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Marketing and social networks: a criterion for detecting opinion leaders

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Abstract

Purpose – The purpose of this paper is to use the practical application of tools provided by social network theory for the detection of potential influencers from the point of view of marketing within online communities. It proposes a method to detect significant actors based on centrality metrics.

Design/methodology/approach – A matrix is proposed for the classification of the individuals that integrate a social network based on the combination of eigenvector centrality and betweenness centrality. The model is tested on a Facebook fan page for a sporting event. NodeXL is used to extract and analyze information. Semantic analysis and agent-based simulation are used to test the model.

Findings – The proposed model is effective in detecting actors with the potential to efficiently spread a message in relation to the rest of the community, which is achieved from their position within the network. Social network analysis (SNA) and the proposed model, in particular, are useful to detect subgroups of components with particular characteristics that are not evident from other analysis methods.

Originality/value – This paper approaches the application of SNA to online social communities from an empirical and experimental perspective. Its originality lies in combining information from two individual metrics to understand the phenomenon of influence. Online social networks are gaining relevance and the literature that exists in relation to this subject is still fragmented and incipient. This paper contributes to a better understanding of this phenomenon of networks and the development of better tools to manage it through the proposal of a novel method.

Keywords Social network analysis, Marketing, Influencers

Paper type Research paper

1. Introduction

Consumer opinions and behaviors are affected by complex sources of social influence, where online social networks become a new field in which brands and companies must redefine their relationship with their consumers, forcing marketing and advertising professionals need to rethink the paradigms of conventional marketing (Benedetti, 2015).

Prominent leaders and figures naturally emerge within these networks and gain special relevance and interest from a marketing perspective because they have the potential to influence buying behavior in both their first-order contacts and their broad network. The usefulness in identifying these prominent actors and being able to selectively act on them is undoubted and opens new possibilities for the relationship of a brand with its target public. Traditional marketing is complemented by the possibility of operating directly on these actors and generating a multiplier effect based on electronic word of mouth (WOM).

JEL Classification — M31, L86

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As a relatively new and constantly evolving phenomenon, the study of online social networks involves several areas of study. Literature reviewed is incipient in relation to the approach of online social networks from the perspective of social network analysis (SNA) and this work aims to contribute to the understanding of diffusion in online social networks by using the tools provided by marketing and SNA.

In that sense, through exploration, and using concepts and tools from SNA, a method to detect individuals that can potentially influence the behavior, brand perception or purchase decision of other actors within an online social network is suggested.

The first part of this contribution reviews theoretical concepts that relate marketing and SNA, including the study of WOM diffusion, the role of influence in the purchase decision, in the context of online social networks in particular.

In the second part, a method to detect individuals with the potential to efficiently spread a message in relation to the rest of the community based on SNA, particularly a combination of centrality metrics, is proposed.

Then, a case study is presented. The proposed method is applied to a real online community with the objective of detecting actors with potential influence. This selection is then analyzed by variety of tests to determine the effectiveness of the proposed model.

2. Literature review

2.1 WOM in marketing

Consumer rationality in the decision making of buying a product or service is limited by the available information, the individual limitations in processing that information and the time available to do so. This is why people often make purchase decisions that may not be optimal given the circumstances, but satisfy them to some extent (Simon, 1982).

Potential consumers of products and services have sought and valued recommendations through references and acquaintances that have previously made a purchase. Likewise, those who offer these products have turned and validated the role of tools as advertising in all its forms in an effort to generate awareness and influence a purchase decision.

Traditionally the communication of a brand with its potential consumers has been done in a unidirectional way, seeking the transmission of an advertising message with a persuasive purpose, but neglecting feedback and interaction among its consumers. This latter role that has been reserved at best, to market research and intelligence or niche practices (Bacile *et al.*, 2014; Benedetti, 2015).

WOM has been extensively studied and is recognized as a key influencing factor in consumer decisions (Lang and Hyde, 2013; King *et al.*, 2014). WOM has a positive effect on the consumer's relationship with the brand, and on other marketing outcomes (Hudson *et al.*, 2016; Wang and Gon Kim, 2017). Traditional advertising has recognized its effectiveness and it is a key reason for the recruitment of celebrities or opinion leaders to endorse products and services, seeking an emotional or rational connection with a target audience.

Individual propensity and motivation to engage in WOM have been extensively studied and at least eight motives have been identified. Four of them are positive, and the rest are negative (Sundaram *et al.*, 1998).

The relationship between traditional advertising and WOM and its effects on sales have not yet been extensively studied, but at least one work suggests that there is great interdependence between both platforms, having both complementary and non-substitutive roles in consumer behavior (Stephen and Galak, 2010). Hewett *et al.* (2016) postulate that the nature of brand communication has changed with the advent of online technologies, and quantifies the mutual influence in communication between companies, consumers and traditional media, in terms of volume and value, and its effect on consumer sentiment and business results.

2.2 Online social networks

The advent of internet, hyperconnectivity, and Web 2.0 has generated a paradigm shift. A dialogue emerges within the community of potential consumers of a brand instead of simply being the recipient of a message. This interaction profoundly affects the perception and purchasing decisions of the individuals (Benedetti, 2015).

Thanks to internet, consumer markets are becoming better informed, smarter and more demanding of the qualities that are missing in most business organizations (Weinberger *et al.*, 2000).

Online social networks are a novel and transformational phenomenon in the way we relate, think and exchange experiences as a human group. Nowadays the penetration and online time dedicated to the use of networks is massive and has become naturalized, favored by the ubiquity and variety of technological platforms that support these networks, the improvement in communications and the technification of society. Facebook, for example, has 1.71 billion active users worldwide, more than 90 percent of them connected through mobile platforms (Facebook Newsroom, 2016).

Albeit the wide variety of online social networks that exist both in terms of characteristics and purpose, they all have a common feature being that they depend fundamentally on user generated content. This content is often related to brands and has the potential to influence consumers' perception of the brand (Smith *et al.*, 2012; Nam and Kannan, 2014).

The reach of a campaign in social networks happens through replication amid the network users. The price to pay is that the original message is likely to be altered and increased (Peters *et al.*, 2013). Given the right conditions, a message can become viral, implying that it will be replicated and disseminated quickly and without control (Berger and Milkman, 2012). Several models have been elaborated to predict the scope of a message once it takes viral characteristics based mainly on time series analysis and stochastic processes (Subbian *et al.*, 2017).

In any case, the engagement of a social network user through a like, a comment, a share or a retweet amplifies the relationship of the user with the brand. How to increase the chance of an online publication to generate engagement and interaction with the brand has been studied from the perspective of communication design (de Vries *et al.*, 2012) and parasocial interaction (Labrecque, 2014) among other techniques.

Propensity to interact in online media has been defined as a personal trait and scales have been developed to measure it (Blazevic *et al.*, 2014; Hollebeek *et al.*, 2014). Personal attachment to online social media has also been positively related to consumer behaviors and brand advocacy. This makes some people a desirable target to maximize the effectiveness and efficiency of campaigns designed for social media (VanMeter *et al.*, 2015).

The concept of electronic WOM becomes paramount. Social networks become hubs in which users engage through comments and expressing attitudes and feelings that they are willing to share on topics of interest. This has a critical impact in brand image and awareness of a brand (Jansen *et al.*, 2009).

Several previous studies suggest a greater strength of user generated content in generating interest in a topic, surpassing commercially generated content (Bickart and Schindler, 2001; Gauri *et al.*, 2008), as well as the effect of WOM on trust, loyalty and purchase intent (Awad and Ragowsky, 2008; Chen *et al.*, 2011; Pavlou and Ba, 2002), and the importance of user communities in the generation of brand value (Nambisan and Baron, 2007).

