Characterising Cryptocurrency Project Networks Using Graph-Based Analysis

Jerome Zhen Hao Wong

A thesis
submitted in partial fulfillment of the
requirements for the degree of

Master of Science

University of Washington

2022

Committee:

Prashanth Rajivan

Shuai Huang

Ashis Banerjee

Program Authorized to Offer Degree:
Industrial & Systems Engineering

University of Washington

Abstract

Characterising Cryptocurrency Project Networks Using Graph-Based Analysis

Jerome Zhen Hao Wong

Chair of the Supervisory Committee:
Prashanth Rajivan

With the introduction of smart contracts by the Ethereum blockchain in 2015, cryptocurrencies can now function as decentralized applications (dApps). Over the years, the proliferation of dApps has grown exponential and in 2020, the cryptocurrency market has onboarded and grown from a marketcap of 200 billion at the start of 2020 to almost 3 trillion at its peak valuation by the end of 2021. Users' interactions with these dApps via the blockchain results in immutable and publicly available records which stores rich information and complete traces of financial activities. Such interactions are often studied from a network perspective but lack a unified approach and tend to focus on the blockchain rather than the dApps. This thesis aims to use networks as a general language to describe dApps as an interacting system in the real world. This thesis proposes a new framework titled Graph Analysis of Cryptocurrency Project Network (GAPNET) to analyze dApps using a collection of graph-based methods. The framework brings together different methods based on Graph Properties and Token Price Correlation. In the thesis, I use this framework to analyze the growth of selected dApp networks in the Ethereum and Binance Chain, investigate relations to real-world networks, and correlate graph properties to token price. Lastly, I close by formulating conjectures from the experiments and provide future research directions. In the long-term, this framework could be used for providing insights to users interested in investing and participating in dApps.

TABLE OF CONTENTS

LIST OF FIGURES

GLOSSARY

CONSENSUS MECHANISM: a method for validating entries into a distributed database and keeping the database secure

STAKING: participation in a proof-of-stake system to put your tokens in to serve as a validator to to the blockchain and receive rewards

ON-CHAIN: transactions that occur on the blockchain that are reflected on the distributed, public ledger

PROOF OF WORK: a blockchain consensus mechanism involving solving of computationally intensiv epuzzles to validate transcations and create new blocks

PROOF OF STAKE: - a cryptocurrency consensus mechanism for processing transactions and creating new block in a blockchain via staking

CROSS-CHAIN: it is a technology that enahnces the interconnection between blockchain networks by allowing the exchange of information and value. In doing so, it breaks the siloed nature of blockchains to create an intertwined distributed ecosystem

YIELD FARMING: a way to earn interest by investing in decentralized finance markets

ALTCOIN: a term used to describe any other cryptocurrency that is not bitcoin - an alternative digital currency

ERC20: tokens are fungible tokens that are designed and used on the Ethereum platform

NON-FUNGIBLE TOKENS: are coins or tokens that cannot be replaced by another identical coin or token

ERC721: A token standard for non-fungible Ethereum tokens

ACKNOWLEDGMENTS

The author wishes to express sincere appreciation to University of Washington, where he has had the opportunity to work with his advisor Assistant Professor Dr Prashanth Rajivan. The author would also like to express his sincere appreciation to the company CertiK that supplied the data used in this paper, for which he was also advised by Mr Muhan Zou and Miss Cathy Song in the Waterdrop Data Science Team.

Chapter 1

INTRODUCTION

The roots of cryptocurrency can be traced back to 1982 where the American cryptographer David Chaum proposed the first of its kind blockchain protocol through his dissertation [12]. He later went on to develop a digital currency with a anonymous transaction system called eCash under his company, DigiCash, in 1990. It initially attracted attention from large banks but never really took off, leading to the bankruptcy of his company in 1998. His work laid the critical and foundational path needed for Bitcoin to take over as its eventual successor. Under the backdrop of the global economic downturn in 2008, enters Satoshi Nakamoto, the moniker given to the founder of Bitcoin. Nakamoto wanted to invent a system that would be detached from the traditional financial systems after witnessing the collapse of the banking infrastructure and increasing distrust in institution in the 2008 financial crisis. He would publish the infamous paper titled, Bitcoin: A Peer-to-Peer Electronic Cash System [43], which described the use of a peer-to-peer network solution so solve the problem of double-spending. As digital currency does not exist as a physical possession unlike a bill or coins, spending the digital currency might not mean that it has been removed from the user, which leads to the "double-spend" problem. Nakamoto's approach introduced a public ledger, Merkle roots and trees, timestamps, incentives and a decentralized consensus mechanism in order to prevent the alteration of encrypted data which is later verified for its authenticity of transaction based on a majority consensus mechanism called proof-of-work. Hackers would need a large amount of computational power in order to reverse transaction and attack the network. Since its inception, many other alternatives have emerged with their own sets of rules of transactions and usage namely Ethereum and Binance Smart Chain of which the cryptocurrency projects that are discussed in this paper are built on top of.

