Advanced Visualization of Twitter Data for its Analysis as a Communication Channel in Traditional Companies

Carmen Zarco [a,*], Elena Santos [a], Oscar Cordón [b]

[a] *Departament of Market Research, Universidad Internacional de La Rioja, Logroño, Spain*

[b] *Instituto Andaluz Interuniversitario de Ciencia de Datos e Inteligencia Computacional (DaSCI), University of Granada, Granada, 18071, Spain*

Abstract

The adoption of Twitter as communication channel can provide a significant benefit to firms, allowing them to improve their reputation and check its consistency with their mission and goals, monitor how customers respond to a business decision, and achieve product awareness. However, Twitter engagement is difficult for many companies due to the large amount of human and financial resources required. The aim of this contribution is to identify the situation of Twitter adoption by those kinds of traditional companies, aiming to discern the communication strategies applied from a global and relational view, analyzing the common and differential characteristics. To do so, we propose a methodology based on the use of Twitter data related to presence and impact as well as advanced visualization methods based on social network analysis techniques. It will allow us to obtain visual representations (maps) of the similarity relations with respect to the positioning of the different companies on Twitter. The nature of the brand communication model developed can be established considering the distribution and spatial location of each company on the map. Therefore, the generated maps become technological watch tools allowing a specific company to develop competitive analysis with respect to competitors. We validate our proposal on a specific market, comprised by the wineries holding the Qualified Denomination of Origin Rioja in Spain. These firms have a great sense of tradition, making them reluctant to use technology-based marketing strategies even if wine consumers are highly active users on Twitter.

Keywords: Twitter, Communication, Information Visualization, Social Network Analysis, Wineries, Denomination of Qualified Origin Rioja.

Introduction

Social media has become an important media platform that connects a third of the world's population [1]. As a result, there has been a redistribution of budgets for communication in organizations as advertisers move away from traditional media and invest more resources in digital advertising and social networks. In fact, it is estimated that 58% of registered brands on Twitter have more than 100,000 followers each [2]. The emergence of these social networking platforms and their increasing adoption by customers have precipitated a paradigm shift, significantly altering the way in which customers communicate and interact with each other and with businesses. For example, some studies have shown how there is a direct correlation between the polarity of customer's electronic word-of-mouth [3] in Twitter regarding their direct service experiences with firms and these firms' company value in some sectors as airline companies [4].

The use of Twitter as a global digital platform for social interaction does not permit any discussion. It currently has 328 million active users per month, records 1,000 million unique monthly visits to websites with access to the platform, generates more than 500 million tweets a day, is available in more than 40 languages and 79 percent of users come from outside the United States [5] [6]. Twitter has not only become a trend among social network users but has also become an object of study for more and more researchers in the academic and business world. In academia, it has been studied particularly in the fields of [5]:

- Political communication
- Crisis communication
- Brand communication
- Concrete experiences of using Twitter as a secondary or alternate channel (backchannel)
- Relationships

We can find some representative examples of the above fields. The issue of event detection for emergency response from Twitter data is tackled in [7]. The authors focus on the difficult task of uncovering informative event-related information from the large amount of tweets created by people about the incident in real time. The proposed method is validated using posted tweets about the 70 incidents caused by severe storms that struck the Sydney area in 2015. Another interesting application is developed in [8] where a location inference method is used for geotagging tweets with traffic-related content identified in the Twitter stream in order to provide this information in real-time to end-users and transportation managers. In [9], geotagged tweets claiming about high temperatures are used for real-time urban climate monitoring and the consequent risk management.

In particular, the emergence of Twitter has transformed brand communication. Firms has been abruptly obliged to move from a classical environment where the brand image was exclusively controlled by their own marketing and public relation departments to a new, unexplored ecosystem where Twitter (and other social media) allows consumers to express and spread their opinions or complains about the brand and its products. Nowadays, consumer relationship building on social media has a significant impact on a brand's reputation even if many managers ignore brand communication models for these media due to either aversion or lack of awareness [10].

The way in which corporations can benefit from Twitter has been largely analyzed in the last few years [11]. The analysis of Twitter data can be useful to monitor brand's reputation (tracking the strength, passion, sentiment, reach, and growth of the brand as well as the overall consumer engagement) and to check its consistency with the firm's mission and goals. For example, the use of Twitter as a strategic communication tool for non-profit organizations is considered in [12]. The authors analyze the factors leading to use Twitter to communicate with the stakeholders in this area. They conclude that these kinds of organizations should implement one-way and two-way communication strategies in both their Twitter profile and tweets for an optimum use of Twitter.

Twitter analysis also allows brands to obtain valuable feedback about their products and competitor's products by listening to consumer's conversations. This feedback can be used for targeted advertisement as well as for different business intelligence and technological watch tasks as identifying how customers respond to a business decision taken by the brand (e.g. a new marketing campaign) and competitive analysis regarding competitors. Furthermore, Twitter has proven to be a very successful marketing tool improving customer engagement and electronic word-of-mouth, which increases brand and product awareness. As a single example, the use of data mining techniques to explore customer engagement on Twitter is considered in [13]. Electronic word-of-mouth patterns were identified from a set of IKEA tweets and then classified in three groups: objective statements, subjective statements, and knowledge sharing. The study concluded that IKEA successfully engaged customers in knowledge sharing, while negative opinions were mainly disseminated in a limited circle. Methods were also introduced to identify prosumers actively participating in product development in order to more closely match the company's products to consumer needs.

Hence, although Twitter engagement becomes an excellent opportunity to improve companies' communication models, it also brings some important problems. The adoption of brand communication strategies on Twitter requires specialized staff, specific budgets, and large amounts of time. This makes many firms unable or reluctant to adopt them, especially for the case of Small and Medium Enterprises whose resources are more limited [11].

Our main objective will be to identify the Twitter communication model developed by the companies in a specific market as well as its impact in terms of their degree of engagement, presence, and activity. We intend to study this communication model from a global and relational perspective, analyzing what characteristics are shared by these companies that use Twitter to a lesser or greater degree as well as those that differentiate them. With this aim, we make use of presence and impact data obtained directly from Twitter accounts and advanced data visualization tools based on social network analysis techniques [14], which will allow a detailed analysis of the existing relationships between the different organizations from the perspective of their use of Twitter as a communication channel. We will obtain visual representations (maps) of the similarity relations with respect to the positioning of the different organizations on Twitter (in terms of engagement and impact) that are easily interpretable by the information analyst considering the distribution and spatial location of each company in the map.

In this way, the maps obtained from the proposed Twitter data analysis and information visualization methodology become a technological watch and competitive intelligence tool. They allow a specific company to identify and monitor its presence and impact on Twitter compared to that of their competitors. The brand communication model adopted by each organization is decisive in terms of the brand's competitive advantage and these maps allow us to uncover it from a global perspective. The insights obtained can thus help a specific company to know its positioning with respect to their competitors and their consumers as well as to take actions to improve it.

Considering the high levels of competition within the business world and specifically within the Spanish wine industry, it is not surprising that many brands seek new and innovative ways of communicating with consumers. As a consequence of their social and viral capacities social networks such as Twitter have become increasingly popular points of contact with the customer, creating a new forum for interaction between customers and wine brands [11] [15]. As a case study to validate our methodology, we intend to analyze how well known companies for their great sense of tradition such as wineries with Qualified Denomination of Origin (DOCa) Rioja adopt Twitter as a means of communication, thus taking an important step on their way to incorporating new technologies into their business communication policies in the digital age. This information will allow us to recognize if highly traditional companies like wineries adopt Twitter as a bidirectional communication channel or otherwise maintain a more classical stance based on persuasion.

Theoretical framework

Marketing professionals have recognized the value of social media platforms, quickly integrating them into the development of marketing strategies, especially in tasks that are focused on communication [16].

Wine is an experiential product which inherently implies socialization and which builds communities around the pleasure of sharing experiences [17]. Spanish wine brands compete to attract and retain consumers and many of them are adopting social networks to reach their consumers and communicate their brand, quality, and personal experience [18]. Through social media that common element of appreciation and consumption of wine is improved by creating communities. Hence, it is particularly important for those involved in the wine industry to have an active presence in social networks [19].

Some wine brands are achieving success through social networks, with documented examples that show that both small and large wineries have achieved a positive return on investment through the implementation of successful strategies in these media. Several academic studies have explored the practices of social networks within the wine industry. Of the wineries studied in Australia, Canada, New Zealand, Spain, Italy, South Africa and the US, 35% reported using social networks for the main reason of communicating with customers about events in the winery and promoting the wines [20]. In addition, some experts argue that social networks help with wine sales because word-of-mouth is particularly effective among wine consumers and the socialization aspect of these networks is appropriate for wine, allowing consumers to exchange information and encourage others to try different wines [19].

The wine industry is progressively recognizing the increasingly relevant role that social networks have as an appropriate and valuable tool to reach consumers. When consumers search for wines and wineries on the Internet, they are bombarded with a massive volume of brand messages, which means that the content must be creative, polished and clear if what a brand wants is to capture the attention of users. Producing a quality wine is important but there is also a need to give it the presentation it deserves, communicating accurately with consumers. Communication activities are in a state of evolutionary development in which new trends continually arise and to which wineries must adapt if they want their campaigns to be successful [16].