People trust on disinterested online opinions. They have the effect of generating knowledge about products and services, suggesting that companies should focus on mechanisms that facilitate WOM (Duan *et al.*, 2008).

According to a Nielsen study on 30,000 internet users in 60 countries around the world, eight out of ten people rely on product or service recommendations made by acquaintances, and two-thirds of respondents rely on third party reviews posted online. Trust in traditional paid media, such as TV spots, newspapers, magazines and even online media such as sponsored online videos, search advertising or social networks advertising fall well below (The Nielsen Company, 2015).

2.3 Influencers and opinion leaders

Within these networks, some individuals stand out and gain interest from a marketing perspective because they have the potential to influence buying behavior in both their first-order contacts and in the rest of their network.

Influence has been studied in marketing literature from various perspectives. Seminal works as the two-step flow communication model, postulates that people follow opinion leaders who in turn are influenced by the media (Katz and Lazarsfeld, 1955). More recently, a model of influence networks was proposed that extends the original two-step model proposing that influence is not unidirectional but can flow in any way, and also ponders the role of easily influenced individuals as multipliers in the diffusion of innovations (Watts and Dodds, 2007).

Influential individuals have been categorized as hubs, as they have a large number of social links, and classified into innovators or followers. Both classes have a significant role in the diffusion of an innovation, and the rate of adoption of an innovation by these hubs allows to make predictions about the success of a campaign in its early stages (Goldenberg *et al.*, 2009).

The diffusion of innovations model studies and classifies individuals in relation with their permeability and speed to adopt innovations. Early adopters have a high degree of opinion leadership in social systems and facilitate the diffusion of a product or message (Rogers, 1983).

It is also relevant to the definition of the market maven, as an individual who willingly seeks, owns and shares general information about products and markets. This makes them an attractive target of marketing efforts to accelerate the diffusion of a message (Feick and Price, 1987).

In modern marketing a company's communication cannot depend solely on its own efforts and must take advantage of the power of WOM. To generate and maintain influence within social networks, brands must identify themselves and attract user groups that connect with the brand and act on their behalf. These groups do not necessarily have to be large but they should be influential (Peters *et al.*, 2013; Risselada *et al.*, 2014). Therefore, it is essential to generate relevant content for alpha consumers who are the ones who will propagate the message through the network (Vaz, 2011).

Due to the variety of approaches that address this phenomenon in literature, the terms used to designate individuals that can generate contagion efficiently are different. These terms are often used interchangeably and to refer to individuals who share totally or partially the same set of features.

The advantages of identifying and engaging influential actors within a complex social network include, among others:

- Market research: it may be a good idea to involve influencers in testing concepts or products, as they will influence future adoption by other users or consumers.
- Product testing: likewise, product sampling to these actors can provide support in a new product launch through electronic WOM.
- Direct advertising (Hawkins *et al.*, 1995).

Other advantages include:

- Public relations events: involving opinion leaders in these activities is generally accepted as a good source for positive WOM, keeping the budget for these actions under control.

- Damage control: it may be useful to engage the most influential players in order to moderate and minimize damages to the brand in a crisis scenario.

The process of engaging a group of individuals picked by some particular criterion with the purpose of achieving a multiplier effect in a broader network is known as seeding. Seeding strategies have been used to accelerate the diffusion of information and adoption of products by generating contagion toward potential consumers. The value of seeding programs derives from the interaction of two mechanisms: market expansion and consumption acceleration (Libai *et al.*, 2013).

Various methods to optimize the selection of individuals for a seeding strategy have been proposed. Chen *et al.* (2010), Aral *et al.* (2013), Kempe *et al.* (2015) and Aghdam and Navimipou (2016) address the issue as an optimization problem from an experimental approach. For certain networks, metrics derived from users' attributes and activities have been developed to estimate indicators of popularity and influence (Grossek and Holotescu, 2009).

This paper proposes a methodology to identify influential actors in online social networks, which is determined by the engagement of these actors through comments. The content of the comments is not analyzed, beyond a simple semantic analysis. Nor it is tried to assess if these individuals exerted influence in the sense to affect the behavior of other actors through their interventions. For this reason these individuals will be referred to as "potential influencers."

To this effect, potential influencers are defined in the context of this work as "those individuals located in a position within the online social network from which they could potentially achieve greater outreach of the diffusion of a message deriving out of their connection structure."

2.4 SNA

Online social networks are themselves social entities that function as an aggregate of the behaviors of their undivided components. SNA has been applied in many fields of science (Molina, 2004) and the potential of its use in marketing studies is enormous. Networks can be classified according to their morphology into at least six regular structures varying in number of clusters, cohesion and interconnectivity (Smith *et al.*, 2014). Likewise, each of the members of the network can be analyzed individually from metrics that describe their position within the network relations structure, such as centrality metrics (Hansen *et al.*, 2011).

Previous studies suggest that the structural situation of an actor within a network is a good indicator of opinion leadership. SNA can detect the central actors of a network and these actors will tend to be opinion leaders within that network (Van der Merwe and van Heerden, 2009).

Despite the importance of these individuals, the bulk of research in relation to influence has focused on their personal, social and behavioral traits but not on the relationships they have within a social network (Balkundi and Kilduff, 2006; Tucker, 2008).

The application of SNA to marketing in online social networks is still incipient. Because it is a relatively new phenomenon, the specific literature of this particular point is still scarce (Paquette, 2014).

This contribution explores the possibility of detecting potential influencers in online social networks through the use of tools derived from traditional SNA, in particular centrality metrics.

3. Methodology

3.1 Model of detection of potential influencers

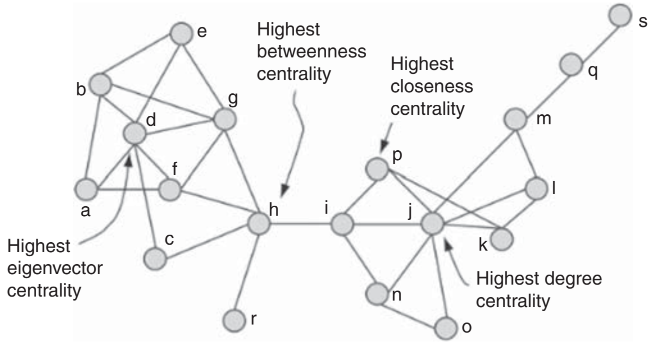
SNA provides several methods that can be used to describe and weigh different characteristics of the network in general, the individuals that make it up, and the connections or links between these individuals. The most relevant in relation to this work are metrics that refer to attributes of individuals in relation to the rest of the network:

- Degree centrality, which counts how many direct connections each individual has with other actors within the same network. It is a local measure of the importance of a node.
- Eigenvector centrality, also ponders the quality of these connections: an actor with the same degree centrality that another can be more influential within a network if its connections are with actors who are in turn well connected. Information about the whole structure of the network is required for its estimation as eigenvalues and eigenvectors associated to the network adjacency matrix are estimated, obtaining information on the direct and indirect importance of each node in particular. It is a global measure of the importance of that actor in the network.
- Betweenness centrality measures the number of paths that pass through a node to reach any other node in the network with respect to the total number of paths in the network that allow these same nodes to connect, showing the extent to which an actor is on the shortest path between two other nodes. It can be thought of as a "bridge" within the network, in which the actor takes a strategic position in the flow of communication between different groups. An individual with a high betweenness centrality can present the shortest path for the diffusion of a message through an extensive network. It is also a global measure of the importance of that actor in the network.

Figure 1 shows clearly the difference between these metrics, pointing out the individuals with the best score for each of them:

The highest degree centrality individual is "j" because it has the most connections to other vertices (total of 7). Highest eigenvector centrality is achieved by "d" because it has quality connections with actors who in turn are well connected. The individual with the highest betweenness centrality is "h." It has few connections, but it plays a vital role as the only link between three separated clusters: If "h" disappeared, groups "a, b, c, d, e, f, g," "i, j, k, l, m, n, o, p, q, s" and the individual "r" would lose contact with each other.

