Network analysis: quantitative methods in tourism

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Abstract

This chapter considers a tourism system as a network of interconnected organizations, and uses the recent methods of network science to analyze the structural and dynamic characteristics of these complex systems. A brief account is given of the major techniques, the interpretation of the outcomes in this context and of the tools that can be used. Both static (structural) and dynamic features are discussed. A number of examples from the recent literature show how these methods have been applied so far and what outcomes are available. It is also shown how, besides the pure academic interest, these results can help in providing a deeper and better knowledge of the issues at stake and how useful they can be to inform policy and governance activities.

Keywords

tourism destinations; governance of tourism systems; complex systems; network analysis; network science; quantitative methods

Introduction

The understanding of relationships and the possibility to exploit this understanding is the essence of scientific method. Connections between particles, objects or people have been investigated and modeled in order to study the systems they form and the dynamic behaviors they exhibit. The outcomes of these investigations have allowed us to better realize how many phenomena evolve and given us better capabilities (even if sometimes quite limited) to predict future configurations. These studies have also allowed us to find similarities in different settings, thus extending our abilities to describe events or solve problems.

Tourism, probably more than any other sector of human activities, is a world of relationships. The quality and the quantity of the connections established between companies, organizations and people is a crucial element in the determination of structural and dynamic characteristics of the system and of the parts that compose it. This (obvious) realization, leads to the consideration that the application of methods and techniques developed to study a set of relationships would be able to provide a wealth of interesting outcomes on the structural and dynamic properties of these systems.

The aim of this chapter is to provide an overview of how quantitative network analysis methods have been and can be used in the study of a tourism system and what kind of conclusions can be drawn.

The 'object of study' considered here is a tourism destination. A tourism destination (or more simply a destination in the following), the place towards travelers move to spend their time, can be broadly defined as a geographical area that offers the visitor opportunities of exploiting a variety of attractions and services (Jafari, 2000). Scholars and practitioners consider it a fundamental unit of analysis for the understanding of the whole tourism sector. Essentially, it is a complex adaptive socio-economic system. It shares many (if not all) of the characteristics usually associated with such entities: non-linear relationships among the components (private and public companies and associations), self-organization and emergence of organizational structures, robustness to external shocks (for a more complete discussion on these issues see: Baggio, 2008). The dynamic set of relationships on which a destination is essentially built naturally leads to the consideration of a network analytic approach essential for a full understanding of tourism systems in their static and dynamic configurations.

The rest of this work is organized as follows. Section 2 contains a brief introduction to the main concepts and methods of the study of networks. Although in this work the mathematical treatment has been reduced to a minimum, the reader interested in this field will greatly benefit from a good working knowledge of linear algebra (matrices are fundamental objects in the study of a network). Useful references are the books by Gentle (2007), Poole (2005), or Kaw (2008).

Network science

In the last few years, building on the tradition of social network analysis (Hannemann & Riddle, 2005; Wasserman & Faust, 1994) and taking advantage of the availability of large quantities of data and powerful computing facilities, a multidisciplinary ensemble of researchers has contributed to the foundation of what is now called the *science of networks* (Watts, 2004). The main theoretical bases for these studies are rooted in statistical physics (or statistical mechanics), a fundamental field of physics which uses statistical methods for addressing a wide variety of issues, with an inherently stochastic nature. The main result, and power, of this approach is in two important concepts: *universality* and *scaling* (Amaral & Ottino, 2004). The scaling hypothesis, born in the study of critical phenomena, has put forward the idea that some relationships, called scaling laws, may help in relating the various critical-point parameters which characterize the singular behavior of a system under certain conditions. The statistical treatment of many systems shows that several properties are independent of the specific *form* of their constituents. This suggests the hypothesis that universal laws or results may show up in diverse complex systems, whether they be social, economic or biological. The concept of universality, in statistical physics and complex systems theory, has the basic objective of capturing the essence of different systems and classifying them into distinct classes showing similar behaviors or structures.

In other words, universality and scaling assumptions provide the basis to justify an approach by analogy, widely used in a number of different disciplines (Turner, 1955). The basic idea is that when a similarity between different phenomena may be established, it can be assumed that there exists some common underlying law or principle. This may be especially true where such a similarity exists between the functions of elements in different systems or between their structures.

If structural relations can be reproduced in a simplified form in a known environment, a mathematical model can be assembled which can then be used in different settings.
Obviously, the usefulness of this approach depends on whether the consequences that can be drawn can be tested or observed and on the correctness of the theoretical framework in which the analogies are set (Gentner, 1983). The effectiveness of this procedure has been proved in innumerable cases and in various disciplines (Gentner, 2002; Krieger, 2005; Wigner, 1960). From an epistemological point of view, although the concept needs to be taken with caution to avoid potential abuses (Daniel, 1955), it has been claimed that theories (stated as a set of postulates) not showing even a formal analogy to some already existing system of abstract relations, would provide no means to understand how the theory could be applied to concrete problems (Nagel, 1961). One recognized use to analogy is its catalyzing function. Many times in the history of science (in physics, for example, with scientists such as Faraday, Coulomb, Helmoltz, Maxwell), the use of an analogy has served as initial aid in the development of new discipline. Known models and criteria may initially help in finding a path through large quantities of data, evidence, phenomena and to start organizing all these into organic sets. For example his knowledge of the mechanics of fluids, and the similarities discovered between the behaviors of electricity and magnetic bodies, then well separated fields of inquiry, ultimately led Maxwell to formulate his unified theory of electromagnetism.
Using the laws and methods of physics applied to social systems can be, and has been, questioned. It must be noted here that in studying a socio-economic system we are mainly interested in its global behavior and in the possibility of making predictions at this level rather than detailing the acts of every single element (individual actors). The main objective is to gather an understanding of possible regularities which may arise from the apparently irregular behavior of single individuals (Majorana, 1942). In this perspective, the comparison with empirical data has the primary objective of verifying whether the trends seen in the data are compatible with a *reasonable* microscopic modeling of the individuals and whether they are self consistent or require additional factors.
In this situation, only high level characteristics, such as symmetries, critical transitions or conservation laws are relevant. These, as the principles of statistical physics show, do not depend on the microscopic details of the system. Therefore, as Castellano et al. (2009: 593) state: “With this concept of universality in mind, one can approach the modelization of social systems, trying to include only the simplest and most important properties of single individuals and looking for qualitative features exhibited by models.”
The network approach, with its quantitative techniques, is applied more and more to the study of a socio-economic system such as a tourism destination, and has shown to be quite effective mainly when it relies strongly on a sound and accepted qualitative interpretation of the phenomena described.

