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# Complexity, Network Science & Tourism

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Innsbruck: IFITT Education Group, July 2013

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Suggested citation:
Baggio, R. (2013). *Complexity, Network Science & Tourism.* Innsbruck: IFITT Education Group. [Online at: http://www.ifitt.org/home/view/the_ifitt_eTourism_curriculum]

# 1 Introduction

*We are not students of some subject matter, but students of problems.*
*And problems may cut right across the borders of any subject matter or discipline.*
Karl Popper (1963:88)

Tourism is one of the most important economic activities in the World. The revenue generated has become a very important resource and a key factor in the balance of payment for many countries and regions and has been a major contributor to their economic growth. As a natural consequence, it has become, in the last decades, a discipline studied by a growing number of researchers, practitioners, experts and consultants. Their main objective is to describe and understand the composition and the dynamics of the sector and, based on this knowledge, to be able to foresee future behaviors of the system and its components. This is the basis for a great number of decisions, involving single operators as well as governing bodies at different levels (Hall et al., 2004).

When choosing a method for studying a phenomenon or a subject, we inevitably make assumptions on the nature of the object of study. These assumptions direct the way a scholar formulates a research question, structures theories and models, carries out empirical work and interprets empirical evidence. This is also true in the study of tourism. The task of understanding a tourism system is not easy, tourism is difficult to measure and analyze. The main reason resides in the fact that it is an "industry" with no traditional production functions, no consistently measurable outputs and no common structure or organization across countries or even within the same country (see for example OECD, 2000). The World Tourism Organization's definition of tourism as comprising (UNWTO, 1995):

> "the activities of persons travelling to and staying in places outside their usual environment for not more than one consecutive year for leisure, business and other purposes."

looks fuzzy if examined with the glasses of a scientist. Too many different elements and interpretations fall into the terms contained in the official definition of tourism. Tourism activities traverse a number of traditional economic sectors and it is a real challenge for all the official bodies in charge of *measuring* them when it comes to identifying the units to be accounted for. Moreover, this definition creates serious problems to all those seeking to model the phenomenon in order to predict its behavior.

As much authors have discussed, tourism is a fragmented industry, geographically dispersed with many small specialist businesses contributing to an overall product experience. To deal with such an environment, a number of hierarchical organizational structures have been developed to provide cohesion in planning and policy and to stimulate and coordinate destination marketing and promotion. These structures are useful in allowing government to engage with organizations in the tourism sector and in providing a measure of formal coordination especially amongst larger operators. However, as noted by many, this approach has not been able to provide fully satisfactory outcomes. In a pioneering work, Faulkner and Valerio (1995) start from the realization of the deficiencies and the unreliability of many demand prediction and forecasting methods to call for the need of more appropriate ways to explain and understand tourism phenomena. In recent years a new approach has gained momentum. Many scholars believe it able to overcome the difficulties of describing *complex* systems and to give better representations and better tools to handle the issues involved.

This approach starts with the understanding that the reductionist hypothesis born with the origin of *modern science* is limiting too much of our ability to describe the real world. The methods devised by Galileo, Newton, Laplace, and many others, can only give us a very limited power and, more importantly, are not able to return reasonable explanations for a wide number of phenomena.

In his seminal paper *More is different*, Phil Anderson states (1972: 393):

> "The workings of our mind and bodies, and of all the animate or inanimate matter of which we have any detailed knowledge, are assumed to be controlled by the same set of fundamental laws, which except under certain extreme conditions we feel we know pretty well" but "the ability to reduce everything to simple fundamental laws does not imply the ability to start from those laws and reconstruct the universe" and "at each stage entirely new laws, concepts, and generalizations are necessary, requiring inspiration and creativity to just as great a degree as in the previous one."

These ideas have contributed to set a new perspective in our view of natural phenomena, a new view which today is known as *science of complexity* (Waldrop, 1992). If we agree with this vision, then existing notions of operations and distribution channels should be revisited through a different articulation (Pearce, 2009).

Although it may look far from a practical perspective, analyzing real world phenomena, deriving models and building theories is a crucial endeavor. Only with sound theoretical frameworks, in fact, it is possible to abstract from single-case events and develop a line of thought attitude that allows caring of similar but different situations with a guarantee (for what is possible) of being able to face new conditions and to make effective decisions on how to behave. As Farrell and Twining-Ward note (2004: 276):

> "It is frequently acknowledged that tourism study is lacking in substantial theory of its own […] and has failed to capitalize on progress made in other disciplines. Consequently, as a field of study it appears isolated and research and teaching appear to have grave shortcomings attributable to its multidisciplinary history, organization, and relations with other fields that should inform the study."

The efforts directed towards the establishment of sounder and more rigorous methodological approaches to tourism research continue with the objective to assemble a reasonable set of paradigms (in the Kuhnian sense) that may raise the status of this area of study to an accepted scientific discipline. This is not an easy task and has to confront the fact, well described by Franklin and Crang (2001) that, up to now, tourism studies have produced a wealth of investigations, case studies, surveys but seem to have given up on a deeper reflection on the possible theoretical foundations of the matter. Probably, as Franklin and Crang argue, the reason may be traced to the excessive dominance exercised by policy-led and industry sponsored works that strongly push towards a restricted focus on their priorities and perspectives.

Social and economic settings such as a region, a district or a tourism destination are archetypical complex systems. This means, essentially, that in examining these systems we expect to find a number of different components (the stakeholders), of different size and functions, connected between them in many possible ways which are typically dynamic and of nonlinear nature. The overall result is a system whose behavior is almost unpredictable and unmanageable (at least in traditional terms). It can show properties which cannot be derived by simply composing the behaviors and the features of its components. In some cases it is able to resist huge external shocks (e.g. natural disasters, or financial crises) without altering too much its conditions, in some cases another similar system can be completely disrupted by the consequences of some apparently insignificant event. Some stakeholder can be catalyst for incredible socio-economic growths, while in other situations similar behaviors do not have any recognizable effects (Baggio, 2008b; Bar-Yam, 1997).

If the perspective must be changed, also the tools used to analyze or predict and to control[1] structure and behaviors of the system must be different from what used to be. As it is conceivable, analytic methods (i.e. the formulation and analytical solution of mathematical equations that describe a system and its evolution) are quite ineffective. Methods and techniques need to rely on model building and numerical simulations (such as Montecarlo methods, agent-based models, or numerical solutions of equations etc.). In this way, by testing the system's reactions to different values for the model's parameters, it is possible to build evolutionary scenarios to be studied in order to derive effective ways to govern the system (see for example section 5.2, and Bankes, 2002).

Among the many different possible modeling methodologies, one has become, in the last years, very popular and has shown its power and trustworthiness. Based on the idea that the most relevant characteristics of a system are its components and the relationships between them, a large number of scientists, have devised a set of tools, methods and theories able to analyze and model a networked system, so that a new discipline is now active: network science (Watts, 2004). The main theoretical framework in which these investigations are embedded is the set of theories known as statistical physics (or statistical mechanics). This is one of the fundamental fields of physics, and uses statistical methods for addressing physical systems composed of many elements. A wide variety of issues, with an intrinsic stochastic nature, are treated with these methods. It provides a framework for relating the microscopic properties of individual atoms and molecules to the macroscopic properties of materials observed in everyday life. Thermodynamics, and thermodynamic properties, for example, can be explained as a natural result of these methods.

The main result, and power, of this approach is in the recognition that many systems exhibit universal properties that are independent of the specific form (topology) of their constituents. This may suggest the hypothesis that certain universal laws may show up in many types of complex systems, whether they be social, economic or biological (Amaral & Ottino, 2004). In other words, these assumptions give us the basis to justify an approach by analogy. When a similarity between different phenomena may be established, it can be assumed that there exists some common underlying 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 simple form in a known environment, a mathematical model can be assembled and its results extended to similar (unknown) systems (Daniel, 1955; Gentner, 1983; Wigner, 1960).

Using the laws and methods of physics applied to social systems can be questioned, and indeed it has been. However, it must be considered here that in studying a socio-economic system as such, we are mainly interested in its global behavior and in the possibility of making predictions at this level rather than guessing the conduct of every single element (individual actors). The objective is to understand how regularities may emerge (when they do) out of the apparently erratic behavior of single individuals (Majorana, 1942). Therefore,

[1] control, in the "engineering" sense, means the capability of modifying the inputs given to a system in order to achieve a specific behavior or to drive the system along a specific path. The objective of a control theory is to calculate solutions for the proper corrective action of a controller that may result in system stability

as it happens when using traditional statistical methods, we can disregard single individuals and concentrate on the aggregate properties of the whole ensemble.

Objective of this contribution is to better discuss these considerations and to provide a description of the main, state of the art, methods used to critically study complex tourism systems with a focus on those belonging to network science.

## 1.1 A digression on tourism destinations

Tourism destinations are the main object of study here. A tourism destination is commonly 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). Essentially, a destination is (UNWTO, 2002):

> "a physical space in which a visitor spends at least one overnight. It includes tourism products such as support services, attractions and tourism resources within one day's return travel time. A destination 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, habitually, the analysis of a destination's structure draws upon the theory of industrial clusters, including their mechanisms of formation and evolution (Hjalager, 2000). The main models of clusters and networks of companies or organizations have been developed by investigating the manufacturing sector, with limited attention to service sectors of the economy such as tourism. Tourism destinations, however, differ from a traditional cluster in a number of aspects. For example, they differ in how they are formed, their focus on the service component, the characteristics of tourism products and their relationships, and the tourism production system itself. Firstly, tourism is essentially a service industry in which the product is not well defined and is composed of many different elements (Sinclair & Stabler, 1997; Wahab & Cooper, 2001). The tourist usually purchases it in advance and consumes it at the destination. The diversity of elements which form the product requires a range of providers that are an integral component of the same industry (Gollub et al., 2003). Therefore, the traditional models of industrial networks and clusters need modifications and adaptations 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 in determining regional income levels (Brenner & Weigelt, 2001; Krugman, 1991), in attracting foreign investment (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 in turn further enhances growth by reducing the cost of innovation in the region where the economic activities converge.

Models of clusters are based on the premise that firms located in a geographical area share common values, rules and language such 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 in the cluster because this tacit nature of the knowledge makes the information difficult to access by elements outside the community (Morrison, 2004). Co-location within a concentrated geographical area is a basis for the development of other characteristics of a cluster. For example, an important factor for a functioning cluster is the formation of close ties or alliances among the different actors and the establishment of co-operation in order to improve the competitiveness of the group beyond the incidental (usually external) effects that promote the gathering (Andersson et al., 2004; Mishan, 1971).

At first approximation, a tourism destination is an example of such a collaborative cluster. Mutually dependent attractions, services, transportation and environmental/cultural resources emphasize the need for collaboration, driven mainly by customer demand. 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 arise 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 other (similar or diverse) systems. The development of new 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, there are fundamental differences between the two concepts as can be seen in the work of two 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; with the participating firms connected by horizontal or vertical relationships and concentrated within a specific area. Some external entities such as public institutions may complement them, but the focus remains the entrepreneurial and business dimension. On the other hand, the Italian school of research interprets a district more widely, as an extension of this specialized spatial concentration. Becattini (1990) adds to the focus on industries a full recognition of the importance of the social environment of the area in which the district works. He includes regional governments and trade associations and, perhaps more importantly in this age of globalization, the understanding of the role of the linkages with the external world. This broader approach seems to be much closer to the reality of these agglomerations and is much more suitable as a framework for the study of a tourism destination. However, even taking this broader approach the district model needs to be adapted in order to be used as a framework in the tourism field. As discussed above, the tourism product is primarily a service product, with the qualities of intangibility, inseparability, heterogeneity and perishability and therefore different from industrial goods (Vanhove, 2005). In addition, both time and space separate the purchase and the consumption of a tourism product, so that potential visitors are not able to fully assess product attributes prior to consumption (Burns, 1999; Cooper et al., 2005; Mill & Morrison, 1992).

A tourism destination, when interpreted as a district, is composed of two main classes of interacting components (Antonioli Corigliano, 2000; Capone, 2004; Lazzeretti & Petrillo, 2006; Stamboulis & Skayannis, 2003): a large endowment of resources: natural, cultural, artistic, but also artificially built resources such as museums, theme parks or sport complexes, and a group of actors: economic, non-economic and institutional, whose prevalent activity is providing tourism-related services to visitors and travelers (see also Flagestad & Hope, 2001).

In a Porterian cluster, the stakeholders of a destination district include only those whose core activity is tourism. However in the tradition of the Becattinian School, the stakeholders would also include the local social system, the various institutional entities (such as local, regional and national government, associations and the community) and other organizations whose activity, although not directly of a touristic nature, is deemed essential for the successful sustainable functioning of the system as a tourism destination. In this approach, and in the age of the Internet, the geographical delimitation of the destination can be relaxed somewhat since virtual groupings with entities external to the specific area might be established, thus overcoming the need for a strict physical proximity.

A tourism destination is not a static system but 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 is built, traditionally, around the idea of a tourism area life cycle (TALC) originally proposed by Butler (1980). This model is created by applying theories of the evolution of product life cycles to the development cycle of a tourism destination. These theories date from the 1960s (Bass, 1969; Rogers, 1962) and were well established in consumer marketing studies by the time 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 a decline 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: i) exploration; ii) involvement; iii) development; iv) consolidation, and then stagnation followed by either a decline or rejuvenation. These stages follow an s-shaped logistic curve similar to the one used to describe the general evolution of an industrial district.

The TALC model is effective as a general conceptual model of the behavior of tourism districts (Agarwal, 1994; Baum, 1998; Cooper & Jackson, 1989) although it has been subject to a number of criticisms (Butler, 2005a, 2005b). It must be noted here, in fact, that the excessive simplifications needed to formulate this model make it a little trivial and not really able to capture all the different possibilities and the rich interactions that such systems exhibit. As a consequence, many real behaviors and outcomes can be hardly represented, unless in cases where the evolution is relatively linear and stable over the observational timeframe and no major disruptions occur, whether internal or external to the system.

# 2 Complexity and complex systems

It might be useful, for better understanding the complex system approach, to examine briefly the historical development of the ideas at its basis.

## *2.1 The "standard" approach to research*

Western civilization has set up and refined, in the course of its history, a more or less standard way for scientifically studying a phenomenon, tackling an issue or solving problem. This standard way, however, is modified in many cases by individual convictions and viewpoints that, even if seldom defined fully or coherently, may have wide effects. Personal philosophical and epistemological beliefs have always played a crucial role in the history of science, and in many cases have deeply influenced the development of ideas and knowledge.

The general approach consists of a series of steps: i) examine the object of study and define an objective; ii) decide whether our knowledge and techniques are sufficient to address it; iii) explore what and how others have produced in similar circumstances; iv) collect some empirical evidence; v) derive the appropriate conclusions; and, finally, vi) sketch some action that should lead to meet the aims of the work conducted. In doing that, researchers use a vast array of specific techniques, epistemological positions and philosophical beliefs (Losee, 2001).

