Tether:
A Study on Bubble-Networks

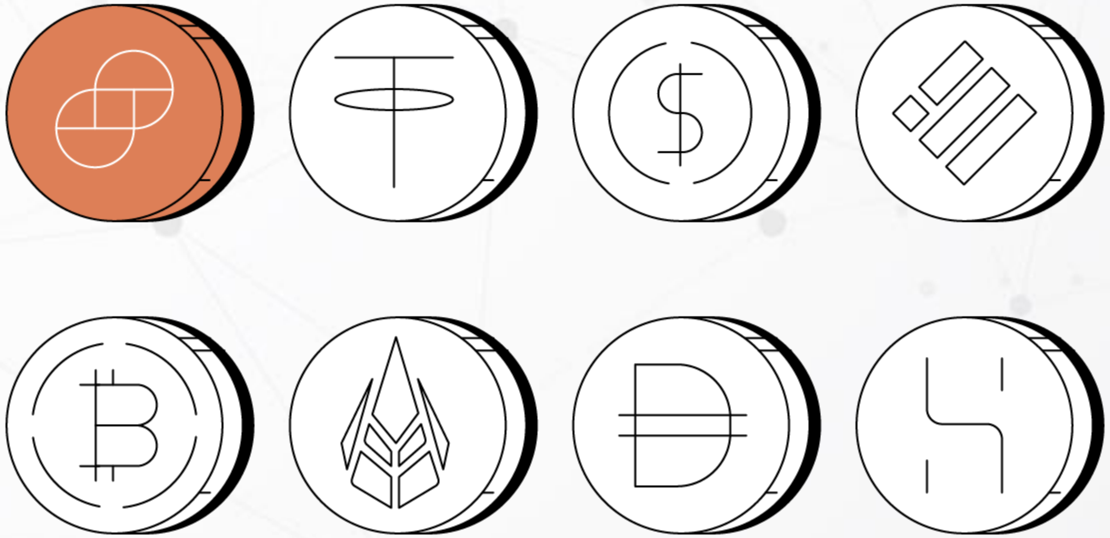
Giovanni Rosa *and Remo Pareschi*

Università degli Studi del Molise

frontiers in Blockhain

Stablecoins

Cryptocurrencies whose values are tied to external assets (US dollar or gold) to maintain a stable price



Stablecoins

Traditional Collateral (Off-Chain)

Crypto Collateral (On-Chain)

Algorithmic Stablecoins

Commodity-Backed Stablecoins

What is Tether (USDT)?

Tether is a Stablecoin

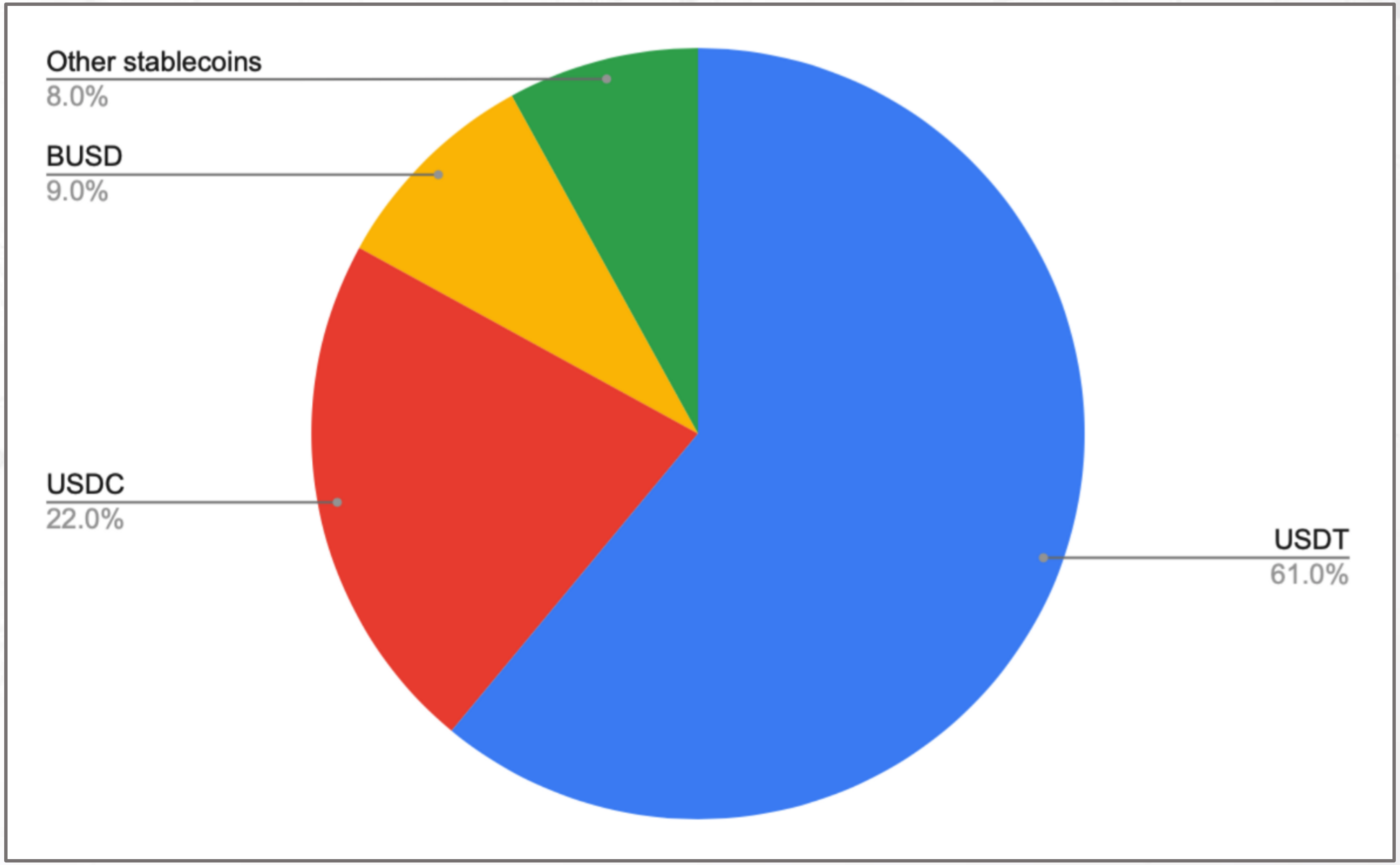
1 USDT is intended to remain equal to $1

What is Tether (USDT)?

Why Tether?

#	Name	Price	24h %	7d %	Market Cap	Volume(24h)	Circulating Supply
4	Tether USDT	$1.00	-0.03%	0.05%	$76,577,833,287	$69,716,240,091 69,584,570,078 USDT	76,433,204,084 USDT
6	USD Coin USDC	$1.00	-0.10%	0.03%	$41,726,505,217	$4,923,615,789 4,917,598,626 USDC	41,675,511,150 USDC
14	Binance USD BUSD	$1.00	0.10%	0.07%	$13,819,485,695	$5,059,320,464 5,052,192,118 BUSD	13,800,014,686 BUSD
19	Dai DAI	$1.00	0.39%	-0.06%	$9,159,049,805	$720,482,214 718,664,209 DAI	9,135,938,625 DAI
21	TerraUSD UST	$1.00	0.02%	0.01%	$8,752,637,967	$172,062,386 171,727,883 UST	8,735,622,146 UST

Why Tether?



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Bitfinex Used Tether Reserves to Mask Missing $850 Million, Probe Says

New York attorney general alleges cryptocurrency-exchange operator drained popular coin's reserves to conceal missing funds

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MARKETS

Bitfinex Used Teth
Million, Probe

New York attorney general allege

Is Tether a black swan?

Bernhard Mueller Jun 18 · 14 min read

A risk assessment by a DeFi security dude. Note: I worked as a security auditor and engineer in the blockchain space for three years and participated in audits and formal verification of DeFi protocols such as Aave, Bancor and mStable which also involved assessing economic risk. Consider this a complementary Tether risk assessment that Tether didn't ask for.

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23 MINS AGO

Euro zone bond yields rise, eyes on cen banks

26 MINS AGO

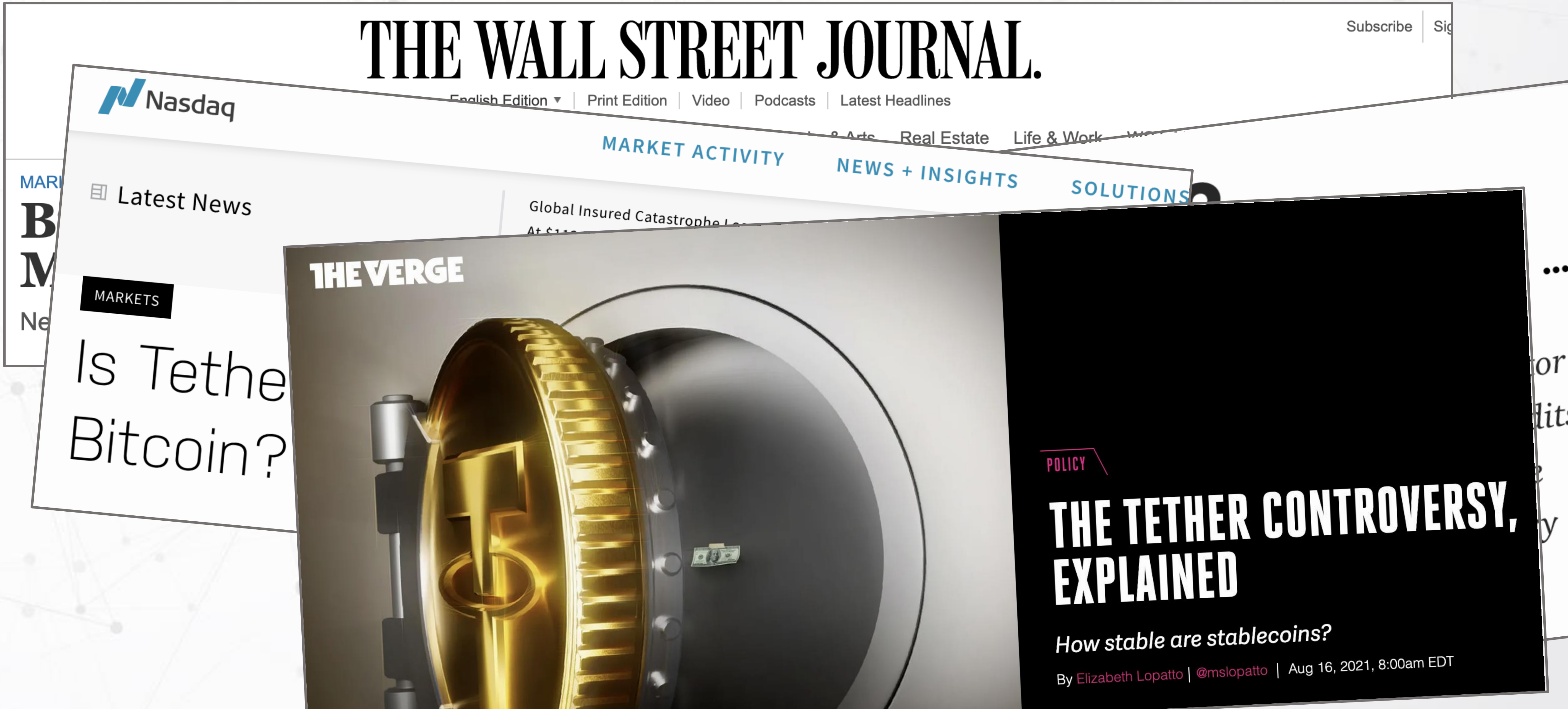
MARKETS

Is Tether Pumping The Price Of Bitcoin?

worked as a security auditor
rs and participated in audits
Aave, Bancor and mStable
nsider this a complementary

and formal verifica
which also involved assessing econo
Tether risk assessment that Tether didn't ask for.

Why Tether?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MARKETS
Is Tethe
Bitcoin?
THE VERGE
POLICY
THE TETHER CONTROVERSY, EXPLAINED
How stable are stablecoins?
By Elizabeth Lopatto | @mslopatto | Aug 16, 2021, 8:00am EDT

The problem

“Bubble Effect”

Speculative trends to push up the Bitcoin price where masses of Tethers are exchanged with Bitcoins

The problem

Tether reserve consists of US dollars plus “other collateral”

Strong relationship between Bitfinex and Tether

The objective

Use Social Network Analysis to analyze the Tether transaction graph

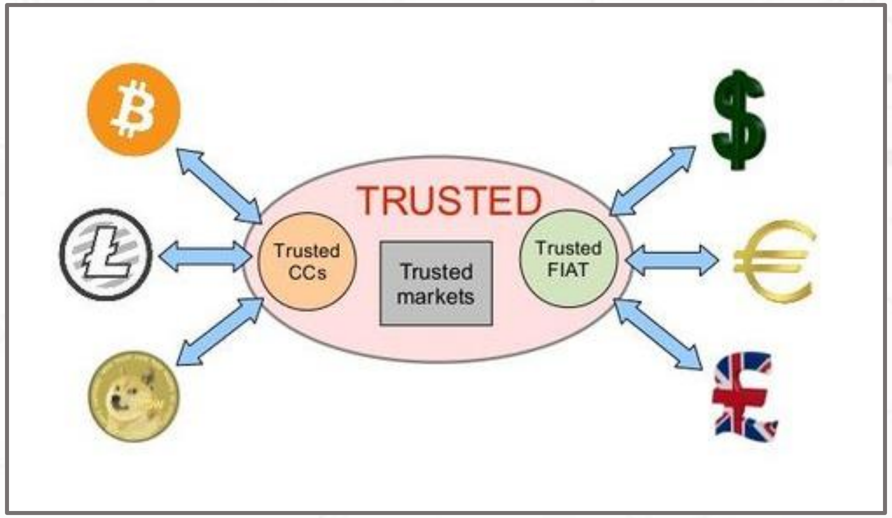
How Tether transactions works?

