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Dissecting bitcoin blockchain: Empirical Analysis of Bitcoin network (2009-2020)

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Abstract

Bitcoin system (or Bitcoin) is a peer-to-peer and decentralized payment system that uses cryptocurrency named bitcoins (BTCs) and was released as open-source software in 2009. Unlike fiat currencies, there is no centralized authority or any statutory recognition, backing, or regulation for Bitcoin. All transactions are confirmed for validity by a network of volunteer nodes (miners) and after collective agreement is subsequently recorded into a distributed ledger "Blockchain". Bitcoin platform has attracted both social and anti-social elements. On the one hand, it is social as it ensures the exchange of value, maintaining trust in a cooperative, community-driven manner without the need for a trusted third party. At the same time, it is anti-social as it creates hurdles for law enforcement to trace suspicious transactions due to anonymity and privacy. To understand how the social and anti-social tendencies in the user base of Bitcoin affect its evolution, there is a need to analyze the Bitcoin system as a network. The current paper aims to explore the local topology and geometry of the Bitcoin network during its first decade of existence. Bitcoin transaction data from 03 Jan 2009 12:45:05 GMT to 08 May 2020 13:21:33 GMT was processed for this purpose to build a Bitcoin user graph. The characteristics, local and global network properties of the user's graph were analyzed at ten intervals between 2009-2020

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with a gap of one year. Small diameter, skewed distribution of transactions, power-law distributed in and out degrees, disconnected graph, and presence of large connected components were the observations from network analysis. Thus, it could be inferred that despite anti-social tendencies, Bitcoin network shared similarities with other complex networks. Network analysis also uncovered twenty types of legal and anti-social entities operating on Bitcoin and provided a path for uncovering these anti-social entities.

Keywords: Bitcoin, Network Science, Graph Algorithms, Exploratory Data Analysis

1. Introduction

Originally proposed in 2008 by an unknown individual (or a group of individuals) who used a pseudonym "Satoshi Nakamoto", Bitcoin cryptocurrency has since then emerged as the most successful cryptocurrency amongst its peers, reaching an adoption level unrealized by older digital currencies [1, 2, 3]. As on 19th March 2020, Bitcoin has a market cap of USD\$98,584,789,143 with 18,277,112 bitcoins (BTC's) in circulation each with a value of USD\$5,393.89. Bitcoin differs from its traditional online banking peers by relying on a decentralized consensus scheme for verifying the correctness and authentic nature of currency transfers between users [4, 5, 6]. The decentralized consensus scheme is made possible by an organized collective of nodes in the Bitcoin system known as "miners". The miners confirm each transaction for authenticity. This increases security in the Bitcoin system and ensures the core philosophy of Bitcoin "Maintain trust in an untrusted environment" without the need for a trusted third party as a reward miners collect transaction fees for the transactions that they confirm.

Illustrating the transaction fundamentals of bitcoin transfers, consider that user i wants to transfer n bitcoins to user j . Then i will need a bitcoin wallet, which holds all his private keys and the wallet address of j (Figure 1). Also, the transaction is valid only if user i signs it using his cryptographic key.

Valid transactions are then broadcast over the Bitcoin network, and all miners are informed. Technically, the transaction is not broadcast to all nodes in the Bitcoin network, as a single node can be connected to a maximum 125 (incoming connections=8, outgoing connections=117) other nodes. However, by recursive broadcasts "gossip protocol," a transaction eventually reaches all

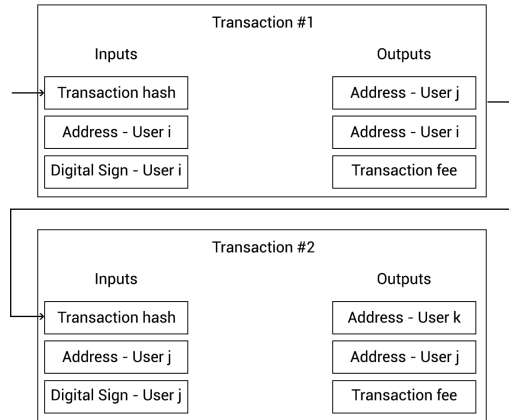


Figure 1: Transfer of bitcoins from user i to j and j to k

27 nodes [1, 7]. Miners keep all received transactions in their memory pool and
 28 combine these transactions to form a "candidate block." Each miner then
 29 competes with other miners to add its candidate block to the blockchain.
 30 The miner who succeeds gets a reward in BTC's and broadcasts its newly
 31 mined block to other miners. Other miners will independently verify the
 32 newly mined block before adding it to their blockchain.

33 Since Bitcoin's inception in 2009, the initial two years saw slow adoption
 34 with hardly 1000 unique addresses and less than 10000 transactions per day
 35 [1, 8]. However, as bitcoin became financially significant, there was an ex-
 36 ponential growth in transactions from 2012-2016, which also saw the entry
 37 of serious users, investors, speculators, and independent mining industries.
 38 Before the popularity of bitcoin, the users were mostly crypto-enthusiasts.
 39 The change in the profile of Bitcoin's user base was also evident from the
 40 increase in the transaction values, fluctuations in BTC price, and volumes of
 41 BTC's. This phase also saw the emergence of Ponzi schemes, money launder-
 42 ing, frauds [9], embezzlements, extortion [10] and tax evasion [11] practices
 43 that used the blanket of secrecy afforded by Bitcoin to mislead the audit trail.
 44 There emerged a diversity even amongst the miners in terms of geography
 45 and size. When Bitcoin was launched, it was feasible for any participant to
 46 become a miner, but as the user base increased, mining became competitive
 47 and required specialized hardware. Miners prefer large warehouses with ac-
 48 cess to cheap electricity [12]. With time, solo miners decreased and gave way
 49 to mining pools.

50 As the scale and complexity of the Bitcoin network increased, research
51 interest too emerged to allow for its better understanding [4, 11, 12, 13, 14].
52 However, analysis of network properties of Bitcoin graph is an interesting
53 domain, albeit one that has received comparatively less attention. A reason
54 for this could be the complexity of identifying users in the Bitcoin network.
55 In the Bitcoin network, identifying users by wallet addresses (aka accounts,
56 bitcoin addresses, public keys, or other unique identifiers used interchange-
57 ably to refer to users' in Bitcoin system) is complicated as these can be
58 generated and discarded multiple times [12]. There is also no upper limit
59 to the identities a single person can create or any limits on the number of
60 transactions or beneficiaries. These factors significantly enhance the hurdles
61 in analyzing the Bitcoin network. To overcome the hurdle caused by multi-
62 ple identities of a single user, heuristic clustering is applied to the Bitcoin
63 network. With heuristic clustering, multiple identities of a single user are
64 grouped into a single identity. This strategy is used in several Bitcoin net-
65 work studies [15, 16, 17, 18] and has the advantage of reducing the number
66 of entities of the Bitcoin network.

67 1.1. Motivation

68 Based on an oft-quoted maxim in network science, "We will never under-
69 stand complex systems unless we develop a deep understanding of the net-
70 works (graphs) behind them" [19], the current paper proposes to shed light
71 on the network properties of Bitcoin. Bitcoin is a diverse ecosystem inhab-
72 ited by users (wallets) that could be ordinary people interested solely in the
73 exchange of assets or mining nodes competing to ensure that the transactions
74 in their memory pool get added to the blockchain. Though the interactions
75 behind entities in other large systems such as the internet, wireless sensor
76 networks [20, 21, 22], social networking websites, citation systems, file shar-
77 ing systems are well studied, However Bitcoin system failed to receive similar
78 attention. Network analysis would also help machine learning based appli-
79 cations of Bitcoin such as illegal transaction detection and forensics improve
80 feature engineering.

81 1.2. Contributions

- 82 • Conducted a comprehensive study of the large-scale Bitcoin system and
83 interactions occurring in it from 2009 to 2020 by constructing a network
84 from the blockchain files.

- 85 • Studied the Bitcoin network at scale based on local and global graph
86 properties (see Section 3.2).
- 87 • Network analysis to uncover types of legal and illegal entities operating
88 on Bitcoin and provide a path for uncovering these entities to aid digital
89 forensic tools.
- 90 • Proposed techniques for detection of illegal entities operating in bitcoin
91 network
- 92 • Used structural information of Bitcoin network to characterize interac-
93 tions and evaluate it at scale
- 94 • Open sourced the Bitcoin network dataset to motivate independent
95 research
- 96 • A time series analysis was performed using previous data obtained of
97 the Bitcoin network. The data for training the machine learning models
98 was from years 2009-2020 and the predictions were made for the year
99 2021.