In this multifaceted scenario, however, one element seems to be well grounded and accepted. When facing a big problem, a large system or a complicated phenomenon, the best method is to split it into smaller parts that can be managed more easily. Once obtained the partial results, we can recompose them to find the general solution. This notion is known as *reductionism*. It can be summarized with the words of the man who formalized the idea: René Descartes. In the *Discourse on Method* (1637: part II) he states that it is necessary

> "to divide each of the difficulties under examination into as many parts as possible, and as might be necessary for its adequate solution,"

and in the *Regulae ad directionem ingenii* (rules for the direction of the mind), he says quite clearly (1701: rule V):

> "Method consists entirely in the order and disposition of the objects towards which our mental vision must be directed if we would find out any truth. We shall comply with it exactly if we reduce involved and obscure propositions step by step to those that are simpler, and then starting with the intuitive apprehension of all those that are absolutely simple, attempt to ascend to the knowledge of all others by precisely similar steps."

and (1701: rule XIII)

> "If we are to understand a problem perfectly, we must free it from any superfluous conceptions, reduce it to its simplest terms, and by process of enumeration, split it up into its smallest possible parts."

Reductionism is rooted into ideas that evolved from the pre-Socratic attempts to find the universal principles that would explain nature and the quest for the ultimate constituents of matter. The whole western tradition then elaborated on these concepts that were admirably distilled in the 16th and 17th century. Copernicus, Galileo, Descartes, Bacon, Kepler came to a rigorous formulation of the methodology needed to give an accurate meaning to *science*. This work was refined very fruitfully by Isaac Newton in his *Philosophiae Naturalis Principia Mathematica* (1687). The book was so successful and so widely distributed that scholars of any discipline started to apply the same ideas to their own field of enquiry, especially in those areas that did not have a strong empirical tradition such as the study of human societies and activities.

The reasons for the wide influence were the simplicity, coherence and apparent completeness of the Newtonian proposal coupled with its agreement with intuition and common-sense. In the following decades many researchers tried to extend this perspective also to other environments. Scholars such as Thomas Hobbes, David Hume, Adolphe Quetelet, Auguste Comte (to cite only a few), worked with the objective explaining aggregate human behavior by using analogies from the world of physics, and employing its laws. Vilfredo Pareto and Adam Smith adopted the mechanical paradigm to the field of economics[2]; the idea of having universal laws, or relying on mathematical analytic expressions and even terms such as equilibrium or the formulation of gravity models are directly derived from the Principia.

The universality of Newton's laws, however, was to be challenged quite soon, when people started realizing that going beyond simple individual objects introduced a number of supplementary variables, typically due to mutual interactions, so that a solution could not be easily obtained unless by disregarding higher order terms in the mathematical formulation and limiting the description to a simplified and linearized description. For example, the gravitational theory was quite accurate in dealing with simple systems, but failed when applied to more complicate assemblies. The motion of planets in the solar system was described rather well, in first approximation, but the strange perturbations of Mercury's orbit could not find a place in the model. Going deeper into the theory it was shown that, actually, when increasing the number of bodies to be considered, the motion of the system's elements was almost unpredictable. Poincaré (1883) finally realized that even a small three-body system can produce such complicated outcomes that the equations describing it become extremely complex and practically unsolvable. The stability conditions for equilibrium in the motion of a system were later studied and characterized by Lyapunov (1892). This work provided the first evidence of the fact that, in some cases, even minor changes in initial conditions of relatively simple systems, described by deterministic relationships, would result in widely differing trajectories. It is what is called dynamical instability or sensitivity to initial conditions, that today we identify with *chaos*.

The problem of dealing with a system composed of a large number of elements gained much attention in the first half of 19$^{th}$ century. The practical issue of increasing the efficiency of the newly developed steam engines led a number of scientists to leave the path drawn by Newton and to approach the issue from a different point of view. The problem is to study the behavior of a gas in which a very large number of particles interact (just to give an idea, one liter of air contains about $3 \cdot 10^{22}$ molecules). Explicitly writing so numerous equations and solving the system was absolutely impossible. Statistical techniques were therefore thought to be the only possible tool. Nicolas Sadi Carnot, James Joule, Rudolf Clausius, William Thomson (Lord Kelvin) created a new discipline, thermodynamics, based on these ideas.

Their results were quite successful and, elaborating on them, James Clerk Maxwell, Ludwig Boltzmann and Josiah Willard Gibbs, at the end of 19$^{th}$ century, systematized the matter into what is known today as statistical mechanics (or statistical physics). The central idea is that the knowledge of an incomplete set of measurements of some system's properties can be used

[2] after having introduced and agreed to an "utilitaristic" view of the social world, which assumes that the value of use of any good can be fully reflected by its uni-dimensional value of exchange (price).

to find the probability distributions for other properties of the system. For example, knowing the number of molecules of a gas in a certain volume and its temperature, at thermal equilibrium (i.e. when no spatial or temporal variations in temperature exist), it is possible to calculate the pressure, the specific heath or other quantities.

Statistical physics is a very rigorous formal framework for the study of the properties of many-body systems (i.e. composed of a large number of interacting particles), where macroscopic properties are derived statistically from extensive and intensive[3] quantities related to the system, and its microscopic properties can be described in terms of probability distributions. Furthermore, it is possible to have a better understanding of the conditions in which critical modifications of the system, or sudden changes of its state (phase transitions) occur. Our understanding of phase transitions and critical phenomena, then, has led to the development of two important new concepts: *universality* and *scaling* (Amaral & Ottino, 2004).

When studying critical phenomena, or critical conditions in the system's evolution, a set of relations, called scaling laws, may be determined to help in relating the various critical-point features by characterizing the singular behavior of some system parameters and of response functions. The predictions of the scaling hypothesis are supported by a wide range of experimental work, and also by numerous calculations on model systems (Kadanoff, 1990; Stanley, 1999).

The concept of universality in statistical physics and complex systems has the basic objective of capturing the essence of different systems and classifying them into distinct classes. The universality of critical behavior pushes the investigations on the features of the microscopic relationships important for determining critical-point exponents and scaling functions. Statistical approaches can thus be very effective in systems when the number of degrees of freedom (and elements described by a number of variables) is so large that an exact solution is not practical or possible. Even in cases where it is still possible to use analytical approximations, most current research utilizes the processing power of modern computers to simulate numerical solutions. Here too, experimental work, and numerical simulations have thoroughly supported the idea (Kadanoff, 1990; Stanley, 1999).

However, the main result, and power, of this approach is in the recognition that many systems exhibit universal properties that are independent of the specific form of their constituents. This, as said, suggests the hypothesis that certain universal laws may apply to many different types of systems, whether they be social, economic, natural or artificial (Amaral & Ottino, 2004). For example, natural ecosystems can be well described in terms of their food webs. The analysis of a wide number of such systems, examined in terms of the networks composed of the different species and their predation relationships, show remarkable similarities in the shapes (topologies) of these networks (Garlaschelli et al., 2003). This happens independently for *apparently* significant differences in factors such as size, hierarchical organization, specific environments, or past history. The universality and scaling hypotheses seem thus valid in this field and might open the way to a reconsideration of the possibility to establish some general treatment of the problems in environmental engineering.

[3] in physics an intensive property of a system is a property that does not depend on the size or the amount of material in the system. Examples are the temperature and the hardness of an object. No matter how small a diamond is cut, it maintains its intrinsic hardness. By contrast, an extensive property is one that is additive for independent, non-interacting subsystems, thus depending e.g. on size or mass such as the amount of heat required to melt one ice cube. The ratio of two extensive properties, such as mass and volume, is scale-invariant, and this ratio, the density, is hence an intensive property.

In other words, these assumptions give us the basis to justify an extensive use of analogy, so that an inference can be drawn on the basis of a similarity in certain characteristics of different systems, typically their structural configuration (topology). That is to say: if a system or a process A is known to have certain traits, and if system or process B is known to have at least some of those, an inference is drawn that B also has the others. On many occasions mathematical models can be built and numerical simulations run in order to transfer information from a particular system to another particular system (Daniel, 1955; Gentner, 1983; Gentner & Jeziorski, 1993).

### 2.1.1 Widening the perspective: a systemic view

As seen, the Newtonian classical approach was, in many ways, extremely successful for scientists and problem solvers, but showed a strong limitation when taken to extremes or applied to unsuitable issues such as complex systems composed of many interconnected elements. Simplification, such as the idea of a rational *homo economicus* in economics, leads to outcomes that often misrepresent the object of study and do not allow a full explanation of the phenomena tending to disregard the complex network of relationships existing and their effects. A possible solution is to widen the perspective and consider the problem under study as a single entity.

A systemic view is centered on the concept of system, seen as a configuration of elements joined together by a web of relationships and sensible to external forces that may modify its structure or behavior. In this approach we abandon the traditional idea of cause and effect, which is directly connected with that of predictability, and use statistical methods for creating possible evolutionary scenarios and assign them a probability to happen. This is, in essence, the idea of complex adaptive systems.

## *2.2 Complex adaptive systems*

The natural language concept of complexity has several meanings, usually related to the size and the number of components in a system. There is still no universally accepted definition, nor a rigorous theoretical formalization, of complexity. Nonetheless, it is currently a much investigated research topic. Intuitively we may characterize a complex system as (Pavard & Dugdale, 2006: 40):

> "a system for which it is difficult, if not impossible to reduce the number of parameters or characterising variables without losing its essential global functional properties".

Basically, we consider a system complex if its parts interact in a non-linear manner. There are rarely simple cause and effect relationships between elements and a small stimulus may cause a large effect, or no effect at all. The non-linearity of the interactions among the system's parts generates a series of specific properties that characterize the complexity of its behavior. A well know example in economics is the law of diminishing returns: the decrease in the marginal (per-unit) output of a production process as the amount of a single factor of production is increased, while the amounts of all other factors of production stay constant. For example, the use of fertilizer improves crop production on farms, but this "linear" relationship is valid only to a certain extent. At some point, adding more and more fertilizer improves the yield less per unit of fertilizer, and excessive quantities can even reduce the yield.

It is important to highlight the difference between complicated and complex. A complicated system is a collection of a number, often very high, of elements whose collective behavior is the cumulative sum of the individual ones. In other words, a complicated system can be decomposed in sub-elements and understood by analyzing each of them. On the contrary, a complex system can be understood only by analyzing it as a whole, almost independently by the number of parts composing it.

For example, as Amaral and Ottino (2004: 147) note:

> "A Boeing 747-400 has more than 3 ×106 parts. In complicated systems, such as the Boeing, parts have to work in unison to accomplish a function. One key defect (in one of the many critical parts) brings the entire system to a halt. This is why redundancy is built into the design when system failure is not an option. More importantly, complicated systems have a limited range of responses to environmental changes. […] a Boeing without its crew is not able to do much of anything to adjust to something extraordinary."

On the other hand, a *simple* object made of only two elements, a double pendulum, a pendulum hanging from another pendulum, is well known to any physics student for its totally unpredictable, chaotic behavior (under the basic Newtonian laws of motion). A *simple* school of fishes, composed of a few dozen elements, is able to adapt its behavior to the external conditions without apparent organization but following a few very easy rules regarding local interaction, spacing and velocity (Reynolds, 1987).

Generally, as Bar-Yam (1997) notes, a complex system is a mesoscopic structure, composed of a number which is not too low nor too high (but even this distinction is rather confused).

A special class of complex systems is the one composed by those that influence and are influenced by the external environment and in which the interactions among the elements are of a dynamic nature. In a *complex adaptive system*, this is the term used to denote this type of system, the parts (Stacey, 1996: 10):

> "interact with each other according to sets of rules that require them to examine and respond to each other's behaviour in order to improve their behaviour and thus the behaviour of the system they comprise."

Complexity science studies the behavior of large collections of simple interacting units and their capacity to evolve with time. In many cases, when the relationships that bind these units are nonlinear and dissipative[4], complex phenomena show up from their collective dynamic behavior. Non-equilibrium structural reorganizations (of a spatial, temporal or spatio-temporal nature) spontaneously appear on a macroscopic level creating new emergent properties. This is referred to as self-organization, the most important visible characteristic of a complex system (Coveney, 2003).

Rigorously, complex systems are difficult to define and there is little consensus on what a complex system is. However, scholars and practitioners in the field have a relatively clear idea of what symptoms characterize them. The most relevant of these are (Bar-Yam, 1997; Levin, 2003; Waldrop, 1992):

- *non-determinism*. It is impossible to anticipate precisely the behavior of a CAS even knowing the functional relationships between its elements. The dependence of the system's behavior from the initial conditions is extremely sensitive and appears to be extremely erratic; the only predictions that can be made are probabilistic;

[4] a dissipative system is an open system that freely exchanges energy and matter with the external environment and is operating out of, and often far from, equilibrium.

- *presence of feedback cycles (positive or negative)*. The relationships among the elements become more important than their own specific characteristics and the feedback cycles can influence the overall behavior of the system;
- *distributed nature*. Many properties and functions cannot be precisely localized, in many cases there are redundancies and overlaps; it is a distributed system;
- *emergence and self-organization*. a number of emergent properties are not directly accessible (identifiable or foreseeable) from an understanding of the components. In a CAS, global structures may emerge when certain parameters go beyond a critical threshold. In these cases, generally, a new hierarchical level appears that reduces the complexity. This is formed by groups of elements that share similar characteristics and behaviors, therefore the system can be modeled by considering only a reduced set of elements; in other terms its complexity is reduced. After a while, however, small differences among the elements add up (the non-linear effects of higher order) and the system evolves, increasing its complexity up to the next self-organization process. One effect of such a characteristic is the capability to show a good degree of robustness to external (or internal) shocks. The system is capable to absorb the shock and to remain in a given state or regain the state unpredictably fast (system is resilient). At the critical points of instability the system will reorganize through feedback mechanisms. However, the very same system could be disrupted by some apparently small perturbations that happen to spread quite fast and grow by creating an avalanche. At a global level the system is homogeneous or symmetric; after a self-organization process, however, symmetry is lost (breaks), one configuration dominates all others. From an empirical point of view it is virtually impossible to determine why the system prefers one specific configuration instead of possible alternatives, or what type of perturbations may create a disruption or be absorbed;
- *self-similarity*. It implies that the system considered will look like itself on a different scale, if magnified or made smaller in a suitable way. The self-similarity is evidence of a possible internal complex dynamics of a system. A CAS is at a critical state between a chaotic state and a completely ordered one, a condition that has been also called a self-organized criticality. If parameters $N$ and $z$, describe a self-similar system, they are related by a power-law relationship: $N \sim z^k$. A power law means that there is no *normal* or *typical* event, and that there is no qualitative difference between large and small fluctuations.
- *limited decomposability*. It is quite impossible, to study the properties of a dynamic structure by decomposing it into functionally stable parts. Its permanent interaction with the environment and its properties of self-organization allow it to functionally restructure itself; only a “whole system” approach can explain CAS characteristics and behaviors. For example it is quite impossible to describe the behavior of a flock of birds by simply considering all the animals as independent entities and by summing up their movements. In fact they follow very simple rules, and although there is no centralized control structure dictating how individual animals should behave, local, and to a certain degree random, interactions between them lead to the emergence of *intelligent* global behaviour, unknown to the individual agents.

