Travel and Tourism: into a Complex Network

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It is discussed how the worldwide tourist arrivals, about 10\% of world’s domestic product, form a largely heterogeneous and directed complex network. Remarkably the random network of connectivity is converted into a scale-free network of intensities. The importance of weights on network connections is brought into discussion. It is also shown how strategic positioning particularly benefit from market diversity and that interactions among countries prevail on a technological and economic pattern, questioning the backbones of traveling driving forces.

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I. INTRODUCTION

The movement of tourists on a worldwide scale is responsible for a traveling mobility of hundred millions tourist arrivals every year, representing the largest movement of humans ever out of their usual environment, strongly influencing local, regional, national and international economies, being one of the fastest growing economic sector. Tourism is a consequence and a dynamic force on the integration of world trade and markets, forming the global economy. But how is this integration evolving? However, regardless the crucial role of tourism, there is a lack of quantitative considerations of its flows, although it is essential for understanding the self-organization of human traveling patterns, and global wealth net flows.

Research on social networks has around 50 years, empirical and theoretically, partly because social life is relational\textsuperscript{[1, 2]}. These studies contributed much for the clarity of the importance of relational systems. Such networks are represented as a set of nodes denoting people, companies, or other social actors, which are joined by edges the patterns of the relational structure, representing friendships, partnerships, collaborations, etc. The increasing availability of real networks data and the nowadays capacity of analyzes large data, have enhanced new analytic methods to characterize networks, extending our knowledge on the description of these systems\textsuperscript{[3, 4, 5]}.

A large variety of real world systems are structured in the form of networks, from social, biological, economic, infrastructure and information networks\textsuperscript{[3, 6, 7, 8, 9]}. Network theory have been build up largely from observation of the properties of many real world networks, and by comparation of their structures. Due to the interesting results, research on complex networks has significantly increased during the last years. These methods have been applied to a wide variety of real world networks, like airline connections\textsuperscript{10}, financial relations\textsuperscript{11, 12, 13}, companies partnerships, ecological networks, movies actors, world trade, WWW\textsuperscript{14}, scientific collaboration network\textsuperscript{15}, human acquaintance patterns\textsuperscript{16}, among others\textsuperscript{17, 18, 19}.

Tourism is one of the fastest growing economic sectors, representing more than 10.2\% of world GDP, and reached a record of international tourist arrivals with 763 million in 2004. Different theoretical perspectives on tourism recognize clusters and networks as one of the main competitive factors in tourism. An organizational perspective applying social network analysis was introduced in 1996\textsuperscript{20}. Since then tourism researchers have been introducing network analysis on measuring international business, drive tourism\textsuperscript{21, 22}, and more recently on electronic tourism with a web graph structure of a destination\textsuperscript{23, 24}.

The research aims to show that network analysis has appropriate methods to study the worldwide tourist arrivals, as a network system. This paper is organized as follows. An introduction to the international tourism on section IA and to network theory on section IB. The empirical analysis (section II) focuses on topological and weighted analyze (section II A) and degree correlation (section II B). Conclusion are drawn on section III.
A. Worldwide Tourist Arrivals

In this research we use a network approach to study international tourism on the year of 2004. International tourist arrivals reached a record of 763 million in 2004 (see Fig. 1). The international arrival of tourist is yearly measured by the World Tourism Organization (WTO, the major intergovernmental body concerned with tourism) over 208 countries and territories around the world [25]. Worldwide earnings on international tourism reached in 2004 a new record value of US 623 billion.

FIG. 1: Worldwide Tourism is a complex network The map of the world tourism network is displayed with an exponential grey scale according to the intensity of connections.

International tourist arrivals are analyzed to study *inbound* tourism and *outbound* tourism. *Inbound* tourism, involving the non-residents received by a destination country from the point of view of that destination. *Outbound* tourism, involving residents traveling to another country from the point of view of the country of origin.

This study provides information on the role played by network theory on the structure of international travel flows.

