ARTICLE IN PRESS

Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A novel consensus based prediction strategy for data sensing

Cong Sui [a], Zongyao Wang [b], Renzhen Ye [c,*]

[a] Laboratory Experimental Economics, School of Finance, Dongbei University of Finance and Economics, Dalian 116025, Liaoning, PR China
[b] Artificial Intelligence Laboratory, Surrey International Institute, Dongbei University of Finance and Economics, Dalian 116025, Liaoning, PR China
[c] College of Sciences, Huazhong Agricultural University, Wuhan 430074, Hubei, PR China

ARTICLE INFO

Article history:
Received 29 January 2015
Received in revised form
20 May 2015
Accepted 22 May 2015

Keywords:
Data sensing
Contagion
Consensus algorithm
Distributed system
Noise models

ABSTRACT

Financial contagion problems have been extensively studied in area of financial research. Most of the works focus on studying the contagion effect on the financial system. Contagion prediction is considered as one of the most important strategies to prevent contagion. But the prediction issue is seldom researched in the financial area. Traditional financial management uses a centralized method to predict contagion risk. But the central management cannot instantly acquire complete information of entire network. A decentralized method is needed to achieve a prediction in real time. This paper introduces a distributed risk contagion prediction strategy of the financial network. Firstly, consensus algorithm is used to distributively acquire contagion risk information of the entire financial network. This distributed strategy enables the system to instantly predict the risk of contagion. Secondly, the impact of the financial crisis could enormously influence the convergency of consensus algorithm. So a consensus based Kalman filter (CAF) is proposed to maintain the convergency of consensus and ensure the accuracy of the prediction. Finally, the strategy is tested in different kinds of financial systems which are impacted by different levels of the financial crisis. The simulation result shows that the strategy is robust, flexible and feasible for practical use. It also proves that the proposed strategy can provide an accurate prediction in any condition.

1. Introduction

With development of interbank markets, financial institutes have been firmly connected by interbank liabilities and formed a complex financial network [1]. The globalized financial network brings new opportunities and problems [2,3]. Financial institutes can easily accomplish transactions via the interbank market in seconds. The financial network is convenient for liquidity management and provides protection mechanisms for institutes. However, the protection mechanisms could gradually turn into interbank contagion under the impact of the financial crisis [4]. Because of the contagion, a tiny fluctuation of a single financial institute could result in a regional financial disaster, even cause a global financial crisis [5]. The U.S. subprime mortgage crisis in 2007 and Eurozone crisis in 2010 have already proved that the financial network is highly complex and unstable. In recent years, more and more network theories have been applied to analyse financial networks. The research can be categorized as statistic research and dynamic research.

The statistic financial network research can date back to the Allen–Gale model which was introduced in 2000. It states that interbank contagion spread speed and spread route are related to network topology [6]. In the same year, Freixas compares the impact of financial contagion in a full connected network and a loop type network [7]. Both of this research focused on a special type of network topology. With the development of research, more and more people focus on the features of the real financial network topology. Soramaki et al. analysed 9000 US institutes in the Federal Reserve System. They concluded that the US financial system is a scale-free network [8]. Becher et al. got a similar conclusion about the UK financial network after analyzing CHAPS (Clearing House Automatic Payment System) [9]. One of the most important features of the financial network is that the degree of nodes follows the power law distribution. In [10], Boss et al. proved that Austria financial network follows power law distribution with a power law index 1.87. Santos and Cont stated that the power law index of the Brazil financial network is between 2.23 and 3.37 [11]. A more detailed work was done by Krause and Giansante who analysed contagion risk of network with different power law indexes [12].

Dynamic financial network research has a shorter history than statistic network research. The dynamic network research focuses on interaction strategy between institutes. Iroi et al. believed that liquidity impact and contagion are caused by random behaviours

* Corresponding author.
E-mail address: yerenzhen@gmail.com (R. Ye).

http://dx.doi.org/10.1016/j.neucom.2015.05.145
0925-2312/

Please cite this article as: C. Sui, et al., A novel consensus based prediction strategy for data sensing, Neurocomputing (2016), http://dx.doi.org/10.1016/j.neucom.2015.05.145

(withdraw and deposit) of customers [13]. In [14], Afonso and Shin applied proportional function to build a lending strategy model of institutes. But institutes lending strategy is changing with the interbank market environment. So the proportional function cannot completely reflect the real condition. In [15], Lenzua and Tedeschib applied expected profit function to build lending strategy. A dynamic contagion model was established based on the expected profit function. A similar work was done by Georg in [16]. The paper takes risk, profit, liquidity and preference into consideration. A dynamic model is also built based on multi-agent theory.

Up to now, most of the financial network research is related to the failure of financial systems with different structures [17,18]. However, the key of preventing contagion and stabilizing financial systems is the prediction of contagion risk. Traditional prediction is executed by a central institute (such as central bank). The central institute will collect information, process data and execute prediction. But the interbank information varies from time to time. The process of information collection and data processing will cause considerable delay and prevent effective prediction. As a typical distributed system, financial network urgently needs a distributed prediction mechanism which can effectively solve the delay problem.

