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Working Paper No. 7
URL: www.dondena.unibocconi.it/wp7

October 2008

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http://www.dondena.unibocconi.it

ISSN 2035-2034

Network science and socio-economic systems
A review focused on a tourism destination

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Abstract

The study of network representations of physical, biological, and social phenomena has developed rapidly in recent years. This paper presents a review of important results and methods of the science of networks with an application to the field of socio-economic systems. The basic definitions and computational techniques are described and the effects of a network's topology on its dynamic properties are examined and illustrated using a tourism destination as a case study (Elba, Italy). A static structural characterization of the network formed by destination stakeholders is followed by a dynamic analysis of the information diffusion process. The outcomes and the implications of this analysis for improving destination management are discussed.

Keywords

complex systems, network science, tourism destination, destination management

Introduction

Connections and relationships are among the most important elements characterizing the shape and the behavior of the physical and the social world as we understand it. Most parts of the natural and the social sciences are, in essence, founded on the study of relationships. As a result a 'science of networks' is receiving increased attention from a growing number of scholars interested in researching the structural and dynamic properties of networks. A large part of the systems we examine, from biological cells to organizational communication interactions to linguistic texts, can be conceptualized as sets of 'objects' connected by links: a network.

A review of the literature of network research shows that the structure (topology) of a network is a measurable and, at least to some extent, predictable property that greatly affects its overall dynamic behavior and which can be used to explain a wide number of processes. These include the spread of viruses over a computer network or of diseases in a population, the formation of opinions, the diffusion of information or knowledge and robustness to external shocks. These processes all exhibit a strong dependence on the basic topological features of the network representing the system under study. Network analysis techniques can also provide diagnostic tools for cataloguing and analyzing the patterns of relationships in networks such as groups of people or organizations (Caldarelli, 2007). This has led to the birth of a new discipline, which many authors have started to call *network science*. Network science is the study of network representations of physical, biological, and social phenomena with the objective of devising predictive models (Watts, 2004). The main questions asked in network science concern the topological measures used to characterize the properties of a network and how these properties affect the behavior or evolution of the systems under study and the processes occurring on them. Answers to these questions, beside their obvious theoretical interest, can have a wide 'practical' impact on our ability to engineer and control a complex system, from improving Web searches for tourism products and Internet routing to evaluating the risks of ecological damage as a result of human actions through tourism.

With its origins credited to the famous paper by Leonhard Euler (dated 1736) on the Königsberg bridges' problem, the ideas at the heart of the modern science of networks are over 250 years old. However, they did not find a wider audience until the mid 1990s when the availability and accessibility of data and the availability of powerful computation tools allowed scientists to develop effective models, theories and simulations of the static and dynamic properties of networks. The topology of complex systems, represented as networks, has been shown to be a fundamental feature of many systems (Boccaletti et al., 2006). The contribution of scientists from many different disciplines has revealed how behaviors and processes can be described and explained by taking into account the system's general connectivity properties.

Tourism is no exception here. There is a significant literature on the importance of the relationships between tourists and service organizations and between tourism companies themselves. (Lazzeretti & Petrillo, 2006; Morrison et al., 2004; Pavlovich, 2003; Stokowski, 1992; Tinsley & Lynch, 2001). The main focus is on tourism destinations, thought to be an essential unit of analysis for the understanding of the whole tourism system (Buhalis, 2000; Framke, 2002; Georgulas, 1970; Ritchie & Crouch, 2003; Vanhove, 2005). However, only a few works are available which examine a tourism destination from a network point of view. Of those only a few use the available quantitative methods of network science (Baggio, 2008; Pforr, 2006; Scott, Cooper, & Baggio, 2008; Shih, 2006). In this field, quantitative network tools can provide a novel view of the destination system and give managers the potential to improve functions such as the flow of information or the governance of destinations.

The aim of this paper is to review the quantitative methods of analysis of complex networks with an application to the tourism field. The paper is specifically focused on understanding the tourism destination which can be represented as a network by enumerating the stakeholders composing it and the linkages that connect them.

The remainder of this paper is organized as follows. After a brief presentation of the concept of tourism destination, and an historical account of network studies in the wider literature, the reader can find an outline of the general theoretical framework in which the modern science of networks is embedded. The main models and metrics for a static and a dynamic analysis of a complex network are then discussed along with guidance on interpreting the metrics described in the framework of a socio-economic system such as tourism.

Where possible, examples from the tourism field are given. Examples will also be provided from other fields, with the additional benefit of emphasizing the ‘universal applicability’ of network analysis methods. The methods and results presented here have also the objective of contributing, from an interdisciplinary viewpoint, to the methodological foundation of tourism (Tribe, 1997).

Tourism destinations

A tourism destination, as defined by the UN World Tourism Organization (UNWTO, 2002) is:

> “A physical space in which a visitor spends at least one overnight. It includes tourism products such as support services and attractions, and tourism resources within one day's return travel time. It has physical and administrative boundaries defining its management, and images and perceptions defining its market competitiveness. Local destinations incorporate various stakeholders often including a host community, and can nest and network to form larger destinations”.

From a more general point of view, this constellation of specialized companies, organizations and communities gathered into a confined geographical location (even if its boundaries are often poorly defined) can be seen as a form of industrial cluster or district. Thus the analysis of its structure may draw upon the theory of industrial clusters, of their formation mechanisms and their evolution (Hjalager, 1999).

The main models of clusters and networks of companies or organizations have been developed by investigating industrial sectors, with limited attention to the service sectors of the economy such as tourism. Tourism destinations, however, deal with different offerings and have peculiar differences with respect to a ‘traditional’ district. The formation mechanisms, the focus on the service components, the characteristics of the ‘products’ and the relationship between them and the ‘production’ system are some of the peculiarities which make a tourism destination different from an industrial cluster. First of all, tourism is essentially a service industry in which the ‘product’ (i.e. a package sold by a tourism agency) is not really well defined and is composed of many different elements (Johns, 1999; Sinclair & Stabler, 1997; Wahab & Cooper, 2001). The tourist usually purchases this package in advance and consumes it at the destination. The diversity of elements which form the package causes the establishment of a wide layer of intermediaries which are an integral component of the same industry (Gollub et al., 2003). Therefore, the models of industrial networks and clusters need modification and adaptation when tourism is the main object of study (Gnoth, 2002, 2006).

Concentration effects in general economic or industrial activities have been studied and measured in detail. Theoretical and empirical research has found that agglomeration effects generally play a crucial role for regional income levels (Brenner & Weigelt, 2001; Krugman, 1991), for the attractiveness toward foreign investments (Barrell & Pain, 1999) and for the competitiveness of the area in which they occur (Norton, 1992). Moreover, economic growth and geographic agglomeration have been found to be self-reinforcing (Martin & Ottaviano, 2001); concentration of industries increases with economic growth and, by reducing the cost of innovation in the region where the economic activities converge, it enhances growth.

An idea at the basis of most literature on industry clustering is that firms sited in a geographical area share common ideals, rules and languages so that the social environment they form is homogeneous. Social, cultural and operational contiguity favors the spread of tacit information and knowledge among local actors. This constitutes a competitive advantage for the participants to the cluster (Morrison, 2004; Norton, 1992) because this tacitness makes them difficult to access by elements outside the community. Co-location within a concentrated geographical area is a basis for development of other characteristics of a cluster. The most important factor for a functioning cluster is the formation of close ties or alliances among the different actors and the degree of cooperation established to improve the competitiveness of the group beyond the incidental (usually external) effects that promote the gathering (Andersson et al., 2004; Mishan, 1971).

A tourism destination, in first approximation, may be considered an example of such a cluster. The mutually dependent attractions, services, transportations, and environmental or cultural resources emphasize the need for collaboration. This is mainly driven by demand. In fact, as Gunn states (1997: 108): "A traveler is more likely to seek the great diversity and volume of services when they are located together. And businesses in such clusters benefit from local as well as travel trade."

Destination clusters generally establish spontaneously and evolve and change over time, driven by both internal and external factors. They are not isolated entities, but open systems with complex linkages to a number of similar or diverse other systems. The development of new competitive products and services is very often done in cooperation with other ensembles, and the interface between different agglomerations allows the creation of new value (Nordin, 2003).

The terms *cluster* and *district* are often used almost interchangeably. However, the two concepts have a fundamental difference. This can be seen in the works of the two most influential scholars in this field.

Industrial clusters are "geographic concentrations of interconnected companies and institutions in a particular field" (Porter, 1998: 78). The basic characterizing feature is the belonging to a specific sector; the participating firms are connected by horizontal or vertical relationships and concentrated in a specific area. They may be complemented by some 'external' entities such as the public institutions. The focus, however, remains the entrepreneurial and business dimension.

On the other hand, the vision of the Italian school interprets a *district* as an extension of this specialized spatial concentration idea. Becattini (1990) adds to the focus on 'industries' a full recognition of the importance of the social environment (including regional governments and trade associations) of the area in which the district works and, perhaps more important in this globalization age, the understanding of the role of the linkages with the 'external' world. This approach seems to be much closer to what the reality of these agglomerations is and much more suitable as a framework for the study of a tourism destination.

Even in this case there are differences for which the *district* model needs some adaptation to be used as a framework in the tourism field. As said, the 'product' has peculiar characteristics: it is mainly a service product, whose intangibility, inseparability, heterogeneity and perishability make it rather different from 'usual' industrial goods (Vanhove, 2005). In addition, the acquisition and consumption of the tourism product is typically separated by space and time so that potential visitors are unable to fully assess product attributes prior to consumption (Burns, 1999; Cooper et al., 2005; Mill & Morrison, 1992).