Betweenness and eigenvector centralities have very desirable properties for the location of an influencing potential. A combination of both features would simultaneously include those actors who connect dispersed groups through highly connected actors. *A priori*, the potential for diffusion is very large. Modern social networking theory suggests that individuals who are central to their close networks and have links to outside networks



Source: Ortiz-Arroyo (2010)

Figure 1.
Different measures of centrality applied over an example network

usually acquire a combination of power and superior knowledge. Leaders do not necessarily have to be central to of each important network as this would be at expense of a marginal position in another network. There is a trade off in the construction of this social capital (Balkundi and Kilduff, 2006).

Our proposal is an adaptation of the matrix model presented by Scoponi *et al.* (2016) to classify the actors of a social network in terms of their level of influence through two complementary metrics. Members of the network that simultaneously meet the highest values of both betweenness and eigenvector centrality should be classified as potential influencers as shown in Figure 2.

This matrix represents a two-dimensional scatter plot in which the individual components of a network are plotted according to their betweenness centrality (*x*-axis) and their eigenvector centrality (*y*-axis). Then, according to a relevant criterion to determine thresholds in each dimension, this plane is divided into quadrants, allowing classifying every actor into four different groups:

(1) potential influencers with a high degree of betweenness and eigenvector centrality;

(2) brokers or individuals with high betweenness centrality and low eigenvector centrality;

(3) actors with important connections, their low score in betweenness centrality suggesting a limited outreach to groups outside their local community; and

(4) secondary actors.

For the case study, thresholds were defined in the 95th percentile of each one of these two dimensions. Consequently, 5 percent of the cases were selected in each one of the independent metrics, which when combined yield approximately 2.5 percent of the cases, as represented in Figure 3.

The selection criterion seeks to select users who can be considered a minority or elite in terms of their ability to efficiently diffuse a message within the network. The selection of too small group of influencers can make a marketing action lack the desired outreach or diffusion speed. Conversely, the selection of a very large group of influencers can produce decreasing and in some cases negative results (Aral *et al.*, 2013; Sela *et al.*, 2016).

It is important to clarify that when applying this method, thresholds should be adjusted according to the purpose of the analysis, the size and characteristics of the network, operational and budgetary constraints.

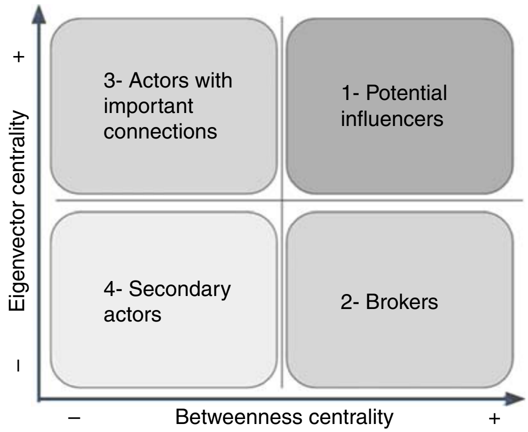


Figure 2.
Matrix to detect potential influencers within a social network based on the work of Scoponi *et al.* (2016)

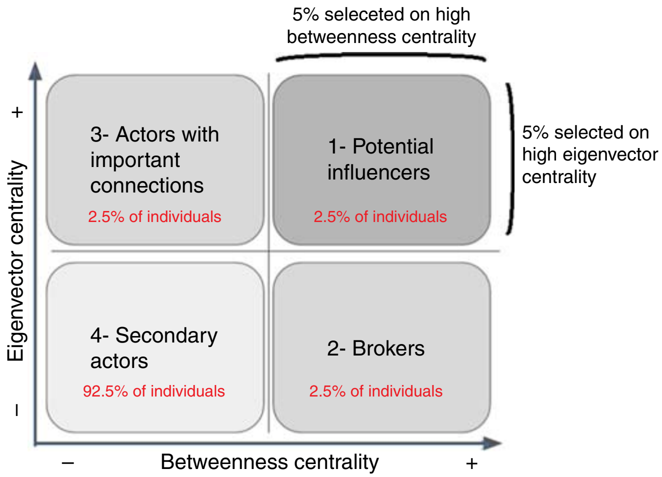


Figure 3.
Matrix to detect potential influencers within a social network based on the work of Scoponi *et al.* (2016) with 5 percent thresholds

3.2 Selection of a SNA software and a case study

NodeXL (Smith *et al.*, 2010) was selected as the main tool to analyze the proposed case study over other SNA applications available in the market due to its versatility, analysis possibilities and import of popular social networks. NodeXL is an open source Excel template that features data import directly from the main social networks (Hansen *et al.*, 2011). NodeXL Pro version 1.0.1.354 was used for the development of this case.

For the selection of the case study, Facebook was selected among other online communities as being the most popular social network globally. In Argentina, Facebook has a penetration close to 50 percent of the total population (eMarketer, 2016) surpassing the regional average.

Facebook is a social network created in 2004 by Mark Zuckerberg and others. As of June, 2016, there were 1,710 million active users worldwide, more than 90 percent of them connected through mobile platforms (Facebook Newsroom, 2016).

As unit of analysis, the official Facebook fan page of the entity that organizes the "Maratón de Buenos Aires" (www.facebook.com/maratonbuenosaires/) was chosen. The Buenos Aires marathon is a sporting event that takes place annually in October in its full version of 42 kilometers and in September in the half marathon modality. Both races are very popular and the number of runners grows annually. In total, 27,822 runners registered in both events combined in 2015 (Frieni, 2016).

Fan page counted more than 58,000 followers in July 2016, and although it generates content and interaction with its community throughout the year, activity peaks occur on dates close to the main races. For this reason, it was defined as date range for the case study all the content generated in the page by the organizers and users between August 31, 2015 (one week before the half marathon) and October 17, 2015 (one week after the full marathon).

One of the reasons this community was chosen is the high level of community engagement and activity, allowing capturing as much activity as possible between users and user generated content regardless of the level of activity of the community administrator.

It was also chosen because of the potential utility of this research on the marketing of products and services generated around such an event for different stakeholders:

- The event organizer himself, to promote the event, expands his network of contacts, assess attitudes, opinions and feelings of their own community.
- Competing or similar events, to broadcast or promote their own activities efficiently through high potential diffusion actors in the running community.

- Manufacturers and marketers of sports apparel, to focus on promotional or merchandising campaigns ensuring maximum outreach with a limited budget, detect niches; boost the development of brands and product lines.
- Lodging providers and transportation services to detect and engage communities of foreigners attending the event, who may potentially require their services.

Facebook as an online social networking platform offers several interaction alternatives, each reflecting a different type of relationship between user and content. When analyzing a social network, each one of these interactions or the aggregation of them can be seen as links between people of different direction and intensity.

The interaction of this network par excellence is the "like," which indicates that the user liked or considered interesting some content. The like is specially designed for mobile devices, allowing the user to reflect a reaction to content quickly and efficiently, both through the traditional "thumb up" icon and the "emojis" introduced in February 2016. The usefulness of Facebook's organic likes as an indicator of an attitude or purchase intention toward a brand is challenged in recent publications (Mochon *et al.*, 2017; John *et al.*, 2017). The same ease of use that makes it so popular determines that likes are abused and are not generally considered as an indicator of a strong link (PewResearch Center, 2014). An additional problem is that its polarity cannot be analyzed: it does not indicate a positive or negative value, nor it does contain text that allows making that analysis.