The topology of a network

The topology (the structural characteristics) of a network (a tourism destination network, in our case) is an essential systemic property that may greatly influence the overall dynamic behavior of the system and explain a number of processes from the diffusion of ideas to the robustness to external or internal shocks, to the optimal distribution of the relationships among the network components. The networked structure of a tourism destination and its importance have been acknowledged by several authors. The study of the relationships among destinations’ stakeholders is considered an appropriate approach to describe these systems and to give better insights into the whole industry and its organizational configurations (Tremblay, 1998).

The simple existence of a network in a tourism district is not sufficient to generate effective synergies, it is the structure of such networks that is thought to be a crucial determinant (Michael, 2003). The existing theories and research on the relationships between competing and cooperating firms in a tourism destination confirm this role. In a tourism environment where many and diverse small companies operate, the overall success of the destination is more often found when firms interact more frequently between them. Furthermore, efficient information transfer and cooperation in marketing or operational activities or in sharing knowledge strongly influence the success of a destination and of its stakeholders (Gnoth, 2004).

Multiple ranges of network types exist; they can be categorized according to type of organization, configuration of inter-organizational connections, degrees of formality, or level of intensity of the linkages between members. The success of such networks (in terms of economic and social benefits achieved) depends on a number of different factors: clarity of objectives; organizational structure and leadership; capabilities to manage human, financial and physical resources; and participation of the members. Most of these benefits are difficult to quantify. The evaluation of their qualitative aspects can be very complex, but these benefits are deemed important to fully understand the characteristics and functioning of social groups (Dredge, 2005). The many examples studied confirm a clear relationship between the success of a destination and the structure of the network of its stakeholders. This is valid also for *virtual* tourism networks, those that include elements not necessarily geographically close, but spread on an international basis and connected (e.g. via computerized linkages) by a common vision and an efficient exchange of information and knowledge (Morrison et al., 2004).

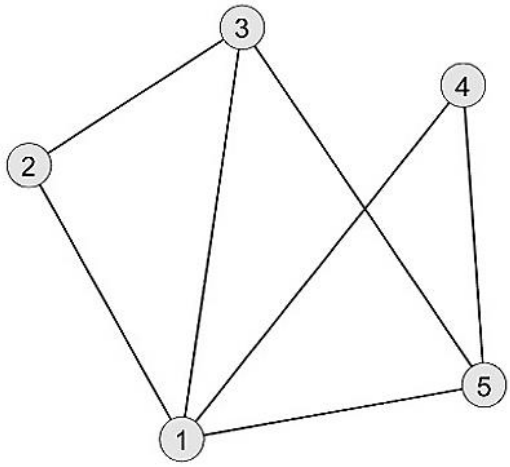
Many complex systems can be described in terms of networks of interacting elements. A significant number of researchers have shed light on the topological aspects of many kinds of social and natural networks and on the effects they have on a large series of dynamic processes. The reader interested in more details can browse the excellent reviews by Albert and Barabási (2002), Boccaletti et al. (2006), Lewis (2009), Newman, (2003). Less *technical* introductions to network analysis can be found in the works by Barabasi and Bonabeau (2003), Borgatti et al. (2009), Evans (2004), Newman (2008), Watts (2004). From these studies we recognize that the topology of a network is a knowable property and that the techniques implemented can be used as a diagnostic method for collecting and analyzing data about the patterns of relationships.

When it is possible to gather a reliable and significant set of data on a destination's stakeholders and their relations, it is possible to apply the methods and the techniques developed to study the networked organization and derive useful theoretical and practical insights into the structure and the dynamic behavior of a tourism system (Scott et al., 2008a).

Quantitative network analysis

All the computational methods employed in network analysis start from a matrix representation of a network. Mathematically, a network is a graph $G(V,E)$ composed of a set V of elements called vertices or nodes and a E is a set of pairs of distinct nodes, called edges or links. The number of nodes n is called the order of the graph and the number of edges m is called the size.

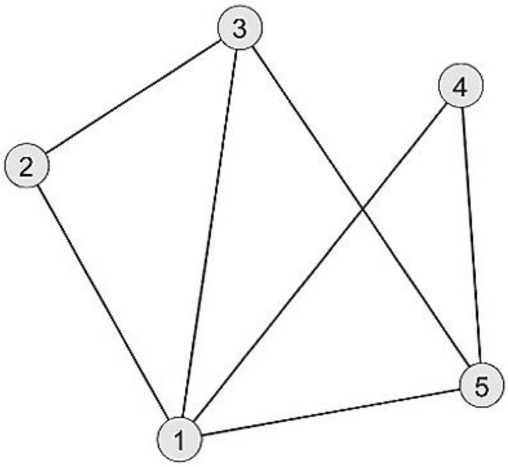
A node can represent simple objects (a protein in a metabolic network or a person in a friendship network) or complex entities (a firm or a website). A link designates some type of relationship between two nodes. This relationship can include a simple information exchange, a chemical reaction, a force etc. Links can be symmetric (an information exchange) or directed (a trip from a destination to another) and can be assigned a weight *w* measuring a strength, an importance or a value. This typology definition is also transferred to the whole graph, we thus identify undirected (symmetric), directed, weighted graphs or combinations of these (e.g. undirected weighted graph).