100 So far only I Alqassem *et al.* [12] and X Lee *et al.* [13] have provided a de-
101 tailed graph-theoretic assessment of Blockchain cryptocurrencies. However,
102 X Lee *et al.* focused on Ethereum blockchain, and I Alqassem *et al.* focused
103 on the time period of 2009-2014 to analyze Bitcoin systems. Although these
104 papers provide a technical foundation for the current work, there is no over-
105 lap. Ethereum is not just a crypto-currency but also a platform that enables
106 distributed applications. Analysis cannot be compared between Ethereum
107 and Bitcoin. Bitcoin has higher volumes, users and market cap so affects
108 more users and should therefore receive more attention. I Alqassem *et al.*
109 [12] worked on Bitcoin 2009-2014 so the current papers extended their work
110 to 2020. Additionally, observations and conclusions on future outlook of
111 Bitcoin were made using time series analysis. Time series models are data-
112 driven. So observations and conclusions are obtained after experimentation.
113 The data is allowed to speak for itself and used for predicting growth outlook
114 for year 2021.

115 The rest of the paper is organized as follows: Section 2 gives the related
116 work done on Bitcoin and other cryptocurrencies. The procedure to convert
117 raw data into a processed form is outlined in Section 3, followed with a
118 description of network analysis tools in Section 3.2 and discussion of results

119 in Section 4. The paper concludes in Section 5, mentioning future works for
120 subsequent research.

121 2. Related work

122 The related work reviewed can be divided into two categories: First, the
123 work that examined the Bitcoin system itself. Second, work that examined
124 other blockchain-based systems.

125 2.1. Bitcoin studies

126 The journey of Bitcoin, which builds upon nearly two decades of ideas
127 proposed in mailing lists, forum posts, blogs [23], wikis, and source code
128 found in cryptographic circles, is described by F Tschorsch *et al.* [14]. How-
129 ever, the authors focused more on framing a tutorial on Bitcoin that includes
130 an outline of selective existing literature. I Alqassem *et al.* have provided
131 a longitudinal network-based analysis of Bitcoin systems from 2009-2014.
132 The authors have commented upon the changing nature of bitcoin users over
133 time and also drew attention to various structural properties of the Bitcoin
134 system viz. longest connected component, network diameter, densification
135 power law, degree assortativity, time-evolving community structure and in-
136 equality in the network [12]. The authors agreed that analyzing the Bitcoin
137 system presents challenges due to the anonymity seeking behaviors of the
138 user base. Though the results highlighted key differences between the Bit-
139 coin network and networks of other systems, the continuous developments
140 and fluctuations in the complex cyber-physical Bitcoin systems necessitate
141 another up-to-date review. T Chang *et al.* analyzed the various heuristics
142 that are proposed in the literature to identify all public keys that belong to
143 the same user. The heuristics create an approximation of the original Bitcoin
144 network by merging multiple user identifiers to a single identifier and reduc-
145 ing number of entities in the network. Previous studies on network analysis
146 of cryptocurrencies [12, 13, 11] to have used heuristics and hence, it is a tried
147 and tested method for improving network analysis. S Park *et al.* scanned
148 the live Bitcoin network for 37 consecutive days in 2018 to track the behavior
149 of the miners. The authors commented upon Bitcoin network statistics such
150 as the number of users, the geographic distribution of users, Bitcoin wallet
151 protocols, and messages propagating in the network [1].

152 *2.2. Studies on other blockchain-based systems*

153 Y Li *et al.* used the Ethereum transaction graph (interactions between
154 smart contracts and users) to explore the relationship between the graph
155 structure and crypto-currency price fluctuations [24]. H Sun *et al.* attempt
156 clustering analysis on Ethereum data to segment malicious users from the
157 rest [25]. S Ferratti *et al.* has used global network statistical measures such
158 as the order of the network, degree distribution, distance, clustering coef-
159 ficient, and the tendency of exhibiting a "small world" effect [26]. Based
160 on the observations from these measures, the authors have speculated about
161 the online behavior of Ethereum users, the geographic distribution of miner
162 nodes, and the characteristics of transactions. While S Ferratti *et al.* ar-
163 gued for the advantages of studying the blockchain structure through a com-
164 plex network perspective, their focus remained on the Ethereum blockchain
165 structure only. X Lee *et al.* studied the Ethereum blockchain at scale and
166 applied network analysis measures to characterize interactions between users
167 in Ethereum [13]. The authors studied the network characteristics (vertex
168 count, edge count, self-loop count, and edge density), local network prop-
169 erties (degree distribution, correlation of out and indegree, node centrality
170 measures) and global network properties (reciprocity, assortativity, connected
171 component distribution, diameter, path length, adhesion, cohesion). Just like
172 [26], the authors focused on Ethereum blockchain only but have emphasized
173 that a similar line of network analysis could be extended to another web
174 of blockchain networks. The work in the current paper relies on tools and
175 methods given by S Ferratti *et al.* [26] and X Lee *et al.* [13] but targets
176 a longitudinal analysis of Bitcoin network. Table 1 gives the methods and
177 results of network-based studies on blockchain and other real-world systems.

Table 1: Results of published network studies

System under review	Network theory used	Observation
Twitter [27]	Gini index	Dominant nodes are present
Facebook [28]	Assortativity coefficient	Negative assortativity
Social networking websites [29]	Diameter and Average path length	Small
Social networking websites [29]	Clustering coefficient	High
Social networking websites [30, 31]	Average degree, Edge density	High
World wide web [30, 31]	Degree distribution	In and out degree distribution follow power law
Protein-protein interaction [31]	Degree distribution	Power law
World wide web [32]	Small world effect	19 hops between any two webpages
Facebook [32, 33]	Strongly connected component (SCC)	99.8% - 100% nodes and edges are covered.
Citation networks [32, 33]	Graph structure	Acyclic
Citation network [30]	Degree distribution	In and out degree distribution follow power law
Film actors [30]	Degree distribution	Power law
Company directors [30]	Degree distribution	No power law
Co-authorship network [34]	Degree distribution	No power law
Ethereum network [13]	Vertices, arcs, self-loops, edge density, degree distributions, centrality measures, reciprocity, assortativity, SCC	In and out degree distribution follow power law. Density is low, reciprocity is positive, assortativity is negative. SCC has 98-99% nodes and edges.
D Ding <i>et al.</i> [35]	Study topological connectivity and message routability of P2P overlays	Degree and Connectivity Analysis
D Ding <i>et al.</i> [36]	Study topological connectivity and message routability of P2P overlays	Degree and Connectivity Analysis

178 It can be observed from Table 1 that using a unified set of tools and
179 principles, networks of different fields can be studied. This is because, despite
180 variations, networks grow following certain basic principles [37].

181 **3. Bitcoin blockchain to Graph**

182 Bitcoin blockchain dataset in raw form was obtained from full node at
 183 VJTI Blockchain lab ¹. The dataset was of size 268GB and consisted of
 184 blockchain in the form of blk.data files. All blocks and transactions from 03
 185 Jan 2009 12:45:05 GMT to 08 May 2020 13:21:33 GMT were present in the
 186 dataset. This raw data was then converted to CSV files using the blockchain
 187 parser built by the VJTI Blockchain lab ². The processed dataset, which is
 188 in the form of ".csv" files were made available for download ³. Table 2 shows
 189 the four ".csv" files of the processed dataset.

Table 2: Description of processed dataset

Relation	Attributes		
Output	tx_hash:START_ID	wallet_address:END_ID	amount
Address	wallet_address:ID		
Inputs	wallet_address:START_ID	tx_hash:END_ID	amount
Transactions	tx_hash:ID	timestamp	

190 From the Transactions dataset, it is possible to obtain the count of
 191 transactions occurring in that year. Each transaction (tx) is identified in
 192 blockchain by a unique hash (tx_hash: ID) and has a timestamp, which is
 193 the UNIX time of the transaction. For the year 2009, transactions start from
 194 03 Jan 2009 12:45:05 GMT, and for the year 2020, transaction up to 08 May
 195 2020 13:21:33 GMT is considered. Bitcoin entities were identified using an
 196 API⁴ [38]. Table 3 and 4 describes the dataset.

