# Data Analysis of Digital Currency Networks: Namecoin Case Study

Tao-Hung Chang and Davor Svetinovic

Department of Electrical Engineering and Computer Science
Masdar Institute of Science and Technology, Abu Dhabi, UAE
{tchang, dsvetinovic}@masdar.ac.ae

***Abstract*—Financial transaction networks are some of the largest networks in existence. A relatively new type of financial networks is the digital (crypto) currency network, e.g., Bitcoin. Namecoin is an alternative crypto currency, based on Bitcoin, with additional features such as DNS. Namecoin network has more than 2 million nodes and almost 17 million edges. The analysis of such a crypto currency network can help us model or predict the future growth of the transaction networks. In order to analyze the transaction network graph over time, we analyzed the Namecoin blockchain data in 7 six months intervals. Our findings suggest different user behavior and developing pattern compared to Bitcoin.**

## I. Introduction

The previous research in network analysis of crypto currency networks concentrated mostly on Bitcoin [1], [2], [3]. However, there are many other alternative crypto currencies. Most of them are derived from Bitcoin, e.g., Namecoin, Dogecoin and Litecoin. Although Namecoin adopts the structure of Bitcoin, it has its own blockchain and a different purpose other than just being a crypto currency. Namecoin is the first crypto currency that acts as a decentralized domain name system.

From the previous research we know that Bitcoin network is similar to many other types of networks, e.g., social networks [3]. This means it should be possible to predict the future development of Bitcoin network, since it follows many general network assumptions. This phenomenon brings up the question, are other crypto currencies such as Namecoin following the same pattern? If so, we might be able to predict the growth of other networks as well. If not, what are the differences between the networks? What are the reasons that cause the differences? The answer can help us understand the relationship between Bitcoin and other crypto currencies and predict their developing patterns.

In order to build and analyze the network graph for Namecoin, we obtained blockchain data from the a blockchain exploration website (multiple websites are providing the same service), which contained the most up-to-date blockchain data for Bitcoin and Namecoin. After extracting the transaction inputs and outputs information from the blockchain data, each pair of input and output in the same transaction forms an edge in the network. Furthermore, we applied the network analysis tool and community detection algorithm on the networks. This information helped us obtain a deeper insight in the relationship between Bitcoin and Namecoin networks.

In this study, we discovered a number of similarities and differences between Bitcoin and Namecoin networks. Namecoin network does not follow the assumptions that exist in many other social networks, e.g., constant average degree assumption and shrinking diameter assumption. We also examined many other properties of Namecoin network to find out what might be the reasons that caused this phenomenon.

Leskovec [4] indicated that the average out-degree of the nodes grew over time, which conflicts with the standard Density Power Law modeling assumption. The other discovery was that the standard assumption of slowly growing diameter did not fit into the real world networks [5], [6]. They found the diameter shrank as the networks grew.

Gonzalez [7] conducted a research on Google+. They analyzed and evaluated the connections and activities among the users in the largest connected component. They found that despite the increasing size of Google+, the relative size of the largest connected component had been decreasing. This finding might have been caused by the empty Google+ accounts. The researchers only considered the accounts that connected with the LCC as the active accounts.

Gong [8] introduced addition of user attributes when analyzing social networks. They claimed that the attributes of users could have a significant impact on the network structure. Other research also indicated that social-attribute network could enhance the link prediction, attribute inference [9], [10] and community detection [11].

## II. Research Method

In this paper, we focus on the following two questions. First, does the growth of Namecoin network follow the Densification Law over time? Second, what are the differences between Namecoin and Bitcoin regarding to their network pattern over time? In particular, do they have the same pattern since Namecoin is derived from Bitcoin?

The Namecoin blockchain data is obtained from a website, http://webbtc.com. After downloading the database dump, the next step is to load it in a database and extract the data that is needed for the research. The original raw data contains all the information in the blockchain, including block ID, transaction ID, input address, output address and the amount of Namecoin for each transaction. After building the network graph with the transaction information that is extracted from the database,

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we applied Networkit and igraph package in R to analyze the Namecoin network. The main goal of applying those tools was to find out the developing patterns and properties of the network.

The Namecoin blockchain data that is used in this research is from 2011/04/17 to 2014/10/13. In order to see the growth of the network, the data is accumulated and analyzed in 7 six month periods, as shown in Table I.