Ethereum was developed in 2015 as a transaction-based state-transition machine which is made up of accounts. When assets and information are transferred between accounts, it is recorded on the Ethereum blockchain and this causes a transition in its 'world state'. The two types of accounts present in Ethereum - users and contracts, allows for complex applications and interactions to be built on top of the blockchain, unlike Bitcoin which mostly faciliates transfers of assets between users. Ether is the native asset that the Ethereum blockchain uses. It also allows for the creation of Tokens via methods implemented in smart contracts. Users are able to transact ether or these tokens which allows for the flourishing of various complex asset-transfer-ecosystem of fungible (ERC20) token assets to occur.

Binance Smart Chain is a fork of Ethereum with a few adjustments which makes up for the shortfall of its cousin, long block times and high transaction costs. It is a smart contract platform and has similar functionalities compared to Ethereum, albeit opting for a different consensus mechanism. Its native token is Binance Coin (BNB). Through various incentives and tools in its ecosystem, Binance, its parent company, has attracted many developers previously from the Ethereum platform to migrate over to build on the competing chain.

Public blockchains that support smart contracts such as Ethereum and BSC presents an interesting environment for which users and autonomous agents through the form of conditionally triggering code (smart contracts), can cohabit and interact with one another. Unlike social networks where participants are human users or the traditional financial networks where all interactions are a form of transfer of value or assets, blockchain networks such as Ethereum and BSC, resemble more like the Internet or World Wide Web, where users and programs interact through a set of predefined rules of engagement. In addition, smart contracts themselves can interact with one another through calling, invoking or killing each other in order to balance and advance the state of the blockchain. Users, through the form of a cryptocurrency wallet, are able to interact with smart contracts deployed by the cryptocurrency projects to trigger the predefined functions that the smart contract have been coded to do. Each of these cryptocurrency wallets and smart contracts are addresses that a user or a program can interact with, forming connections that can be modelled as a network graph. With how blockchain naturally lends itself to forming networks, I am motivated to study the cryptocurrency project that are deployed on the Ethereum and BSC blockchain networks through the lens of graph analysis. For the purposes of this paper, the term Decentralised Applications (DApps) and Cryptocurrency Projects will be used interchangeably.

1.1 Motivations

As of May 2022, there exist more than four thousand decentralized applications (DApps of which about 73% are deployed on the Ethereum chain[55], with the number of DApps on the Binance Smart Chain (BSC) coming in at third. With so many DApps now available for investors and potential users, they are faced with the conundrum of having to sort through the noise for the signal. By providing a graph based approach to analyze new potential projects, new users are able to gain additional insights about a projects network properties, and see how they related to their real world counterparts, before deciding to participate in them.

Past works [60, 50, 11, 33, 42, 18] have modelled transactions in public blockchains using static and temporal graphs and applied graph analysis to generate new observations in insights in the network. It is however surprising that there is very little research on the application of a framework in order to conduct graph analysis of *cryptocurrency projects*. Furthermore, most existing tools available for users [3, 29, 25, 36, 44] only provide analysis of cryptocurrency projects on an individual basis and do not provide analysis when many of them are compared together. In this paper, we investigate the the characteristics of cryptocurrency projects from a graph perspectives. In particular, we look to address three main research questions:

(1) How do cryptocurrency projects resemble other social networks in terms of network graph properties?

(2) Are transaction graph properties in cryptocurrency projects a strong indicator for price action in their respective native token?

(3) How cryptocurrency projects price action influence and are correlated to one another?

1.2 Contributions

In this paper, a series of studies are conducted on cryptocurrency projects on the Ethereum and BSC blockchain networks which includes temporal graph analysis and token price correlation. A framework is proposed titled Graph Analysis of Cryptocurrency project Network (GAPNET) which is used as a unified platform to conduct various graph analysis of cryptocurrency projects simultaneously. In particular, GAPNET is composed of three modules: (1) Crypto Project Data Management; (2) Crypto Project Graph Analysis; and (3) Crypto Project Token Price Analysis. Crypto Project Data Management filters down raw blockchain data into datasets that can be loaded into a graphing software used in the experiment. Then, Crypto Projects Graph Analysis is proposed to investigate pertinent graph properties related to the interactions that occur in the cryptocurrency projects to better understand the projects through its network characteristics and how it relates to traditional networks like the Internet or Social Media. At the same time, Crypto Project Token Price Analysis would compare projects through the changes of the price action of each cryptocurrency project's native token and see they influence and are correlated to one another. The experimental results provide useful indicators and insight that could aid in allowing new users to make an informed decision on participating in their cryptocurrency project of choice.

Chapter 2

BACKGROUND AND RELATED WORK

This section covers some background information and concepts that would be introduced in the rest of the paper. I will be introducing the concept of distributed ledger technology (DLT), specifically in the form of a blockchain, the representation of complex systems that happen on the blockchain as a network graph, past work that have been done on characterising cryptocurrency network work and correlating those metrics to its token price.