The district interpretation of a tourism destination considers it as formed by two main classes of interacting components (Antonioli Corigliano, 1999, 2000; Capone, 2004; Lazzeretti & Petrillo, 2006; Stamboulis & Skayannis, 2003):

- a large endowment of resources: natural, cultural, artistic, but also artificially built, such as museums, theme parks or sport complexes;
- a network of groups of actors: economic, non-economic and institutional, whose prevalent activity is providing tourism-related services to visitors and travelers.

The stakeholders of a destination district include, in the tradition of the Becattinian school, not only those whose core activity is 'tourism' as it would be in a Porterian cluster, but also the local social system, the various institutional entities (local or country governments, associations etc.) and other organizations whose activity, although not directly of *touristic* nature, are deemed essential for the good functioning of the system as a tourism destination. Even the geographical delimitation can be somewhat relaxed since virtual groupings with entities external to the specific area can be established, thus overcoming the need for a strict physical proximity.

A tourism destination is not a static system. It evolves over time passing through different evolutionary phases. The analysis of the development of tourism destinations is an important theme in tourism studies. The literature on this subject has been built, basically, around the idea of a tourism area life cycle (TALC), originally proposed by Butler (1980). This model is composed by applying to the development cycle of a tourism destination the theories on the evolution of products (product life cycle model), dating from the 1950s, that were well established in consumer marketing studies by the time that Butler adapted the framework. A new product is launched, achieves acceptance and growth until competitors gain market share (Gardner, 1987). Then, innovation or repositioning is necessary to withstand declines in sales and profits. Butler applies these principles to dynamic, market-driven tourism development and suggests that successful destinations pass through a sequence of growth stages (exploration, involvement, development, consolidation, then stagnation followed by either a decline or a rejuvenation) that follow an *s-shaped* logistic curve and is similar to the one used to describe the general evolution of an industrial district).

The TALC model has been applied to many areas and in many cases has proved to be quite effective in describing or explaining the tourism history of a district. It has been commented on, improved, developed and criticized numerous times (Butler, 2005a, 2005b). Many authors have used it to demonstrate its application in specific situations (Agarwal, 2002; Baum, 1998; Cooper & Jackson, 1989).

The concept of tourism destination implies a systemic approach in tourism studies – an approach in which the main focus is given to the activities and the strategies to foster the development of an area pictured as an interconnected system of actors cooperating in order to supply integrated tourist products.

Network science

The historical development of network science reveals a number of streams of thought (Scott, Baggio, & Cooper, 2008; Scott et al., 2007). One is mathematically-based social network analysis, considering the abstract characteristics and properties of 'ideal' networks such as found in the work of Burt (1992; 1997). The second is qualitative social science-based in which a network is viewed as an analogy for the interactions between individuals in a community such as the policy networks approach of Rhodes (1990; 1997). The third is the physicist's view of complex networks explored in the framework of statistical physics and complexity theory (Albert & Barabási, 2002; Boccaletti et al., 2006). While each of these three streams has advantages for the study of tourism, this paper focuses on the latter stream of thought.

A network is normally represented by a drawing in which the various elements are shown as dots and the connections among them as lines linking pairs of dots. This drawing, a mathematical abstraction, is called a graph and the branch of mathematics known as graph theory establishes the framework providing the formal language to describe it and its features. This tradition was begun by Euler (1736) in the 18^{th} century, and formally established by König (1936) at the beginning of 20^{th} century and has provided a widespread set of tools for analyzing graphs and the networks represented by them. The application of networks in the social sciences using graphs and related tools (i.e. social network analysis) developed in the first half of 20^{th} century (Barnes, 1952; Moreno, 1934; Radcliffe-Brown, 1940; Simmel, 1908). The basic idea is that the structure of social interactions influences individual decisions, beliefs and behavior (Scott, 2000). The analyses are conducted on patterns of relationships rather than concentrating upon the attributes and behaviors of single individuals or organizations (Wasserman & Galaskiewicz, 1994). By the end of 1990s, the methods and possibilities of social network analysis were well established and formalized (Freeman, 2004; Scott, 2000; Wasserman & Faust, 1994; Wellman & Berkowitz, 1988), and network analysis also was adopted as a diagnostic tool in applied fields such as management and organization studies (Cross et al., 2002; Haythornthwaite, 1996; Tichy et al., 1979). Social network analysis studies, while useful, tended to view the social system as static and were often criticized on the basis that they ignored the dynamic nature of organizations and groups.

Meanwhile scientists examining many natural and artificial systems had documented dynamic behavior that was non-linear and indeed exhibited complex or chaotic patterns over time. This led, in the second half of the 20th century to detailed study and modeling of such nonlinear complex systems, facilitated by the power of modern computers albeit based upon ideas which date from the 18^{th} century. The consideration of the dynamic properties of networks began in the 1960s with the seminal work of Erdös and Rényi (1959, 1960, 1961) who presented a model of a random network. The authors showed that dynamic growth in the number of connections gives rise to phenomena such as the formation of giant fully connected subnetworks, which seem to arise abruptly when some critical value of link density is attained. This finding attracted the interest of statistical physicists, well accustomed to analysis of these kinds of critical transitions in large systems. Three provocative papers (Barabási & Albert, 1999; Faloutsos et al., 1999; Watts & Strogatz, 1998) in the late 1990s placed the analysis of networked systems in the context of statistical physics, providing a strong theoretical basis to these investigations, and justifying the search for universal properties of networked objects. The models proposed in this context have made it possible to describe the static, structural and dynamic characteristics of a wide range of both natural and artificial complex networks and have highlighted the linkage between the topological properties and the functioning of a system, almost independent of the nature of the system's elements (Boccaletti et al., 2006; Caldarelli, 2007; Watts, 2004). There is a growing literature applying these methods to the exploration of social and economic systems, driven by the interest in self-organizing processes and emergence of ordered arrangements from randomness (Ball, 2003; Castellano et al., 2007; Stauffer, 2003).

Complexity and network science: the theoretical framework

There is no formal designation of a complex adaptive system despite a growing literature and debate by many. Instead, many authors characterize a system as complex and adaptive by listing the properties that these systems exhibit (see for example Cilliers, 1998; Levin, 2003; Ottino, 2004). The most common and significant properties are:

- the system is composed of a large number of interacting elements;
- the interactions among the elements are nonlinear;
- each element is unaware of the behavior of the system as a whole, it reacts only to locally available information;
- the system is usually open and in a state far from equilibrium; and
- complex systems have a history, their actual and future behavior depend upon this history and are particularly sensitive to it.

Many real world ensembles are complex adaptive systems, as in economics where "even the simple models from introductory economics can exhibit dynamic behavior far more complex than anything found in classical physics or biology" (Saari, 1995: 222).

The tourism sector shares many of these characteristics. A tourism destination encompasses many different companies, associations, and organizations and their mutual relationships are typically dynamic and nonlinear (Michael, 2003; Smith, 1988). The response of stakeholders to inputs from the external world or from inside the destination may be largely unpredictable (Russell & Faulkner, 2004). During the evolution of the system it is possible to recognize several reorganization phases in which new structures emerge such as the development of a coordinating regional tourism organization. Besides these 'particular' or unique behaviors, however, the system as a whole may also be found to follow general 'laws'. Models such as the one by Butler (1980), although discussed, criticized, amended and modified (Butler, 2005a, 2005b), are generally considered able to give meaningful descriptions of a tourism destination and, in many cases, have proved useful tools for managing destination development despite the peculiarities of individual case studies. More detailed studies can be found which have assessed the 'complex' nature of tourism systems, both in a qualitative and a quantitative way (Baggio, 2008; Farrell & Twining-Ward, 2004; Faulkner & Russell, 1997).

According to Amaral and Ottino (2004), the toolbox available to study such complex systems derives from three main areas of research: nonlinear dynamics, statistical physics and network science. First, research since the end of the 19th century, the physicist's view of complex networks mentioned above, has yielded several mathematical techniques which allow approximation of the solutions to the differential equations used to describe a nonlinear system which were proven to be non-solvable analytically. Today, the availability of powerful computers makes it possible to use numerical models and simulations able to apply these techniques and thus chaotic and complex systems can be described in terms of the collective behaviors of their elementary components.

Second, research in statistical physics has provided macroscopic (statistical) approximations for the microscopic behaviors of large numbers of elements which constitute a complex system. In particular, it provides a theoretical foundation to the study of phase transitions (such as the one occurring to water in passing from liquid to solid or vapor) and the critical conditions governing them. Within the statistical physics framework, the analysis of data, the development and evaluation of models, or the simulation of complex systems are carried out with the help of tools such as nonlinear time series analysis, cellular automata, and agent-based models (see Shalizi, 2006 for an excellent review).

Two important concepts stem from this statistical physics tradition: universality and scaling (Amaral & Ottino, 2004). Universality is the idea that general properties, exhibited by many systems, are independent of the specific form of the interactions among their constituents, suggesting that findings in one type of system may directly translate into the understanding of many others. Scaling laws govern the variation of some distinctive parameters of a system with respect to its size and the mathematical expression of these laws applied to complex and chaotic systems involves a power law, now considered a characteristic signature of self-similarity.

The third area of research is based on the idea that a network can be used to represent many complex systems. The interactions among the different elements lead, in many cases, to global behaviors that are not observable at the level of the single elements, and they exhibit characteristics of emergence typical of a complex system. Moreover, their collective properties are strongly influenced by the topology of the linking network (Barabási, 2002; Buchanan, 2002). This is the approach followed in the rest of this paper.

Characterization of complex networks

Born at the intersection of physics, mathematics, biology, sociology, economics and other disciplines, network science employs specific terminology and methods. Moreover as a 'young' discipline, new definitions, algorithms and interpretations are frequently proposed, and the consequent lack of 'uniformity' may create difficulties in approaching the topic. This situation is discussed in the extensive reviews by Boccaletti et al. (2006) or da Fontoura Costa (2007), or books such as those by Caldarelli (2007) or Dorogovtsev and Mendes (2003).