The nodes in the Namecoin network represent each Namecoin address and the edges represent the relationships between the addresses. For instance, a transaction with two input and three output addresses forms six edges in the network. The addresses that have never been used as input in any transaction are excluded from the network since those nodes have no connection to the other nodes.

To know the trend of how the network grows, there are some essential properties we need to examine, e.g., the number of edges, the number of nodes and the average degree of the network. The largest connected component (LCC) and the community size in the network are also important factors to understand the structure of the network. Hence, we also look into the relative size and the diameter of the LCC, the number and the size of the community.

## III. Result and Evaluation

From the Namecoin blockchain data, we were able to generate the input file for Networkit [12], [13], [14], a network analysis software. The file contains the edge list of the network. Other than Networkit, we also used R and igraph package to analyze the Namecoin network. The Namecoin data was divided into 7 six months intervals. The dates of each interval are shown in Table I. The evaluation of Namecoin network is focused on three different perspectives: the properties of the network graph, the largest connected component (LCC) and the community structure.

### A. Properties of the Network Graph

For the data in Table I, the number of nodes represents the total number of public keys in the network, which are the accounts that have being used as input addresses in transactions. The number of edges shows the relationship between accounts. If two nodes are linked together, it means they made transaction with each other. Moreover, in both Bitcoin and Namecoin, each transaction can have multiple inputs and outputs, e.g., a transaction X has two inputs and three outputs, which generates six edges in the network graph for the transition X. The historical Namecoin market prices in Table I are collected from the website Crypto-Currency Market Capitalizations (https://coinmarketcap.com/).

As we can see from Figure 1, Namecoin has had significant growth only in the first year. However, Bitcoin grew over 100 times bigger in the first year. The difference might exist because during 2009 to 2010, crypto currency was a new concept for users, and Bitcoin was the only crypto currency in the market. All the users who wanted to try crypto currency had to choose Bitcoin. After Bitcoin got famous in 2011, all the other crypto currencies started to appear in the market, such as Namecoin and Litecoin which were launched in 2011. With all the new competitors in the market, the growth of Namecoin has started to slow down as shown in Figure 1.

To have a deeper insight in Namecoin network, we calculated the value of assortativity. The assortativity value means the preference for the nodes in the network to connect to the other nodes with similar degree. Its value lies between $-1$ and 1. If the value is close to 1, it means the nodes with high degree in the network tend to connect to other nodes with high degree. This phenomenon exists in many social networks. On the other hand, if the value is closer to $-1$, it means the nodes with higher degree tend to connect to the nodes with lower degree. This characteristic can be found in the technological and biological networks [15]. As shown in Table II, the assortativity values for Namecoin network are negative and closer to $-1$. This suggests that the nodes with lower degree in the Namecoin network tend to connect to the nodes with higher degree in the network.

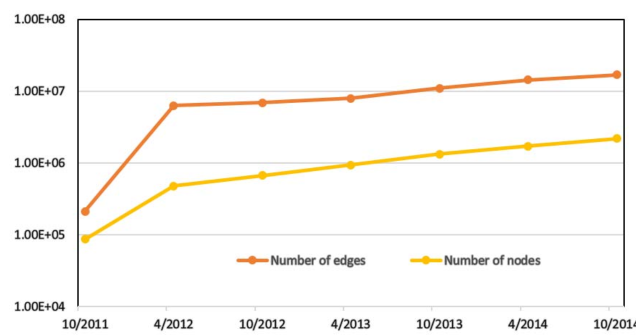


Fig. 1. The number of nodes and edges overtime

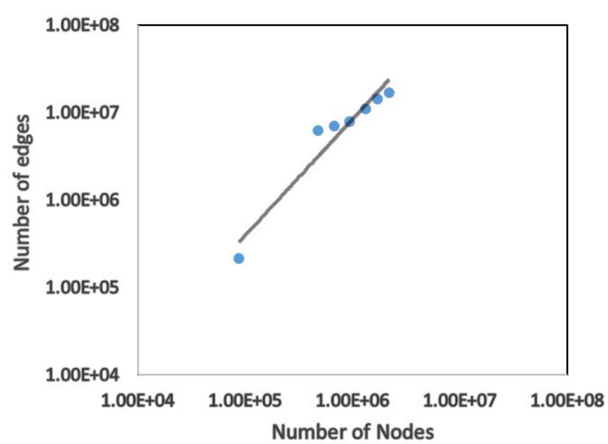


Fig. 2. Ratio edges/nodes (log scale)