2.1 Blockchain as a Form of Distributed Ledger Technology

Cryptocurrencies avoid the problem of the single point of failure that plagues traditional centralized financial systems by storing data into distributed ledgers, effectively decentralizing the ownership of this data to multiple entities. DLTs are essentially a form of database that is distributed and immutable. Most DLTs are also permissionless and therefore, no prior approval is needed in order to participate in the usage of the ledger.

While DLTs can be implemented in different ways, cryptocurrency relies on blockchain specifically. Blockchain is a type of data structure that stores transactions into containers that are called blocks. These blocks are then linked together through cryptography essentially forming a chain between one block to another, giving rise to its eponymous term - blockchain. In order to verify the consistency and correctness of the transactions that occur on a blockchain, the nodes involved employ a consensus mechanism to agree on the actual state of the distributed ledger. Different schemes are available and the first of its kind that was proposed to be used by Bitcoin was called Proof of Work (PoW), which required the nodes involved to solve complex and computationally heavy mathematical puzzles in order to validate the blocks and transactions that are contained within it. Such an activity is called "mining". On top of processing simple transfer of asset transactions, Ethereum is also able to execute contracts written in code. These pieces of code stored in contracts are called smart contracts.

As PoW have certain limitations in terms of transaction speeds and ever increasing need for more compute power and electricity, other consensus mechanisms have been proposed that improve on the foundation of PoW. Namely, Proof of Stake (PoS) uses their respective chain's token to validate the transactions that are processed. In PoS, validators, as opposed to miners, are randomly selected from a pool of validators randomly based on a predetermined algorithm. This requires far less compute power compared to PoW where miners have to compete to add a block. This allows a large number of transactions to be added onto a block and less fees are needed to be able to do so as well. BSC adopts such a consensus mechanism and has seen widespread adoption due to its low cost of transfer fees and barrier to entry in security of network compared to Ethereum.

2.2 Representing Complex Systems as Graphs

Graphs can be an effective way to represent complex systems where entities interact with one another. A graph G can be defined as $G = (V, E)$ where V is set of nodes and E is a set of edges which links represent connections between pairs of nodes. The edges of an undirected graph symbolizes links that can go in both directions: A can be connected to B and B is also connected to A. In contrast in directed graphs, the edges are non commutative and can only go in one direction: either A to B or B to A. Graphs can also be weighted by marking edges with weights which represents a numerical value of a property such as distance, number of interactions etc.

There are different interpretations of the edge and nodes in a graph. For example, in a map, the nodes could represent different locations and the weights between the nodes are the numerical values of the distance between the two locations. For the case of network graphs in cryptocurrency projects, nodes represent unique address that can either belong to an user or a smart contract, and the presence of an edge represent an interaction between the two nodes, and depending on the nature of the node, which could be user or a piece of code, the nature of the interactions could be a simple transfer transaction or a trigger of a complex sequence of contracts.

2.3 Graph Analysis of Cryptocurrency Networks

Cryptocurrency network and graph based analysis are made possible due to the nature of blockchain as a public ledger technology. The transparency of transactions that get recorded on-chain allows for anyone to access these transactions to be studied. Bitcoin has been studied via various graph based analysis to determine behavioral usage of the token [20] as well as to de-anonymize pseudonymous Bitcoin accounts via clustering of these behavioral patterns [15, 37]. Ethereum the is second most popular cryptocurrency network after Bitcoin. Ethereum's ability for operationalize and implement smart contracts have allowed many decentralized application (dApps) to be built on top of the network. The development of the transaction graph was first highlighted by [32] which allowed for the analysis of connections between transaction graph properties as well as price dynamics. Price anomaly prediction and hidden co-movement of tokens were investigated via the concept of persistent homology. Their insight led to the discovery that the ethereum network holds valuable insights to price changes beyond conventional non graph-based analysis. Ethereum transactions have also been modeled with a time-series snapshot network (TSSN) by [61], capturing the spatial and temporal aspects of the network. A temporal biased walk (TBW) algorithm was employed to travese the network which embeds accounts via their transaction records. This was extended further by phising node classifcation and link prediction using graph embedding algorithms. Similar to our research would be [50] which proposes a framework for analysis of Ethereum network under the acronym DANET: A Detailed Analysis of Ethereum Network. That study analyzes the Ethereum blockchain and does not focus on any specific tokens or price dynamics. Our research would constitute a price analysis of tokens component under the framework.

2.4 Network Property Measurements on Cryptocurrency Tokens and Networks

Despite many past work done on the analysis of the network properties of Bitcoin [24, 49], graph based analysis have been better suited for account-based blockchain networks such as Ethereum [13, 58, 65], where interactions can be a transfer of value and/or an execution of a smart contract. ERC20 tokens as a whole on the Ethereum chain has been shown to follow a power-law distribution [58]. ERC20 tokens tend to contain less and smaller hubs compared to social networks and heavy tails in the degree distribution are not as evident when compared to social network. Utility of ERC20 tokens also vary across different cryptocurrency projects which might lead to few projects gaining enough trust from users to survive. This leads to aggregation of big hubs that can diminish the impact on the market dynamics by smaller but more influential nodes. Non-fungible tokens under the ERC721 token standards have also been analyzed in [11], where a systematic analysis of of NFT transactions were conducted and determined to have similar network structures to those measured in social networks.