In short, following Cilliers (1998), it is possible to characterize a system as complex and adaptive by listing these main properties:

- a large number of elements form the system;

- interactions among the elements are nonlinear and usually have a somewhat short range;
- there are loops in the interactions;
- complex systems are usually open and their state is far from equilibrium;
- complex systems have a history, the “future” behavior depends on the past one
- each element is unaware of the behavior of the system as a whole, it reacts only to information or perturbations available to it locally.

Examples of complex adaptive systems include many real world ensembles: the patterns of birds in flight or the interactions of various life forms in an ecosystem, the behavior of consumers in a retail environment, people and groups in a community, economic exchange processes, the stock-market, the weather, earthquakes, traffic jams, the immune system, river networks, zebra stripes, sea-shell patterns, and many others.

### 2.2.1 Complex systems evolution

A CAS is a dynamical system. It is, therefore, subject to some kind of evolution which may be characterized by two variables: an order parameter and a control parameter. The first one represents, in some way, the internal structure of the system, capturing its intrinsic order. The second one is an external variable which can be used to induce phase transitions in a system. For example, let us consider a certain volume of water close to the boiling point.

The order parameter is the density difference between the liquid and vapor phases; the temperature the control parameter. By increasing the temperature (providing energy, heath, to the system) it is possible to bring the water to the boiling point. At the critical temperature Tc = 100 °C, the water starts boiling and the order parameter undergoes an abrupt change. It has the value zero in the random state (above the transition temperature) and takes on a nonzero value in the ordered state (below the transition).

More generally, the variation of the order parameter can lead the system to a critical point (bifurcation) beyond which several stable states may exist. The state will depend on small random fluctuations that are amplified by positive feedback. It is impossible to determine or to control which state will be attained in a specific empirical system; “in practice, given the observable state of the system at the beginning of the process, the outcome is therefore unpredictable.” (Heylighen, 2003: 12). Not even the control parameter (by itself) can be used to predict the system dynamics. Nonetheless, it is possible to sketch a general dependency of *global conditions* of a system on a control parameter.

Starting from a completely ordered and stable system (Figure 2.1), an increase in the control parameter will evolve it. The system passes through a periodic state, then to a situation characterized by a complex behavior, then to a completely chaotic state. This last state can be adequately described with Wolf (1986: 273):

> “In common usage chaos is taken to mean a state in which chance prevails. To the nonlinear dynamicist the word chaos has a more precise and rather different meaning. A chaotic system is one in which long-term [quantitative] prediction of the system’s state is impossible because the omnipresent uncertainty in determining its initial state grows exponentially fast in time.”

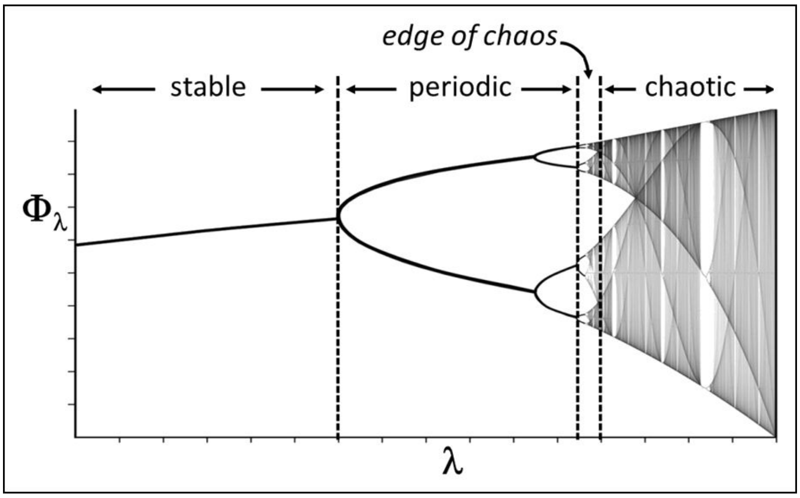


Figure 2.1 A schematic representation of the evolution of a system ($\Phi_\lambda$) dependent on a control parameter ($\lambda$). By changing $\lambda$ the system goes though different phases: stable, periodic (multi-stable), chaotic. The edge of chaos region is a configuration of adaptive complexity.

Many of the real systems we know live at the boundary between complexity and chaos. A situation frequently called *edge of chaos*, where a system is in a condition of fragile equilibrium, on the threshold of collapsing into a rapidly changing state, which may set off a new dynamic phase (Waldrop, 1992). The type of behavior may depend on the initial state of the system and the values of its parameters, while the boundaries are given by the critical values of the parameter. In the critical regions, called attractors, the system is locally stable. Overcoming a critical state we find a catastrophic bifurcation, then, as the evolution continues, the system moves towards a new attractor, waiting for the next perturbation able to create a bifurcation (Figure 2.1).

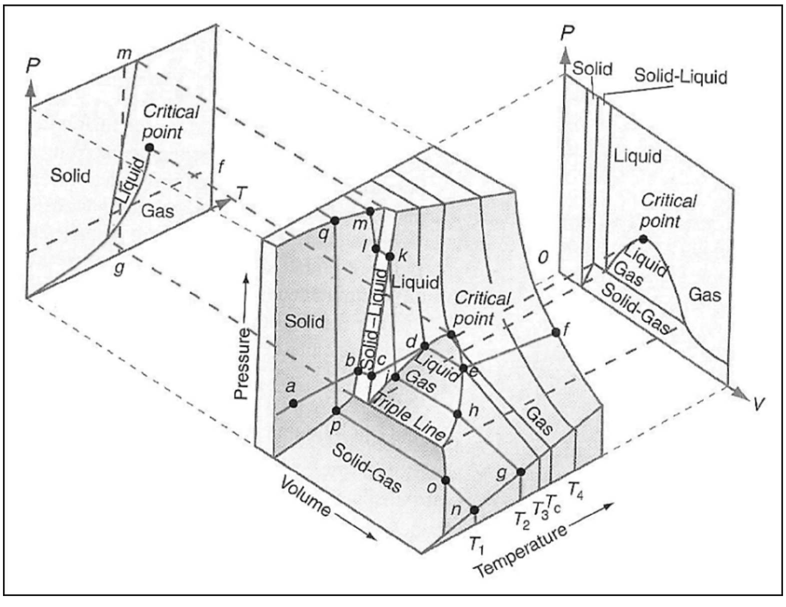


Figure 2.2 Phase space diagram for water. The different areas and the lines of transition between phases are shown as function of the three system's parameters: temperature, volume and pressure

The history of a complex system is usually depicted by drawing its movement in the *phase space*. This is a geometrical n-dimensional space, in which the coordinates are the variables of the system. A dynamical system, at least in theory, can be described by a number of differential equations (equations of motion) comprising a number of variables. They are chosen in such a way that complete knowledge of all the variables determines the state of the system at one time in a unique way. The phase space is the set of all possible states of the system.

A well-known example is the phase diagram for water (Figure 2.2) that shows, in a simple and readable way, all the possible states, and the possible transitions between them, of a *water system* as function of the control parameters: temperature, volume and pressure. For example, in regions far from the critical boundaries, the volume of a certain mass of water vapor is well predictable based on its temperature (and pressure), but in ranges very close to the phase transition it is almost impossible to know exactly what will happen and the relationship between temperature and volume changes abruptly after very small variations.

Chaos theory essentially studies nonlinear effects on deterministic systems, while complexity theory studies definite patterns on non-deterministic systems. The focus of chaos theory is on the manner in which simple systems give rise to complicated unpredictable behaviors, while complexity theory focuses on how systems consisting of many elements can lead to well-organized and (almost) predictable behaviors. As time evolves, a point representing a system state in the phase space describes a trajectory (or orbit). The knowledge of this orbit implies the solution of the equations of motion. Stable orbits (attractors) mean stable system behaviors. This apparent continuity in the possible evolution of a system (from an orderly phase to a complex behavior to a chaotic unpredictable dynamics) has led many to think of chaos and complexity phenomena as belonging to a *unified* discipline (Chris Langton quoted by Lewin, 1999: 12):

> “You are dealing with non-linear dynamical systems. In one case you may have a few things interacting, producing tremendously divergent behaviour. That's what you'd call deterministic chaos. It looks random, but it's not, because it's the result of equations you can specify, often quite simple equations. In another case interactions in a dynamical system give you an emergent global order, with a whole set of fascinating properties.”

## *2.3 The analysis of complex systems*

The toolbox of the complexity scientist has today become quite crammed. Several techniques have been developed to deal with the task of describing a complex system. Many of them originate from the work of 19th century scientists, but only modern computational facilities have made it possible to solve them. Following Amaral and Ottino (2004), we can group these tools in three main classes: nonlinear dynamics, statistical physics and network theory.

### 2.3.1 Nonlinear dynamics

A striking characteristic of complex systems is the nonlinearity of the interactions among the components. The main consequence is that the equations describing its behavior (provided they exist) can be solved only in very rare cases. The work of Poincaré cited previously is considered to be the starting point of a study tradition in nonlinear dynamics.

Since his work, a number of mathematical techniques have been developed to approximate the solutions of the differential equations used to describe such systems. Only the availability of modern powerful computers, however, made it possible to find *solutions* (which, in nearly all cases, are obtained by numerical approximations). Much of the mathematics of chaos theory, for example, involves the repeated iteration of simple formulas, which would be impractical to do otherwise.

Nonlinear dynamic systems are capable of exhibiting self-organization and *chaos*. This mechanism is called *deterministic chaos*, since the equations of motion which generate such erratic, and apparently unpredictable behavior do not contain any random terms. Deterministic chaos refers to the irregular (chaotic) motion generated by a system whose evolution is governed by dynamic laws that uniquely determine the state of the system at all times from a knowledge of the system's previous history. The source of irregularity is the exponential divergence of initially close trajectories in a bounded region of phase-space. This divergence can be measured with the aid of the theory proposed by the 19$^{th}$ century Russian astronomer Aleksandr Mikhailovich Lyapunov (Kantz & Schreiber, 1997). In this sense, chaotic behavior can be regarded as very complex dynamics.

This sensitivity to initial conditions is sometimes popularly called the *butterfly effect*, suggesting the idea that chaotic weather patterns can be altered by a butterfly flapping its wings. A practical implication is that it is essentially impossible to formulate long term predictions about the behavior of a dynamic system: even if it would be possible to fix the initial conditions to a predetermined, finite accuracy, their errors would increase at an exponential rate. Examples of systems exhibiting nonlinear (chaotic) behavior are: the atmosphere, the solar system, plate tectonics, turbulent fluids, mixing of colored dyes, economies, stock markets, population growth or the "simple" double pendulum (Gleick, 1987; Waldrop, 1992).

### 2.3.2 Statistical physics

Statistical physics (or statistical mechanics) is one of the fundamental fields of physics. It uses statistical methods for addressing physical problems. A wide variety of issues, with an inherently stochastic nature, is treated in such a way. It provides a framework for relating the microscopic properties of individual atoms and molecules to the macroscopic ones of materials observed in everyday life. Thermodynamics, and thermodynamic properties can be explained as a natural result of statistics and mechanics (classical and quantum). The main result, and power, of this approach is in the bypass of some classical mechanics problems, such as the impossibility of solving the three-body problem, by dealing with systems composed by a large number of elements, reasoning in terms of statistical ensembles.

One more important outcome of the use of statistical physics methods is the use of discrete models. The fundamental assumption is that some phenomena can be modeled in terms of computer programs (algorithms) rather than in terms of analytical expressions. Cellular automata and their evolutions: individual based models and agent based models (ABMs) are an example of discrete time and space models developed for a computer utilization (see for example Baggio, 2011; Bonabeau, 2002; Wolfram, 2002). Other numerical simulations are Montecarlo methods, as well as discrete event-based systems dynamics modeling or other stochastic simulation methods. In many cases, then, more than one technique is used in the same simulation.

Agent Based Modeling (ABM) is an essentially decentralized, individual-centric (as opposed to system level) approach to model design. When designing an agent based model the modeler identifies the active entities, the agents (which can be people, companies, projects, assets, vehicles, cities, animals, ships, products, etc.), defines their behavior (main drivers, reactions, memory, states, ...), establishes the connections between them, puts them in a certain environment, and runs the simulation. The interactions between agents and between them and their environments are asynchronous. The actions follow discrete-event signals or a sequential schedule, this setup allows for the cohabitation of agents with different environmental settings. The global behavior then emerges as a result of these *local* interactions between many individual behaviors. Applications exist in many fields of physical, chemical, biological and social sciences; propagation of fire, predator-prey models diffusion of diseases or the evolutions of artificial organizations can be represented with ABMs (Baggio, 2011; Bertels & Boman, 2001; Johnson & Sieber, 2010).

### 2.3.3 Network theory

Most complex systems can be described as networks of interacting elements. In many cases these interactions lead to global behaviors that are not observable at the level of the single elements and that share the characteristics of emergence typical of a complex system. Moreover, the collective properties of dynamic systems composed of a large number of interconnected parts are strongly influenced by the topology of the connecting network. The mathematical models of network structures have been developed in graph theory. A graph is a generalization of the geometrical concept of a set of dots (vertices, nodes), connected by links (edges, arcs). The main theoretical framework in which these investigations are embedded is the set of theories known as statistical physics (or statistical mechanics).

The rest of this contribution is dedicated to describe the main concepts and methods of network analysis and to discuss their application to tourism systems.

## *2.4 Tourism destinations as complex networked systems*

The tourism sector, as an economic activity, shares many of the characteristics we have identified as typical of a complex system. A destination comprises many different companies and organizations. The relationships among them exhibit a wide diversity and have been described in many different ways (Michael, 2003; Pavlovich, 2003; Pavlovich & Kearins, 2004; Smith, 1988), but, very often, they do not have any linear characteristic nor have they any static trait. The reaction of the different stakeholders to inputs that may come from the external world or from what happens inside the destination may be largely unpredictable as the outcomes of their conducts. Nonetheless, the system as a whole looks to follow some general *laws* (Butler's idea of tourism area life cycle, for example).

Even if not always explicitly defined as such, the idea that tourism is a complex adaptive system has been with us for a long time (see for example Leiper, 1979). Despite the lack of a clear and rigorous definition, a large number of researchers and practitioners has set several models, methods and approaches that have helped (and still do so) to understand structures and dynamic evolutions, and provided means to manage systems, to predict their effects or to optimize their functioning. Many authors have employed complexity and chaos based approaches to tourism starting from the realization of the *complexity* and instability of these systems (Edgar & Nisbet, 1996; McKercher, 1999). In fact "tourism is new enough, chaotic enough, and in the past unregulated enough to be a very attractive field" (Russell & Faulkner, 2004: 562).

A number of studies have explicitly identified the principles of complexity theory. One is the work carried out by Russell and Faulkner. The authors suggest that (2004: 557): "the more pertinent features of chaotic system that are particularly relevant to the examination of destination development are: i) edge-of-chaos phenomena; ii) self-organizing behavior; iii) the butterfly effect; iv) lock-in effect; v) self-similarity and vi) bifurcation.

Self-organization is a characteristic of tourism systems able to bottom-up create new structures (Baggio, 2008b), especially when a triggering event occurs. This capacity assures a "tremendous adaptive ability" to the system (McKercher, 1999: 428), and it is generated not by the system itself, but rather by its entities, as suggested by Russell and Faulkner (2004).