	1	*2*	*3*	*4*	*5*
1	0	1	1	1	1
2	1	0	1	0	0
3	1	1	0	0	1
4	1	0	0	0	1
5	1	0	1	1	0

Figure 1 An undirected unweighted network (left) and its adjacency matrix (right)

A network graph is usually represented by an $n \times n$ matrix A, called an adjacency matrix (n is the number of nodes). The matrix elements $a_{x,y}$ have value *0* if there is no link between node x and node y. If a link is present, the value will be 1 for unweighted graphs, w for weighted graphs. An undirected graph has a symmetric matrix representation. Due to this equivalence between a network, its graph and its adjacency matrix the three terms are used interchangeably (see



	1	*2*	*3*	*4*	*5*
1	0	1	1	1	1
2	1	0	1	0	0
3	1	1	0	0	1
4	1	0	0	0	1
5	1	0	1	1	0

Figure 1). The matrix representation allows using the powerful methods of linear algebra for a quantitative analysis.

A wide array of measurements of the topological characteristics exists (a thorough review can be found in da Fontoura Costa et al., 2007 which contains also the analytic expressions used for the calculations). Some of these are have been recognized to be the most important to fully differentiate network topologies and are the most used in the literature:

- *degree*: the number of links each node has, and *degree distribution*, the statistical distribution of links;

- *average path length*: the mean distance (number of links) between any two nodes and *diameter*, the maximal shortest path connecting any two nodes;
- *closeness*: the mean weighted distance (i.e. the shortest path) between a node and all other nodes reachable from it;
- *betweenness*: the extent to which a node falls between others on the shortest paths connecting them;
- *eigenvector*: a measure of the influence of a node in a network. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more than equal connections to low-scoring nodes;
- *clustering coefficient*: the concentration of connections of a node's neighbors; it provides a measure of the heterogeneity of local density of links;
- *efficiency* (at a local or global level): which can be interpreted as a measure of the capability of the system to exchange information over the network;
- *assortativity*: the correlation between the degrees of neighbor nodes; and
- *modularity*: the quality of a partition of the network into modules or communities. High values of modularity are found when the connections between the nodes within modules are denser than those between nodes belonging to different modules.

Network topological measurements are used to identify classes of structural types. Many classification schemes have been proposed, but in the literature networks are broadly grouped based on a few important characteristics. The first one is the form of the degree distribution. Networks with a poissonian (or gaussian) distribution are called generically random networks, or Erdös-Rényi, (ER) networks from the work of the authors that first proposed a model, based on a randomly distributed set of links (Erdös & Rényi, 1959, 1961). The presence of both high clustering and short path lengths has been named small-worldness (SW) by Watts and Strogatz (1998) and is a feature well represented in many social networks.

When the degree distribution follows a power-law (i.e. the number N of nodes with degree k is distributed as $N(k) \sim k^{-\alpha}$), another quite common property of a vast number of natural and artificial networks, the graph is termed scale-free (SF). The name refers to the fact that it is not possible to find a characteristic *scale*, the average degree of a Poissonian distribution (Barabási & Albert, 1999). These networks, probably the most diffused, show a limited number of nodes with very high degrees (the hubs of the system) and a large majority of nodes with low numbers of neighbors. Figure 2 shows an example of degree distributions for an ER and a SF network.

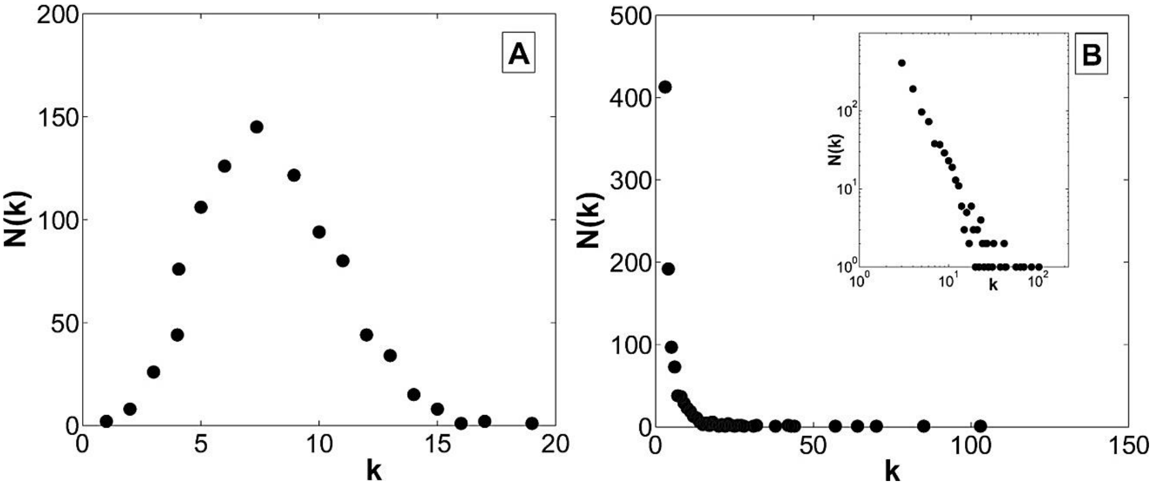


Figure 2 The degree distributions for a random (A) and a scale-free network (B). In panel B is also shown the distribution plotted on log-log scales, as usually done, to better see the power-law shape.

These classifications are not firmly set and networks exhibiting more topological features concurrently are quite common. SF networks may have high small-worldness, or show marked deviations from a pure power-law distribution (initial or final portion of the curve might exhibit a different slope).

Many dynamic processes have been studied and simulated. The general outcomes of these investigations put a strong emphasis on the close relationship between the unfolding of such processes and the topology of the underlying network. It has been shown that a scale-free network can sustain (before being almost completely disrupted) a casual removal of nodes and links much better than a random one, but is much more sensitive to targeted *attacks* to the most connected elements. The diffusion of viruses (human or computer) or ideas is greatly favored by a non-homogeneous distribution of the relations between the network elements and high clustering or modularity can have a greater effect than improvements in the single nodes capabilities to accept or reject these transfers (Barrat et al., 2008).

Data collection

The collection of the data needed to conduct a network analysis is a delicate issue. In a *real* environment, when social or economic systems are concerned, it is quite impossible to gather a *complete* set of nodes and links. At best it is possible to obtain a sample of these elements to analyze. This, however, requires a careful treatment. Standard statistical considerations cannot be used in an area of investigation where *normality* is more an exception than a rule. For example, a sample of a network missing some critical hubs may lead to erroneous conclusions about its topology.