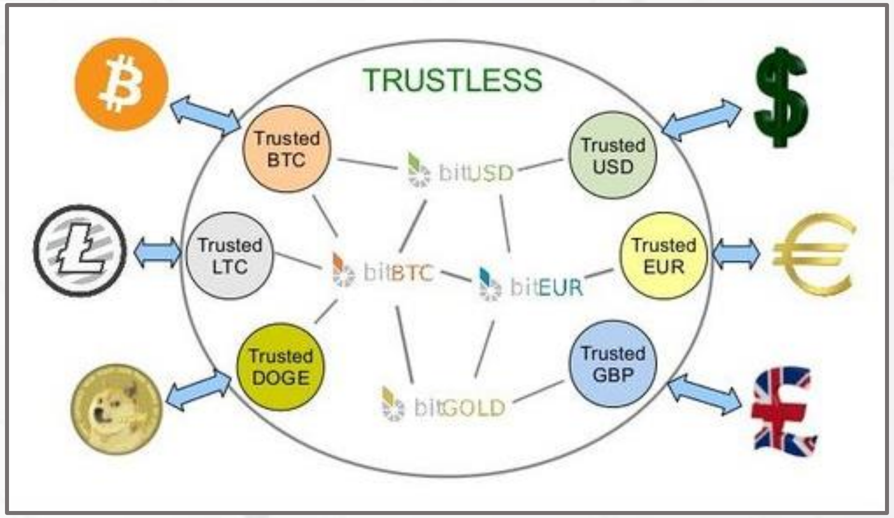
OMNI - Omni Layer, Bitcoin network

TRC20 – TRON Network

ERC20 - Ethereum Blockchain

How Tether transactions works?





Centralized Exchange (CEX)

Decentralized Exchange (DEX)

CEX vs DEX

CEX – Centralized crypto exchanges:

1. There will be third party operator
2. Fiat currency transactions will be allowed
3. Market Makers & Takers will be part of the platform
4. Entries will be in Database most of the times until the cashout or coin pull happens
5. The volume of the transaction will be more
6. Better Speed of Trading (No Real Time Crypto Node update)
7. Liquidity will be more comfortable
8. Robust Know Your Customer (KYC) and Anti-Money Laundering (AML) practices
9. Private Keys stored in system & associated with User credentials in the crypto exchange application
10. Prone for hacking/cracking of the system

DEX – Decentralized crypto exchanges:

1. No third party operators
2. Fiat currency transactions will not be allowed
3. Most of the times Market Takers will only be part of the platform
4. Direct updating of trading transactions on Crypto Nodes. No database entries
5. The volume of the crypto trading transaction will be very less
6. Low-grade Speed of Trading (Due Real Time Crypto Node update)
7. Liquidity will be the challenge (only handle Crypto Coins on Nodes)
8. No, Know Your Customer (KYC) & Anti-Money Laundering (AML) practices
9. No Private Keys in the application
10. Not the first choice of hacking/cracking of the system

Related studies

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Do the Rich Get Richer? An Empirical Analysis of the Bitcoin Transaction Network

Dániel Kondor[1]*, Márton Pósfai[1,2], István Csabai[1], Gábor Vattay[1]

1 Department of Physics of Complex Systems, Eötvös Loránd University, Budapest, Hungary, **2** Department of Theoretical Physics, Budapest University of Technology and Economics, Budapest, Hungary

Abstract

The possibility to analyze everyday monetary transactions is limited by the scarcity of available data, as this kind of information is usually considered highly sensitive. Present econophysics models are usually employed on presumed random networks of interacting agents, and only some macroscopic properties (e.g. the resulting wealth distribution) are compared to real-world data. In this paper, we analyze Bitcoin, which is a novel digital currency system, where the complete list of transactions is publicly available. Using this dataset, we reconstruct the network of transactions and extract the time and amount of each payment. We analyze the structure of the transaction network by measuring network characteristics over time, such as the degree distribution, degree correlations and clustering. We find that linear preferential attachment drives the growth of the network. We also study the dynamics taking place on the transaction network, i.e. the flow of money. We measure temporal patterns and the wealth accumulation. Investigating the microscopic statistics of money movement, we find that sublinear preferential attachment governs the evolution of the wealth distribution. We report a scaling law between the degree and wealth associated to individual nodes.

Citation: Kondor D, Pósfai M, Csabai I, Vattay G (2014) Do the Rich Get Richer? An Empirical Analysis of the Bitcoin Transaction Network. PLoS ONE 9(2): e86197. doi:10.1371/journal.pone.0086197

Editor: Matjaž Perc, University of Maribor, Slovenia

Received August 14, 2013; **Accepted** December 6, 2013; **Published** February 5, 2014

Funding: This work has been supported by the European Union under grant agreement No. FP7-ICT-255987-FOC-II Project. The authors thank the partial support of the European Union and the European Social Fund through project FuturICT.hu (grant no.: TAMOP-4.2.2.C-11/1/KONV-2012-0013), the OTKA 7779 and the NAP 2005/KCKHA005 grants. EITKIC_12-1-2012-0001 project was partially supported by the Hungarian Government, managed by the National Development Agency, and financed by the Research and Technology Innovation Fund and the MAKOG Foundation. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing Interests: The authors have declared that no competing interests exist.

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Introduction

In the past two decades, network science has successfully contributed to many diverse scientific fields. Indeed, many complex systems can be represented as networks, ranging from biochemical systems, through the Internet and the World Wide Web, to various social systems [1–7]. Economics also made use of the concepts of network science, gaining additional insight to the more traditional approach [8–13]. Although a large volume of financial data is available for research, information about the everyday transactions of individuals is usually considered sensitive and is kept private. In this paper, we analyze Bitcoin, a novel currency system, where the complete list of transactions is accessible. We believe that this is the first opportunity to investigate the movement of money in such detail.

Bitcoin is a decentralized digital cash system, there is no single overseeing authority [14]. The system operates as an online peer-to-peer network, anyone can join by installing a client application and connecting it to the network. The unit of the currency is one bitcoin (abbreviated as BTC), and the smallest transferable amount is 10^{-8}BTC. Instead of having a bank account maintained by a central authority, each user has a Bitcoin address, that consists of a pair of public and private keys. Existing bitcoins are associated to the public key of their owner, and outgoing payments have to be signed by the owner using his private key. To maintain privacy, a single user may use multiple addresses. Each participating node stores the complete list of previous transactions. Every new payment is announced on the network, and the payment is validated by checking consistency with the entire transaction history. To avoid fraud, it is necessary that the participants agree on a single valid transaction history. This process is designed to be computationally difficult, so an attacker can only hijack the system if he possesses the majority of the computational power of participating parties. Therefore the system is more secure if more resources are devoted to the validation process. To provide incentive, new bitcoins are created periodically and distributed among the nodes participating in these computations. Another way to obtain bitcoins is to purchase them from someone who already has bitcoins using traditional currency; the price of bitcoins is completely determined by the market.

The Bitcoin system was proposed in 2008 by Satoshi Nakamoto, and the system went online in January 2009 [14–17]. For over a year, it was only used by a few enthusiasts, and bitcoins did not have any real-world value. A trading website called MtGox was started in 2010, making the exchange of bitcoins and conventional money significantly easier. More people and services joined the system, resulting a steadily growing exchange rate. Starting from 2011, appearances in the mainstream media drew wider public attention, which led to skyrocketing prices accompanied by large fluctuations (see Fig. 1). Since the inception of Bitcoin over 17 million transactions took place, and currently the market value of all bitcoins in circulation exceeds 1 billion dollars. See the

Kondor et al. 2014

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Data driven analysis of Bitcoin properties: exploiting the users graph

Damiano Di Francesco Maesa · Andrea Marino · Laura Ricci

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Abstract Data analytics has recently enabled the uncovering of interesting properties of several complex networks. Among these, it is worth considering the BITCOIN blockchain, because of its peculiar characteristic of reflecting a niche, but also a real economy whose transactions are publicly available. In this paper we present the analyses we have performed on the users graph inferred from the BITCOIN blockchain, dumped in December 2015, so after the occurrence of the exponential explosion in the number of transactions. We first present the analysis assessing classical graph properties like densification, distance analysis, degree distribution, clustering coefficient, and several centrality measures. Then, we analyse properties strictly tied to the nature of BITCOIN, like rich-get-richer property which measures the concentration of richness in the network.

1 Introduction

The study of methods and tools for the analysis of complex networks has recently gained momentum, due to the presence of complex relational data in different fields. Network analysis has been applied in different scientific areas, like the analysis of biological systems [1], transportation systems [2] and social networks [3]. A novel application field is that of the networks modelling economic transactions occurring in some economic area. However, the analysis of real-life economy networks is not easy as there is no central entity registering all the transactions, since the transaction records are distributed over a large number of commercial entities or banks. An exception is that of transactions generated by digital cryptocurrencies which have been recently proposed to enable a point to point value exchange, so overcoming the need of a third party financial intermediary. Current cryptocurrencies require a distributed public ledger to work, so providing a unique opportunity for analysis of currency transactions.

BITCOIN [4], the first true digital currency, was proposed in 2008 by Satoshi Nakamoto, a pseudonym, and the first client went online in 3rd of January 2009. From then, the system has gained wide mass media coverage and widespread popularity among the broad public of non specialists, so resulting in the first example of cryptocurrency economy worthy of analysis. After almost seven years since the inception of BITCOIN, an economic community has risen around it. BITCOIN still represents a niche and peculiar economical community, nevertheless its importance in the real world has grown enough so that it no longer represents an experimental currency exploited only by computer science specialists. Several events of the BITCOIN economy, like the wild speculation, the value fluctuation and a major exchange failure witness that a true economic system has born around it.

The Bitcoin system operates according to a peer-to-peer philosophy, which avoids the need of a bank account maintained by a central authority. In BITCOIN, each user has a unique address that consists of a pair of public and private keys. Each amount is associated

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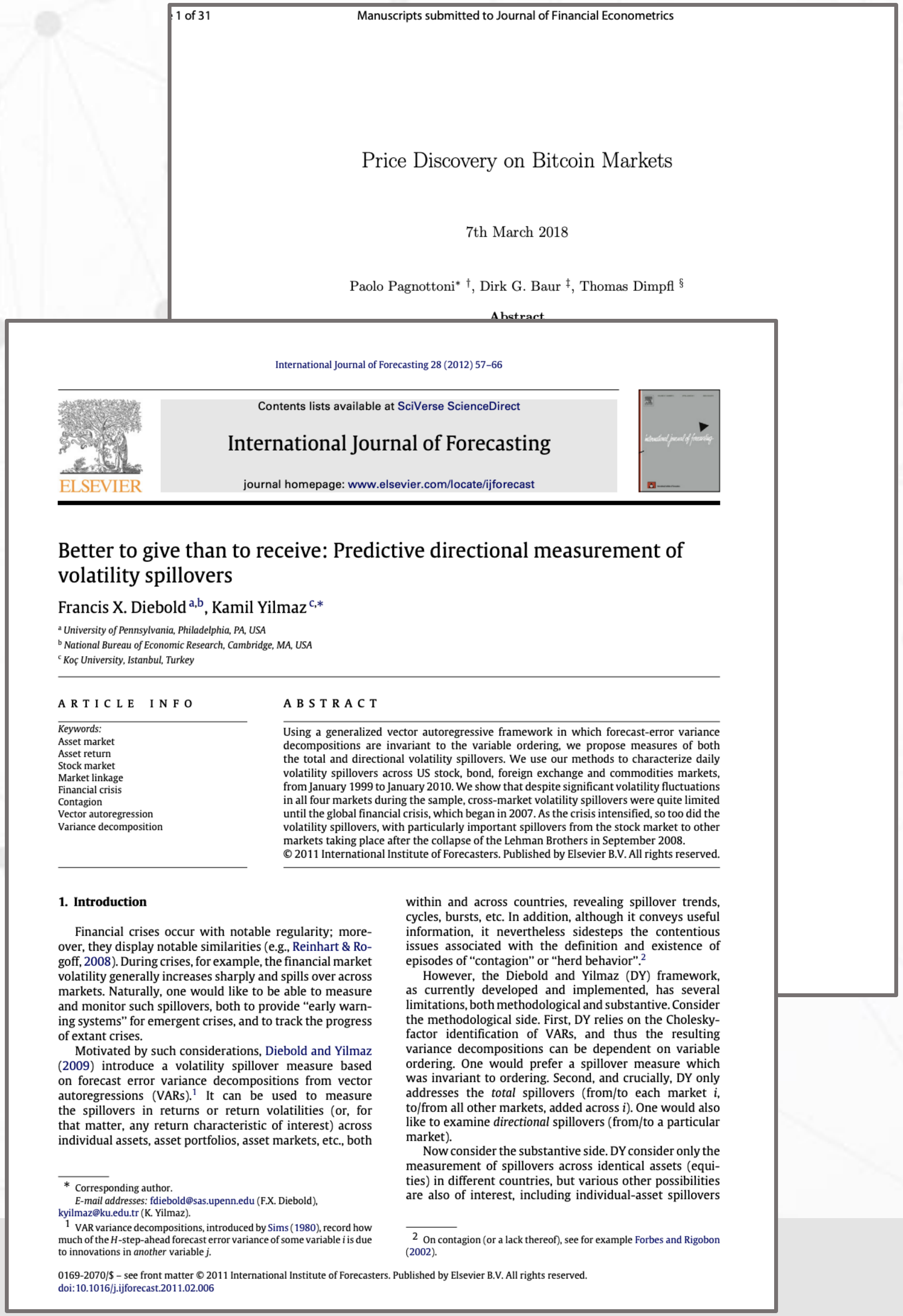
Maesa et al. 2018


1 of 31 Manuscripts submitted to Journal of Financial Econometrics

Price Discovery on Bitcoin Markets

7th March 2018

Paolo Pagnottoni* †, Dirk G. Baur ‡, Thomas Dimpfl §

Abstract

International Journal of Forecasting 28 (2012) 57–66

Contents lists available at SciVerse ScienceDirect

International Journal of Forecasting

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

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Better to give than to receive: Predictive directional measurement of volatility spillovers

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ARTICLE INFO

Keywords:
Asset market
Asset return
Stock market
Market linkage
Financial crisis
Contagion
Vector autoregression
Variance decomposition

ABSTRACT

Using a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering, we propose measures of both the total and directional volatility spillovers. We use our methods to characterize daily volatility spillovers across US stock, bond, foreign exchange and commodities markets, from January 1999 to January 2010. We show that despite significant volatility fluctuations in all four markets during the sample, cross-market volatility spillovers were quite limited until the global financial crisis, which began in 2007. As the crisis intensified, so too did the volatility spillovers, with particularly important spillovers from the stock market to other markets taking place after the collapse of the Lehman Brothers in September 2008.
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1. Introduction

Financial crises occur with notable regularity; moreover, they display notable similarities (e.g., Reinhart & Rogoff, 2008). During crises, for example, the financial market volatility generally increases sharply and spills over across markets. Naturally, one would like to be able to measure and monitor such spillovers, both to provide "early warning systems" for emergent crises, and to track the progress of extant crises.

