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# COMMUNITIES OF FOLLOWERS IN TOURISM TWITTER ACCOUNTS OF EUROPEAN COUNTRIES

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**ABSTRACT:** Microblogs have been widely adopted by travelers to search, organize, share, and annotate their travel stories and experiences, and by Destination Marketing Organizations (DMOs) to promote countries' image. Twitter is the most popular microblogging site and one of the top-10 most visited websites on the Internet. Building relationships, convenience of networking, and expanding online branding opportunities have been recorded as the perceived benefits of using Twitter. The paper records tourism Twitter accounts of 37 European countries. It also records indexes of Twitter performance and influence and indexes of followers' community involvement. Next, the mentions/replies (m/r) network of the followers for each account is constructed in order to study whether it demonstrates community characteristics. Clustering coefficient, assortativity, and degree skewness are used as network indexes to explore whether m/r networks present the properties of small-worlds and scale-free networks, and are characterized by homophily. These indexes are then associated with Twitter performance indexes to explore how m/r networks differentiate across accounts of different popularity and performance. Findings reveal that m/r networks of followers do not constitute communities, but rather the people use tourism organizations' Twitter accounts as announcement boards or as one more channel for one-way communication with the public.
**Keywords:** Twitter, communities, followers, mentions/replies network.

## INTRODUCTION

Nowadays, ICTs offer Destination Marketing Organizations (DMOs) tremendous opportunities for communicating their offer-

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ing, creating new markets, enhancing their visibility on the market, strengthening their competitiveness, reducing costs, and creating new competitive advantages (Katsoni & Venetsanopoulou, 2013; Dwyer & Kim, 2003). In particular, social media become the primary medium by which travel information is shared (Xiang & Gretzel, 2010) and offer DMOs the opportunity to reach a global audience with limited resources (Hays et al., 2013). DMOs use social networking sites, media sharing sites, microblogs, blogs, online communities like Facebook, Twitter, YouTube, and MySpace, allowing tourists to interact and share their views and experiences, travel advice, suggestions, and recommendations with potentially unrestricted virtual communities (Sotiriadis & van Zyl, 2013; Xiang & Gretzel, 2010). Traditional recommendations, have limited reach, 10 persons on average. Recommendations within social media may diffuse online like a virus, among hundreds or even thousands of "friends" or "followers" (Hausmann, 2012; Kotler & Armstrong, 2009; Miller & Lammas, 2010; Sigala, 2007). Thus, DMOs have to adopt and integrate social media in their marketing strategies in order to better communicate with online target audiences (Milwood et al., 2013), to build ongoing relationships with the destination's visitors, to stimulate traffic and trigger actions by consumers and meeting planners (TIG Global, 2009).

Twitter is the most popular microblogging site, with more than 645,750,000 registered users worldwide, 284 million monthly active users, who in total post an average of 58 million tweets per day. Twitter supports more than 35 languages and is one of the most vibrant online communities in the world with 80% of Twitter active users on mobile, 77% of accounts are outside the U.S. and 135,000 new Twitter users are signing up every day (Statistic brain, 2014; Twitter, 2014).

Up to now, little research effort has been devoted at investigating Twitter use by DMOs (Hamill et al., 2010; Hassan, 2013; Nguyen & Wang, 2012; Stepchenkova et al., 2013) and especially in comparative studies (Antoniadis et al., 2013; Bayram & Arici, 2013; Milwood et al., 2013). This paper explores the potentiality of community formation among followers of tourism Twitter accounts of 37 European countries, by measuring social networking and Twitter performance indexes. It studies the mentions/replies (m/r) networks of the followers for these accounts and explores whether the properties of small-world and scale-free networks apply to them. Next, these indexes are correlated with the relative Twitter accounts activity. Studying these indexes and their intercorrelations adds to understanding how followers' activity associates with the general performance of the accounts.