Mathematically speaking (Bollobás, 1998), a network is represented by a graph G which is an ordered pair $G: = (V,E)$. The following conditions apply: V is a set, its elements are called vertices or nodes; 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 size. The degree of a node is the number of edges connecting it to some other nodes. A node (also called vertex, actor) can represent simple 'objects' (a word in a semantic network), or complex ones (a firm or a biological individual) when we want to concentrate on the overall properties of the ensemble rather than on the individual's behavior.

An edge (also termed link or tie) denotes some type of relationship between two nodes. It can be a simple information exchange, a chemical reaction, a force, a road and so forth. Links can be symmetric (an information exchange) or directed (a flight from one airport to another) and can be assigned a weight w, i.e. a measure of strength, importance, value. These characteristics of links are also transferred to the whole graph. We thus speak of undirected (symmetric), directed, weighted graphs or combinations of these (e.g. directed weighted graph). The graph can also be represented by an $n \times n$ matrix A, called an adjacency matrix. If there is an edge from some node x to some node y, then the element $a_{x,y}$ has a value different from 0. Its value will be 1 for unweighted graphs, w for weighted graphs. If the graph is undirected, A is a symmetric matrix. There is a full correspondence between a graph, a network and an adjacency matrix, therefore the three terms are used indiscriminately. In particular the identification between a graph and an adjacency matrix makes available to a network scientist all the powerful methods of linear algebra to investigate network characteristics. Figure 1 gives an example of different types of networks and their adjacency matrices.

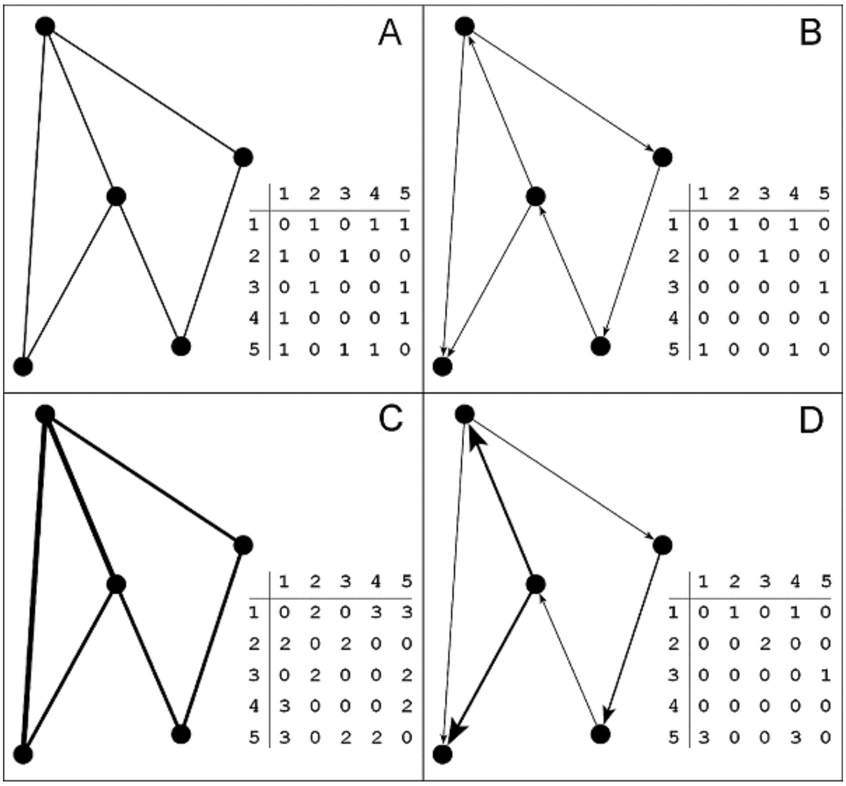

Figure 1 Different graphs: undirected (A), directed (B), weighted undirected (C) and weighted directed (D) with their adjacency matrices

The inter- and multi-disciplinary origin of network science has led, as said, to a wide variety of quantitative measurements of their topological characteristics (see da Fontoura Costa et al., 2007 for a thorough review). The literature on complex networks commonly uses the following, which have been found to typify more fully a network's structure. In the following formulas: n = number of nodes; m = number of links; k = nodal degree (number of links a single node has); d = distance (length of shortest path connecting any two nodes); the subscript i (or j) refers to a generic node. Based on the adjacency matrix (a_{ij} is an element of the matrix), m and k can be calculated as follows: $m = \sum_i \sum_j a_{ij}$ and $k_i = \sum_i a_{ij}$.

The main network metrics are:

- *density*: the ratio between m and the its size and the maximum possible number of links that a graph may have: $\delta = \frac{2m}{n(n-1)}$;
- *path*: a series of consecutive links connecting any two nodes in the network, the *distance* between two vertices is the length of the shortest path connecting is them, the *diameter* of a graph is the longest distance (the maximum shortest path) existing between any two vertices in the graph: $D = \max(d_{ij})$, the *average path length* in the network is the arithmetical mean of all the distances: $l = \frac{1}{n(n-1)} \sum_{i \neq j} d_{ij}$. Numerical methods, such as the well known Dijkstra's algorithm (Dijkstra, 1959), are used to calculate all the possible paths between any two nodes in a network.

- *clustering coefficient*: represents the degree of concentration of the connections of the node's neighbors in a graph and gives a measure of local inhomogeneity of the link density. It is calculated as the ratio between the actual number t_i of links connecting the neighborhood (the nodes immediately connected to a chosen node) of a node and the maximum possible number of links in that neighborhood: $C_i = \frac{2t_i}{k_i(k_i - 1)}$. For the whole network, the clustering coefficient is the arithmetic mean of the C_i: $C = \frac{1}{n}\sum_i C_i$;
- *proximity ratio*: the ratio between clustering coefficient and average path length normalized to the values the same network would have in the hypothesis of a fully random distribution of links: $\mu = \frac{C/l}{C_{rand}/l_{rand}}$;
- *efficiency* (at a global E_{glob} or local E_{loc} level): a measure of the capability of the networked system (global) or of a single node (local) to exchange information. $E_{glob} = \frac{1}{n(n-1)}\sum_{i \neq j}\frac{1}{d_{ij}}$. $E_{loc,i} = \frac{1}{k_i(k_i - 1)}\sum_{l \neq m}\frac{1}{d'_{lm}}$; for the whole network its average (called local efficiency of the network) is: $E_{loc} = \frac{1}{n}\sum_i E_{loc,i}$;
- *assortative mixing coefficient*: gauges the correlation between the degrees of neighboring nodes. If positive, the networks are said to be assortative (disassortative otherwise). In an assortative network, well-connected elements (having high degrees) tend to be linked to each other. It is calculated as a Pearson correlation coefficient; dg_i is the degree of node *i*, dn_i the mean degree of its first neighbors: $r = \frac{\sum_i (dg_i - \overline{dg})(dn_i - \overline{dn})}{\sqrt{\sum_i (dg_i - \overline{dg})^2 \sum_i (dn_i - \overline{dn})^2}}$; the standard error can be calculated by using the bootstrap method (Efron & Tibshirani, 1993).

One important factor, found to be a strong characterizer of a network topology is the distribution of the degrees of its nodes. This is usually expressed as a statistical probability distribution *P(k)*, i.e. for each degree present in the network, the fraction of nodes having that degree is calculated. The empirical distribution is then plotted and fit to find a functional (continuous) relationship. A cumulative version of the degree distribution *P(>k)* is also used. It gives the probability (fraction) of nodes having degree greater than a certain value (from the list of the values existing in the network).

A complex network exhibits, in many cases, some form of substructure. Local subgroups can have a 'thickening' of within-group connections while having less dense linkages with nodes outside the group (see Figure 2). The study of this modular structure of *communities* has attracted academic attention, since communities are a common trait of many real networked systems and may be central for the understanding of their organization and evolution. It may be possible, for example, to reveal social structure through communication patterns within a community.

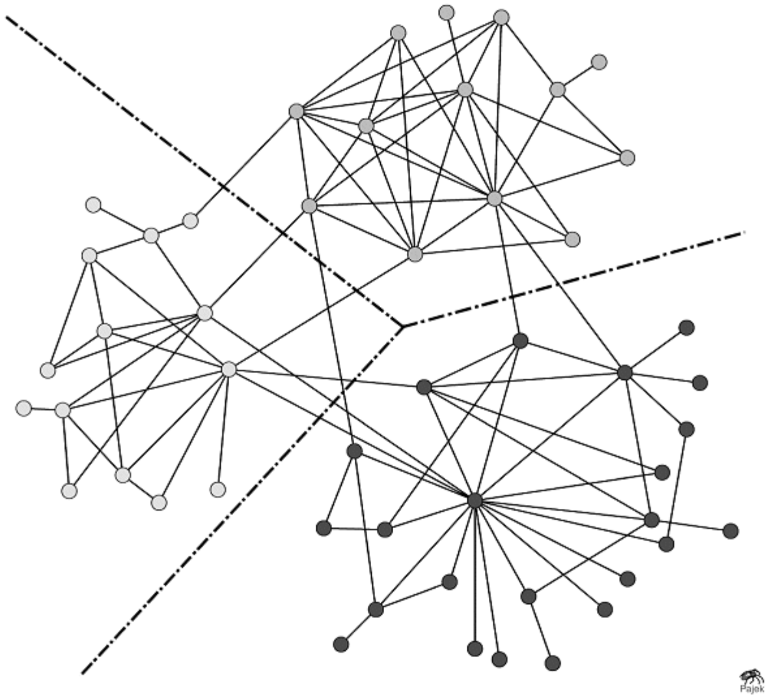

Figure 2 A modular network with a strong modularity (modularity index = 0.57). Dotted lines mark the three communities characterized by having a denser set of links inside them than towards other components of the network

Different definitions of modularity exist and several methods have been proposed to measure it. They rely on numerical algorithms able to identify some topological similarity in the local patterns of linking (Arenas et al., 2004; Danon et al., 2005). In all of them, however, a measure called the *modularity index* is used to gauge the effectiveness of the outcomes (Clauset et al., 2004; Girvan & Newman, 2002). It is defined as: $Q = \sum_i (e_{ii} - a_i)^2$, where e_{ii} is the fraction of edges in the network between any two vertices in the subgroup i, and a_i the total fraction of edges with one vertex in the group. In other words, Q is the fraction of all edges that lie within a community minus the expected value of the same quantity in a graph in which the nodes have the same degrees but edges are placed at random. All of the metrics described in this section can be calculated with the help of standard software packages such as as Pajek (Batagelj & Mrvar, 2007) or Ucinet (Borgatti et al., 1992).