Table 3: Distribution of transactions in Bitcoin blockchain network (2009-2015)

	2009	2010	2011	2012	2013	2014	2015
Transactions	32741	185410	1902443	8459093	19645798	25265702	45689861
Inputs	2810	108965	1902443	5716084	15407017	33300547	54564769
Outputs	32643	143863	2595309	5981241	16278420	34586691	57150816
Max BTC's in a tx	22500	96999	550000	158336.30	194993.50	217517.63	172841.81
Max inputs in a tx	320	901	529	673	1757	674	1519
Max outputs in a tx	2	98	2002	2792	3075	5352	13107
Input sending highest amount	COINBASE	COINBASE	CoinJoin Mess	DeepBit.net	DeepBit.net	Unknown	Unknown
Output receiving highest amount	Unknown	Unknown	CoinJoin Mess	DeepBit.net	DeepBit.net	Unknown	Unknown
Total BTCs sent	1978736	22667790	297984085	925215501	429732306	264107039	548006072

¹<https://www.vjti-bct.in/>

²<https://github.com/pranavn91/blockchain>

³<https://drive.google.com/open?id=1pEpBAUXKgQX0BP8ircQgd9yXiucLY14h>

⁴<https://www.walletexplorer.com>

Table 4: Distribution of transactions in Bitcoin blockchain network (2016-2020)

	2016	2017	2018	2019	2020
Transactions	82634637	104081930	81393458	119729415	39978670
Inputs	90773554	128642149	77568478	128768057	52805351
Outputs	95783964	144361281	104780607	133558733	54179450
Max BTCs in a tx	99489.99	87082.81	109735.6	157457.612	182501
Max inputs in a tx	677	1089	1061	1347	1442
Max outputs in a tx	11515	6626	5027	7266	6990
Input sending highest amount	Unknown	Unknown	Unknown	Unknown	Unknown
Output receiving highest amount	Unknown	Unknown	Unknown	Unknown	Unknown
Total BTCs sent	1068404725	896026050.66	290858051.91	515972850.159	128637285.824

197 By parsing through the Bitcoin blockchain dataset, a transaction graph
 198 (representing the exchange of bitcoins between wallet addresses) was built.
 199 Each transaction has multiple inputs and outputs, as shown in Figure 2.
 200 This transaction graph is refined further by heuristic clustering to obtain the
 201 user’s graph (see Figure 3). The heuristic used for clustering is called the
 202 regular inputs heuristic, i.e., all input addresses in a transaction belong to
 203 the same user [5, 15]. The user’s graph (payments made between users) leads
 204 to meaningful analysis compared to the transaction graph [15, 16, 17, 18].
 205 Additionally, the results from the user’s graph of Bitcoin can be compared
 206 with social network analysis of other real-world systems viz. web, social
 207 networking websites, citation graphs. A similar comparison is not possible if
 208 the transaction graph of Bitcoin is considered.

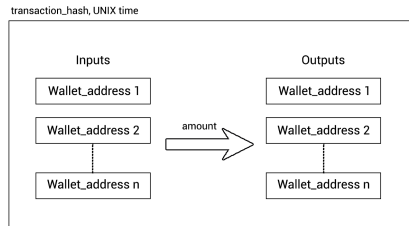


Figure 2: Multi-input multi-output transactions

209 The heuristic clustering reduces the multi-input multi-output transac-
 210 tions to a form more suited for network analysis. Multiple inputs are clus-
 211 tered, and a single address is used as a starting point for the transaction.
 212 The details of the heuristic clustering strategy are given in [15, 16, 17, 18].
 213 Figure 3 graphically shows the information of each attribute and relation in
 214 the dataset after heuristic clustering is applied.

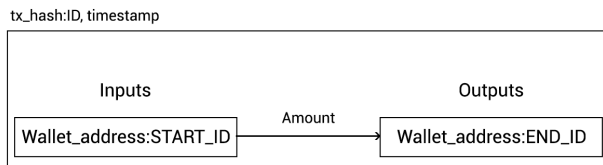


Figure 3: Illustration of attributes of processed dataset

215 *3.1. Experimental setup*

216 The preprocessing code is in Python 3.6, and the code for network analysis
 217 is in R. The network analysis functions are from the igraph package of R [39].
 218 The experiments are performed on a single core 1 TB Intel(R) Xeon(R) Silver
 219 4114 CPU@2.20GHz.

220 *3.2. Network measurements of Bitcoin network*

221 For this study, Bitcoin user graph is represented as a network $G = (V, E)$,
 222 where V refers to the addresses of users' wallets, while E represents a bitcoin
 223 exchanges between these wallets. The timestamp of transaction, tx_hash,
 224 and amount are attributes of E . As multiple transactions can occur between
 225 wallet_addresses, G is a directed multi-graph. Using tools described in Sec-
 226 tion 3.3, an analysis of the Bitcoin network G is performed for the period
 227 2009-2020.

228 *3.3. Description of tools for Network analysis*

- 229 1. Vertex count (order of graph) $|V|$ and edge count (size of graph) $|E|$
 230 2. Graph density (G_D): Number of edges present graph G amongst all
 231 possible edges in G . G_D for undirected and directed graphs is given by
 232 below equations 1 and 2 respectively.

233
$$\frac{2|E|}{|V|(|V| - 1)} \tag{1}$$

234
$$\frac{|E|}{|V|(|V| - 1)} \tag{2}$$

3. Average degree d

$$d = \frac{1}{|V|} \sum_{u \in V} d(u) = \frac{2m}{n} \tag{3}$$

- 235 4. Degree distribution of graph $P(k) = \frac{n_k}{n}$ is fraction of nodes in the
 236 network with degree k i.e. n_k where n is the Graph order.
- 237 5. Probability distribution
- 238 (a) Power law: $y = k^{-\alpha}$ (k =constant, α =exponent)
- 239 (b) Exponential: $y = e^{-\lambda k}$ (λ = mean time between events)
- 240 (c) Lognormal: $y = \frac{1}{k} e^{-\frac{(\log k - \mu)^2}{2\sigma^2}}$ (μ =scale parameter, σ =shape pa-
 241 rameter)
- 242 (d) Poisson: $\frac{e^{-\mu} \mu^x}{x!}$
- 243 6. Adhesion or edge connectivity E for connected graph G is the mini-
 244 mum number of edges $\lambda(G)$ whose deletion from a graph G disconnects
 245 G .
- 246
- 247 7. cohesion - a minimum number of vertices needed to remove to make
 248 the graph not strongly connected
- 249 8. Diameter is the length $\max_{(u,v)} d(u,v)$ of the "longest shortest path"
 250 (i.e., the longest graph geodesic) between any two graph vertices (u,v)
 251 of a graph, where $d(u,v)$ is a graph distance.
- 252
- 253 9. Average path length $L = \sum_1^E(G) \frac{d(u,v)}{E(G)}$
- 254
- 255 10. reciprocity ρ as given in Eq. 4 is the measure of the likelihood of ver-
 256 tices in a directed network to be mutually linked.
- 257

$$\rho = \frac{\sum_{i \neq j} (a_{ij} - \bar{a})(a_{ji} - \bar{a})}{\sum_{i \neq j} (a_{ij} - \bar{a})^2} \quad (4)$$

- 258 11. Assortativity: level of homophily of the graph.

$$r = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2} \quad (5)$$

260 where,

- 261 • q_k number of edges leaving the node, other than the one that
- 262 connects the pair j, k
- 263 • σ_q standard deviation of q in Eq. 5

- 264 • e_{jk} refers to the joint probability distribution of the remaining de-
265 grees of the two vertices

266
267 12. Number of connected components of a graph G is $c(G)$. A connected
268 component is a set of vertices all of which are connected, and un-
269 connected to the other nodes in the network. The weakly connected
270 components are found by performing breadth-first search. The strongly
271 connected components are implemented by two consecutive depth-first
272 searches.

273 13. Degree Centrality of a vertex v_i is defined as $deg(v_i)/2|E|$

274 14. Betweenness centrality $C_B(v)$ of $v \in V$ is the fraction of times v occurs
275 on any shortest path connecting any other pair of vertices $s, t \in V$.
276 Let σ_{st} be the total number of shortest paths connecting vertex s with
277 vertex t . Let $\sigma_{st}(v)$ be the number of these shortest paths containing
278 v . The geodesic centrality of v is:

$$C_B(v) = \sum_{s \neq t \neq v} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (6)$$

279 15. Size of largest strongly connected component N_s - a set of vertices in
280 a directed graph such that any node is reachable from any other node
281 using a path following only directed edges in the forward direction.

$$N = \max_{F \subseteq C} |F| \quad (7)$$

$$C = \{C \subseteq V \mid \forall u, v \in C : \exists w_1, w_2, \dots \in V : u \sim w_1 \sim w_2 \sim \dots \sim v\}$$

282 16. Relative size of the largest connected component (N_{rel}) equals the size
283 of the largest connected component divided by the size of the network

$$N_{\text{rel}} = \frac{N}{n}. \quad (8)$$

17. Number of triangles defined in the following way is independent of the
orientation of edges when the graph is directed.

$$t = |\{\{u, v, w\} \mid u \sim v \sim w \sim u\}| / 6 \quad (9)$$

18. Global clustering of a network is the probability that two incident edges are completed by a third edge to form a triangle

$$c = \frac{|\{u, v, w \in V \mid u \sim v \sim w \sim u\}|}{|\{u, v, w \in V \mid u \sim v \neq w \sim u\}|} \quad (10)$$

284 Tools for network measurement can be divided into three groups: mea-
 285 sures for characteristics (vertex count, edge count, edge density), measures
 286 of local network properties (radius, local clustering coefficient, node degree)
 287 and measures for global network properties (degree distribution, adhesion,
 288 cohesion, components, centralization, k-cores).

