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A multi-way analysis of international bilateral claims

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ABSTRACT

The paper presents a new methodology aimed at detecting the modularity structure of an evolving weighted directed network, identifying communities and central nodes inside each of them, and tracking their common activity over time. The method is based on tensor factorization and it is applied to the Consolidated Banking Statistic, provided by the Bank of International Settlements. Findings show that data are well represented by three communities. The temporal pattern of each community varies according to the events involving the member nodes, showing a decrease of activities during crisis periods, such as the 2008 financial crisis and the European sovereign debt crisis.

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1. Introduction

Many financial systems can be fruitfully represented as networks involving elementary structural entities, such as banks, hedge funds, etc. and specific relations between them. Studies that analyze the empirical characteristics of financial networks in different jurisdictions have systemically found the existence of a community structure (see Soramaki et al., 2007; Iori et al., 2007, 2008; Cocco et al., 2009; Craig and Von Peter, 2014; Fricke, 2012; Fricke and Lux, 2015 among others). The community structure reveals how a network is internally organized, and indicates the presence of special relationships between nodes, that may not be easily accessible from direct empirical tests. In other words the community structure refers to the occurrence of groups of nodes that are more densely connected internally than with the rest of the network. This definition, suitable for undirected networks, has usually been (wrongly) applied to directed networks by assuming a member of a community having balanced out-links and in-links connections with the other members. This symmetric assumption can seriously be violated when a member may only play one main role, source (lender) or terminal (borrower), in the community. Asymmetric communities are common in directed networks where the direction implicitly expresses an asymmetric relationship among its nodes. A recent survey (Malliaros and Vazirgiannis, 2013) provides a broader definition of community structure as set of nodes that share common or similar features together. Financial networks, where links represent flows of funds and institutions have exposures on both sides of their balance sheets, are typical examples. In addition, much of the focus of community detection algorithms has been devoted on identifying disjoint communities. However, it is well known that nodes in a network are naturally characterized by multiple community memberships (Xie et al., 2013). Also in financial networks, it is very common for an institution to participate in more than one community, i.e., communities are often overlapped. Beside community membership distributions, not all vertices are equal in a community and some vertices might be special in the sense that they are linked with almost all others. In literature, such vertices are known as hubs, leaders, or centers. In financial market, determining who central players are, is key to design policies that try to prevent and mitigate contagion. Not surprisingly, the research in network theory has dedicated a vast amount of effort to deal whit this topic (Financial Stability Board, 2013; Battiston et al., 2012). Various measures of centrality had been proposed in network theory such as those based on counting the first neighbors of a node (degree centrality), or those based on the spectral properties of the graph (see Perra and Fortunato, 2008; Bonacich, 1972; Bonacich and Lloyd, 2001; Katz et al., 1973; Brin and Page, 2012; Kleinberg, 1999). These measures provide information on the position of each node relative to all the others. In general, centrality measures rank vertices without paying attention to whether the network is characterized by a community structure and how this structure, in turn, affects the ranking. Only in Cao et al. (2013), the authors propose a novel model to identify overlapping communities and central nodes, in case of undirected static network. In the context of financial markets, developing a measure

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that captures the institutions' systemic importance by revealing also the community structure (that proxies the most plausible areas of contagion of institutions' distress) may enhance a better understanding of the system functioning. Finally financial networks are highly dynamic. Although it is always possible to create a static network representation by aggregating over the temporal evolution of the system, such temporally-aggregated representation may overlook essential features of the system or may confound structures that can be teased apart only by retaining the time-varying nature of the data. Few studies pioneered approaches to community detection in temporal networks (Gauvin et al., 2014) but none of these works addressed at the same time the issue of identifying communities and central nodes inside each community in evolving directed weighted networks.

In this paper we employ a technique for multiway-data proposing a new methodology to detect the modularity structure of an evolving weighted directed network and to identify central nodes inside each community, tracking their common activity over time. This method is based on the fact that a temporal network is naturally represented as a time-ordered sequence of adjacency matrices, each one describing the state of the system at a given point in time. The adjacency matrices are thus combined in a single mathematical object: a three-way tensor. In the last ten years, interest in tensor analysis has expanded to different fields. Examples include signal processing (Chen et al., 2002; Comon, 2000), numerical linear algebra (De Lathauwer et al., 2000, 2001), computer vision (Vasilescu and Terzopoulos, 2002a,b) numerical analysis (Beylkin and Mohlenkamp, 2002, 2005), data mining (Acar et al., 2005, 2006) graph analysis (Kolda and Bader, 2006), and more, but applications to economics are still scarce (Bonacina et al., 2015).