The butterfly effect (Lorenz, 1963), perhaps an icon of these theories, refers to a major change in the system caused (triggered) by apparently small changes. The butterfly effect is related to the initial conditions of the system (Russell & Faulkner, 1999) and it helps to explain "how seemingly similar destination areas can evolve in completely different manners. It also explains the unpredictable nature of tourism development, where even slight changes in initial conditions can lead to profoundly different outcomes" (McKercher, 1999: 429).

Tourism complex systems can show a high sensitivity to apparently unrelated events which, even despite their low significance, may trigger major changes. These triggering events are what Taleb (2007) names *black swans*. A black swan event: i) is a surprise (to the observer); ii) has a major impact on the system; iii) after the event is rationalized by hindsight, as if it had been expected. A recent example, affecting demand (Laws & Le Pelley, 2000) can be the negative publicity generated by several high profile business conventions in the United States in 2009. The US administration criticized companies engaging in such activities during periods in which profits were low and layoffs occurring. As a consequence, many firms cancelled their planned conventions, resulting in significant losses in some resort areas such as Las Vegas (Friess, 2009).

The lock-in effect is related to the pervasiveness of some initial conditions that create a sustainable head-start (Russell & Faulkner, 2004), explaining "why accidents of history are still current today" (McKercher, 1999: 429). At a tourism destination, "the lock-in effect might be evident in the continuing concentration of tourist accommodation capacity and attractions around a location, which was originally advantaged by access to rail transport. With the passage of time, rail transport might have become less relevant as a means of access for tourists, but the original location might retain its dominance owing to agglomeration effects" (Russell & Faulkner, 1999: 415).

Self-similarity is both a characteristics of the way the different elements form a system and a result of the functioning of the system itself. Focusing on the parts, each entity could be similar to others but not identical (Komulainen, 2004), focusing on the process, the chaotic functioning of the system tends to produce similar but not identical effects, as "the pounding of the ocean on the shoreline leaves a fractal coast" (Legge, 1990: 132). Tourism systems show self-similar characteristics in their structures and (often) in their dynamic behaviors (Baggio, 2008b; Russell & Faulkner, 2004)

Finally, bifurcation is closely related to the edge of chaos. When the system overcomes a critical point (or region) of the phase space and enters into a new phase. Here, the values of the system's parameters undergo abrupt changes (Langton, 1990), and alternatives emerge that tend to create Y-shaped junction bifurcations (Gleick, 1987). Here, as well, some scholars such as Lacitignola et al. (2010), or Russell and Faulkner (1999) or McKercher (1999) (although only at a qualitative level) have found evidence in tourism systems.

As stated, the techniques belonging to network science are probably the most promising series of methods that can be used to study a complex system. In the field of tourism, they provide a view into the network of relationships that may give tourism organization managers means to improve the flow of information and to target opportunities where this flow may have a crucial impact on regulatory or business activities.

Moreover, research in other areas has maintained that a dynamic and open network can greatly influences the capabilities of a socio-economic system to express a good level of creativity and innovation, so important for its growth (Schilling & Phelps, 2007; Uzzi & Spiro, 2005). It also provides a good resilience, the capability to resist external shocks, and improves the reaction times towards environmental modifications making it able to adapt better and more quickly. This, in a period where speed has become a paradigm, is a real big advantage, which may make the difference for the system, but also its components, between surviving and becoming extinct.

# 3 Network science and tourism systems

Although become quite popular in recent times, network analysis and its methods have a long tradition. Here we briefly sketch the development of the concepts and report about the main applications to the tourism field. This is relatively young, the first works have had the main objective of assessing the possibility to use the techniques and to tune a methodological path with the objective to provide both theoretical and practical outcomes. A few case studies have shown the feasibility of this approach and the interest and usefulness of the outcomes.

## *3.1 Historical development of the network concept*

An examination of the broad literature on the historical development of the network concept reveals a number of streams of thought. These can be divided into a mathematical-based stream examining the abstract characteristics and properties of *ideal* networks, and a social science stream where a network is viewed as an analogy for the interactions between individuals in a community. These two streams merged to some extent around the middle of the 20th century with the application of mathematical techniques to describe the complex social network patterns found in sociological studies. Most recently, findings from the study of complexity in physics, biology and computer sciences have been applied in the study of social systems.

In mathematics a network is represented by a diagram in which the various elements are shown as dots and the connections among them as lines that link pairs of dots. This diagram is called a graph and the branch of mathematics known as graph theory constitutes the framework providing the formal language to describe a network and its features. The origins of graph theory are attributed to the Swiss mathematician Leonhard Euler (1707-1783) and to his paper *Solutio problematis ad geometriam situs pertinentis* published in (1736).

In the paper, Euler deals with the now famous problem of the bridges of Königsberg. The citizens of the city used to entertain themselves by trying to work out a route crossing each of the cities' seven bridges only once. All the attempts had always failed, so that many believed that the task was impossible (Biggs et al., 1976). Euler proved this impossibility, giving also a simple criterion which determines whether or not there is a solution to any similar problem with any number of bridges connecting any number of areas. Whilst providing the solution to a particular problem, the real importance of Euler's paper is that it considers the object of study from an abstract point of view, giving significance to the structural characteristics rather than the pure geometrical ones. The title itself reflects this abstract approach and Euler's work forms the cornerstone of the discipline known as topology, envisioned almost a century before by Leibniz: the *geometria situs* (Leibniz, 1693).

In the early 20th century, the ideas and techniques developed for the study of these abstract objects were applied to the completely different field of sociology. Realizing that a group of individuals can be represented by enumerating the actors of the group and their mutual relationships, sociologists began to use graph theory and methods to describe and analyze patterns of social relations (Freeman, 2004; Wasserman & Faust, 1994). Jacob Moreno (1934) introduced the topic of sociometry and, by using diagrams of points and lines to represent relations among persons (sociograms), he aimed to identify the structure of relationships around individuals, groups, or organizations in order to study how these configurations may affect beliefs or behaviors.

From the sociological and anthropological point of view, networks form part of the structural tradition where researchers hypothesize that variations in the pattern of relationships surrounding social actors affect the behavior of those actors and correspondingly, that people also consciously manipulate situations to create desired structures (Stokowski, 1992). Wellman (2002: 83) writes that:

> "The concern of structural analysts with the direct study of networks of concrete social relations connects strongly back to post-World War II developments in British social anthropology. Then as now, anthropologists paid a good deal of attention to cultural systems of normative rights and duties that prescribe proper behaviour within such bounded groups as tribes, villages, and work units."

Early examples of the use of the concept a *social network* to examine ties between people include Barnes (1952) who examined a Norwegian fishing village and explained such key social processes as access to jobs and political activity. Soon afterward, Bott's (1957) work brought the network concept to the wider attention of social scientists. She developed the first distinct measure of network structure, *knit* (now called density), to show that densely knit English extended families were more apt to contain married couples who did most things independently rather than jointly. Other *sociometrists* used network diagrams to represent interpersonal relations in small groups (e.g. Coleman, 1958) and such techniques were later used to study phenomena such as communication, the diffusion of innovation and the spread of diseases.

A parallel development in the political science literature took a more ethnographic and qualitative approach. In this tradition, researchers seek to examine how patterns of ties in social systems allocate resources. According to Wellman (2002: 91):

> "…Structural analysts have developed 'resource mobilization' analyses to explain political behaviour. They showed such behaviour to be due to structured vying for resources by interest groups - and not to reflect the aberrant cravings of a mob. Their work emphasized how patterns of links between interest groups structure coalitions, cleavages, and competitive relations and how direct and indirect ties differentially link individuals and groups to resources."

Most recently, findings from the study of complexity in physics, biology and computer sciences have been applied in the study of social systems. This work has been driven by interest in self-organizing processes and the emergence of structure from randomness. This stream of literature has contributed a wide range of possible metrics for network analysis and, more importantly, it has provided evidence of similar connections between network structures, their functions and their dynamic evolution in diverse types of networks including those found in the social sciences (Albert & Barabási, 2002; Boccaletti et al., 2006; da Fontoura Costa et al., 2011).

### 3.1.1 Traditions of network analysis

Within a great diversity in the study of networks, various authors have identified commonalities. Kilduff et al. (2006) suggest that there are four core concepts in social network theory: (i) the primacy of relations between organizational actors; (ii) the ubiquity of actors' embeddedness in social fields; (iii) the social utility of network connections; and (iv) the structural patterning of social life. Wellman (2002) lists five characteristics of structural network analysis:

1. behavior is attributed to constraints on action caused by structure not due to internal motivations;
2. analyses focus on the relations between units, instead of trying to sort units into categories defined by the inner attributes (or essences) of these units.
3. the relationships among network members jointly affect each other's behavior rather than only other members individually;
4. structure is treated as a network of networks that may or may not be partitioned into discrete groups. It is not assumed a priori that tightly bounded groups are, intrinsically, the building blocks of the structure;
5. the units of analysis for network studies are not individuals but the whole network.

Built around these common or core concepts, network analysis is used in a variety of disciplines and subject areas. Each of these has developed its own traditions and indeed Berry et al. (2004) consider that in network analysis there are three traditions focused on personal social network analysis, policy network analysis and (inter-) organizational network analysis. In addition, there are a variety of uses of network concepts in situations where the objects of study are not socially related to people or enterprises but involve other linkages such as transport connections (Lew & McKercher, 2002).

One further tradition is that based on application of complexity theory and network theory from the physical sciences. This considers tourism and other socio-economic systems as complex systems. A number of researchers have used this approach as the basis for examining tourism phenomena, even if their analysis, so far, has been mainly performed qualitatively (Farrell & Twining-Ward, 2004; Faulkner & Russell, 2001; McKercher, 1999). More recently, however, quantitative assessments of the characteristics of a tourism destination based on numerical analysis have been provided (Baggio, 2008b; Baggio et al., 2010b). Such studies offer, among other outcomes, the tempting possibility of describing the effect of proposed changes in network structures on properties such as information or knowledge dissemination (see for example section 5.2).

In conclusion, it is possible to identify four different traditions in the study of social networks (Berry et al., 2004; Dredge, 2006). Each of these traditions makes certain assumptions, favors particular methods for the study of networks and seeks to answer some central question. The personal social network (1) and intra-organizational network (2) traditions, for example, share similar types of methods and emphasize quantitative studies (although using different units of analysis) while policy network studies (3) emphasize case study and qualitative methods. The physical network tradition (4) applies mathematical techniques derived from graph theory and statistical physics on the assumption that common laws underlie systems with similar topological characteristics.

## *3.2 A summary of the research so far in tourism*

A handful of studies exist which have dealt mainly with tourism destinations or communities. The main objectives of this line of research is to apply network analytic methods in order to better understand the structural characteristics of a tourism destination as it comes out from the "spontaneous" arrangements of the relationships between the different stakeholders, independently from preconceived ideas typically based on traditional division by type of business (accommodation, intermediaries, services etc.) or geographical location, or the assessment of the relationships between the destination and its virtual representation in the Internet. Furthermore, given the important influence of the network topology on the unfolding of processes such as information or knowledge diffusion, or patterns of tourists' movements, the research aims at describing these processes with the objective of optimizing them by looking at the possibility of intervening on the organization of the destination. The final objective is to provide a deeper knowledge of the evolutionary paths and the dynamical behavior of the systems can be studied in order to find the best governance styles for ensuring a sustainable growth of the systems and all their components.

First of all the main topological characteristics of a tourism destination network have been measured. It has been found that a scale-free topology exists. This means that there are a few nodes with many connections, acting as hubs, and many nodes with a limited number of links. This is common to many other systems. The destinations examined have also a very low density of connections and low clusterization, that is not many well defined communities (groups of nodes with more links between them than to other nodes of the network) can be identified (Baggio et al., 2010b; da Fontoura Costa & Baggio, 2009; Del Chiappa & Presenza, 2013; Luthe et al., 2012; Scott et al., 2008a; Scott et al., 2008b). This is an important result, because weaknesses (or differences) in the connectivity patterns of the destination can be independently identified (Scott et al., 2008b). There is also a significant managerial implication. As discussed previously, the network approach emphasize the need for a destination to be a collaborative environment. This can now have a natural measure in the metrics of the destination network (Baggio, 2007). Then, by comparing the networks of destinations considered to be at different development stages it has also been possible to correlate, at least roughly, the structural evolution of a destination (assuming a TALC–like model: Butler, 1980) with its evolutionary path (Baggio, 2008a; Baggio et al., 2007).

Important or critical stakeholders in a destination have been identified. They are located in the core of the network and form an influential assembly controlling the governance of the system. When these groups show good cohesiveness (high local density of links) the whole system achieves better outcomes. A further confirmation for the necessity of creating interconnected communities for the production of integrated tourism experiences (Cooper et al., 2009). As expected, public stakeholders are the most important elements (Presenza & Cipollina, 2009). They own the critical resources (economic, environmental or organizational), have the highest centrality and hold the greatest legitimate authority over others (Timur & Getz, 2008).

One of the advantages of a network representation is that numerical simulations can be performed with reasonable ease. They allow to conduct experiments when it would not otherwise be feasible for theoretical or practical reasons. Different configurations can be designed and several dynamic processes simulated. This allows to better understand how these configurations affect the behavior of the whole destination system.

Information and knowledge flows are relevant determinants of the system's wellbeing. Overall efficiency, innovation and development are strongly influenced by them, and the way in which the spread occurs shape the speed by which individual actors perform and plan their future (Argote & Ingram, 2000). A used way to study this problem is based on an analogy with the diffusion of a disease (Hethcote, 2000). Yet, differently from standard epidemiological models, it has been demonstrated that the structure of the network is highly influential in determining the basic unfolding of the process (López-Pintado, 2008).

A series of simulations run on a real destination network shows, as expected, that the speed of the information diffusion process vary in accordance with the capacities of the single actors to acquire and share information. They also show, however, that the increase in speed is much higher when the modularity of the network is increased by reconfiguring the linkages (Baggio & Cooper, 2010). This can be a very important suggestion for possible actions. Some more modeling coupled with qualitative estimations of the possible returns might help building of scenarios to be analyzed and discussed. The making decisions on which approach, or which mixture of approaches, to adopt might therefore be much better supported.

Network analysis methods have been applied also to the virtual network of the websites present in a destination. The results have allowed to gauge the level of utilization of advanced communication technologies and measure the usage (or the waste) of important resources, universally considered crucial in a globalized market. Moreover, the topological similarity between the real and the virtual components has been assessed thus leading to the conjecture that the webspace of a tourism destination can be a faithful representation of its real structure (Baggio, 2007; Baggio & Antonioli Corigliano, 2009; Piazzi et al., 2012). More recently, the same techniques have been employed to show the strong structural integration of real and virtual elements in a destination so that the idea of a tourism digital business ecosystem can be better explores (Baggio & Del Chiappa, 2013)

Other studies (Baggio et al., 2010a; García-Amado et al., 2012; Inácio et al., 2012; Leung et al., 2012; Luthe et al., 2012; Oliveira et al., 2013) have confirmed the essence of the outcomes described here reassessing the usefulness at both theoretical and practical level of network analytic methods to study issues concerning governance, social capital, decision-making, collective action or demand and supply patterns using cases from different parts of the World.