2.5 Temporal Analysis of the Internet and Social Networks

Web searches have been analyzed in past literature by modeling each web page as a node and forming connections between them as edges [8]. They include popular search engines such a Google, Baidu and Microsoft Bing. These analysis were used to assess the effectiveness of content, marketing campaigns , and trend identification among usage patterns [26, 38]. Social network analysis, similarly, have been modeled as directed graph where the nodes represent users and the edges are connections between them. In the pioneering work at Facebook and Twitter presented in [40], researchers were able to propose a methodology to examine social networks at scale and through topological property measurements, they were able to establish the occurrences of influential and hubs nodes that drive sentiments in a network [10, 46, 56].

2.6 Cryptocurrency Price Analysis and Correlation

Price correlation are often used in the traditional financial markets to interpret the relationship between and within asset classes. Specifically, the minimum spanning tree (MST) has been used to visualize the asset prices in a graph visualization [35, 48]. In the papers, Mantegna state that because correlation coefficient is not a metric, it cannot directly used as a distance in the network. Instead, the correlation coefficients are calculated based on the pairs and then distances is calculated after. In [18], an MST was applied on daily closing prices of the top 50 cryptocurrencies based on market cap determined by CoinMarketCap. Similarly, our project would be employ but on monthly closing prices and on cryptocurrency projects specifically.

Chapter 3

METHODOLOGY

3.1 Proposed Framework of Analysis: GAPNET

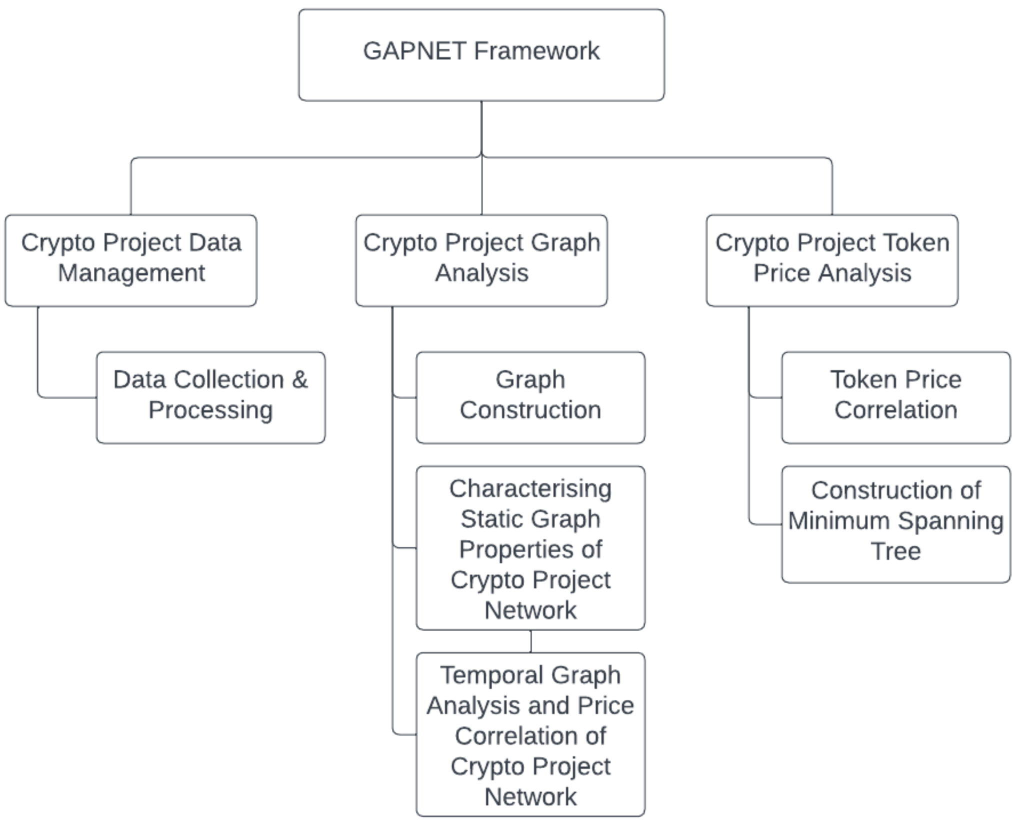

Figure 3.1: Proposed GAPNET Framework of Analysis

Figure 3.1 shows the consolidated framework for analysis of cryptocurrency project network and transactions - GAPNET. It includes 3 main components that are served as a workflow from the beginning where the data is collected and managed till the tokens' price are analyzed. The following sections elaborates on each of the following components in the framework.

