Tourism destinations:
A universality conjecture based on network science

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ABSTRACT

The structural characteristics of a tourism destination are of crucial importance since they influence its dynamic behavior. Many studies have shown that destinations have apparently similar topologies. The question posited in this paper is to what extent does this similarity hold, and whether these topologies can be considered as a universal trait. This study reanalyzes available data to test this conjecture. In particular, several quantities representing the topological structures of the destination are calculated; further, we obtain size-invariant and scalable similarity scores. The results indicate that destinations hold structurally similar, and arguably universal, characteristics. This finding is important as it suggests that there are some very basic (and consistent) strategies destination managers can develop when designing plans and actions.

KEYWORDS

network science, tourism systems, destination structure, destination design, universality

INTRODUCTION

In the last few decades the study of tourism has produced a wealth of research that has examined innumerable aspects of this complex phenomenon from many points of view. One of the most important outcomes of these studies is the finding that a systems approach is requisite for effectively designing and managing a destination as efficiently and effectively as possible so to ensure a good social and economic evolution (Framke, 2002; Fyall & Garrod, 2019; Haugland et al., 2011). Indeed, recent research indicates that the interplay of the different stakeholders is a core determinant for both the success of individual actors and that of the entire destination (Beritelli et al., 2007; Rodríguez-Díaz & Espino-Rodríguez, 2008; Stienmetz & Fesenmaier, 2019).

Managing a destination to ensure balanced social and economic progress is essentially a matter of designing and implementing a strategic path able to consider the diverse systemic challenges such as the dynamicity of the broad environment within which the destination is embedded, the tensions arising from the competition among the various internal components and those created by the growing visitors' flows, and the influence of the remarkable advances and availability of technological tools (Buhalis, 2000; Gretzel et al., 2006; Li et al., 2017). Empirical indications of these effects come, for example, from the verification that the economic value generated by tourism is strongly dependent on the structure of supply- side and demand-side interactions and that some kind of 'network orchestrator' management style can be effective in better handling the economic impacts of tourism in a destination (Stienmetz & Fesenmaier, 2019). As Holston maintains (2011), a proper design implies that customers understand the 'product' and its value, articulates the basis for differentiating products and services from the competition, and helps and supports all management activities by establishing a structure able to offer opportunities for creativity, innovation and collaboration, and effective mechanisms to address possible problems. In these considerations one element appears to play a central role: the relationships within the dynamic behavior of the system in terms of its functions and structural characteristics. These relationships are well known and well researched in a wide number of fields, and has helped to gain a better understanding of the properties of organic molecules (Le Couteur & Burreson, 2003), metabolic systems (Ma & Zeng, 2003), proteins (Lee et al., 2007), food webs (Pimm, 1982), the human brain (Batista-García-Ramó & Fernández-Verdecia, 2018), the animal and vegetable kingdoms (Thompson, 1917) or engineered systems such as transports (Guimerà et al., 2005) or technological architectures (Gubbi et al., 2013). This research demonstrates that for all these systems the structural organization (i.e., topology) strongly constrains the range of dynamic behaviors and therefore the outcomes of underlying dynamic processes.

The primary objective of this article is to examine the structure of tourism destinations. In particular, this paper reports the initial results of research focused on assessing the potential existence of 'universal' topological characteristics within tourism destinations. The starting point is the well-recognized vision of tourism destinations as complex adaptive systems (Baggio, 2008, 2020; Baggio & Sainaghi, 2011) and fits within the theoretical framework of network analytic methods embedded within statistical physics (Cimini et al., 2019; Kittel, 2004; Stauffer, 2004). The paper is organized in three sections as follows. The first section introduces the foundations of complexity science as it relates to the study of tourism destinations. The second section describes the research approach used to test our conjecture of universality including the data used and resulting metrics and the proposed methods employed for testing this conjecture. The third and final section includes extensive discussion of the outcomes of the analyses along with their implications, limitations and suggestions for future research.

BACKGROUND

The theoretical background for this paper lies in the domain of complexity and network sciences. This discussion first provides an overview of complexity science within the context of tourism; then, we provide a brief discussion of the basic ideas and techniques of network science. We anticipate here that a full discussion of these two areas is outside the scope of this journal, but we provide a comprehensive set of references for those readers interested in deepening their knowledge on these subjects.

Complex tourism systems

Tourism is a strange and fascinating phenomenon. Strange because despite a three-quarters century effort of a wide number of scholars and practitioners no one has produced a satisfactory definition of the set of activities and organizations concerned with the movement of millions of people across the World (Darbellay & Stock, 2012; Laesser et al., 2020; Leiper, 1979). This strangeness makes the study of this domain a fascinating endeavor. Despite the vagueness, there are some characteristics that provide a path for understanding the phenomenon and for attempting some form of control. These characteristics are extensively discussed in the domain of complexity science where the primary purpose is to provide an understanding of the pervasive components of the world we live in, namely complex systems (Lewin, 1999; Mitchell, 2009; Phelan, 2001).

In essence these are systems composed of a certain number of elements (not necessarily equal or similar), linked by dynamic and non-linear relationships, that exhibit hierarchical structures of subsystems and components that are endowed with natural behaviors or engineered functions. The behaviors of the components and subsystems causally influence one another at many levels, and the propagation of these causal stimuli creates chains of events that result in the overall behavior and function of the system in ways that often cannot be easily (or at all) predicted from the individual features or dynamics. These emergent behaviors may extend in both temporal and spatial dimensions (Vattam et al., 2011). Moreover, a typical complex system has a continuous exchange with the environment in which it is embedded and therefore influences, and is influenced by, these exchanges (Baggio, 2008; Johnson, 2009). Frequently cited examples of complex systems are the brain, the immune system, biological cells, metabolic networks, ant colonies, the Internet and the World Wide Web, economic and financial markets, and human social structures (Mitchell, 2009). The relationships between the components of a system, the collective behaviors and the interactions with the environment, are the primary objects of study of complexity science. A central point is that complex systems are investigated as holistic entities, given the impossibility to comprehend all their manifestations as compositions of individual traits and behaviors. As such, complexity science is an alternative paradigm to reductionism, which tries to explicate systems in terms of their constituent elements and the individual interactions between them (Anderson, 1972).

