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Attention Analysis of Owners Committee: A Method for Visualizing Time Series Data

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Abstract

Owners committee is a executive body of the owners assembly, Some people will search this on the network. We will analyze this keyword search to get the corresponding network. We will analyze it from a new perspective and find some interesting phenomena that we can't get with other models. The advantages of using this model are as follows: i) their topology inherits the features of the associated time series, which ends up resulting on supplementary information through the degree distribution; ii) and also, this novel connection between time series and complex networks opens a broad range of possibilities within the study of complex signals.

Keywords

Owners committee, attention, visibility graph.

1. Introduction

"Owners committee" is defined as the executive body of the owners assembly, entrusted by the owners assembly to manage the common parts and common affairs of all the owners. [1] The academic circles have discussed owners committee, Baoyu Liudiscussed the legal status of the owners committee from the perspective of substantive law and procedural law.[2] Yu Liu discussed the legal status of the owners committee from the perspective of comparative law and social practice.[3] Professor Qi Enping discussed Whether the owners committee can be a party in a civil lawsuit[4]. Hong Yan discussed the supervisory mechanism of the owners committee. Based on the Baidu search index, this article analyzes the degree of concern of owners committee. This analysis lays the foundation for exploring the reasons behind the concern of the owners committee, and then provides a basis for the construction of a sound legal system for the owners committee.

This article digs the situation of China's owners committee from the perspective of time series. In order to mine more information about time series, it is possible to study the time series from the view angle of complex networks. This transformation has been studied a lot. Zhang Xiaolian [5] studied the time series by constructing complex networks with pseudo-periodic time series, and studied the relationship between the topology of the constructed network and the dynamics of the original time series [6]. Xu et al. Constructed a method to map the time series to the nearest neighbor network [7]. Marvan et al. Introduced the concept of recursive networks [8]. Lucasa et al. Introduced the visibility map (VG) algorithm for time series [9]. The visibility graph algorithm not only retains the characteristics of the time series, but also relates the time series to the characteristics of the complex network [10]. Using Visibility graph algorithms, it is possible to determine whether the system under study is deterministic and random based on the characteristics of the complex network constructed. Et al. [11]. At present, time series analysis based on the VG method has been applied to different fields. Xinghua Fan used the VG method to analyze the similarity and heterogeneity of price time series of seven carbon pilot

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markets in China [12]. Zhou Cheng solves the characteristics of shield tunnel parameters by introducing the visibility map model implemented in the complex shield tunnel network in subway construction. [13]. Peng-Fei Dai maps the four economic policy uncertainty indices of the United States and China through the VG method For a complex network and study the topology of the network [14].

2. Model

2.1. Time Series Visualization Principle

This paper uses the time series visualization method proposed by Lacasa et al. (2008) for network construction [17]. Construct a network for each subsystem in the value chain transformation system. First, the discrete time series data of subsystem x (t) is mapped to the nodes of the network, and the edges of the network are constructed according to visual criteria: Any two-point data (t ^ a, x ^ a) and (t ^ c, x ^ c) in) can be connected to establish a connected edge, and any point between the two points (t ^ b, x ^ b) When t ^ a <t ^ b <t ^ c, all are satisfied.

$$x^b < x^a + (x^a - x^c)\frac{t^a - t^b}{t^c - t^a} \tag{1}$$

As shown in FIG. 1, the height of the histogram bar in FIG. 1 represents the data value of each time point. If the tops of the two histogram bars are visible to each other, the corresponding two points are connected in the network in the figure.

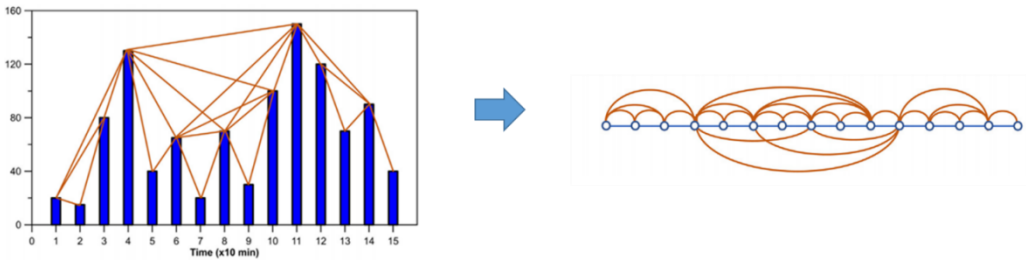

Figure 1. Visibility graph

Second, an adjacency matrix is constructed based on the time series nodes and edges, and a network graph is formed, as shown in Figure 2.

