness to advertising messages) were used.

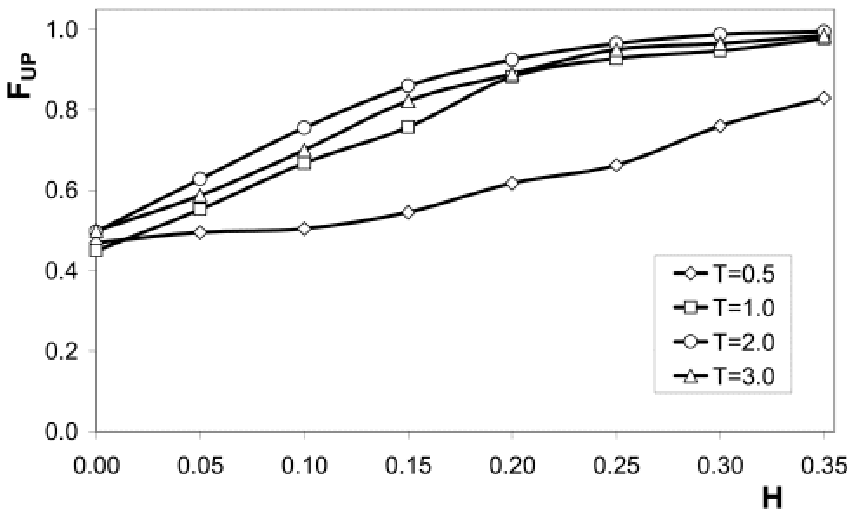

Figure 1 The results of the simulations of the ADV process. F_{UP} is the fraction of elements with spin=+1, H is the external magnetic field, T is the temperature

As expected, the fraction of people convinced by the advertising message has a clear dependency on the intensity of the advertising campaign and on the level of social cohesion (temperature T) in the target group. It must also be noticed that the effect of cohesion is higher than the one due to the campaign intensity, at least up to a certain level. If temperature is very high (cohesion is low, see the curve for T=3), it leads to a 'randomization' of the target group opinions and to a lower effectiveness of the advertising efforts.

The simulation of the WOM process is depicted in Figure 2. The curve represents the fraction of informed individuals (F_{IN}) at each time step (t_{STEP}).

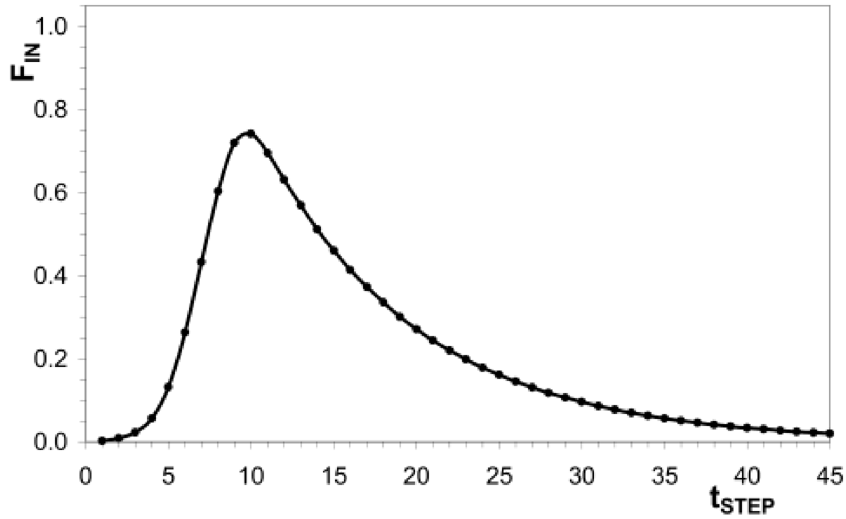

Figure 2 The simulation of the WOM process. The curve represents the fraction of informed individuals (F_{IN}) at each time step (t_{STEP})

In this case, in a relatively short period of time (10 steps) the number of informed individuals reaches a maximum of 74%. Then the number decreases (individuals 'forget'). In the WOM process no external intensity field is taken into account, the process is almost independent from the efforts of the informing organization and depends only on the set of relationships between the members of the social group. In other words, once a suitable medium is chosen (an Internet social network, for example) only a minimum effort is needed to start the process and to achieve a good result.

By comparing the two situations (ADV and WOM) we can better understand the two methods and the higher effectiveness, at least in the short term, of WOM. In fact, a very intense advertising effort is needed to reach the same (74%) level of informed people, and this level is dependent on a moderate cohesion of the group. If the cohesion is very high (or responsiveness is low, T=0.5) this proportion is attained only with a very high expenditure of resources (very high H intensity).

Concluding remarks

This paper set out to examine the effect of WOM compared to advertising on travel using a modeling approach. Moreover, the effect on WOM of the structure of the social networks amongst a population in the target market was examined. By comparing the two situations WOM was found to have higher effectiveness and this level is dependent on a moderate cohesion of the target group. If the cohesion is very high (T=0.5) this proportion is attained only with a very high expenditure of resources. These results are in line with the prior research that notes the effectiveness of WOM (Hogan et al., 2004) compared to advertising but provides in addition a means of including the effect of cohesion and relationship topology on WOM transmission. This effect has been noted before in the diffusion of innovation literature (Rogers, 1983) where the effect of diffusion through a connected social system has been studied although the connection between group cohesion and WOM in the context of advertising and especially new digital media has not been discussed.

This study is an initial exploratory study and the results are indicative of a need for further research. As also stated previously, the validity of the results presented here cannot be extended beyond the specific case analyzed, but the methods adopted are of general validity and increasingly researchers are using them to model different phenomena in the social world. More outcomes are expected which will be able to refine the models and to take into account less ‘elementary’ interaction patterns.

Clearly this is an area of potential interest and suggests that the structural characteristics (such as cohesion) of a target market be considered in developing marketing campaigns. It may also be useful in the study of viral marketing programs. In this area there has been some recent work on modeling the effect of size of a person’s network but not on its cohesiveness (Smith et al., 2007). Further research in this area, examining the effects of social and digital networks appears to be promising, in particular by improving the calibration of the model with better estimates of the cohesiveness and the topology of the target populations.

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