# 4 Elementary network theory

A drawing in which the various elements are shown as dots and the connections among them as lines linking pairs of dots is representative of a network. This drawing, a mathematical abstraction, is called a graph

Mathematically speaking, a network is represented by a graph *G* which is an ordered pair *G:= (V,E)* (Bollobás, 1998). 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 or actor) can represent simple objects (a word in a semantic network) or complex ones (a firm or a biological individual) taken as single entity. A link (also termed edge or tie) denotes some type of relationship between two nodes. This relationship can include a simple information exchange, a chemical reaction, a force or a transaction. Links can be symmetric (an information exchange) or directed (a flight from one airport to another) and can be assigned a weight *w*, that is a measure of strength, importance or value. The 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).

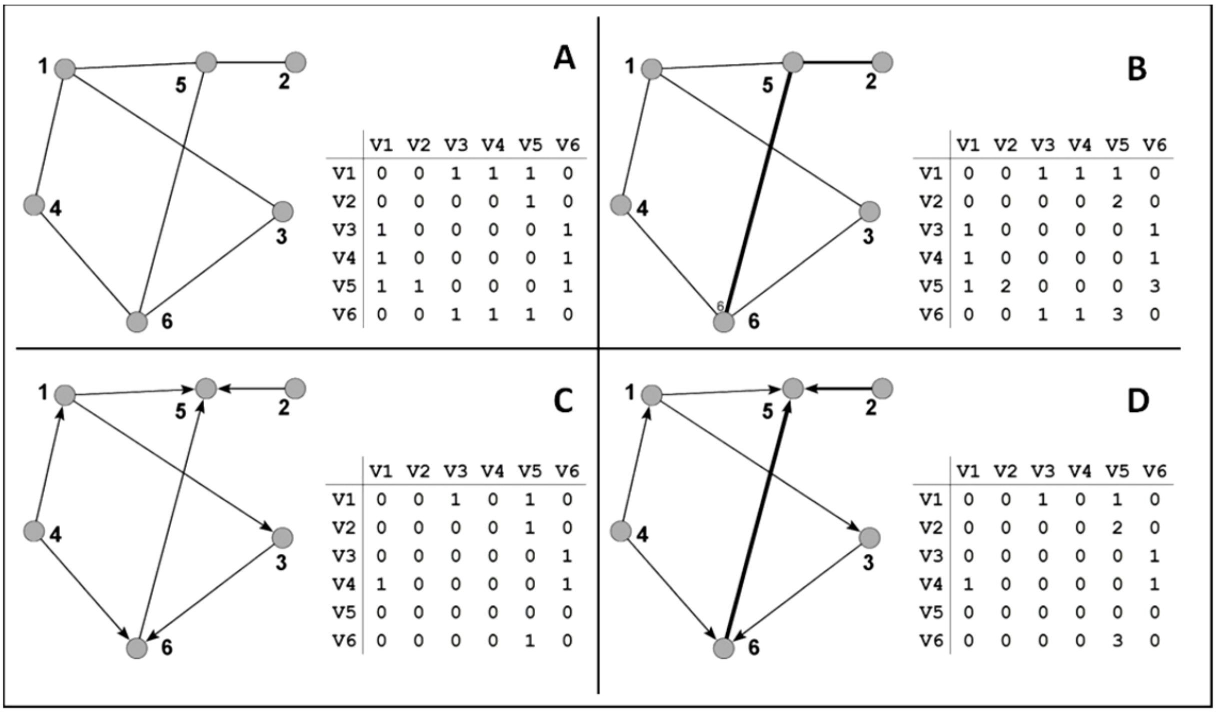


Figure 4.1 Different graphs: undirected (A), weighted undirected (B), directed (C) and weighted directed (D) with their adjacency matrices

The graph can also be represented by an $n \times n$ matrix *A*, called an adjacency matrix. If there is an link 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 brings the powerful methods of linear algebra or used by a scientist for the investigation of network characteristics. Figure 4.1 gives an example of different types of networks and their adjacency matrices.

A special type of network is the bipartite graph (or bigraph), in which nodes can be divided into two disjoint sets U, V such that every link connects a node U in to one in V ; that is, U and V are each independent sets, formally G = (U,V,E) (Figure 4.2, A).

Bipartite networks are also called affiliation or two-mode networks and are used to represent a wide variety of situations such as events and people attending them, authors and papers or football players and clubs. In each of these the network has a link between one member of the first group and one of the second, but no links between members of the same group.

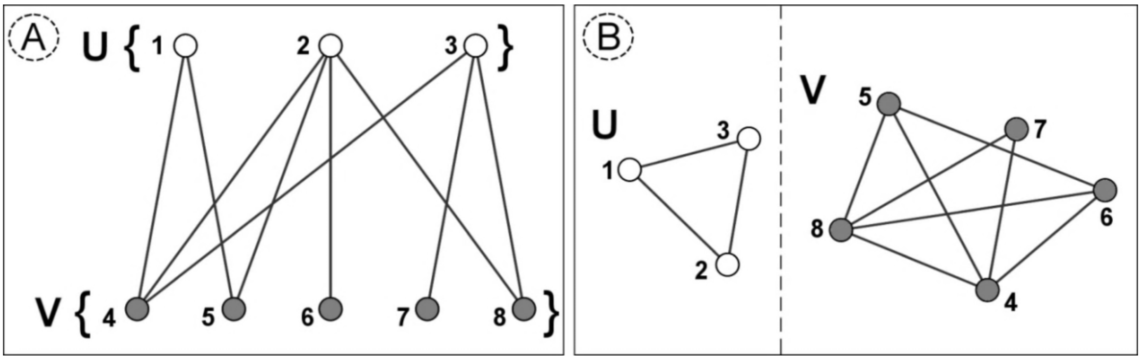


Figure 4.2 A bipartite network (A) with its two one-mode projections (B)

Frequently, a bipartite network has been analyzed by compressing it to a one-mode projection. A new network is built that contains nodes of only either of the two sets, and two U (or, alternatively, V) nodes are connected only if when they have at least one common neighboring V (or, alternatively, U) node (Figure 4.2, B). The one-mode projection, obviously, is always less informative than the original bipartite graph, therefore some appropriate method for weighting connections would be in order. Optimal weighting methods reflect the nature of the specific network, conform to the study objectives and aim at minimizing information loss.

A better possibility is to develop appropriate methods for analyzing the bipartite network as it is. A good treatment in this area, along with the adaptation of the main metrics discussed in section 4.1 to the two-mode case can be found in the work of Guillaume and Latapy (Guillaume & Latapy, 2006; Latapy et al., 2008). In the rest of this work, bipartite networks are not ignored. The interested reader can refer to the works cited for the details.

## *4.1 Network measurements*

The inter- and multi-disciplinary origin of network science, as previously discussed, has led to a wide variety of quantitative measurements of its topological (structural) characteristics (see da Fontoura Costa et al., 2007 or Newman, 2010 for a thorough review). The literature on complex networks commonly uses the following measures to describe a network's structure. In the following formulas: $n$ = number of nodes (order of the network); $m$ = number of links (size of the network); $k$ = 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 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 arithmetic 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.
- *closeness* is the inverse of the sum of the distances from a node to all others: $Cl = \frac{n(n-1)}{\sum_{i \neq j} d_{ij}}$ ;
- *clustering coefficient*: represents the degree of concentration of the connections of the node's neighbors in a graph and gives a measure of local nonhomogeneity 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 $C_i$: $C = \frac{1}{n} \sum_i C_i$ ;
- *beetweenness*: number of shortest paths from all vertices to all others that pass through a node. It can be calculated as: $B = 2 \sum_{i \neq q \neq j} \frac{\sigma_{ij}(q) / \sigma_{ij}}{(n-1)(n-2)}$, where $\sigma_{ij}$ is the total number of shortest paths between nodes $i$ and $j$ and $\sigma_{ij}(q)$ is the number of those paths that pass through $q$;

- *efficiency* (at a global $E_{glob}$ or local $E_{loc}$ level): 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: $E_{loc} = \frac{1}{n} \sum_i E_{loc,i}$ ;
- *eigenvector*: assigns relative scores to all nodes in the network based on the idea that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Eigenvector centrality of node $q$ is the value of the

$q^{th}$ element of the eigenvector associated with the highest eigenvalue of the adjacency matrix;

- *assortative mixing coefficient*: the Pearson correlation coefficient between the degree of a node and those of its first neighbors. If positive, the network is said to be assortative (otherwise disassortative). In an assortative network, well-connected elements (those with high degrees) tend to be linked to each other. It is calculated as: $r = \frac{\sum_i (dg_i - \overline{dg})(dn_i - \overline{dn})}{\sqrt{\sum_i (dg_i - \overline{dg})^2 \sum_i (dn_i - \overline{dn})^2}}$, where $dg_i$ is the degree of node $i$, $dn_i$ the mean degree of its first neighbors; the standard error can be calculated by using the bootstrap method (Efron & Tibshirani, 1993).

When non normalized by definition (clustering coefficient, for example) the individual metrics are usually normalized (although normalization factors vary in the literature, here those provided are some of the most commonly used).

All the formulas reported above are referred to a symmetric (undirected) unweighted network. In many cases the extension to a directed or weighted network is trivial, it is sufficient to replace the $a_{ij}$ link with its weighted value $w_{ij}$, or consider $a_{ij} \neq a_{ji}$. Terminology also changes and we speak of in-degree and out-degree, for example, to mean links connecting nodes in a specified direction. In other cases, however, the translation is not simple at all. The interested reader will find detailed descriptions in the literature cited (e.g. Newman, 2010).

### 4.1.1 Fitting a degree distribution

The distribution of the degrees of the nodes of a network is an important parameter of a network topology. This is usually expressed as a statistical probability distribution $N(k)$, 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. This is a delicate task, mainly when the degree distribution shows a long exponential tail (see section 4.1.3), and (all or in part) seems to follow a power-law: $N(k) \sim k^{-\gamma}$.

When such a distribution is found the estimate of the exponent of the distribution is an important and delicate task. The empirical detection is made difficult by the large fluctuations that occur in the tail of the distribution. A simple technique would be to calculate a linear OLS (ordinary least square) fit of the log transformed distribution. In fact: $N(k) \sim k^{-\gamma}$ translates into $\log(N(k)) \sim -\gamma \log(k)$. This method, however, is known to produce systematically biased estimates of the exponent by greatly underestimating it, and should not be used in most circumstances.

Figure 4.3 shows an example of the results obtained in the three cases. The exponents calculated are: OLS = 1.16; CUM = 2.17; CSM = 2.32±0.27. The differences are evident.

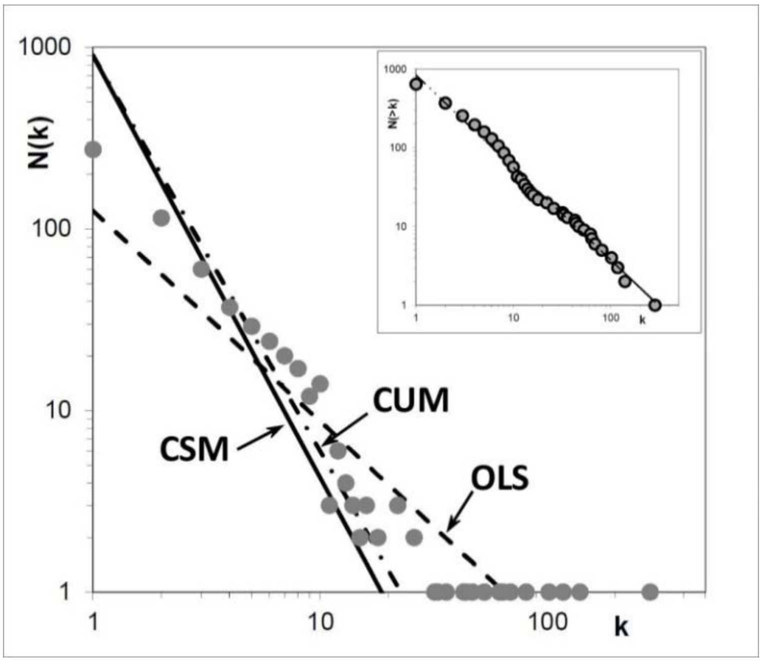


Figure 4.3 A degree distribution with the three (OLS, CUM, CSM) calculated fits. The inset shows the cumulative distribution

### 4.1.2 Modules and communities

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 4.4). 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 to the understanding of their organization and evolution. For example, a community's social structure is revealed through the communication patterns within it.

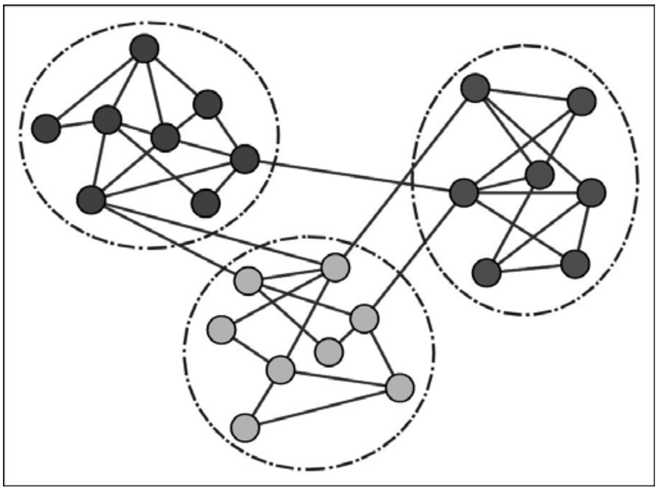

Figure 4.4 A modular network with a strong modularity (modularity index = 0.55). Dotted lines mark the three communities characterized by having a denser set of links inside them than towards other components of the network

Different definitions of modularity exist and researchers in this discipline have proposed several methods to measure it. These methods rely on numerical algorithms that can identify some topological similarity in the local patterns of linking (Fortunato, 2010). In all of them however, a measure called the *modularity index* is used to gauge the effectiveness of the outcomes. It can be calculated as: $Q = \sum_{s=1}^{N_M} \left[ \frac{m_s}{m} - \left( \frac{2m_s}{2m} \right)^2 \right]$, where $N_M$ is the number of modules, $m$ is the number of links in the network, $m_s$ is the number of links between the nodes in module $s$ ($2m_s$ is the sum of the degrees of the nodes in module $s$ and $2m$ the sum of degrees in the whole network). . In other words, $Q$ is the fraction of all links that lie within a community minus the expected value of the same quantity that could be found in a graph having nodes with the same degrees but with a random distribution of the links.

For easing the comparison between networks with different numbers of communities, the index can be normalized by the number of modules $N_M$ (Du et al., 2009): $Q_{norm} = \frac{N_M}{N_M - 1} Q$.

### 4.1.3 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): $P(k) \approx \frac{\langle k \rangle^k}{k!} e^{-\langle k \rangle}$.