2.2. Centrality Analysis

In this paper, from the point of view of degree centrality, intermediate centrality and eigenvector centrality of complex networks, we make a quantitative analysis of patent inventors in all patent cooperation networks in the United States from 1975 to 1983.

2.2.1. Degree Centrality

Degree centrality is the most direct measure of centrality in network analysis. The greater the node degree of a node, the higher the degree centrality of this node, and the more important the node is in the network. For a graph G with n nodes G = (V, E), the degree centrality CD (v) of the node v is:

$$C_D(v) = \frac{\deg(v)}{n-1} \tag{2}$$

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For graph G, the complexity of computational centrality is Θ (V2) in the representation of dense adjacency matrices and Θ (E) in the representation of sparse matrices, where V is all points and E is all edges.

The definition of centrality can be extended (from nodes) to graphs. Let v * be the node with the highest degree of centrality in G. Define X: = (Y, Z) for n nodes in the connection graph to maximize the following quantity (H) (let y * be the node with the highest degree of centrality in X):

$$H = \sum_{j=1}^{|y|}[C_D(y^*) - C_D(y_j)] \tag{3}$$

The degree centrality of graph G is defined as follows:

$$C_D(v) = \frac{\sum_{j=1}^{|Y|}[C_D(y*) - C_D(y_j)]}{H} \tag{4}$$

When graph G has one node connected to all other nodes, and all other nodes are connected to only this one central node, H is the largest (star graph). In this case H = (n − 1) (n − 2), the degree centrality of graph G can be simplified as:

$$C_D(G) = \frac{\sum_{j=1}^{|V|}[C_D(v*) - C_D(v_j)]}{H} \tag{5}$$

2.2.2. Betweenness Centrality

Intermediate is a measure of the centrality of the node in the graph (there is also an edge intermediate). The nodes that appear in the shortest path of many other nodes have higher median values.

For a graph G with n nodes: = (V, E), the intermediate CB (v) of the node v is calculated as follows:

For each pair of nodes (s, t), calculate all shortest paths between them;

For each pair of nodes (s, t), find the part on the shortest path by judging (here, node v);

Accumulate the parts found for each pair of nodes (s, t).

Or more succinctly:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{6}$$

Among them, σ_{st} is the number of shortest paths from s to t, and $\sigma_{st}(v)$ is the number of nodes v passing through the shortest path from s to t. It can be divided by the number of node pairs excluding node v ((n − 1) (n − 2) for directed graphs, (n − 1) (n − 2) / 2 for undirected graphs) One. For example, in a directed star graph, the intermediate value of the center node (in all possible shortest paths) is (n − 1) (n − 2) / 2 (normalized to 1), while the intermediate value of the leaf node (not in any shortest path) is 0.

The intermediate and compact centrality of all nodes in the calculation graph includes the shortest distance between all nodes in the calculation graph. Modifying the Floyd–Warshall algorithm can find the shortest path complexity of each pair of nodes is Θ (V3). In the sparse graph, the Johnson algorithm is more efficient and is O (V2logV + VE). In the unweighted graph, Brande's algorithm is used to calculate the median centrality of O (VE).

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The assumption in calculating the intermediaries and tight centrality of all nodes in the graph is that the graph is undirected and allows multiple edges. In particular, when dealing with network graphs, in order to keep the relationship simple, the graph usually has no loops or double edges (edges represent connections between people or nodes). In this case, since each shortest path is calculated twice, using the Brande algorithm will halve the final centrality value.

2.2.3. Closeness Centrality

In topology and related mathematical neighborhoods, compactness is a basic concept in topological space. Intuitively, when two sets are arbitrarily close, we say that they are close. This concept is easy to define in a metric space that defines the distance between elements in space, but it can be generalized to a topological space without a specific metric distance.