"Shares" and "comments" on the other hand are more complex forms of interaction and indicate a greater engagement of the user with the content. Sharing involves replicating the content through the user's own page, with the potential to replicate in turn to other users and grow exponentially (Subbian *et al.*, 2017). Commenting implies generating a text in the form of an opinion directly addressed to that content, or to comments generated previously in that content.

In many cases comments are trivial and will not generate dialogue among users. On the other hand, there are occasions in which users engage with content, giving it visibility, replicating, and augmenting by adding reactions and opinions. When that content becomes electronic WOM, and by analyzing the underlying structure of connections generated by the transmission of the message, potential influencers can be detected.

While NodeXL allows importing likes, shares and comments, it was observed that using the likes significantly increased the volume of imported data without adding value to the analysis. Therefore, in this case it was defined to use only comments as indicators of links between the individuals. Likes could potentially be added to the analysis by giving them a low weighting to reflect their lower information quality without completely discarding them. Surely this may be an aspect of this work to be developed in the future.

4. Results

4.1 Network analysis

A graph with 977 vertices or actors including the page administrator was obtained. These vertices are linked through 25,613 unique edges between them corresponding to comments, as seen in Table I.

Betweenness and eigenvector centralities are both measures of the individual nodes of the network and relate to the diffusion potential of a node. The values of the results obtained are shown in Figures 4 and 5.

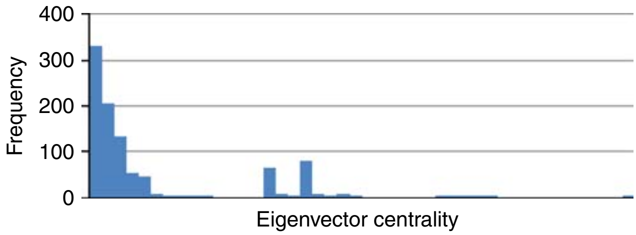
The resulting graph, visualized with NodeXL according to a Harel-Koren Fast Multiscale layout (Harel and Koren, 2000) is presented in Figure 6, where each circle corresponds to a node or user of the network. The size and opacity of each user is proportional to their eigenvector centrality value, and the color corresponds to subcommunities automatically identified. These communities represent groups of nodes highly related to each other in communities or clusters technically referred to as modules. Specifically the algorithm used is the one proposed by Clauset *et al.* (2004). The communities themselves are not studied in our work, although they could be addressed on future research.

From the application of the model of detection of influents proposed with quadrant thresholds defined, according to the detailed criterion, in 1,744.97 for betweenness centrality and 0.0035 for eigenvector centrality, 26 influential actors were obtained. This number does not include the user "Marathon of Buenos Aires (Official Group)" that belongs to the community manager.

Table I. Oficial Maratón de Buenos Aires Facebook fan page analysis overall graph metrics for comments generated between August 31, 2015 and October 17, 2015

Graph metric	Value
Graph type	Directed
Vertices	977
Unique edges	25.613
Duplicate edges	17.774
Total edges	43.387

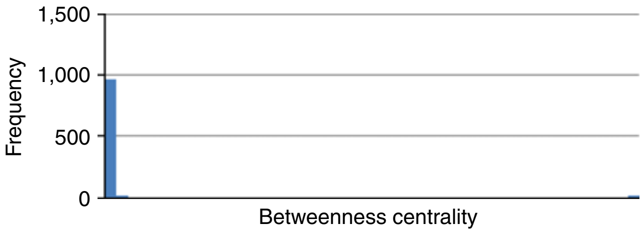
Source: Made with NodeXL www.smrfoundation.org/nodexl/



Minimal eigenvector centrality	0.00008
Maximum eigenvector centrality	0.00868
Average eigenvector centrality	0.00102
Median eigenvector centrality	0.00046

Source: Made with NodeXL www.smrfoundation.org/nodexl/

Figure 4. Distribution of eigenvector centrality values for users of Oficial Maratón de Buenos Aires Facebook fan page based on comments generated between August 31, 2015 and October 17, 2015



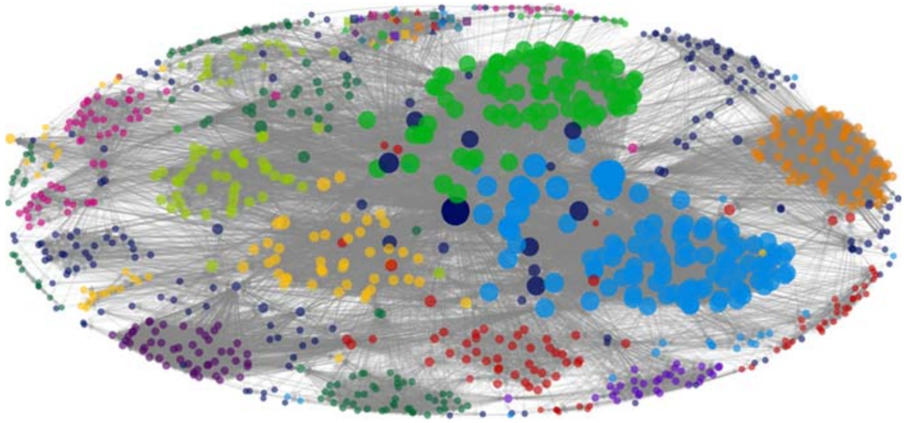
Minimal betweenness centrality	0.000
Maximum betweenness centrality	582,594.081
Average betweenness centrality	913,711
Median betweenness centrality	0.000

Source: Made with NodeXL www.smrfoundation.org/nodexl/

Figure 5. Distribution of betweenness centrality values for users of Oficial Maratón de Buenos Aires Facebook fan page based on comments generated between August 31, 2015 and October 17, 2015

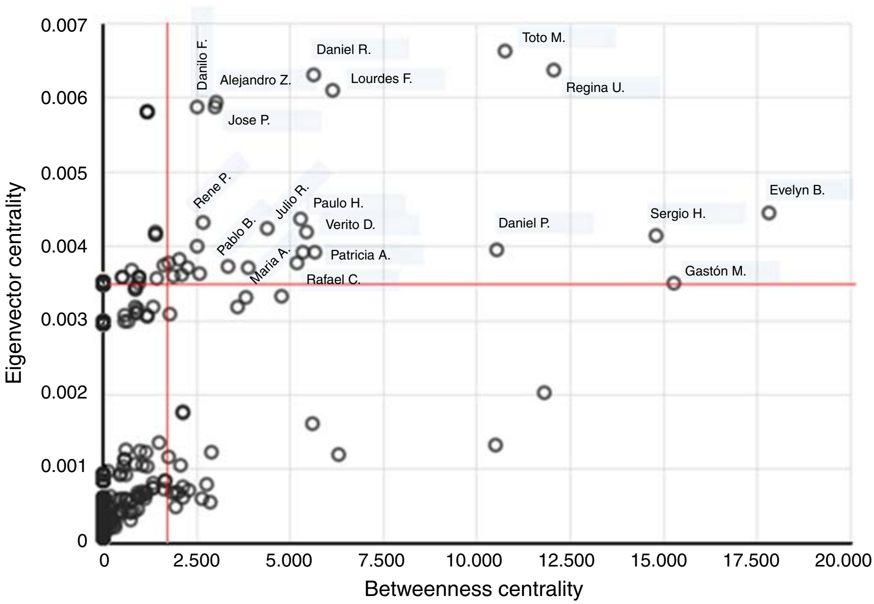
Figure 7 shows the results of the application of the model through the scatter diagram representing all the individuals that compose this network (except for the community manager), and the quadrant thresholds represented by red lines.

Figure 8 shows again a graph representing all the actors in this network with their relationships. Potential influencers are highlighted in red, whereas the rest of the users of the network are shown in light gray.