Looking at these considerations it is not difficult to realize that the tourism destination is a prototypical complex phenomenon and the understanding of the destination is of crucial importance to society. Indeed, many studies have been conducted of various components of tourism destinations by scrutinizing many of its internal components (the stakeholders: tourists, residents, companies, groups, media, associations etc.) and their relations (internal, between themselves and external, with the environment) using a reductionist approach. More recently, however, Baggio and his colleagues (Baggio, 2008, 2020; Baggio & Sainaghi, 2011) have begun to consider tourism destination as a dynamic and complex system. Several techniques have been proposed for analyzing destination systems, all coming from the work done in this respect in many disciplinary domains. Example of studies include nonlinear analysis of time series (Olmedo & Mateos, 2015; Po & Huang, 2008), statistical physics (Cole, 2009) (Provenzano, 2014; Ulubaşoğlu & Hazari, 2004), agent-based modeling (Amelung et al., 2016; Johnson & Sieber, 2011; Pizzitutti et al., 2014). However, it is argued that network sciences is the most powerful approach for investigating the structure of a destination.

Network science in a nutshell

Topological analysis has been widely adopted to uncover patterns or structures from various real-world complex systems which consist of a large number of components whose interactions produce nontrivial phenomena inexplicable by analyzing the individual elements. Behind a complex system, there is a network that defines these interactions and therefore to understand a complex system we map the network (and its structure) behind it. Networks embody the true geometry of complex systems and the extensive work done in the last decade on many theoretical and empirical facets has led to the finding that, despite the many differences, networks are governed by a series of fundamental laws which determine and limit their behavior (Barabási, 2007, 2012; Solé et al., 2003). In this perspective, the common language originating from graph theory (Bollobás, 1998; Diestel, 2016) is used to model a system. This language is a rigorous framework and can be used to formalize a system of interacting entities (agents) by letting each entity play the role of a node and where various types of interaction can be described as links (weighted or unweighted, directed or undirected, multiple or single). Moreover, representing a network as a square matrix (adjacency matrix) whose elements specify whether pairs of vertices are connected or not allows for quantifying different aspects of the system. As such, network science provides very powerful tools with which to count, map and evaluate the patterns of connections between the elements of any system, be it a natural, artificial, social or economic.

From an applied perspective, network analysis provides the foundation needed to design and manage destination management activities as they need to be grounded in a deep knowledge of the system's features. The importance (and usefulness) of systems analysis is exemplified by studies in a range of issues including the study of topological and dynamic features of destinations, information and knowledge diffusion mechanisms and the behavior of management teams or to the patterns characterizing the flows of visitors (Baggio, 2017; Casanueva et al., 2016; van der Zee & Vanneste, 2015). These studies demonstrate that a central issue in destination design (and management) is the concept of process which describes the dynamic relationships of information (or materials) and the structure of the relationships within the system (Capra, 1985; Gault et al., 1987; Miller, 1984), and they confirm that the success of any destination is based upon the fit between the products and services (the processes) and the organizational structure (Fujimoto, 2007; Jones, 2014; Ottino, 2004; Stienmetz & Fesenmaier, 2017).

A thorough network study evaluates the system at three levels:

- *Local (microscopic)*: Analyses at this level focus on the properties of the single components (nodes). Most relevant quantities are: number of links each node has (degree); clustering coefficient (density of links of the node's immediate neighbors); the capability to reach any other node (closeness); the role played as connector between different areas of the network (betweenness); the overall influence of a node (derived from the principal eigenvector of the adjacency matrix). Normalized versions of these metrics are usually called centrality (e.g. degree centrality, betweenness centrality etc.);

- *Intermediate (mesoscopic)*: Analyses at this level examine possible sub-structures such as modules (or communities); that is, groups of nodes more densely connected between themselves than to than to other parts, or the presence of hierarchies in the topology. Other mesoscopic structures are motifs or graphlets, patterns of connections involving small subsets of nodes, whose distribution characterizes many system functions; and,

- *Global (macroscopic)*: Analyses at this level focus on large-scale topological characteristics where the measures include the statistical distributions of the local metrics and, above all, degree distribution which describes the capability of the system to react to a number of dynamic processes. Many real and artificial networks exhibit a power-law degree distribution (few nodes with many connections and many with few links). In this case we have no typical degree or scale (as it would be for the mean of a Gaussian shape), hence the scale-free name given to these networks. Other measures used are the average path length (average distance between any two nodes), the diameter (longest distance between any two nodes), the correlations existing between the distributions of different metrics, and the average values of the microscopic metrics over the whole network.

