Internship in Sun Yat-sen University

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1   Background

Using Shenzhen private equity fund to establish network models and detect the potential economic risk in the Shenzhen economic market. During the internship, we totally establish three kinds of networks. By means of their topology, we find some interesting things.

Basically, we made some data cleaning and data processing before the modeling job. The raw data is divided into 20 timestamps (a timestamp every 3 months), which represent their investment property from 2014 to 2019. The property consists of 5 mean categories, stock, fund, debt, warrant, and others. In this model, we used a vector of these five categories' market value percentages to represents their attribute. To define the links between each private equity fund, the similarity between any two funds are determined by their $Cosine similarity$, which the equation is like:

$$similarity = cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$

where A and B represent the attribute vectors of private equity funds A and B.

According to the above-mentioned equation, we got an adjacency matrix of hundreds of private equity funds. Directly, we can establish a fully connected network. However, the attributes of a fully connected network are weak, so that we designed the following three kinds of network to observe the changing trend in the private equity fund market.
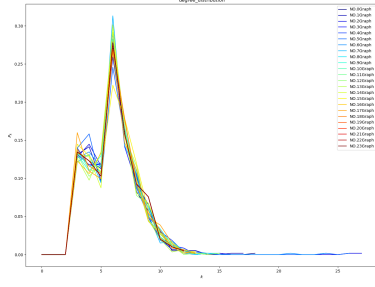
2 PMFG network

PMFG is short for Planar Maximally Filtered Graph, which is designed to filter the network information based on the MST(minimum spanning tree) algorithm. In the PMFG theorem, a graph without homeomorphism structure can have at most $3(n-2)$ links with n nodes in a graph. In this way, we reduce a fully connected network to a series of network with the fixed link number $3(n-2)$. The PMFG network's topology is roughly like the architecture in Figure 1, where the nodes with degree 3 have been colored by red, and degree 6 has been colored by green, which will be exclaimed following.
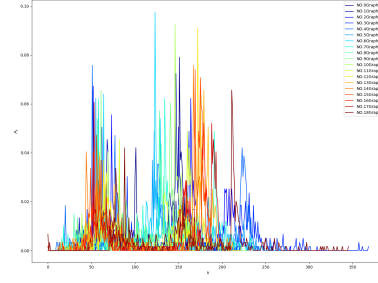
NO.0 PMFG
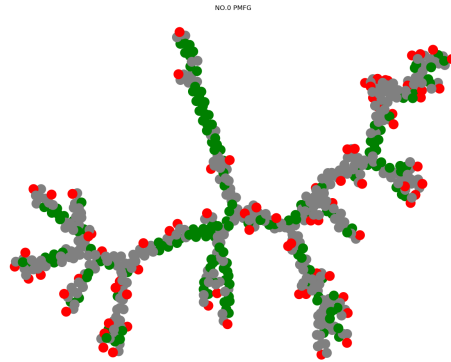
Fig. 1. Topology of PMFG network in 1st timestamp.

In Figure 2 is the degree distribution plot of the 23 PMFG networks. From this result, we can find an obvious bimodal phenomenon, consists of degree 3 and 6 approximately. So that we colored the special nodes with these two degrees and plot its network architectures. From the Figure 1 we can see that degree 3 are mostly at the end of the network while the degree 6 seems to be the trunk of the network.

To prove the bimodal phenomenon is not an accident, we construct random networks and plot their degree distribution plot. Figure 3 is the degree distribution plot of random networks and there no obvious similarities with the private equity fund network in topology.

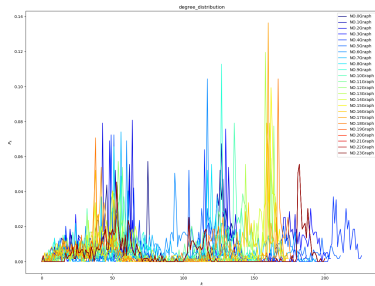**Fig. 2.** Degree distribution of the PMFG networks.   **Fig. 3.** Degree distribution of random networks' PMFG.
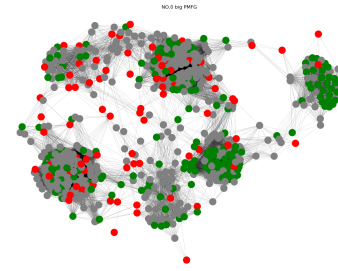
By the way, the purely PMFG network contains a lot of drawbacks. One of them is that some networks can't be constrained in a PMFG, which will make a big influence on the experiment. Next step, we establish the Big PMFG networks to make up for deficiencies.