Twitter and its users

Twitter, founded in early 2006, can be described as a microblogging platform and as a social network [21]. It is a microblog because through the web or the smartphone you can post short messages of 280 characters called tweets. In turn, it is a social network because its members have a profile page with personal information and can connect to other members following them and getting direct access to their content.

Twitter has two special characteristics that differentiate it from other similar platforms: the limitation in the number of characters that can be used in each message (originally 140 and now 280) and the way in which the relationships between users develop: a friendly relationship is not required to interact with others and relationships can be established with unknown users, making it easier to make contact with specialists in specific topics and access updated information related to the area of interest [22].

In addition, the limitation on the use of characters promotes the capacity for synthesis, allows for better communication between issuers and recipients, favors the exchange of information [23], facilitates collaboration and contributes to the development of communication skills [24].

According to [25] 81% of Internet users look for information online before buying a product or service, especially in high involvement categories with travels coming first, followed by mobile phones and then vehicles. Among the reasons for using the Internet to obtain up-to-date and useful information before purchasing a product or service are: making a profitable and economical decision (66%), finding detailed and valuable information about the products (60%), and preparing a buy at a store before seeing the product and the nearest point of sale (55%).

Regarding the tools used when searching for information about products and services, the web search engine has been the most commonly used tool in Europe since 2009 (employed by seven out of ten users), followed by the manufacturers' websites, consumer opinion sites, retailer websites, and price comparison pages. However, social media has increased its presence and three years later there are already 54% of cybernauts who think that social networks are a good place to learn about products and brands [25].

In Spain there are a total of 4.5 million Twitter users according to the latest data provided by the IAB Spain report [26]. Of these users, 60.12% are men and 39.88% are women. 42.56% have an age between 35 and 44 years, 24.9% between 45 and 50 years, and 20.83% between 25 and 34 years [27]. Although growth in the number of Twitter users has stagnated, it can be seen that its daily use does evolve. 59% of Twitter users access the platform daily, compared to 46% just a year ago. This means that the most faithful and intensive users are staying on the microblogging platform [26].

Wine consumer profile

The consumption of wine in Spain experienced an increase in 2016 after several decades of decrease. According to the data managed by the *Spanish Observatory of the Wine Market* [28], the demand for wines registered positive behavior with a growth rate ranging from 2.5% to 4%, reaching a total of 9.8 million hectoliters. Even so, and according to the experts, these figures are far below what is foreseeable for a producer country with a great winemaking tradition such as ours. The most important consumption increase corresponds to sales in the beverage retailers, followed by the restaurant business and direct sales made both online and in the wineries themselves, without taking into account the self-consumption data that is difficult to measure [29].

According to the report produced by *Nielsen* for the *Spanish Observatory of the Wine Market* [30], the socio-demographic profile of Spanish wine consumers is mainly male, although at this moment 43% of consumers are women. In terms of age, it becomes clear that the increase in the consumer rate also increases with age. Product penetration among the youngest groups (18-34 years old) is 52%, which increases to 59% and 67% in the 35-54 and over 54 years age groups, respectively.

Wine as a product inherently implies socialization and builds around the pleasure of sharing wine experiences. This exchange and the building of the community are processes that are also rooted in virtual social networks, including microblogging ones such as Twitter, which share similar principles to face-to-face human relations [31]. Social networks and communicating through them allow us to improve the common element of wine appreciation and consumption. Therefore, it is particularly important for those actors involved in the wine industry to have an active presence on them.

Wine companies and communication policies

Researchers and marketing specialists insist on the importance of Social Media and social networks as an easy and low-cost service, which makes them a communication choice that provides an immediate connection with a large number of consumers [32]. However, these experts also argue that there is still a long way to go in the wine industry sector before they become truly efficient communication and marketing tools [33]. Meanwhile, experts in the wine sector have raised an important concern about the ineffective communication policy of most Spanish wineries, despite the significant media presence that wines have [34].

Without any doubt, organizations depend on their communication policies and the image that their products show in the media. In addition to mass information markets, especially television and press, fragmentation is currently taking place on the Internet in numerous “mini-markets”, each requiring its own communication tools and specific approach to tackle the growing sophistication of consumers [35].

As previously stated, the goal of wineries is to make a good wine and give it an attractive price, but it is also their job to effectively communicate its existence to their present and future interest groups, their consumers, and their general audience. This task must be handled through traditional media (television and press) while simultaneously using social networking platforms and channels. Wineries need to consider how much a good communication policy affects the mobilization of the wine consumer, how communication creates and enhances the image of the winery brands, and how that process promotes the purchase [36]. The traditional media channel their messages about wines through advertising, the news produced by their editors, and the work of each winery to ensure free dissemination spaces. This promotes their wines, their ideas and their people so as to build an attractive and explanatory journalistic account of their activity. However, consumers want to participate more than ever in communication processes and, for this reason, the question is no longer just how to reach them but also how they arrive at wineries and how they interact with each other [17].

Methodology

To carry out this analysis of the use of Twitter as a communication channel for wine companies with DOCa Rioja, we have compiled data related to their presence in this microblogging network. Of the more than 590 wineries owning this denomination, we have found that only 191 have presence and activity on Twitter. One of the most important handicaps we found was the duplicity of names of some wineries that converged on the same profile within the social network. Of these 191 wineries, three were removed because of having such profile duplicity on Twitter: *Bodegas Berceo*, *Faustino Rivero*, and *Bodegas Pujanza* (that is, two different wineries, generally of large size, used the same Twitter account in the three cases), thus resulting in a final number of 188 wineries/Twitter accounts. Four variables (*Tweets*, *Followers*, *Following*, and *Likes*) were collected from each account to represent presence and activity data. The information was collected between December 20 and 30, 2017. These specific dates were selected as they comprise one of the most important seasonal periods for the wine industry, corresponding to the Christmas campaign. Wineries become very active in social media (and of course in other mass media) during this period as well are there being great consumer activity, thus making the acquired data significantly representative for our analysis. Note that the proposed methodology is not affected by the length of the data acquisition period as it works with aggregated data of the variables.

The basis of our study will be certain techniques of social network analysis (SNA) [14] [37] and visualization [38]. These allow the design of visual maps that show the characteristics of the Twitter communication models of these wineries holding the DOCa Rioja. The use of SNA techniques has demonstrated its ability to generate high-quality schematic visualizations of network-based representations in various fields of knowledge: psychology (to represent the cognitive structure of a topic) [39], system modeling (to design and analyze fuzzy systems) [40], software debugging (to detect bugs in implementations of multi-agent systems) [41], multiobjective optimization (to visualize the composition of non-dominated solutions, assisting the decision maker) [42], multimedia web search results [43], and scientometrics (to analyze different kinds of scientific domains) [44] [45], among others. In particular, the use of a visualization methodology of this kind is proposed in [46] to analyze brand positioning by establishing relationships among brands as well as among brand and product attributes based on the structure of online web searchers developed by the users. The analysis of the visual maps generated using SNA and represented by network layout and multidimensional scaling methods is aimed at identifying the positions of individual brands and their relationships in the minds of consumers from web search information (co-occurrences of keywords in the web search)[1].

In our case, we will first define a measure of similarity based on the different Twitter indicators associated with each winery. In this way, we will obtain a symmetric relational matrix that will determine the similarity between the communication strategies applied by each pair of wineries. This relational matrix will define the structure of the corresponding social network of wineries. We will apply a network pruning algorithm, an efficient variant of the *Pathfinder* method [47], on the resulting similarity matrix in order to prune the associated network, reducing relationships between the communication models defined by the wineries' Twitter accounts to maintain only those that are most salient (i.e. significant) at the global level. Although this characteristic is not required in our

[1] Information visualization techniques have also shown to be useful for machine learning, data mining and knowledge discovery tasks [57].

application domain, it becomes a powerful indicator of the quality and flexibility of the Pathfinder algorithm and justifies its choice for our methodology.

To obtain the visual map, we will apply a force-based social network layout algorithm, the *Kamada-Kawai* method [48], to locate the nodes and draw the network. A label map will also be obtained with the names of the wineries where the positions are determined by their existing relationships and with a color scale which represents additional information about the communication model.

The following sections present the different components of the methodology for generating our visual maps in a more detailed way. As software tools we have used *Microsoft Excel*®, using *Visual Basic* macros, *Gephi* [49], and implementations of social network pruning algorithms made by members of our research group, as we will describe below.

Similarity measure and construction of the social network

In this first step we consider the data of the four main variables: *Tweets*, *Followers*, *Following*, and *Likes*. These data have been normalized by obtaining the maximum value of each variable and dividing each value by this maximum. In this way, each wine company is associated with a four-dimensional vector with the four components taking values in [0,1], that is, a 4-dimensional point in real space $[0,1]^4$.