289 4. Experimental study

290 Bitcoin users graph is studied using the tools given in Section 3.3. The
 291 entire Bitcoin network is studied at eleven intervals, as seen in the results.
 292 The year in the results corresponds to a Bitcoin users graph built from trans-
 293 action data considered from 01 Jan 12:00:00 AM GMT to 31 Dec 11:59:59
 294 PM GMT of that year. An exception is the year 2020, which is built us-
 295 ing transaction data from 01 Jan 2020 12:00:00 AM GMT to 08 May 2020
 296 13:21:33 GMT.

297 4.1. Bitcoin Network characteristics

298 Table 5 gives the bitcoin users graph. Two versions of edge density are
 299 indicated by (S) for a simple, undirected version of the user’s graph and
 300 (D) for the directed user’s graph. Multiple directed edges between two users
 301 are collapsed to a single undirected edge to obtain edge density (S). Vertex
 302 count in Table 5 and 6 gives the total senders and receivers in that calendar
 303 year. Bitcoin users have increased till 2017, leading to the price of BTC’s
 304 reaching its peak in Dec 2017. The following years have seen a decline in
 305 both users and the value of BTCs. In 2009, out of 32741 transactions, 32522
 306 were COINBASE transactions. The highest number of BTCs transferred in
 307 a single transaction was 22500, and 320 were the highest number of inputs
 308 present in a transaction. Limited edges were created as transactions between
 309 users were less. The edge density is low in both the directed graph (Edge
 310 density (D)) and the undirected graph (Edge density (S)) for the period
 311 2009-2020 compared to social networks. The low density is due to the skewed
 312 distribution of transactions amongst the users. 99.8% of the total users in
 313 2009 made almost a single transaction. This declined to 73.24% by 2020.

Table 5: Characteristics of Bitcoin blockchain network (2009-2015)

	2009	2010	2011	2012	2013	2014	2015
Vertex count	32644	143943	2599119	6001831	16337189	34693993	57381025
Edge count	32808	233872	4642054	19710026	49336100	78077032	145496703
Edge density (S)	6.16e-05	2.25e-05	1.28e-07	3.4e-07	0.94e-07	3.7e-08	2.37e-08
Edge density (D)	3.08e-05	1.12e-05	6.87e-07	5.4e-07	1.85e-07	6.48e-08	4.42e-08

Table 6: Characteristics of Bitcoin blockchain network (2016-2020)

	2016	2017	2018	2019	2020
Vertex count	57107986	78724132	53049193	32288199	3160555
Edge count	29365348	625420597	330885984	230911982	24840651
Edge density (S)	5.2e-08	0.49e-07	0.68e-07	1.12e-07	1.18e-06
Edge density (D)	9e-08	1.01e-07	1.17e-07	2.21e-07	2.49e-06

314 Till the year 2010, Bitcoin was used by crypto-enthusiasts and year 2011
315 saw the entry of the first mixing service and mining pools. Both these services
316 involve transactions with one or limited inputs and several outputs. Conse-
317 quentially, the maximum number of outputs in a single transaction increased
318 from 98 in 2010 to 2002 in 2011 and has remained in range of 2000-7000. This
319 leads to observation that "Number of outputs" can be used to discriminate
320 between different types of users in Bitcoin.

321 4.2. Vertex degree distribution

322 The procedure mentioned by C Gillespie [40] was followed to understand
323 the distribution of in (see Table 7 and 8) and out degrees (Table 9 and 10) of
324 users graph. In 2009, for the distribution of in degrees, the minimum value
325 from which the power-law distribution was fitted i.e., (x_{min}) was 4 and for
326 exponential x_{min} was 1, log-normal x_{min} was 1 and poisson x_{min} was 5. For
327 2010, x_{min} was 31 for power law, 183 for exponential, 29 for log-normal and
328 4351 for poisson. In 2011, x_{min} was 397 for power law, 279 for exponential,
329 359 for log-normal and 8079 for poisson. In 2012, x_{min} was 621 for power law,
330 72053 for exponential, 608 for log-normal and 5352 for poisson. In 2013, x_{min}
331 was 987 for power law, 76728 for exponential, 1151 for log-normal and 4751
332 for poisson. In 2014, x_{min} was 1615 for power law, 99867 for exponential,
333 1702 for log-normal and 154 for poisson. In 2015, x_{min} was 2994 for power
334 law, 99891 for exponential, 1950 for log-normal and 359 for poisson.

Table 7: Likelihood ratio tests for comparing in degree distribution (2009-2015)

Distributions	Parameters	2009	2010	2011	2012	2013	2014	2015
Power law	α	1.99	1.54	2.35	1.86	1.88	1.98	2.12
Exponential	λ	0.11	0.001	0.011	0.004	0.002	0.002	0.0001
Log-normal	μ	1.79	2.59	-26.61	-52.63	-29.818218	-21.38	2.62
	α	1.01	2.65	5.06	8.42	6.50	5.55	2.61
Poisson	μ	13.83	4992.6	26133.67	43568.6	43778.7	7764.21	8610.67

335 In 2016, x_{min} was 2318 for power law, 99549 for exponential, 1510 for
336 log-normal and 5 for poisson. In 2017, x_{min} was 3118 for power law, 99671
337 for exponential, 99671 for log-normal and 6294 for poisson. In 2018, x_{min} was
338 1862 for power law, 96500 for exponential, 2179 for log-normal and 11175 for
339 poisson. In 2019, x_{min} was 2674 for power law, 97258 for exponential, 97258
340 for log-normal and 1 for poisson. In 2020, x_{min} was 2588 for power law, 95384
341 for exponential, 1939 for log-normal and 1 for poisson. From Table 7 it is
342 observed that power-law and log-normal are better fit to data than exponen-
343 tial or poisson. Moreover, X_{min} values indicate that tail of the distribution
344 follows power law. α value indicates inverse relationship between degree and
345 frequency of such nodes. High degree nodes such as mixing services and pools
346 would form LSCC/LWCC making it easy for identifying them on Bitcoin.

Table 8: Likelihood ratio tests for comparing in degree distribution (2016-2020)

Distributions	Parameters	2016	2017	2018	2019	2020
Power law	α	2.1	2.11	1.92	2.4	2.2
Exponential	λ	0.001	0.001	0.001	0.001	0.003
Log-normal	μ	5.15	-194.65	-17.11	-398.36	-7.01
	α	2.06	12.1	5.29	15.85	3.78
Poisson	μ	7918	29039.39	63050.8	5095.25	4054.3

347 In 2009, for the distribution of out degrees, the minimum value from which
348 the power-law distribution was fitted i.e., (x_{min}) was 4 and for exponential
349 x_{min} was 3, log-normal x_{min} was 1 and poisson x_{min} was 12. For 2010, x_{min}
350 was 14 for power law, 5136 for exponential, 15 for log-normal and 42 for
351 poisson. In 2011, x_{min} was 520 for power law, 42350 for exponential, 145 for
352 log-normal and 252 for poisson. In 2012, x_{min} was 667 for power law, 93316
353 for exponential, 562 for log-normal and 2210 for poisson. In 2013, x_{min} was
354 1073 for power law, 94828 for exponential, 94828 for log-normal and 2244 for
355 poisson. In 2014, x_{min} was 1540 for power law, 98344 for exponential, 1544
356 for log-normal and 2334 for poisson. In 2015, x_{min} was 2251 for power law,
357 98992 for exponential, 2214 for log-normal and 300 for poisson.

Table 9: Likelihood ratio tests for comparing out degree distribution (2009-2015)

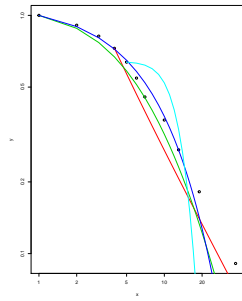
Distributions	Parameters	2009	2010	2011	2012	2013	2014	2015
Power law	α	1.33	1.42	1.73	1.74	1.85	1.86	1.87
Exponential	λ	0.25	0.06	0.013	0.005	0.002	0.002	0.001
Log-normal	μ	-7.27	-4.52	-52.81	-7.835970	-137.41132	-18.89	1.25
	α	6.10	5.14	8.31	4.77	10.3	5.73	3.14
Poisson	μ	10851.33	3754.7	4516.74	27558.8	24466.7	25145.02	14322.95

358 In 2016, x_{min} was 2224 for power law, 99977 for exponential, 1722 for log-
359 normal and 2314 for poisson. In 2017, x_{min} was 5338 for power law, 96639
360 for exponential, 2820 for log-normal and 1 for poisson. In 2018, x_{min} was
361 4308 for power law, 97340 for exponential, 6600 for log-normal and 10649 for
362 poisson. In 2019, x_{min} was 9124 for power law, 98154 for exponential, 98154
363 for log-normal and 1 for poisson. In 2020, x_{min} was 842 for power law, 84442
364 for exponential, 456 for log-normal and 69 for poisson.