In general, when considering a structured network (scale-free, for example) it is not possible to easily determine the significance of the sample collected. The researcher needs to judge and make educated guesses on the topology exhibited by the whole network. To help guiding such a guess, a number of studies, based on numerical simulations, provide ways to infer the modifications in the main metrics due to a selection of part of a network's components (Kossinets, 2006; Lee et al., 2006; Leskovec & Faloutsos, 2006).

Software tools

Software tools are indispensable for assessing the different properties of a network, modeling dynamic processes or performing simulations. Many programs exist (both freeware and commercial). The most used and known are: UCINET (license at a small fee, available at: http://www.analytictech.com/ucinet/) and Pajek (freeware, available at: http://pajek.imfm.si/) and Gephi (freeware, available at: http://gephi.org/). They come from the tradition of social network analysis and offer a relatively complete set of functions to calculate most of the basic metrics. Pajek and Gephi also provide good visualization capabilities.
Other, more complex operations (analysis of weighted networks or simulations, for example) definitely need some programming skills, as standard packages do not usually provide many functionalities for these. The task is made easier due to the availability of many scripts and programs developed by the community of scientists involved in the field. Often used, as development environment, is Matlab (http://www.mathworks.com/) for its good matrix-algebra calculation characteristics. Basic sets of scripts, such as the following, can greatly help the interested reader in developing own procedures:

- Complex Networks Package by L. Muchnik. Available at: http://www.levmuchnik.net/Content/Networks/ComplexNetworksPackage.html
- Brain Connectivity Toolbox by O. Sporns. Available at: https://sites.google.com/site/bctnet/
- MatlabBGL: a Matlab package based on the C++ Boost Graph Library by D. Gleich. Available at: https://github.com/dgleich/matlab-bgl/

A well developed and rich library is available for the freely available Python programming language: Networkx (http://networkx.github.io/). Other languages such as R, C++, Gauss, Java etc. have been used, and toolboxes, scripts and programs are available on the Web. A good survey with a comparison of the main functions can be found at:
http://en.wikipedia.org/wiki/Social_network_analysis_software.

Interpretation of the main network metrics

The different metrics discussed in the previous sections have important interpretations and implications for what concerns the structure and the behavior of the system.
At an individual level (single nodes) they are usually associated with a notion of importance (in network terms: centrality). Thus higher degree means having more connections than others and being able to reach directly more other elements, higher closeness means being able to reach all other nodes *more quickly*, high betweenness means being important bridges between different parts of the network (and also being a bottleneck), higher eigenvector indicates higher importance because connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes (Google's PageRank is a variant of the eigenvector centrality measure), higher clustering coefficient means having denser local neighborhoods and thus higher degree (capability) of collaboration or cooperation.
It must be noted that the network literature has not found an agreement on the "best" metric to indicate the importance of a single node. Different measures point out different aspects, therefore a suggestion can be to use a synthetic indicator which can be calculated as the geometric mean of the normalized versions of a set of metrics (typically degree, clustering coefficient, eigenvalue centrality, betweenness, closeness).
At a global level (whole network), the form of the degree distribution has a direct influence on the properties of a network and accounts for its basic topology. A power-law degree distribution is

considered to be the signature of complexity in a system. In fact, features of self-similarity and self-organization which are the most important characteristics of a complex system, are mathematically rendered, at least asymptotically, through a power-law distribution of certain parameters (size of components, number of connection, distribution of elements etc.). A power-law relationship is scale-invariant, i.e. no characteristic value can be defined to "summarize" the parameter (in a Gaussian distribution this would be the average) and the behavior of the parameter is the same when examined at different scales (Baggio et al. 2010). Moreover, such a distribution explains well the typical resilience of a complex system that can be at the same time quite robust with respect to random shocks leading to the (undifferentiated) removal of nodes and have high fragility when targeted attacks are directed toward the most important (highly connected) elements (Newman, 2010).

However, the degree distribution alone cannot convey all the information on the network structure. In fact, two networks can have similar distributions yet exhibit different static or dynamic characteristics that are, generally, determined by the presence of a correlation between the degrees (Bounova & de Weck, 2012). This correlation (assortativity) plays an important role in determining how a propagation process (perturbations, information or influence diffusion) unfolds on the network. If a perturbation starts from a node (and highly connected nodes are powerful amplifiers) it can affect with a certain probability its first, second, and sometimes even more distant neighbors in the corresponding network. Moreover, the resilience of a network, that is its capacity to withstand external or internal shocks without being disrupted but recovering in a reasonable period of time, is very sensitive to degree correlations. In short, the more assortative a network is, the higher its resilience (Serrano et al., 2007).

The average clustering coefficient can provide an indication of the extent to which the tourism organizations work together collaborating or cooperating, i.e.: forming cohesive communities inside the destination. Along this line, the assortativity coefficient indicates a tendency to form cooperative or collaborative groups. The extent to which collaborative or cooperative practices are common in a destination can be judged also by looking at the modularity index obtained after having identified the best community subdivision with one of the many stochastic algorithms existing. More importantly, the clustering coefficient can be used to uncover the hierarchical organization of the networked system. Ravasz and Barabási (2003) have shown that the relationship between the average clustering coefficient and the degree of the nodes signals a hierarchical structure when it follows a power-law functional form: $C_{ave}(k) \sim k^{-\alpha}$.

Local and global efficiency indicate the capability of the networked system (global) or of a single node (local) to exchange information (or other). The underlying idea is that it is easier to transfer information from one node to another if they are closer to each other. Global and local efficiencies depend strongly on the general topology of the network (number and distribution of connections), and, in the case of a weighted network may be influenced by the value associated with each connection which affects the calculation of the shortest (lowest weight) path between two nodes.