Motivated by such considerations, Diebold and Yilmaz (2009) introduce a volatility spillover measure based on forecast error variance decompositions from vector autoregressions (VARs).[1] It can be used to measure the spillovers in returns or return volatilities (or, for that matter, any return characteristic of interest) across individual assets, asset portfolios, asset markets, etc., both within and across countries, revealing spillover trends, cycles, bursts, etc. In addition, although it conveys useful information, it nevertheless sidesteps the contentious issues associated with the definition and existence of episodes of "contagion" or "herd behavior".[2]

However, the Diebold and Yilmaz (DY) framework, as currently developed and implemented, has several limitations, both methodological and substantive. Consider the methodological side. First, DY relies on the Cholesky-factor identification of VARs, and thus the resulting variance decompositions can be dependent on variable ordering. One would prefer a spillover measure which was invariant to ordering. Second, and crucially, DY only addresses the *total* spillovers (from/to each market *i*, to/from all other markets, added across *i*). One would also like to examine *directional* spillovers (from/to a particular market).

Now consider the substantive side. DY consider only the measurement of spillovers across identical assets (equities) in different countries, but various other possibilities are also of interest, including individual-asset spillovers

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1 VAR variance decompositions, introduced by Sims (1980), record how much of the *H*-step-ahead forecast error variance of some variable *i* is due to innovations in *another* variable *j*.

2 On contagion (or a lack thereof), see for example Forbes and Rigobon (2002).

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doi:10.1016/j.ijforecast.2011.02.006

VAR and VEC models to describe market dynamics

Diebold et. al (2012)
Pagnottoni et. al (2018)

Experimental Procedure

Network Analysis

The term network analysis refers to the process of analyzing social structures (networks) in the form of graphs (mathematical representation)

The main feature is the focus on the **interactions** between the **actors** that make up the network

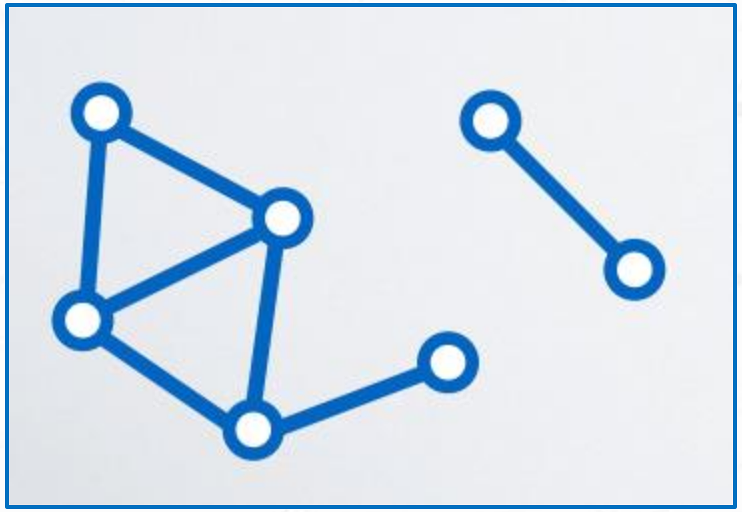
Network Analysis

In the context of cryptocurrencies such as the Tether

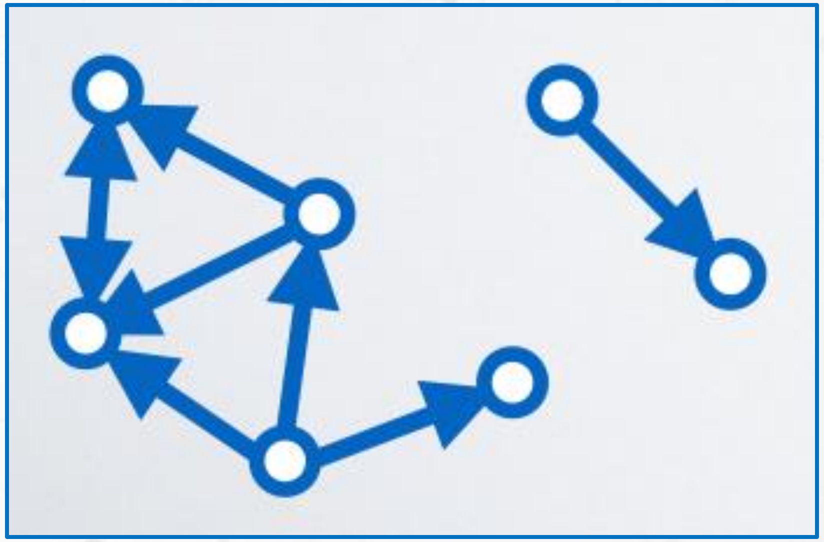
The **nodes** are **money holders**

The **edges** that connect them are the **transactions** through which money change hands from one actor to another.

Network Analysis



Undirected networks



Directed networks

Network Analysis Metrics

Node degree

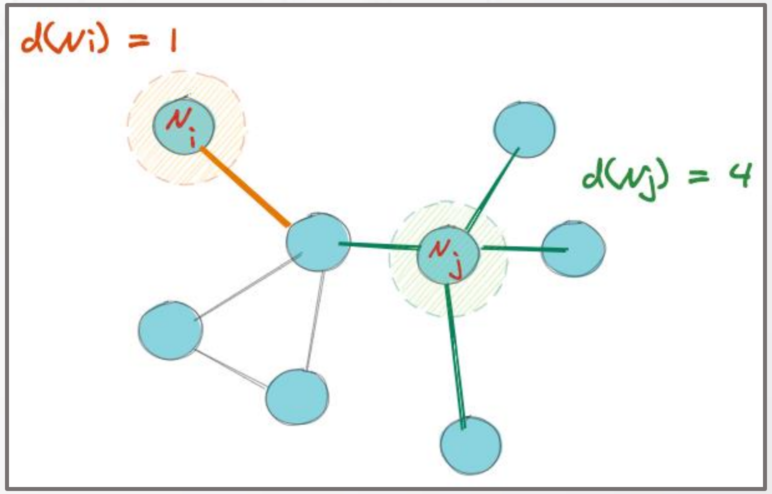
assigns a score based on the number of connections each node receives

Node Average Degree

number of edges with respect to the number of nodes

Node Indegree and **Node Outdegree**

(directed networks only)



Clustering coefficient

Measures the interconnection of a graph: the higher its value, the denser the network

“What fraction of neighbors of a node are connected to each other?”

Network Analysis Metrics

Network Diameter and Node Degree

Metrics related to centrality analysis and network size

Hyperlink-Induced Topic Search (HITS)

Measures Hub value, how many other nodes the node points to, and authority score, how many hub nodes point to a given node.

Network Analysis Metrics

Betwenness Centrality

Which nodes are "bridges" between nodes in a network, which are the most influential nodes for the flow of transactions

Modularity class

Community and modules detection

Network Analysis Metrics

Page Rank

Measures the influence of the nodes in the network

Assortativity Coefficient

Measures if the nodes tend to connect to similar ones

Study Context

Omni

OmniExplorer.info

Mining of USDT transactions

October 2014 - February 2021

Study Context

Omni

OmniExplorer.info

Mining of USDT transactions

October 2014 - February 2021

Group trasactions by address

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October 2014 - February 2021

↓

Group trasactions by address

↓

Known address labeling

Study Context

Omni

OmniExplorer.info

Mining of USDT transactions
October 2014 - February 2021

↓

Group trasactions by address

↓

Known address labeling

↓

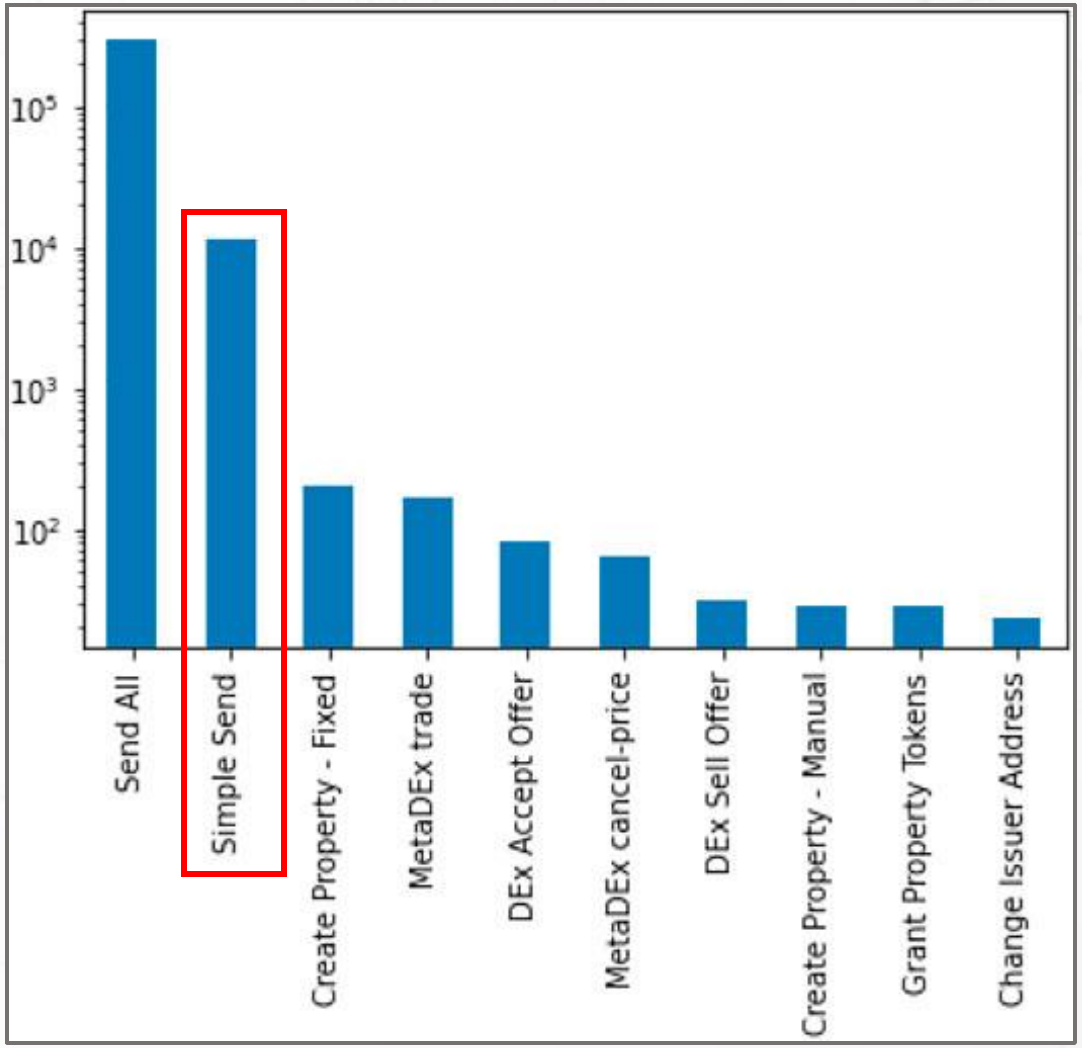
50.000 Tether threshold

Dataset example

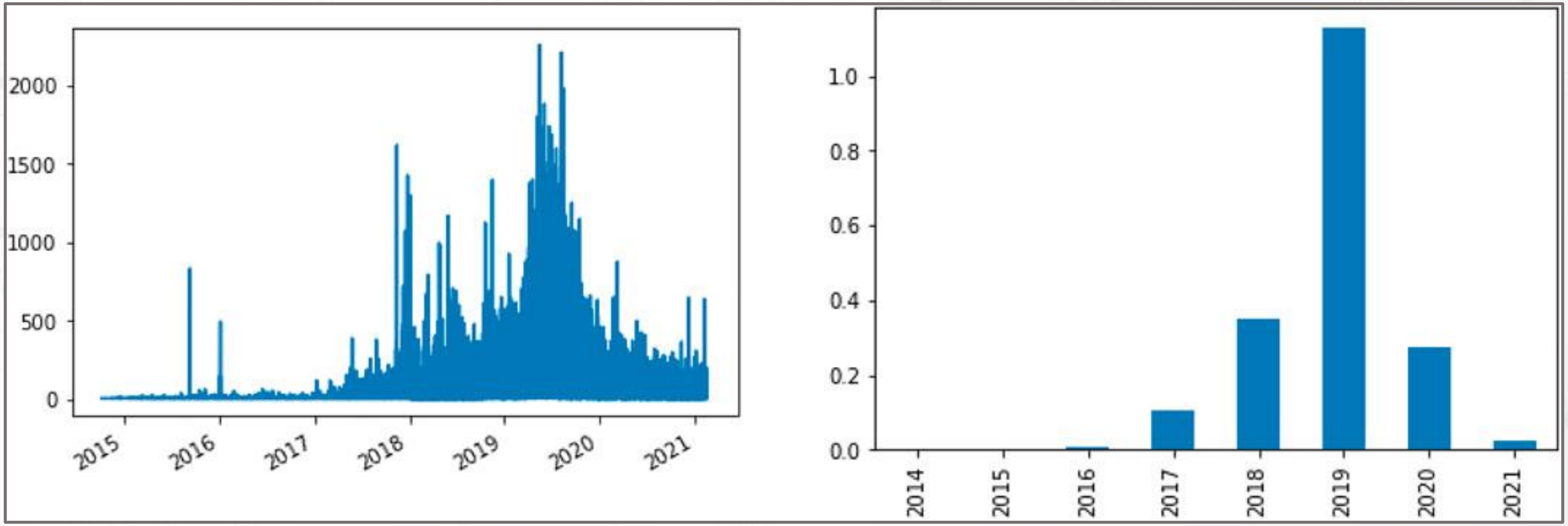

```
{
   "_id":586643,
   "blockhash":"0000000000000000001e359f892bcd4f47ca1f551b7eab152160ab8349c48310",
   "count":6,
   "transactions":[
      {
         "amount":"2060.00000000",
         "block":586643,
         "blockhash":"0000000000000000001e359f892bcd4f47ca1f551b7eab152160ab8349c48310",
         "blocktime":1563872760,
         "confirmations":32070,
         "divisible":true,
         "fee":"0.00018180",
         "flags":null,
         "ismine":false,
         "positioninblock":9,
         "propertyid":31,
         "propertyname":"TetherUS",
         "referenceaddress":"1JebtkdGNiA8mQYXtKBApN4nvinNZQFTDp",
         "sendingaddress":"1HckjUpRGcrrRAtFaaCAUaGjsPx9oYmLaZ",
         "txid":"43ef72637b0707168b9d38ba0d09b2db3fd3f67db7e78c00d38511431b5badb6",
         "type":"Simple Send",
         "type_int":0,
         "valid":true,
         "version":0
      },
      ...
    ]
}
```