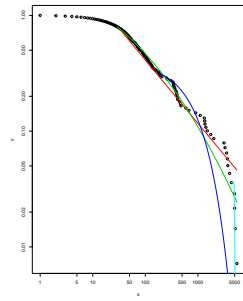
Table 10: Likelihood ratio tests for comparing out degree distribution (2016-2020)

Distributions	Parameters	2016	2017	2018	2019	2020
Power law	α	1.77	2.58	2.34	2.7	2.07
Exponential	λ	0.001	0.001	0.0006	0.0007	0.0051
Log-normal	μ	7.3	7.76	4.8	-338.17	5.56
	α	1.8	1.13	2.02	11.65	1.67
Poisson	μ	15859.95	5967.4	28175.95	5362.98	2580.6

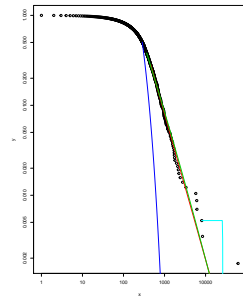
365 Figure 4 and 5 show the fitting of four heavy-tailed distributions to in-
366 degree and out-degree distribution of users graph respectively. Four distribu-
367 tions considered are discrete power law (red), exponential (dark blue), log-
368 normal (green), and Poisson (light blue). Distribution is fit as per protocol
369 specified by C Gillespie [40].



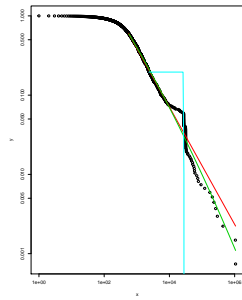
(a) 2009



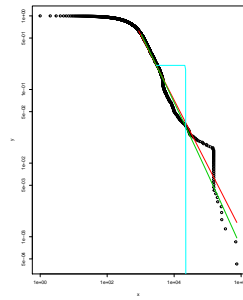
(b) 2010



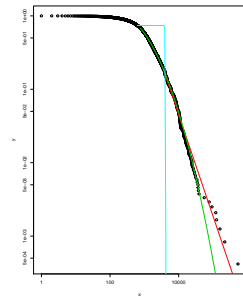
(c) 2011



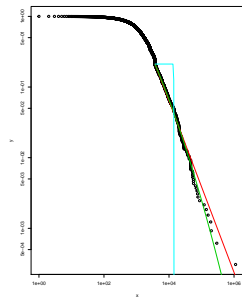
(d) 2012



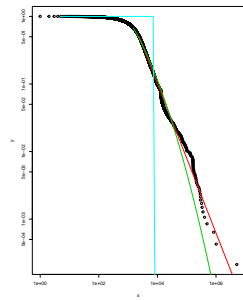
(e) 2013



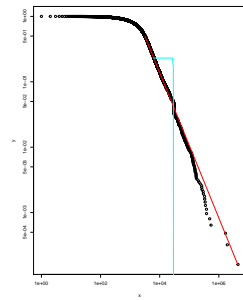
(f) 2014



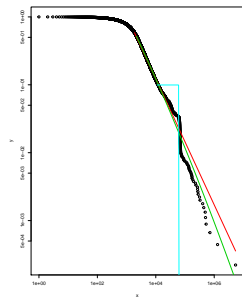
(g) 2015



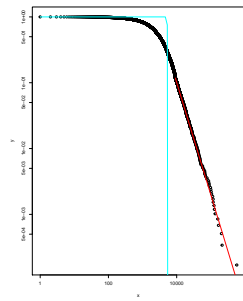
(h) 2016



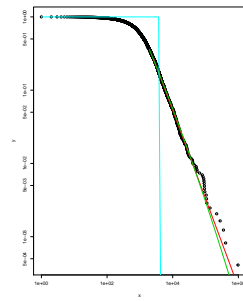
(i) 2017



(j) 2018

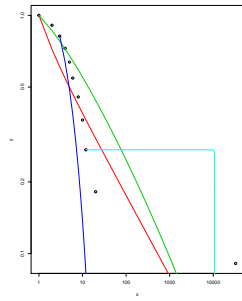


(k) 2019

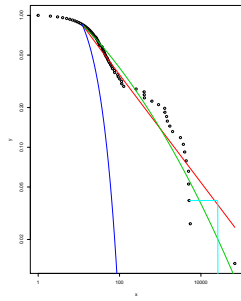


(l) 2020

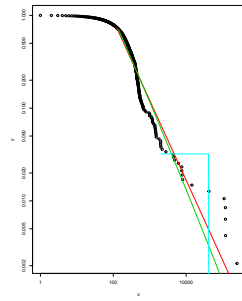
Figure 4: In-degree distribution of Bitcoin users graph (2009-2020)



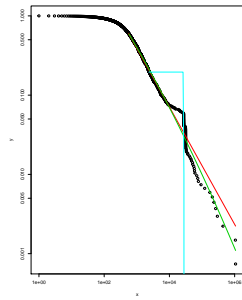
(a) 2009



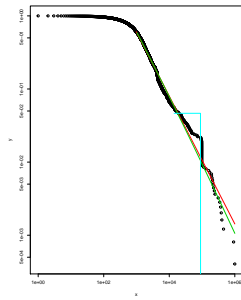
(b) 2010



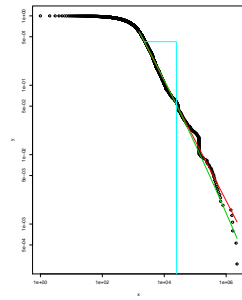
(c) 2011



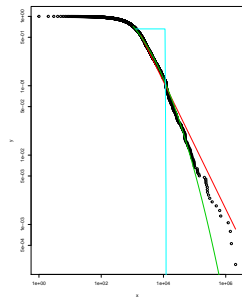
(d) 2012



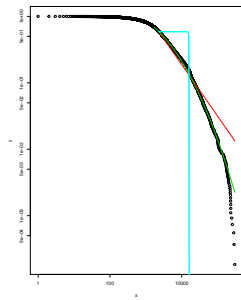
(e) 2013



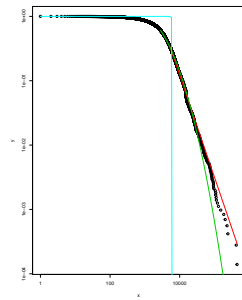
(f) 2014



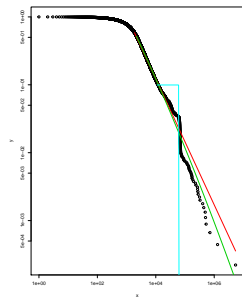
(g) 2015



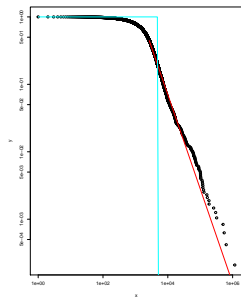
(h) 2016



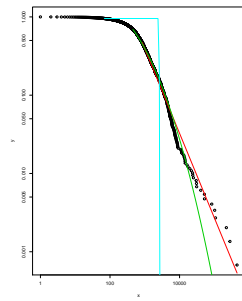
(i) 2017



(j) 2018



(k) 2019



(l) 2020

Figure 5: Out-degree distribution of Bitcoin users graph (2009-2020)

370 As claimed for most complex networks, even bitcoin users graph followed
371 the "scale-free" property as power-law exponent ranged from 1.54-2.4 for
372 in-degree distribution and from 1.42-2.7 for out-degree distribution. x_{min}
373 indicated that the tail of the in and out-degree distributions fit the power
374 law. High degree entities such as mixing services, gambling websites and
375 pools will occupy the tail of the degree distribution. Whereas, ordinary users
376 shall be at the other end of the spectrum. Thus, the location of the entity
377 on the degree distribution curve could reveal its nature.

378 4.3. Bitcoin: Global networks properties

Table 11 and 12 give the global network properties of bitcoin users graph. Measures marked with # could not be computed on the current configuration of the system.