In graph theory, compactness is a measure of the centrality of a node in the graph. Nodes that are "shallower" (that is, have shorter geodesic distances) than other nodes have higher compactness. In network analysis, compactness tends to represent the minimum path length, because this gives higher values to more central nodes, and it is often associated with other metrics (such as degree). In network theory, compactness is a complex measure of centrality. It is defined as the average geodesic distance of node v to other reachable nodes (such as the shortest path):

$$\frac{\sum_{t\in V\setminus v} d_{G(v,t)}}{n-1} \tag{7}$$

Where n≥2 is the size of the connected part V in the network starting from v. Tightness can be regarded as a measure of the time taken to propagate information from a given node to other reachable nodes in the network.

Some people define compactness as the reciprocal of this amount, but the two methods of transmitting information are the same (here, speed is evaluated instead of time). The closeness CC (v) of the closeness node v is the inverse of the sum of the geodesic distances to all other nodes V:

$$C_C = \frac{1}{\sum_{t\in V\setminus v} d_G(v,t)} \tag{8}$$

Tightness can be obtained by different methods and algorithms. Noh and Rieger (2003) proposed random-walk centrality, which is a measure of the speed of random propagation of information from other nodes in the network to a (given) node-random -Walk version for tight center.

Another measure of tightness is the information centrality of Stephenson and Zelen (1989) [], which is somewhat similar to Noh and Rieger's method. In essence, it is the harmonic average length of the path ending in node i. This length will be smaller when i has many short paths connecting other nodes.

To measure the vulnerability of the network, Dangalchev (2006) [] modified the definition of compactness so that it can be applied to non-connected graphs, and the overall compactness is easier to calculate:

$$C_c(v) = \sum_{t\in V\setminus v} 2^{-d_G(v,t)} \tag{9}$$

Opsahl (2010) proposed an extension to disconnected networks.

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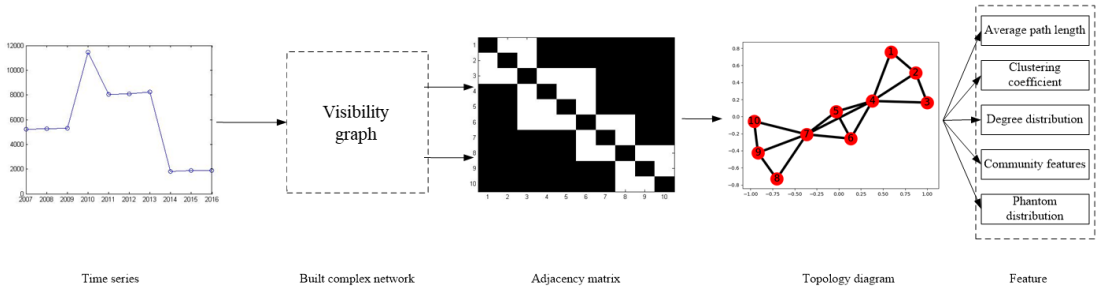

Figure 2. Time series network construction process and network feature extraction.

2.3. Division of Communities

Since Barabasi and Albert [13] pioneered research methods for complex networks, researchers in various fields have begun to look at the current world from the perspective of complex networks. According to the network theory, we construct actual data into complex networks. These data are described and divided into different categories. In the field of complex networks, the community structure is a very interesting phenomenon in complex networks. How to find the community structure in the network has become an important research topic. In general, compared to nodes outside a group, a group of nodes in the network has significantly more connections within the group than connections outside the group, which means that the association within the group is significantly higher than the group External relevance [16]-[17]. Finding the community structure from a large-scale network is still a very important scientific problem. At present, generally, the optimal community division can be achieved by optimizing certain specific indicators. Among them, the module proposed by Newman [18] and others Degree Q is the most commonly used method, and its specific form is shown in formula (10):

$$Q=\sum_{i=1}^{K}\left[\frac{l_i^{in}}{L}-\left(\frac{d_i}{2L}\right)^2\right]=1-\frac{L_{inter}}{L}-\frac{1}{K}-\frac{1}{K}\sum_{j=2}^{K}\sum_{k=1}^{j-1}\left(\frac{d_j-d_k}{2L}\right) \tag{10}$$

Where K is the number of clusters and L is the total number of edges in the network, l_i^{in} and $d_i=l_i^{in}+l_i^{inter}$ represents the number of edges in the cluster of cluster i and the total number of edges, and L_{inter} represents the total number of edges between clusters. The degree of modularity Q is defined as "the number of edges inside the cluster, minus the expected value of the same number of edges that fall in a random network when the cluster structure is not considered". The value of Q can indicate the quality of the cluster structure, the more the Q value Large means that the clustering structure in the network is more obvious.