TABLE I
NAMECOIN NETWORK GRAPH PROPERTIES THROUGHOUT THE SEVEN SNAPSHOTS.

| No. | Timestamp | Block depth | Number of nodes | Number of edges | Average degree | Market price |
|---|---|---|---|---|---|---|
| 1 | 17-Oct.-2011 | 22,577 | 86,802 | 213,081 | 4.91 | 0 |
| 2 | 17-Apr.-2012 | 51,982 | 475,207 | 6,281,330 | 26.44 | 0 |
| 3 | 17-Oct.-2012 | 79,676 | 672,704 | 6,930,268 | 20.6 | 0 |
| 4 | 17-Apr.-2013 | 106,371 | 941,492 | 7,956,849 | 16.9 | 0.52 |
| 5 | 17-Oct.-2013 | 148,464 | 1,322,056 | 11,015,736 | 16.66 | 0.45 |
| 6 | 17-Apr.-2014 | 172,455 | 1,711,086 | 14,248,677 | 16.65 | 2.27 |
| 7 | 17-Oct.-2014 | 201,393 | 2,174,773 | 16,838,021 | 15.48 | 1.02 |

Figure 2 shows the ratio of the number of edges and the number of nodes over time (see Densification Power Law (DPL) plot [4]). To determine whether Namecoin network follows the densification law, we examined the slope of data. The data fits with a line of slope $S = 1.32$ and $R^2 = 0.93$. Although the network is growing denser, we can see that there is a significant growth only between the first two points. Furthermore, we also checked the DPL plot without the first interval data. The slope of the new DPL plot drops to $0.68$ with the $R^2 = 0.95$. The result shows that the overall trend does not represent the real situation since the network has been growing sparsely in the past three years. The average degree of the network, shown in Table I, also shows the same phenomenon. There is only a significant growth of the average degree between the first two points. The value of the average degree keeps decreasing after the second snapshot.

Combining all the findings above, we suggest that Namecoin network does not follow the Densification Law and the constant average degree assumption. The network does not grow denser over time. The result is also in line with the findings from the largest connected component analysis.

### B. Properties of the Largest Connected Component (LCC)

Figure 3 shows the diameter and relative size of the LCC in Namecoin network. The relative size of LCC is calculated by dividing the number of nodes that connect to the LCC by the number of nodes in the network. The diameter is the longest shortest path among all the nodes that connect to the LCC. For most of the social networks, including Bitcoin network [3], [4], the diameter grows rapidly at first, then shrinks after a period of time. This is called the shrinking diameter. It also means that the nodes that connect to LCC are also well connected with each other.

For the Namecoin network, the LCC connects to almost 99% of the nodes in the network, and there is no sign of shrinking diameter for the LCC throughout all the snapshots. New nodes tend to connect to the present LCC, such as the trading or exchange platforms rather than the other low degree nodes. This causes the growth of the diameter instead of shrinking. This result aligns with our previous finding that the nodes with higher degree tend to connect to the nodes with lower degree and vice versa.

### C. Properties of the Community Structure

The other important factor to analyze for the network is the community structure. Figure 4 and Table II represent