Source: Available at: www.smrfoundation.org/nodexl/

Figure 6. Oficial Maratón de Buenos Aires Facebook fan page graph made with NodeXL from comments generated between August 31, 2015 and October 17, 2015



Notes: Signs are shown indicating first name and first letter of the surname for several potential influencers. Quadrant thresholds are indicated with red lines. The fan page administrator is excluded. Elaborated in Microsoft Excel

Figure 7. Scatter plot representing users of the official Buenos Aires marathon fan page on Facebook between August 31, 2015 and October 17, 2015 according to their betweenness centrality (X-axis) and eigenvector centrality (Y-axis)

4.2 Performance of influencer detection model

The model performance was analyzed through different techniques. In a first instance, the average of comments received and issued by individuals selected by the model was compared vs unselected individuals and overall total. This information is presented in Table II.

The high number of comments both received and issued by the selected users is an indicator of the traffic generated by these actors within the network to which they belong and therefore the influence they have or is attributed to them. As shown in Table II, the total of comments in these users is 350 percent higher than the general average, indicating a higher level of activity.

Likewise, the average issued comments/total comments ratio is inferior in selected individuals with respect to the rest of the actors of the network indicating a multiplier effect in their interventions not present in the rest of the users, which is consistent with the definition of influencer proposed at the beginning of this work.

If each of the quadrants of the model is analyzed separately, it can be noted that the average total number of comments (issued plus received) is higher than the average when centrality measures are used to classify individuals separately, but the combination of both dimensions outperforms them separately, which suggests that the model is efficient identifying influential actors, as can be seen in Table III.

This leads to the conclusion that there is a synergistic effect in the use of these two metrics that prove to be complementary as far as the detection of influence traits is concerned.

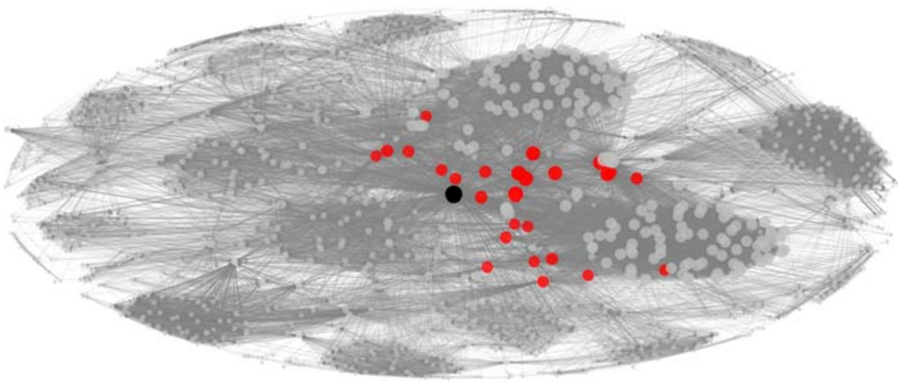


Figure 8. Oficial Maratón de Buenos Aires Facebook fan page graph made with NodeXL from comments generated between August 31, 2015 and October 17, 2015

Notes: Potential influencers according to the proposed model are shown in red. Page administrator is shown in black

Source: Available at: www.smrfoundation.org/nodexl/

Table II. Comments received and issued by individuals selected by the model compared vs unselected individuals and overall total analysis

Values	Potential influencers	Unselected individuals	Overall total
Individual count	26	950	976
Received comments (avg)	0.77	0.16	0.17
Issued comments (avg)	5.85	1.6	1.71
Total comments (avg)	6.62	1.76	1.89

Note: Made with Microsoft Excel

4.3 Sentiment analysis

Sentiment analysis, also known as opinion mining, refers to the application of natural language processing, text analysis and computational linguistics to identify and extract subjective information with the purpose of determining the attitude of an interlocutor or writer regarding a subject or the general contextual valence of a document (Bodendorf and Kaiser, 2009).

NodeXL performs sentiment analysis by counting word frequency on up to three previously defined groups of words (Minqing and Bing, 2004). These groups of words are called "lexicons." Two groups of words were adapted from a lexicon in Spanish containing words indicative of positive vs negative sentiment (Gravano and Dell' Amerlina Ríos, 2014) in order to determine if there is polarization toward one or the other end in the comments of the actors detected as influential, in relation to those who are not (Serrano Puche, 2016).

Sentiment analysis did not show significant differences in the frequency counts of comments of potential influential actors with respect to the rest of the community, on the contrary the proportion of words of like and dislike is similar in both groups, as can be seen in Table IV.

This balance proves that though being more influential, polarity in comments and opinions from potential influencers is *a priori* not different than the rest of the community.

Seen in another way, it could be assumed that a contagion effect to the rest of the network of a desired state of mind could be achieved efficiently by operating on the limited group of influencers detected in this network, given the capacity of replication that these particular actors have and the affinity with the rest of the community.

4.4 Simulation of the role of potential influencers

Once the target network was captured, relations were modeled computationally to carry out diffusion tests. Agent-based simulation methodology (Larrosa, 2016) allows, among many other features, to represent agents operating in networks and analyze the resulting diffusion processes. Agent-based simulation has the advantage that it captures the structure of the social network in which the analyzed phenomenon occurs (Libai *et al.*, 2013). It is an area of research that is used by various branches of science. Goldenberg and others (2009) use it for diffusion studies and Bozanta and Nasir (2014) provides a concise contribution of the many contributions of this methodology to marketing. A broad domain programming environment in the academic literature (Larrosa, 2012) that employs this approach is

Selection by eigenvector centrality		
True	3.26	6.62
False	1.64	4.35
	False	True
Selection by betweenness centrality		

Note: Made with Microsoft Excel

Table III. Total comments analysis in each separate quadrant

Values	Potential influencers	Unselected individuals	Overall total
Total word count	90,422	672,033	762,455
% Positive valence words	30.8	32.2	32.1
% Negative valence words	30.4	30.9	30.8

Note: Made with NodeXL and Microsoft Excel

Table IV. Sentiment analysis on comments generated by the model compared vs unselected individuals and overall total

Netlogo (Wilensky, 1999). Specifically, the nodes, their links and the directionality of the nodes were replicated. The resulting directed graph is shown in Figure 9 along with an example of the simple diffusion simulation which is explained below.

A simple simulation exercise in network diffusion was performed. According to the criterion of identification of influential actors in the network presented in Figure 2, data were obtained from ten random agents that fit the criteria of each category. They were named as presented in the four quadrants, i.e. "Potential influencers," "Brokers," "Actors with important connections" and "Secondary actors."

Once the random agents in each group were selected, an attribute was assigned to each node that simulates a piece of information that the node would distribute along its own network of direct connections. This attribute is represented by a color that each agent distributes to its direct outgoing connection network, causing these connections to distribute them to their own direct connections, repeating the process iteratively. Figure 10 represents a graphic example of this diffusion process with the orange color representing the piece of information. It is a basic epidemic model without immunization where information circulates as a contagious virus. It is shown at each step how this information expands quantitatively in the network, from the inception or seeding of the information (step 0). Only ten diffusion steps were simulated. Figure 10 shows markedly higher information penetration profiles for the category of "Potential influencers" as defined by this research.

