Collaboration and cooperation in a tourism destination: a network science approach

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Abstract

The extent of collaboration and cooperation is an important determinant for the development of a tourism destination. These features are usually assessed through qualitative investigations. This letter proposes a quantitative approach based on the evaluation of the modularity characteristics of the network of the destination stakeholders. The results of a sample analysis are reported.

Keywords: tourism destinations; collaboration; network analysis; modularity

Introduction

A significant strand of the tourism literature has dealt with the issues related to collaborations and partnerships (Bramwell & Lane, 2000; Hall, 1999) and has widely recognised this condition as an important determinant of the success and competitiveness of a tourism destination. The literature has looked after these questions by using case studies and empirical investigations, reviewed the programs put in place or assessed the outcomes in terms of destination's growth.

When studying these matters, two questions arise. The first one relates to the possibility to assess the degree of collaboration or cooperation. The second one concerns the identification of the best conditions in which a significant pattern of collaboration can exist and the actions needed to favour such conditions.

In the endeavour to study collaboration relationships in a destination, the understanding of the patterns of linkages among the components and the evaluation of the system's structure are crucial issues. Considering a destination as a networked system of interrelated components allows us to adopt the framework of network science and to develop its methods to answer the questions posed (Provan et al., 2005).

The aim of this letter is to present a network analytic approach to the assessment of collaboration and cooperation in a tourism destination and to give an example of application of the concepts by discussing a real case.

Background

In the study of industrial clusters, the formation of close ties or alliances among the different actors and the degree of cooperation established are considered important elements to improve the competitiveness of the group beyond the incidental (usually external) effects that promote the gathering (Andersson et al., 2004). Looking at a destination as a peculiar type of industrial cluster, the tourism literature has long recognised and emphasised this need for collaboration (Gunn, 1997).

Network analysis methods provide a means to study such topics. The availability of powerful computerised systems and large quantities of data have provided a wealth of models and techniques for the study of networks (Boccaletti et al., 2006), allowing improvements in the methods social network analysis had provided (Freeman, 2004). The most important result of this interdisciplinary effort is the recognition that the structural (topological) characteristics of a network are a fundamental and measurable characteristic of the system, strongly affecting its functioning. More importantly, it has been shown that many processes are directly influenced by the system's topology and possess some kind of 'universality' for which different topologically equivalent systems, even if they are of different nature, exhibit similar behaviours. This allows a wide class of phenomena in dissimilar settings to be studied, and makes it possible to share important results and models across diverse disciplines (Castellano et al., 2007). The application of these methods to tourism is quite recent, but has already shown to be an interesting way for assessing a number of attributes of the systems studied (Baggio et al., 2010; da Fontoura Costa & Baggio, 2009).

As the network science literature shows, most natural and artificial networked systems exhibit a non-trivial topology. One of the elements assessed is the presence of non-homogeneous groupings inside the network (Fortunato, 2010). In a social and economic network, these modules have a natural interpretation as communities formed by collaborative or cooperative actors.

Materials and Methods

The presence and the extent of collaboration patterns in a tourism network can be measured in several ways. The simplest is the one proposed by some authors (Baggio, 2007; Barber et al., 2006) who use the clustering coefficient as a rough measure. This metric represents the degree of concentration of the connections of the node's neighbours in a graph and gives the amount of local non-homogeneity of the link density.

A different proposal comes from the possibility to identify some form of substructures. Local subnetworks may have denser connections between members of the *community* than with actors outside the group. This arrangement is a common feature of many real systems and is central for the comprehension of their composition and evolution. Many methods have been devised to identify communities and to measure their size (Fortunato, 2010). They rely on numerical algorithms able to identify topological similarities in the local configurations of links. The commonly adopted measure to gauge the modularity of a network is called the *modularity index*. It is defined as: $Q = \sum_i (e_{ii} - a_i)^2$, where e_{ii} is the fraction of edges in the network between any two nodes in the subgroup i, and a_i the total fraction of links originating from the group and connecting nodes belonging to different ones. 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 links placed at random. The index is always smaller than one, and can be negative when the network has no community structure, or when a subgroup has less internal links than towards the other groups.

Usually, the possible communities in a network are identified by iterating some kind of numerical algorithm and by trying to maximise the modularity index which serves as quality function. Once obtained this result, the list of the community members can be derived. These algorithms differ in their computational complexity (and consumption of resources) and in their effectiveness in identifying the 'real' community structure.

These quantitative methods were applied to a tourism destination network in order to assess the extent of collaborative practices between its stakeholders. The destination used as a case is the Island of Elba, Italy (for a detailed discussion see Baggio et al., 2010). The island is a typical summer destination with an economy prevalently bound to tourism activities. The tourism stakeholders (hotels, intermediaries, attractions etc.) are mostly family-run small and medium companies who, for their strong 'independence', seem not to feel the necessity of extensive levels of cooperation or collaboration. A number of associations and consortia work in the area trying to defeat this attitude by cultivating various programs (Pechlaner et al., 2003).