The many metrics defined for measuring the features of a network provide rigorous quantitative assessments describing the dynamics of the system and therefore the potential for various evolutionary paths. Their precise definitions can be found in the large literature of network science (Barabási, 2016; Cimini et al., 2019; da Fontoura Costa et al., 2007). Importantly, this literature demonstrates that the topological features of complex networks strongly influence the underlying dynamic processes such as the diffusion of information or opinions, information search, cooperation among organizations, etc. (Baggio and Cooper, 2010; Baggio and Del Chiappa, 2014; Barrat et al., 2008; Boccaletti et al., 2006). As such, these analyses across the three levels of the system enable managers to design and evaluate potential strategies by simulating system structure; further, these analyses make it is possible to 'experiment' with different patterns, configurations and settings or different dynamic processes that would be otherwise impossible for theoretical or practical reasons. The understanding gained about the behavior of system can then be used to assess the potential efficacy of alternative management (including design) actions (Hartmann, 1996; Stauffer, 2003).

Statistical physics and complex networks

The theoretical framework in which network science is embedded is statistical physics (or statistical mechanics), one of the fundamental fields of physics. This is a rigorous formal framework for the study of the properties of many body systems (i.e. composed of a large number of interacting elements), allows for deriving statistically the macroscopic properties of a system from incomplete measurements of intensive (i.e. independent from dimensions of the system) and extensive (i.e. size-dependent) quantities related to the system, and when system's microscopic properties are expressed in terms of probability distributions (Kittel, 2004; Landau & Lifshitz, 1980). Our understanding of this framework has led to the development of two important concepts: scaling and universality (Amaral & Ottino, 2004; Kadanoff, 1990). Scaling laws are the relations that connect the various critical-point features by characterizing the singular behavior of some system parameters and of some response functions (Stanley, 1999). The concept of universality, on the other hand, describes the essence of different systems and classifies them into distinct classes. Indeed, one of the main results of the application of network science is the recognition that many systems exhibit global properties independently from the specific form and characteristics of their components. Therefore, it can be concluded that certain universal laws may apply within many different types of systems, whether they are social, economic, natural or artificial. For example, studies show that natural ecosystems and their food webs, the human brain and its active areas under external stimuli, the routes between airports, the components of complicated software systems, are remarkably similar in their topological configurations (Cimini et al., 2019; da Fontoura Costa et al., 2011). And, importantly, this similarity is independent from structural details such as size, specific settings, topical areas, hierarchical organization, or past history. In this study, we seek to extend this work by beginning the process of examining the universality of 'tourism destinations' as a system. In particular, we seek to test whether there are universal topological characteristics that can be identified by identifying a 'representative' tourism destination structure and, possibly, the basic mechanisms which underlie the formation of this structure.

RESEARCH APPROACH

The tourism destination is conceptualized as a system where networks can be used to represent different states of the system. In this study we test whether there are universal topological characteristics which underlie the formation of seven different destinations. More specifically, we test whether all elements within the destination-based networks can be considered as belonging to the same equivalence class. The seven destination-based networks used in this study are the following:

- AusWest: Western Australia (Raisi et al., 2020);
- Cremona: city of Cremona, Italy (Milo, 2015);
- Elba: island of Elba, Italy (Baggio et al., 2010b);
- Gallura: the region of Costa Smeralda-Gallura, Sardinia, Italy (Del Chiappa & Presenza, 2013);
- Goldcoast: the Gold Coast region, Australia (Scott et al., 2008);
- Livigno: the city of Livigno, Italy (Sainaghi & Baggio, 2014);
- Sibiu: Sibiu county, Romania (Grama & Baggio, 2014).

The dimensions (number of nodes and links) of the seven destination-based networks are shown in Table 1. As can be seen, the destinations have different dimensions and span from single cities (Cremona, Livigno) to small and medium geographical areas (Elba, Sibiu, Gallura, Halland) to larger regions (Western Australia) to entire countries (Fiji, Austria). They come from different countries and continents, and are of different nature (sea: Elba, Gallura, Gold Coast, Halland; mountain: Livigno; city: Cremona; internal country destinations: Sibiu, Western Australia; countries: Fiji, Austria). The dimensions of the seven destination-based networks vary as well in a couple of orders of magnitude. It is argued, therefore, that this set of seven destinations is sufficiently diverse to be considered a 'reasonable' sample for the purpose of initially testing a conjecture of 'universality' in structural properties among tourism destinations.

Table 1 Order (number of nodes) and size (number of links) of the networks

Name	Nodes	Links
AusWest	577	995
Cremona	90	223
Elba	1028	1642
Gallura	1808	2485
Goldcoast	75	362
Livigno	523	1389
Sibiu	478	2222
WebAT	2341	13598
WebFiji	492	377
WebHalland	535	388
WebWAU	1515	5540

In addition, we consider four destination networks based upon the web presence of the different destination stakeholders. The justification for using these digital views is consistent with much recent research indicating that they are reliable 'representations' of destination networks (Baggio, 2007; Baggio & Del Chiappa, 2016; Baggio et al., 2010b). Given this interpretation, the digital web networks (inherently directed) were symmetrized as a connective relationship between the various entities (therefore naturally bidirectional). It is important to note here that given the high 'non-normality' of practically all the properties of a complex network, a sampled series of observations cannot be easily assessed using traditional statistical methods (see e.g. Clauset et al., 2008; Costenbader and Valente, 2003; Handcock and Gile, 2010; Kossinets, 2006; Lee et al., 2006). The additional 'digital' networks included in this study are:

- WebAT: the tourism web space of Austria (Piazzi et al., 2012);
- WebFiji: the tourism webspace of the Fiji Islands (Baggio et al., 2007);
- WebHalland: tourism websites of the Halland County, Sweden (Éber et al., 2018);
- WebWAU: the tourism webspace of Western Australia (Raisi et al., 2017).