Small-world networks, in which nodes are more closely (topologically) arranged than in random networks are characterized by an average path length that increases logarithmically (or more slowly) with the number of nodes: $L_{ave}(n) \sim \ln(n)$. Another way for assessing the *small-worldness* of a network is to compare the ratio between the clustering coefficient and the average path length of the network with those of a network with the same number of nodes and links but with links placed at random. This quantity is called proximity ratio (Humphries & Gurney, 2008): μ =

$(C/L)/(C_{rand}/L_{rand})$. The ratio can be calculated considering that in a purely random ER network the average clustering coefficient is given by: $C_{rand} = k_{ave} / n$ (Albert & Barabási, 2002), while the average path length is approximated by (Fronczak et al., 2004):

$$L_{rnd} = \frac{\ln(n) - \gamma}{\ln(k_{ave}) + 0.5}$$

(in both formulas k_{ave} is the average degree, n the number of nodes and γ is the Euler constant $\gamma = 0.577216$).

It is important to note here that in order to have a significant meaning, all the metrics should be compared either to those of some known family of similar systems, or to a null model. In this case a simple solution is to generate a network having the same order (number of nodes) and size (number of links) of the network studied, but with links placed at random. This, however, disregards the possible effects of high heterogeneity of the degree distribution, therefore a better possibility is to prepare a randomized version of the original network obtained by rewiring it while preserving the degree distribution (Maslov & Sneppen, 2002). Obviously, given the "randomness" of a null model, the relative metrics should be calculated as averages over a certain number of different realization of the null model (at least 10, better 100).

Network analysis in tourism, the main results

The large set of possibilities offered by network science have been relatively well explored by the recent tourism literature (van der Zee & Vanneste, 2015), even if, in some cases, only at a very elementary level. From the studies produced we can see how the topological characterization and the identification of the peculiarities of a tourism destination have led to the recognition of the structured shape of the networks examined. Almost in agreement with what the general literature on social and economic networks has found, tourism destinations examined exhibit a marked scale-free shape of the degree distribution (da Fontoura Costa & Baggio, 2009; Ren, 2009). One example is in Figure 3, which refers to a Romanian destination: Sibiu described in Grama & Baggio (2014).

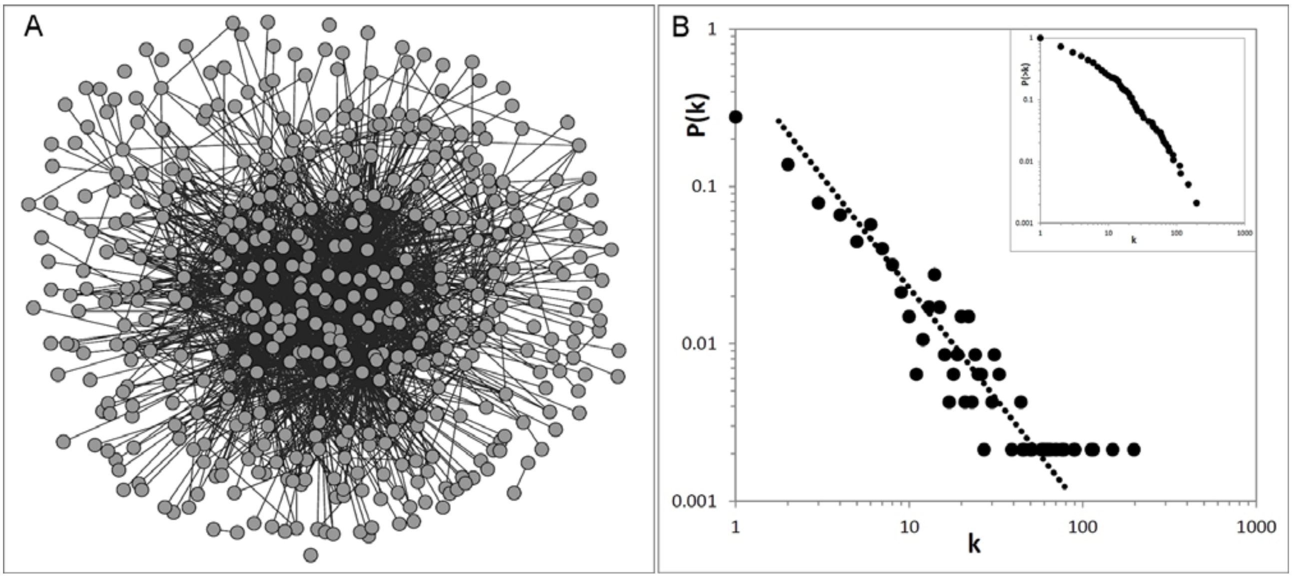


Figure 3 The network of a tourism destination with its degree distribution (panel B). The dotted line has the only purpose to guide the eye. Inset in panel B shows the cumulative degree distribution.

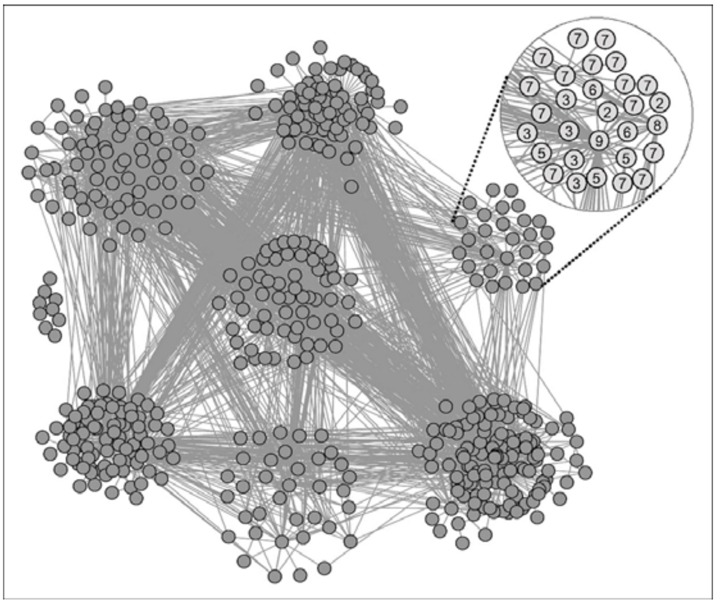


Figure 4 Modules identified algorithmically in a destination (the same of figure 3). The inset shows and enlarged view of the corresponding community. Numbers on nodes indicate different types of business.