The similarity measure for the wineries' communication policies on Twitter is defined by means of the Euclidean distance between their corresponding 4-dimensional points:

$$D(\vec{x},\vec{y}) = \sqrt{\sum_{i=1}^{4}(x_i - y_i)^2}$$

resulting in the following expression:

$$D(\vec{x},\vec{y}) = \sqrt{\begin{matrix}(Tweets_x - Tweets_y)^2 + \cdots \\ (Following_x - Following_y)^2 + \cdots \\ (Followers_x - Followers_y)^2 + \cdots \\ (Likes_x - Likes_y)^2 + \cdots\end{matrix}}$$

The distance values for each pair of wineries are normalized again by computing the maximum distance and dividing every value by the latter. As our interest lies in identifying the similarity existing between the wineries when they apply their communication policy on Twitter, what we do next is to invert that standardized distance:

$$S(\vec{x},\vec{y}) = 1 - D(\vec{x},\vec{y})$$

To compute the similarity matrix, we have implemented a macro in *Visual Basic* for *Excel*, developed in the *Excel* sheet where the values of the four indicators have been compiled. This matrix contains the nodes and links relating the different wineries depending on the degree of similarity obtained from the collected data. It is a square, symmetrical matrix of 188×188 real numbers, where the diagonal is not considered (the similarity of a Twitter account to itself is a maximum but of course not significant). This matrix defines the associated social network, a non-directed weighted network composed of 188 nodes, corresponding to the wineries analyzed, and weighted links whose weight indicates the similarity value between the Twitter accounts of the two wineries it connects.

Pruning of the social network

The visualization of social networks presents several problems such as [50]: i) quality (the larger the network, the more likely there are errors in the data); ii) complexity (more variables, more detail, more categories); iii) speed (the focus is often on getting results from our network quickly enough to be considered an interactive process); and iv) analysis (what order of complexity is required for the algorithms that handle large networks?). In particular, the large dimension that we usually find in social networks generates difficulties in obtaining graphical representations useful for analysis as it can cause an information overload for the analyst, reducing the interpretability of the graphic representations expected to be obtained. In our case, our social network of communication strategies of DOCa Rioja wineries on Twitter presents a reduced number of nodes but a very significant density. Obtaining of an aesthetic visualization requires the reduction of the dimensionality of the set of links of the network (i.e., a pruning of the network) to generate a structure that reveals the fundamental underlying structure. This structure should maintain every node but only keep the most important relations. In the specialized SNA literature, there are three predominant alternatives for carrying out this task in weighted networks [51]:

a) The first method discards links with weights below a certain threshold [52]. This approach, although easy to implement, does not consider the intrinsic structure of the underlying network. Therefore, the transformed network may not show the nature of the original one and even connected components can become disconnected from each other, not properly representing reality.

b) The second method is based on obtaining a minimal spanning tree from the network [53]. This guarantees a fixed and minimum number of links (the number of nodes minus one) but does not always reflect the underlying information in an appropriate way due to the possibility of an excessive pruning.

c) The third and last method establishes restrictions on the paths of the network and those links that do not satisfy them. The *Pathfinder* algorithm [39] [54] is the method usually applied, being known for its mathematical properties associated with the preservation of triangular inequality in paths of the network of length q (parameter of the algorithm). Some of these properties are the conservation of links, the ability to model symmetric and asymmetric relationships, the preservation of the subnets of the original network, and the representation of the most significant relationships present in the data. The distances of the paths considered to check the triangular inequality are calculated using a parametric distance (the *Minkowski* metric) with the parameter r. Those links that violate the triangular inequality (that is, for which there are alternative paths of length q with a distance lesser than or equal to the weight of the original link) are removed. A link that does not verify the triangular inequality will never belong to a geodesic path and is eliminated for being considered redundant. The result of applying the *Pathfinder* method with parameters q and r to a weighted social network is a new weighted social network called PFNET(r,q). The distances in the paths are measured with the *Minkowski* parametric distance where r=1 corresponds to the Manhattan distance, r=2 to the Euclidean distance, and r=∞ to the Chebyshev distance, equivalent to the greatest weight in the edges of the path. The algorithm allows us to build a sequence of networks of decreasing complexity by increasing the value of $q \in \{2, \ldots, n-1\}$. The PFNET(r,q=1) corresponds to the original network and the PFNET(r,q=n-1) is composed of the least possible number of links. In fact, the PFNET(r=∞,q=n-1) is the union of all the minimal spanning trees of the original network.

The use of PFNETs presents a series of significant advantages for the visualization of data, such as [55]:

1) They constitute a quantitative paradigm for the design of social networks. In domains where an objective measure of similarity/distance is available, they provide a unique representation of the underlying structure that is not possible to obtain with other methods of dimensionality reduction. For example, PFNETs model asymmetric relationships. This is not possible with other techniques such as multidimensional scaling (MDS) [51] which does not allow any link to be shown (relations between objects are only represented by their positions in the spatial layout). Likewise, they represent local relationships more accurately than MDS, which must optimize a global criterion.

2) They do not suffer from the existing restrictions in many clustering algorithms.

3) They only show the most significant relationships between the components of the network.

The positive characteristics of PFNET networks have lead us to adopt this pruning technique in our methodology. Specifically, in this paper we will use an efficient implementation of the *Pathfinder* algorithm, the *Fast-Pathfinder* variant [47], whose implementation is available on *GitHub* (https://github.com/aquirin/pathfinder), applying the maximum pruning intensity by taking values $r=\infty$ and $q=n-1$ looking for the obtaining of very interpretable maps.

Layout of the social network

Once a PFNET or any other type of social network has been obtained, there is a wide range of methods available that develop its automatic visualization. Force-based algorithms are the most used methods to draw network structures in the area of Information Sciences [38]. Their aim is to locate the nodes of a network in a two-dimensional or three-dimensional space so that either all the links are approximately equal in length or correspond globally with the theoretical distances between the nodes of the graph. As a collateral effect, these methods also produce few crossings between links, allowing us to obtain a representation as aesthetic and pleasant as possible. This family has the classic algorithms of *Kamada-Kawai* [48] and *Fruchterman-Reingold* [55] as their most representative instances although there are recent proposals capable of scaling up to massive-size networks [38].

In our case, we will use the *Kamada-Kawai* algorithm, which has proven very effective when combined with *Pathfinder* networks in other problems such as system modeling and scientometrics. In addition, in order to enrich the visualization, we will consider a color scale for the nodes and the labels where the blue color reflects the lowest value and the red color the highest value of the measure considered, ranging through green, yellow, and orange, which represent medium low, medium, and medium high values, respectively.

Summary of the Procedure

This section is devoted to summarize the proposed methodology in the form of a schematic procedure. In order to generate the maps that graphically represent the Twitter communication model developed by the companies from the specific market considered, there is a need to follow the steps shown as follows:

1. *Network Generation*: Using the Euclidean distance over the arrays of the variables considered and then normalizing and inverting the results we obtain the measures of similarity, obtaining a real square matrix that relates the wineries depending on their degree of similarity (a social network). This task is developed using a simple *Visual Basic* code directly implemented as a macro in the *Microsoft Excel* spreadsheet containing the values of the four Twitter variables taken for each winery.
2. *Network Scaling*: a network scaling method is applied to reduce the dimensionality of the obtained network by onlt keeping the most important relations. A quick variant of the *Pathfinder* algorithm, *Fast-Pathfinder*, is considered with parameters $q=n$-1 (lengths of the paths that must preserve the triangular inequality) and $r=\infty$. These parameter values ensure the maximal pruning and thus the most interpretable maps. This task is developed using using the implementation available on GitHub (https://github.com/aquirin/pathfinder), developed by our research group.
3. *Network Drawing*: force-based algorithms are devoted to represent this kind of information in an aesthetically pleasing way. The *Kamada–Kawai* algorithm will be used in our approach because it has been proved very

effective in combination with *Pathfinder*. It is applied by using the *Force Atlas 2* algorithm available in *Gephi*. The default parameters have been used, changing the *Scaling* to 3.0 and activating the options *Dissuade Hubs* and *Avoid Overlapping*. The *Label Adjustment* algorithm in *Gephi* was also applied after applying *Force Atlas 2*. Finally, to make the map more informative, the color scale in the nodes corresponds to a theoretical variable called *Twitter Positioning*, whose value is equivalent to the average of the four Twitter variables considered for each winery.

Obtained visualizations and analysis of results

The current section is devoted to the validation of the proposed methodology by generating a series of maps of Twitter positioning of wineries with DOCa Rioja and the analysis of one of those maps to perform a knowledge discovery task.