3. Data source: Baidu Search Index

Data is collected from Baidu search index. This paper analyzes the data of these three indexes from January 1, 2018 to November 25, 2019, which are PC search index, mobile search index, PC plus mobile search index, and the search keyword is "venture capital".

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4. Application

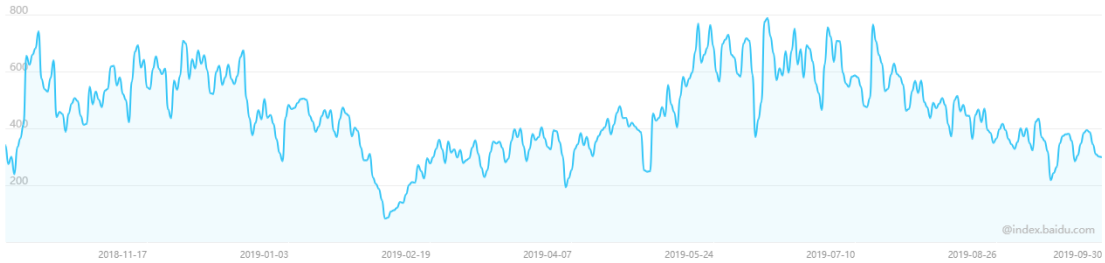

Figure 3. Changes in the mobile search index from October 1, 2018 to September 30, 2019.

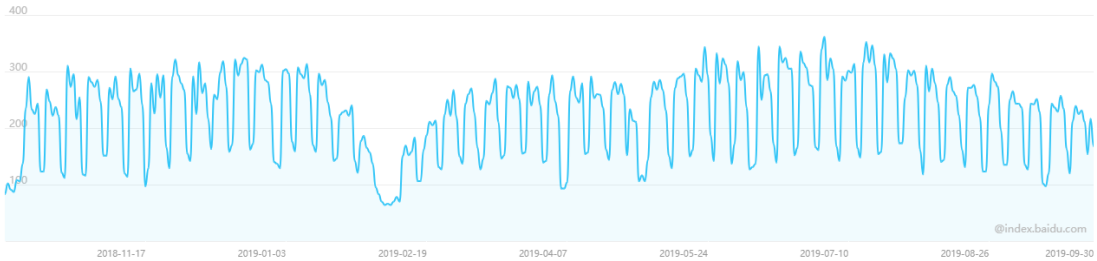

Figure 4. Changes in the search index on the PC from October 1, 2018 to September 30, 2019.

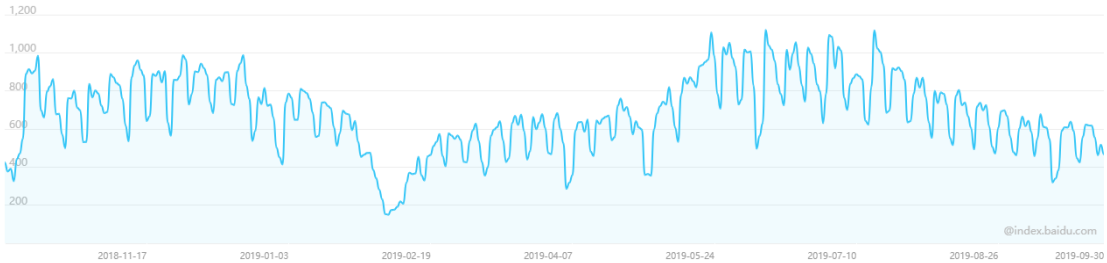

Figure 5. Changes in PC + mobile search index from October 1, 2018 to September 30, 2019.

As described in part B, we aim to transform time series data into complex network forms. The parameters for the network are shown in Table 2 below. We find that the number and average degree of mobile search edges are the largest in the three networks, which reflects more peaks and troughs in mobile search. The diameter of the three networks is 9, indicating the shortest number of sides between the two time points of the longest distance. The average path length is 4.232, 4.537 and 4.217 respectively, indicating the average edge between any two time points. The clustering coefficients of the three networks are 0.748, 0.749 and 0.757 respectively.