3.2 *Cryptocurrency Project Data Collection*

3.2.1 Project Selection

Rank	Project	Category	Smart Contract Address
4	ShibaSwap	Ethereum/DEX/DeFi/Memes	0x95ad61b0a150d79219dcf64e1e6cc01f0b64c4ce
5	ApeCoin	Ethereum/NFT/DAO/Metaverse/Content Creation	0x4d224452801aced8b2f0aebe155379bb5d594381
6	PancakeSwap	BSC/DEX/DeFi	0x0e09fabb73bd3ade0a17ecc321fd13a19e81ce82
7	Decentraland	Ethereum/Solana/Polygon/NFT/Metaverse/Play to Earn	0x0f5d2fb29fb7d3cfee444a200298f468908cc942
8	The Sandbox	Ethereum/Near/Polygon/Gaming/Play to Earn/Metaverse NFT	0x3845badade8e6dff049820680d1f14bd3903a5d0
9	Aave	Avalanche/Polygon/DeFi/DAO/Lending Borrowing	0x7fc66500c84a76ad7e9c93437bfc5ac33e2ddae9
10	1inch Network	Avalanche/BSC/Polygon/DeFi/DEX	0x111111111117dc0aa78b770fa6a738034120c302
11	Metahero	BSC/Gaming/Metaverse/NFT	0xd40bedb44c081d2935eeba6ef5a3c8a31a1bbe13
12	Frax	Avalanche/BSC/Fantom/Polygon/Ethereum/Solana/DeFi/Stablecoin/Lending Borrowing	0x853d955acef822db058eb8505911ed77f175b99e
13	Unus Sed Leo	Ethereum/CEX/Lending Borrowing	0x2af5d2ad76741191d15dfe7bf6ac92d4bd912ca3

Table 3.1: Top 10 Projects from the Certik Leadership Board (17th April 2022)

Projects were selected based on the Certik Leaderboard. Projects that have been audited by Certik would be onboarded onto the security intelligence monitoring platform Skynet. On the platform, Skynet would actively monitor and display on-chain insights of the token smart contracts. The projects are ranked based on 6 security primitives with a score that ranges between 0 to 100. They serves as a indicator for how secure the cryptocurrency projects are. The 6 security primitives are: static analysis, on-chain monitoring, social sentiment, governance & autonomy, market volatility, safety assessment. A brief description of each component is described below:

- Static Analysis - Source code/byecode scanning via static analysis tool suites
- On-chain Monitoring - Utilizing real-time security monitors and intelligence systems
- Social Sentiment - Analyzing social growth, geo-graph and wider sentiment variables
- Governance & Autonomy - Contract checking and activity tracing over decentralized practices

- Market Volatility - Measuring over assets' financial factors and market metrics

- Safety Assessment - Leveraging fact-based and multi-faceted safety evaluations

3.2.2 Profiles of Selected Projects

Shibaswap

Shibaswap [53] is a decentralized exchange (DEX) that is run on the Ethereum blockchain. It is one the projects of the popular Shiba Inu Coin which has found great success as a meme coin due to its close relations to Dogecoin. It provides a means for users to swap token and provide liquidity and also offers other additional features such as staking, governance and an NFT market.

Apecoin

Apecoin is the native coin of the popular Non-Fungible Token (NFT) series Bored Ape Yacht Club (BAYC) [22]. The NFT collect showcases a series of apes that look bored and has the celebrities such as Justin Bieber and Eminiem named as one of the owners of the apes in the collection. Its meteroic rise as one of the must have NFT collections as well as celebrity endorsements and VC backings have allowed Yuga Labs, the creator of BAYC, to price its apes as much as over $400,000. Users can buy Apecoin to participate in governance of the Decentralized Autonomous Organisation (DAO) and also gives them access to exclusive access conventions, merchandises, games and services that has been built in the ecosystem.

Pancakeswap

Pancakeswap [1] is the DEX on the BNB Chain. It was created during the wave of food-theme related projects which saw massive popularity in 2021. On top of its farming and staking capabilities, it offers a lottery systems where users can contribute to a pool for a chance to win the entire lottery. It's fun and gamified style of user interaction has attracted a massive following. The project also lends credibility through the support of Binance.

Decentraland

Decentraland [4] is an online game build on the Ethereum chain with a focus on NFT. It allow users to own digital pieces of real estate, items and other customizable assets to be bought and traded in the game. It runs as a DAO and allow token holders of the native Decentraland token, Mana, to vote on in-game features and policies.

The Sandbox

Much like Decentraland, The Sandbox [41] expands on the metaverse by providing a NFT gaming platform for users to create, sell, use and montetize their own NFTs. Users can create their own NFT characters, make their own games and participate in marketplace activities to trade in-game assets. Users can also advertise on a piece of digital real estate by renting or borrowing LAND, Sandbox's NFT token.

Aave

Aave is a decentralized finance (DeFi) protocol that allows users to lend and borrow digital assets and tokens. Much like traditional finance, interest is incurred or earned when users borrow or lend their digital assets respectively to the protocol. In place of banks, smart contracts act as the intermediary to facilitate those processes such as liquidation, collaterization and approval of loans and borrowing.

1inch

1inch [57] is a Dex Aggregator that scrapes decentralized exchanges like Shibaswap and Pancakeswap to allow users to get the best price when they make a trade of their tokens on the platform. The proliferation of different Dexes with thier own individual methods of determining price allows for the existence of arbitrage which can be exploited by a Dex Aggregator such as 1inch.