+

379 indicates approximation used for computation as given by M Jackson *et al.*
380 [41]. In 2009, as transactions were infrequent, adhesion and cohesion were
381 zero indicating a sparsely connected graph where information transfer was
382 slow due to long diameter. As the majority were COINBASE transactions in
383 2009, the graph had high centralization tendency, low reciprocity, girth, and
384 assortativity. Till 2010, crypto-enthusiasts dominated the transactions, and
385 transactions were less, and diameter increased. In 2011, mixing services and
386 miner pools entered, and the DeepBit.net mining pool had 61897 incoming
387 and 120756 outgoing connections. CoinJoin Mess, a mixing service, had 903
388 incoming and 1800 outgoing connections in 2011. The presence of mining
389 pools and mixing services decreased the diameter and average path length
390 while leading an increase in reciprocity. In 2012, SantoshiDice.com, a gam-
391 bling website, saw 810474 incoming and 1055385 outgoing connections. In
392 2013 too SantoshiDice.com continued to get the highest incoming and out-
393 going connections. In 2014, SantoshiDice.com had the maximum incoming
394 connections (1592352), whereas CoinJoin Mess had the maximum outgoing
395 (2256302). In 2015, another online gambling site LuckyBit.it had the highest
396 incoming connections at 1655881, and CoinJoinMess had the highest outgo-
397 ing connections at 2256344.

Table 11: Global network properties (2009-2015)

	2009	2010	2011	2012	2013	2014	2015
Adhesion	0	0	0	0	0	0	0
Cohesion	0	0	0	0	0	0	0
Diameter	7	5525	0.03 ⁺	0.06 ⁺	0.06 ⁺	0.05 ⁺	0.05 ⁺
Average path	1.01	748.54	0.03 ⁺	0.06 ⁺	0.06 ⁺	0.05 ⁺	0.05 ⁺
Radius	6	1	#	#	#	#	#
Reciprocity	6.11e-05	0.02	0.008	0.2	0.16	0.03	0.019
Girth	3	3	3	3	3	3	3
Assortativity	-0.55	-0.31	0.17	0.12	0.06	0.04	0.17
Centralization	0.99	1	0.99	0.99	0.99	1	1
C_d	0.5	0.23	0.04	0.15	0.05	0.03	0.02
C_c	0.99*	2.1e-06	#	#	#	#	#

398 In 2016, with 300120 outgoing connections, Faucetbox.com (bitcoin re-
399 ward site) was very active. In 2017 highest connections were recorded by
400 Poloniex.com, a crypto exchange with 4473190 incoming and 445628 outgo-
401 ing connections. In 2019, Huobi.com-2, a bitcoin exchange platform, had the
402 highest outgoing connections. Due to anonymity, the identity of an entity
403 with the highest incoming and outgoing connections in 2018 was not found.

Table 12: Global network properties (2016-2020)

	2016	2017	2018	2019	2020
Adhesion	0	0	0	0	0
Cohesion	0	0	0	0	0
Diameter	0.09 ⁺	0.11 ⁺	0.1 ⁺	0.11 ⁺	0.13 ⁺
Average path	0.09 ⁺	0.11 ⁺	0.1 ⁺	0.11 ⁺	0.13 ⁺
Radius	#	#	#	#	#
Reciprocity	0.016	0.003	0.0016	0.0009	0
Girth	3	3	3	3	3
Assortativity	-0.026	-0.005	-0.022	0.28	0.09
Centralization	0.99	0.99	0.99	1	0
C_d	0.044	0.031	0.05	0.02	0.15
C_c	#	#	#	#	#

404 Reciprocity is close to 0 indicating that Bitcoin is majorly for payments
405 or investments and not for exchange of BTC's between account owners. As-
406 sortativity in range $-1 - 0$ indicates that low degree nodes (ordinary users,
407 enthusiasts, small investors) are linked to high degree nodes (gambling hubs,
408 exchanges, pools, mixers). Due to the high transactions received by such en-
409 tities the centralization remained close to 1. Based on these observations,

410 transaction based features would be key in discriminating entities. These
 411 features would be - Total transactions in which wallet has participated (T_x),
 412 Total incoming transactions to the wallet (T_x^{in}), Total outgoing transactions
 413 from the wallet (T_x^{out}), Average number of incoming transactions received by
 414 an address of a wallet (A_v), Total number of addresses sending BTC to the
 415 wallet (T) and Ratio of Transaction count and address count (R) gives the
 416 average number of times an address of the wallet was reused for a transaction.

417 4.4. Community structure

418 Usually, triangles, transitivity, and clustering coefficient are higher in
 419 social networks than non-social networks [13]. These parameters indicate
 420 the tendency of entities in the network to form dense communities. In 2009,
 421 the Largest Weakly Connected Component (LWCC) was the entire graph,
 422 and Largest Strongly Connected Component (LSCC) was minimal. Triangles
 423 and clustering coefficients were also negligible. In 2010, WCC was 25, and
 424 SCC was 108482. In 2011, WCC was 1400, and SCC were 2029127. In 2012,
 425 WCC was 6165, and SCC were 3149100. In 2013, WCC was 15122, and
 426 SCC was 9888167. DeepBit.net formed the largest SCC and largest WCC in
 427 2011. SantoshiDice.com formed the largest SCC and largest WCC in 2012
 428 (see Table 13).

Table 13: Community structure (2009-2012)

		2009	2010	2011	2012
LSCC	Triangles	0	9580	104368	3797352
	Nodes	2 (0%)	34709 (24.1%)	567144 (21.8%)	2846171 (47%)
	Edges	5 (0%)	75367 (32.2%)	1345036 (28.9%)	13908941 (70%)
	Articulation pt.	0	72	638	1389
	C	NaN	0.003	0.003	9.1e-05
LWCC	Triangles	9	18708	3102649	4267711
	Nodes	32644 (100%)	143880 (100%)	2593961 (100%)	5979901 (100%)
	Edges	32808 (100%)	233829 (100%)	4638181 (100%)	19693726 (100%)
	Articulation pt.	79	20774	496060	1440988
	C	2.4e-05	1.11e-05	0.0005	0.0001
Full network	Triangles	9	18709	3102700	4267910
	Articulation pt.	79	20784	497641	1447747
	C	2.4e-05	1.11e-05	0.0005	0.0001

429 In 2013, 2014 and 2015 too the largest SCC and WCC were formed by
 430 SantoshiDice.com (see Table 14). In 2014, there were a total of 40508 WCC
 431 and 24516983 SCC in the network. In 2015, WCC was 253244, and SCC
 432 were 35766309 in the network.

Table 14: Community structure (2013-2015)

		2013	2014	2015
LSCC	Triangles	7751768	5140336	21461343
	Nodes	6437119 (39.4%)	10157747 (29.6%)	17445491 (30.2%)
	Edges	32501745 (65.8%)	41139689 (52.3%)	85078065 (58.9%)
	Articulation pt.	9270	14777	14790
	C	0.0002	0.0008	0.0004
LWCC	Triangles	7751768	6832830	25928531
	Nodes	16282225 (100%)	34556782 (100%)	57084066 (100%)
	Edges	49292728 (100%)	77961419 (100%)	145254102 (100%)
	Articulation pt.	4282322	7775376	13682985
	C	0.0002	0.0001	0.0002
Full network	Triangles	9102472	6834251	25931343
	Articulation pt.	4297982	7809891	13771043
	C	0.0002	0.0001	0.0002

433 In 2016, unknown wallets had formed the largest WCC and SCC. In 2017,
 434 Bittrex.com, a crypto trading exchange, formed the largest SCC. In 2019, the
 435 largest SCC was formed by Bitcoin exchange service Huobi.com-2. In 2016,
 436 WCC was 871640, and SCC was 46385054 in the network. In 2017, WCC
 437 was 1476165, and SCC were 69375203. In 2018, WCC was 1032588, and
 438 SCC were 30074974. In 2019, WCC were 967845 and SCC were 26896674
 439 (see Table 15).

Table 15: Community structure (2016-2020)

		2016	2017	2018	2019	2020
LSCC	Triangles	125423937	95674389	62367145	24089648	0
	Nodes	10698736 (18.7%)	9306342 (3%)	3242666 (6.1%)	844423 (2.7%)	1
	Edges	120658573 (41.1%)	169589795 (15.07%)	62330136 (18.8%)	18010394 (8.2%)	0
	Articulation pt.	1259	2206	717	522	0
	C	0.0015	0.0009	0.0004	0.004	0
LWCC	Triangles	213985326	210765433	214016097	88648952	0
	Nodes	53556287 (93.7%)	74366786 (94.4%)	47785524 (90.7%)	26470992 (85.5%)	123583 (0.03%)
	Edges	287695383 (93.7%)	618579809 (98.9%)	325783461 (98.4%)	212922543 (97.8%)	403262 (0.01%)
	Articulation pt.	5333181	6854728	4535938	3167225	4785
	C	0.0005	0.0003	0.0001	0.0004	0
Full network	Triangles	214055511	287646955	214094259	88721557	0
	Articulation pt.	6212728	6987676	5488866	4060330	351463
	C	0.0005	0.0003	0.0001	0.0004	0

440 The LSCC increased from 2009-2012 to close to 47% of all nodes of the
 441 graph in 2012 and then has declined to 2 – 3% of all nodes by 2019. LWCC
 442 has remained in a range of 97 – 98% of the total nodes. LWCC and LSCC
 443 were formed mainly because of mixing services, gambling services, and crypto
 444 exchanges. The LSCC formed in past years (see Table 16) confirms this.
 445 Reuse of addresses for transferring BTCs led to the compromise of anonymity

446 of bitcoin users. Thus, another feature to discriminate entities is suggested
 447 - Ratio of Transaction count and address count (R). This feature gives the
 448 average number of times an address of the wallet was reused for a transaction.