A detailed analysis (Baggio et al., 2010) has highlighted very low density of connections, low clusterization and a negative degree-degree correlation (i.e. highly connected nodes tend to link low degree elements). These have been interpreted as indication of the known tendency of tourism stakeholders to retreat from forms of collaboration or cooperation. This conclusion is further confirmed by a modularity analysis. Moreover, the analysis has unveiled that some form of aggregations exist, even if not very well defined or highly significant. The community structure identified goes beyond preset differentiations (by type of business, for example) of the agents (Figure 4). In other words, companies of the same type (e.g. hotels), tend to connect with some other company which runs a different business. The same applies when geographical locations are taken into account (Baggio et al., 2010; da Fontoura Costa & Baggio, 2009, Grama & Baggio, 2014).

This is an important result, because documented and justified weaknesses in the cohesiveness of the destination can be addressed by policy and management approaches which will need to take into account the ‘natural’ system’s tendency to reshape itself autonomously (self-organize) and may derive from the outcomes some indications for actions and plans.

As a further important managerial implication, the network approach emphasizes the need for competitive destinations to be collaborative. By highlighting the relationships that form a value-creation system, it is possible to detect differences in measures of inter-organizational cohesion at different tourism destinations (Scott et al., 2008b). In fact, as Romeiro and Costa (2010) show in their study of a rural tourism business group, networked structures contribute to the creation of a cohesive destination, and the sharing of resources enables innovative local responses to the global market challenges. Moreover, the positive effects of the network permeate beyond the tourism industry and enable a more coordinated and sustainable management of natural resources, thus contributing to the development of the whole territory.

Similar conclusions come from a study conducted on the network of stakeholders associated with farmers’ markets (Hede & Stokes, 2009). The strategic establishment of an appropriate and effective network of stakeholders for both organizational longevity and tourism sustainability is

recognized. On the other hand, an excessive tightness of a cluster participants within the network can become detrimental in the long term to its sustainability and for its potential to develop tourism.
Camprubí et al (2008) develop a conceptual model for the creation of a tourism image of a destination, focusing on the role of tourism agents' relational networks. They find two potential gaps in the induced destination image formation process. One is a lack of coherence between the induced tourism image and the supplied tourist product, the second concerns the several tourism images simultaneously emerging when an excessive individualism of the actors is present. The position of relevant actors in the network and the structure of the network are identified as determinant factors of the emergence (or inhibition) of these gaps.
Beside the structural features (e.g. the number of paths of distinct lengths between pairs of nodes, as well as the number of reachable companies), some dynamic characteristics have been examined. The capability to reach a node from another one and the associated probabilities have been measured and analyzed leading to a series of important findings related to the interactions between tourism companies. Among the several results, it is shown that the type and size of the companies influence strongly these characteristics while their geographical position does not seem to matter (da Fontoura Costa & Baggio, 2009).
These outcomes, and the implications they have, can be used to inform the managerial approach which need some more conceptualization (March & Wilkinson, 2009), but may be effectively employed when stakeholders are analyzed. Social network analysis can be a powerful tool to collect information and identify which individuals and categories of stakeholder play more central roles in the network, as Prell et al. (2007) do. In the case presented, for example, the authors show how statutory bodies do not appear as very central, despite that, however, they have a great influence over the ways policies are written and enacted, and thus manipulate the behavior of stakeholders.
Governance networks and the literature on sustainable development can be merged to find feasible ways to foster a growth which balances external and internal needs (Erkuş-Öztürk & Eraydın, 2010). To do that, the development of tourism core-competencies is important and a networking approach of tourism firms can be highly beneficial. Network analysis can help in providing a development path for policy maker actions based on the evaluation of local resources and competencies (Denicolai et al., 2010).
The role tourism stakeholders play in a destination is a crucial factor for many activities. The recognition of these roles and of the position single actors assume in the system have an impact on the ways local governance networks operate, and on the effects of the governance styles on local tourism policy (Beaumont & Dredge, 2010). In general, the distribution of power, influence, and prominence among the actors in a tourism destination is largely uneven (Bendle & Patterson, 2008). Moreover, multiple ownerships can be present which can create strong webs of power. These involve tourists and significantly affect the business structure and the operation of the destination (Mottiar & Tucker, 2007).
The assessment of importance for the destination stakeholders can be conducted by using network analysis methods. When this is done, the qualitative knowledge of the phenomenon can help in refining the interpretation of the results and distinguish the important members in a destination; those who are reputed to contribute most to the tourism activities. As expected, public stakeholders are more important for both management and marketing activities than private companies (Presenza & Cipollina, 2009). Destination management organizations or actors possessing critical resources have the highest centrality and local government bodies are perceived to hold the greatest legitimacy and power over others in destination development (Timur & Getz, 2008). The key

stakeholders are located in the core of the network and form an elite that is seen as more salient while peripheral elements are seen as less important. This suggests that destination management is controlled by a limited number of stakeholders (Cooper et al., 2009) as further confirmation of the necessity of creating cohesive inter-organizational network for the production of integrated tourism experiences.

The effects of a good position in a destination network for what concerns the quality and the quantity of the links are visible and have shown to be correlated with good operational performance Sainaghi & Baggio, 2014). Furthermore, the network topological characteristics can allow an assessment of the level of creativity and innovation that a system is able to express. The idea is that beyond "individual" characteristics, a well-formed set of relationships between the different actors is able to favor the dissemination of creative and innovative practices (Baggio, 2014).

These results are reinforced by the combined quali-quantitative approach to these type of studies. In fact, the comparison between the perceived (through a series of interviews) importance of organizations in a destination and their network characteristics has brought to the identification of a set of metrics able to render this feature and to ways to use them (Cooper et al., 2009).

Network analysis methods have been applied also to the virtual network of the websites belonging to destination's stakeholders. The results are similar to those obtained by studying the *real* destination network (Baggio, 2007; Baggio et al., 2007a). This has allowed to estimate the level of utilization of advanced communication technologies among the actors in a destination and measure the extent to which they exploit (or waste) resources universally deemed to be crucial for today's survival in a highly competitive globalized market (Baggio, 2006).