Metahero

Metahero [16] is project that is built on the BSC. It combines 3d scanning technology with NFTs. Users are given the ability to turn real life objects into unique avatars and objects in the digital world. Along with its marketplace, users and creators are able to trade music, gaming, and other related digital assets on the platform.

Frax

Frax [21] is an algorithmic stablecoin platform which maintains a peg to the US dollar through its native token (FRAX) by collaterising with USD coin (USDC) and trading of its governance token (FXS), which allows for the maintenance of its market capitalization.

Unus Sed Leo

Unus Sed Leo [59] is a utility token that was created by the company iFinex in response to a financial crisis of its that resulted in the loss of $850 million of the banking services they were using back in 2018. It is used on the Bitfinex exchange as a substitute for trading fees, expands development of the iFinex ecosystem and aims to recoup the monetary loss to stkaeholders back in the crisis it faced in 2018.

3.2.3 Datasets and Environment Setup

The two main types of accounts in found in account-centered model, which all cryptocurrency projects adopt, are namely externally owned accounts (EOA) and contract accounts (CA). An EOA can be thought of as a bank account where users can deposit or draw money from. They record some dynamic state information of the account balance and can create accounts and invoke the function of a smart contracts. CA contains a piece of executable bytecode and is triggered when the predefined conditions are met. It is additionally able to maintain state information like the hash value of the bytecode of its account balance. The figure (to be added) below show the three main types of functions that transaction in smart contract enabled blockchains such as Ethereum or BSC can complete. They are namely money transfer, contract creation, and contract invocation [60].

The main aim of this research is to analyze the graph properties of a set of cryptocurrency projects in a specific time frame. This includes all transactions logged in the time period between between April 2021 to March 2022 in the span of one year. Some of the sizes of the graphs collected exceeds 100 thousand nodes and edges and most modern python libraries are not equipped to deal with visualization of such graphs which is the most memory intensive task in the framework. As such, the open source dedicated large graph network visualization and analysis tool, Gephi, was used in order to carry out the visualization and analysis. This would allow users without access to cloud computing powers to have access to such network analysis easily. The experiments in the study was conducted on on 16-inch Macbook Pro 2019 with a 2.3Ghz 8-Core Intel Core i9, 16Gb 2667 Mhz DDR4 RAM, and an Intel UHD Graphics 630 1536MB graph card. NetworkX, python Igraph and Networkit libraries were used for the analysis on top of Gephi.

3.2.4 Data Extraction

Data was collected via CertiK's cloud-based data warehouse. In practice, the data collected is not proprietary as all transaction that happen on a blockchain belong on a public ledger and can be readily collected via syncing to the respective blockchain nodes. In fact, Google's BigQuery contains publicly available Ethereum dataset that can be queried in order to get the respective projects to be analyzed based on their smart contract addresses. The data collected from the Ethereum and Binance Smart Chain transaction data was from "2021-04-01" to "2022-03-31" for the listed projects in table 3.1.

3.2.5 Data Processing

Raw data collected from the data warehouse is processed into two files, one that contains the list of unique nodes as well as an edgelist, in preparation for analysis. In order to establish the nodes and edges, only the two columns - FROM_ADDRESS and TO_ADDRESS are considered in our research. In the research, Gephi, an open-sourced network analysis and visualization software is used to conduct network visualization as well as to determine network properties of the graphs.

Figure 3.2: Data Processing from Raw Transaction Data

3.3 Transaction Graph Analysis

Transaction graphs [42, ?] are where the vertices represent addresses and edges represent transactions between the two addresses. These addresses could belong to an EOA or CA. More formally, the transaction graphs of the projects are an attributed directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V} = \{v_1, v_2, v_3, \ldots, v_n\}$ and $\mathcal{E} = \{e_1, e_2, e_3, \ldots, e_m\}$ where $n = |\mathcal{V}|$, $m = |\mathcal{E}|$. Finally, $e = (u, v, w)$ is defined where u and v represent two vertices in $\mathcal{V}$, and w represents the weight of the edge between u and v.

3.3.1 Definitions of Network Properties and Measurements

Monthly Transaction Graph(MTG) *[42] refers to the graph that a particular token has had activity in in the form of a transfer of said token. It is represented in the form* $MTG_n = (V_n, E_n)$ *where* V_n *contains the set of nodes in the graph and each* $v \in \mathcal{V}_n$ *refers to an address (either an EOA or CA) that appears in the (n+1)-th month since the stipu-*

lated beginning of the chosen time period of the activity of that coin. E_n *represents the set of edges of the graph where each edge* $e = \{v', v''\}$ *shows the transfer between two vertices* $v', v'' \in \mathcal{V}_n$

Cumulative Monthly Transaction Graph (CMTG) *[42] refers to the graph of each coin that is represented in the form* $CMTG_n = (V_{C_n}, E_{C_n})$ *in which* V_{C_n} *and* E_{C_n} *are its set of nodes and edges respectively.*

$$V_{C_n} = \bigcup_{i=0}^{n} V_i, \text{ where } V_i \text{ is the set of nodes of } MTG_i \tag{3.1}$$

$$E_{C_n} = \bigcup_{i=0}^{n} E_i, \text{ where } E_i \text{ is the set of edges of } MTG_i \tag{3.2}$$