Name	Description	Type
tx_hash	The unique id of the transaction; same as the BTC txid.	string
block_height	The numeric height of the block in the BTC blockchain.	integer
block_hash	The unique id of the BTC block the transaction is in	string
block_time	The timestamp of the BTC block the transaction is in	datetime, GMT 0
position_in_block	The numeric position of the transaction within the block	integer
sending_address	The BTC address of the sender	string
reference_address	A BTC address used as reference. Same as the recipient address in the case of "Simple Send"	string
tx_type	The transaction type, with "Simple Send" being the most popular. Valid values are listed on Omni Layer's spec	string
amount	The amount of token in the transaction	float
version	The transaction version number	integer
is_valid	1 if the transaction is valid; 0 if it is not;	integer
fee	The transaction fee in BTC	float

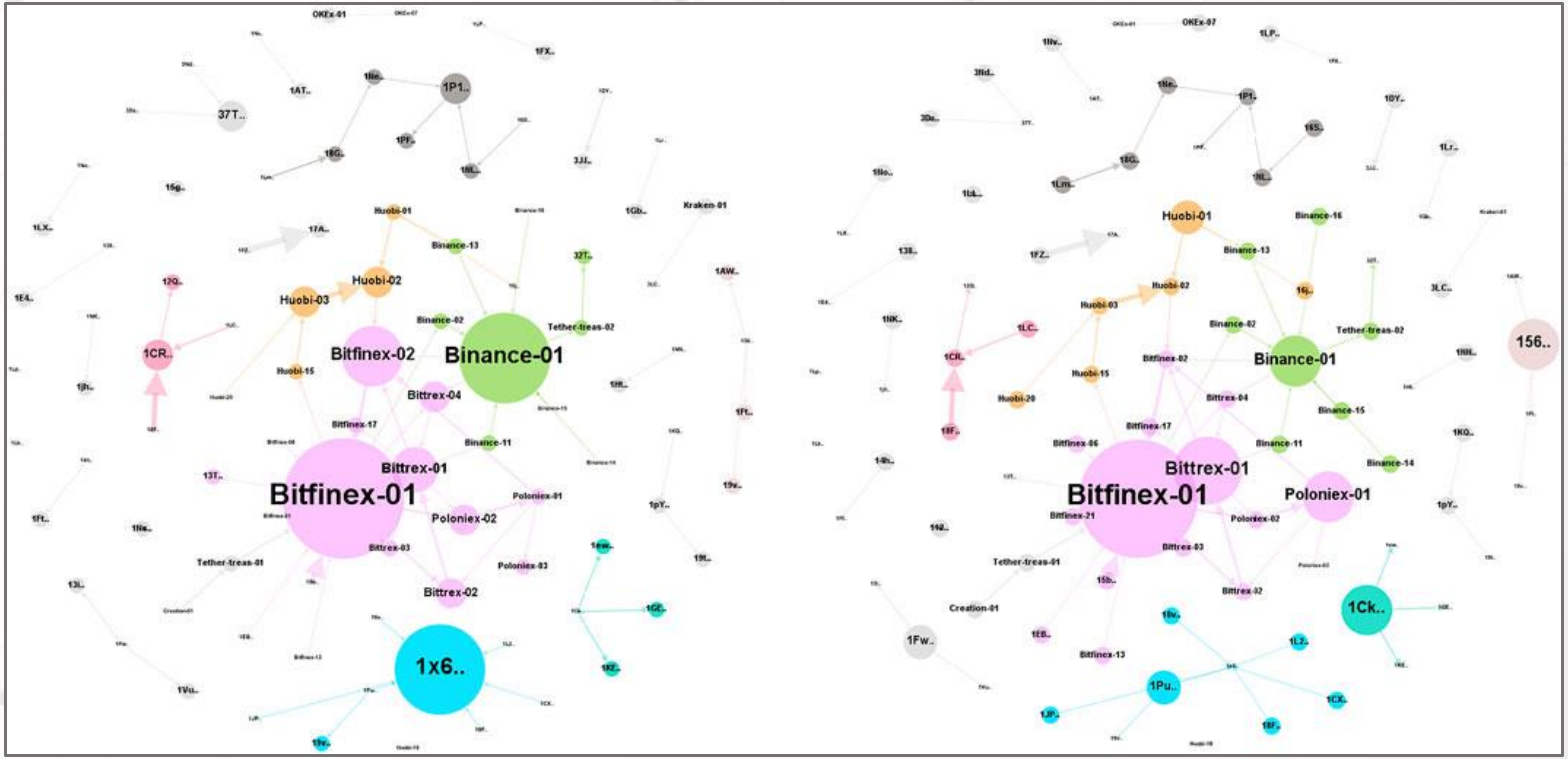
Transaction Types



Number of Transactions Over Time



Network graph from the top 100 transactions until March 2020



Known Address Labeling

Rich List

Top USD₮ Balances

Last Updated: Dec 14 11:09 AM UTC

Address	Balance	Protocol	Remark
TMuA6YqfCeX8EhbfYEg5y7S4DqzSJireY9	7,000,000,001	trc20	Binance Cold Wallet
TV6MuMXfmLbBqPZvBHdwFsDnQeVfnmiuSi	6,224,160,056	trc20	
0x5754284f345afc66a98fbb0a0afe71e0f007b949	1,929,305,962	erc20	Tether Treasury
TT1DyeqXaaJkt6UhVYFWUXBXknaXnBudTK	1,870,000,000	trc20	
0xa929022c9107643515f5c777ce9a910f0d1e490c	1,705,532,955	erc20	
TM1zzNDZD2DPASbKcgdVoTYhfmYgtfwx9R	1,645,475,214	trc20	

Known Address Labeling

tbl_df 11 x 4 | tbl_df 1 x 4

reference_address <chr>	sending_address <chr>	total.recv <dbl>	cum.freq <dbl>
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1G47mSr3oANXMafVrR8UC4pzV7FEAzo3r9	116284467.0	0.4166848
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1DcKsGnjpD38bfj6RMxz945YwohZUTVLby	98361062.4	0.7691443
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1MEPB525tEHRFLdq6aR8d2t8jaaRQj2iWX	50000000.0	0.9483105
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1LAnF8h3qMGx3TSwNUHVneBZUEpwE4gu3D	8642120.4	0.9792780
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1FnnDJ4qBK3RdTkxciRUtkNtJpg2pXLkSN	1988980.8	0.9864051
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1ApkXfxWgJ5CBHzrogVSKz23umMZ32wvNA	1510262.0	0.9918169
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	115E3baxJZsJHeTay1jvUh3nSTHBJhkskc	723608.0	0.9944098
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	37Tm3Qz8Zw2VJrheUUhArDAoq58S6YrS3g	640052.2	0.9967033
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1FoWyxwPXuj4C6abqwhjDWdz6D4PZgYRjA	550001.1	0.9986742
	fU4pgZw	250000.0	0.9995700

Previous 1 2 Next

tbl_df 11 x 4 | tbl_df 1 x 4

sending_address <chr>	reference_address <chr>	total.sent <dbl>	cum.freq <dbl>
19Qcmdh2FEZnTEFeEbQvWPSvfLuRBcjyo4	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	279070545	1

1 row

1JEUdCKEFDJhFADK7GsVpq6qxJqWv8KZwY	Binance-15	Binance
1PqajDc5zrxtwFbwSwQvUwNg66dmrW4Rfv	Binance-16	Binance
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	Bitfinex-01	Bitfinex
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	Bitfinex-02	Bitfinex
1GjgKbj69hDB7YPQF9KwPEy274jLzBKVLh	Bitfinex-03	Bitfinex

Results

Network Overview

Basic network measures such as the number of nodes and edges, diameter and community.

Metrics:

Modularity class,

Node Degree,

Network Diameter

Network Overview

	2014	2015	2016	2017	2018	2019	2020	2021
n. nodes	-	58	250	9,844	54,303	128,819	147,292	149,459
n. edges	-	98	507	18,379	116,884	282,428	319,972	324,308
Network diameter	-	9	12	13	16	24	24	24
n. communities	-	6	10	146	127	219	254	260
Strongly connected components	-	14	29	2,651	11,454	31,960	36,428	36,981
Total Tether sent	-	48,705,674	401,020,997	30,484,533,292	28,169,563,184,080	28,288,155,873,269	29,490,161,306,594	29,492,469,336,583

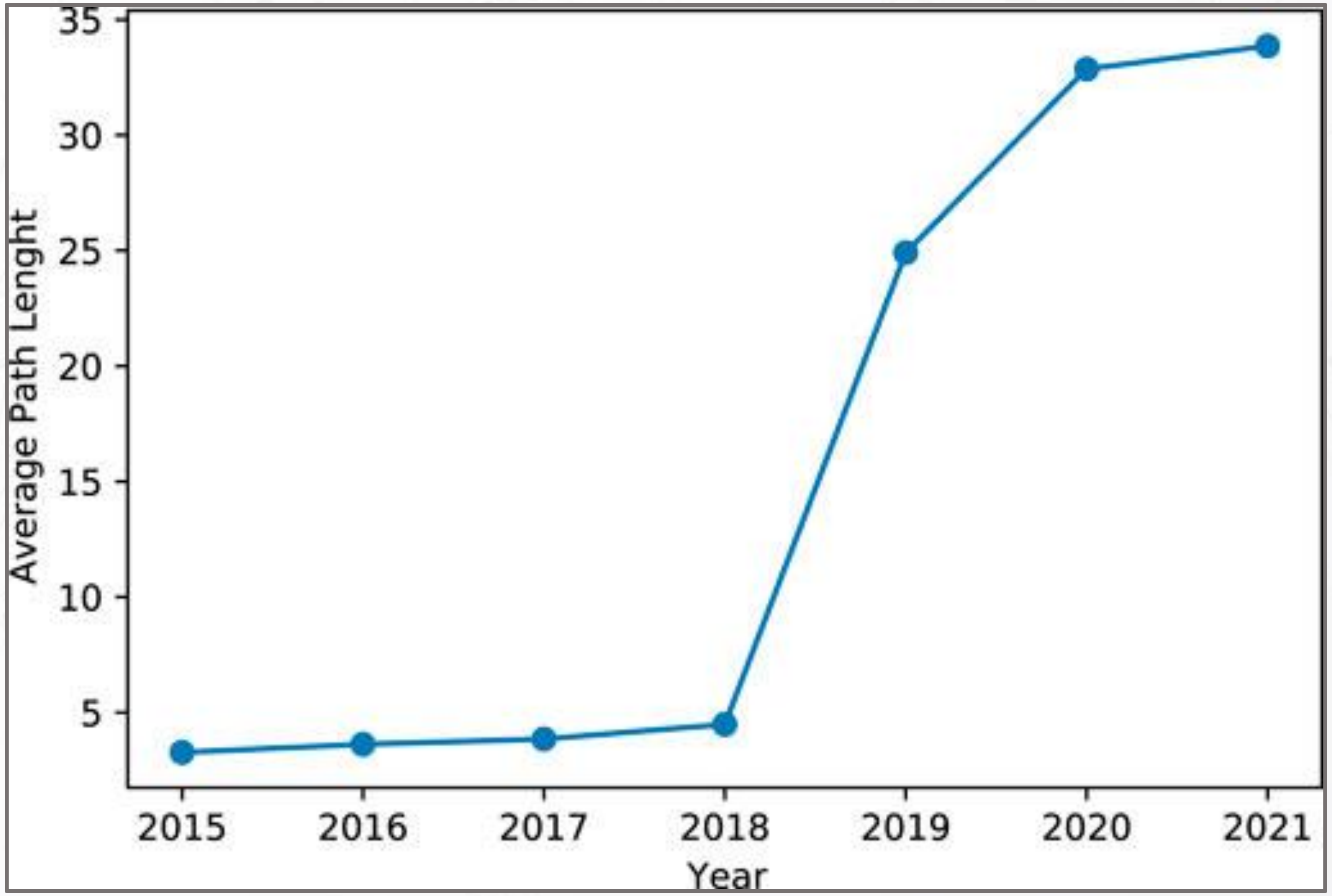
SmallWorld Property

A Smallworld is a particular property of social networks where each node is just a few steps away from the other nodes

Metrics:

Network Diameter (high and constant diameter over time, with low average path distance)

SmallWorld Property



Centrality Analysis

Verify whether the most relevant nodes of the network are indeed exchanges, thus confirming their strong impact on the flow of transactions.