B. Network Theory

We argue that network theory provides an explanatory framework of interrelationships of how countries as tourism destinations interact, relate, and evolve. Techniques and indicators of network theory are introduced for measuring relation in the international network theory.
Most complex networks share common properties that have common underlying structural principles \[4, 7, 14\]. Real world networks have been shown to display structural properties different from random graphs model.

The centrality of nodes on a network is of primary importance, as more competitive nodes have better strategic positions \[8, 26\]. Several measures of centrality have been developed, like degree centrality, closeness, betweenness, eigenvector centrality, information centrality, among others. Centralization refers to the extent to which a network revolves around a single node, and also to the propensity of the node to diffuse information, knowledge or infections.

Degree centrality is one of the most used measures of node prominence \[27\]. The degree of a node, represents the prominence of a node, and equals the number of edges connected to it. The statistical characterization of real networks displays a large number of node degrees, \( k \), and the appearance of hubs, nodes with large degree \[28\]. Additionally these networks show a scale-free degree distribution, characterized by a power-law behavior \( P(k) \sim k^{-\theta} \) \[7, 14\].

Despite the wide range of application, complex networks have developed to the characterization different topological networks, undirected and directed, unweighted and weighted \[19\]. The techniques firstly applied to undirected and unweighted networks are lately adapted to weighted and/or directed networks \[5, 29, 30\]. Topological properties have a very strong influence on propagation of knowledge and disease, as well as on robustness and vulnerability \[7, 31\]. Despite the importance of topological issues, weighted analyzes characterize the heterogeneity of weights and non-trivial correlation \[19\].

Directed edges are considered when the edge from node \( i \) to node \( j \) (\( i \to j \)) is different of the edge from node \( j \) to node \( i \) (\( j \to i \)). Many real networks are also weighted networks, in the case of social networks it is often relevant to assign a weight (strength) to each edge, measuring how good or strong is a relationship \[2, 16\].

## II. EMPIRICAL ANALYSIS

Follows the empirical study of worldwide tourist flows, for the year of 2004. Topological and weighed analyzes are performed on section II A. The way tourism destinations couple together is analyzed through degree-degree correlations on section II B.

### A. Topology and Weights

We used the data gathered by WTO over these 208 where countries and territories are considered nodes, \( N \), and an edge exists from node \( i \) to node \( j \) when there are tourists from country \( i \) to country \( j \). Notice that the network is directed, the edge from \( i \) to \( j \) is different of the edge from \( j \) to \( i \), respectively \( i \to j \) and \( j \to i \). On our case we have 5775 edges, \( L \), representing arrivals of tourists from one country to another, on the year of 2004. For an unweighted network node is one of the most studied centrality measures in social network analysis.

An important statistical property to directed networks is reciprocity \[9\], meaning on the tourism network the appetency to exchange tourists. The links in the network are composed by 10% bidirectional links and 30% of asymmetric links. If country \( j \) has tourist arrivals from country \( i \), then the probability that country \( i \) has tourist arrivals from \( j \) is only \( \frac{1}{4} \), so the network is significantly directed. Notice also that 60% of all the pairs of countries are not connected to one another.

The tourism international network is a giant component, so that all countries have a path or paths to any of the other countries. The fact of being a giant network and having a small shortest path length can imply fast transferring of knowledge and information.

On a directed network the nodes have \textit{in} and \textit{out} degree, where the \textit{in} degree of a node \( i \), \( k_{\text{in}}(i) \), is the number of nodes directed to node \( i \), and the \textit{out} degree of \( i \), \( k_{\text{out}}(i) \), is the number of nodes that \( i \) is directed to. The \textit{in} degree of a country is an indicator of its attractiveness has a destination country, \textit{destination attractiveness indicator}, which increases with the number of origin countries that have flow of tourists to the destination on analyzes. The \textit{out} degree of a country is an indicator of its emanation has a tourism origin country, \textit{destination emanation indicator}, which increases with the number of countries that the country on analyzes has flow of tourists to.