Table V shows the diffusion reach data of nodes with respect to the category "Potential Influencers" (representing the total of the nodes reached). The "Potential influencers" curve captures 30 percent more nodes on average than the category that follows it, "Brokers," and

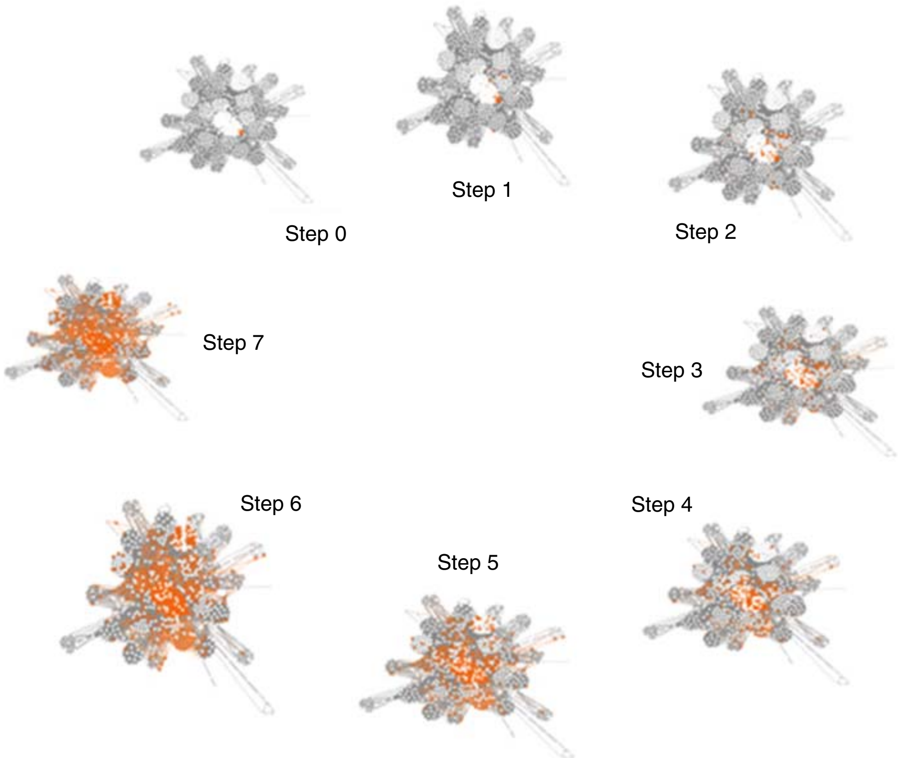


Figure 9.
Model of the target network and diffusion simulation example

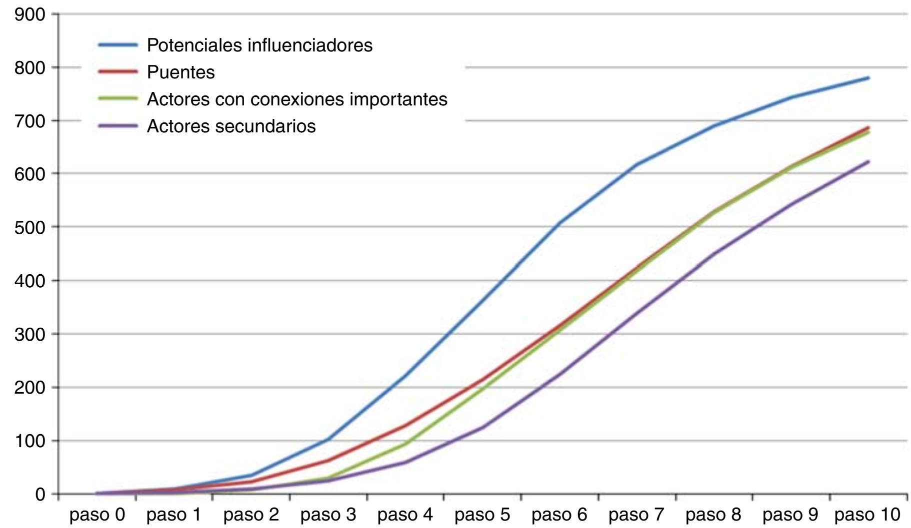


Figure 10. Penetration profile in each category according to the proposed model

Table V. Diffusion reach data of nodes with respect to the category "potential influencers"

	Step 1 (%)	Step 2 (%)	Step 3 (%)	Step 4 (%)	Step 5 (%)	Step 6 (%)	Step 7 (%)	Step 8 (%)	Step 9 (%)	Step 10 (%)	Avg. (%)
Brokers	83.0	68.6	61.3	57.7	59.1	62.4	68.6	76.8	82.6	88.0	70.8
Actors with important connections	21.3	22.3	29.7	42.5	54.5	60.7	67.9	76.4	82.5	87.0	54.5
Secondary actors	25.5	28.0	24.9	27.3	34.5	44.3	54.8	65.2	73.2	79.9	45.8

between 45 and 55 percent more than the categories "Actors with important connections" and "Secondary actors," respectively. Also, it is observed that the "Potential influencers" increase the degree of penetration sharply in the initial steps compared to the rest of the curves in relative terms, situation that tends to reduce only very slowly in the subsequent steps.

This extremely high immediate diffusion rate and its continuity throughout the diffusion period is an expected feature in an influencer.

5. Conclusion

The purpose of this contribution, as mentioned, is to use the tools provided by SNA to achieve instruments that help to identify the different network structures in online social networks and within these the influential actors from a marketing perspective.

A model to detect relevant actors within a social network based on tools from social network theory and taking advantage of specific computer applications of SNA in general and online social networks in particular was proposed.

This model was tested on a real social network and the results show that:

- The proposed model is effective to detect actors with potential to efficiently spread a message, gaining influence from their position within the network.
- The analysis of social networks in general and the proposed model in particular are useful to detect subgroups of components of a social network with particular characteristics that are not evident from other types of analysis.

The proposed method may be particularly useful for marketing and digital marketing managers by facilitating the detection of prominent actors within a social network, with the advantage that it is a simple but powerful method for viewing, analyzing and communicating findings. Knowing the influential potentials, as stated above, can generate savings and advantages in regular marketing department practices as market research activities, product launches, direct marketing and public relations campaigns among others.

This work presents the limitation that the proposed model has only been tested on a very specific domain network such as the community of people following a sporting event, and on a single social network as Facebook. Expanding the experimentation on different networks and on other online social networking platforms would be necessary to strengthen the conclusions of this work.

Another limitation of this work lies in the criteria used to conclude that the individuals detected by the proposed system are influential. Several metrics, sentiment analysis and simulation techniques were applied. It would be desirable to add evidence to support this model through other methods such as direct experimentation on a real social network, and also considering factors as homophilia and characteristics of relations such as frequency and intensity (Aral *et al.*, 2013; Chen *et al.*, 2017).

We also point out as a potential limitation to the proposed method that the way of identifying potential influencers is limited to the analysis and conjugation of two common metrics. It should be mentioned however that it is the simplicity of this method what makes it an adaptable and versatile tool for the analysis of online social networks, where the availability of information may be limited and is continually modified by updates in privacy policies.

In any case, it is clearly exposed that with this conjunction of theoretical knowledge and computational tools it is possible to capture the complexity of the interaction within a social network. Also, this analysis allows the detection the main groups and individual actors of the event. This clarity in the description and analysis, we believe, cannot be found using other more traditional tools.

References

Aghdam, S.M. and Navimipou, N.J. (2016), "Opinion leaders selection in the social networks based on trust relationships propagation", *Karbala International Journal of Modern Science*, Vol. 2 No. 2, pp. 88-97, doi: 10.1016/j.kijoms.2016.02.002.

Aral, S., Muchnik, L. and Sundararajan, A. (2013), "Engineering social contagions: optimal network seeding in the presence of homophily", *Network Science*, Vol. 1 No. 2, pp. 125-153 , doi: 10.1017/nws.2013.6.

Awad, N. and Ragowsky, A. (2008), "Establishing trust in electronic commerce through online word of mouth: an examination across genders", *Journal of Management Information Systems*, Vol. 24 No. 4, pp. 101-121, available at: www.jstor.org/stable/40398913

Bacile, T., Ye, C. and Swilley, E. (2014), "From firm-controlled to consumer-contributed: consumer co-production of personal media marketing communication", *Journal of Interactive Marketing*, Vol. 28 No. 2, pp. 117-133, doi: 10.1016/j.intmar.2013.12.001.