Generation of maps

Figures 1 and 2 show two visualizations resulting from applying the methodology presented in Section 3 to the data available from the 188 wineries. The difference between both representations is related to the parameterization applied to generate the underlying PFNET networks. In both cases, the parameter of *Minkowski* distance takes value $r=\infty$ as in previous studies it has been proven that it allows a higher level of pruning and consequently a better visualization. Nevertheless, the first display corresponds to the PFNET($r=\infty$,$q=2$), which maintains 245 links of the 17,578 of the original network by requiring triangular inequality to be satisfied only on paths of length 2. The second shows the PFNET($r=\infty$,$q=n-1$), which causes the strongest pruning intensity and which presents the minimum number of links to maintain connectivity in the original network of 188 nodes, 187.
The visualizations were obtained using the *Force Atlas 2* algorithm, one of the implementations of the *Kamada-Kawai* method available in *Gephi*. The default parameters have been used, changing the *Scaling* to 3.0 and activating the options *Dissuade Hubs* and *Avoid Overlapping*. Once the network visualization was obtained, the *Label Adjustment* algorithm in *Gephi* was also applied. The color scale corresponds to a theoretical variable called *Twitter Positioning*, whose value is equivalent to the average of the four indicators considered for each winery.

In both cases, the visual representations obtained are clear and allow us to identify important aspects of the analyzed data. The local relations are clearly identified and the distances between the nodes, determined by the layout algorithm to make them match the global distances of the network, clearly represent the similarities and differences between the communication strategies of the different wine companies. Likewise, there is a center-periphery effect, common in this type of representation. It can be noted that, the wineries located in the central part have more similar behavior to each other. Meanwhile, those positioned at the different extremes of the map show a clearly differentiated communication policy with those in the center (that is, significantly different values in the four indicators and, therefore, in the similarity measure) and this is consequently different among the wineries located at different extremes as well. These facts cause a clustering behavior in the network, which we will analyze in the next section.

Figure 1. PFNET(r=∞,q=2) network of the communication model of wineries with DOCa Rioja in Twitter (the color scale of nodes and labels is based on the global positioning of the Twitter accounts)

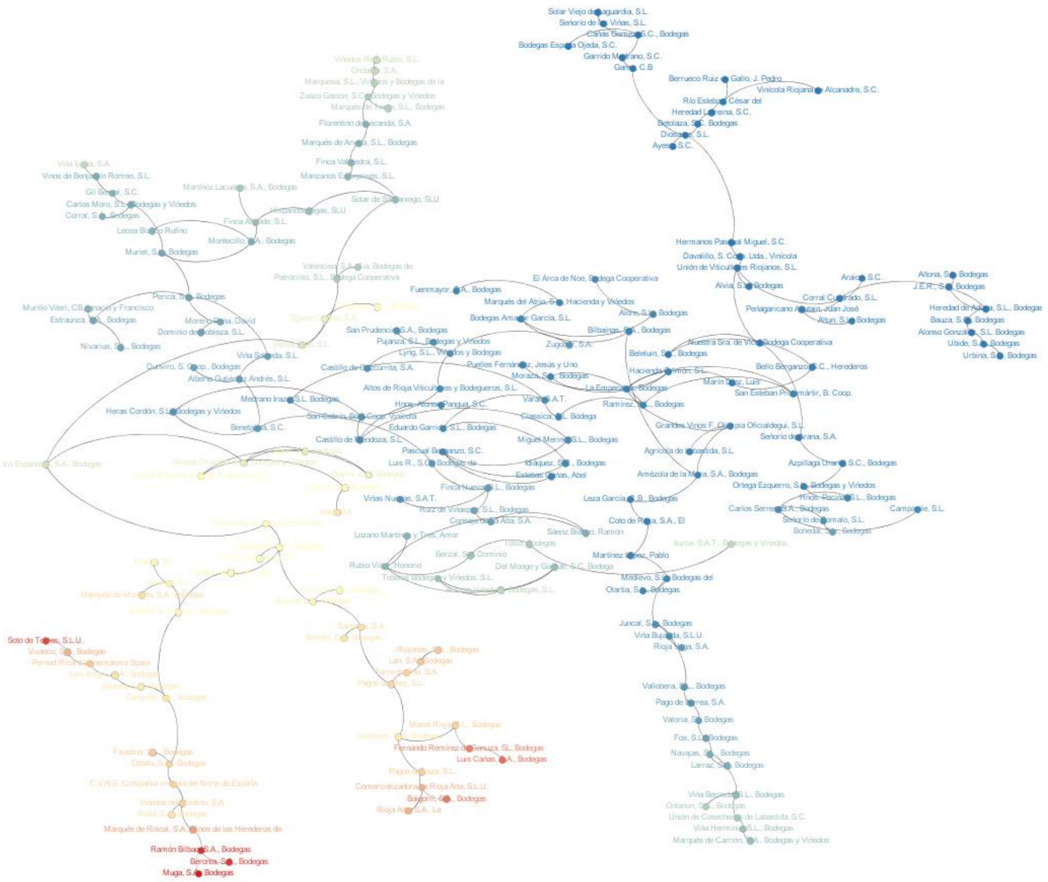

Figure 2. PFNET(r=∞,q=n-1) network of the communication model of wineries with DOCa Rioja in Twitter (the color scale of nodes and labels is based on the global positioning of the Twitter accounts)

Notice also that the small differences in distribution of the nodes between both visualizations result from the different structures of the underlying networks, which in turn are a consequence of the presence of more or less information depending on the intensity of the pruning performed.

Regarding the color scale, it allows us to clearly observe which wineries have a more active communication strategy on Twitter using the global perspective of the four indicators (that is, those that present a higher aggregated value and therefore have a more red tone in the map) and those that have less activity (lower aggregated value, blue tone). It can be easily observed how wineries that are close to each other present similar color tones (and therefore communication strategies), justifying the positioning of the nodes on the map. To simplify the subsequent analysis, Figure 3 shows the label map associated with the network in Figure 2, in which the nodes and the links are hidden but the positions of the labels in the plane and the color scale representing its positioning on Twitter are kept. We can observe how the wineries with a more active communication model are located in the bottom left part of the map, with *Muga*, *Beronia*, *Ramón Bilbao*, *Soto de Torres*, *Baigorri*, *Luis Cañas*, and *Fernando Ramírez de Ganuza* being the most notable, in that order.

Figure 3. Label map of the network in Figure 3 (the color scale in the labels is based on the global positioning of the Twitter accounts)

Figure 4 shows four different visualizations of the label map in Figure 3 where the color scales are not associated with the global positioning but with the value obtained in each specific indicator. By comparing these four maps with the one shown above, some interesting conclusions can be drawn.

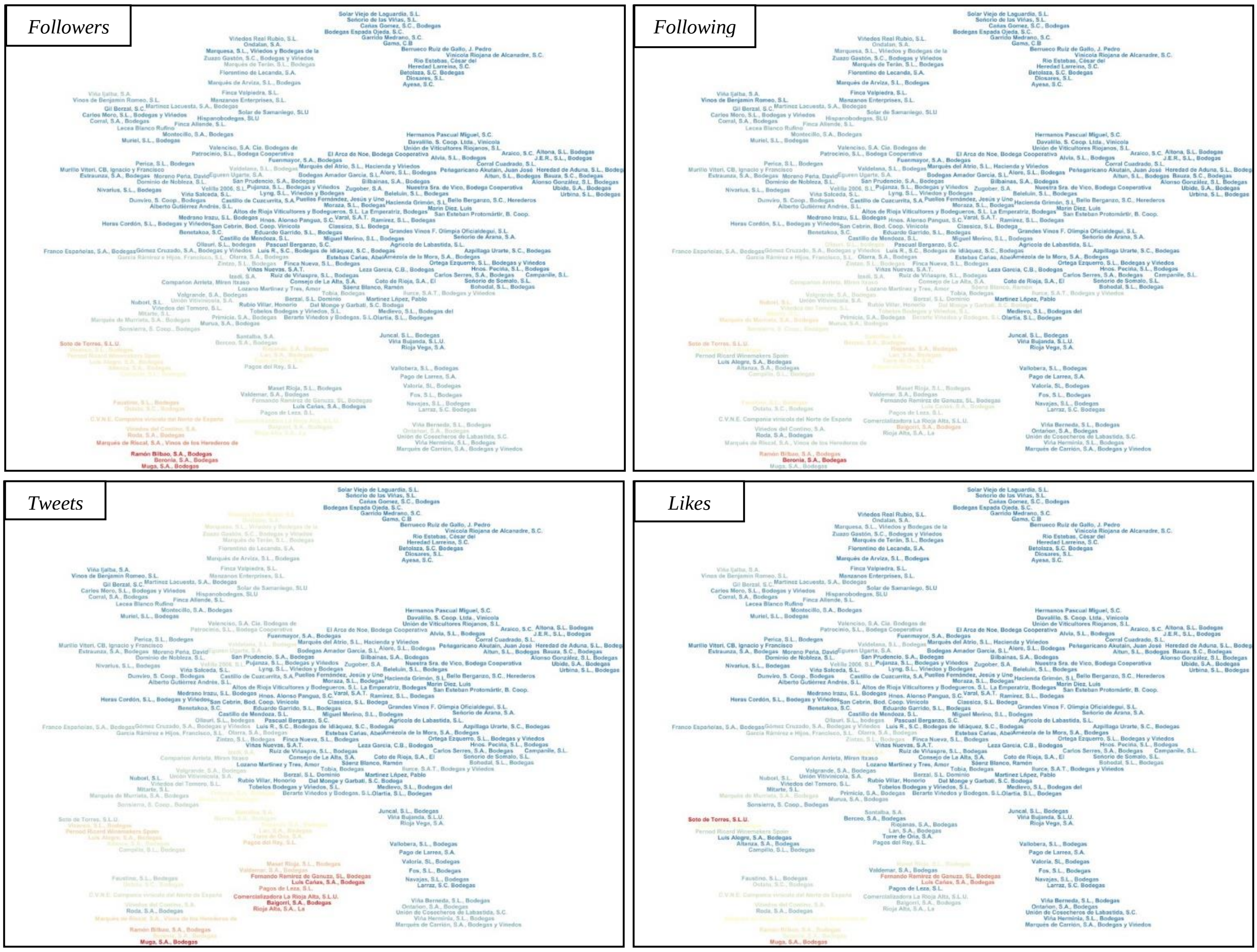

Figure 4. Label maps with color scales on the four variables: Followers (top left), Following (top right), Tweets (bottom left), and Likes (bottom right)

We can verify that in the first map, where the values of the *Followers* variable are considered, the *Muga*, *Beronia*, and *Ramón Bilbao* wineries, located in the bottom left-hand corner, have the most outstanding values. These three companies stand out clearly above the remainder due to the high number of followers they show, exceeding 21,000 in the three cases. We consider that in these three specific cases the brand and the product awareness produces a high number of followers on the social network.