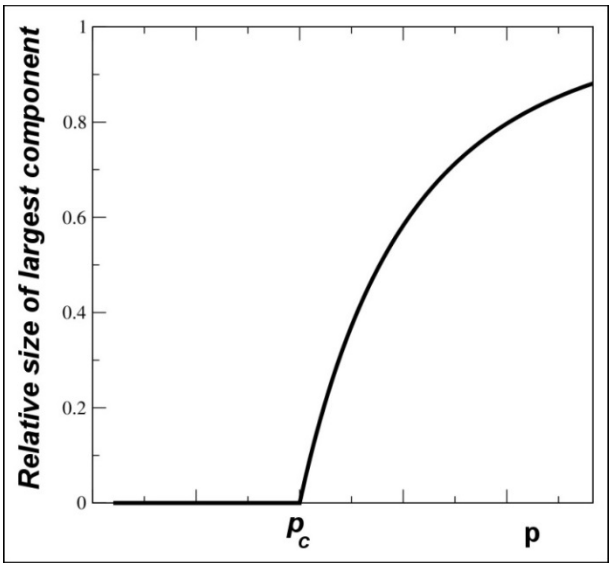


Figure 4.5 Formation of a giant component in an ER network shown by drawing the relative size of the largest component as function of the connection probability $p$ ($p_c$ is the critical threshold)

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. Above a certain critical threshold $p_c$, a giant cluster forms (Figure 4.5). This giant cluster is a very large group of connected nodes encompassing most if not all of the nodes (depending on the value of $p>p_c$). Below $p_c$ the network has 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) discuss 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) networks. In a small-world network, 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., 2011).

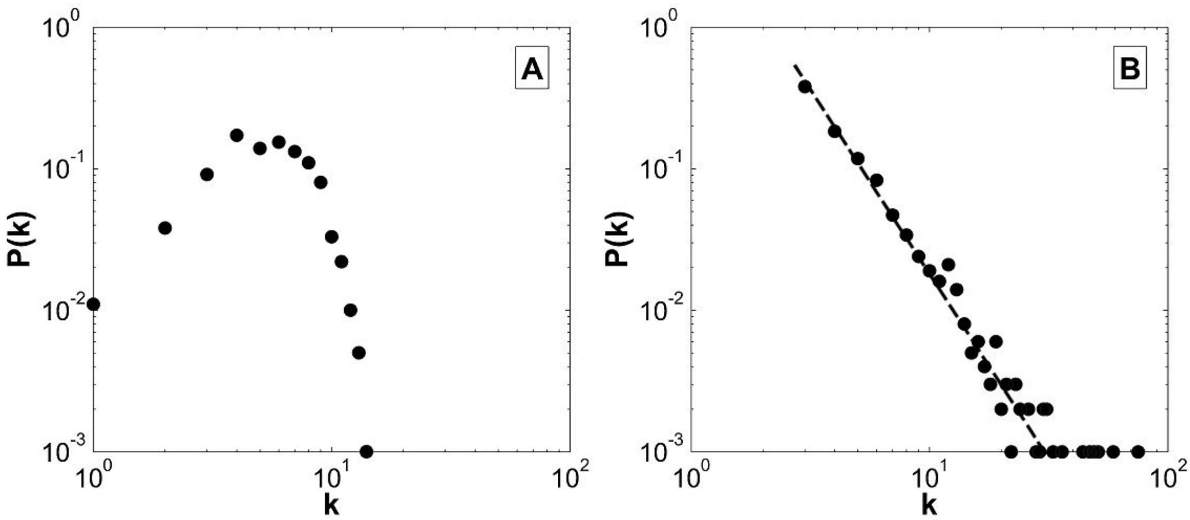


Figure 4.6 Degree distributions: Poissonian (A) and Power-law (B). The distributions refer to networks of the same order (1000 nodes) and size (3000 links) and are drawn on a chart with logarithmic axes. While the Poisson (random) distribution shows a characteristic curved shape, the power-law distribution can be fit with a straight line (dotted line in B)

On the other hand, Faloutsos et al. (1999) and Barabási and Albert (1999) 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 (often called hubs), while a large number of nodes have a low degree (see Figure 4.6).

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[5]. 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. A large number of real networks demonstrate this kind of rich-get-richer phenomenon although several additions and modifications are required to account for the differences measured between the theoretical model and the real networks.

This basic model is modified in a number of ways: by introducing a fitness parameter which increases the probability that a newly added node will be selected by 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 on the number of nodes a newcomer may connect to. Moreover, even in networks that are not growing by the addition of nodes, links can be added, deleted or moved (rewired) to adapt the network to specific conditions. Thus other mechanisms, besides the preferential attachment family, exist that are able to generate a power-law degree distribution (Caldarelli, 2007; Newman, 2010). 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 the 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 in the description of those critical states between a chaotic and a completely ordered state, a condition known as self-organized criticality (Bak et al., 1988). In other words finding a power law is one more confirmation of the complexity of networked systems.

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 inter-organizational networks within destinations (Scott et al., 2008b); 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.

This wide variety of network models and empirical cases can be summarized using 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 which act 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 of attaching to an already highly connected node. This is the case of the tourism web network analyzed by Baggio (2007) and the Australian destinations studied by Scott et al. (2008b);

[5] it must be noted that SW and SF characteristics are independent and may be present at the same time in a network.

- *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) and India (Bagler, 2008) or the flow of tourists across countries (Miguéns & Mendes, 2008).

Clearly the literature on complex networks demonstrates the strong relationship between the topological structure and the functioning of the system described. It also provides useful measures of the structural characteristics of the diverse networked systems presented here based on a variety of models.

### 4.1.4 Dynamic Processes

A complex system is a dynamic entity: think of economies, companies or tourism destinations 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 (Frechtling, 2001; Song & Li, 2008) are good testimonials of the dynamic nature of these systems and the appeal of the study of these characteristics.

Analysis of the topological properties of complex networks provides interesting and useful outcomes from a theoretical point of view. It is no surprise to find that this area has received a great deal of attention. The growth processes of all the basic network types discussed in the previous section (the random (ER) graphs and the different types of scale-free networks) have been studied. In this section we describe two dynamic processes which may occur to, and within, a network and which are significant for a tourism destination, our unit of analysis. These are resilience and diffusion of information.

The first characteristic, a system's resilience, is verified in many real-world systems. In a complex network it can be *empirically* 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 that is under attack is strongly dependent upon its basic topology (Albert et al., 2000; Crucitti et al., 2004).

In the case of a purely random removal (Figure 4.7), a SF network is more robust than an ER network, it preserve a good overall connectivity even after the removal of a large fraction of nodes. When the high degree nodes are targeted, however, the attack proves to be much more disruptive. Removing just a small fraction of these (about 15%) can completely destroy connectivity and leave the system as a set of isolated islands.

A mathematical representation of a system can be used to perform simulations of processes. A simulation can be a powerful tool to create different scenarios and the numerical methods invented 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). Obviously, as the most important literature on the subject reports (Balci, 2003; Stauffer, 2003), when a social system is involved some precautions must be taken.

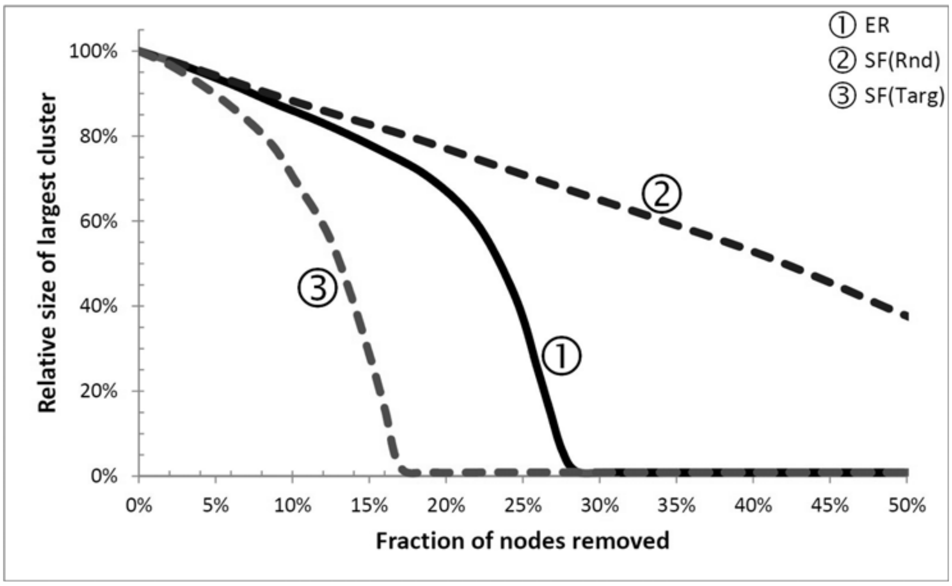


Figure 4.7 Effects of random (errors) and targeted removals (attacks) for random (ER) and scale-free (SF) networks on the relative size of the largest component of the network (adapted from Boccaletti et al., 2006). The SF network shows a better capacity to absorb random removals (2) than an ER network (1), but is much more sensitive to targeted attacks to the high degree nodes (3)

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 other analytical results available, or real responses of the system measured empirically in some situation (Adrion et al., 1982). If this happens, numerical simulations of socio-economic systems can provide very effective tools to support management practices. These represent a significant departure in approach from the usual, and open the way for the adaptive approach advocated by those convinced that a tourism destination is a complex, and sometimes even chaotic, system that should be dealt with in a non-deterministic way (Baggio et al., 2010a; Farrell & Twining-Ward, 2004; Faulkner & Russell, 1997).

The second characteristic is the diffusion of information through a network. In a tourism destination, the diffusion of information or knowledge is a crucial process for balanced development. Here, the determinants favoring this process are of paramount importance (Argote et al., 1990; Cooper, 2006). The network effects of 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.

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 such as SF networks, this threshold does not exist (see Figure 4.8). Once initiated, the diffusion process unfolds over the whole network (Pastor-Satorras & Vespignani, 2003).

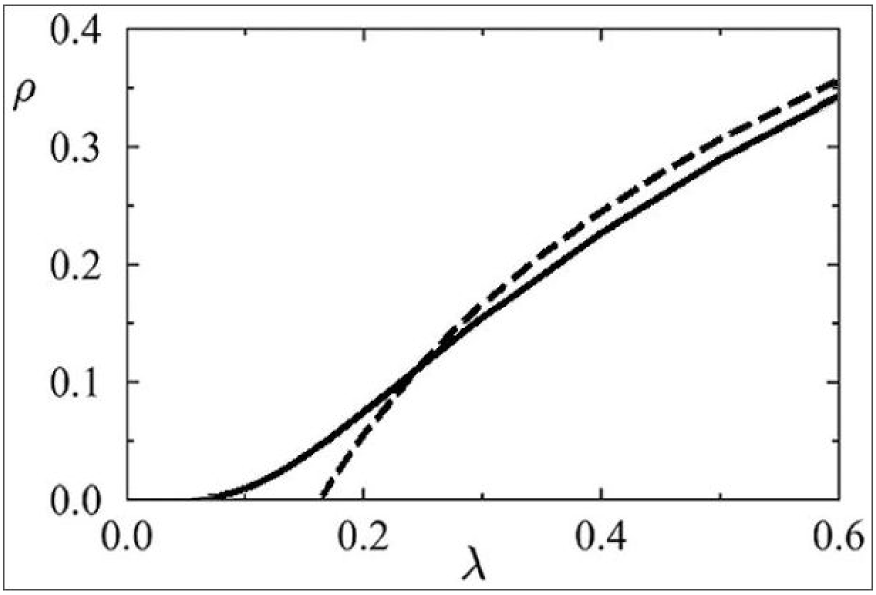


Figure 4.8 Fraction of infected individuals (ρ) as a function of spreading rate (λ) for a SF network (solid line) compared to an ER network (dotted line) (after Pastor-Satorras & Vespignani, 2003). In an ER network the presence of a threshold for initiating the diffusion is evident while an SF network is lacking a critical onset of the epidemic

Finally, it must be noted that the analysis of many network properties can be conducted by looking at the distributions of the eigenvalues (called spectrum) of the adjacency matrix. Spectral methods have proved to be quite effective and, in some cases, easier to *handle* than more traditional algorithmic techniques. (see for example Seary & Richards, 2003; Van Mieghem, 2010).

## *4.2 Reading the numbers*

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 2008b; Baggio et al. 2010b). 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; Serrano et al., 2007). 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 (Newman, 2002). In short, the more assortative a network is, the higher its resilience (Serrano et al., 2007).

The average clustering coefficient can provide (as said) 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, as said, 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 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; Walsh, 1999): $\mu = (C/L)/(C_{rand}/L_{rand})$. 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 $\gamma$ 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, as suggested (Guimerà et al., 2004), is to prepare a randomized version of the original network obtained by rewiring it while preserving the degree distribution. 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).

## *4.3 Methodological issues*

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

### 4.3.1 Data Collection

Fully enumerating the data relating to the totality of a network (nodes and links) is not possible on many occasions. This failure is especially true for social and economic systems, and is certainly the case for a tourism destination. Using sampling to study complex networks is possible but this requires careful application. Standard statistical considerations apply as long as we are considering a system in which the elements are placed at random, as in the case of an ER network, and where the significance of the sample is assessed with standard methods (Cochran, 1977). We have seen however 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*. As a result, a sample of a network missing some critical hubs leads to erroneous conclusions about its topology.

The problem has been highlighted 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; 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.

Table 4.1 Effects of sampling on SF network properties. As the sampling fraction of nodes or links decreases (⇩), the quantity may increase (⇧), decrease (⇩), stay the same (⬄), or behave according to the specific situation (⇳)

| | Degree distribution exponent | Average path length | Clustering coefficient | Betweenness | Assortativity |
|---|---|---|---|---|---|
| **Nodes ⇩** | ⇧ | ⇧(⇩) | ⇳ | ⇧ | ⬄ |
| **Links ⇩** | ⇧ | ⇧(⇩) | ⇩ | ⇧ | ⬄ |

For example, according to the literature, in the case of a SF network (Table 4.1), 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, but increases when links are sampled (Kossinets, 2006; Lee et al., 2006; Wang et al., 2012).

### 4.3.2 Epistemological consideration

As economists are the experts on consumer attitudes and sociologists on human social interaction, physicists are considered experts in simplifying complicated problems. However, one usually does not ask a physicist about stock-market forecasts (Duan & Stanley, 2011), neither does one immediately think of a physicist when the issue concerns controlling civilian crowds (Helbing et al., 2005). Scientists dealing with many real problems do not take kindly to the propensity of physicists entering their field of study and proposing overly simplified theories. One even often hears jokes about physicists assuming chickens to be spherical. However, simplifications and assumptions happen, sometimes, to be pretty helpful in solving a specific real-life problem. As Duncan Watts writes (Watts, 2003: 61-62):

> "Physicists, it turns out, are almost perfectly suited to invading other people's disciplines, being not only extremely clever but also generally much less fussy than most about the problems they chose to study. Physicists tend to see themselves as the lords of the academic jungle, loftily regarding their own methods as above the ken of anybody else and jealously guarding their own terrain. But their alter egos are closer to scavengers, happy to borrow ideas and techniques from anywhere if they seem like they might be useful, and delighted to stomp all over some else's problem. As irritating as this attitude can be to everybody else, the arrival of the physicists into a previously non-physics area of research often presages a period of great discovery and excitement. Mathematicians do the same thing occasionally, but no one descends with such fury and in so great a number as a pack of hungry physicists, adrenalized by the scent of a new problem."