Network models

After Euler (1736), probably the most important advancement in the study of networks is the work done by Erdös and Rényi. In a series of papers (Erdös & Rényi, 1959, 1960, 1961) they propose a model (ER model) in which a network is composed of a set of nodes and the links are placed randomly between pairs of nodes with probability p. The resulting degree distribution (in the limit of large numbers of nodes and links) follows a Poisson law with a peak $\langle k \rangle$ (the average degree of the network): $P(k) \approx \frac{\langle k \rangle^k}{k!} e^{-\langle k \rangle}$.

Diameter, clustering coefficient and average path length of an ER network are proportional to the number of nodes and the probability p. The network also shows an interesting behavior when the connection probability increases. Over a certain critical threshold p_c, a very large group of connected nodes encompassing most if not all of the nodes (depending on the value of $p>p_c$), a giant cluster, forms. Below p_c the network is composed of several disconnected subgraphs.

In the late 1990s, three influential papers (Barabási & Albert, 1999; Faloutsos et al., 1999; Watts & Strogatz, 1998) presented empirical evidence of networks exhibiting topological characteristics different from those hypothesized by Erdös and Rényi. Watts and Strogatz (1998) discussed networks in which, contrary to what was expected from an ER model, the clustering coefficient was much higher, and, at the same time, the average path length remained small. Reminding them of the Milgram experiment (Milgram, 1967), they named these networks small-world (SW). In a small-world network, and as happens in many social networks, any two nodes are likely to be connected through a very short sequence of intermediate neighbors. Many examples of real world networks have this characteristic (da Fontoura Costa et al., 2008).

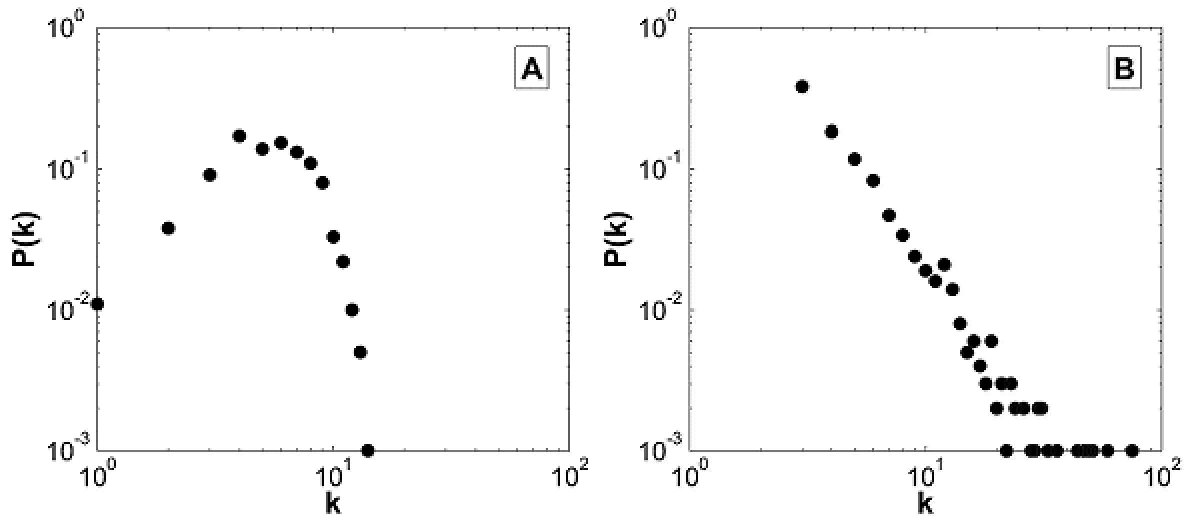

Figure 3 Degree distributions: Poissonian (A) and Power-law (B). The distributions refer to networks of the same order (1000 nodes) and size (3000 links) and are drawn on a chart with logarithmic axes. While the Poisson distribution shows a characteristic curved shape, the power-law distribution is a straight line

Faloutsos et al. (1999) and Barabási and Albert (1999), on the other hand, found evidence of networks having a degree distribution quite different from the random Poissonian ER distribution. Their networks exhibit a power-law scaling: $P(k) \sim k^{-\gamma}$ with an exponent $\gamma > 1$. In other words, in their networks, a small fraction of nodes have a large number of immediate neighbors (they are often called hubs), while a large number of nodes have a low degree (see Figure 3).

These networks are called *scale-free* (SF) because they do not have a distinctive 'scale'; a typical number of connections per node as is found in a Poissonian ER network in which the average (mean) degree characterizes the distribution. The SF model, first proposed by Barabási and Albert (1999), is a dynamic model. The power-law degree distribution is obtained if we consider a network as formed by adding nodes at successive time intervals, and adding links with a preferential attachment mechanism. A new node will connect with higher probability nodes with high degrees. This kind of rich-get-richer phenomenon has been observed in a large number of real networks, and has had several additions and modifications to account for the differences measured between the theoretical model and the real networks.

Thus, we can modify the basic model by thinking of introducing a fitness parameter, which greatly increases the probability that a newly added node has to be selected by the subsequent nodes; an aging limitation for which a node's capability to accept connections ends at a certain time interval (age); or an information constraint which puts a limit to the number of nodes among which a newcomer can select those to connect. Moreover, even in networks not growing by the addition of nodes, links can be added, deleted or moved (rewired) to adapt the network to specific conditions, and, thus besides the preferential attachment family, other mechanisms able to generate a power-law degree distribution exist (Albert & Barabási, 2002; Bornholdt & Schuster, 2002; Caldarelli, 2007; Dorogovtsev & Mendes, 2003; Durrett, 2006; Li et al., 2005; Newman, 2003b).Mixed topologies have also been studied, both as abstract models (Mossa et al., 2002) and empirical observations (Baggio et al., 2007; Pennock et al., 2002). The main characteristic of these networks is that they have a degree distribution which follows a power law for most part, but also has a bending or cut-off point. In statistical physics, power laws are associated with phase transitions (Landau & Lifshitz, 1980; Langton, 1990) or with fractal and self-similarity characteristics (Komulainen, 2004). They also play a significant role for the description of those critical states between a chaotic and a completely ordered one, a condition known as self-organized criticality (Bak, 1996; Bak et al., 1988). In other words finding a power law is one more confirmation of the 'complexity' of the networked systems studied.

As previously noted, many real networks exhibit scale-free properties. Tourism-related examples include the world-wide airport network (Guimerà & Amaral, 2004), the websites of a tourism destination (Baggio, 2007), the structural properties of interorganisational networks within destinations (Scott, Cooper, & Baggio, 2008), the paths followed by tourists reaching a destination by car (Shih, 2006), or the world-wide flows of tourist arrivals (Miguéns & Mendes, 2008). Many of these networks also exhibit small-world properties.

The wide variety of network models and empirical cases can be summarized following the classification proposed by Amaral et al. (2000). These authors use the degree distribution *P(k)* to identify three broad classes of networks:

- *single-scale*: the degree distribution behaves exponentially (or with Gaussian or Poissonian tails). Members of this class are the random ER graphs and small-world networks. The latter, even if characterized by large clustering coefficients and short average path lengths still exhibit a Poissonian degree distribution;
- *scale-free*: the dynamic networks unveiled by Barabási with a power-law degree distribution. They are characterized by having few nodes acting as very connected hubs and a large number of low degree nodes. No characteristic mean nodal degree (scale) exists. These networks grow with the addition of new nodes and new links that follow specific mechanisms such as the preferential attachment in which a new node has a higher probability to attach to one of the most connected ones. This is the case of the tourism web network analyzed by Baggio (2007) and the Australian destinations studied by Scott, Cooper and Baggio (2008b);
- *broad-scale*: a large class of networks with mixed types of degree distributions. Most of these have a basic power-law shape with a sharp cut-off of the low degree tail (exponential or Gaussian decay). Examples are the airport networks of China (Li & Cai, 2004) or India (Bagler, 2008) or the flows of tourists across countries (Miguéns & Mendes, 2008).

Besides the general depiction of the structural characteristics of the diverse networked systems presented, and beyond the different models and interpretations proposed, the literature on complex networks almost unanimously points out the strong relationship between the topological structure and the functioning of the system described.

Dynamic processes

A complex system is a dynamic entity. Economies, companies or tourism destinations can be thought of as living organisms existing in a state quite far from a static equilibrium. The only time in which they are in a full static equilibrium is when they are dead (Jantsch, 1980; Ulgiati & Bianciardi, 1997; Weekes, 1995). In the literature, the growing interest in development of models for a tourism destination (Butler, 2005a, 2005b), or the numerous methods devised to forecast some characteristic such as tourist demand (Song & Li, 2008; Uysal & Crompton, 1985; Witt & Witt, 1995, 2000) are good testimonials of the dynamic nature of these systems and the appeal of the study of these characteristics.

As discussed above, analysis of the topological properties of complex networks has provided interesting and useful outcomes as well as intriguing from a theoretical point of view. It is no surprise then to find that this area has received even a greater attention. Growth processes have been studied for all the basic network types discussed in the previous section: the random (ER) graphs and the different types of scale-free networks. In this section we describe two dynamic processes which may occur to and in a network that have a great importance for a tourism destination, our unit of analysis.