The destination network was built by identifying the core tourism companies, organisations and associations operating at Elba and the relationships among them. The business relations between organisations were collected by accessing publicly available sources such as listings of the members of associations, management boards, industrial groups, catalogues of travel intermediaries, marketing flyers and brochures. These data were then verified with interviews to knowledgeable informants (director of the tourism board, directors of associations, and tourism consultants). This triangulation allowed the assessment of the validity of the data collected. In summary, the network can be reasonably estimated to be almost 90% complete. The basic topological characteristics of the network were assessed elsewhere (Baggio et al., 2010).

Modularity analysis methods

A modularity index with respect to what may be considered a standard subdivision in such a system was calculated. The groupings analysed were: geography (the municipalities of the island), type of business (accommodation, intermediaries, services etc.) and company size (roughly evaluated as: large, medium, and small). In addition, different algorithms were used to infer stochastically a modularity decomposition of the network.

The first method was originally proposed by Girvan and Newman (2002) with the improvements and modifications by Clauset et al. (2004). In it (CNM), the links are classified according to their betweenness. Edge betweenness is the number of shortest paths between all node pairs that run along the edge, high betweenness edges are identified as bridges between groups. The algorithm proceeds iteratively by deleting all the links with largest betweenness values and recalculating the values for the newly obtained network. At each step the modularity index is also calculated. The partition with the highest Q is selected as best solution.

The second algorithm uses a spectral bisection method based on the properties of the spectrum of the modularity matrix. This is derived from the adjacency matrix of the network and has been shown to well represent the topological characteristics of a network (details can be found in Newman, 2006). The algorithm (EIG) considers the distribution of the eigenvalues and eigenvectors of the modularity matrix in order to find the best partitioning of the graph.

A third algorithm (WLK) simulates random walks on the network. The procedure unfolds by assuming that a random walker tends to be trapped in dense parts of a network corresponding to communities (Latapy & Pons, 2006). Q is used to identify the best partitioning.

The last algorithm (INF) is based on information theoretic measures. The modular structure is considered a condensed description of a graph which approximates the whole information contained in its adjacency matrix. It is possible, then, to imagine a communication process in which the subdivision of a network in different groups represents a synthesis of the full structure that a signaller sends to a receiver (Rosvall & Bergstrom, 2007). The first one knows the full network structure and wants to send as much information as possible about it to a receiver over a channel with limited capacity. The signaller encodes the network into modules in a way that maximises the amount of information about the original network and minimises the amount of information transferred. This can be quantitatively assessed by the maximisation of the mutual information (a quantity expressing how much one random variables tells us about another). The optimisation information is performed by simulated annealing, a probabilistic technique for optimisation problems. Once found the best partitioning, the modularity index is calculated.

These algorithms were chosen for their efficiency and effectiveness (Danon et al., 2005; Fortunato, 2010) and for the availability of specific software programs. The modularity analysis was performed by using the main connected component of the Elban tourism network (i.e. all isolated nodes were removed). The values obtained were compared with the values calculated for a randomised version of the original network obtained by rewiring it while preserving the degree distribution. As suggested in the literature (Guimerà et al., 2004), this is a valid null-model, useful to interpret network measurements which otherwise would be difficult to gauge.

Results and discussion

The Elba network is characterised by a scale-free topology (power-law scaling of the degree distribution) which is consistent with that generally ascribed to many artificial and natural complex networks. The system has a very low connectivity (link density = 0.003) with a very large proportion (37%) of disconnected elements (Baggio et al., 2010). In agreement with previous studies (Pechlaner et al., 2003), these results provide quantitative evidence of the fragmentation of the ensemble of Elban tourism operators.

Table 1 shows the values of the modularity index calculated using the subdivision by geography, type of business and company size of the stakeholders. The values are quite small and for two of them are negative, meaning a propensity to have more connections outside own group than inside.

Table 1. Modularity index Q of the Elba destination network when standard subdivisions are used

Grouping	No. of modules	Q
Geography	9	0.047
Type	8	-0.255
Size	3	-0.086

The results of the experiments performed with the algorithms described in the previous section are shown in Table 2.

Table 2. Modularity index Q calculated for different stochastic algorithms

		CNM	EIG	WLK	INF
Original network	No. of modules	11	19	42	58
	Q	0.396	0.281	0.333	0.249
Rewired network	No. of modules	12	15	47	50
	Q	0.367	0.267	0.320	0.230

As can be seen, different algorithms provide different results. In particular the first two, CNM and EIG, have a known resolution limit (Fortunato & Barthélemy, 2007), and identifies a lower number of communities with respect to the other algorithms. However, what is important for the present work is the consideration that all the *Q* values calculated by using the numerical algorithms are higher than those calculated on the basis of predefined groupings. The randomly rewired network shows modularity values slightly lower than those calculated for the original network (the values reported are averages over 10 iterations).