Temporal Graph Measurements

Relative Growth Rate *[42] in the time period* $[t1, t2]$ *is calculated using the following equation:*

$$RGR = \frac{lnS_2 - lnS_1}{t2 - -t1}, \text{ where } S_i \text{ is the size at time } t_i \tag{3.3}$$

Repetition Ratio *[33, 42] refers to the ratio of the of the repetitive nodes or edges in the MTG in a month compared to the previous month. The reptition ratio of the nodes in the n+1 -th month is defined as follows:*

$$RR_{V_i} = \frac{n(V_{MTG_i} \cap V_{MTG_{i-1}})}{n(V_{MTG_i})}, \text{ where } V_{MTG_i} \text{ is the size of the node set of graph } MTG_i \tag{3.4}$$

Similarly, the repetition ratio of the edges in the n+1 -th month is defined as:

$$RR_{E_i} = \frac{n(E_{MTG_i} \cap E_{MTG_{i-1}})}{n(E_{MTG_i})}, \text{ where } E_{MTG_i} \text{ is the size of the node set of graph } MTG_i \tag{3.5}$$

Density *[42] represents the ratio between the edges present in a graph and the maximum number of edges that graph can obtain. For the graph with node set V and edge E, it can be defined by the formula:*

$$D = \frac{2 \times n(E)}{n(V) \times (n(V) - 1)} \tag{3.6}$$

Global Network Properties

Reciprocity *[11, 42, 52] is a measure of the likelihood of vertices to be mutually linked. It is defined as the ratio of the number of arcs that points to both directions, to the total of number of arcs in the graph. It serves as a way to observe the tendency of a vertex to respond to another vertex stimulus in a communication network.*

Assortativity (ρ) *[11, 42, 52] measures the preference of vertices getting attached to other vertices that are similar in graph properties such as vertex degree. Assortativity, ρ lies in the range: $-1 \leq \rho \leq 1$. A network is assortative (ρ tends to 1) when the high-degree vertices are, on average, linked to other vertices with low degree. A netwokr is disassortative (ρ tends to -1) when, on average, high-degree vertices are linked to vertices with lower degree.*

Average Clustering Coefficient (ACC) *[11, 42, 52] refers to the means of the local clustering coefficients of all the vertices in the graph. It is also sometimes referred to as* ***transitivity****. Clustering coefficient measures the tendency of a graph vertice to create a cluster with other vertices in the graph. It is defined as:*

$$C = \frac{3 \times \text{number of triangles}}{\text{number of triads}} \tag{3.7}$$

A triad is a set of.3 nodes that at least two pairs of them are connected. A triangle is a set of 3 nodes that all three pairs of them are connected and each triangle is consisting of

3 triads [47]. Similarly, the average clustering coefficient can be defined as:

$$\overline{C} = \frac{1}{n}\sum_{i=0}^{n} C_i \tag{3.8}$$

Average Shortest Path Length (ASPL) *[11, 42, 52] refers to the average number of steps along the shortest paths for all possible pairs of network nodes. The shrotest path can be computed by using the classic Dijkstra's algorithm [17], and the procedure is iterated for n*(n-1) times in the worst case.*

Small World Coefficient *(σ) [52] is a metric that is used to characterises a small network. In practice, the ACC and ASPL are compared with a random graph created with the same number of nodes and edges. A graph can be said to show small world properties if, compared to a random graph of the same size, the ACC is higher and the ASPL similar or smaller. The small world coefficient is defined by:*

$$\sigma = \frac{\frac{C}{C_r}}{\frac{L}{L_r}} \tag{3.9}$$

In the definition above, C refers to the ACC of the selected graph and C_r is the corresponding ACC of the random graph. Similarly, L is the ASPL of the selected graph and L_r is the ASPL of the random graph. The higher the σ of the analyzed graph, the more defined its small world behavior is. In this research, the random graph is generated using the Erdos-Renyi model in Gephi.

3.4 Token Price

By investigating the correlation between the cryptocurrency projects through their token price, we are able to apply a more sophisticated network tool such as the Minimum Spanning Tree (MST) algorithm in order to detect clusters between connections of data patterns [63]. A correlation matrix of the monthly closing prices of the selected tokens from the stipulated time period is generated. These correlation values are assigned to edge weights and the correlations between the tokens can be converted to an edgelist. In this framework, Kruskal's Algorithm is employed to construct the MST.

3.4.1 Minimum Spanning Tree

A MST reduces the edges down to a subset of edges which connects all the nodes together, without any cycles and with the minimum total edge weights. Therefore, the MST graph is the connection of all the tokens with the minimum total correlation values. This essentially provides a skeleton of the graph by minimising the number of edges and reducing the clutter in the network graph. By looking at the MST, an investor could potentially identify if the set of cryptocurrency that they are interested in have similar risk and identify cryptocurrency projects that show few correlations with the others, and investigate them as potential opportunity for diversification.