The first characteristic, verified in many real-world systems, is their resilience, i.e. “the capacity of a system to absorb disturbance and reorganize so as to still retain essentially the same function, structure, identity, and feedbacks” (Walker et al., 2004: 2). In a complex network this can be assessed by looking at how its structural characteristics change when links or nodes are removed from the network. Several numerical simulations have shown that the behavior of a complex network ‘under attack’ is strongly dependent upon its basic topology (Albert et al., 2000; Boccaletti et al., 2006; Crucitti et al., 2004). If we use, for example, the efficiency of a network as a metric to compare different conditions, we find a situation like the one depicted in Figure 4.

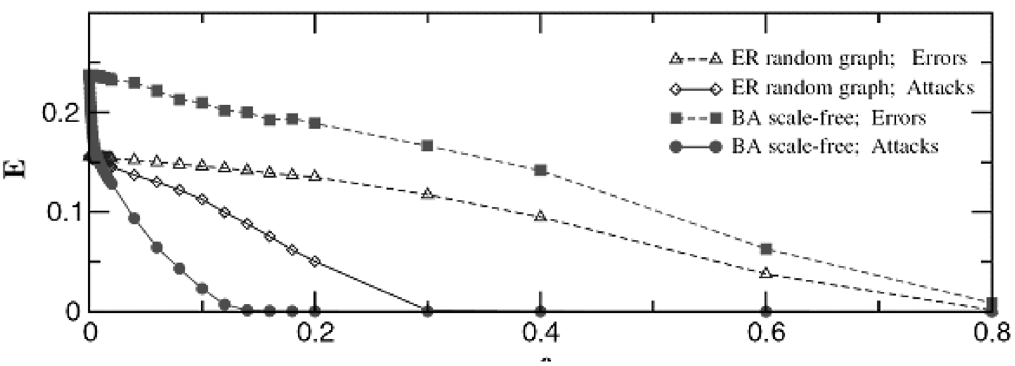

Figure 4 Effects of random (errors) and targeted removals (attacks) for random (ER) and scale-free (BA) networks (f is the fraction removed) on the efficiency (E) of the system (adapted from Boccaletti et al., 2006). The BA network shows a better capacity to absorb random removals than an ER network, but is much more sensitive to targeted attacks to the high degree nodes

In the case of a purely random removal, a SF network’s efficiency decreases at a much lower rate than an ER network. The scale-free topology adds robustness to the system. When the high degree nodes are targeted, the attack proves to be much more disruptive if the attack is directed toward the hubs of an SF network. Removing just a small fraction of these (less than 15%) can completely destroy the connectivity and leave the system as a set of isolated islands. Models based on this type of analysis could explain the resilient behavior of tourism systems after suffering major shocks such as the 9/11 attacks on the USA (see also Baggio, 2008).

One of the advantages of being able to represent a system with a 'mathematical' object is that it is easier to perform a simulation of some kind of process. A simulation can be a powerful tool to create different scenarios and the numerical methods invented so far have been transformed into computer programs and used in a wide number of disciplines. For systems such as social groups, this technique is, in many cases, the only one available to perform experiments and to study different settings (Axelrod, 2006; Gilbert, 1999; Inbar & Stoll, 1972). Obviously, as the most important literature (e.g. Balci, 2003; Gilbert, 1999; Stauffer, 2003) on the subject reports, when a social system is involved some precautions must be taken. In order to ensure the reliability and validity of the results, some conditions must be met: a strong conceptual model is the most important prerequisite, along with the credibility which may derive from the specific techniques used and the comparison with possibly available analytical results or real responses of the system (Adrion et al., 1982; Balci, 2003). If this happens, numerical simulations of socio-economic systems can provide very effective tools to support management practices different from the usual, and make feasible that adaptive approach advocated by those convinced that a tourism destination is a complex, and sometimes even chaotic, system and that should be dealt with in a non-deterministic way (Farrell & Twining-Ward, 2004; Faulkner & Russell, 1997; Russell, 2006).

The diffusion of information or knowledge is a crucial process for the balanced development of a destination and the determinants which may favor this process are of paramount importance (Argote et al., 1990; Cooper, 2006; Cooper & Scott, 2005). The network effects on this process are well known (Valente, 1995; Wendt & Westarp, 2000), but the possibility of a numerical simulation in the framework of network science can be of great theoretical and practical value.

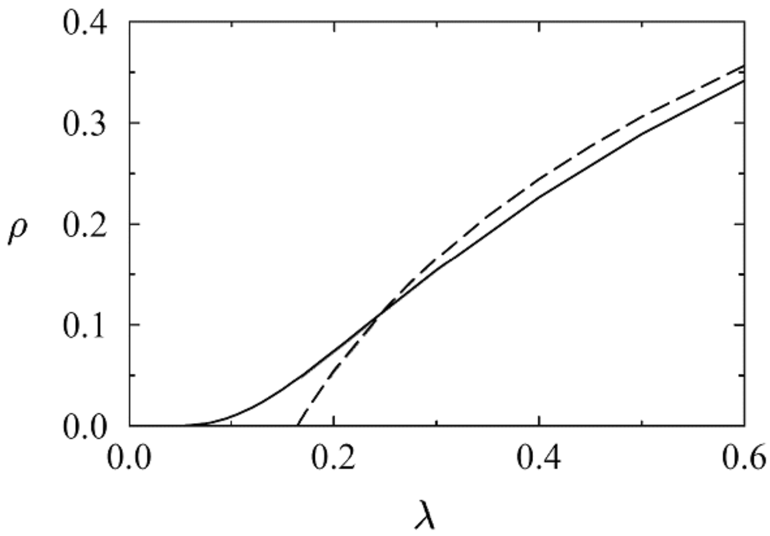

Figure 5 Fraction of infected individuals (ρ) as a function of spreading rate (λ) for a SF network (solid line) compared to an ER network (dotted line) (after Pastor-Satorras & Vespignani, 2003). In an ER network the presence of a threshold for initiating the diffusion is evident while an SF network is lacking a critical onset of the epidemic

Let us consider the diffusion of a message in a network and observe the influence of the network topology. Epidemiological diffusion is a well-known phenomenon for which complete mathematical models have been devised (Hethcote, 2000). It has been known since the work of Kermack and McKendrick (1927) that the process shows a clearly defined threshold condition for the spread of an infection. This threshold depends on the density of the connections between the different elements of the network. However, this condition is valid only if the link distribution is random (as in an ER network). In some of the structured, non-homogeneous networks that make up the majority of real systems (e.g. SF networks), this threshold does not exist (see Figure 5). Once initiated, the diffusion process unfolds over the whole network (Pastor-Satorras & Vespignani, 2003).

Methodological issues

There are two key issues to be considered in progressing network science and the study of tourism. The first of these is the epistemological legitimacy of applying the laws and methods of physics to a social activity such as tourism. The second relates to the practicalities of collecting data pertaining to a network.

Epistemology

Applying the laws and methods of physics to a socio-economic system such as a tourism destination may raise an issue of epistemological legitimacy and is an area where there is little relevant prior literature. While a variety of works deal with these questions for both natural and social sciences, and examine the attitudes and positions of researchers with regard to their approaches and methodologies (Durlauf, 1999; van Gigch, 2002a, 2002b), the specific problem of the applicability of a ‘physical’ approach to social systems is discussed very little and mostly only as a secondary topic. Physicists do not seem to feel the necessity to epistemologically justify their use of the knowledge and tools of physics in investigating other fields. Justifications and discussions are the job of the epistemologist and usually come very late in the development of a field of study. Certainly justifications are not considered necessary when, as in the case of network science, a discipline is still in a very early stage of development.

From a sociologist’s perspective however, the application of physical network theory may be rejected as irrelevant because it fails to address the recursive agency in the behavior of groups of people. Recursive agency refers to the ability of individuals to recognize their networked relationships and take proactive steps to change or modify their behavior. Thus, the applicability of ‘physical laws’ governing human behavior is refused as non applicable. One of the reasons for this refusal can be that a non-physicist has, sometimes, a mistaken idea of what physics is. Bernstein et al. (2000), for example, consider that sociologists mistakenly believe the ideas of physics are mainly those of Newtonian mechanics where single or small sets of particles are studied. Such particles have well defined characteristics (mass, velocity, energy) and, more importantly, their equations of motion can be described and investigated. Based on this idea, sociologists consequently object that a ‘social actor’ is completely different from these homogeneous particles, as a social actor’s behavior is influenced by their personal history, beliefs and personality and thus a system of particles is too simplistic a representation.

However, physicists may have different aims from achieving such individual predictive outcomes. For example in studying a socio-economic system we may be focused on its global behavior and in the possibility of making predictions at a system level rather than seeking to predict the conduct of single elements (individual actors). This alternative aim seeks to understand how regularities may emerge (when they do) out of the apparently erratic behavior of single individuals (Majorana, 1942). In this perspective, a comparison of theoretical predictions with empirical data has the primary objective of verifying whether the trends seen in the data are compatible with a ‘reasonable’ conceptual modeling of the idealized actors and whether there is some level of consistency or additional factors are required to provide an explanation.

In these circumstances, as Castellano et al. (2007) note, only high level characteristics, such as symmetries, energy balance, or conservation laws are relevant. These, as the findings of statistical physics show, do not depend on the individual details of the system but possess some universal characteristics. Thus if the aim is to examine such global properties, it is possible to “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” (Castellano et al., 2007: 2). These considerations lead us to justify the application of the laws and methods of statistical physics to the study of a socio-economic system such as a tourism destination, with the condition that the quantitative techniques rely on sound and accepted qualitative interpretations of the phenomena as described in this paper.