The data collection procedures followed standard protocols whereby the digital networks were collected using crawlers and checking the obtained data with sample visual inspections. Further, a similar approach was used for all the entities: a multiple-source scrutiny that collects all available public documental data on the components (companies, associations, groups, organizations etc.) of the different systems, and in some cases survey questionnaires administered to a sample of the tourism stakeholders. The nodes of the network are the core tourism operators of the destination (i.e. accommodations, intermediaries, restaurants, travel agencies etc., as defined by (UNWTO, 2000).The results of this process were complemented by selected interviews with local knowledgeable informants for validating the data collected and evaluating type and reliability of the relationships identified. For more details on the single cases the reader is referred to the original papers cited above.

Despite the many measures existing that describe the different structural and dynamic characteristics of a network, no single one is considered to be a sufficient and reliable ‘global indicator’. Following and extending the measures proposed by Berlingerio et al. (2013), a feature vector containing 38 values was developed to characterize the most important topological properties of each network. All metrics used in describing the eleven tourism destinations are commonly applied in network science and are described below (Baggio et al., 2010b; Barabási, 2016; da Fontoura Costa et al., 2007; Newman, 2010):

Local metrics:

- degree (deg): number of links for each node;
- clustering coefficient (cc): fraction of node’s neighbors that are neighbors of each other;
- closeness (clo): mean distance from a node to all other nodes;
- betweenness (btw): fraction of all shortest paths in the network that contain a given node;
- eigenvector centrality (eig): measure of the influence a node has (eigenvector associated with the largest eigenvalue of the adjacency matrix);
- local efficiency (lef): efficiency in information transfer between a node and the rest of the network.

For all local metrics the following statistics were calculated: mean (_mn), median (_md), standard deviation (_st), skewness (_sk), kurtosis (_ku). All local metrics were normalized before calculating the different statistics.

Global metrics:

- density (den): ratio between the actual number of links and the maximum possible;
- diameter (dia): largest value for the shortest paths in the network;
- average path length (pth): average shortest path length in the network;
- assortativity (ass): correlation coefficient between the degrees of each node and those of its neighbors;
- global efficiency (gef): gobal efficiency in information transfer;
- Gini index of degrees (gin): Gini index of the degrees of the network;
- modularity index (mdl): degree to which the network may be subdivided into clearly separated groups;
- spectral gap (eigap): difference between the absolute values of the two largest eigenvalues of the adjacency matrix, which is closely bound to the behavior of a network with respect to dynamic processes such as synchronization or epidemic diffusion (Gago, 2011; Van Mieghem, 2010).

RESULTS

The first step in testing for universality among the tourism destinations was made by assessing the degree distributions *P(k)* of the eleven networks. Figure 1a shows the cumulative degree distributions of the respective networks. Apart from some variations due to the different sizes and densities of the networks it is clear that the shapes are quite similar. In particular the largest part of the distributions follows a power-law: $P(k) \sim k^{-\alpha}$. The exponents and standard deviations were estimated using the maximum likelihood estimation method described by Clauset et al. (2009) and are shown in Figure 1b (values are in table 2).

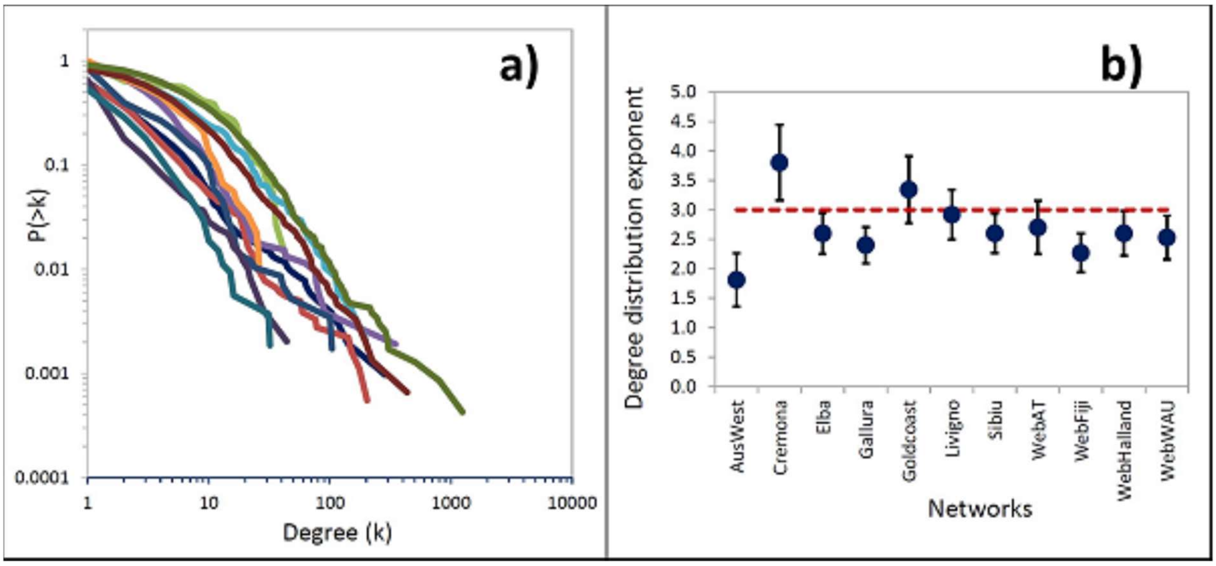

Figure 1 Cumulative degree distributions (a) of the 11 networks, b) the exponents of the degree distributions

Table 2 Exponents of the degree distributions

Network	Exponent
AusWest	1.81±0.45
Cremona	3.80±0.64
Elba	2.60±0.14
Gallura	2.40±0.07
Goldcoast	3.34±0.57
Livigno	2.92±0.21
Sibiu	2.60±0.17
WebAT	2.70±0.18
WebFiji	2.27±0.09
WebHalland	2.60±0.38
WebWAU	2.53±0.19