Metrics:
Node Degree,
HITS,
Page Rank,
Betwenness Centrality

Centrality Analysis

2015		2016		2017		2018		2019		2020		2021	
Identity	**Value**	**Identity**	**Value**	**Identity**	**Value**	**Identity**	**Value**	**Identity**	**Value**	**Identity**	**Value**	**Identity**	**Value**
17YkZEBjr1	0.28	Bitfinex-01	0.22	Bitfinex-01	0.10	Binance-01	0.07	Huobi-01	0.07	Huobi-01	0.07	Huobi-01	0.07
1NehvNpdtF	0.10	Poloniex-01	0.11	Bittrex-01	0.10	Huobi-03	0.07	Binance-01	0.06	Binance-01	0.06	Binance-01	0.06
1Nf3oM2pmo	0.10	17YkZEBjr1	0.06	Poloniex-01	0.08	Bitfinex-01	0.07	Bitfinex-01	0.04	Bitfinex-01	0.04	Bitfinex-01	0.04
1CiiNGcpEU	0.03	Bitfinex-02	0.04	Bitfinex-02	0.06	Huobi-02	0.06	Huobi-03	0.04	Huobi-03	0.03	Huobi-03	0.03
1JdmTjSwz6	0.03	Poloniex-02	0.03	Huobi-02	0.05	Bittrex-01	0.03	Huobi-02	0.03	Huobi-02	0.03	Huobi-02	0.03
1CGqVMcEhk	0.03	1NehvNpdtF	0.02	Poloniex-02	0.05	Bitfinex-02	0.02	37Tm3Qz8Zw	0.03	37Tm3Qz8Zw	0.03	37Tm3Qz8Zw	0.03
15PuzKaFj5	0.02	Tether-treas-01	0.02	Binance-01	0.04	37Tm3Qz8Zw	0.02	Bittrex-01	0.02	Bittrex-01	0.02	Bittrex-01	0.02
1D1q8NLnva	0.02	Poloniex-03	0.02	Bittrex-02	0.03	Poloniex-01	0.02	1G47mSr3oA	0.02	1G47mSr3oA	0.01	1G47mSr3oA	0.01
16nGCDXKHQ	0.02	1KomZAekbS	0.02	Poloniex-03	0.01	1G47mSr3oA	0.01	Bitfinex-02	0.01	Bitfinex-02	0.01	Bitfinex-02	0.01
1CK8nh7Xs9	0.02	1Nf3oM2pmo	0.02	Gate.io-01	0.01	Poloniex-02	0.01	Poloniex-01	0.01	Poloniex-01	0.01	Poloniex-01	0.01

Page Rank Score Over Time

Centrality Analysis

Authority		Betwenness centrality		Degree		In-degree		Out-degree	
Identity	Value	Identity	Value	Identity	Value	Identity	Value	Identity	Value
Huobi-01	0.64	Huobi-01	9.99	Huobi-01	53,029.00	Huobi-01	28,198.00	Huobi-01	24,831.00
Binance-01	0.22	Binance-01	5.33	Binance-01	34,563.00	Binance-01	14,603.00	Binance-01	19,960.00
Huobi-03	0.13	37Tm3Qz8Zw	2.37	37Tm3Qz8Zw	17,701.00	Huobi-03	11,032.00	Huobi-02	11,433.00
37Tm3Qz8Zw	0.12	Huobi-03	2.07	Huobi-03	16,023.00	37Tm3Qz8Zw	8,014.00	37Tm3Qz8Zw	9,687.00
1G47mSr3oA	0.09	1G47mSr3oA	1.81	1G47mSr3oA	12,901.00	1G47mSr3oA	6,308.00	Bittrex-01	7,151.00
Huobi-02	0.07	Bittrex-01	1.79	Huobi-02	12,586.00	Bittrex-01	4,445.00	1G47mSr3oA	6,593.00
1x6YnuBVee	0.03	Huobi-02	1.70	Bittrex-01	11,596.00	Kraken-01	2,411.00	Huobi-03	4,991.00
Bittrex-01	0.03	1x6YnuBVee	0.89	Bitfinex-01	5,646.00	Bitfinex-01	2027.00	1x6YnuBVee	3,793.00
Bitfinex-01	0.03	Bitfinex-01	0.77	Kraken-01	4,964.00	1Fi9J5TeaW	1991.00	Bitfinex-01	3,619.00
Kraken-01	0.02	Poloniex-01	0.72	Poloniex-01	4,953.00	1PFtrRjbq4	1908.00	Poloniex-01	3,116.00

Centrality Measures

Rich-Gets-Richer Property

Measures the concentration of richness among the nodes.

It is verified using transaction amounts over time

Subtraction between inbound and outbound amounts

Rich-Gets-Richer Property

2015		2016		2017		2018		2019		2020		2021	
Identity	Amount	Identity	Amount	Identity	Amount	Identity	Amount	Identity	Amount	Identity	Amount	Identity	Amount
17YkZEBjr1	1,301,458	Poloniex-01	8,152,171	Bittrex-01	691,235,452	17A5bQSe7T	9,998,994,644	17A5bQSe7T	9,998,994,644	1PnLCcrxuG	900,000,000,000	1PnLCcrxuG	900,000,000,000
Poloniex-01	235,270	Poloniex-03	4,200,000	Poloniex-03	540,000,000	1CR5kH38kN	8,999,984,999	1CR5kH38kN	8,999,984,999	3D5LgbevwJ	79,999,998,570	3D5LgbevwJ	79,999,998,570
1Nf3oM2pmo	194,813	Tether-treas-01	4,168,588	Poloniex-01	168,703,683	18G5Z5dAat	1,586,470,150	Bitfinex-01	7,175,096,614	3GEUMrnrLT	30,000,001,430	3GEUMrnrLT	30,000,001,430
16nGCDXKHQ	106,436	Bitfinex-01	3,060,507	Huobi-02	160,269,699	1KEDKpAEVb	1,299,999,749	1NsQdzXELw	2,499,999,999	1BJJWBuCCu	30,000,000,000	1BJJWBuCCu	30,000,000,000
12wGH4QEG4	98,606	39LPwKLBAE	304,000	Bitfinex-01	154,507,803	1ewQXCis2X	1,200,000,000	3JJmBeeoBg	2,099,992,984	19yATbHhpC	29,899,999,000	19yATbHhpC	29,899,999,000
1HPkbQzq4v	75,889	Bittrex-01	160,890	Binance-01	136,847,304	1GEhwSnBeS	1,200,000,000	15gQz63cWK	1,896,982,198	17A5bQSe7T	9,998,994,644	17A5bQSe7T	9,998,994,644
1LD5zWpvge	71,628	377UotoWsG	150,905	Poloniex-02	74,542,404	12QyZbQShD	1,000,000,000	1SAFEXg6ah	1,627,239,281	1CR5kH38kN	8,999,984,999	1CR5kH38kN	8,999,984,999
1JfkjRUe1C	70,394	39LGppUP1s	113,320	Tether-Hack-02	61,900,000	13iqbGcZwS	900,000,000	18G5Z5dAat	1,586,470,150	Bitfinex-01	7,171,006,428	Bitfinex-01	7,213,379,540
1LVjAedtED	59,654	16nGCDXKHQ	106,436	Gate.io-01	43,999,774	Huobi-02	759,276,913	1KEDKpAEVb	1,299,999,749	1NsQdzXELw	2,499,999,999	1NsQdzXELw	2,499,999,999
1JYbYSBhv5	58,818	3LpE7HD4E1	99,682	OKEx-01	42,327,029	1PFZycjjt5	712,264,749	32TLn1WLcu	1,265,000,000	3JJmBeeoBg	2,099,992,984	3JJmBeeoBg	2,099,992,984

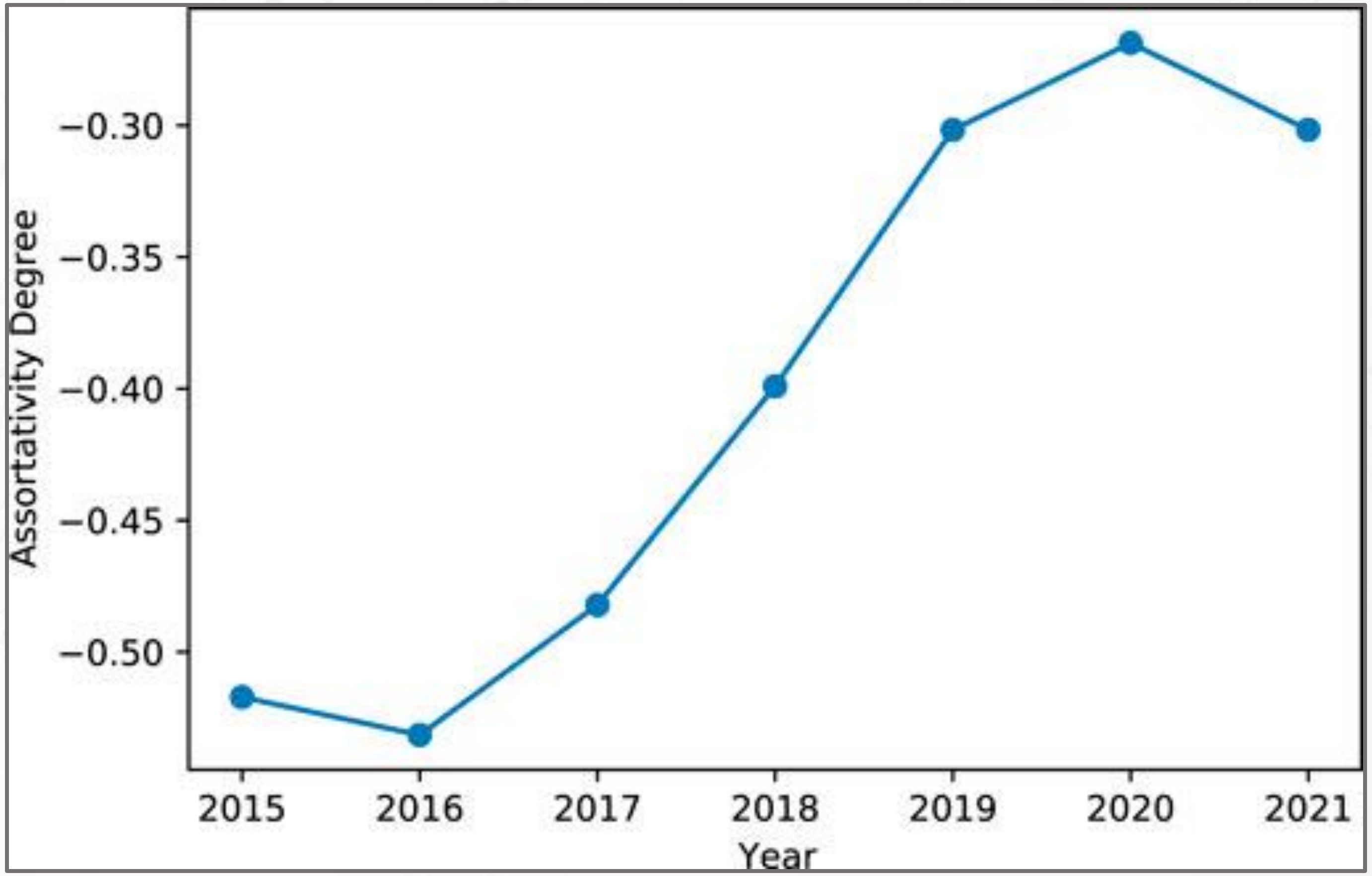
Assortativity

An assortative network is a network which has nodes that have the preference to connect to similar nodes

A network is **assortative** when on average the high-degree nodes are connected to other nodes with high-degree

A network is **dis-assortative** when the connections between high-degree nodes and low-degree nodes are inverted

Assortativity



Final Thoughts

Limitations and Future Directions

Include with transactions from platforms different from OMNI (i.e., TRON and BSC)

Only transactions happening in CEX are considered. Actually, DEX transactions are not taken into account

Small transactions are not currently analyzed

Limitations and Future Directions

Studying financial bubbles can help in the risk management of crypto investments

It can also help to avoid scams

Summary

- The Tether transaction network does not enjoy the **SmallWorld** property, with the robustness and reliability it carries with it