Data analysis:

	Comprehensive	PC	mobile
Edge	2911	2278	2899
Average degree	8.431	6.584	8.379
Diameter	10	9	10
Average path length	4.678	5.01	4.432
Density	0.012	0.01	0.012
Modularity	0.788	0.825	0.77
Number of communities	10	15	10
Cluster coefficient	0.731	0.745	0.731

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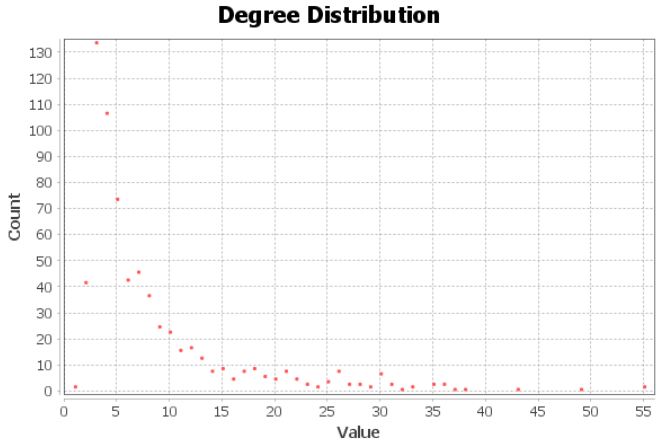
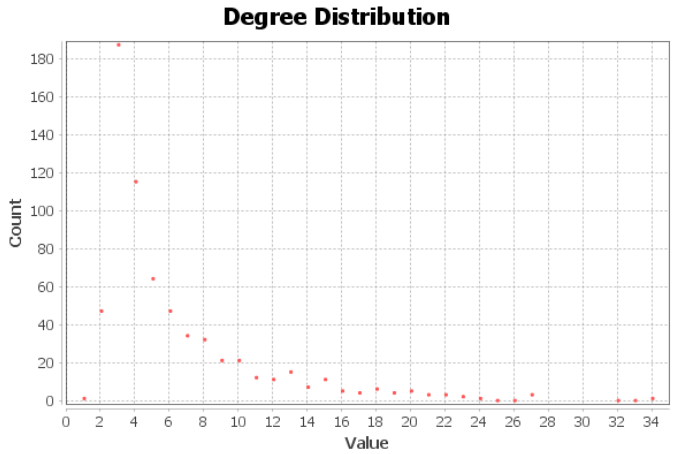
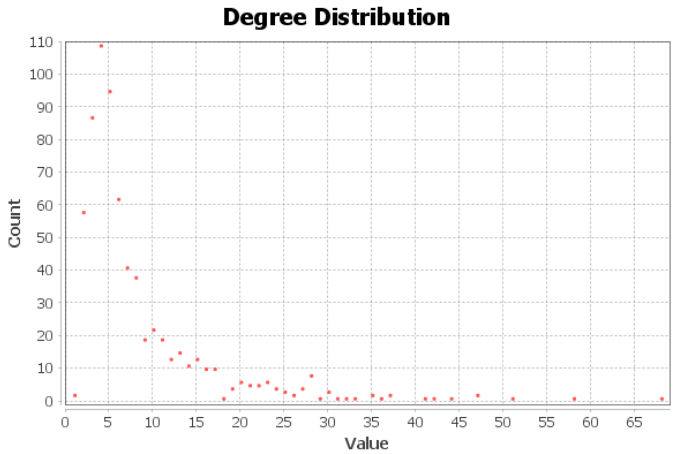


Comprehensive



PC



mobile

Figure 6. Degree distribution of Comprehensive, PC and mobile.

First, we focus on the degree distribution of these three complex networks. Figure 10 shows the cumulative distribution P (k) of the network mapped from PC plus Mobile, PC and Mobile terminal series. Obviously, the VGgraph conforms to the tail P (k) ~ k- quantities of some kind of power law. And these three data trends are very similar to each other, also show the phenomenon of fat tail.

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Power law distribution is a common statistical phenomenon. From table 3 and table 9, it is not difficult to find that the degree distribution of PC plus mobile devices, PC and mobile search is power-law distribution, and there are many time nodes with fewer connection edges, and the number of nodes increases with the degree.

These indicators prove that the time series network of venture capital is an obvious small-world network, which indicates that the hot events at the critical time point greatly affect the attention of venture capital.

We use fast modular method to cluster in the network node. The results are shown in figure 10 below. Obviously, the densities of the three networks are similar. Mobile search networks have significantly fewer subgroups than PC search.