These results indicate that a distinct modular structure exists even if it is not very well defined or highly significant (Guimerà et al., 2004); moreover, the groups identified by using these methods are different in number and composition (geography, business type or size) from the others (see an example in Figure 1)

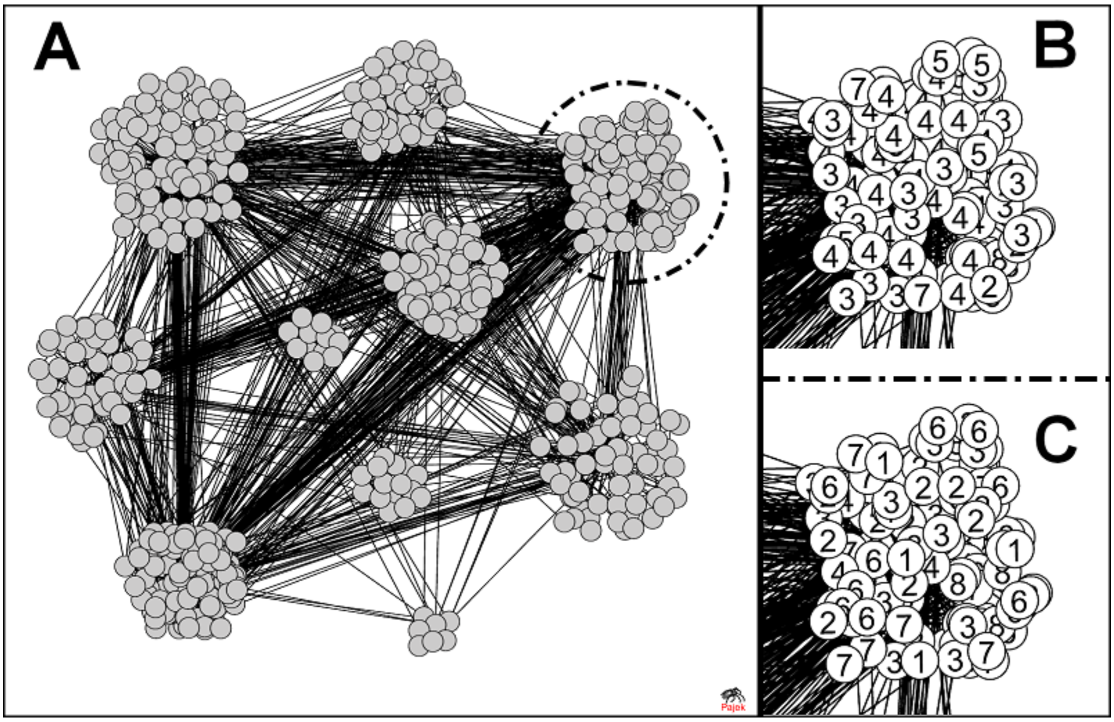

Figure 1. Modules identified by algorithm CNM (panel A). Panel B and C show and enlarged view of the community circled in panel A. Numbers on nodes indicate different types of business in panel B and geographic locations in panel C.

Concluding remarks

The metrics derived in this work provide quantitative evidence of the fact that the network of tourism operators analysed is very fragmented and that the local stakeholders exhibit a very low degree of collaboration or cooperation. If we consider traditional characteristics such as the information contained in the geographical or business typology, no communality characteristics can be found. The modularity solutions found in this way are far from optimal. On the other hand, the system seems to exhibit self-organisation properties which cause the formation, even if limited, of agglomeration of linkages producing a number of informal communities and an informal community structure.

The topology generated by the system of connections between the stakeholders of the destination induces a certain level of self-organisation which goes beyond predetermined differentiations of the organisations. From a destination management viewpoint, this result is important. It can provide indications on how to optimise some performance, for example optimal communication channels or even productivity in collaborations, taking into account the spontaneous characteristics of the complex destination system. This way it is possible to find a practical way to follow the ideas and practices of an adaptive approach to the management of a tourism destination which has been advocated by some scholars and in some cases has shown a good degree of effectiveness (Agostinho & Teixeira de Castro, 2003; Farrell & Twining-Ward, 2004).

One more consideration is in order. As complex adaptive system, a destination is an entity which is quite difficult to manage. Deterministic and rigid attempts at directing it are destined to fail for the strong self-organising characteristics of such systems. This means that the most effective attitude is an adaptive one, requiring a flexible approach for changing it dynamically and be prepared to react swiftly to the modifications that may occur within the system or in the external environment.

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