A fundamental aspect of real-world networks is the degree distribution \[31\], representing the distribution of the number of links of nodes. In binomial random graphs \[6, 8\], nodes have similar degree, although many real-world networks have some nodes that are significantly more connected than others, many of those are scale free, having connectivity distributions that decay as a power law. A probable mechanism for this occurrence is preferential attachment \[31\], meaning that nodes with high degree are preferential. Network’s topology displays the degree distribution \( P(k) \), probability that a node has degree \( k \), which applied to tourist arrivals - directed network \[32\] - are studied two degree distribution functions, \( P_{\text{in}}(k) \) representing the probability that a node has \( k \) nodes directed to itself (probability of countries with tourism from \( k \) \textit{inbound} countries), \( P_{\text{out}}(k) \) representing the probability that a
node has a total of \( k \) edges to other nodes (probability of countries with tourism to \( k \) outbound countries). Most networks have a scale-free degree distributions \([31]\), which have a power law tail \( P(k) \sim k^{-\theta} \).

An exponential network is provided by the usual random graph, with \( P(k) \) decreasing exponentially fast, although scale-free networks display a hub-like hierarchies, with \( P(k) \) decreasing as a power law \([3]\). In our case, the in and out degree distributions decrease exponentially fast, cumulative distribution functions. On Fig. 2 (a) and (b), respectively \( P_{\text{in}}(k) \) and \( P_{\text{out}}(k) \). The topological network does not displaying scale-free behavior, similar result on \([18]\).

![Fig. 2: Log-normal plot of degree distribution, for (a) in degree \( P(> k_{\text{in}}) \) and (b) out degree \( P(> k_{\text{out}}) \), with an exponential decay.](image)

The degree distributions decay is greatly faster than the power-law degree distribution depicted in other social \([16]\), technological \([14]\), economic \([33]\), and biological networks. Random networks are described by growing model of random link assignment and models of sublinear preferential attachment \([34]\). Accordingly, the inbound and outbound degree distributions reasonably suggest a growth model in which new connections are chosen as a result of sublinear preferential attachment, where higher degree countries are more likely to add new connections. While, plausibly, destinations are chosen randomly, not being clear if there is any advantage for making new connections with high in degree countries.

The weighed analysis is essential because of weights heterogeneity. The network can be expressed by its adjacency matrix \( A = \{a_{ij}\} \), dimension \( N \times N \), where \( a_{ij} = 1 \) if and only if there is an edge from \( i \) to \( j \), and \( a_{ij} = 0 \) otherwise. The weighted adjacency matrix is \( W = \{w_{ij}\} \), where \( w_{ij} \) equals the flow from \( i \) to \( j \). Notice that \( w_{ij} \) represents the weight of the edge \( i \to j \) and \( w_{ji} \) represents the weight of the edge \( j \to i \), so \( w_{ij} \) and \( w_{ji} \) are different.

The present network is asymmetric and weighted. The range of the weights goes from 0 to 19.369.677 with an average value of 81.813, revealing a high heterogeneity of weights. See Fig. 1.

The probability distribution function of the weights, \( P(w) \sim w^{-\gamma} \) has a power–law behavior, with exponent \( \gamma = 1.55 \), see Fig. 3.

It is also relevant to study the strength of the nodes, which on a directed network each node has in strength, \( s_{\text{in}}(i) \) (eq. 1), and out strength, \( s_{\text{out}}(i) \) (eq. 2). It measures the strength of the nodes on relation to the total weight of their connections. On the tourist arrivals network in strength represents the inbound tourism, and out strength represents the outbound tourism. Strength is a measure of centrality for weighted networks:
FIG. 3: On the plot is showed the flow of tourists with a scale-free behaviour $P(w) \sim w^{-\gamma}$ where $\gamma = 1.55$, with dominance of hubs. The inner plot displays the cumulative of $P(w)$ and the cumulative of the power-law with $\gamma = 1.55$, $F(w)$.