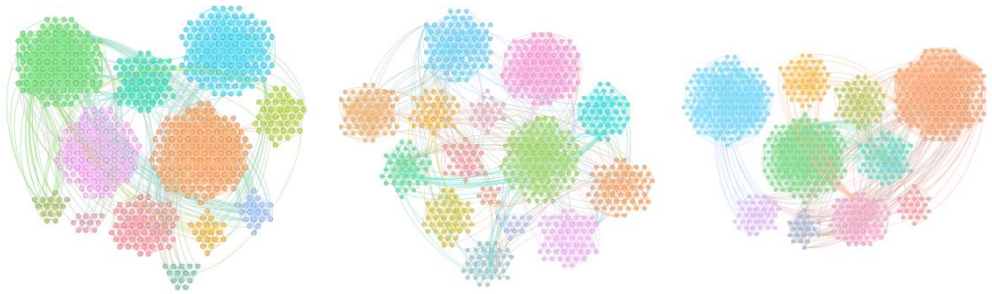

Figure 7. Comprehensive network diagram, PC network diagram and Mobile network diagram

In the case of PC search, the search heat is relatively small and the peak is smaller than that of mobile search. When clustering, the network distance increases with time, so clustering results show more subgroups. The largest subcategory of these was the node that emerged six months later and continued to decline in the search index due to high search popularity at the 2018 China venture capital forum in June, while ConsenSys layoffs news broke through December. We recommend that PC users stay focused on venture capital.

Mobile search is significantly more volatile than PC. Due to the huge user group and the hot news push function, the search popularity of mobile terminals for key events has increased sharply, showing an obvious peak in the time series. Due to the influence of hot events, such as the issuance of 51 credit CARDS in March, the investment in encrypted currency companies announced in June and the Andreessen Horowitz agreement, and the China venture capital forum held in June 2019, mobile network clustering results show the characteristics of small groups and large scale.

5. Conclusion

The results show that the multifractal analysis of Owners Committee time series is a suitable tool to describe the nonlinear dynamics of Owners Committee. VGs have been proven to have the following advantages: 1) its topology inherits the characteristics of related time series, and finally obtains supplementary information through the degree distribution; moreover, this new connection between time series and complex networks opens up a wide range of research for complex signals Possibility.

In summary, constructing a time series network of Owners Committee from Baidu search indicators has special advantages for analyzing the development of the venture capital industry. Provide important reference for the formulation of laws and regulations of Owners Committee. By collecting the search data of Owners Committee through the PC and mobile phones, we can

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distinguish between temporary and long-term concerns, and conduct further professional analysis and public understanding of Owners Committee. This is of great significance for building a reasonable governance structure for Owners Committee.

With the rapid accumulation and expansion of data, we can analyze and mine data from more dimensions and deeper levels. Next, we will use big data to further optimize the time series network model, and then pay attention to Owners Committee, perform the features of deep learning exploration, the impact of key events, and use these characteristics to promote the improvement of Owners Committee system.

References

[1] Chen Huabin, Law on Differentiated Ownership of Buildings, China University of Political Science and Law Press, August 2018, p. 296.

[2] Liu Baoyu and Sun Chao, "On the Legal Status of the Owners' Committee: From the Dual Perspectives of Substantive Law and Procedural Law", Politics and Law, No. 2, 2009, pp. 33-39.

[3] Liu Yu, "Thinking about the Legal Status of the Owners' Committee", Law Journal, No. 9, 2009, pp. 131-133.

[4] Qi Enping, Huang Ning, "On the Ability of the Parties in the Owners' Committee", Law Application, No. 4, 2009, pp. 28-31.

[5] J. Zhang, M. Small, Complex network from pseudoperiodic time series: Topology versus dynamics, Phys. Rev. Lett. 96 (23) (2006) 238701,

[6] J. Zhang, J.-F. Sun, X.-D. Luo, K. Zhang, T. Nakamura, M. Small, Characterizing pseudoperiodic time series through the complex network approach, Physica D 237 (2008) 2856–2865

[7] X.-K. Xu, J. Zhang, M. Small, Superfamily phenomena and motifs of networks induced from time series, Proc. Natl. Acad. Sci. USA 105 (50) (2008) 19601–19605,

[8] N. Marwan, J.F. Donges, Y. Zou, R.V. Donner, J. Kurths, Complex network approach for recurrence analysis of time series, Phys. Lett. A 373 (46) (2009) 4246–4254,