Balkundi, P. and Kilduff, M. (2006), "The ties that lead: a social approach to leadership", *The Leadership Quarterly*, Vol. 17 No. 6, pp. 419-439, doi: 10.1016/j.leaqua.2005.09.004.

Benedetti, A. (2015), *Marketing en redes sociales: Detrás de escena*, AMDIA, Buenos Aires.

Berger, J. and Milkman, K.L. (2012), "What makes online content viral?", *Journal of Marketing Research*, Vol. 49 No. 2, pp. 192-205, doi: 10.1509/jmr.10.0353.

Bickart, B. and Schindler, R. (2001), "Internet forums as influential sources of consumer information", *Journal of Interactive Marketing*, Vol. 15 No. 3, pp. 31-40, doi: 10.1002/dir.1014.

Blazevic, V., Wietrz, C., Cotte, J., de Ruyter, K. and Keeling, D. (2014), "GOSIP in cyberspace: conceptualization and scale development for general online social interaction propensity", *Journal of Interactive Marketing*, Vol. 28 No. 2, pp. 87-100, doi: 10.1016/j.intmar.2013.09.003.

Bodendorf, F. and Kaiser, C. (2009), "Detecting opinion leaders and trends in online social networks", SWSM'09, November 2, Hong Kong, doi: 10.1145/1651437.1651448.

Bozanta, A. and Nasir, A. (2014), "Usage of agent-based modeling and simulation in marketing", *Journal of Advanced Management Science*, Vol. 2 No. 3, pp. 240-245, doi: 10.12720/joams.2.3.240-245.

Chen, W., Wang, C. and Wang, Y. (2010), "Scalable influence maximization for prevalent viral marketing in large-scale social networks", *Proceedings KDD'10*, *Washington, DC*, *July 25-28*, doi: 10.1145/1835804.1835934.

Chen, Y., Fay, S. and Wang, Q. (2011), "The role of marketing in social media: how online consumer reviews evolve", *Journal of Interactive Marketing*, Vol. 25 No. 2, pp. 85-94, doi: 10.1016/j.intmar.2011.01.003.

Chen, X., van der Lans, R. and Phan, T.Q. (2017), "Uncovering the importance of relationship characteristics in social networks: implications for seeding strategies", *Journal of Marketing Research*, Vol. 54 No. 2, pp. 187-201, doi: 10.1509/jmr.12.0511.

Clauset, A., Newman, M.E.J. and Moore, C. (2004), "Finding community structure in very large networks", *Physical Review E*, Vol. 70 No. 6, p. 066111.

de Vries, L., Gensler, S. and Leeflang, P. (2012), "Popularity of brand posts on brand fan pages: an investigation of the effects of social media marketing", *Journal of Interactive Marketing*, Vol. 26 No. 2, pp. 83-91, doi: 10.1016/j.intmar.2012.01.003.

Duan, W., Gu, B. and Whinston, A.B. (2008), "Do online reviews matter? – An empirical investigation of panel data", *Decision Support Systems*, Vol. 45 No. 3, pp. 1007-1016, doi: 10.1016/j.dss.2008.04.001.

eMarketer (2016), "Latin America loves Facebook", Available at: www.emarketer.com/Article/Latin-America-Loves-Facebook/1013651 (accessed July 2016).

Facebook Newsroom (2016), "Users statistics", available at: https://newsroom.fb.com/company-info/ (accessed July 2016).

Feick, L. and Price, L. (1987), "The market maven: a diffuser of marketplace information", *Journal of Marketing*, Vol. 51 No. 1, pp. 83-97, doi: 10.2307/1251146.

Frieni (2016), "Maratón internacional de Buenos Aires", available at: https://frieni.com/event/1253/maraton-internacional-de-buenos-aires/ (accessed July 2016).

Gauri, D., Bhatnagar, A. and Rao, R. (2008), "Role of word of mouth in online store loyalty", *Communications of the ACM*, Vol. 51 No. 3, pp. 89-91, doi: 10.1145/1325555.1325572.

Goldenberg, J., Han, S., Lehmann, D. and Hong, J. (2009), "The role of hubs in the adoption process", *Journal of Marketing*, Vol. 73 No. 2, pp. 1-13, doi: 10.1509/jmkg.73.2.1.

Gravano, A. and Dell' Amerlina Ríos, M. (2014), "Spanish DAL: a Spanish dictionary of affect in language", Reporte Técnico, Departamento de Computación, FCEyN-UBA Buenos Aires.

Grossek, G. and Holotescu, C. (2009), "Indicators for the analysis of learning and practice communities from the perspective of microblogging as a provocative sociolect in virtual space", *The 5th International Scientific Conference eLSE – eLearning and Software for Education*, *Bucharest*, *April 9-10*.

Hansen, D., Shneiderman, B. and Smith, M. (2011), *Analyzing Social Media Networks with NodeXL: Insights from a Connected World*, Morgan Kaufmann, Burlington.

Harel, D. and Koren, Y. (2000), "A fast multi-scale method for drawing large graphs", *GD'00 Proceedings of the 8th International Symposium on Graph Drawing*, Springer Verlag London, pp. 183-196, doi: 10.1007/3-540-44541-2_18.

Hawkins, D., Best, R., Coney, K. and Carey, K. (1995), *Consumer Behavior: Implications for Marketing Strategy*, McGraw-Hill, New York, NY.

Hewett, K., Rand, W., Rust, R. and van Heerde, H. (2016), "Brand buzz in the echoverse", *Journal of Marketing*, Vol. 80 No. 3, pp. 1-24, doi: 10.1509/jm.15.0033.

Hollebeek, L., Glynn, M. and Brodie, R. (2014), "Consumer brand engagement in social media: conceptualization, scale development and validation", *Journal of Interactive Marketing*, Vol. 28, No. 2, pp. 149-165, doi: 10.1016/j.intmar.2013.12.002.

Hudson, S., Huang, L., Roth, M.S. and Madden, T. (2016), "The influence of social media interactions on consume-brand relationships: a three-country study of brand perceptions and marketing behaviors", *International Journal of Research in Marketing*, Vol. 33 No. 1, pp. 27-41, doi: 10.1016/j.ijresmar.2015.06.004.

Jansen, B., Zhang, M., Sobel, K. and Chowdury, A. (2009), "Twitter power: tweets as electronic word of mouth", *Journal of the American Society for Information Science and Technology*, Vol. 60, No. 11, pp. 2169-2188, doi: 10.1002/asi.v60:11.

John, L.K., Emrich, O., Gupta, S. and Norton, M. (2017), "Does 'liking' lead to loving? The impact of joining a brand's social network on marketing outcomes", *Journal of Marketing Research*, Vol. 54 No. 1, pp. 144-155, doi: 10.1509/jmr.14.0237.

Katz, E. and Lazarsfeld, P.F. (1955), *Personal Influence: The Part Played by People in the Flow of Mass Communications*, The Free Press, New York, NY.

Kempe, D., Kleinberg, J. and Tardos, E. (2015), "Maximizing the spread of influence through a social network", *Theory of Computing Journal*, Vol. 11, pp. 105-147, doi: 10.4086/toc.2015.v011a004.

King, R., Racherla, P. and Bush, V. (2014), "What we know and don't know about online word-of-mouth: a review and synthesis of the literature", *Journal of Interactive Marketing*, Vol. 28 No. 3, pp. 167-183, doi: 10.1016/j.intmar.2014.02.001.

Labrecque, L. (2014), "Fostering consumer-brand relationships in social media enviroments: the role of parasocial interaction", *Journal of Interactive Marketing*, Vol. 28 No. 2, pp. 134-148, doi: 10.1016/j.intmar.2013.12.003.

