Introduction

With the increasing rate of developing cryptocurrencies and their efficiency in financial exchanges, issues such as analysis of blockchain network structure, creating stabilized conversion rates for them and understanding the behavior of users in this type of market has gained more significance than the past. On the other hand, the new generation of financial exchanges which are based on digital assets have revolutionized financial transactions with the help of advent of cryptocurrencies, which has created a new wave of changes in economic markets and economic prospects. On the other hand, due to sharp price fluctuations in digital cryptocurrencies, in order to be able to increase their efficiency in human daily life, they need protocols and mechanisms to stabilize their conversion rates. Thus, economic system analysts need to analyze the mechanism better before publishing a cryptocurrency and evaluate the performance of that system.

One of the most important methods ever used is identifying economic systems to know the behavior of the main actors in an economic network and the rate of currency fluctuations in them. Nowadays, by using computer science and machine learning, the behavior of economic market players can be left to be done by the computers to obtain better and more efficient analysis.

For this reason, we intend to use the exchange data of an online exchange in which there exists digital cryptocurrency exchanges to help advance the behavioral recognition of the agents, as well as to address the issue of how much the new generation of online exchanges that are distributed and located on the blockchain network platform, can compete with the traditional exchange model. One of the main features of these exchanges is the lack of a third party for currency exchange in a financial system. In this article, we use Stellar network data so that we get cryptocurrency exchanges on the one hand, and on the other hand, we work with a new generation of online exchanges.

The data in this network is a set of transactions between users and offers to buy or sell different assets. Because of these transactions and exchanges, new data are created in the network that are connected by linking two offers of buying and selling with the same amounts and they create a financial exchange process in the network. In fact, it can be said that financial exchange data are created by merging offers to buy and sell assets in the Stellar network.

Following the analysis and behavioral recognition of the operators of this financial market, we have used Co-clustering algorithms. The main difference between Co-clustering algorithms and other ones is that, in this algorithms, clustering is performed on all elements of a vector (data row) and even if one of the elements of that vector is different from the corresponding elements of that vector in other data, that vector cannot be in a cluster with similar vectors [1]. This issue is while nowadays we need to be able to put data that differs in some features in a cluster.

For example, we want to divide the types of agents in an economic market into several groups based on their degree of activity: active agents, moderately active agents, low activity agents, and noise agents. This is while the behavioral patterns of the agents who are in the cluster of active agents may be

completely different from each other, but they are still put in the same cluster. Based on this feature, it can be expressed that algorithms examine the proximity of data of a single matrix simultaneously based on columns and rows. Also, place them in clusters with a higher coheriant (Coherient) [1].

In this paper at the first step, we have evaluated our data using the Smooth Plaid and SLF-PARAFAC algorithms that are presented by [1].

History of activities

In [2] by using the data obtained from China future market and Co-clustering methods, the participants in this market have been divided into five different clusters. In this article, the main purpose was to better knowing and understanding the efficiency of SLF-PARAFAC and SPM algorithms so that they can evaluate the performance of these two algorithms in comparison with the other clustering algorithms and also in contrast to each other. However, the main issue that have not been considered in this article is that if the data with much higher dimensions are evaluated by these two algorithms, then how efficient these two algorithms will be.

In [3] has tried to examine and evaluate a theory called Chaos on the four most important cryptocurrencies (Bitcoin, Etherium, Lightcoin and Ripple) which have the largest market capitalization that has been circulating in the cryptocurrency markets until 2017. In fact, the main goal of this study was to be able to identify the major changes that can occur in the economic market based on important transactions in the network, , so that they could evaluate and investigate one of the cryptocurrency market failures from the year 2017 to early of 2018 based on transactions.

In [4] the article also tried to identify the extent of the impact of Etherium and Bitcoin on other cryptocurrencies in the digital cryptocurrency market by examining the two cryptocurrencies of Etherium and Bitcoin. This happened due to the usage of Filtered return series in order to make a correlation matrix between cryptocurrencies.

Using the mentioned method in this article, they first examined their data with F-Test to identify the structural break point . The structural break point based on the Chow statistics was a regulations-related announced by Korea. After that they divided their data set into two part, Pre and Post-regulation periods. Then they feed their data to Bitcoin-Ethereum filtering algorithm which utilized the filtered return series instead of the plain return series to construct the correlation matrix among the cryptocurrencies.

After analyzing their data, they examined the effect of Bitcoin and Etherium cryptocurrencies on other cryptocurrencies and realized that by changing the conversion rate of these cryptocurrencies, the price of other cryptocurrencies changes under the influence of these cryptocurrencies.

In [5] they have also divided the blockchain network data into groups using clustering methods to obtain a better analysis of the structure of the blockchain network. The main purpose of this paper was to get a better view for the analysis and evaluation of blockchain networks. In this article, by using Euclidean distance between transactions, they have evaluated the amount of transaction distance and found out that the blockchain networks developers can use the method presented in this article to improve their analyze of blockchain network.

In article [6], it has also been pointed out that blockchain has great potential for being in use in finance, gaming, financial transfers, gambling and the supply chain, however, one of the serious challenges in this area is the behavioral analysis of the network users and categorizing them based on their behavior.

Accordingly, an algorithm that is called BPC has been presented in this paper that measures the distance between two sequences of different lengths with using DTW.

After this, they have compared their method with several traditional clustering algorithms, which it have shown that the method presented in this paper with a different number of clusters has provided a better and more acceptable result.

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