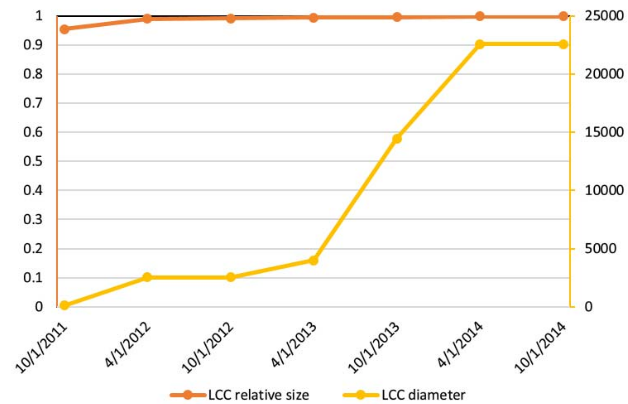


Fig. 3. The properties of the LCC

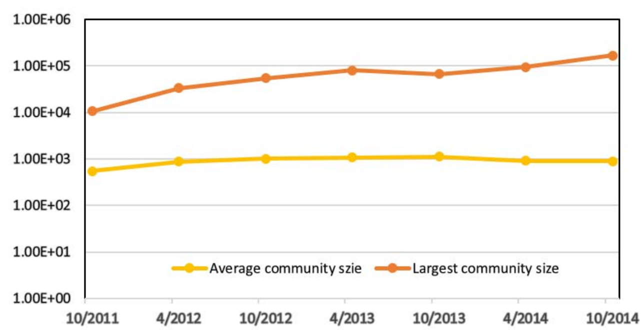


Fig. 4. The properties of the community structure

the properties of the community structure for the Namecoin network. In Table II, the growth of the number of communities in Namecoin network is increasing for all the snapshots. Moreover, the size of the largest community grows over ten times bigger after all the snapshots, while the average size of communities remains stable. This situation suggests that there are many small size communities in the network. However, the previous results from the analysis of LCC and the whole network point out that nodes in the Namecoin network are not well connected with each other and the density of Namecoin network is slightly decreasing. The possible explanation is that the community structure of the Namecoin network is not

TABLE II
ASSORTATIVITY VALUES AND NUMBER OF COMMUNITIES

| No. | Date | Ass. Value | Comm. Value |
|---|---|---|---|
| 1 | Oct-11 | 0.007 | 159 |
| 2 | Apr-12 | $-0.243$ | 542 |
| 3 | Oct-12 | $-0.193$ | 672 |
| 4 | Apr-13 | $-0.22$ | 874 |
| 5 | Oct-13 | $-0.266$ | 1169 |
| 6 | Apr-14 | $-0.214$ | 1889 |
| 7 | Oct-14 | $-0.197$ | 2450 |

significant which leads to a large number of communities but relatively sparse connections within these communities.

The findings in [16] are aligned with our findings. The authors analyzed the use of Namecoin, and the results showed that Namecoin is essentially a kind of side-chain of Bitcoin. They also pointed out certain user behaviors such as merge-mining which cause the Namecoin network to have a different network development from the Bitcoin network.

## IV. CONCLUSION

The results of this study provide the adequate information to answer the research questions. According to the data we collected for the Namecoin network, the growth for Namecoin network only follows the densification law in the first year. This result is different from Bitcoin network. The density of Bitcoin network keeps increasing with almost the same rate during more than five and a half years [3].

Furthermore, Namecoin network does not follow the constant average degree assumption. From Table I, we can see that the average degree of Namecoin network shows only the significant growth between the first two phases and it starts to slightly decrease after that. As for the shrinking diameter assumption, based on our analysis of the LCC, the network connects to 99% of the nodes in the network and the diameter of the network keeps growing. Since the new nodes tend to connect to the nodes with higher degree rather than each other, this phenomenon causes the growing diameter and decreasing network density. In summary, the Namecoin does not have the same growth pattern as the Bitcoin network.

Other than the fact that Namecoin network is smaller than Bitcoin network, the significant differences are the shrinking diameter and the network density. The decreasing density in Namecoin network causes the unclear community structure. On the other hand, the Bitcoin network grows denser over time which leads to a strong community structure.

All the differences listed above point out that the users for Namecoin and Bitcoin have different behaviors. Since Bitcoin is the oldest and the most dominant crypto currency in the market, it is reasonable that it has a denser and larger network than Namecoin. Moreover, the liquidity for Bitcoin is much higher than Namecoin. Most of the exchange platforms only provide the service to exchange Bitcoin for other fiat currencies. If the users want to exchange other crypto for fiat currencies, they have to exchange it to Bitcoin first.

The other reason that might cause the difference is that Bitcoin is much more valuable than Namecoin based on the market price and it has a higher volatility. These are the incentives for the users to use Bitcoin as an investment tool rather than Namecoin. The original idea for Namecoin was to create a decentralized domain name system. Users can pay Namecoin to register and update their domain name. However, there are websites that provide service to allow users to register a decentralized domain name by Bitcoin. Those are the potential reasons that might cause the differences between Namecoin and Bitcoin networks, and all are visible in the network structure. Thus further studies and the improvement of our ability to understand transaction network patterns will lead to an even better understanding on how to design crypto currencies.

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