Lang, B. and Hyde, K. (2013), "Word of mouth: what we know and what we have yet to learn", *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, Vol. 26, pp. 1-18.

Larrosa, J.M. (2016), "Agentes computacionales y análisis económico", *Revista de Economía Institucional*, Vol. 18 No. 34, pp. 87-113, doi: 10.18601/01245996.v18n34.07.

Larrosa, J.M.C. (2012), "Introducción a la economía computacional basada en agentes con aplicaciones NetLogo", EdiUNS: Bahía Blanca (Argentina), 216pp.

Libai, B., Muller, E. and Peres, R. (2013), "Decomposing the value of word-of-mouth seeding programs: acceleration versus expansion", *Journal of Marketing Research*, Vol. 50 No. 2, pp. 161-176, doi: 10.1509/jmr.11.0305.

Minqing, H. and Bing, L. (2004), "Mining and summarizing customer reviews", *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, *Seattle, WA, August 22-25*, doi: 10.1145/1014052.1014073.

Mochon, D., Johnson, K., Schwartz, J. and Ariely, D. (2017), "What are likes worth? A Facebook page field experiment", *Journal of Marketing Research*, Vol. 54 No. 2, pp. 306-317, doi: 10.1509/jmr.15.0409.

Molina, J.L. (2004), "La ciencia de las redes", Apuntes de Ciencia y Tecnología No. 11, junio 2004.

Nam, H. and Kannan, P. (2014), "The informational value of social tagging networks", *Journal of Marketing*, Vol. 78 No. 4, pp. 21-40, doi: 10.1509/jm.12.0151.

Nambisan, S. and Baron, R. (2007), "Interactions in virtual customer environments: implications for product support and customer relationship management", *Journal of Interactive Marketing*, Vol. 21 No. 2, pp. 42-62, doi: 10.1002/dir.20077.

Ortiz-Arroyo, D. (2010), "Discovering sets of key players in social networks", *Computational Social Networks Analysis: Trends, Tools and Research Advances*, Springer-Verlag, London, pp. 27-47, doi: 10.1007/978-1-84882-229-0_2.

Paquette, H. (2014), "Social media as a marketing tool: a literature review", Paper No. 2, Major Papers by Master of Science Students, University of Rhode Island, Kingston.

Pavlou, P. and Ba, S. (2002), "Evidence of the effect of trust building technology in electronic markets: price premium and buyer behavior", *MIS Quarterly*, Vol. 26 No. 3, pp. 243-268, doi: 10.2307/4132332.

Peters, K., Chen, Y., Kaplan, A., Ognibeni, B. and Pauwels, K. (2013), "Social media metrics – a framework and guidelines for managing social media", *Journal of Interactive Marketing*, Vol. 27 No. 4, pp. 281-298, doi: 10.1016/j.intmar.2013.09.007.

Pew Research Center (2014), "6 new facts about Facebook", available at: www.pewresearch.org/fact-tank/2014/02/03/6-new-facts-about-facebook/ (accessed July 2016).

Risselada, H., Verhoef, P. and Bijmolt, T. (2014), "Dynamic effects of social influence and direct marketing on the adoption of high-technology products", *Journal of Marketing*, Vol. 78 No. 2, pp. 52-68, doi: 10.1509/jm.11.0592.

Rogers, E. (1983), *Diffusion of Innovations*, The Free Press, New York, NY.

Scoponi, L., Pacheco Días, M., Pesce, G., Durán, R., Schmidt, M.A. and Gzain, M. (2016), "Redes de cooperación científico-tecnológica para la Innovación en agronegocios en dos universidades latinoamericanas", Universidad y agronegocios, Editorial de la Universidad Nacional del Sur, Cap 3, pp. 165-211.

Sela, A., Shmueli, E., Goldenberg, D. and Ben-Gal, I. (2016), "Why spending more might get you less, dynamic selection of influencers in social networks", *2016 IEEE International Conference on the Science of Electrical Engineering (ICSEE)*, *Eilat*, pp. 1-4, doi: 10.1109/ICSEE.2016.7806079.

Serrano Puche, J. (2016), "Internet y emociones. Nuevas tendencias en un campo de investigación emergente", *Comunicar: Revista científica iberoamericana de comunicación y educación*, Vol. 24 No. 46, pp. 19-26, doi: 10.3916/C46-2016-02.

Simon, H.A. (1982), *Models of Bounded Rationality: Empirically Grounded Economic Reason*, Vol. 3, MIT Press, Cambridge, MA.

Smith, A.N., Fischer, E. and Yongjian, C. (2012), "How does brand-related user-generated content differ across YouTube, Facebook, and Twitter?", *Journal of Interactive Marketing*, Vol. 26 No. 2, pp. 102-113, doi: 10.1016/j.intmar.2012.01.002.

Smith, M., Rainie, L., Himelboim, I. and Shneiderman, B. (2014), *Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters*, Pew Research Center, Washington, DC.

Smith, M., Milic-Frayling, N., Shneiderman, B., Mendes Rodrigues, E., Leskovec, J. and Dunne, C. (2010), "NodeXL: a free and open network overview, discovery and exploration add-in for Excel 2007/2010", The Social Media Research Foundation, available at: http://nodexl.codeplex.com/www.smrfoundation.org

Stephen, A. and Galak, J. (2010), "The complementary roles of traditional and social media publicity in driving marketing performance", INSEAD working papers Collection, No. 97, p. 1.

Subbian, K., Prakash, B. and Adamic, L. (2017), "Detecting large reshare cascades in social networks", *International World Wide Web Conference Committee*, *Perth*, pp. 597-605, doi: 10.1145/3038912.3052718.

Sundaram, D.S., Mitra, K. and Webster, C. (1998), "Word-of-mouth communications: a motivational analysis", in Alba, J.W. and Hutchinson, J.W. (Eds), *NA – Advances in Consumer Research*, Vol. 25, Association for Consumer Research, Provo, UT, pp. 527-531.

The Nielsen Company (2015), "Global trust in advertising", available at: www.nielsen.com/content/dam/nielsenglobal/apac/docs/reports/2015/nielsen-global-trust-in-advertising-report-september-2015.pdf (accessed July 2016).

Tucker, C. (2008), "Identifying formal and informal influence in technology adoption with network externalities", *Management Science*, Vol. 54 No. 12, pp. 2024-2038, doi: 10.2139/ssrn.1089134.

Van der Merwe, R. and van Heerden, G. (2009), "Finding and utilizing opinion leaders: social networks and the power of relationships", *South African Journal of Business Management*, Vol. 40 No. 3, pp. 65-76.

VanMeter, R., Grisaffe, D. and Chonko, L. (2015), "Of 'likes' and 'pins': the effects of consumers' attachment to social media", *Journal of Interactive Marketing*, Vol. 32, pp. 70-88, doi: 10.1016/j.intmar.2015.09.001.

Vaz, C.A. (2011), "Os 8 P's do marketing digital: o seu guia estratégico de marketing digital", Ed NOVATEC, Sao Paulo.

Wang, Z. and Gon Kim, H. (2017), "Can social media marketing improve customer relationship capabilities and firm performance? Dynamic capability perspective", *Journal of Interactive Marketing*, Vol. 39, August, pp. 15-26, doi: 10.1016/j.intmar.2017.02.004.

Watts, J.D. and Dodds, P. (2007), "Influentials, networks, and public opinion formation", *Journal of Consumer Research*, Vol. 34 No. 4, pp. 441-458, doi: 10.1086/518527.

Weinberger, D., Levine, R., Locke, C. and Searls, D. (2000), *The Cluetrain Manifesto*, Basic Books, Cambridge, MA.

Wilensky, U. (1999), "NetLogo", Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, available at: http://ccl.northwestern.edu/netlogo/ (accessed August 2016).

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