FIG. 4: inbound distribution, $P(s_{in}) \sim s_{in}^{\gamma_{in}}$ with $\gamma_{in} = 0.9$, and outbound distribution, $P(s_{out}) \sim s_{out}^{\gamma_{out}}$ with $\gamma_{out} = 0.95$, inner plots display their cumulative.

\begin{align*}
s_{in}(i) &= \sum_{j \in v(i)} w_{ij}, \quad (1) \\
s_{out}(i) &= \sum_{j \in v(i)} w_{ji}. \quad (2)
\end{align*}

The **in** strength distribution and **out** strength distribution functions are also fitted by a power-law, respectively $P(s_{in}) \sim s_{in}^{\gamma_{in}}$ and $P(s_{out}) \sim s_{out}^{\gamma_{out}}$, where $\gamma_{out} = 0.95$ and $\gamma_{in} = 0.9$, represented on Fig. 4.
FIG. 5: Intensity plays an important role on network behaviour. The relation between degree and strength is closely independent on (a) inbound tourism, \( s(k_{in}) = k_{in}^{\beta_{in}} \) with \( \beta_{in} = 1.1 \), but has a (b) strong relation on outbound tourism, \( s(k_{out}) = k_{out}^{\beta_{out}} \) with \( \beta_{out} = 1.75 \).

Scale free networks have the ability to change scale in order to meet any level of demand. Tourism, among economic sectors has one of the fastest grow rates, and WTO forecasts that international arrivals are expected to reach nearly 1.6 billion [25]. So, two consequences are expected, the network is growing due to a scaling up, with an increase of flows intensity and/or due to a scaling out by new connections between countries.

A power-law behavior of \( P(w) \), \( P(s_{in}) \) and \( P(s_{out}) \) have a strong structural meaning of the network, describing the way weights, and strength centrality, inbound and outbound tourism, are distributed. The weights and strengths range on a large spectrum of values, and the heavy-tailed distribution implies that nodes have a certain probability of having large strength values, where the average of all intermediate values has no meaning.

The observations on topological and weighted network reveal different structural results, therefore the relation of topological and weighted flows is studied in more detail, \( s(k_{in}) \) and \( s(k_{out}) \). The result is depicted on Fig. 5. On the in function:

\[
s(k_{in}) = (k_{in})^{\beta_{in}},
\]

where \( \beta_{in} = 1.1 \). For \( \beta = 1 \) degree and weight are independent [19]. So \( S(k_{in}) \) and \( k_{in} \) are close to independent, revealing a very small relation between them. On the other side, \( s(k_{out}) \):

\[
s(k_{out}) = (k_{out})^{\beta_{out}},
\]

\( \beta_{out} = 1.75 \), revealing a strong relation between out strength and out degree. This means that outbound tourism increases with out degree.

Interestingly, when analyzing the diversity of the market and its strength, comes out that inbound and outbound tourism have distinguished outcomes on Fig. 5. Even so, both have a power-law behaviour, \( s(k) = k^{\beta} \), and unavoidable fluctuations. The diversification of outbound markets (\( > k_{out} \)) has a strong and positive increase on total outbound tourism \( s(k_{out}) = k_{out}^{\beta_{out}} \), with a power of \( \beta_{out} = 1.75 \), meaning that the flow grows 1.75 faster than the degree. On the relation between the inbound tourism and its market diversification, \( s(k_{in}) = k_{in}^{\beta_{in}} \) with \( \beta_{in} = 1.1 \), the relation is close to linear and it comes out that both quantities carry almost the same information [19]. It is concluded that the outbound tourism particularly benefits from market diversity.
B. Degree-Degree Correlations

We turn now to question in which sense do countries couple with one another. Is it in some sort of random choice, or is there a preference on the way they link with each others, meaning a choice that makes some connections more probable than others. In a social context is usually observed an assortative mixing [35], observed when the nearest neighbours of nodes with high degree have also high degree. On economic, technological and biological context is generally observed disassortative mixing, observed when the nearest neighbours of nodes with high degree have low degree.

Degree-degree correlations, illustrate that social networks have assortative mixing and technological and biological networks behave more like disassortative. Worldwide tourist arrivals display disassortative mixing, revealing the economic behaviour over social. The weighted versus topological analysis of degree-degree correlations shows that low (high) degree countries have their inbound edges with large weight directed from countries with low (high) degree.