Obviously not all assumptions can be taken as valid. They must retain the essential features to explain what we observe. Take rubber ball, for example. The complicated system we call *air* is composed of a huge number of molecules of nitrogen, oxygen, and many other. Each one of these molecules is an arrangement of atoms with different weights, and each atom is a system of elementary particles interacting according to specific forces. To explain why the ball expands when filled with air, however, we do not need all these details. It is possible to assume that air is a set of small identical spheres traveling in all directions and colliding among them and with the walls of the ball. These collisions are essentially what is responsible for what we call gas pressure. Everything else can be ignored.

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. There is a variety of works dealing with these questions for both natural and social sciences, examining 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 however, is rarely discussed and if so, usually as a secondary topic. Physicists do not seem to feel the need 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. 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, a sociologist may refuse the use of physical laws to model human behavior on the grounds that such laws do not apply.

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 that 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 their equations of motion can be described and investigated. Consequently, a key objection of sociologists is that a social actor is completely different from these homogeneous particles, and thus the methods of physics are too simplistic a representation to use in social science.

However, the aims of physicists are not about achieving such individual predictive outcomes. In studying a socio-economic system we can focus upon its global behavior and the possibility of making predictions at a system level rather than seeking to predict the conduct of single elements (individual actors). This aim seeks to understand how regularities emerge out of the apparently erratic behavior of single individuals (Majorana, 1942). From this perspective, a comparison of theoretical predictions with empirical data has two key objectives: (i) of verifying whether the trends seen in the data are compatible with a reasonable conceptual modeling of the idealized actors: and (ii) whether there is some level of consistency or if additional factors are required to provide a fuller explanation.

In these circumstances, as Castellano et al. (2009) 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., 2009: 592). 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. The vast theoretical and empirical literature accumulated in recent years has shown network science to be an effective tool for understanding complex socio-economic systems.

Trying to simplify reality down to its elementary components and interactions for explaining a certain phenomenon is what leads physicists to uncover fundamental laws of nature. And schematically, it is also precisely what the network approach is about: the components of the system under study are reduced to elements that retain the essential features we want to address and the interactions between such components are represented by links joining the elements. Elements could be molecules with links representing the collisions among them, but they could also be seen as persons linked by their friendship acquaintances or as enterprises connected among them according to the trades or the agreements they establish.

## 4.4 Software tools

It is rather clear that, apart from the case of very small networks (a few tenths of nodes) the analysis requires appropriate software tools. The area in constantly evolving and new programs continue to appear therefore any list would be of limited validity. The best reference is the Wikipedia page *Social network analysis software* (http://en.wikipedia.org/wiki/Social_network_analysis_software). It contains an extensive list along with the main characteristics of the programs. Some of them (such as NodeXL, Pajek, Gephi, Ucinet etc.) are of general use, while some have been developed for specific tasks, or are a reference to libraries to be used by some programming language.

More personalized or particular analyses (diffusion simulations, for example) may require to write a specific script or program. Programming languages and development environments will require some more effort if writing computer code is not a familiar task, but they offer the greatest flexibility for analysts to design their own algorithms and procedures. Any programming language is suitable, some of them are commercial products and can be quite expensive. In many cases, however, free clones exist. These show a relatively good compatibility with the original language and the Web provides good information about how to translate the scripts between them. Obviously, in many cases and for special functions, a direct translation is not possible and the programs must be completely rewritten. Finally, clones can be a little less stable and reliable than their original counterparts.

Quite used are languages such as Matlab (with its free clone Octave) or Python. These have the advantage of being relatively easy and fast to learn with respect to more traditional languages such as C++, Fortran or Java. These relative higher *usability* however, is at the expense of execution speed (they are all interpreted languages) which can be an issue when very large networks (millions of nodes) need to be examined. For all these a Web search can provide a wealth of programs, functions, toolboxes and libraries quite often freely available.

A final consideration is in order when the network examined is not a *simple* one-mode symmetric unweighted network. In this case it is advisable to check well whether and how the chosen software deals with them. Often, in fact, the network is symmetrized and unweighted before the calculations, thus leading to outcomes different from those expected. When this is not completely clear, a simple test can be performed (most times) by using a network and its symmetric unweighted version. The comparison of the results will make clear whether a difference exists.

# 5 Case study: a tourism destination

This section describes a specific case using the network analysis methods described above. The case covers the Italian tourism destination of the island of Elba. Elba's location is in the center of the Tyrrhenian Sea (Figure 5.1) off the coast of Tuscany, and it 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 (as an island the boundaries are more clear than in other cases), has accessible records concerning tourism actors and has a scale suitable for detailed examination. The core tourism organizations (such as hotels, travel agencies, associations, public bodies), were identified from the official local tourism board and 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 its completeness were validated with a series of structured and unstructured interviews with a selected sample of local *knowledgeable informants* who included 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 network layout has a completeness of about 90%. All the links are considered undirected and of equal weight.

## *5.1 Network topology*

The network obtained is depicted in Figure 5.1.

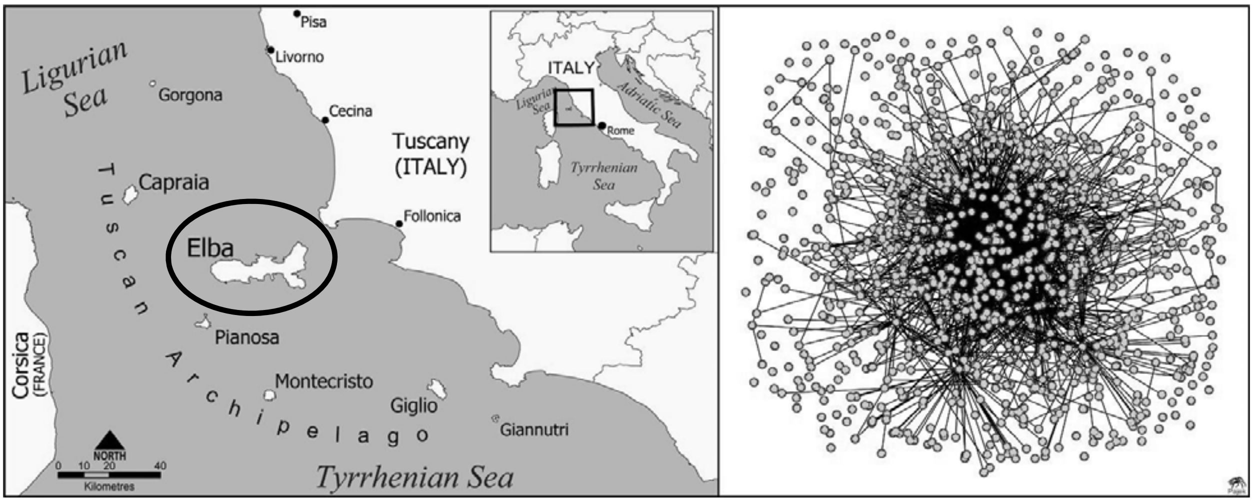


Figure 5.1 Elba island and its destination network

Table 5.1summarizes the metrics calculated for this network. 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 reports typical values for social networks published in the literature (da Fontoura Costa et al., 2011; Newman, 2010).

Table 5.1 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 | --- | $10^{2}$ - $10^{3}$ |
| 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) |

The degree distributions (differential and cumulative) for the network are shown in Figure 5.2. The shape of the distribution follows a power law $N(k) \sim k^{-\gamma}$. The exponent (and its standard error), calculated following the procedure proposed by Clauset et al. (2009) is $\gamma$ = 2.32±0.27.

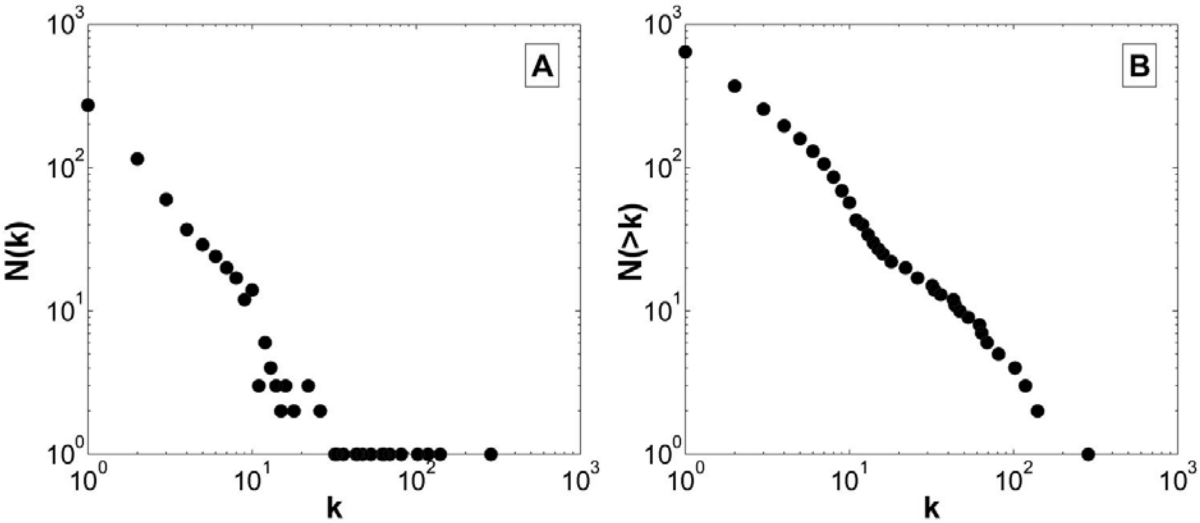


Figure 5.2 The degree distributions of Elba destination network. N is the number of nodes having degree k (A) or greater than k (B, the cumulative distribution)

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 $10^{-1}$ – $10^{-2}$ (Boccaletti et al., 2006; Caldarelli, 2007; Newman, 2010). 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 for a socio-economic network such as Elba, is the assortativity coefficient. This, as seen, represents the tendency of a node to connect with nodes having similar degrees. The correlation has been found to be positive for many of the social networks examined in the literature (Newman, 2002), and, while debated by some authors (Whitney & Alderson, 2008), this positive correlation 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. This indicates 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 by dividing its actors with respect to the type of business (e.g. hospitality, associations, food and beverage services) and geographical location (Elba's municipalities) (Table 2). As a comparison, the modularity was investigated using the algorithm proposed 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 5.2).

Table 5.2 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 Elban network with a randomized distribution of its links (values are averages over 10 iterations). To better compare the different results, the last column of the table contains the normalized value for modularity. 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 clustering in these groups. In other words, no well-defined business-type or geographical groupings can be found in the destination. The fact that the randomized network has a lower but similar modularity with respect to that obtained by using the community detection algorithm on the original network is an indication that a distinct modular structure exists even if it is not very well defined or highly significant (Guimerà et al., 2004). In this socio-economic system, the topology generated by its degree distribution induces a certain level of self-organization which goes beyond pre-set differentiations (by geography or type) of the agents.

Table 5.2 Elba network modularity analysis

| Grouping | No. of groups | Modularity | Normalized Modularity |
|---|---|---|---|
| Geography | 9 | 0.047 | 0.053 |
| Type | 8 | -0.255 | -0.291 |
| CNM | 11 | 0.396 | 0.436 |
| CNM (random) | 12 | 0.367 | 0.400 |

### 5.1.1 The analogy between the real and virtual network

As a further example of the outcomes of the application of network science to a tourism destination, consider the virtual network among tourism companies. Once identified the websites belonging to the tourism stakeholders, the network was built by listing all the hyperlinks among them (Baggio, 2007). 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 the impossibility of finding hyperlinks embedded in Flash applications or Java applets) .

Let us now consider the degree distributions of the real (RN) and the virtual (VN) networks. As Figure 5.3 shows, apart from scale factors, the two distributions look quite similar. A formal confirmation can come from a statistical test. Obviously a non-parametric method must be used in our case and the Kolmogorov-Smirnov (KS) statistic is able to provide trustworthy results (Clauset et al., 2009). 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: $D = \max_x |F(x) - G(x)|$. This statistic is nonparametric and as it is insensitive to scaling issues, it compares only the shapes of the empirical distributions (Siegel & Castellan, 1988). The value for the D-statistic calculated when comparing the degree distributions of RN and VN is 0.229 with a p-value $< 10^{-13}$ thus confirming the substantial similarity between the two distributions and, consequently of the structural characteristics of the two networks.

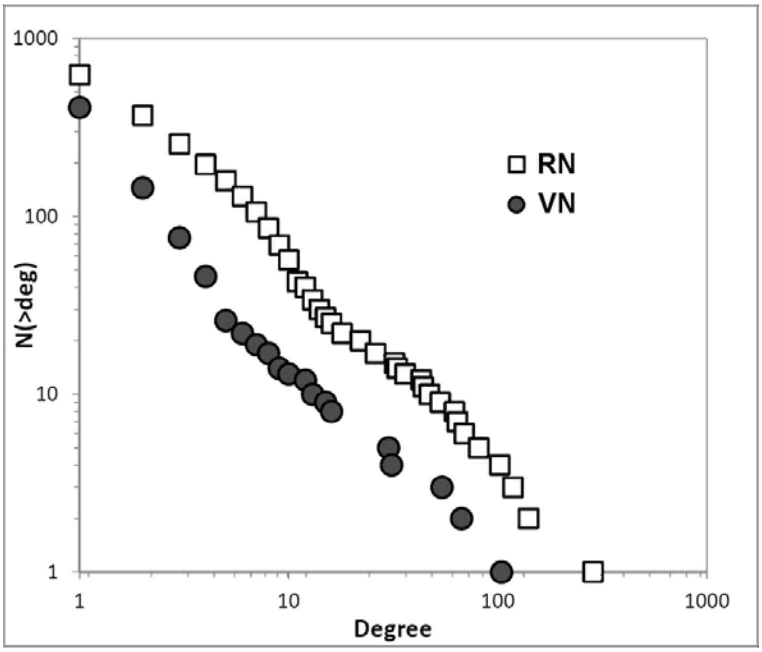


Figure 5.3 A comparison between the degree distributions of the real (RN) and virtual (VN) networks for Elba

A strand of literature considers virtual networks as representations of the social relationships among the actors who are 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 a hyperlink as a strategic resource, and the structure of this network is created by specific aims or communication, 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, for a large part of the World, this is not a severe limitation.

Rather than more or less *randomly* sampling a tourism destination network with the usual methods (Marsden, 1990), the Web provides us with a relatively fast, easy and objective way of sketching the main topological characteristics of such systems.