## TWITTER AND SOCIAL NETWORKS

It is a human tendency that people come together to connect through various social relationships or exchanges and form networks in the structure of society (Backstrom et al., 2006; Herring et al., 2005). Wasserman & Faust (1994) defined a social network as "the set of actors and the ties among them" and Marsden (2000, p. 2727) as a "structure of relationships linking social actors". Social actors may be individuals, organizations, communities, offices, groups, regions, nations, etc. and the ties are social relationships, such as friendship, acquaintance, kinship, evaluation of another person, co-working, commercial exchange, or information exchange and are represented as linkage or a flow between social actors (Balancieri et al., 2007; Martino & Spoto, 2006). Ties can be directed, i.e., one-directional, as in giving advice to someone; undirected, i.e., being physically proximate; dichotomous, i.e., present or absent of a characteristic, as if two people are friends or not; weighted, i.e., strength of friendship (Coulon, 2005).

Social media are a part of everyday life, have altered social interactions, and are increasingly incorporated into people's day-to-day social relationships (Boyd, 2007; Farnham et al., 2004). Facebook, Twitter, YouTube, Flickr, del.icio.us, and other popular social media are turning into community spaces, where users interact with their friends and acquaintances (Anagnostopoulos et al., 2008). Thus, new online social networks have emerged and new ties are developed among people sharing common interests (Vrana et al., 2013). In this line of thought, Musiał & Kazienko (2013, p.31) defined a social network as a "set of human beings or rather their digital representations that refer to the registered users who are linked by relationships extracted from the data about their activities, common communication or direct links gathered in the internet–based systems".

Twitter users create profiles and follow other users. A user's followers are those who subscribe to receive his or her tweets (Hutto et al., 2013). The relationship of 'following' is not mutual, as a user can follow any other user, and the user being followed need not follow back (Hargittai & Litt, 2012; Kwak et al., 2010) and it is relatively open in the sense that the following user does not require the consent of the user he/she follows (Shi et al., 2014). Twitter users may also follow hashtags that can group tweets by topic ('#' followed by a word) and interact with other users and send them direct messages. Writing a tweet addressing a specific user is called a 'mention'. @reply is a tweet directed at a certain user in replying to one of his/hers updates. Twitter users, as they follow, reply, and mention one another, form networks (Pew Internet Research, 2014).

## SOCIAL NETWORK ANALYSIS

There are three kinds of representation of a Social Network: the first one is the simple list of all the elements taken from the set of actors, and the list of the pairs of elements which are linked by a social relationship of some kind. The second has a form of a matrix. If two social actors, I and J, have a relation, then 1 is placed at the cell (i,j), otherwise 0 is placed at this cell. Finally, the third representation comes from the Graph Theory: every social actor is represented by a point, called a node, and the links defined by pairs of individuals, represented by lines between two linked points and are called edges of the graph (Marlow, 2004; Martino & Spoto, 2006). The advantage of a social network representation is that "it permits the analysis of social processes as a product of the relationships among social entities" (Martino & Spoto, 2006 p.54).

Social network analysis (SNA) is an interdisciplinary methodology, developed mainly in social psychology for analyzing patterns of relationships and interactions between social actors (Marlow, 2004; Scott, 2000; Wasserman & Faust, 1994). SNA is rooted in the concepts of nodes and connections and it is based on the assumption of the importance of relationships among interacting nodes (Albrecht et al., 2000), whose starting point and premise is that social life is created primarily by relations and the patterns formed by these relations (Marin & Wellman, 2011). SNA seeks to explain social phenomena through the structural interpretation of human interaction (Marlow, 2004; Wasserman & Faust, 1994) to identify the key actors in terms of gender, age, socioeconomic status, education, etc. and the properties of their relationships in terms of nature, intensity, and frequency of the relationships (Chau & Xu, 2008; Krackhardt, 1996). In mining a network, SNA may reveal structural patterns that have important implications, for example, central nodes that are leaders or hubs, or have a gatekeeping or bridging role between different communities (Albrecht et al., 2000).