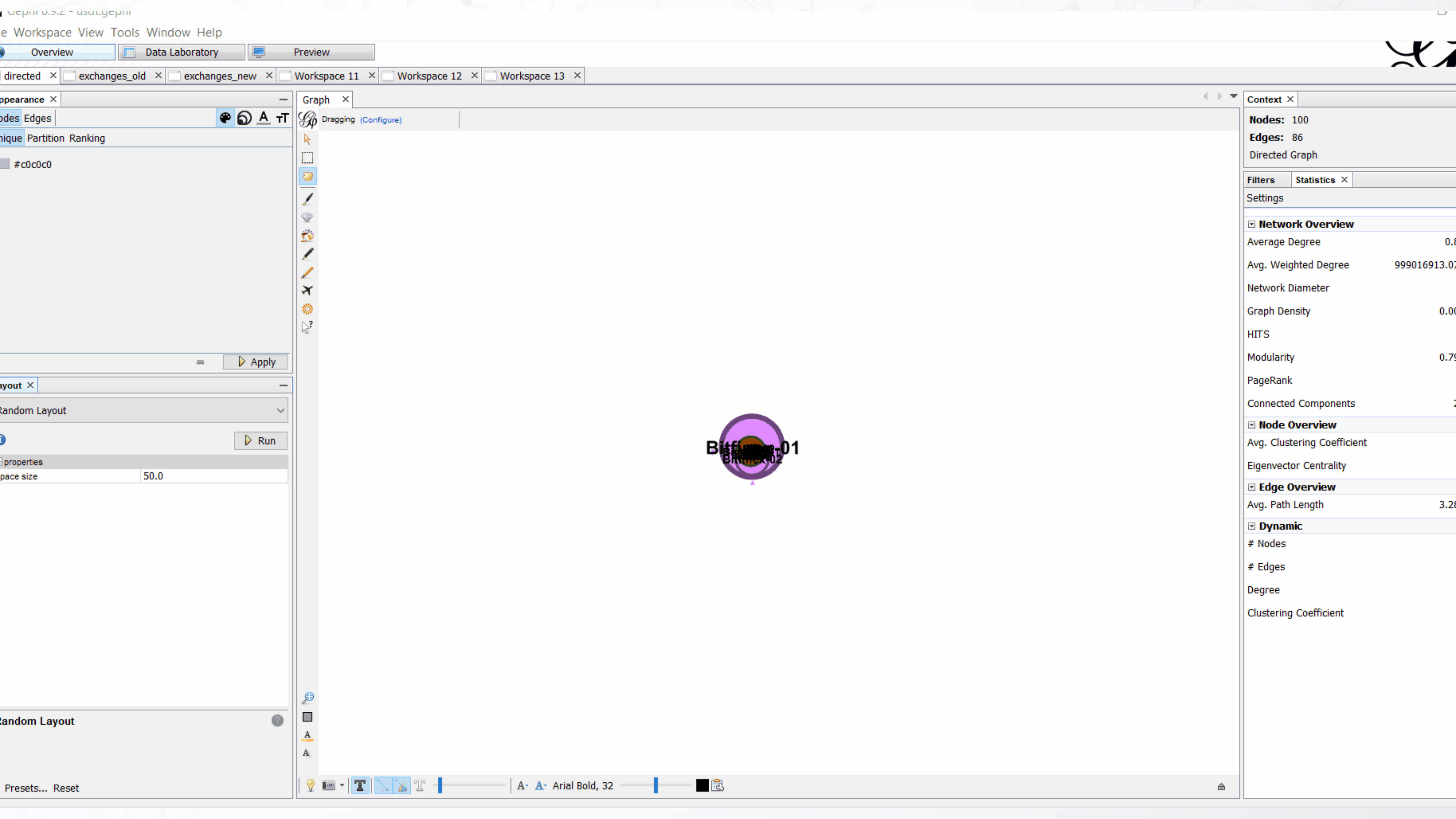
- Cryptopcurrency exchanges are the nodes with the greatest **centrality**

Summary

Assortativity is not found, as the subjects who move Tether on a large scale do not give continuity to their presence and operations, therefore do not get a chance to consolidate stable links between them

Among the exchanges, Bitfinex, which has co-ownership and co-administration relationships with the Tether issuer, can be mostly associated with the **Rich-gets-Richer** property

Gephi Examples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Network Diameter
Graph Density
HITS
Modularity
PageRank
Connected Components
Node Overview
Avg. Clustering Coefficient
Eigenvector Centrality
Edge Overview
Avg. Path Length
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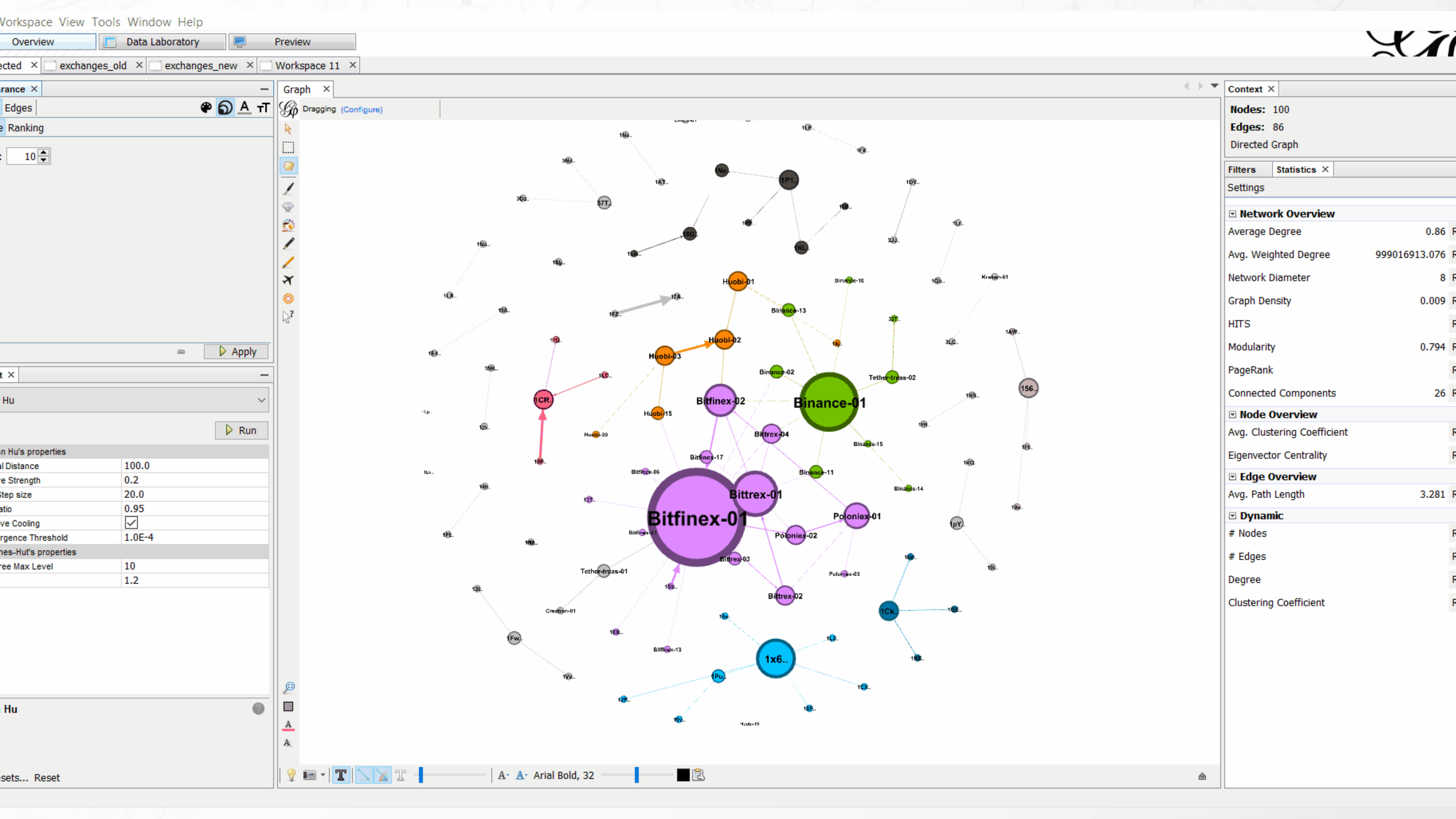
Degree
Clustering Coefficient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Network Overview
Average Degree 0.86