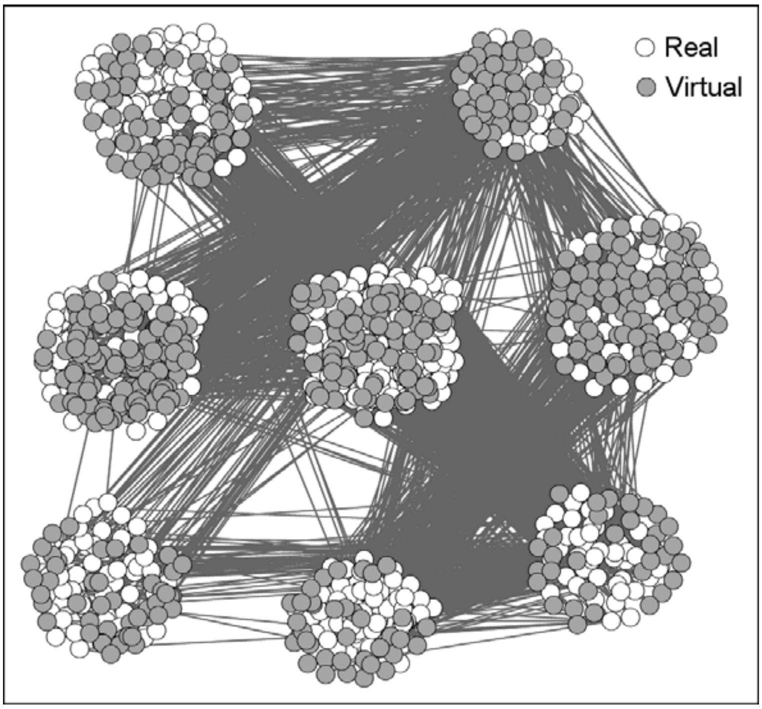


Figure 5.4 Communities found in the Elba digital ecosystem. The real and the virtual components are closely structurally coupled

More than that, starting from this consideration and examining the finer details of the structure of the combined real-virtual network (the one formed by tourism operators and their websites and the linkages between all these), as detected by a modularity analysis (Figure 5.4), it is possible to show that the two components (real and virtual) are so strongly coupled that the term *tourism business digital ecosystem* assumes a valence that is not anymore a purely theoretical one (Baggio & Del Chiappa, 2013).

## 5.2 Dynamic Processes

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 future planning. Productivity, innovation and economic growth are, in fact, 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 test the capability of the system to react to changes in its structural parameters. Here, a simple epidemiological model can be employed where 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 and quite suitable to describe a knowledge transfer process (Barrat et al., 2008; Barthélemy et al., 2005). 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). Absorptive capacity refers to different capabilities to acquire and retain the knowledge available to an actor due to the associated costs or their internal functioning, and to transfer it to other actors. In tourism, this issue is crucial for the large number 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. This was achieved 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 Elban 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 Elban network containing different actors' capabilities. This is to be expected, due to the non-homogeneity of the network. When changing to equal capabilities (the original Elban 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 5.5 shows the cumulative number (as a percentage of total) of stakeholders that are infected as function of time for the different simulations preformed.

Therefore, the interventions made have a significant impact on the information diffusion process. The spread of knowledge is faster if the network's connections are not distributed at random (scale-free in our case), knowledge 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.

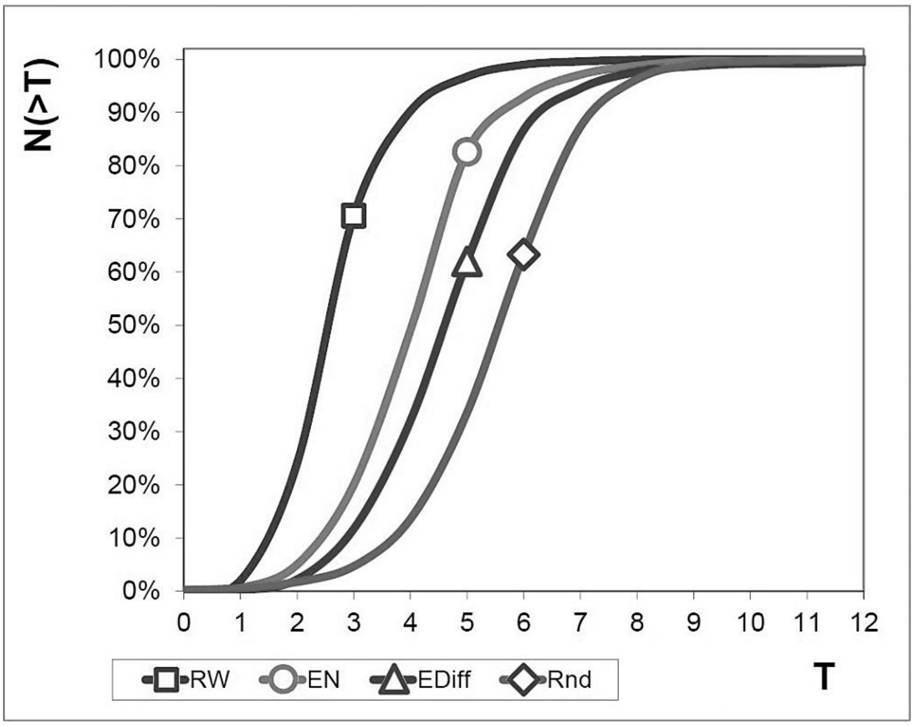


Figure 5.5 Cumulative percentage of informed stakeholders for the simulations performed: rewired network (RW), Elba network with equal probability of transmission (EN), with probabilities scaled according to stakeholder size (EDiff) and a network of same size with a random distribution of links (Rnd). Curves are averaged over 10 realizations of the simulations.

These results naturally suggest policy actions, but provide also a means of "testing" the possible outcomes of these actions. It would be relatively simple, in fact, to modify the network, make some educated guesses on the effects of different actions and re-run the diffusion simulation to assess the results.

## *5.3 Discussion*

The results and the analyses of the Elban tourism destination network turn out to be useful indicators for the understanding of its structure and dynamics. Despite an obvious theoretical interest, these outcomes can provide also valuable indications for the governance of the destination.

The low density and clustering coefficient give a quantitative assessment of the poor collaborative atmosphere, but this could have been missed when not very deep qualitative studies would have been conducted. Same can be said of the tendency to cooperate as measured by the assortativity coefficient. The modularity analysis has then offered evidence of the real division in communities of the destination. In this way actions and policies could be better designed than if continuing to use the traditional typology-based groupings. They would result more effective because founded on appraised self-organized subdivisions rather than directed to practically non-cohesive groups. The simulations on information diffusion can provide ways to simulate different scenarios and test the effects. Finally, the important structural role played by the virtual Web world can further emphasize the necessity to exploit all the possibilities offered by the modern technologies so that the digital ecosystem can work efficiently and effectively.

All these considerations must be, obviously, verified and validated with a good qualitative knowledge of the system, but, in summary, network analytic methods can be a powerful complement to more traditional forms of enquiry in order to support the activities of the governing bodies that aim at a sustainable development of the destination and of all its stakeholders.

# 6 Concluding remarks

This contribution has described the methods and the techniques that complexity science, and in particular network science, provides 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 of the implications of this approach. Network analysis methods are undoubtedly an intriguing and intellectually stimulating exercise. However, no matter how sophisticated and effective theoretical techniques can be, they have little value when applied to a phenomenon without coupling them with sound *physical* interpretations. Translating this into the language of social science this means that a thorough knowledge of the object of analysis is crucial to obtain meaningful outcomes from both a theoretical and a practical point of view. On the other hand, a pure qualitative investigation risks missing or misinterpreting important factors in the study of a complex network, because, as seen, on many occasions the quantitative analysis provides rather unexpected outcomes.

As Gummesson (2007: 226) 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, therefore qualitative and quantitative, natural and social are not in conflict but they should be treated in symbiosis".

In the 21st 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 components of a socio-economic system have been discussed in general management studies. The implications go well beyond the simple study of networks. These methods have the strong potential to inform a wide number of concerns such as the study of organizational structures, the use of technology, the study of epidemiological diffusion (from diseases to marketing or policy messages), the formation of consensual opinions and their impacts (Parkhe et al., 2006)

In this respect, the methods of network science can prove beneficial in deepening the knowledge of the whole system and, coupled with more traditional procedures, can provide powerful tools to enable those adaptive governance practices considered by many the only practical way to steer the collective efforts of multiple organizations (Bankes, 2002; 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 pathways for the researcher interested in the structure, the evolution, the outcomes, and the governance of the system. Further research in this area will need to confirm the results obtained so far by increasing the number of examples studied. The methods employed clearly require some additional refinement both from a practical and a theoretical point of view. The ever growing number of studies in network science on the dynamic evolution of a complex networked system may suggest new models and new approaches which will need careful consideration before they are applied to the field of tourism.

As a final point, it is a firm conviction of the author 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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# Appendix I: Exercises and suggestions

## Exercise

Consider the following adjacency matrix:

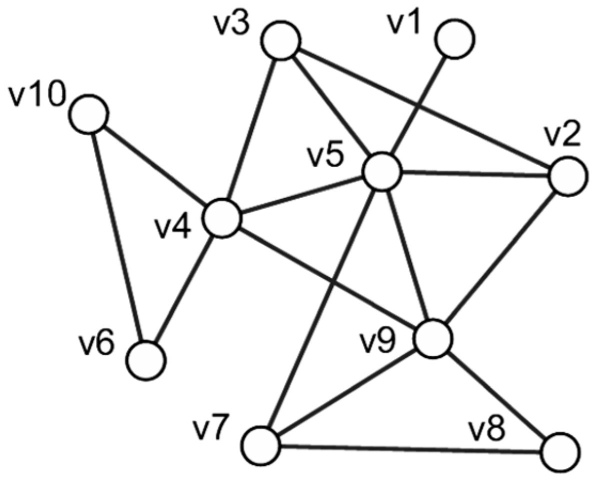
| | v1 | v2 | v3 | v4 | v5 | v6 | v7 | v8 | v9 | v10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **v1** | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| **v2** | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 |
| **v3** | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| **v4** | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |
| **v5** | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 |
| **v6** | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| **v7** | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 |
| **v8** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| **v9** | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| **v10** | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |

Without using any specific software, answer the following:

1. draw the network
2. is the network directed or undirected?
3. is the network connected?
4. what is the number of edges?
5. what is the density of the network?
6. find the node with highest degree
7. find the shortest path between v1 and v10 (list also at least 3 other paths)
8. find a possible candidate "highest betweenness"
9. find a possible candidate "highest clustering coefficient"

By using a network analysis software of your choice input the data (you might need to transform the matrix into a list of links) and check the answers given above and find the diameter and the average values for: degree, clustering coefficient, betweenness, closeness.

**Answers**:




**Network metrics**

| | |
|---|---|
| Total Edges | 16 |
| Diameter | 3 |
| Average distance | 1.680 |
| Density | 0.356 |
| Average degree | 3.200 |
| Average clustering coefficient | 0.603 |
| Average betweenness | 3.900 |
| Average closeness | 0.062 |

| Vertex | Degree | Clustering coefficient | Betweenness | Closeness |
|---|---|---|---|---|
| v1 | 1 | 0 | 0 | 0.050 |
| v2 | 3 | 0.667 | 0.583 | 0.059 |
| v3 | 3 | 0.667 | 1 | 0.063 |
| v4 | 5 | 0.300 | 14.583 | 0.077 |
| v5 | 6 | 0.333 | 12.833 | 0.083 |
| v6 | 2 | 1 | 0 | 0.050 |
| v7 | 3 | 0.667 | 1.250 | 0.059 |
| v8 | 2 | 1 | 0 | 0.050 |
| v9 | 5 | 0.400 | 8.750 | 0.077 |
| v10 | 2 | 1 | 0 | 0.050 |

**Top 3 vertices**

| Degree | Clust. coeff. | Betweenness | Closeness |
|---|---|---|---|
| v5 | v6 | v4 | v5 |
| v4 | v8 | v5 | v4 |
| v9 | v10 | v9 | v9 |

## Suggestions

More than exercises the following are suggestions for practicing one or more of the methods described in the previous pages. The first suggestion is to download, install and start using one of the software for network analysis cited (see section 4.4). All software come with a set of files containing network data which can be useful in order to practice with the different functions. It is important to choose a network of "reasonable" size. If the network is too small some of the measurements might be of little meaning, if it is too big the results can be confusing. Ideally it would be better to start with networks of about 100 nodes.

### Class network

In a course (or a small conference) prepare a list of the participants. Ask each one of the participants to indicate all the friendship relationship with the others. Transform the results into a file that can be read by the software package used. One simple format is the one used by Pajek, which is, usually, also readable by other software programs.
Pajek network files are in plain text, with a very strict format. The format is as follows:

```
*Vertices number_of_vertices
1 "label1"
2 "label2"
  etc…
*Edges (*Arcs if the network is directed)
vertex1 vertex2
vertex3 vertex4
  etc…
```

For example, given the following list of connections

| | |
|---|---|
| Bryan | Anna |
| Anna | Nick |
| Betty | Bryan |
| Nick | Betty |
| Sara | Nick |
| Nick | Bryan |

the Pajek network file is:

```
*Vertices 5
1 "Bryan"
2 "Anna"
3 "Nick"
4 "Betty"
5 "Sara"
*Edges
1 2
2 3
3 1
3 4
4 1
5 3
```

Note that whitespaces are spaces, not tabs. Any program can be used for writing a Pajek file, just make sure to save it as text-only file with a `.net` extension.

Once read the file start the analysis The first step, usually, is to obtain a picture of the network. Then calculate all the relevant global metrics (density, diameter, average path length) and rank the nodes (people). Identify the peculiar elements: highest degree, highest closeness, highest betweenness etc.

**Facebook friends network**

Download the network data of your Facebook friends. Depending on the network analysis software used you can find easily instructions and tutorials with a little Google searching (using something like “facebook friends network data”). Read the tutorial found.

Draw the network and identify the most important members of your community by calculating the most important network metrics (degree, clustering coefficient, betweenness, eigenvalue centrality etc.)

Run a modularity analysis. The method used will depend on the software; if the software allows, run the analysis using different methods. Identify the main groups and compare the partitioning calculated with what you know about your friends; assess the extent to which the algorithm is able to reproduce the real groupings. If you have used different algorithms find the most suitable for your case.

**Website network**

Prepare a list of companies along with their websites. For example the tourism operators in a destination. Record also the type (accommodation, travel agency, restaurant, association, public body, local transport, other tourism services, etc.) and, if possible, the geographical location (using classes such as region, area, closeness to center, etc.) for the different companies.

Browse the websites and record the hyperlinks to other any external websites. It is advisable to limit the browsing to a reasonable depth (3 to 5 levels). Transform the results into a file that can be read by the software package used and start the analysis.

Identify, as for the class network, the most central elements. If you have data on, or can make a reasonable hypothesis on, the relative importance of the different companies, compare these with some of the centrality measures and find the metric most suitable to represent the companies’ importance.

Run a modularity analysis and compare the communities found with those defined in terms of type of business or geography.

## Appendix II: Essential readings

**NB**: all the papers cited here can be found online (full text) with a Google search, at least in their pre-print version.

### Basic

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### Advanced

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## Books

### Popular

Gleick, J. (1987). *Chaos: Making a New Science*. New York: Viking.

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Barabási, A.-L. (2002). *Linked: The New Science of Networks.* Cambridge, MA: Perseus.

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### General

Newman, M. E. J. (2010). *Networks - An introduction.* Oxford: Oxford University Press.

Easley, D., & Kleinberg, J. (2010). *Networks, Crowds, and Markets: Reasoning about a Highly Connected World.* Cambridge: Cambridge University Press.

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