### *Small Worlds*

One of the most known and interesting problems in SNA is that of 'small worlds'. A simple way to formulate the problem is: what is the probability of two individuals randomly selected from almost anywhere on the planet to know each other (Watts, 1999)? A more interesting formulation is that proposed by Travers & Milgram (1969), that takes into account the fact that while two persons may not know each other directly, they may share mutual acquaintances. Travers & Milgram (1969) stated that two persons "a and z may be connected not by any single common acquaintance, but by a series of such intermediaries, a-b-c- . . . -y-z; i.e., a knows b (and no one else in the chain); b knows a and in addition knows c, c in turn knows d, etc." Milgram (1967), claimed that the number of persons necessary to link two randomly chosen, geographically separated persons had a median number of six. This concept is called "six degrees of separation" (Guare, 1990). Many naturally occurring networks have the properties of a 'small world'.

In SNA, a small-world network is a random graph in which most nodes are not neighbors of one another, but most nodes can be reached from every other by a small number of steps. Small-world network hold two properties: small average path length (average node-to-node distance) and relatively large clustering coefficient (the degree to which nodes in a graph tend to cluster together) (Watts & Strogatz, 1998). According to Bender-deMoll (2008) small-worlds 'are locally dense but have sparse shortcut ties to link groups that would otherwise be remote or isolated'.

*Scale-free Networks*

Scale-free networks are networks that are 'characterized by a power--law distribution of a node's degree, defined as the number of its next neighbors, meaning that structure and dynamics of the network are strongly affected by nodes with a great number of connections' (Ebel et al., 2002, p.66). In scale-free networks, there are highly connected nodes, called hubs, that have hundreds, thousands, or even millions of connections, while most of the nodes have just a few links. Thus, in scale-free networks, the absence of a typical scale for the connectivity of nodes is recorded (Choromański et al., 2013). Preferential attachment process has been used to explain the growth in the appearance of power-law distribution (Barabasi & Albert, 1999). Barabasi & Albert (1999) claim that networks expand continuously by the addition of new nodes, and the new nodes are preferentially attached to those that are already well connected. New nodes tend to connect to more popular nodes and thus these nodes acquire more and more links over time. Thus, the "rich get richer". This process generally favors early nodes, which are more likely to become hubs (Barabasi & Bonabeau, 2003).

*Homophily*

Homophily is the tendency of individuals to associate and bond with similar others. Several natural networks are homophilic in the sense that users interact with other users of similar traits. Homophily can be measured using degree assortativity, which indicates the tendency that nodes mostly connect with similar nodes. Assortativity ranges from -1 to 1. High values are associated with highly homophilic networks, while negative values describe networks where users of low activity connect to users of high activity.

## METHODOLOGY

We conducted a survey of the European countries tourism Twitter accounts, during 8-10 October 2013. In total, 37 were recorded, along with their characteristics and performance indexes: @Spain, @VisitBritain, @VisitNorway, @VisitScotland, @Italy_it, @VisitHolland, @VisitGreecegr, @DiscoverIreland, @HungaryTourism, @VisitPortugal, @GermanyTourism, @MySwitzerland_en, @GoVisitDenmark, @VisitMonaco, @OurFinland, @Belgiuminfo, @Austriatourism, @Visit_Poland, @VisitCyprus, @CzechTourism, @Croatia_hr, @VisitSweden, @UK_Franceguide, @SloveniaInfo, @RomaniaTourism, @Visit_Russia, @VisitMontenegro, @VisitMalta, @Visit_Turkey, @VisitEstonia, @Luxembourginfo, @ExplorMacedonia, @VisitLithuania, @VisitIceland, @Travel_Latvia, @VisitSlovakia, @Andorraworld_en. Some central tourism websites did not link to Twitter accounts. In these cases, we found other tourism Twitter accounts for these countries through a search on the Internet (for France and Lithuania we used UK_FranceGuide, and Lithuania UK).