Table 16: Categories and address forming LSCC

Year	Address	Category	Entity name
2010	1Bw1hpkUrTKRmrwJBGdZTenoFeX63zrq33	Unclassified	0091107f8aaff711
2011	1VayNert3x1KzbpzMGt2qdqrAThiRovi8	Miner	DeepBit.net
2012	1VayNert3x1KzbpzMGt2qdqrAThiRovi8	Miner	DeepBit.net
2013	1VayNert3x1KzbpzMGt2qdqrAThiRovi8	Miner	DeepBit.net
2013	1P49eoo8YgWrdYmMJwo7KYAvyhJYtDfWBg	Mixer	BitcoinFog
2014	1VayNert3x1KzbpzMGt2qdqrAThiRovi8	Miner	DeepBit.net
2014	1P49eoo8YgWrdYmMJwo7KYAvyhJYtDfWBg	Mixer	BitcoinFog
2015	1VayNert3x1KzbpzMGt2qdqrAThiRovi8	Miner	DeepBit.net
2015	1P49eoo8YgWrdYmMJwo7KYAvyhJYtDfWBg	mixer	BitcoinFog
2016	1NxaBCFQwejSZbQfWcYNwgqML5wWoE3rK4	Gambling	LuckyB.it
2016	1changeGhAXKoTEkMntbAe1VHh52jFQhh	Gambling	BitZillions.com
2016	19DhUuwoywejreRPhW9XWXKZTmSRNwud8x	Mixer	HelixMixer-old3
2016	184S3jPkbwS7UJbCUYgL7VKeye5aqSKinF	Darkmarket	AlphaBayMarket
2019	1HckjUpRGerrRAtFaaCAUaGjsPx9oYmLaZ	Exchange	Huobi.com-2

449 4.5. k -core decomposition

450 Table 17 and 18 give the core decomposition of bitcoin users graph. The
 451 k -core of a graph is the maximal subgraph in which every vertex has at
 452 least degree k . The core decomposition is a set of all k -cores of a graph.
 453 Core decompositions are used to study the resilience or robustness of a net-
 454 work [42]. Due to the existence of single entities that captured the majority
 455 of all incoming connections, the k -cores had single nodes from 2011-2019.
 456 These single nodes were DeepBit.net (2011), SantoshiDice.com (2012-2015),
 457 Unknown wallets (2016,2018), Bittrex.com (2017), and Huobi.com-2 (2019).

Table 17: Core decomposition (2009-2015)

	2009	2010	2011	2012	2013	2014	2015
Cores in LSCC	5	9930	120262	1065542	347630	333420	601493
Cores in LWCC	24	10964	120262	1065542	347630	333420	601493
Cores in full graph	24	10964	120262	1065542	347630	333420	601493

Table 18: Core decomposition (2016-2020)

	2016	2017	2018	2019	2020
Cores in LSCC	146836	72718	272896	1154252	0
Cores in LWCC	112356	72718	272896	1154252	704
Cores in full graph	375513	72718	272896	1154252	109080

458 *4.6. Time series analysis of Bitcoin network*

459 Figure 6 gives the fluctuations in the characteristics of Bitcoin network
 460 from 2009-2020. To predict the future outlook of the network, time series
 461 analysis is performed. The objective of the analysis is to predict the outlook
 462 of Bitcoin network for year 2021. Four models were selected for the analysis,
 463 the settings are listed:

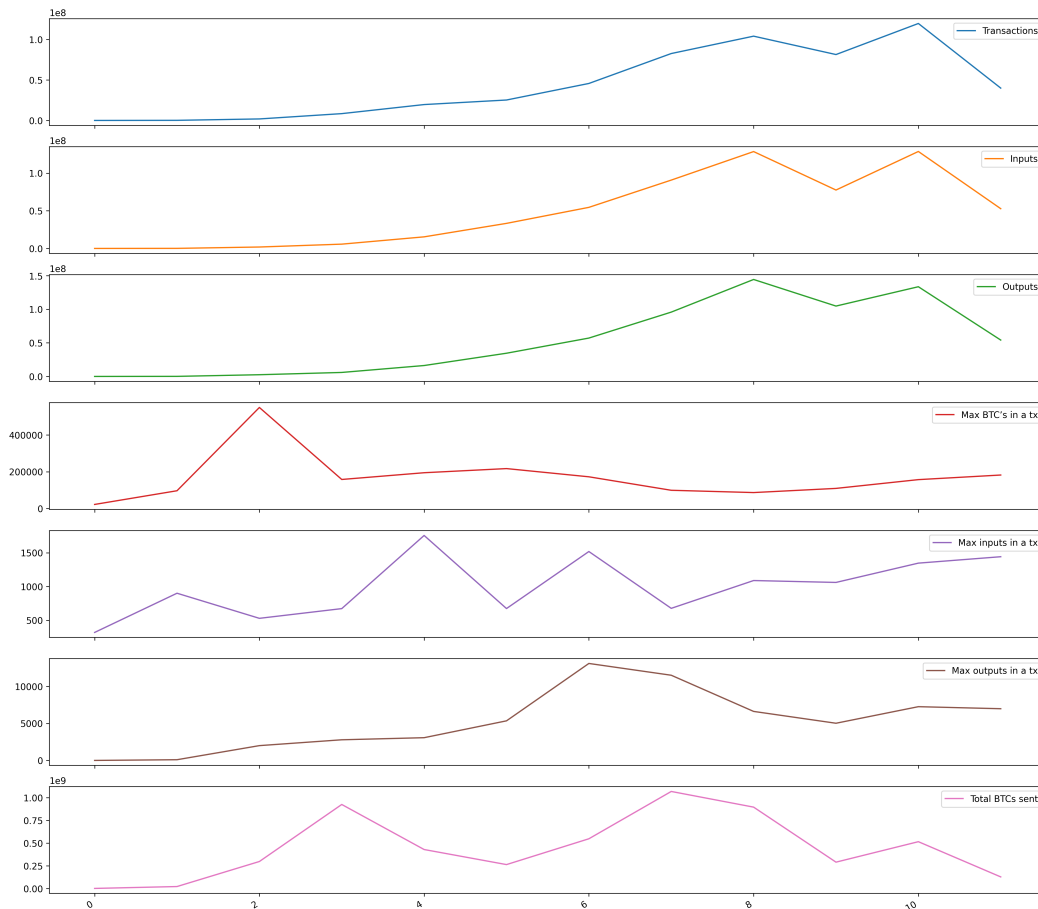


Figure 6: Distribution of transactions in Bitcoin blockchain network (2009-2020)

- 464 • Linear regression
- 465 • Neural network: Two layers NN (units=64, activation=none)
- 466 • Convolutional neural network: Two layers (Filter=32, size=1, stride=1,
467 padding=0)
- 468 • LSTM: Single layer (units=32, activation=none)

469 The four models were trained on a single step, single output time series prediction task on the dataset of Bitcoin network characteristics from
470 2009-2020 viz. data mentioned in Tables 3-10 and 13-18. Results of four
471 models on validation and test set are illustrated in Figure 7. Comparatively,
472 dense models are better suited for the time series prediction although all four
473 models have mean absolute error close to 0.
474

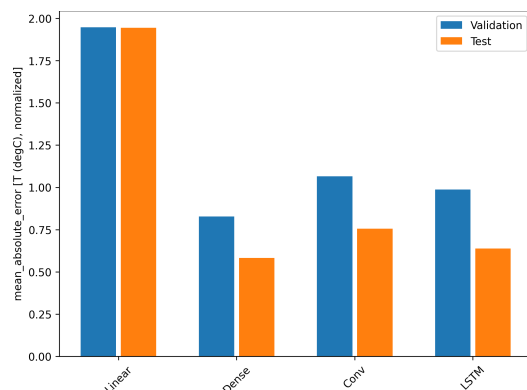


Figure 7: Performance of models on Validation and Test set

475 Dense model was used to predict the characteristics of the Bitcoin model
476 for the Year 2021 and results of the prediction are given in Table 19. Trans-
477 actions, inputs, outputs and Max BTC's in a Tx may continue a downward
478 trend seen in Bitcoin networks since 2019. Degree distributions could not be
479 predicted using past data; However, centralization measures, assortativity
480 and reciprocity were in range of previous years. Assortativity shall remain
481 negative and reciprocity low which conforms to standard notions of Bitcoin
482 networks. The LSCC and LWCC in Bitcoin network shall continue to dom-
483 inate reaching 81% and 99% of the total network size respectively. Cores
484 in full graphs will see a decline to 2018 levels. Overall, it can be concluded
485 that data-driven time series analysis observes normalcy will be restored in
486 the Bitcoin network in the year 2021 from the 2019 all time highs.