In addition to these three wineries, the *Soto de Torres* and *Marqués de Riscal* wineries also play a leading role, represented by a softer tone due to having lower values than the previous ones (over 15,000). While the former stood out in the global positioning (Figure 3), the latter presented a somewhat lower global positioning, which indicates that this particular indicator (Followers) has a greater incidence in its communication model.

In the case of the map where the *Following* variable is considered, the *Beronia* winery is the most remarkable with a total of 10,300 followed profiles. Given this insight, it can be understood that the winery is interested in both maintaining a policy of dialogue with its followers and keeping a balance with the number of following accounts. However, we can also see how *Ramón Bilbao*, *Soto de Torres*, and *Baigorri*, with a lighter tone, maintain a considerable number of followed profiles, with a total of 5,959, 5,038, and 4,877 respectively. It is worth mentioning the significantly lower value of the *Muga* winery, which showed the highest value in the global positioning map of Figure 3. In the current indicator, its value is only 1,357 followed accounts, with a low average tone associated (green) and demonstrating that its high value in the global positioning obtained from the aggregation of the four indicators comes from other indicators and not from the current one.

The map that examines the *Tweets* variable shows some data that we believe are interesting. The *Muga*, *Baigorri*, and *Luis Cañas* wineries are in the lead as those that have communicated most with their followers through a high number of tweets: 17,400, 16,900, and 16,000, respectively. The next three wineries according to this indicator's rank are *Fernando Remírez de Ganuza*, *Pagos de Leza*, and *Comercializadora La Rioja Alta*, whose tweets reach 11,500. This allows us to conclude that, although their values are modest in relation to *Followers* and *Following*, they maintain an active communication policy on Twitter. In this sense, it can be clearly seen how the focus area of activity according to the number of tweets posted is located in the wine companies depicted in the center-bottom part of the map. It should be noted that *Soto de Torres*, which presented significant values in the rest of the indicators, now receives a medium low tone with only 2,810 tweets.

Finally, the map with the *Likes* variable shows behavior that has attracted our attention even more. In this case, the *Soto de Torres* winery leads the ranking with 17,400 likes, showing a very significant difference with the remainder. This fact demonstrates that this profile induces significant activity from its followers and that these followers show an interest in its publications within the social network even though the number of tweets was not as high as that of other wineries, as already seen. The next ones in the rank are *Muga*, *Luis Cañas*, and *Fernando Remírez de Ganuza*, whose likes exceed 12,000 in the three cases. This suggests that these three companies also count on very active followers keeping in mind that the average of likes within all the wineries considered does not reach 1,000. Overall, we can see how the focus of the indicator is located more to the bottom left and central areas and that it is more distributed than in the previous maps. Besides, important wineries according to other indicators such as *Ramón Bilbao* and *Beronia* show now a medium value (reflected in yellow) with 5,846 and 4,008 likes, respectively.

Analysis of the global positioning labels map

In this section we aim to draw additional conclusions related to the spatial distribution of the wineries in the Twitter communication model map. We can observe some interesting behavior. The upper part of the map in Figure 5 mainly shows wineries that have hardly any activity on Twitter. The wineries in this group, such as *Solar Viejo de La Guardia*, *Señorío de las Viñas*, *Bodegas Espada Ojeda*, and *Vinícola Riojana de Alcanadre*, have very similar characteristics as regards the low activity in the four variables analyzed and the presence of a zero value in one or more of them. As an example, the four wineries mentioned receive a zero in the *Likes* variable, along with extremely low values in the other three variables. In addition, the first two, located towards the periphery, also have a zero in the *Tweets* indicator. It should be noted that the visualization algorithm clearly separates this area from the rest of the map with a long link between the *Hermanos Pascual Miguel* and *Diosares* wineries, forming a cluster with differential behavior with respect to the center of the map that we will analyze below. The values of the variables of the six mentioned wineries are reported in Table 1.

Winery	***Tweets***	***Following***	***Followers***	***Likes***
Solar Viejo de La Guardia	0	21	70	0
Señorío de las Viñas	0	11	24	0

Bodegas Espada Ojeda	6	15	17	0
Vinícola Riojana de Alcanadre	57	12	14	0
Hermanos Pascual Miguel	0	49	22	0
Diosares	2	38	16	1

Table 1. Values of the four Twitter variables for the six wineries located in upper part of the map in Figure 5

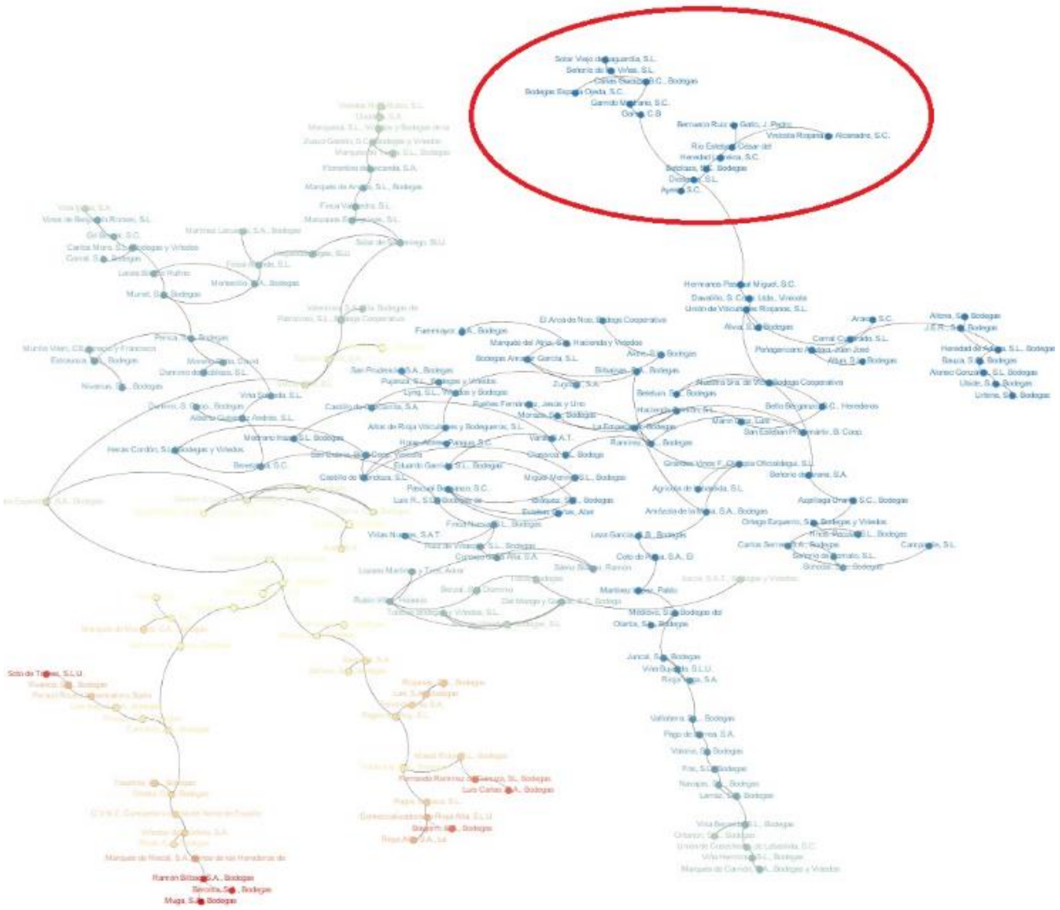

Figure 5. Low activity (almost null) in Twitter

Figure 6 shows how the largest number of wineries is concentrated in the center of the map. This is because most of the wineries using Twitter share very similar data and show very homogeneous behavior. As an example, we can refer to wineries such as *Ramírez and La Emperatriz*, which are located in the most central part of the map and have relatively low values in every variable

(*Tweets*=145, *Following*=258, *Followers*=309, *Likes*=16; and *Tweets*=47, *Following*=176, *Followers*=365, *Likes*=2, respectively). Hence, their communication policy on the social network can become blurred in comparison with that of the rest of the companies in the wine sector.