The number of followers of an account, the number of other accounts an account follows (following), and the number of tweets, are recorded as indicators of Twitter performance. The number of followers describes how many users have subscribed to read the tweets posted by the account. However, not all the followers really "follow" the account by means that they need not read every tweet and they are not necessarily active readers. The number of tweets is an indication of how active an account is and an indirect indication of how old an account is, by means that previously established accounts are likely to post more tweets. Also, Topsy score (provided by Topsy.com, which takes into account the retweets and mentions than matter for a particular Twitter account, as a measure of the users' community involvement for this account), and Total Effective Reach (the total amount of people who are exposed to a tweet or its retweets, for the 10 most popular tweets of an account, provided by http://twtrland.com) were used. The two last performance indexes indicate the community of followers' involvement in reading tweets from the 37 tourism accounts and spreading the information originally provided by the 37 accounts. They provide indications of the real amount of people that read and transmit a tweet and are actively involved in following the account.

In the last step, after recording the followers of the accounts, their mentions/replies (m/r) networks were recorded and constructed. That is, we recorded how the followers of each account mention or reply to each other. This way, we describe the actual activity and involvement of users within a potential community context. It is interesting to record not the users who just happened to follow an account, but those who prove their involvement by mentioning and replying to tweets. This recording pictures the potentiality of the followers to actually get involved, reproduce, and communicate the original information. The properties of this network may give an idea of the potentiality of the followers to act as a community of followers.

To record the 37 m/r networks (one for each account along with its followers), an extended survey was done recording the mentions and replies using NodeXL for Windows, for the latest tweet. These 37 networks were analyzed using Social Networking Analysis. Three indexes were used to explore "Small-World" , "Scale-free", and homophily characteristics of the networks, using the igraph package in R: assortativity, clustering coefficient, and degree skewness of the networks. Small-world networks tend to contain sub-networks, which have connections between almost any two nodes within them. We used clustering coefficient to assess this property. Clustering coefficient is an index ranging from zero to unity, measuring the probability that the adjacent vertices of a vertex are connected: "friends of my friends are my friends". Also, degree assortativity measures the property that highly connected nodes link with other highly connected nodes (positive assortativity ranging up to 1) or the reverse, where highly connected nodes are more likely to link to less connected nodes (negative assortativity ranging up to -1). Finally, if a network has a degree-distribution with a very large skewness, that is, only few users post the most while the large proportion of followers post a little, the network possibly fits with a power-law degree distribution. Networks with power-law degree distributions (scale-free networks) provide evidence that these networks constitute small-worlds.

In the findings section, we present descriptive statistics of the Social Network Indexes at two levels of analysis: indexes are calculated for the entire network of mentioning and replying followers, and also for those who mention/reply to the tourism account. The latest are the directly involved followers to mentioning and replying to the respective tourism accounts, therefore their network indexes are more significant in order to understand potential community formation.

## FINDINGS

For the accounts of some countries, it is impossible to calculate the SNA indexes, mainly because there is no m/r activity among followers of the accounts. In this case, a "Na" label is displayed in the respective tables of findings. Regarding the entire m/r networks, assortativity can be calculated for 25 of the accounts, clustering coefficient for 33, and skewness can be calculated for 35 of the accounts. Frequencies are smaller for the m/r networks of the directly involved followers. From Table 1, it is obvious that mean assortativity is zero, and mean clustering coefficient is nearly equal to zero (having a very low standard deviation), for the entire networks. This is to say that, on average, m/r networks of tourism Twitter accounts are not characterized by a specific communication pattern regarding homophily; active and not active followers communicate with each other with no specific pattern. Also, linkage is not transitive; clustering coefficient implies that there are no connections among neighboring followers. In conclusion, the entire m/r networks do not provide evidence that they constitute small-worlds, at least at the time of the data collection. On the other hand, skewness has a relatively high average that equals 37. Skewness can be big for some accounts, but on average it presents a medium value (it should be noted that values of skewness for such networks could reach the value of 100 or more). There is a tendency for high skewness, which implies that only a few followers present high activity regarding mentions and replies. Regarding skewness, the networks provide some evidence that formations of scale--free networks are constructed. Overall, only small and partial evidence is provided that the particular networks constitute small-worlds.