The similarity of the power-law exponents is a first clue but is not sufficient to assess fully this similarity. One reason is that the fitting procedure tends to smooth possible deviations in the initial or the final region so that two completely different distributions may have similar features (fitted exponent). To overcome this situation a more reliable solution is that of comparing the probability distribution of the degrees using a different method. A simple possibility is to use the Kolmogorov-Smirnov (KS) test; however, the KS test is quite sensitive to the scale and size of the networks compared (since it performs a point-to-point comparison of the distributions) and two networks with different ranges of degrees may provide unreliable outcomes. A better method to address this issue was developed by Aliakbary et al. (2015) and Janssen et al. (2012) where the degree sequence (the list of al degrees) is divided into a number of intervals. Here, we use 8 intervals calculated by a logarithm binning of the degree sequence and is a common approach when dealing with these distributions (see e.g. Virkar and Clauset, 2014). For each interval the mean probability for a node to belong to that interval is calculated. This results in a feature vector that can be compared to the characteristics of another network. The comparison is performed using the Hellinger distance which is a proper metric (distance function), derived as a variation of the Bhattacharyya distance, and particularly apt when probability distributions are involved (Chung et al., 1989). The Hellinger distance is naturally normalized (0=no distance, 1=maximum distance) so the lower the value the higher the similarity between two distributions; note that we use the value 0.5 as a threshold to define a good or bad similarity. The results of this analysis are reported in Table 3.
With an average value of 0.32±0.15 we cannot but confirm similarity exists among the destinations. However, the only values that differ from a low distance are those of the Goldcoast network. This can be explained as due to the small size that probably does not allow to have a "sufficient statistic" and to the fact that, looking at the data collection methods for that case, some of the nodes of the network are generic groups of operators rather than single entities (see Scott et al., 2008).

Table 3. Hellinger distances between all pairs of feature vectors (highlighted values are those higher than 0.5)

	AusWest	**Cremona**	**Elba**	**Gallura**	**Goldcoast**	**Livigno**	**Sibiu**	**WebAT**	**WebFiji**	**WebHalland**	**WebWAU**
AusWest	0										
Cremona	0.398	0									
Elba	0.152	0.416	0								
Gallura	0.191	0.468	0.081	0							
Goldcoast	**0.536**	0.299	**0.534**	**0.565**	0						
Livigno	0.263	0.457	0.153	0.149	**0.587**	0					
Sibiu	0.247	0.306	0.210	0.238	0.440	0.233	0				
WebAT	0.346	0.424	0.290	0.295	**0.597**	0.178	0.241	0			
WebFiji	0.178	0.470	0.235	0.248	**0.551**	0.368	0.369	0.480	0		
WebHalland	0.162	0.478	0.100	0.080	**0.587**	0.205	0.279	0.341	0.187	0	
WebWAU	0.303	0.399	0.237	0.246	**0.564**	0.146	0.176	0.076	0.437	0.295	0

Therefore, it is argued that, on average, the destinations networks exhibit very similar distributions. Indeed, if we cumulate all the degrees we obtain the distribution of Figure 2 (the dotted line is drawn as a reference and represents a pure power-law) whose exponent is α=2.57±0.09, which can then be seen as a typical destination network degree distribution.

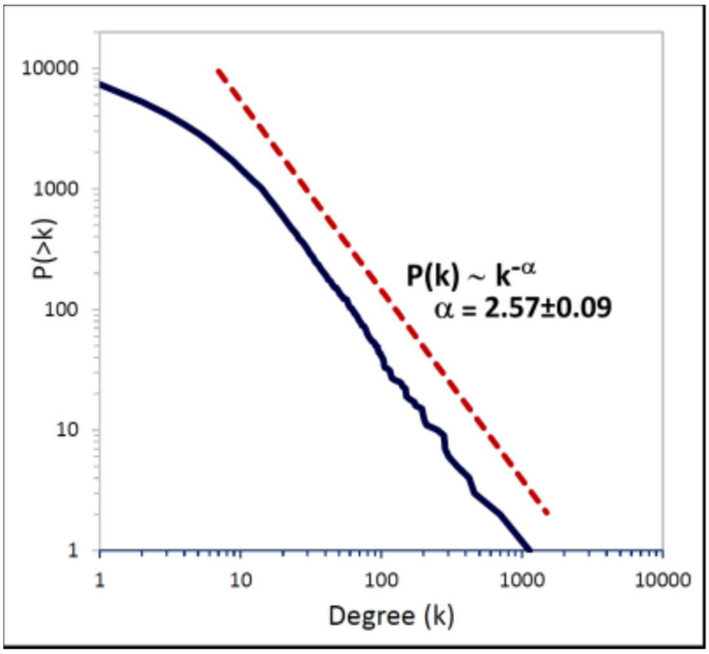

Figure 2 The cumulated degree distribution

The second step in the study examined the structural characteristics of the eleven destination systems in terms of the 38 network measures. The results of these analyses are in Table 4. As can be seen, practically all the local metrics have small values and signal relatively low general connectivity characteristics for the networks examined. The same applies for the efficiency attributes both at a local and global level. This is valid also for the mesoscopic structures that show little heterogeneity. The general compactness expressed by the diameter and the average distance (path length) between any two nodes are, instead, similar or better than those reported in the literature for many other social and economic networks (Barabási, 2016; Newman, 2010; da Fontoura et al., 2011). These outcomes are discussed in the next section.