[9] R.V. Donner, Y. Zou, J.F. Donges, N. Marwan, J. Kurths, Recurrence networks: A novel paradigm for nonlinear time series analysis, New J. Phys. 12 (2010) 033025,

[10] L. Lacasa, B. Luque, F. Ballesteros, J. Luque, J.C. Nuño, From time series to complex networks: The visibility graph, Proc. Natl. Acad. Sci. USA 105 (13) (2008) 4972–4975,

[11] Li, X., Yang, D., Liu, X., Wu, X.M., 2012. Bridging time series dynamics and complex network theory with application to electrocardiogram analysis. IEEE Circuits Syst. Mag. 12, 33–46.

[12] Gao, Z.K., Cai, Q., Yang, Y.X., Dang, W.D., Zhang, S.S., 2016. Multiscale limited penetrable horizontal visibility graph for analyzing nonlinear time series. Sci. Rep. 6

[13] Zhang, J., & Small, M. (2006). Complex network from Pseudo periodic time series : Topology versus dynamics. Physical Review Letters, 96, 238701.

[14] Xu, X., Zhang, J., & Small, M. (2008). Superfamily phenomena and motifs of networks induced from timeseries. PNAS, 105, 19601–19605.

[15] Xiao, D., & Wang, J. (2014). Graph based and multifractal analysis of financial time series model bycontinuum percolation. International Journal of Nonlinear Sciences and Numerical, 15, 265–277.

[16] Yan Hong, Legal Reflections on the Supervision Mechanism of the Owners' Committee, Politics and Law, No. 1, 2006, pp. 73-77.

[17] Chen Huabin, Law on Differentiated Ownership of Buildings, China University of Political Science and Law Press, August 2018, p. 296.

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[18] Liu Baoyu and Sun Chao, "On the Legal Status of Owners Committee: From the Dual Perspectives of Substantive Law and Procedural Law", Politics and Law, No. 2, 2009, pp. 33-39.

[19] Liu Yu, "Thinking about the Legal Status of Owners Committee", Law Journal, No. 9, 2009, pp. 131-133.

[20] Qi Enping, Huang Ning, "On the Ability of the Parties in the Owners Committee", Law Application, No. 4, 2009, pp. 28-31.

[21] Yan Hong, Legal Reflections on the Supervision Mechanism of the Owners Committee, Politics and Law, No. 1, 2006, pp. 73-77.

[22] Topology versus dynamics. Physical Review Letters, 96, 238701.

[23] Xu, X., Zhang, J., & Small, M. (2008). Superfamily phenomena and motifs of networks induced from timeseries. PNAS, 105, 19601–19605.

[24] Xiao, D., & Wang, J. (2014). Graph based and multifractal analysis of financial time series model bycontinuum percolation. International Journal of Nonlinear Sciences and Numerical, 15, 265–277.

[25] Lacasa, L., Luque, B., Luque, J., & Nu, J. C. (2009). The visibility graph: A new method for estimating the Hurst exponent of fractional Brownian motion. Europhysics Letters, 86, 30001.

[26] Pierini, J. O., Lovallo, M., & Telesca, L. (2012). Visibility graph analysis of wind speed records measured in central Argentina. Physica A, 391, 5041–5048.

[27] Albert, Réka, and Albert-László Barabási. Statistical mechanics of complex networks [J]. Reviews of modern physics ,2002,74.(1): 47.

[28] Pastor-Satorras, Romualdo, Alexei Vázquez, and Alessandro Vespignani. Dynamical and correlation properties of the Internet [J]. Physical review letters,2001,87.(25) : 258701.

[29] Podani, J., Oltvai, Z. N., Jeong, H., Tombor, B., Barabási, A. L., &Szathmary, E. Comparable system-level organization of Archaea and Eukaryotes [J]. Nature genetics, 2001,29(1):54-56.

[30] Danon, Leon, Albert Díaz-Guilera, and Alex Arenas. The effect of size heterogeneity on community identification in complex networks. Journal of Statistical Mechanics: Theory and Experiment 2006,2006,11:P11010.

[31] Fortunato, Santo. Community detection in graphs. Physics Reports ,2010,486.(3): 75-174.

[32] M. Girvan and M.E.J Newman. Community structure in social and biological networks [J]. Proceedings of the National Academy of Sciences,2002, 99.(12): 7821-7826.