The findings of the above paragraph refer to the entire networks of followers and the way these followers mention/reply to each other. It is reasonable to assume that these large networks are constituted by individuals who are little connected, so it makes sense that indexes have small values. We continued the analysis further, to explore the values of the same indexes for the smaller and more significant networks of those followers who mention/reply to the tourism accounts, not only to other followers. Along with the three already mentioned indexes, the average shortest path of each network was calculated. This is an average value of how far a follower is from another follower. If this has small values, followers are connected to each other through very few steps and this is an indication of small-world formation. These findings are also reported in Table 1. The average shortest path is really small and this may be a sign of small-world formation. However, the fact that skewness is very small and clustering coefficient is nearly equal to zero contradicts the hypothesis of small-worlds formation.

Further, assortativity is negative, meaning that less active users connect to highly active ones.

When examining the correlation coefficients among Twitter activity indexes and SNA indexes, we find that only correlations of activity indexes with skewness are significant (Table 2). There is a tendency for more active accounts to have higher skewness both of the entire network and the directly involved followers' network. The scale-free property is more intense in more active and established tourism Twitter accounts. Only a few followers originate most of the activity in the most active accounts, and the rest of the followers just follow them. Table 3 presents in detail the highly and significantly correlated indexes.

**Table 1: Descriptive statistics of the SNA indexes**

| | Total m/r network | | | Directly involved followers m/r network | | |
|---|---|---|---|---|---|---|
| | **N** | **Mean** | **Std. Deviation** | **N** | **Mean** | **Std. Deviation** |
| Assortativity | 25 | 0.0064 | 0.1428 | 19 | -0.5666 | 0.1444 |
| Clustering coefficient | 33 | 0.0225 | 0.0828 | 29 | 0.0256 | 0.1235 |
| Skewness | 35 | 37.1854 | 33.0274 | 29 | 3.9958 | 2.8422 |
| Average shortest path | | | | 30 | 1.0855 | 0.1630 |

**Table 2: Correlation coefficients between Twitter indexes and skewness**

| | Skewness (entire m/r network) | Skewness (directly involved followers m/r network) |
|---|---|---|
| Followers | 0.586** | 0.541** |
| Number of Tweets | 0.397* | 0.553** |
| Topsy score | 0.465** | 0.613** |
| Total Effective Reach | 0.531** | 0.614** |

*(*: p<0.05, **: p<0.001)*

**Table 3: Detailed description of the highly correlated indexes, sorted by skewness for the directly involved followers m/r network**

| Accounts | Followers | Number of Tweets | Topsy score | Total Effective Reach | Skewness for the entire m/r network | Skewness for the directly involved followers m/r network |
|---|---|---|---|---|---|---|
| @VisitGreecegr | 28290 | 16540 | 2726 | 56381 | 64.2795 | 10.2190 |
| @VisitScotland | 54119 | 5101 | 2696 | 123220 | 72.0750 | 9.5589 |
| @Spain | 85701 | 7238 | 7374 | 160768 | 55.3585 | 7.9533 |
| @VisitPortugal | 20397 | 42353 | 1342 | 42538 | 49.6812 | 7.0382 |
| @VisitNorway | 20822 | 8774 | 1073 | 290167 | 72.1096 | 6.9949 |
| @VisitBritain | 148118 | 20381 | 7702 | 193593 | 69.0759 | 6.5773 |
| @Italy_it | 47203 | 7144 | 1873 | 155443 | 131.0640 | 6.3849 |
| @MySwitzerland_en | 16497 | 4417 | 968 | 25685 | 33.8709 | 6.2053 |
| @GoVisitDenmark | 10803 | 4168 | 605 | 50649 | 52.5120 | 5.6714 |
| @VisitHolland | 30649 | 7003 | 908 | 107406 | 139.0539 | 5.0196 |
| @DiscoverIreland | 39008 | 13164 | 691 | 63533 | 44.2053 | 5.0078 |
| @Croatia_hr | 8715 | 1850 | 190 | 25546 | 27.5848 | 4.7131 |
| @SloveniaInfo | 6959 | 8313 | 340 | 10447 | 64.6435 | 4.6155 |
| @VisitMonaco | 12556 | 9648 | 723 | 18182 | 56.2459 | 4.5399 |
| @OurFinland | 12263 | 2569 | 629 | 34340 | 13.6969 | 3.5112 |
| @GermanyTourism | 14971 | 4032 | 746 | 39530 | 24.7097 | 3.3773 |
| @CzechTourism | 6006 | 1075 | 225 | 30881 | 40.9145 | 2.8869 |
| @HungaryTourism | 55811 | 2175 | 109 | 87170 | 10.1368 | 2.8162 |
| @Belgiuminfo | 7830 | 2961 | 308 | 35962 | 63.6160 | 2.4004 |