The substantial similarity of the main topological characteristics, coupled with considerations on the mechanisms with which *corporate* websites are interlinked, has suggested an important conjecture. The tourism destination's webspace can be used to collect a significant sample of the underlying socio-economic network. As stated previously (data collection), gathering a meaningful set of data is a delicate task. Network analysis methods can be difficult to use if the collection mechanism is not able to provide a reasonable amount of information on tourism organizations and, above all, their interconnections. The World Wide Web, is argued, can provide an efficient and effective way to gather significant samples of networked socio-economic systems to be used for analyses and simulations (Baggio et al., 2010). The only limitation of this conjecture, at least for what possible to know with the works published so far, is that it is valid where a good diffusion of the WWW (in general and within the tourism domain) is present, condition that is well met in most countries (see e. g. the statistics published by http://www.internetworldstats.com/), but that could raise some concerns in some parts of the World.

By using this assumption, a comparison between the networks of two destinations considered to be at different development stages (Butler, 1980) has allowed to correlate, although for the time being only at a qualitative level, the topological evolution with the development phase. The hypothesis is that in early stages of development, existing tourism organizations have not yet connected to others because they probably do not feel such a necessity or because they have not recognized thus far the existence of other stakeholders (Baggio & Antonioli Corigliano, 2009b; Baggio et al., 2007b). Larger organizations or associations, generally responsible for the higher degrees in the network, still have to establish a connection with the newer nodes or with nodes they do not know yet they exist. This limitation in (some of) the nodes' processing of the information about the rest of the network is able to generate (Mossa et al., 2002) the differences measured in the topologies.

The strong impact of digital information technologies has affected the structural configuration of the tourism system and, specifically, of tourism destinations that can thus be seen as digital business ecosystem. In other words, when examining the relationships among stakeholders within a tourism destination, two components can be considered: a real and a virtual one. A network analysis shows that the two components are structurally strongly coupled and co-evolve forming a single system (Baggio & Del Chiappa, 2014).

Network dynamics

A major advantage of a network representation of a complex system is in the possibility to perform numerical simulations. They allow *experiments* to be performed in fields where these would not otherwise be feasible for theoretical or practical reasons. Different configurations can be designed and several dynamic processes simulated in order to better understand how these configurations influence the behavior of the whole destination system.

Simulation techniques have a good tradition in social sciences (Inbar & Stoll, 1972). The credibility of these techniques is good, provided some basic requirements are met: a solid conceptual model and the limitation to the particular circumstances for which the simulations are run (Küppers & Lenhard, 2005; Schmid, 2005). With these conditions, simulations can be effective and efficient in reproducing different types of processes may be considered a valuable aid in decision making or scenario planning (Axelrod, 2006; Stauffer, 2003).

Information and knowledge flows in a destination network are relevant determinants of the *health* of the system. Productivity, innovation and growth are strongly influenced by them, and the way in which the spread occurs affects the speed by which individual actors perform and plan their future (Argote & Ingram, 2000). A commonly used way to study the problem is the one based on an analogy with the diffusion of a disease (Hethcote, 2000). Differently from traditional epidemiological models, it has been demonstrated that the structure of the network is highly influential in determining the basic unfolding of the process (Da Costa & Terhesiu, 2005; López-Pintado, 2004).

A set of simple simulations has shown these effects (Baggio & Cooper, 2010). Different configurations have been used, based on the single stakeholders' capacities to absorb and transfer knowledge and on different network topologies. It has been shown that the scale-free topology of the tourism destination affects the process by speeding it up with respect to a random (ER) network. Further improvements, then, can be obtained by eliminating differences in the capability of single actors to convey knowledge to other members of the community. The best results in terms of process efficiency, however, have been achieved when the network has been modified (rewired) in order to increase its clustering characteristics (Figure 5).

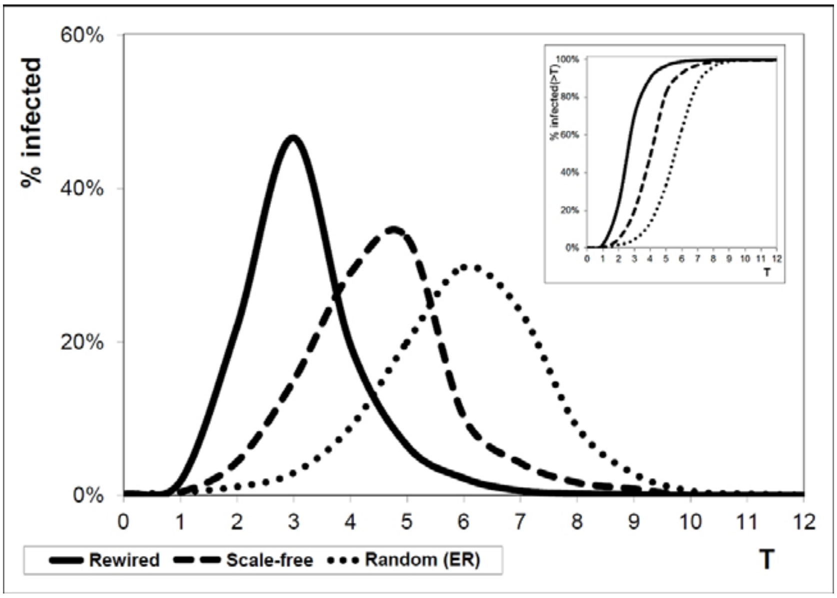


Figure 5 *Infection* curves for the simulations performed on a random (ER) network, a scale-free network and the rewired version. Inset shows the cumulative process. All curves are averaged over 10 realizations of the simulations to allow for the stochasticity of the process.

The conclusion is that a very important factor for the spread of knowledge in a tourism destination is the presence of a well-structured topology in the network of relations that connect the different stakeholders, and that a well-established degree of local cohesion is highly beneficial. In other words, destination stakeholders should be encouraged to form cooperative or collaborative clusters. This is an important indication for governance bodies willing to facilitate these evolutions. After all, a modification of the number or the type of relationships in a destination is within the reach of a governance organization and can be achieved by adopting appropriate actions or policy measures.