Table 4 Network metrics for the destinations examined

	Network										
Metric	**AusWest**	**Cremona**	**Elba**	**Gallura**	**Goldcoast**	**Livigno**	**Sibiu**	**WebAT**	**WebFiji**	**WebHalland**	**WebWAU**
deg_mn	0.006	0.056	0.003	0.002	0.184	0.010	0.019	0.005	0.003	0.003	0.005
deg_md	0.002	0.034	0.001	0.001	0.122	0.006	0.007	0.002	0.002	0.002	0.002
deg_st	0.013	0.058	0.012	0.005	0.182	0.033	0.037	0.015	0.007	0.005	0.012
deg_sk	8.896	2.008	14.414	13.407	0.761	15.645	5.356	20.094	6.335	5.458	12.086
deg_ku	105.997	4.524	274.987	229.568	-0.660	294.662	39.133	557.536	53.380	45.140	233.273
cc_mn	0.097	0.260	0.050	0.091	0.388	0.346	0.321	0.362	0.024	0.035	0.243
cc_md	0.000	0.149	0.000	0.000	0.465	0.286	0.267	0.308	0.000	0.000	0.151
cc_st	0.226	0.317	0.160	0.250	0.367	0.370	0.326	0.322	0.133	0.140	0.300
cc_sk	2.906	1.079	4.468	2.793	0.150	0.647	0.724	0.639	6.344	5.302	1.305

cc_ku	8.086	0.126	21.582	6.486	-1.525	-1.024	-0.566	-0.664	40.948	30.385	0.788
clo_mn	0.196	0.313	0.121	0.089	0.464	0.331	0.353	0.321	0.064	0.043	0.229
clo_md	0.217	0.297	0.160	0.127	0.458	0.391	0.366	0.363	0.066	0.002	0.267
clo_st	0.091	0.066	0.100	0.075	0.121	0.124	0.080	0.106	0.063	0.046	0.110
clo_sk	-1.201	0.246	-0.259	-0.250	-0.833	-1.842	-2.078	-2.309	0.162	0.271	-1.367
clo_ku	0.589	-0.412	-1.712	-1.728	2.685	2.474	7.731	4.415	-1.723	-1.698	0.416
btw_mn	0.004	0.027	0.001	0.001	0.025	0.002	0.003	0.001	0.002	0.002	0.001
btw_md	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
btw_st	0.018	0.053	0.007	0.005	0.047	0.028	0.018	0.010	0.008	0.006	0.008
btw_sk	14.356	3.699	22.934	18.350	2.405	22.140	11.968	35.393	8.548	5.255	26.283
btw_ku	238.444	17.001	610.025	409.658	5.673	497.295	174.041	1359.621	96.560	35.111	834.551
eig_mn	0.018	0.067	0.015	0.008	0.110	0.029	0.027	0.013	0.018	0.012	0.014
eig_md	0.003	0.024	0.002	0.000	0.091	0.027	0.013	0.009	0.000	0.000	0.008
eig_st	0.037	0.081	0.028	0.022	0.099	0.033	0.037	0.016	0.042	0.041	0.022
eig_sk	5.224	1.444	6.469	6.766	0.442	8.793	2.924	9.356	5.714	6.233	5.790
eig_ku	42.391	1.411	78.613	74.880	-1.307	131.335	11.537	169.737	48.825	54.339	59.600
lef_mn	0.118	0.327	0.062	0.100	0.465	0.416	0.420	0.500	0.028	0.038	0.327
lef_md	0.000	0.167	0.000	0.000	0.700	0.417	0.475	0.567	0.000	0.000	0.282
lef_st	0.251	0.359	0.183	0.267	0.417	0.398	0.370	0.347	0.144	0.148	0.340
lef_sk	2.352	0.560	3.654	2.626	-0.137	0.235	0.086	-0.264	5.852	5.080	0.592
lef_ku	4.708	-1.155	13.639	5.372	-1.831	-1.565	-1.510	-1.255	33.869	27.278	-0.952
den	0.006	0.056	0.003	0.002	0.184	0.010	0.019	0.005	0.003	0.003	0.005
dia	8	8	8	14	4	6	7	8	12	14	8
pth	3.809	3.353	3.165	4.196	2.156	2.481	2.751	2.638	4.188	5.480	3.067
ass	-0.121	0.011	-0.329	-0.285	-0.322	-0.250	-0.286	-0.149	-0.254	-0.186	-0.158
gef	0.210	0.358	0.131	0.098	0.516	0.346	0.375	0.337	0.071	0.050	0.242
gin	0.648	0.504	0.780	0.765	0.534	0.636	0.660	0.651	0.678	0.712	0.669
mdl	0.549	0.527	0.410	0.729	0.227	0.427	0.372	0.431	0.741	0.740	0.508
eigap	0.348	0.313	0.263	0.066	0.550	0.318	0.360	0.224	0.207	0.171	0.256

A cosine distance for all possible pairs of vectors was computed to assess the degree of similarity (or difference) across the respective destinations for all network measures. The cosine similarity measure considers the vectors maximally similar if they are parallel (cosine=1) and maximally dissimilar if they are orthogonal (cosine=0). Importantly, this measure disregards the magnitude of the vectors since the goal is to look for similarity not isomorphism; that is, the magnitudes can be influenced by the size, for example, of the networks that would somehow mask the likeness (see e.g. Rawashdeh and Ralescu, 2015; Teng et al., 2012; Wang et al., 2015 for examples of the application of this approach). As shown in Table 5, few comparisons exceed the value of 0.5, which is considered as the critical threshold for considering two elements dissimilar. Thus, it is concluded that the eleven destination-based networks included in this study are topologically very similar.