In evolving network, degree-degree correlations are almost always strong. To measure the correlation on the network over degree, one may also study the average nearest-neighbors degree. This measures the tendency of node $i$ to be connected to nodes with the same degree,

$$k'_{nn}(i) = \frac{1}{k_i} \sum_{j \in v(i)} k_j,$$  \hspace{1cm} (5)

where $v(i)$ denotes the set of neighbors of $i$. Considering that our network is directed, we correlate the in degree of node $i$ with the out degree of its neighbors,

$$k_{nn}(i) = \frac{1}{k_i'_{nn}} \sum_{j \in v(i)} k'^{out}_j.$$ \hspace{1cm} (6)

We can also average the over nodes of the same degree:

$$k_{nn}(k) = \frac{1}{NP(k)} \sum_{k_i=k} k_{nn}(i).$$ \hspace{1cm} (7)

This measure is also called associative mixing if nodes with high degrees have most of their neighbors with high degrees, represented by a growth of $k_{nn}(k)$ with $k$. For a decreasing of $k_{nn}(k)$ with $k$ it is denominated disassortative mixing. This happens when nodes with high degrees have mainly neighbors with low degree. The international tourism network displays disassortative mixed. This behavior is mostly detected on transportation networks, providing a pattern where the hubs connect to the small degree nodes at the periphery of the network [35].

Degree-degree correlation for a weighted network is given by [18],

$$k^w_{nn}(i) = \frac{1}{s_{in}} \sum_{j \in v(i)} w_{ij} k'^{out}_j.$$ \hspace{1cm} (8)

$k^w_{nn}(k)$ measures the local weighted average of neighbors degree. The spectrum of the worldwide tourist flows on topological (equation 7) and weighted degree-degree correlations (equation 8) if represented on Fig. 6.

For $k^w_{nn}(k) > k_{nn}(k)$ the edges with the larger weight are directed to the neighbors with larger degrees, and $k^w_{nn}(k) < k_{nn}(k)$ the edges with the larger weight are directed to the neighbors with lower degrees [18]. The weighted degree-degree correlation is slightly decreasing (Fig. 7), following the same behavior as the topological correlation, but with a slower slop. For low degrees $k^w_{nn}(k) < k_{nn}(k)$ and for high degrees $k^w_{nn}(k) > k_{nn}(k)$, meaning that low degree nodes have their edges with large weight directed from nodes with low degree, and high degree nodes have their edges with large weight directed from nodes with high degree.

III. CONCLUSION

This study provides a complementary perspective to the study of international tourism. It is addressed the importance of weighted and directed network measurements, by quantifying, on its topological and weighted structure, the worldwide tourist arrivals network.
FIG. 6: Log-log plot of in degree – out degree correlations, over in degree, both unweighted $k_{nn}(k)$ and weighted $k_{ww}(k)$ correlations, over $k_{in}$.

FIG. 7: Comparing weighted and topological degree correlation. For low degrees $k_{ww}(k) < k_{nn}(k)$ and for high degrees $k_{ww}(k) > k_{nn}(k)$. Low (high) degree nodes have their edges with large weight directed from nodes with low (high) degree.

The research of tourist arrivals – tourism, defined by the world Tourism Organization, comprising the activities of persons traveling to and staying in places outside their usual environment for not more than one consecutive year for leisure, business and other purposes1 - shows a scale-free behaviour on the weights covering 4 orders of magnitude. It describes short travelling range to long travels, on a global scale, surprisingly having affinity correlations typical from technological and economic networks which question the cultural backbone of tourism and travel. The scaling behavior of tourism flows, on a power-law refers to the self-organization of world trends, where disassortative correlations particularly reveal the influence of economic flows and spread of technologic and knowledge across international borders.

The scale-free nature of the weighted analyses contrary to the random topology opens a new class of networks. This brings us to a more general question: do highly heterogenic and directed real-world networks hide some sort of preferential growing and hub-like structure on a random topological structure?
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