The methodology described in the present paper is based on a particular tensor decomposition technique, the so-called CP decomposition (named after the two most popular and general variants, CANDECOMP developed in Carroll and Chang, 1970 and PARAFAC developed by Harshman, 1970). It can be regarded as a generalization of the singular value decomposition (SVD) applied to tensors. In particular, we focus on non-negative tensor decomposition (Cichocki et al., 2009; Mørup, 2011; Kolda and Bader, 2009; Shashua and Hazan, 2005). Our methodology can be seen as a multidimensional extension of the HITS algorithm (Kleinberg, 1999). This algorithm provides two attributes for each node: an authority score and a hub score. Authority measures prestige: nodes who many other nodes point to are called authorities. If a node has a high number of nodes pointing to it, such a node has a high authority value and this quantifies its role as a source of information. On the contrary, a hub is an actor referring to many authorities and its score measures acquaintance. Hub and authority scores have different interpretation in term of the systemic importance associated to each financial institution. Institutions with high authority score are the main systemically important debtors (borrower) while those having high hub scores are the main systemically important creditors (lenders). In particular, as the HITS algorithm, our technique assigns to each node a centrality score proportional to the sum of the scores of its neighbors, and centrality results from a node having many neighbors, or from having some central neighbors, or both. Thus, two players will be ranked differently as hubs even if they lend the same amount of funds, depending on the behavior of their borrowers. The algorithm will rank higher those that lend to the most systemically important borrower. The same happens for the authority score with respect to the lender: two players that borrow the same amount of funds will be ranked differently depending from the lender they borrow from.

When including also the temporal dimension, the CP decomposition provides a further score related to the temporal evolution of the activity level of the communities over time. The value of the activity pattern of a community in a time span is related to both hub and authority scores of all the players involved in the transactions occurred in that community during a certain period.

The soft partition scheme is proposed by assigning to each node the percentage of its strength centrality that belong to that community. Such an edge decomposition can then be used also to assign nodes to communities according to a hard partition scheme, assigning each node to the community in which it has the highest impact in terms of strength.

The multidimensional data analysis proposed by Maruotti and Vichi (2016) is closely related to our tensor decomposition; both techniques deal with multidimensional longitudinal data where the serial dependence is due to the nature of repeated measurements over time and heterogeneity in the observed units. The main difference with respect to our technique relies on the mathematical and statistical tools adopted in the clustering methods. The multivariate vector autoregressive model of Maruotti and Vichi (2016) allows for the study of how partitions change over time. On the other hand, in tensor decomposition, the communities' members do not change over time but what changes is the relevance of each community in specific time periods. This result gives us the opportunity to relate the communities' activity with some relevant economic events. Moreover our technique provides both soft and hard partition solutions, meaning that one node can be member of more than one community at the same time with a different degree of membership. Additionally we also provide, for each node, two centrality scores that represent the importance of each node as a receiver or as a spreader of liquidity into the system.

The proposed technique is applied to the Consolidated Banking Statistics (CBS) compiled by the Bank of International Settlements (BIS), which include countries bilateral claims. We consider a set of 30 countries each of them represented by the amounts of its foreign claims vis-a-vis the other countries, measured on quarterly basis, from the first quarter of 2005 (Q1-2005) to the last quarter of 2013 (Q4-2013). We find that the emerging communities depend on the creditor's business model and on the geographical proximity between countries. The first community is related to the banking model adopted in the United Kingdom and Japan, where banks pool funds at major offices and redistribute them around the banking group with the United States playing the role of the major hub. The time evolution of the statistics associated with this community shows a stable trend all over the sample. The second community is mostly country specific, associated with the United States, having the largest credit risk against the United Kingdom, Japan and Germany. This community also encompasses most of the non-reporting countries in the BIS statistics. The time scores related to this community reveal that its activity decreased in the first part of the sample, reflecting the subprime mortgage crisis of 2007 and the subsequent financial crisis of 2008–2009.

Finally the third community is specific to countries belonging to the European Union: France, Belgium, Germany and the Netherlands, that share cross-border activity with the two largest banking centers, the United States and the United Kingdom. Switzerland belongs to this community, but also to the first one. The time evolution of the statistics of this community shows that its time activity increased substantially until 2011, abruptly decreasing when the European sovereign debt crisis erupted. The paper is organized as follows: Section 2 provides the data context and the proposed methodology, Section 3 illustrates the main results, Section 4 discusses the economic implications and the stylized facts that drive the obtained outcomes. Section 5 concludes.

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