Table 5 Cosine distances between all pairs of feature vectors (highlighted values are those below 0.5)

	AusWest	Cremona	Elba	Gallura	Goldcoast	Livigno	Sibiu	WebAT	WebFiji	WebHalland	WebWAU
AusWest	1										
Cremona	0.883	1									
Elba	0.998	0.871	1								
Gallura	0.995	0.864	0.995	1							
Goldcoast	0.553	0.806	0.541	0.517	1						
Livigno	0.990	0.844	0.987	0.997	**0.490**	1					
Sibiu	0.975	0.900	0.975	0.953	0.658	0.939	1				
WebAT	0.997	0.871	0.999	0.991	0.558	0.984	0.982	1			
WebFiji	0.893	0.774	0.881	0.888	**0.345**	0.891	0.820	0.861	1		
WebHalland	0.669	0.559	0.644	0.684	**0.107**	0.707	0.530	0.613	0.907	1	
WebWAU	0.984	0.882	0.987	0.968	0.603	0.955	0.996	0.992	0.832	0.550	1

DISCUSSION

Albert Einstein and Leopold Infeld begin 'The evolution of Physics' (1938), one of the best popular science books ever written, by likening a scientist to a detective trying to solve a murder mystery. Now, as 'detectives' in tourism, we have discovered two important clues that may well support the notion that tourism destinations have some universal traits.

The first clue found is a substantial similarity in the power-law shape of the degree distribution. This consistency tells us that tourism destination networks are prototypical complex systems, therefore we expect to find good self-organization capabilities, a relatively good robustness with respect to perturbations that may affect the system, but also a substantial fragility if the main hubs (nodes with the largest degrees) are affected (see e.g. Caldarelli, 2007; Newman, 2005). Moreover, the 'complexity' state means that the predictability window for the behavior of the system is relatively small.

The degree distribution also allows us to infer possible mechanisms for the formation and the growth of a complex system. In particular, the exponent of the power-law degree distribution is compatible with a preferential attachment formation mechanism for the networks (Barabási & Albert, 1999; Barabasi et al., 1999). Also popularly known as 'rich-get-richer', this mechanism indicates that new connections in a network are formed by an entity with a probability proportional to the degree of the receiving node. In other words, new elements joining the network or newly formed connections are made with higher probability to nodes that already have high degrees (Barabási & Albert, 1999; Barabási, 2016). Besides this basic model, similar topologies can be found in networks that do not necessarily grow in terms of nodes or links, but rearrange their connections using preferential attachment criteria (Lee, 2015; Lindquist et al., 2009). This is probably a more realistic explanation for a tourism destination that, generally, does not experience a highly dynamic variation in the number of its components.

A second mechanism can also be considered that is able to generate a power-law as result of some optimization process. In particular, one interesting variation takes into account a local optimization in which the agents (nodes) seek to maximize their outcomes from exchanges with their partners under incomplete, local information without full knowledge about others or about the global network structure (Berger et al., 2004; Pujol et al., 2004). This mechanism is compatible with a preferential attachment and does not imply necessarily a growth in the network but may arise by a number of reconfigurations of the connections. Finally, the departures from a pure power-law at the beginning of the distributions are, as known, given by a finite-size effect (the pure power-law is a model in the limit of an infinite number of nodes), and by limitations of the knowledge of the whole system that an actor may have (Mossa et al., 2002; Štefančić and Zlatić, 2005), for which a tendency to connect only a few other nodes results in deviations from the preferential attachment model.

A combination of these mechanisms seems to be well reasonable when considering the process of establishing relationships in a socioeconomic system such as a tourism destination. A confirmation of the validity of this interpretation can be found in the tourism literature (Chim-Miki & Batista-Canino, 2017; Merinero-Rodríguez & Pulido-Fernández, 2016) in that studies found that when endogenous determinants are analyzed they can be brought back to some form of optimization of an individual agent's own returns, whether they are of economic or emotional or social nature (Czernek, 2013; von Friedrichs Grängsjö, 2003).

Concerning the other topological metrics (the second step of our analyses), we note that the quite small density of links, essentially, indicates that there is very low collaboration or cooperation attitudes among the many groups of tourism operators. This is confirmed by the relatively small clustering coefficient and the negative assortativity which, differently from what it is usually found for a social network is negative (although very small). These quantities, as already speculated previously testify a certain reluctance of the components of our network to team up and their poor attitude towards doing so in the future. For their nature, in fact, the clustering coefficient can be thought of a static measurement, while the assortativity coefficient can be interpreted as expressing a tendency (Baggio, 2007). One more consideration is that a negative assortativity may limit the overall resilience of the system, that is the capability to adapt after a significant shock. In particular, a disassortative (negative assortativity) network is more susceptible when high-degree nodes are involved (Newman, 2002).

The relatively low modularity index is a further confirmation of this scarce collaboration in a destination. What is even more important here is to note that in all these networks the communities identified are composed of a variety of operators belonging to different 'business categories' (see the references to the original studies). Despite a common view of a destination as composed of groups of operators with similar business activities, the self-organization capabilities of this complex system lead to a mesoscopic structure that goes beyond predetermined differentiations of the organizations. This, from a governance viewpoint provides relevant indications, for example, on how to optimize communication channels or increase productivity in collaborations (see e.g. Baggio, 2011).