Other important knowledge diffusion mechanisms are crucial for the success of tourism operators. The diffusion of marketing messages through traditional advertising and word-of-mouth, both well-known and studied techniques can be examined through a series of simulations. It is then possible to compare the effectiveness of traditional advertising to that of word-of-mouth for promoting the services offered to a target market (Baggio et al., 2009). By comparing the two situations the consequences of these two methods have been measured in terms of time needed for reaching a certain fraction of the target population and resources spent. The results show the higher effectiveness, at least in the short term, of word-of-mouth. For the classical paid advertising a more intense effort is needed to reach the same level of informed people.

The dynamics of a virtual network of tourism operators' websites has also been analyzed. The importance of the hyperlinks connecting different websites is very high due to their ability to provide a visitor with a wealth of good quality information and for the role they play in the ranking by search engines. An examination of the web graph of a tourism destination has been conducted by simulating the possible behavior of a visitor. This work has highlighted the influence that the topological structure has on the navigability of the virtual community and on the effectiveness of its positioning on search engine results. The most important outcome of this series of simulations is in the realization that a modest increase in the number of interconnections (unfortunately usually very scarce) may substantially improve the visibility and the navigability of the destination's webspace (Baggio & Antonioli Corigliano, 2009a).

Other applications

Network analysis methods are flexible and adaptable to many diverse areas of study. They have been employed in numerous and creative ways in order to better explore many phenomena. A number of these applications are of interest to tourism academics and practitioners and have received some attention by the scholars in the field.

The movement of tourists and the network formed by the paths followed by them have an undeniable interest for areas where tourism is a crucial economic activity. Network methods emphasize the strategic spatial positioning of tourism resources and help understanding the main driving forces behind these movements (Hu et al., 2008; Miguéns & Mendes, 2008; Shih, 2006).

The networks formed by different means of transportation are also well studied, for the relative simplicity in collecting relevant data. Airports and flight routes, maritime shipping, or railways have been investigated (Bagler, 2008; da Rocha, 2009; Guida & Funaro, 2007; Guimerà & Amaral, 2004; Hu & Zhu, 2009; Liu & Li, 2007; Seaton & Hackett, 2004; Xu & Harriss, 2008). The topological patterns and, in some cases, optimization and modeling possibilities are the main objects of these studies, together with the distributions of passengers and traffic volumes.

Tourism and hospitality studies have been subject to some investigations with the objective to understand the type and the mechanisms underlying different forms of relationships and collaboration patterns between researchers for inferring the development of the knowledge domains. Interesting insights into the way different authors work, their interests, their popularity and the connections to other disciplinary fields can be drawn. The analysis of co-citations arrangements, or of the keywords used to characterize a published work is well used in many disciplines and tourism or hospitality studies make no exception (Benckendorff, 2009; Dilevko & Dali, 2004 ; Gretzel et al., 2008; Hu & Racherla, 2008; Kim et al., 2009).

Examining deeper discursive practices and language can be another way to understand power relationships and power struggles. In particular, control over orders of discourse by institutional and societal power-holders is one factor in the maintenance of their power. The textual content of documents such as the destination marketing plans can be examined by building a network composed of concepts connected by their vicinity in the text. This analysis highlights the relative importance of these concepts and how they relate each other. Core concepts of these management plans can be related to the social impact that tourism has on communities as well as to the importance of its marketing and promotion. (Baggio & Marzano, 2007).

A future agenda

The results described in the previous sections show two important facts. On the one hand, the methods for analyzing networked structures have reached a quite high level of sophistication. Fortunately, the work of the numerous scientists involved in the area has also provided a large array of usable tools for studying networks and the vast majority of these have been made freely available to the scientific community, thus ensuring a high replicability of the investigations. Although not enough firmly theoretically founded, network science has provided a wealth of interesting and valuable results, both theoretical and practical, which span an incredible series of topics.

On the other hand, the examples of application to study of tourism systems highlight the importance and the usefulness of this approach for a better understanding of the structures involved and their functioning. This, coupled with the relative ease with which these techniques can be employed, once the relevant data have been satisfactorily collected, provides academic and practitioners with one more powerful toolset.

As has been made clear, the quantitative approach attains its maximum effectiveness when complemented with a good qualitative knowledge of the object of study. This is more important when applying simulation techniques and building different scenarios. If correctly used, simulations are a powerful tool, but the basic assumptions must represent as faithfully as possible the reality and a good comprehension of what will be implemented is crucial. A good and reliable model, especially when dealing with a complex system, needs continuous interactions between researchers or practitioners and empirical issues (Silvert, 2001).

Network analysis methods are, with little doubts, an intriguing and intellectually fascinating endeavor. Nonetheless, a full understanding of systems and phenomena cannot be achieved without a sound knowledge of the study object. This can only come from qualitative investigations. As Gummesson states (2007: 226): "By abolishing the unfortunate categories of qualitative/quantitative and natural sciences/social sciences that have been set against each other, and letting them join forces for a common goal – to learn about life – people open up for methodological creativity, therefore qualitative and quantitative, natural and social are not in conflict but they should be treated in symbiosis".

When tourism is concerned, the journey of network science has just begun. Researchers interested in this field have a quite crammed agenda before them. First of all, many more examples are needed. More cases and different situations should be analyzed before being able to well gauge the differences and the effects of network topologies and dynamics. Classifications and taxonomies are not possible with the very limited series of examples the literature provides today. A wider range of cases can allow also a better tuning of the different methods and a more reliable choice of the metrics intended to represent and characterize a tourism system. Moreover, a larger set of investigations on the systems' dynamics and their responses to different phenomena can provide a deeper knowledge on the relative importance of structural forms and the unfolding of different processes (knowledge diffusion, formation of opinions, trust building etc.).

Many more issues must still be addressed. One example concerns the relationship between the evolutionary history of a tourism system and possible network growth models. The knowledge of such a relationship could greatly help the process of planning and the development of a destination. Last, but not least, tourism destinations are not isolated systems, they are more and more connected between themselves by a wide range of different linkages (positive and negative, collaboration or competition). Besides that, tourism, at large, can be seen as a huge hierarchically organized multilayered system, in which different levels of structures (often self-organized) are present. The combined effects of hierarchical levels and topologies, when better understood, could offer much better theoretical and practical tools to understand the whole phenomenon and the mechanisms that make it one of the most important sectors of human activities.

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