The vast theoretical and empirical literature accumulated in recent years has shown network science to be an effective tool for understanding complex systems. The empirical study described in this paper gives us an example of the application of network analysis methods to a tourism destination.

Data collection

On many occasions full enumeration of data regarding a network (nodes and links) is not possible. This is especially true for social and economic systems, and is certainly the case for a tourism destination. It is possible to use sampling to study complex networks but this requires careful application. As long as we are considering a system in which the elements are placed at random, as in the case of an ER network, ‘standard’ statistical considerations can be made, and the significance of the sample assessed with standard methods (Cochran, 1977). We have seen, however, in the previous section, that the effects of removing links or nodes from a non-homogeneous system such as an SF network can lead to dissimilar results and is ‘element dependent’. We may easily imagine, then, that a sample of a network missing some critical hubs could lead us to wrong conclusions when examining its topology.

The literature on the subject is not extensive. The problem has been highlighted only as a consequence of recent discoveries in the field. It has been found that in the case of a structured network (scale-free, for example) it is not possible to easily determine the significance of a sample collected. Depending on the results of the analysis of the data available, the researcher needs to judge and make an educated guess of the final topology exhibited by the whole ‘population’, i.e. the whole network. In the cases in which this is possible, then, what can be done is to know how some of the main network metrics vary with the size of the sample and the topology of the network.

More ‘quantitatively’, according to the literature, in the case of a SF network, degree distribution exponent and average path length decrease when nodes or links are sampled, assortativity coefficient has little or no change and the clustering coefficient decreases when nodes are sampled while increases when links are sampled (Kossinets, 2006; Lee et al., 2006; Stumpf & Wiuf, 2005).

A case study: a tourism destination

The network analysis methods described in the previous sections are applied here to a specific case, an Italian tourism destination: the island of Elba which is located in the centre of the Tyrrhenian Sea and is a typical ‘sun and sand’ destination. Elba’s economy depends mainly on the wealth generated by about half a million tourists spending some 3 million nights per year. Elba was selected for study as it is geographically distinct, has accessible records concerning tourism actors and with a scale suitable for detailed examination. The core tourism organizations (hotels, travel agencies, associations, public bodies etc.), identified from the official local tourism board, form the nodes of the network. The connections among them were enumerated by consulting publicly available documents such as membership lists for associations and consortia, commercial publications, ownership and board of directors records. The data obtained and the completeness were validated with a series of structured and unstructured interviews with a selected sample of local ‘knowledgeable informants’ such as the directors of the local tourism board and of the main industrial associations, or consultants active in the area. These interviews revealed a very limited number of links that were not previously discovered and it seems reasonable to assume that the final layout has a completeness of about 90%. All the links are considered undirected and of equal weight. The network thus obtained is depicted in Figure 6.

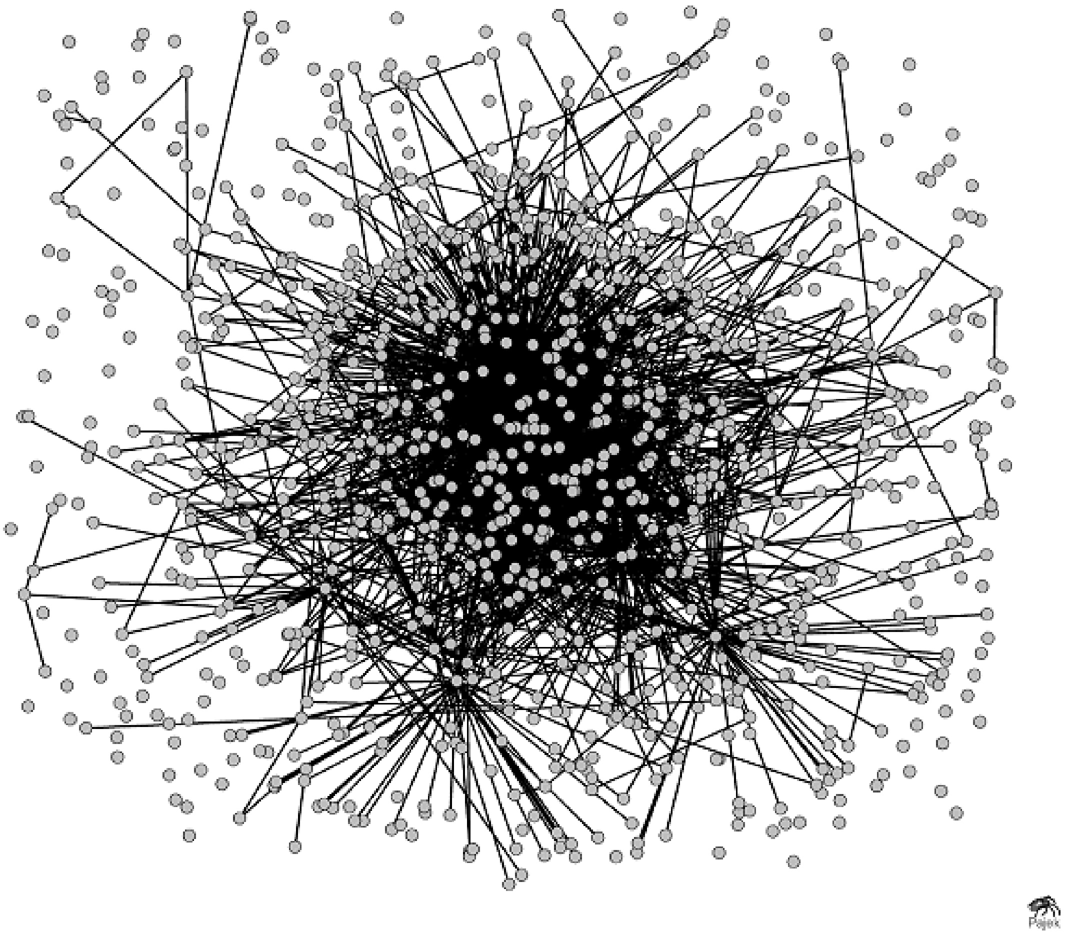

Figure 6 The Elba destination network

The metrics calculated for this network are summarized in Table 1. As a comparison the second column contains the values calculated for a random (ER) network of the same order and size (the values are averages over 10 realizations). The last column of Table 1 reports typical values for social networks published in the literature (see for example Albert & Barabási, 2002; Boccaletti et al., 2006; Dorogovtsev & Mendes, 2002; Newman, 2003b).

The degree distributions (differential and cumulative) for the network are shown in Figure 7. The shape of the distribution follows a power law $P(k) \sim k^{-\alpha}$. The exponent (and its standard error), calculated following the procedure proposed by Clauset et al. (2007) is $\alpha = 2.32 \pm 0.27$.

Table 1 Elba destination network metrics compared with a random network of the same order and size and with typical values for social networks

Metric	Elba network	Random	Social networks
No. of nodes	1028	1028	
No. of links	1642	1642	
Density	0.003	0.003	10^{-1} - 10^{-2}
Disconnected nodes	37%	3%	
Diameter	8	13	10
Average path length	3.16	5.86	10
Clustering coefficient	0.050	0.003	10^{-1}
Proximity ratio	34.09	N/A	10^{2} - 10^{3}
Average degree	3.19	3.25	
Global efficiency	0.131	0.169	10^{-1}
Local efficiency	0.062	0.003	10^{-1}
Assortativity coefficient	-0.164±0.022	0.031±0.033	10^{-1} (>0)

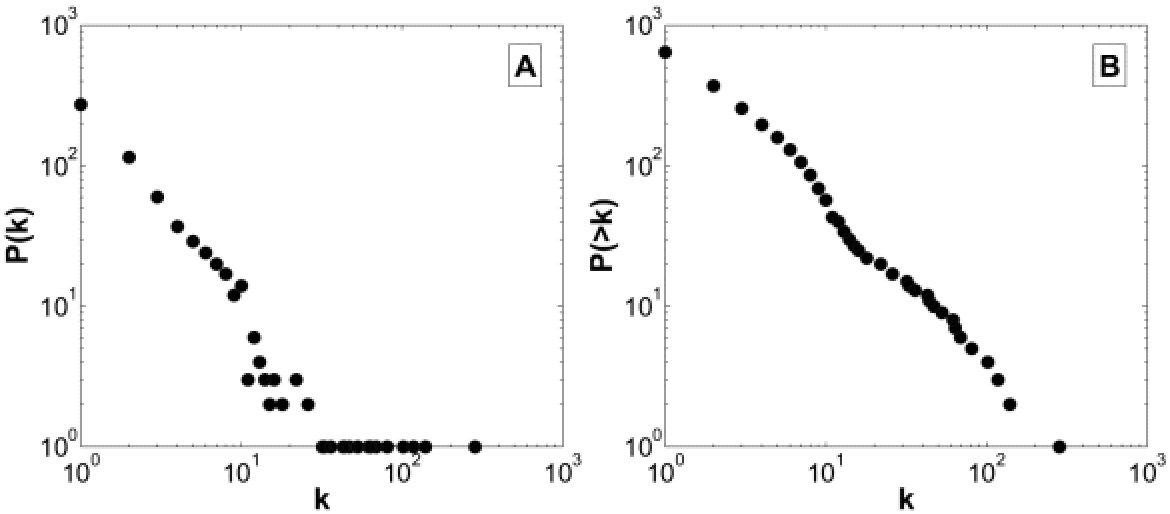

Figure 7 The degree distributions of Elba destination network. P is the frequency of nodes having degree k (A) or greater than k (B, the cumulative distribution)

The density of links is quite low, considering that the values found in the literature for the social networks studied are typically of the order of 10^{-1} – 10^{-2} (Albert & Barabási, 2002; Boccaletti et al., 2006; Caldarelli, 2007). Moreover, the percentage of nodes without connections is very high (39%). This results in a sparse network, also confirmed by the small value of the clustering coefficient. The efficiency of the Elban network is consequently quite low, both at a global and a local level. Another value which is different from what would have been expected in considering a socio-economic network such as Elba is the assortativity coefficient. This, as seen in section 3, represents the tendency of a node to connect with nodes having similar degrees. The correlation has been found positive for many of the social networks examined by the literature (Newman, 2002), and, while debated by some authors (Whitney & Alderson, 2006), this positivity is generally considered to be a distinguishing characteristic of social networks with respect to other systems. On the other hand, the calculated values for diameter and average path length seem to be in line with those of other real social systems and sensibly smaller than those exhibited by a random network, indicating a certain level of compactness of the Elban network, at least for its central connected core.