*(cont.)*

| Accounts | Followers | Number of Tweets | Topsy score | Total Effective Reach | Skewness for the entire m/r network | Skewness for the directly involved followers m/r network |
|---|---|---|---|---|---|---|
| @VisitSweden | 7738 | 1760 | 135 | 24329 | 10.2386 | 2.1862 |
| @Visit_Poland | 8463 | 466 | 40 | 25543 | 14.9285 | 1.8562 |
| @RomaniaTourism | 7794 | 169 | 166 | 9720 | 12.6334 | 1.8562 |
| @VisitCyprus | 6060 | 1165 | 171 | 18965 | 17.2091 | 1.7242 |
| @UK_Franceguide | 4969 | 2251 | 172 | 23873 | 24.2424 | 1.0733 |
| @Visit_Turkey | 1105 | 8036 | 8 | 1470 | 21.8945 | 0.7500 |
| @Austriatourism | 8234 | 619 | 29 | 13511 | 12.7077 | 0.3849 |
| @ExplorMacedonia (FYROM) | 551 | 95 | 4 | 2390 | 27.9247 | 0.3849 |
| @VisitLithuania | 1231 | 169 | 10 | 3480 | 12.8927 | 0.3849 |
| @VisitMalta | 4086 | 162 | 249 | 7793 | 12.1598 | -0.2134 |
| @VisitMontenegro | 1884 | 1140 | 36 | 3242 | 11.1302 | Na |
| @Visit_Russia | 1878 | 15 | 0 | 5185 | 5.60552 | Na |
| @VisitEstonia | 659 | 287 | 44 | 11495 | 7.54570 | Na |
| @Luxembourginfo | 632 | 210 | 32 | 9065 | 12.1438 | Na |
| @VisitIceland | 265 | 3 | 27 | 185 | 6.56168 | Na |
| @Travel_Latvia | 245 | 76 | 0 | 607 | Na | Na |
| @VisitSlovakia | 63 | 10 | 2 | 0 | Na | Na |
| @Andorraworld_en | 17 | 0 | 0 | 0 | Na | Na |

*(Na: Not Applicable)*

## CONCLUSION

This paper located 37 European countries tourism accounts and recorded several characteristics and metrics regarding those accounts. It considered the activity of the accounts by studying the number of followers, the number of tweets, Topsy score, and Total Effective Reach, among other activity indexes. These indexes measure both the amount of people who follow the accounts and the amount of people who are involved in reading and spreading the information they read.

The paper also studied mention/replies networks of followers for these accounts. It studied the way that followers of a tourism organization mention or reply to each other and to the account of the tourism organization. The analysis examined whether the properties of small-worlds, scale-free networks, and homophily apply to these networks. Findings show that mentioning/replying in tourism Twitter accounts hardly provides evidence that small-worlds networks of users are formed. These particular Twitter accounts serve as public notice boards for public announcements, but they originate no further discussion by their followers. M/r networks are not communities of followers but rather groups of followers who occasionally respond to tweets.

Research in other settings shows that followers of local organizations' Twitter accounts are more active. To reach broader conclusions, the analysis should expand to local and specific tourism accounts, besides those studied in this paper, which have a broad or national scope.

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