Avg. Weighted Degree 999016913.076
Network Diameter 8
Graph Density 0.009
HITS
Modularity 0.794
PageRank
Connected Components 26
Node Overview
Avg. Clustering Coefficient
Eigenvector Centrality
Edge Overview
Avg. Path Length 3.281
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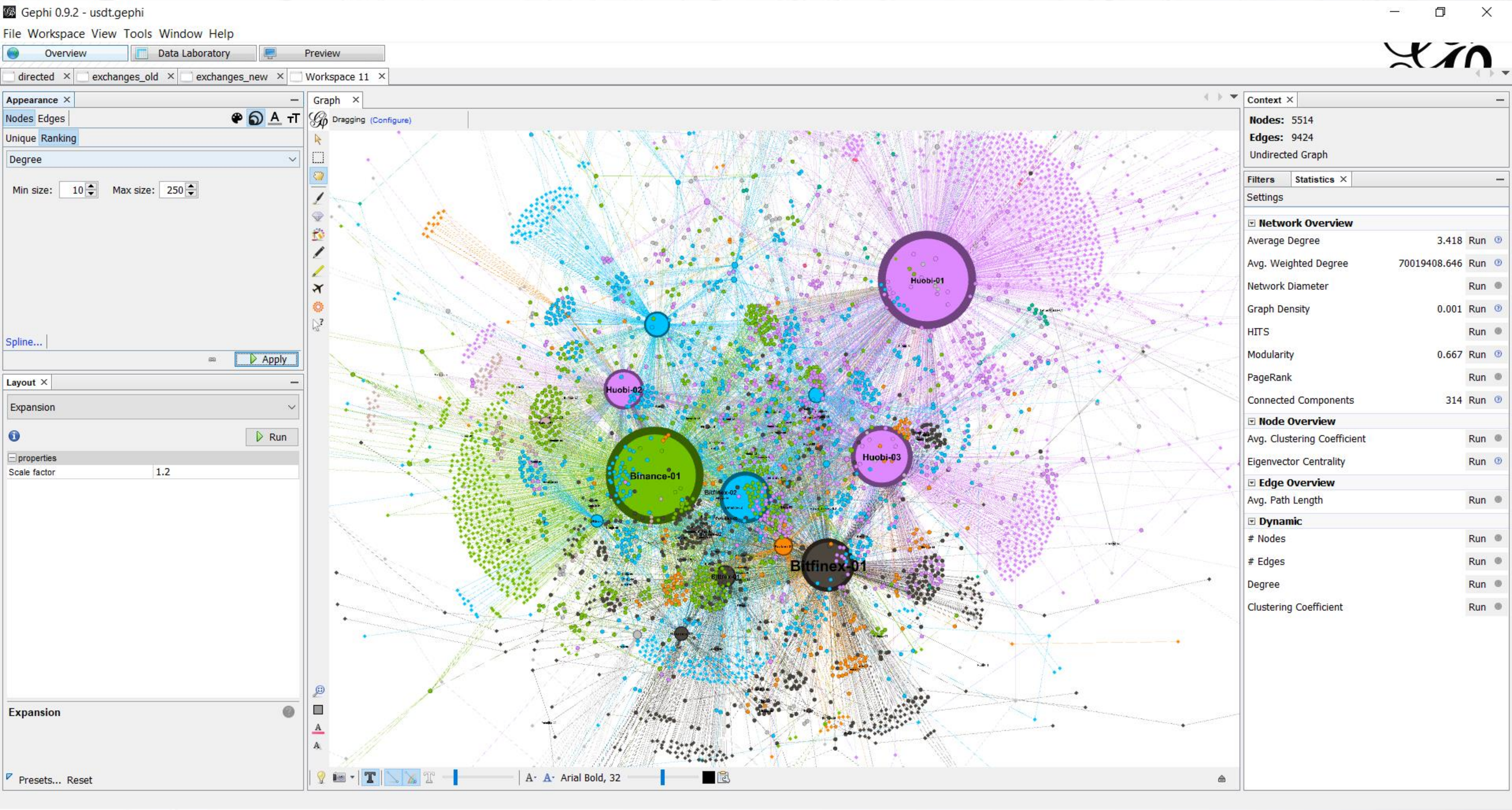
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Edges: 9424
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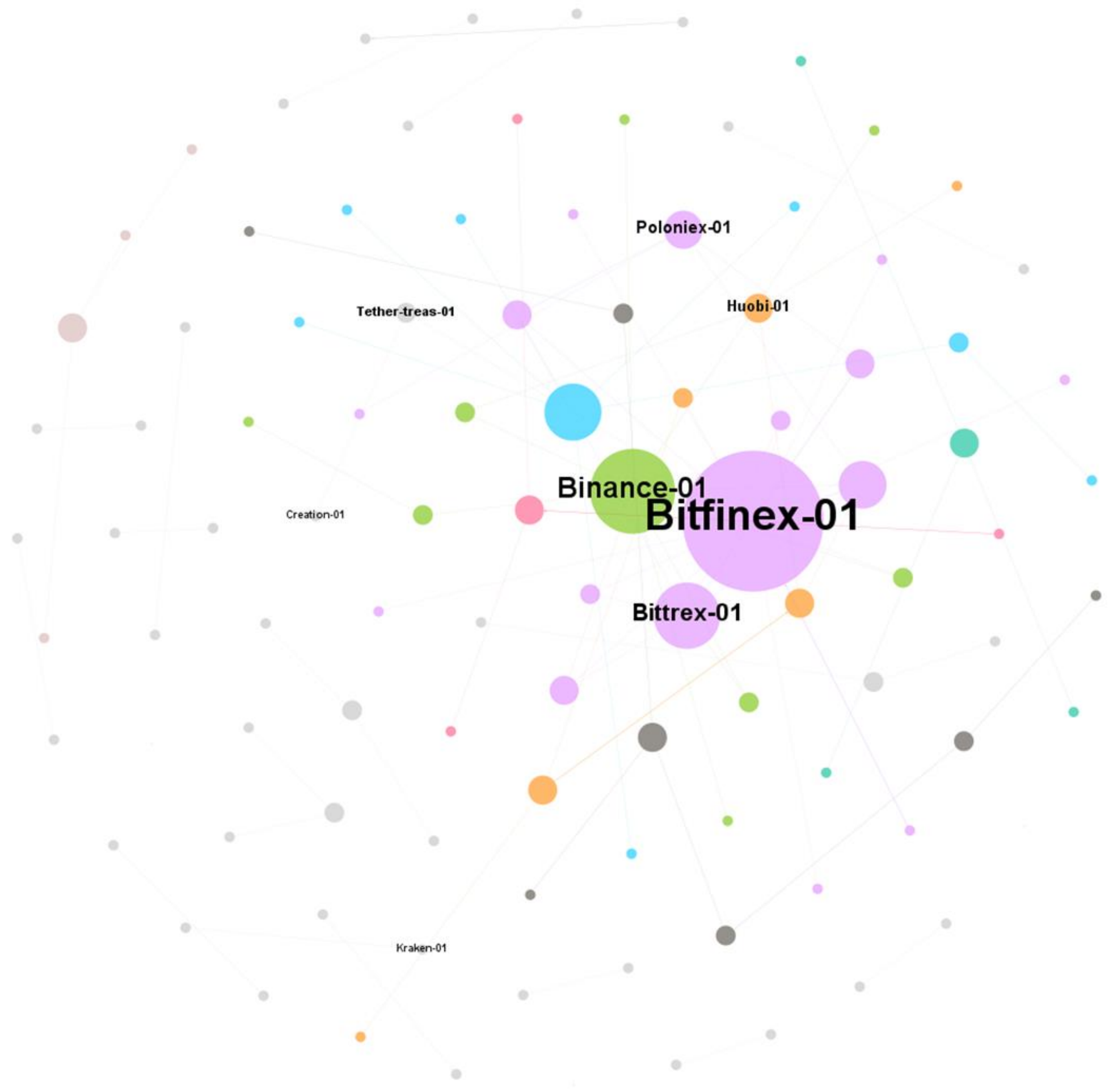
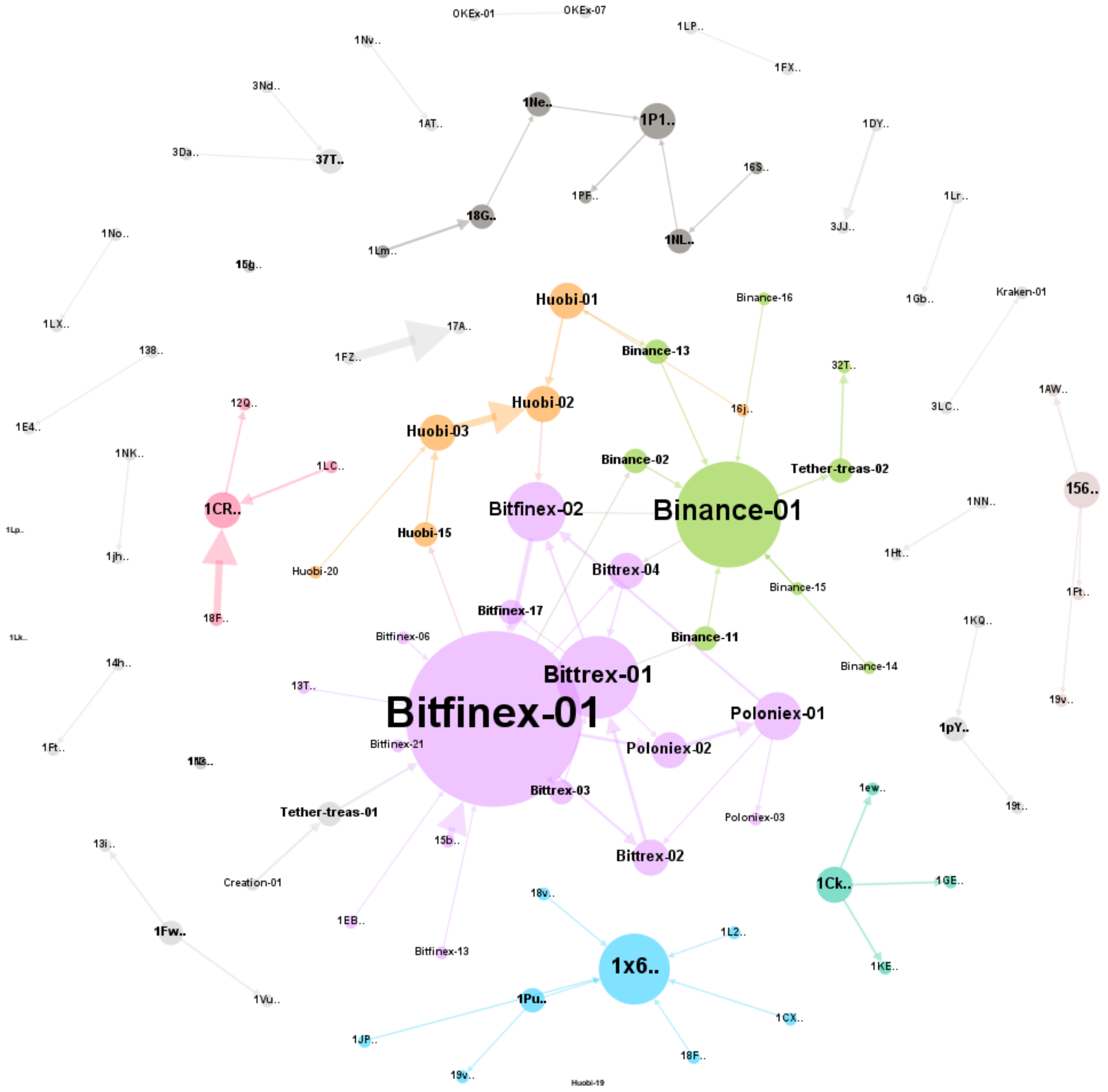
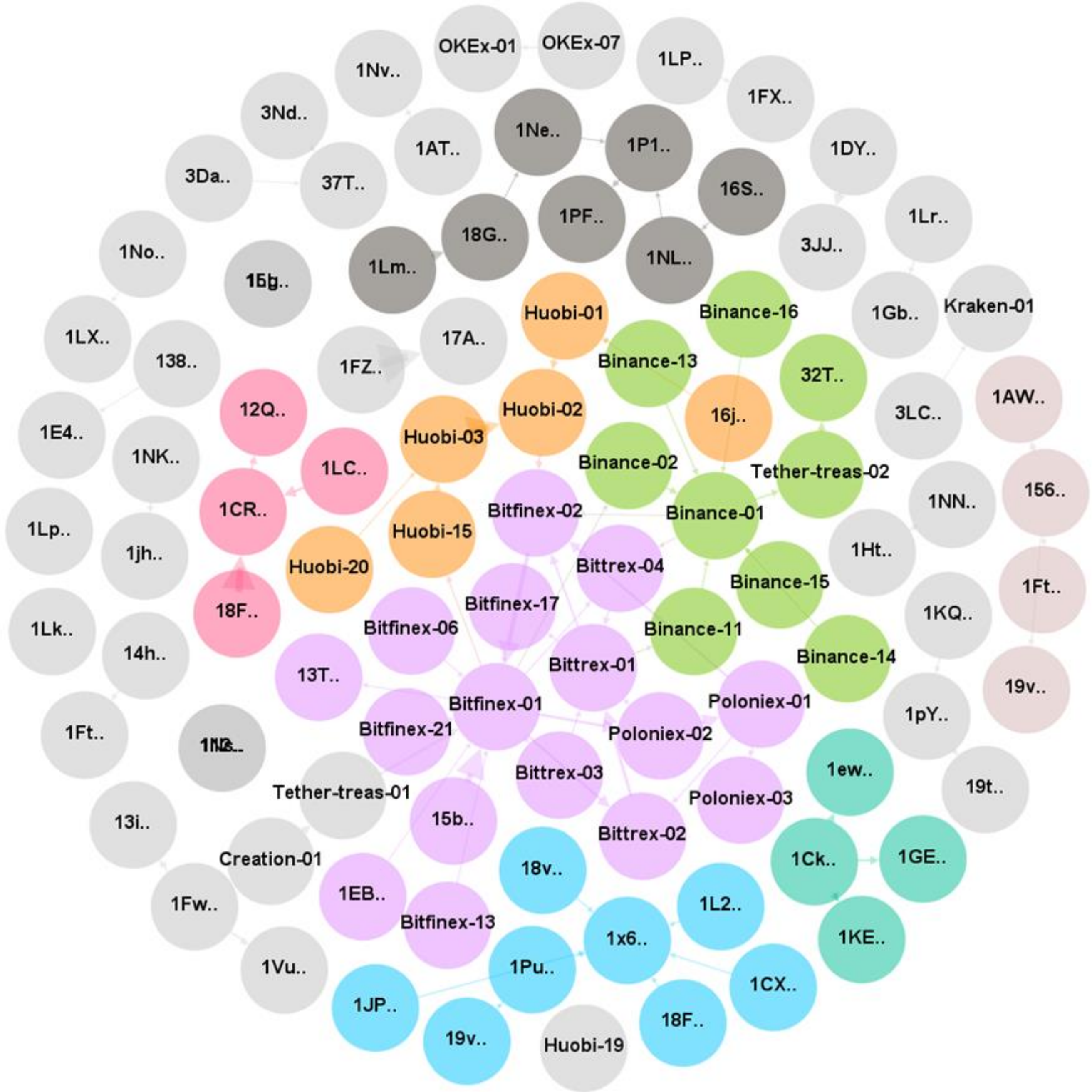
Statistics
Settings
Network Overview
Average Degree 3.418 Run
Avg. Weighted Degree 70019408.646 Run
Network Diameter Run
Graph Density 0.001 Run
HITS Run
Modularity 0.667 Run
PageRank Run
Connected Components 314 Run
Node Overview
Avg. Clustering Coefficient Run
Eigenvector Centrality Run
Edge Overview
Avg. Path Length Run
Dynamic
Nodes Run
Edges Run
Degree Run
Clustering Coefficient Run