This is also confirmed by the proximity ratio which indicates a good level of 'small-worldness' of the network.

The modularity of the network was calculated (Table 2) by dividing its actors with respect to the type of business (hospitality, associations, food and beverage services etc.) and geographical location (Elba's municipalities). As a comparison, the modularity was investigated by using the algorithm by Clauset et al. (2004) which partitions the network on the basis of its connectivity characteristics, without supposing any division in advance (CNM in Table 2).

Table 2 Elba network modularity analysis

Grouping	No. of groups	Modularity	Average Modularity
Geography	9	0.047	0.0052
Type	8	-0.255	-0.0319
CNM	11	0.396	0.0360
CNM (random)	23	0.606	0.0263

Table 2 shows the number of clusters identified (groups) and the modularity index. The last row reports the values calculated (CNM) for a network of the same order as the Elba network with a random distribution of links (values are averages over 10 iterations). To better compare the different results, the last column of the table contains the average modularity over the groups (modularity/number of groups). All groups have a very low modularity. In one case (grouping by type), the negative value indicates that the actors tend to have more connections outside the group to which they belong than with businesses within the group. The higher values found by the CNM algorithm confirm that division by geography or by type of business does not imply any strong of clusterisation in these groups. In other words no well definite business-type or geographical groupings can be found in the destination. The values obtained for the random network are a further confirmation of the very low degree of modularity of the Elba network.

The topological analogy: an example (real and virtual)

As a further example of the outcomes of the application of network science to a system such as the Elban tourism network, let us consider the virtual network among Elban tourism companies. The websites belonging to the tourism stakeholders were identified (only 'full' websites, with their own address were considered, discarding sets of pages embedded in the portals of other organizations) and the network (WN) was built by listing all the hyperlinks among them. This was accomplished by using a simple crawler and complementing the data obtained with a 'manual' count of the hyperlinks to overcome the limitations of the program used (such as, for example, the impossibility of finding hyperlinks embedded in Flash applications or Java applets) (Baggio, 2007). Table 3 shows the topological characteristics of the WN network compared with those of the 'real' network (TN) described in the previous section.

As can be seen, apart from scale factors, most of the values have differences which are lower than an order of magnitude. Since in a complex network the distributions of these metrics are not normal, a simple comparison of their averages (arithmetic means) is an insufficient way of establishing similarities or dissimilarities. In these cases, as already proposed by some researchers (Clauset et al., 2007; Leskovec & Faloutsos, 2006), the Kolmogorov-Smirnov (KS) statistic is considered able to provide trustworthy results. The KS D-statistic gives the maximum distance between the cumulative probability distributions of empirical data *F(x)* and *G(x)* over the entire *x* range: $D = \max_x \left| F(x) - G(x) \right|$. The statistic is nonparametric and as it is insensitive to scaling issues, it compares only the shapes of the empirical distributions (Siegel & Castellan, 1988).

Table 3 Topological characteristics of the real (TN) and the virtual (WN) Elban networks

Metric	TN	WN
Number of nodes	1028	468
Number of edges	1642	495
Density	0.003	0.005
Disconnected nodes	37%	21%
Diameter	8	10
Average path length	3.16	3.70
Clustering coefficient	0.050	0.014
Degree distribution exponent	2.32	2.17
Proximity ratio	34.10	12.21
Average degree	3.19	2.12
Global efficiency	0.131	0.170
Local efficiency	0.062	0.015
Assortativity coefficient	-0.164	-0.167

The values for the D-statistics calculated when comparing the distributions of the Web network with those of the real network are the following: degree = 0.119; clustering coefficient = 0.147; local efficiency = 0.125. For comparison, the same values have been calculated for a random sample (RN) of the same size as WN, extracted from the real one. The values (averages over 10 realizations) are: degree = 0.147; clustering coefficient = 0.178; local efficiency = 0.184. The consistently lower values of the D-statistic in the case of the web network (with respect to the random sample) can be considered a good confirmation of the likeness of their structural characteristics.

A strand of literature considers virtual networks as representations of the social relationships among the actors originating them. In essence: “computer networks are inherently social networks, linking people, organizations, and knowledge” (Wellman, 2001: 2031). Even if some argue that that the links are created in a rather unpredictable way, and it is not possible to find unambiguous meanings (Thelwall, 2006), private or public organizations and companies consider an hyperlink as a strategic resource, and the structure of this network is created by specific communicative aims, rather than by accidental choices (Park & Thelwall, 2003; Vaughan et al., 2006).

Based on these considerations and the network analysis, it is possible to formulate the following conjecture: *the network of websites belonging to a cluster of (tourism) companies is a reliable sample of the whole socio-economic network formed by them.* The obvious limitation is that the area taken into account must show a significant diffusion of the Internet and the Web. Yet nowadays this, for a large part of the World, is not a severe limitation.

Rather than more or less ‘randomly’ sampling a socio-economic network with the usual investigation methods (Marsden, 1990), the Web provides us with a relatively fast, easy and objective way of sketching the main characteristics of such networks. The literature has produced much evidence on the issue of network sampling and the effect it might have on the topological characteristics of the whole network (Kossinets, 2006; Lee et al., 2006). This must be taken into account in deriving the insights that network analysis methods can provide.

Dynamic processes

Through their mathematical representation, networked systems are excellent candidates for numerical simulations. Indeed simulation is receiving increased attention as a powerful method to support complex analysis and planning activities for social and economic systems. Information and knowledge flows in a destination are important factors for the general 'well-being' of the system. and the manner in which the diffusion unfolds influences the competitive advantage of individual actors and their planning of future actions. Productivity, innovation and economic growth, in fact, are strongly influenced by these processes, and the way in which the spread occurs can determine the speed by which individual actors perform and plan their future actions at the destination. In other words the structure of the network will be influential in determining the efficiency of the destination's attempts to share knowledge and innovate (Argote & Ingram, 2000).

A computer simulation can help assess the efficiency of information flows across the destination and testing the capability of the system to react to some changes of its structural parameters. A simple epidemiological model can be employed. In this, nodes are either 'susceptible' to receiving information or already 'infected' by it (i.e. they have received it). Despite its simplicity, this model is a reliable approximation (see for example Barthélemy et al., 2005; Xu et al., 2007), and quite suitable to describe a knowledge transfer process. The simulation was conducted as follows: within a network, one randomly chosen stakeholder starts the spread by infecting a fraction k_i of its immediate neighbors. At each subsequent time step, each infected element does the same until all the network nodes have been infected and the process ends. In this study the model was run by adopting two different configurations. In the first case, the capacity of a stakeholder to transfer knowledge (spread infection) is used as a parameter for the model. It is defined as a probability $p(k_i)$ which determines the number of neighbors infected by a single actor. This justifies an important difference between the diffusion of information and knowledge and the spread of viruses. Viruses are indiscriminate, infecting any susceptible individual. Knowledge, on the other hand, is transferred only to a limited set of the individuals with which an actor has interactions (Huberman & Adamic, 2004).

Particular actors, then, can have different 'absorptive capacities' (Cohen & Levinthal, 1990; Priestley & Samaddar, 2007), i.e. different capabilities to acquire and retain the knowledge available to them due to the associated costs or their internal functioning, and to transfer it to other actors. In tourism, this issue is crucial for the high prevalence of small businesses that typically rely on external contacts for information. In the reasonable assumption that $p(k_i)$ depends on the size of the stakeholder, the network nodes were divided into three classes: large, medium and small (in our case we have the following proportions: large = 8%, medium = 17%, small = 75%). The values for $p(k_i)$ used in the simulations run are (arbitrarily) set as: $p(k_{large}) = 1$, $p(k_{medium}) = 0.8$, and $p(k_{small}) = 0.6$.

The second type of simulation aims at testing the influence of a network's structure, and particularly how the cohesion among stakeholders can affect the knowledge transfer process. In this case the experiment was performed with a modified version of the original network obtained by rewiring the connections while leaving unchanged the original connectivity (i.e. the number of immediate neighbors of each stakeholder and overall density of linkages), in order to obtain a higher clustering coefficient and a higher efficiency. The algorithm used is similar to the one proposed by Maslov and Sneppen (2002). The new network has a clustering coefficient $C = 0.274$ and a mean local efficiency $E_{loc} = 0.334$, as opposed to the original one whose values are $C = 0.084$ and $E_{loc} = 0.104$ (only the fully connected component of the Elba network was used, i.e. all isolated nodes were removed). As a comparison, a random network (same order and density, and random distribution of edges) was used. The time of peak diffusion, which can be used as an indicator of the process efficiency, decreases by 16% when comparing the random network with the Elba network containing different actors' capabilities. This, as expected, is due to the non-homogeneity of the network. When changing to equal capabilities (the original Elba network) a 22% reduction in the time of peak diffusion is found. A further consistent decrease (52%) is found when the local densities (clustering) are increased. Figure 8 shows the cumulative number (as a percentage of total) of stakeholders that are 'infected' as function of time for the different simulations preformed.