The "Distributed System" is derived from a computer network system. In a modern computer network, there is no central computer or slave computer. All the computers share a public network resource and cooperatively implement a certain task. Because of highly robustness and extensiveness, the distributed system is also applied to areas other than computer science. In artificial intelligence, the distributed system is applied to build multi-robot systems. In [19], Wang and Gu applied the distributed system to achieve cooperative target tracking with a group of WIFI-robots. In sociology, distributed system is used to analyse social network topology and information transmission pattern. In [20], Gambhir and Aneja analysed the social network from the perspective of social psychology. In engineering science, the distributed system is used to build large scale network systems, such as electric network control system [21], air traffic control system [22], and wireless communication network [23]. With the development of communication and e-commercial, distributed features of a financial network are increasingly apparent. But distributed system theories are seldom used in a financial network. As a newly emerging research area, many significant problems are still waiting to be solved. This paper will deal with one of the most important unsolved problems: how to build an effective contagion risk prediction system for a financial network.

In general, researchers seldom dedicate themselves to distributed financial contagion risk prediction research. This is because a central system is commonly used to predict financial risk. But the centralized method cannot effectively implement contagion risk prediction because of processing delay. On the other hand, the distributed method has been widely used in many research areas. It can deal with many problems that the centralized method cannot solve. But the distributed system is seldom used in financial science. This paper presents a distributed strategy for a financial network to predict contagion risk. The contribution of this paper includes: (1) Consensus algorithm will be applied to building distributed prediction strategy. Consensus algorithm enables the institutes instantly to acquire and process the contagion risk information via interaction. But the convergency of consensus algorithm cannot be ensured when the financial system is impacted by a financial crisis. (2) A "consensus based Kalman filter" is built to maintain convergency of the algorithm. This algorithm enables the prediction strategy to provide an accurate estimation of contagion risk.

The outline of this paper is arranged as follows. Section 2 establishes a financial network model which is the base of prediction strategy. Section 3 is the core of this paper. Consensus algorithm is introduced to achieve distributed prediction and a "consensus based Kalman filter" is built to stabilize prediction strategy. Section 4 gives simulation results of prediction strategy. Section 5 is the conclusion.

2. Financial system modelling

2.1. Interbank network modelling

It has been proved that financial contagion is caused by interbank interactions (interbank loans and interbank borrowing). The interactions link the financial institutes and form a complex financial network. So a financial network can be modelled as a graph which is composed of vertices (financial institutes) and edges (interaction between institutes). Two institutes with lending and borrowing relationship are considered as neighbors. In a graph, we use $\mathcal{E}_{ij}$ to denote an edge starting from vertex i to vertex j. Topology of a network can be represented by a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ is the set of vertices and $\mathcal{E}$ is the set of edges. Any two vertices will be considered as neighbors if they are connected by an edge. Because institutes cannot borrow or lend money to themselves, so $\mathcal{E}_{ii} \notin \mathcal{E}$. Fig. 1 illustrates a sample financial network.

The institute i has four neighbours which are connected by real lines. The neighbours of institute i can be presented as $N_i = \{j_1, j_2, j_3, j_4\}$. The neighbours of institute i also have other neighbours which are connected by dashed lines. All these institutes and edges form a financial network.

The structure of a graph can be described by an adjacent matrix (A) with elements:

$$\begin{cases} a_{ij} = 1 & (\mathcal{E}_{ij} \in \mathcal{E}) \\ a_{ij} = 0 & (\mathcal{E}_{ij} \notin \mathcal{E}). \end{cases} \tag{1}$$

It can be seen that the adjacent matrix A is an integer matrix with rows and columns indexed by the vertices. The ij-entry of A is 1 if i and j are neighbours, otherwise it is 0:

$$A = \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & \ddots & a_{ij} & \vdots \\ \vdots & a_{ji} & \ddots & \vdots \\ a_{n1} & \cdots & \cdots & 0 \end{bmatrix}. \tag{2}$$

The matrix A demonstrates the interaction relationship between institutes. It also reflects the features of a financial network.

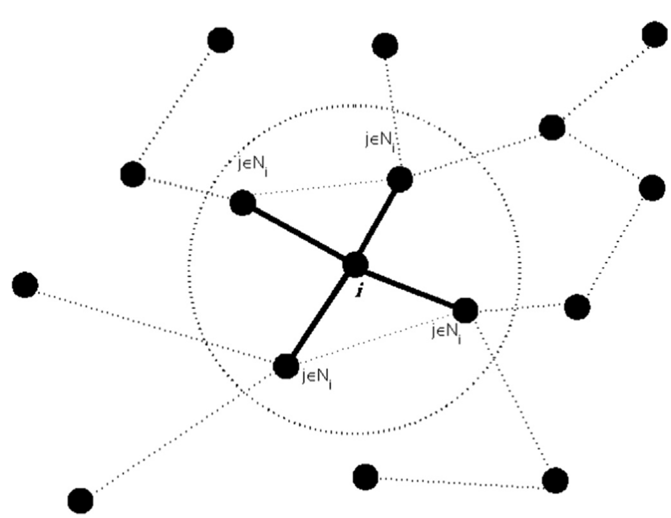

Fig. 1. Financial network topology.

Please cite this article as: C. Sui, et al., A novel consensus based prediction strategy for data sensing, Neurocomputing (2016), http://dx.doi.org/10.1016/j.neucom.2015.05.145