3   Big PMFG network

Big PMFG network is based on the PMFG network, designed to solve some of the networks that can be constrained into a PMFG. THE big PMFG network will stop the construct as soon as the last note has been connected to the network. However, the result didn't give us many surprises. Its degree distribution seems to be more like random networks.

**Fig. 4.** Degree distribution of Big PMFG networks.   **Fig. 5.** Topology of Big PMFG network in 1st timestamp.

Figure 4 shows the degree distribution of Big PMFG networks and Figure 5 is the topology of Big PMFG network in 1st timestamp, where the nodes labeled in PMFG networks with

degree 3 or 6 have also been colored. The topology can't give us too many hints about the cause of the bimodal phenomenon.

4 Threshold network

The Threshold network is much different from the PMFG networks. Firstly, we used the original adjacency matrix and pick out the minimum of the maximum value of each node. Then set these values as a threshold and it can regard each of the nodes is connected in this network. Add the links, whose weight bigger than the threshold, and construct the network. The degree distribution of the Threshold network is in Figure 6.
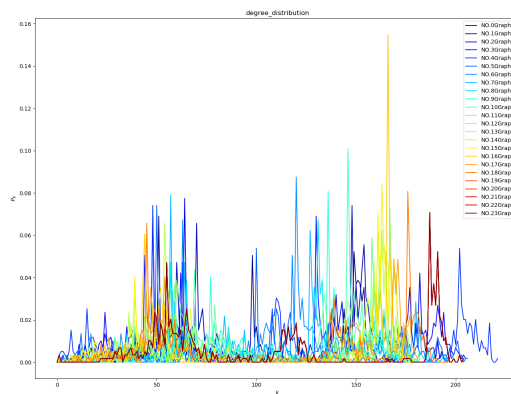

Fig. 6. Degree distribution of Threshold network.

In this network, we compare their series topological properties and observe their average weight's diversification. Figure 7 shows that from 13th to 15th timestamp has a sharp decline, which identical to the stock market crash in 2017, for the private equity fund take the most influence from the stock market.

More than these, we also took the cluster analysis based on the degree in it. Figure 8 shows the last cluster result in the network series. According to the result we obtained, the variance of clustering reduces as time goes on. So that we guess the private equity fund
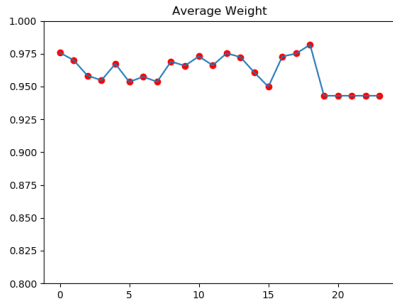
Fig. 7. Average weight's diversification.
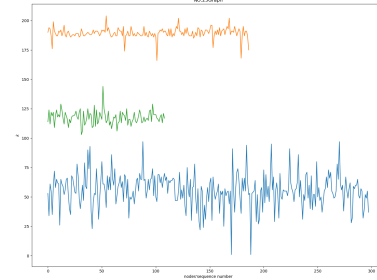
Fig. 8. Cluster analysis in last timestamp.

market converges gradually and different fund companies become small groups, though the efficient market theory.

5   Acquisition

During the internship at Sun Yat-sen University, I made a lot of friends who work on financial research. We discuss the project and study from each other. The profound influence thing is Dr. LI Sai-Ping, he will come to the laboratory and discuss the paper with us. He leads us to the scientific research career and teaches us how to think and do during the research. From this internship, I practiced my programming skills and had a deeper understanding of the network, economics, and physics. I really appreciate this treasure experience.

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