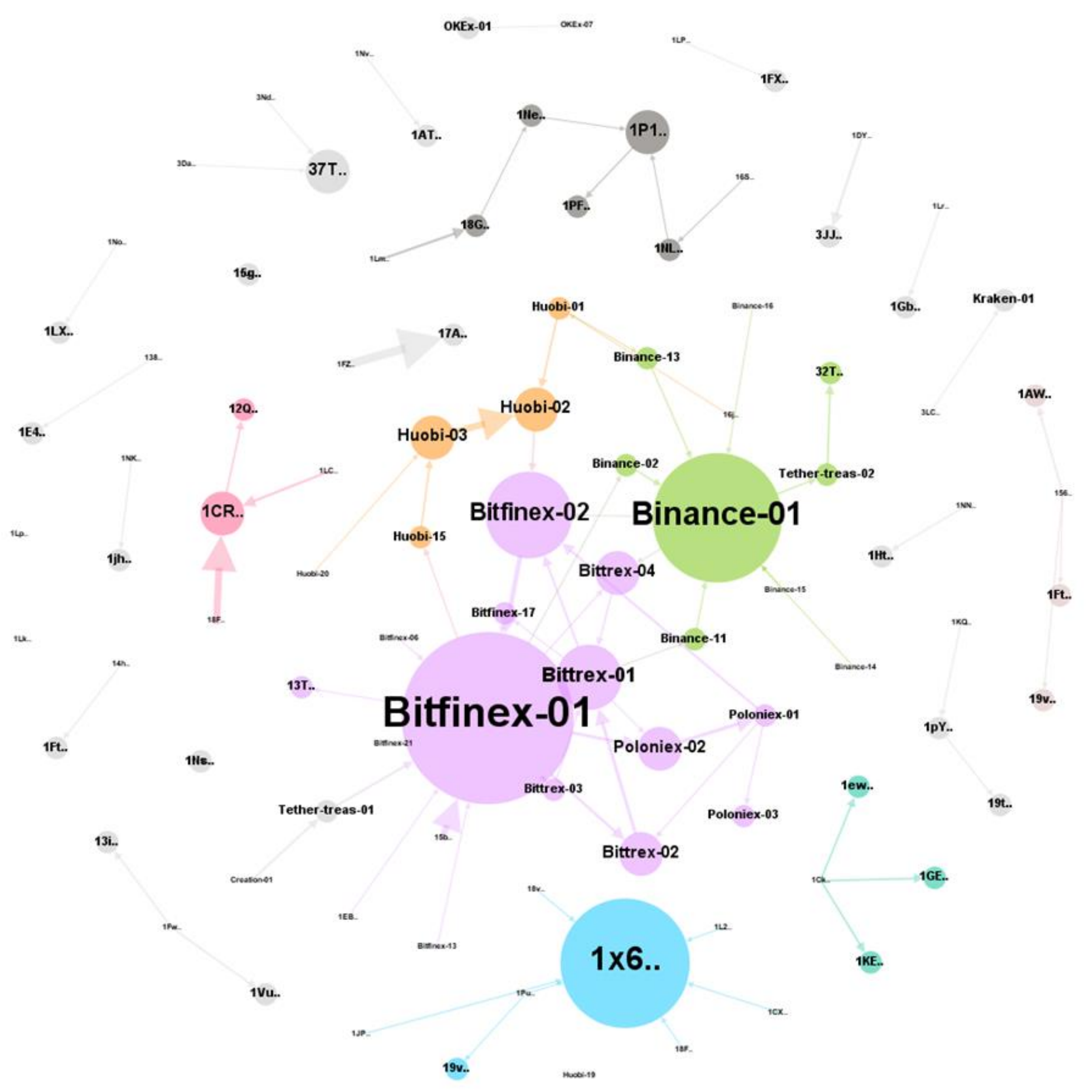
Top 100:
Modularity class
+ degree

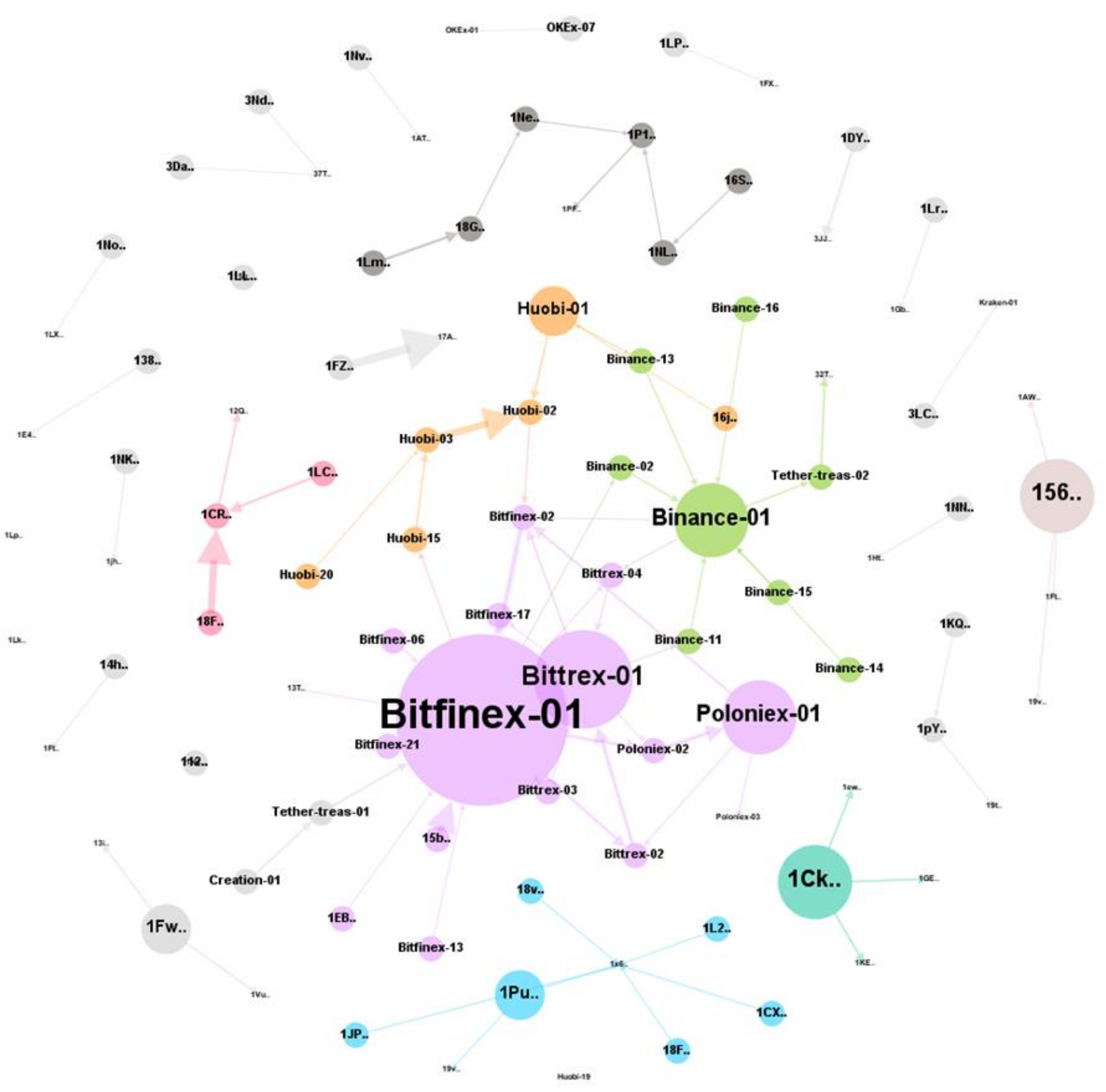


Top 100:
Modularity class
+ degree

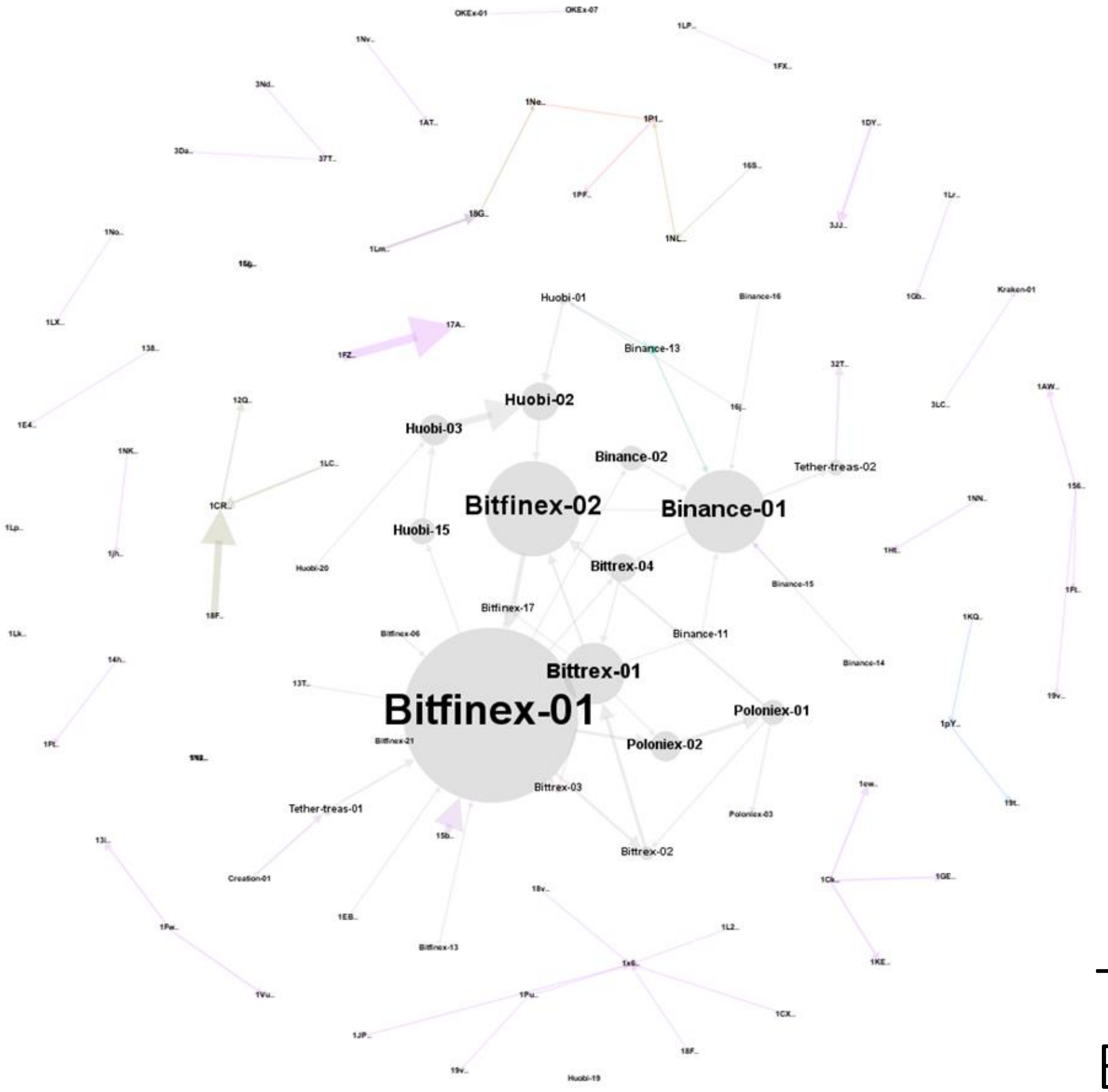


Top 100:
Modularity class

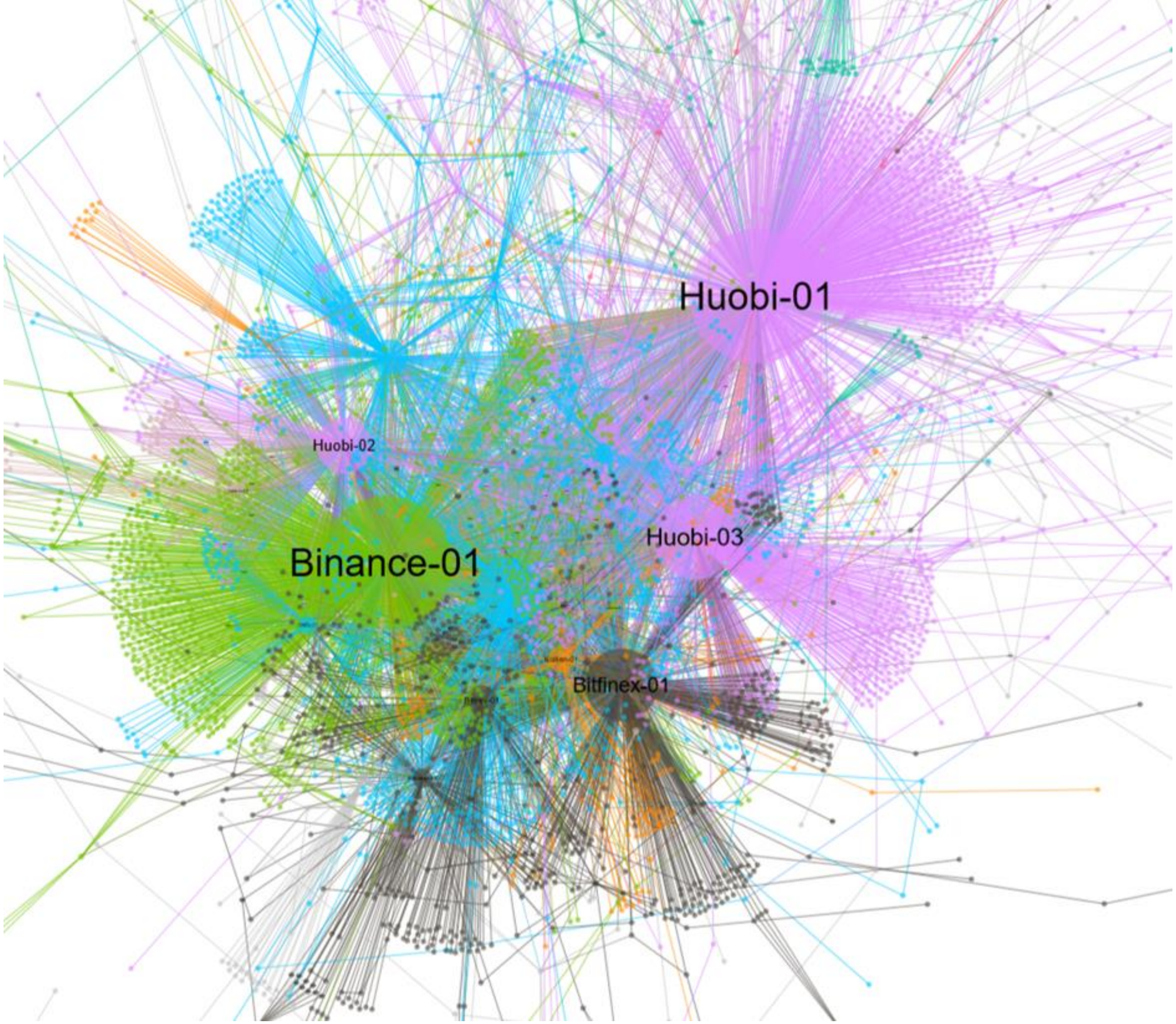




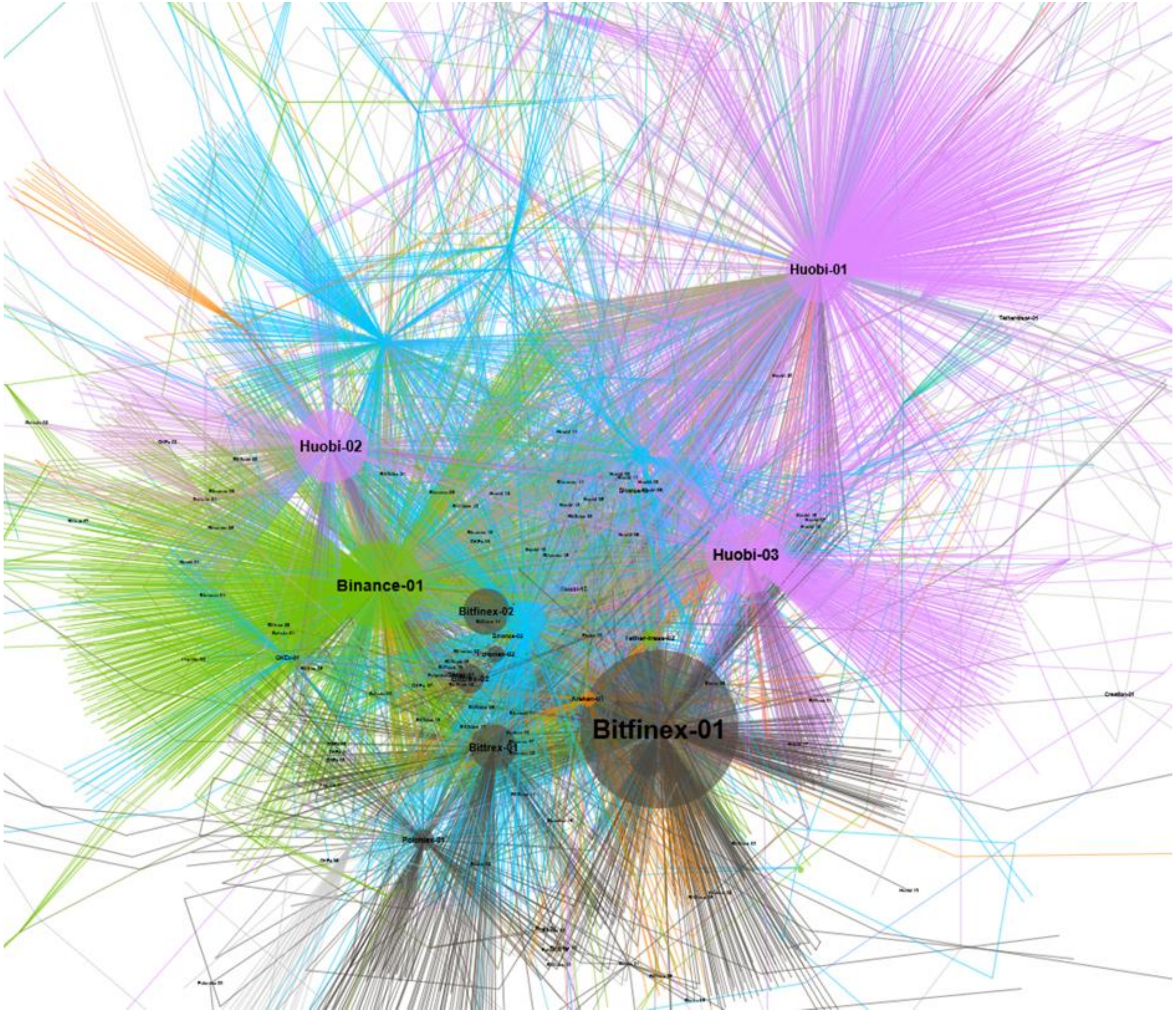
Indegree vs outegree



Top 100:
Betwenness centrality



Top 10000:
Modularity class
+ degree



Top 10000:
Modularity class
+ weighted degree