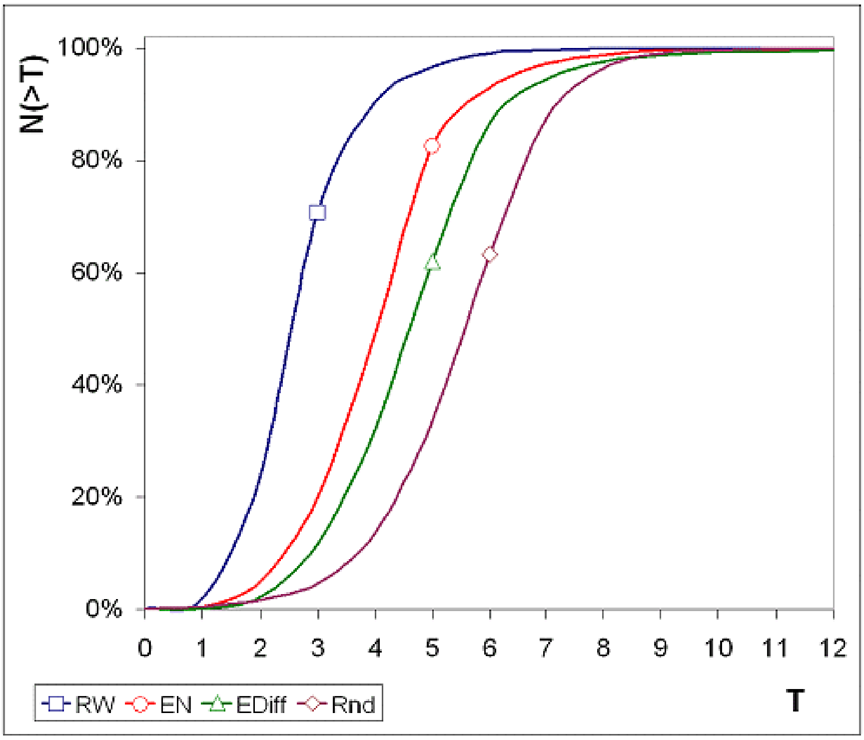

Figure 8 Cumulative percentage of informed stakeholders for the simulations performed: rewired network (RW), Elba network with equal probability of transmission (EN), with probabilities scaled according to stakeholder size (EDiff) and a network of same size with a random distribution of links (Rnd). Curves are averaged over 10 realizations of the simulations.

The interventions made therefore have a significant impact on the information diffusion process. In other words: the spread of knowledge is faster if the network's connections are not distributed at random (scale-free in our case), it improves if all the stakeholders have equal absorptive capacities (the maximum) and is even more enhanced when the extent of formation of local groupings (collaborative communities) increases.

Discussion

The Elba tourism destination network has been characterized as a complex network whose main traits are common to many other natural and artificial systems. Its scale-freeness has been assessed. Despite this similarity, the structure differs from those exhibited by other complex systems mainly in its high sparseness and a very low degree of local clustering. In 'tourism' terms this means that the local stakeholders exhibit a very low degree of collaboration or cooperation. A quantitative measurement for this feature is naturally derived from the metrics used for the network analysis. In particular, as argued elsewhere (Baggio, 2007), the clustering coefficient (very low in this case) can be used as a measure of the extent of the degree of collaboration and the assortativity coefficient (very low and negative) can be thought of as representing the tendency to form such collaborative groups. The qualitative knowledge of the destination (Pechlaner et al., 2003; Tallinucci & Testa, 2006) and the data gathered during the interviews conducted at the destination substantiate the interpretation given. This apparent lack of collaboration among operators belonging to the same type has proved to be detrimental when thinking about the capacity of innovation which might help them face the challenges of the contemporary highly competitive and globalized market. It has been shown, in fact, that a collaborative approach and intense exchanges, even in seemingly competitive organizations such as the group of Sydney hotels described by Ingram and Roberts (2000), may allow a valuable amalgamation of best practices, with the result of improving the performance and profitability of the whole group and its members. The low level of modularity unveiled further confirms this reading. It is interesting to note, in the results of the analysis, that the highest modularity value is obtained with the usage of a 'generic' numeric algorithm (Clauset et al., 2004). This community structure, in the common understanding of the phenomenon (Arenas et al., 2004), can be considered better than those which can be found based on the other criteria used: type of business and geographical location within the destination.

Moreover both the number and the composition of the clusters identified are different (Table 2). The system, in other words, exhibits self-organization properties which lead to the formation, to some extent, of an agglomeration of ties and produces a number of informal communities and an informal community structure. It can be concluded that the information contained in the geographical or business typology data does not fully represent the communality characteristics, and the modularity solutions found in this way are non optimal. This evidence has been also found in other social networks (Minerba et al., 2008).

From a destination management viewpoint, this result is important. It can provide indications on how to optimize some performance, for example, optimal communication pathways or even productivity in collaborations, overcoming rigid traditional subdivisions. It can provide a more practical tool to go along with the ideas and practices of an adaptive approach to the management of a tourism destination which has been advocated by some scholars (Farrell & Twining-Ward, 2004).

A word of caution is necessary when considering extending the considerations made on network clustering and modularity to other cases. It has been shown, for example, that significant values for the clustering coefficient can be also be accounted for by a simple random graph model (i.e. in which edges are placed at random), under the constraint of a fixed degree distribution $P(k)$. The emergence of this effect is a 'statistical fluctuation' due to the form of the degree distribution in networks with a finite number of elements (Newman, 2003a; Newman et al., 2001). A correct interpretation of the result, therefore, can only be achieved by complementing the quantitative assessment with a deep knowledge of the social system under study, which typically comes from a tradition of qualitative investigations.

The worth of the methods presented here is well demonstrated by looking at the comparison made between the real and the virtual networks of the Elban tourism stakeholders. Even with the limitations discussed previously, it has been possible to formulate a conjecture – the similarity between the topologies of the two networks – which can prove extremely useful in speeding up and easing the process of collecting data to perform network analyses for socio-economic systems such as tourism destinations.

The information diffusion process analyzed provides us with some more important results. The simulated measurements of the diffusion speed confirm, first of all, the improvement in the efficiency of the whole process due to the existence of a structured network in place of a randomly linked system. Two conceptually different situations were simulated. The first one considered the stakeholders of the destination as elements with different capabilities to acquire and consequently retransmit information or knowledge. The second one assessed the effects of a change in the topology of the network obtained by optimizing it with respect to its efficiency. The results show a clear improvement in diffusion speed when all the actors are considered to have the same capacity to transfer information or knowledge. This is an important indication for a destination manager. Putting in place measures and actions aimed at reducing the differences in the absorptive capacities of the destination stakeholders can have a highly beneficial impact on the overall system. However, the results indicate that a similar effect, but with an even higher magnitude, can be obtained by optimizing the network efficiency. The exchange of information among the nodes is much improved if the connectivity of the network is modified so as to increase the local efficiency, and consequently the clustering coefficient.

In other words, a very important determinant for the spread of knowledge in a socio-economic system such as a tourism destination is the presence of a structured topology in the network of relations that connect the different stakeholders, and more than that, the existence of a well-identified degree of local cohesion. This supports the notion that destination stakeholders should be encouraged to form clusters and to both compete and cooperate in order to exchange knowledge and hence to raise the overall competitiveness of the destination. Quantitative network methods can, therefore, not only assess this effect, but, more importantly, give practical indications on how to improve the process. By performing different simulations with different sets of initial parameters (distribution of absorptive capacities or different levels of clustering), it is possible to obtain different settings and evaluate the effects of the choice of parameters on the final result.

Conclusion

This paper has described the methods and the techniques that network science has assembled so far for the study of complex adaptive systems and as an example of their application, the case of a tourism destination has been discussed along with some implications this approach.

Taken alone, network analysis methods are undoubtedly an intriguing and intellectually stimulating exercise. Physicists know, however, that no matter how sophisticated and effective theoretical techniques can be, they have little value if applied to a phenomenon without coupling them with sound ‘physical interpretations’. Translated into the language of social science this means that a thorough knowledge of the object of analysis is crucial to obtain meaningful outcomes both from a theoretical and a practical point of view. This knowledge is the one provided by qualitative methods. As Gummesson points out: “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” (2007: 226), therefore “qualitative and quantitative, natural and social are not in conflict but they should be treated in symbiosis” (2007: 246).

In the twenty first century, the strong focus on issues such as partnership, collaboration, cooperation and the benefits of the tools available for the investigation of the relationships between the elements of a socio-economic system have been discussed several times in the area of general management studies. The implications, it is argued, go well beyond the simple study of networks. These methods are recognized to have a strong potential to inform a wide number of concerns such as the use of technology, the study of epidemiological diffusion (from diseases to marketing or policy messages), the formation of consensual opinions and the impacts of these on organizational structure and performance (Parkhe et al., 2006).

In this respect, the methods of network science can prove highly beneficial in deepening the knowledge of the whole system and, coupled with more traditional procedures, can provide powerful tools to enable those *adaptive* management practices considered by many the only practical way to steer the collective efforts of multiple organizations (Bankes, 1993; Farrell & Twining-Ward, 2004; Holling, 1978; Ritter et al., 2004).

The possibility of using quantitative techniques to analyze the relationships between tourism operators opens new paths for the researcher interested in the structure, the evolution, outcomes, effectiveness and the governance of the system. This work, therefore, strongly supports the idea that triangulation of research methods can give the clues necessary to improve the analysis of tourism systems and their components (Davies, 2003). Further research in this area will first need to confirm the results obtained so far by increasing the number of examples studied. The methods employed in this paper clearly require some additional refinement both from a practical and a theoretical point of view. Moreover, the ever growing number of studies in network science, mainly from what concerns the dynamic evolution of a complex networked system, may suggest new models and new approaches which will need careful consideration for the applicability to the tourism field. As a final point, it is a firm conviction of the authors that a more rigorous establishment and adoption of methodological tools such as those used in this work, can be a powerful way to help tourism research transition towards a less *undisciplined* array of theories and models (Echtner & Jamal, 1997; Tribe, 1997).

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