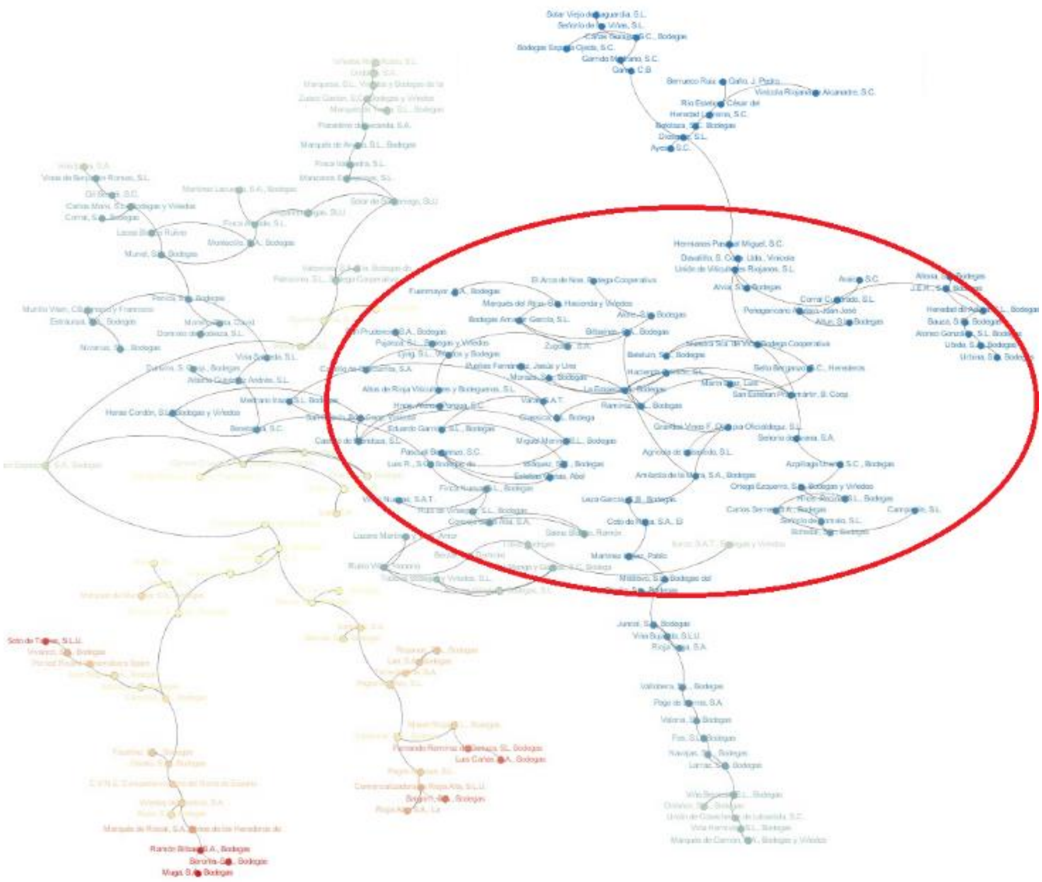

Figure 6. Homogeneous behavior with low values in every variable

This behavior ends up confirming the already mentioned concern that organizations have regarding their communication policies and the limited use they make of new technologies and the tools available to carry out a powerful, actual, and innovative communication policy. As we approach the bottom area and especially the left area of the map, the color changes, turning to green, which indicates a greater value in the different indicators. The usefulness of the information provided by the links at the local level can be recognized for the *Ilurce* winery. Although it is located in the center of the bottom part, it is linked to the branch on the left formed by the group of wineries with green hue (*Tobia*, *Berzal*, and *Rubio Villar* in one branch; *Del Monge y Garbati* in another, etc.). Specifically, the values shown by the *Ilurce* winery profile are *Tweets*=1,418, *Following*=1,514, *Followers*=2,998, and *Likes*=180, values clearly higher than those of the wineries in the central area.

The values of the variables of the wineries included in this second group are listed in Table 2.

Winery	***Tweets***	***Following***	***Followers***	***Likes***
Ramírez	145	258	309	16
La Emperatriz	47	176	365	2
Ilurce	1,418	1,514	2,998	180
Tobia	795	1,301	2,657	484
Berzal	459	1,490	1,380	768
Rubio Villar	348	1,665	1,202	125
Del Monge y Garbati	66	1,986	1,526	46

Table 2. Values of the four Twitter variables for the eight wineries located in central part of the map in Figure 6

In Figure 7 we can see how the wineries are grouped in the bottom part in three well differentiated groups. The wineries in these three groups have higher values in the analyzed variables than those located in the central part of the map analyzed in Figure 6. However, we can recognize that each group has a different nature.

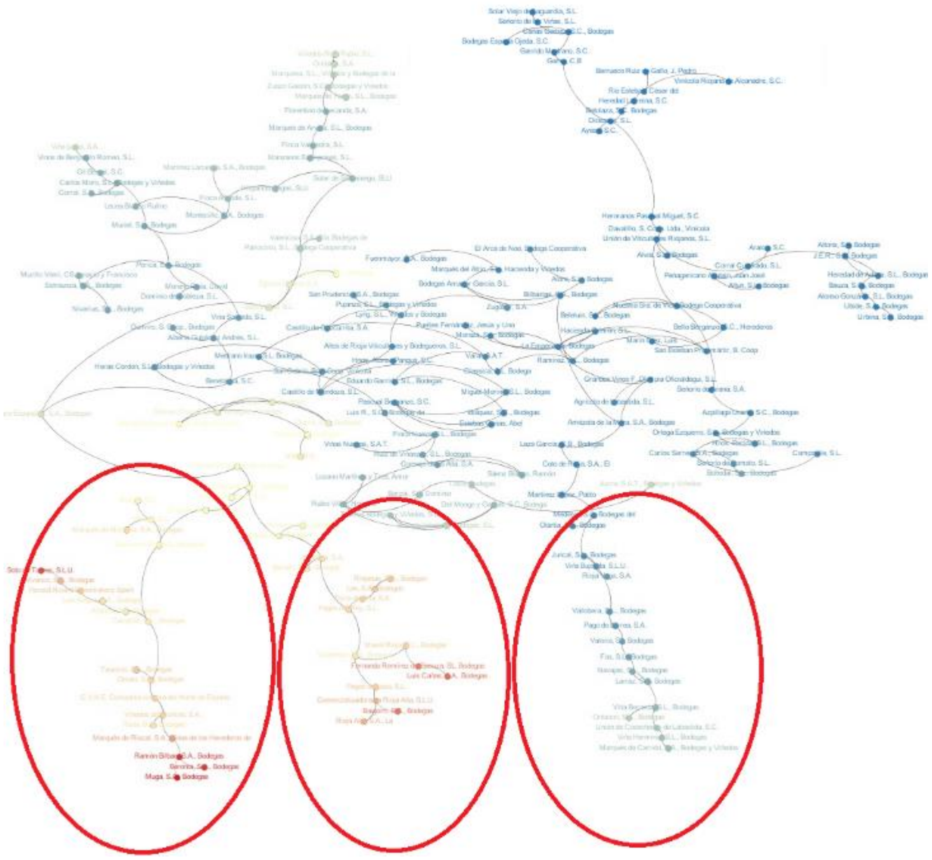

Figure 7. Differential behaviors for communication models on Twitter

The group on the left comprises the wineries that have a high number of followers such as *Ramón Bilbao* with 24,800, *Muga* with 21,700, and *Faustino* with 10,400. The red and yellow tones of this area indicate that the values of the rest of the variables are also high, identifying the set of wineries with the most active use of communication on Twitter.

In contrast, the group in the center includes wineries with the highest values in *Tweets*, where *Fernando Remírez de Ganuza*, *Luis Cañas*, and *Baigorri* stand out with 13,000, 16,000, and 16,900 tweets respectively. Again, the red and yellow tones reflect high activity, albeit with a different communication model.

Finally, the third group to the right is made up of wineries that show relatively high values in *Tweets* and *Followers* but have a lower activity from a global viewpoint (green tones, corresponding to low average values). Within this group we find wineries as *Marqués de Carrión*, *Unión de Cosecheros de Labástida*, *Ontañón*, and *Viña Herminia*. All of them comfortably exceed 1,500 tweets and have a total number of followers ranging from 2,500 to 4,000. This shows that these wineries have a continuous activity compared to most of those located in the central part, although it is not as intense as the wineries that are located further to the left (in the other two variables, *Following* and *Likes*, the average values are around 400).

Table 3 collects the values of the variables for the mentioned wineries included in the three subgroups described above.