Table 19: Prediction of Bitcoin network for Year 2021

Year	Transactions	Inputs	Outputs	Max BTCs in a tx
2021	17916462.0	19343784	134251.34	15666966.0
Max inputs in a tx	Max outputs in a tx	Total BTCs sent	Vertex count	Edge count
1176.0	2485	9928711	269887	2283282
Edge density (S)	Edge density (D)	Power law α in	Exp lambda in	Lognormal μ in
4.39e-06	3.64e-06	0.034	0.13	0.83
Lognormal alpha in	Poisson in	Power law α out	Exp lambda out	Lognormal μ out
0.46	0.53	1.15	-0.11	0.2
Lognormal alpha out	Poisson out	Diameter	Avg path length	Reciprocity
-0.07	-1.01	6.7e-02	4.4e-02	3.8e-02
Assortativity	Centralization	Cd	Triangles (LSCC)	Nodes (LSCC)
-0.2	0.99	4.7e-02	8.6e+06	1.5e+05
Edges (LSCC)	AP (LSCC)	C (LSCC)	Triangles (LWCC)	Nodes (LWCC)
5.1e+06	5.9e-03	5.2e+04	2.9e+07	1.8e+07
Edges (LWCC)	AP (LWCC)	C (LWCC)	Triangles (Full)	Nodes (Full)
6.5e+07	3.7e+06	1.4e-04	1.8e+07	2.4e+06
Edges (Full)	Cores (LSCC)	Cores (LWCC)	Cores (Full)	
7.3e+05	2.5e+05	1.65e+05	4e+05	

487 *4.7. Summary of Results with Discussion and lessons learnt*

- 488 • The edge density is low in both the directed graph (Edge density (D))
- 489 and the undirected graph (Edge density (S)) for the period 2009-2020
- 490 compared to social networks

- 491 • 99.8% of the total users in 2009 made at the most a single transaction
- 492 this declined to 73.24% by 2020.

- 493 • Even bitcoin users graph followed the "scale-free" property as power-
- 494 law exponent ranged from 1.54-2.4 for in-degree distribution and from
- 495 1.42-2.7 for out-degree distribution

- 496 • LWCC and LSCC were formed mainly because of mixing services, gam-
- 497 bling services, and crypto exchanges.

- 498 • k-cores had single nodes from 2011-2019

499 Comparing complex networks with bitcoins users graph, it is seen that it
500 shares certain features with the Ethereum network. Unlike social networks
501 (Twitter, Facebook, Actors, Directors, Co-authorship, citation), it has no
502 giant LSCC but follows properties of "scale-free" networks.

Table 20: Comparison with other complex networks

Complex network	Hubs?	Assortativity	Small diameter?	C	Degree distribution	Giant LSCC	Edge density
Bitcoin	Yes	(-)	Yes	Low	Power law	No	Low
Citation	NA	(-)	NA	Low	Power law	NA	Low
WWW	Yes	(+)	Yes	Low	Power law	Yes	Low
Social networking	Yes	(-)	Yes	High	Power law	Yes	High
Protein-Protein	NA	(+)	NA	Low	Power law	NA	Low
Co-authorship	NA	(+)	NA	Low	No power law	NA	Low
Ethereum	Yes	NA	Yes	Low	Power law	Yes	Low
Film actors	NA	NA	NA	NA	Power law	NA	Low
Company directors	NA	NA	NA	NA	No power law	NA	Low

503 With the use of deanonymizing and network analysis, common types of
 504 services on Bitcoin network datasets were able to be identified. These are
 505 listed as follows:

- 506 • Exchanges: Allow trading of BTC to fiat currencies
- 507 • Pools: Individual users combine their processing power for mining
 508 blocks
- 509 • Gambling: Allow placing of bets using BTCs
- 510 • Wallets: Store BTC private keys and balance
- 511 • Payment gateways: Allow accepting payment for services in BTCs
- 512 • Miner: Organizations competing to mine blocks
- 513 • Darknet markets: Selling and buying goods using BTCs
- 514 • Mixers: Remove traceability of BTCs from source
- 515 • Trading sites: Purchase equities using BTCs
- 516 • P2Plenders: Crowdsourcing BTCs for loans
- 517 • Faucets: Reward in BTCs to subscribers
- 518 • Explorer: Educational websites provide API to explore Bitcoin
- 519 • P2PMarket: Marketplace for second-hand goods where buyers can con-
 520 tact sellers, payments in BTCs
- 521 • Bond markets: Buying bonds or debt instruments in BTC

- 522 • Affiliate marketers: Pay per click in BTC
- 523 • Video sharing: Payment in BTCs for viewing videos
- 524 • Money launderers: Convert fiat currencies to BTC
- 525 • Cyber-security providers: Provide cybersecurity products for BTC
- 526 • Cyber-criminals: Blacklisted by governments
- 527 • Ponzi: High yield investment scams

528 To build a system for detection of these entities in Bitcoin network and
 529 aid forensic tools, network analysis conducted in the current paper identified
 530 discriminating features. Feature list is given in Table 21. These features can
 531 be used to build a classifier for detecting or identifying illegal activities or
 532 users in Bitcoin.

Table 21: List of Features

Feature symbol	Feature description
T_x	Total transactions in which wallet has participated
B	Current BTC present in the wallet
T_x^{in}	Total incoming transactions to the wallet
T_x^{out}	Total outgoing transactions from the wallet
L	Total active life of the wallet
A_w	Total addresses of the wallet
A_v	Average number of incoming transactions received by an address of a wallet
T	Total number of addresses sending BTC to the wallet
R	Ratio of Transaction count and address count. Gives the average number of times an address of the wallet was reused for a transaction.

533 5. Conclusion and Future works

534 Since its launch in 2009, Bitcoin has seen a steady increase in its user base
 535 and transactions, both volume and value. As it aims to promote the exchange
 536 of value without reliance on a trusted third party, it could be speculated
 537 that the network form of the Bitcoin system should be decentralized and
 538 disconnected without any giant connected component. This would mean a
 539 robust structure. However, in reality, there are connected components in
 540 the bitcoin users graph. These components have emerged due to gambling
 541 websites, mixing services, crypto trading exchanges, and mining pools. These

542 services have been easier to identify due to the high incoming and outgoing
543 connections they have with other bitcoin users. From 2011, these entities
544 have created giant connected components in bitcoin users graph. A result of
545 their presence was a reduction in diameter, average path length, and radius.
546 Additionally, "scale-free" property, was observed in bitcoin users graph as
547 preferential attachment occurred.

548 The blanket of anonymity and secrecy provided by Bitcoin has made it
549 difficult to label each and every address with a label. However, network
550 analysis can shed light on this confidentiality and reveal the nature of the
551 bitcoin user. There is no straightforward application of network analysis on
552 bitcoin data as bitcoin users are identified by addresses, and a single user can
553 have multiple addresses. This issue of multiple identities is not seen in other
554 networks. Heuristic clustering, such as combining multi-inputs to a single
555 transaction as a single entity, can reduce this issue to some extent and hence
556 is commonly used in bitcoin network studies.

557 Even with clustering and network analysis without labeled datasets, lim-
558 ited progress can be made in tracing entities on the Bitcoin network. To
559 overcome this drawback, features related to each entity can be extracted
560 from the blockchain to train a supervised learning technique for identifying
561 unknown wallets.

562 Bitcoin scenario has changed drastically in the last 3 months - e.g. Feb
563 20, 2020 - BTC @10k USD, March 12, 2020 - BTC@4k USD, April 2020 -
564 BTC@6k-9k, May 8 - BTC again @10k (reward halving will be happening
565 on 11 May 2020). BTC is detaching itself from linearity of cryptocurrency
566 market (i.e. Since last 3 months, BTC and ETH were going neck to neck
567 in terms of percentage pricing variation). This detachment may be because
568 of the following considerations: Pandemic Work From Home culture created
569 opportunity for people to shift focus on stock markets and cryptocurrency
570 markets. BTC is reemerged as a parking heaven (hedging / protection against
571 inflation) - due to USD influx of 7 Trillion - COVID 19 stimulus printing of
572 money - and other bailouts by governments across the World. India legalized
573 crypto currencies from March 2020 first week (after a ban of about 2 years) -
574 and market started buzzing with large number of new players/small investors.
575 Steady emergence of Internet of Trusted Things - which sees blockchain as a
576 platform to build trust.

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