From a dynamic point of view the structured scale-free topology suggests that processes such as the diffusion of information and knowledge or the synchronization of opinions are favored with respect to some more randomly dispersed connectivity patterns (Baggio & Cooper, 2010; López-Pintado, 2008; Zhang et al., 2016). Same can be said of the spectral gap, whose values are bound to the stability of synchronization processes, which increases with lowering the value of the gap (Almendral & Díaz-Guilera, 2007). Moreover, by improving some clustering or local cohesion capability, these processes can be made much more efficient and effective. If we see a destination as a network of organizations and communities which functions using the exchange of resources such as information or investments through the network, these considerations provide a valuable suggestion: that of constructing simulation models able to reproduce these processes and to test their characteristics with respect to modifications in the system's global and local structure (see e.g. Baggio & Cooper, 2010; Baggio & Del Chiappa, 2014; Del Chiappa & Baggio, 2015).

Designing effective strategies or governance systems will need to better consider this point and resort to a good adaptive governance approach rather than a decisionist management attitude, which would inevitably collide with these characteristics (Baggio et al., 2010a). In this respect the preparation of a series of simulation tools might provide more reliable information for the preparation of scenarios that form the undoubtable basis for this type of activities.

The second clue comes from the comparison of the network properties examined through the calculation of the cosine differences. They essentially tell us that, apart from small deviations due to the diverse amounts of data collected for some destinations, there are no significantly large differences in the feature vectors made of the measures used. As such, it is argued that that these two clues confirm the validity of the conjecture that, from a topological (structural) point of view, there is a kind of universality in the characteristics of a tourism destination.

In summary, the findings suggest that it is possible to sketch a 'typical' destination. This summary can be obtained by averaging the main global properties of a destination network from the measurements taken. The summary is reported in table 6 (mean values) along with typical values for social networks as reported by various literature surveys or contained in the KONECT collection (Barabási, 2016; Boccaletti et al., 2006; Cimini et al., 2019; da Fontoura Costa et al., 2011; Kunegis, 2013).

Table 6 Global topological metrics

Metric	Mean values	Typical social network
Density	0.027	~10^{-1}-10^{-2}
Diameter	8.818	~10
Average path length	3.389	~10
Clustering coefficient	0.201	~10^{-1}
Assortativity	-0.212	~10^{-1} (>0)
Global efficiency	0.249	~10^{-1}
Modularity index	0.515	0.6-0.8
Spectral gap	0.280	---
Gini index of degrees	0.658	0.6-0.8
Degree distribution exponent	2.57±0.09	2-3

Further, it is interesting noting that modifications in the structural characteristics of a destination network can provide more favorable conditions for ensuring a higher level of creativity and innovation attitudes that so important are for their social and economic prosperity and development (Gabe, 2011; Richards & Wilson, 2007). In fact, it has been shown that in a socioeconomic environment, certain network configurations can greatly favor these traits. It happens with networks that exhibit a good combination of weak ties, with high quality information spread, and a number of strongly connected communities that provide an internal efficient information exchange (Fleming et al., 2007; Podolny & Baron, 1997). And tourism destinations definitely need to go towards these settings (Baggio, 2014), goal that can be obtained by simulating possible favorable topologies and deriving hints for policies that may effectively produce such changes.

CONCLUDING REMARKS, LIMITATIONS AND FUTURE RESEARCH

Tourism is a fascinating and intriguing phenomenon. It includes so many different entities, activities and processes that it is practically impossible to come to a logical description, let alone a definition. However, it is generally agreed that the tourism destination is a fundamental unit and key to understanding, and therefore managing, the phenomenon. For example, research shows that the efficiency of the different stakeholders is an important determinant for the competitiveness of the destination (Assaf et al., 2017; Ivanov & Ivanova, 2016), and that 'healthy' environmental conditions (e.g. efficient destination governance and functioning) positively affect the performance of the stakeholders (Lado-Sestayo & Fernández-Castro, 2019; Molina-Azorin et al., 2010). Additionally, a thorough knowledge of the structural and dynamic characteristics of the destination are essential to the governance of the destination itself as well as its strategies, policies or activities (products and services). For a complex destination system, the lenses of network science have proved to be quite effective in describing complex associations within a tourism destination and have enabled researchers to uncover details that would not have been easily recognizable.

The goal of the research reported here was to test the proposition that some topological properties of destinations are very consistent; that is, universal. To achieve this goal, we analyzed the main features of a sample of destination-based networks where it is posited that even if equivalence in network structures are not complete, a substantial similarity undoubtedly exists thereby confirming the essential meaning of the universality hypothesis. The results of this study provide substantial evidence indicating that tourism destinations operate as systems whose structures possess common features. Besides the theoretical interest, the existence of a general *model* can help to direct future and more detailed and focused investigations in specific cases and in informing the range of potential impacts of various design, planning and governance activities.

The methods and the theoretical framework are rigorous and well founded, the major limitation to what presented here might be the relative smallness of the sample used, even if the different sizes, locations and typologies make this a good sample that can ensure us of the validity of the conjecture. One interesting addition to this line of reasoning would be to consider also how spatial (geometrical) configurations could influence the conjecture mainly for what concerns the establishment and continuation of the different relationships.

We further note here that the results do not 'prove' similarity as confirmation requires many more, and more detailed, studies. However, we argue that the clues described are sufficient to formulate our conjecture; that is, a "*conclusion or a proposition which is suspected to be true due to preliminary supporting evidence, but for which no formal proof or disproof has yet been found*" as Wikipedia defines it (https://en.wikipedia.org/wiki/Conjecture). Finally, it is recommended that future research examine in greater detail new and more complete databases which may be used test the universality hypothesis, or to provide counterexamples, which may then lead to a better understanding of tourism destinations. Since, in the end, the advancement of science may come more from dissent than from unanimity, and we should try to "*prove ourselves as wrong as quickly as possible, because only in that way can we find progress*." (Feynman, 1967: 158).

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