Winery	***Tweets***	***Following***	***Followers***	***Likes***
Ramón Bilbao	9,511	5,959	24,800	5846
Muga	17,400	1,357	21,700	12600
Faustino	2,727	3,135	10,400	2011
Fernando Remírez de Ganuza	13,000	1,260	3,828	12100
Luis Cañas	16,000	2,053	1,500	12500
Baigorri	16,900	4,877	5,537	2328
Marqués de Carrión	1,652	435	2,505	442
Unión de Cosecheros de Labástida	1,555	776	3,079	174
Ontañón	1,730	381	4,328	336
Viña Herminia	1,730	767	2,465	94

Table 3. Values of the four Twitter variables for the ten wineries located in the bottom part of the map in Figure 7

Concluding remarks

Nowadays, organizations are facing new opportunities and challenges that social networks have brought. In this new scenario, firms must evaluate the potential value of this social phenomenon to justify the resource investment in the adoption of social networks.

Social media facilitate the distribution of information, references, and electronic reviews by word-of-mouth through on-line social networks, discussion forums, blogs, and microblogs, including Twitter. Hence, the use of Twitter as an additional brand communication channel has become an excellent opportunity to improve their communication models.

Nevertheless, as the amount of information available in the digital environment increases, determining the credibility of message, source, and means becomes significantly more relevant for assessing the credibility of communication in general. Furthermore, Twitter engagement requires great effort for brands, including the need to hire or train specialized staff, create specific budgets and invest significant amounts of time, making many firms unable or reluctant to adopt them.

In this contribution we have proposed a network-based visualization methodology to uncover the communication model traditional companies follow on the Twitter social network. To do so, we have generated several maps that provide an aesthetic visualization of the distribution of the companies depending on the value of the variables considered. As a case study, we have carried out an analysis of the quantitative data collected from the Spanish wineries holding the DOCa Rioja in Twitter. This was intended to uncover the communication model these companies (belonging to a mature market and showing a great sense of tradition) follow on this platform. The study conducted has allowed us to develop an approach to learning about the engagement and positioning of the wineries and assessing the state of their digital communication policies.

One of the main conclusions drawn is the limited presence of these organizations on the social network, since only 188 wineries out of a total of 591 (approximately 32%) have a Twitter account and not all of them communicate actively and directly. This fact conflicts with the profile of both the wine consumer and the Twitter user whose main characteristics match (men between the ages of 35 and 54). That would be a strong reason to carry out a solid communication policy on this social media platform as it is a virtual setting where the target audience of the Spanish wine market is concentrated.

Through the maps obtained, we have been able to recognize that the wineries accumulating a greater number of followers are those which have a consolidated and recognized brand name. Nevertheless, this does not mean that these wineries maintain constant communication with their followers through the social network because in the number of Tweets the prominent wineries did not show a high number of notifications. The only exception was *Muga*, which both showed a high number of followers and maintained constant activity within the microblogging network.

Meanwhile, the wineries that receive a large number of likes from their followers are those attracting more followers but not those that post more tweets. This fact is due to the loyalty of these followers who do not remain passive when receiving notifications from the wineries. All these insights make us recognize that the Spanish wine market, specifically the wineries with DOCa Rioja, still shows certain deficiencies in its communications in the digital world. As already mentioned, the mission of wineries is not only to produce a good wine and to assign it an attractive price but also to communicate the existence of their product effectively to its present and future interest groups, its consumers, and the general audience. To do so, they must use both the means of traditional communication and the innovative channels and platforms of social networks. Wineries must ask themselves how much a good communication policy affects the mobilization and engagement of the wine consumer, how communication creates and enhances the brand image of wineries, and how that process instigates the purchase. We should not forget that, despite the decline in sales, wine has the advantage of being the food product with the highest prominence in the mass media and that it is subject to a wealth of comments and information that attract considerable interest from users and consumers.

Meanwhile, we can perform a critical analysis of the network-based visualization methodology considered in the development of our study. It is clear that social media analytics and information visualization are highly useful tools to support companies' activities in many different areas. For example, they can be used for brand reputation monitoring, listening to consumer conversations in order to get feedback about their products (useful for targeted advertisement, for example), tracking consumers' responses to business decisions (e.g. marketing campaigns), identifying opinion leaders, and applying competitive analysis (tracking competitors' products and reputation). There is a large number of general-purpose commercial and free social media tools available nowadays to perform some or all of these tasks. In general, they are based on scrapping social media data, searching for keywords/phrases and top users (based on followers, likes, posts, mentions, etc.), perform some kind of filtering to present only the relevant information to the manager, and representing the obtained using graphical illustrations or time charts, either in isolation or in comparison with the competitors' data. Some tools also incorporate sentiment analysis and opinion mining tools [56] to obtain additional insights about the products, the growth of the brand image, etc. from the consumer's comments.

Our proposal is much more specific as it is focused on identifying and monitoring the communication model applied by a set of brands in a specific market from a global perspective. It thus works with the brand positioning information on Twitter related to overall user engagement, the firm's activity in terms of the number of tweets written, and the positive response from the customer in terms of the number of likes received. This information is represented using an advanced network-based information visualization technique that allows us to identify the characteristics of the market in terms of the communication model applied by each company. The generated maps become a technological watch and competitive intelligence tool allowing managers to identify and monitor the presence of their company on Twitter compared to that of their competitors. The insights obtained can therefore help the decision making of a specific company in order to uncover the positioning of its competitors and to improve its own positioning in comparison with theirs.

To our knowledge, this is a differential task with respect to the existing social media analysis tools and the existing proposals in the academic literature. Our data analysis and visualization methodology is easy to apply, can be reproduced from the description provided in the current contribution, and the results are extremely informative for managers. In addition, the proposed methodology is general-purpose. It can be applied to any social media (or can even combine information crawled from different social media during the same period). Obviously, it is not specific to the Spanish wine market analyzed in this manuscript, but can be applied to any other market at any regional, national, and international level. Likewise, it can be employed on different periods to compare the maps obtained for each of them (for example, in the case of the wineries, for two different Christmas campaigns), thus becoming a monitoring tool of the evolution of the market ecosystem. Of course, it shows some limitations, which are mainly related to the problems of social network visualization reported in [46] and reviewed in Section 3.2. To our mind, the most important is related to working with markets composed of a large number of companies since the dimension of the network can reduce the interpretability of the maps obtained. The maps generated in the current contribution correspond to 188 wineries and are thus easy to interpret. Of course, this problem can be fixed by incorporating additional pruning strategies for the considered companies, limiting them to the most important ones according to the values of the considered indicators, and also by using hierarchical representations based on node collapsing [45].

References

[1] K. Nelson-Field, E. Riebe y B. Sharp, «What's Not to “Like?”: Can a Facebook Fan Base Give a Brand The Advertising Reach It Needs?,» *Journal of Advertising Research,* vol. 2, nº 52, pp. 262-269, 2012.

[2] K. Smith, «Brandwatch,» 2019. [On line]. Available: https://www.brandwatch.com. [Last time accessed: 4 January 2019].

[3] R. Ferguson, «Word of mouth and viral marketing: taking the temperature of the hottest trends in marketing,» *Journal of Consumer Marketing,* vol. 25, nº 3, p. 179–182, 2008.

[4] J. Xun y B. Guo, «Twitter as customer’s eWOM: an empirical study on their impact on firm financial performance,» *Internet Research,* vol. 27, nº 5, pp. 1014-1038, 2017.

[5] S. Percastre-Mendizábal, C. Pont-Sorribes y L. Codina, «Propuesta de diseño muestral para el análisis de Twitter en comunicación política,» *El profesional de la información,* vol. 26, nº 4, pp. 579-588, 2017.

[6] Twitter, «Twitter,» 2019. [On line]. Available: http://www.twitter.com. [Last time accessed: 2 January 2019].

[7] F. Laylavi, A. Rajabifard y M. Kalantari, «Event relatedness assessment of Twitter messages for emergency response,» *Information Processing & Management,* vol. 53, nº 1, pp. 266-280, 2017.

[8] J. Gonzalez-Paule, Y. Sun y Y. Moshfeghi, «On fine-grained geolocalisation of tweets and real-time traffic incident detection,» *Information Processing & Management,* p. In press, 2019.

[9] D. Murakami, G. Peters, Y. Yamagata y T. Matsui, «Participatory sensing data tweets for micro-urban real-time resiliency monitoring and risk management,» *IEEE Access,* vol. 4, pp. 347-372, 2016.

[10] J. Kietzmann, K. Hermkens, I. McCarthy y B. Silvestre, «Social media? Get serious! Understanding the functional building blocks of social media,» *Business horizons,* vol. 54, nº 3, pp. 241-251, 2011.

[11] M. Buelarca y S. Buelarca, «Twitter: a viable marketing tool for SMEs?,» *Global Business & Management Research,* vol. 2, nº 4, pp. 296-309, 2010.

[12] M. Gálvez-Rodríguez, C. Caba-Pérez y M. López-Godoy, «Drivers of Twitter as a strategic communication tool for non-profit organizations,» *Internet Research,* vol. 26, nº 5, pp. 1052-1071, 2016.

[13] S. Okazaki, A. Díaz-Martín, M. Rozano y H. D. Menéndez-Benito, «Using Twitter to engage with customers: A data mining approach,» *Internet Research,* vol. 25, nº 3, pp. 416-434, 2015.

[14] S. Wasserman y K. Faust, Social Network Analysis: Methods And Applications (Structural Analysis in the Social Sciences), Cambridge: Cambridge University Press, 1994.

[15] N. Barber, T. Dodd y R. Ghiselli, «Capturing the younger wine consumer,» *Journal of wine research,* vol. 19, nº 2, pp. 123-141, 2008.

[16] M. Stelzner, «Social Media Marketing Industry Report,» *Social media examiner,* pp. 1-52, 2014.

[17] J. Bruwer y G. Wood, «The Australian online wine buying consumer: motivation and behaviour perspectives,» *Journal of Wine Research,* vol. 6, nº 3, pp. 193-211, 2005.

[18] Vinography, «Social Media and the Wine Industry: A New Era,» 2012. [On line]. Available at: http://www.vinography.com/archives/2012/02/social_media_and_the_wine_indu.html. [Last time accessed: 20 December 2018].

[19] D. Wilson y S. Quinton, «Let's talk about wine: does Twitter have value?,» *International Journal of Wine Business Research,* vol. 24, nº 4, pp. 271-286, 2012.

[20] A. Alonso, A. Bressan, M. O'Shea y V. Krajsic, «Website and Social Media Usage: Developments of Wine Tourison, Hospitality and the Wine Sector,» *Tourism Planning and Development,* vol. 25, nº 3, pp. 229-248, 2013.

[21] M. Thelwall, K. Buckley y G. Paltoglou, «Sentiment in Twitter events,» *Journal of the Association for Information Science and Technology,* vol. 62, nº 2, pp. 406-418, 2011.

[22] H. Rodríguez, B. Restrepo y L. Fernando, «Conocimientos y uso del twitter por parte de estudiantes de educación superior,» *Sophia,* vol. 11, nº 1, pp. 44-52, 2015.

[23] M. Lin, E. Hoffman y C. Borengasser, «Is social media too social for class? A case study of Twitter use,» *TechTrends,* vol. 57, nº 2, pp. 39-45, 2013.

[24] G. Siemens, «La enseñanza superior y las promesas y los peligros de las redes sociales,» *RUSC,* vol. 8, nº 1, pp. 157-163, 2011.

[25] J. Pérez Dasilva, A. Genaut Arratibel, K. Meso Aierdi, T. Mendiguren Galdospín, I. Marauri Castillo, L. Iturregui Mardaras, M. Rodríguez González y D. Rivero Santamarina, «Las empresas en Facebook y Twitter. Situación actual y estrategias comunicativas,» *Revista Latina de comunicación social,* nº 68, pp. 676-695, 2013.

[26] IAB, «Estudio Anual de Redes Sociales,» Madrid, 2017.

[27] C. Delgado von Eitzen, «Blog de ChristianDvE (Beta),» 2016. [On line]. Available at:

http://www.christiandve.com/2016/10/perfil-usuario-twitter-espana-resultados/. [Last time accessed: 9 October 2018].

[28] Observatorio Español del Mercado del Vino, «OEMV,» 2017. [On line]. Available at: http://www.oemv.es. [Last time accessed: 5 Octubre 2018].

[29] G. Sogari, T. Pucci, B. Aquilani y L. Zanni, «Millennial Generation and Environmental Sustainability: The Role of Social Media in the Consumer Purchasing Behavior for Wine,» *Sustainability,* vol. 9, nº 10, p. 1911, 2017.

[30] Nielsen, «Caracterización del consumidor español de vino,» 2017.

[31] C. Cochran, «Wineries embracing social networking,» *San Francisco Chronicle,* p. 7, 2010.

[32] R. Dolan, J. Conduit, J. Fahy y S. Goodman, «Facebook for wine brands: an analysis of strategies for Facebook posts and user engagement actions,» de *9th Academy of Wine Business*, Adelaide, 2016.

[33] R. Fuentes Fernández, R. Vriesekoop y B. Urbano, «Social media as a means to access millennial wine consumers,» *International Journal of Wine Business Research,* vol. 29, nº 3, pp. 269-284, 2017.

[34] Castro Galiana, R. , «Blog Las bodegas, los vinos y las políticas de comunicación,» 2014. [On line]. Available at: http://castrogaliana.com/las-bodegas-los-vinos-y-las-politicas-de-comunicacion/. [Last time accessed: 2 October 2018].

[35] A. Mariani, E. Pomarici y V. Boatto, «The international wine trade: Recent trends and critical issues,» *Wine Economics and Policy,* vol. 1, nº 1, pp. 24-40, 2012.

[36] M. Foster , A. Francescucci y B. West, «Why users participate in online social networks.,» *International Journal of e-Business Management,* vol. 4, nº 1, pp. 3-19, 2010.

[37] J. Scott, Social Network Analysis: A Handbook, Sage Publications, 2000.

[38] S. Kobourov, «Force-directed drawing algorithms,» de *Handbook of Graph Drawing and Visualization*, R. Tamassia, Ed., 2012.

[39] D. Dearholt y R. Schvaneveldt, «Properties of pathfinder networks,» de *Pathfinder associative networks: Studies in knowledge organization*, 1990, p. 1–30.

[40] D. Pancho, J. Alonso, O. Cordón, A. Quirin y L. Magdalena, «FINGRAMS: visual representations of fuzzy rule-based inference for expert analysis of comprehensibility,» *IEEE Transactions on Fuzzy Systems,* vol. 21, nº 6, pp. 1133-1149, 2013.

[41] E. Serrano, A. Quirin, J. Botia y O. Cordón , «Debugging complex software systems by means of pathfinder networks,» *Information Sciences,* vol. 180, nº 5, pp. 561-583, 2010.

[42] K. Trawinski, M. Chica, D. Pancho, S. Damas y O. Cordón, «moGrams: A Network-based Methodology for Visualizing the Set of Non-dominated Solutions in Multiobjective Optimization,» *IEEE Transactions on Cybernetics,* vol. 48, nº 2, pp. 474-485, 2018.

[43] U. Rashid, M. Viviani y G. Pasi, «A graph-based approach for visualizing and exploring a multimedia search result space,» *Information Sciences,* nº 370–371, pp. 303-322, 2016.

[44] F. Moya-Anegón, B. Vargas-Quesada, Z. Chinchilla-Rodríguez, E. Corera-Álvarez, F.

Muñoz-Fernández y V. Herrero-Solana, «Visualizing the marrow of science,» *Journal of the Association for Information Science and Technology,* vol. 58, nº 14, pp. 2167-2179, 2007.

[45] B. Vargas-Quesada y F. Moya-Anegón, Visualizing the structure of science, Springer Science & Business Media, 2007.

[46] S. P. Jun y D. H. Park, «Visualization of brand positioning based on consumer web search information: Using social network analysis,» *Internet Research,* vol. 27, nº 2, pp. 381-407, 2017.

[47] A. Quirin, O. Cordón, J. Santamaría, B. Vargas-Quesada y F. Moya-Anegón, «A New Variant of the Pathfinder Algorithm to Generate Large Visual Science Maps in Cubic Time,» *Information Processing and Management,* vol. 44, nº 4, p. 1611–1623, 2008.

[48] T. Kamada y S. Kawai, «An algorithm for drawing general undirected graphs,» *Information Processing Letters,* vol. 31, nº 1, pp. 7-15, 1989.

[49] M. Bastian, S. Heymann y M. Jacomy , «Gephi: an open source software for exploring and manipulating networks,» de *International AAAI Conference on Weblogs and Social Media*, 2009.

[50] A. Unwin, M. Theus y H. Hofmann, Graphics of large datasets: visualizing a million, Springer Science & Business Media, 2008.

[51] C. Chen y S. Morris, «Visualizing evolving networks: Minimum spanning trees versus pathfinder networks,» de *INFOVIS 2003*, 2003.

[52] M. Zizi y M. Beaudouin-Lafon, «Accessing hyperdocuments through interactive dynamic maps,» de *Proceedings of the 1994 ACM European conference on Hypermedia technology*, 1994.

[53] S. Noel, C. Chu y V. Raghavan, «Visualization of document co-citation counts,» *IEEE Symposium on Information Visualisation*, 2002.

[54] R. Schvaneveldt, F. Durso y D. Dearholt, «Network structures in proximity data,» *Psychology of learning and motivation* , Academic Press, 1989, pp. 249-284.

[55] T. Fruchterman y E. Reingold, «Graph drawing by force-directed placement,» *Software: Practice and experience,* vol. 21, nº 11, pp. 1129-1164, 1991.

[56] J. Serrano-Guerrero, J. Olivas, F. Romero y E. Herrera-Viedma, «Sentiment analysis: A review and comparative analysis of web services,» *Information Sciences,* nº 311, pp. 18-38, 2015.

[57] J. Martínez-Martínez, P. Escandell-Montero, E. Soria-Olivas, J. Martín-Guerrero y A. Serrano-López, «A new visualization tool for data mining techniques,» *Progress in Artificial Intelligence,* vol. 5, nº 2, pp. 137-154, 2016.