Chapter 4

RESULTS

4.1 Characterising Graph Properties of Selected Projects

4.1.1 Graph Visualization

Figure 4.1: Network Visualization of the Cryptocurrency Project 1inch

Rank	Contract	Name	Type
1	0x26aad2da94c59524ac0d93f6d6cbf9071d7086f2	Uniswap V2: 1INCH 10	Contract Address
2	0x71660c4005ba85c37ccec55d0c4493e66fe775d3	Coinbase 1	Exchange Wallet
3	0x28c6c06298d514db089934071355e5743bf21d60	Binance 14	Exchange Wallet
4	0x2faf487a4414fe77e2327f0bf4ae2a264a776ad2	FTX Exchange	Exchange Wallet
5	0xee262adcd9ecc0476452e302cf3c822f634dafaf	CulmulativeMerkleDrop	Contract Address
6	0x2057cfb9fd11837d61b294d514c5bd03e5e7189a	Unknown	Contract Address
7	0xe931b03260b2854e77e8da8378a1bc017b13cb97	Uniswap V3: 1INCH2	Contract Address
8	0xA0446D8804611944F1B527eCD37d7dcbE442caba	GovernanceMothership	Contract Address
9	0x76f3cf8d1b1335bfccc89ea81ab761ebe34db810	Unknown	Unknown
10	0xb7f830845e9f385372ae6fb160aa968908f5bfbc	Unknown	Unknown

Table 4.1: 1inch Top 10 Highest Degree Node in March 2022)

The main static graph properties based on the data collected previously will be discussed. The month of March 2022 was used as a sample of the entire network graph of the respective cryptocurrency project.

4.1.2 Static Transaction Graph Characteristics

Projects	Nodes	Edges	Diameter	Mean Distance
Shibaswap	236648	272541	14	30.474
ApeCoin	85982	161177	20	9.917
PancakeSwap	374334	982293	24	22.733
Decentraland	37815	47992	23	5.096
The Sandbox	39837	59131	15	5.043
Aave	14644	20414	16	5.469
1inch Network	8448	12381	18	5.91
Metahero	26855	34178	12	3.201
Frax	3049	7329	11	4.053
Unus Sed Leo	154	161	11	4.513

Table 4.2: Network Graph Statistics for Each Cryptocurrency Project in Terms of Number of Vertices, Edge, Diameter and Mean Distance of the Month March 2022

Network	Alpha		Diameter	Mean Distance
	Outdegree	Indegree		
Web [8]	2.09	2.67	905.00	16.20
Social Networks [40]	1.80	1.63	22.66	5.55
ERC-20 Tokens [13]	2.80	2.60	-	2.00

Table 4.3: Power-Law Coefficient, Diameter and Mean Distance of Web, Social Network and ERC20 Token Networks from Past Works

Basic Graph Properties

For the analysis, only transactions between EoA and transaction from EoA to CA are considered. This is done so as the main objective of the paper is to investigate the interactions between users and the selected cryptocurrency projects, much like the interactions observed in other social networks. Table 4.2 summarizes graph measurements of the selected crytocurrency project for the month of 2022 in terms of number of nodes, edges diameter and mean distance. The graphs were visualized under appendix A to better observe the structure. The network graph of 1inch is illustrated in figure 4.1 as an example. The size of each node is proportional to its weighted degree, which implies that the node has many transactions coming in and going out of the address. The nodes are clustered and colored based on the communities detected using the Louvain method [5] and the circular pack layout is selected to better segregate the graphs into its communities. It is interesting to note that the diameter and mean distance of the analyzed projects are similar to the ones observed in social networks that were measured in [40], with the exception of shibaswap, apecoin, and pancakeswap with mean diameters that are much higher than the ones observed in the other projects. This could be due to respective spikes in network usage due to launches of new initiatives and projects for those projects in the month of March. For PancakeSwap, an annoucement by binance of the launch of a 'mini-program' saw its native token CAKE rally by 27% [31]. New partnerships with payment gateways for ShibaSwap allowed for increased usage of its native token SHIB [39]. Lastly, ApeCoin saw increase interest and hype coming into the launch of their native token APE in March 2022 and saw its price soar by 90% on its second day of trading [30].

General Topological Properties

One can see through the graph visualization that there exists multiple large nodes that serve as hubs within and outside of its communities. The distribution of the fundamental property that determine the size of these nodes, in and out-degree, can provide insights into the usage behaviors of the cryptocurrency project. A high indegree would suggests higher inflow of transactions. If this is EoA that is owned by a user, this could suggest that the user is accumulating more tokens. A high outdegree could suggest outflow of transactions which might suggest tokens being exchanged for other tokens and a loss of interest in the token. In real world networks like social media and the World Wide Web, the degree distributed are highly skewed and long-tailed, indicating a significant portion of information about node interactions need to be extrapolated from the analysis of their tails. This would also suggest the existence of high degree hubs. In Ethereum ERC20 Token Networks shown in [58], these high degree hubs are often exchanges. This is congruent with the top 10 highest degree nodes found in all the projects in appendix B. Table 4.1 shows an example of the top 10 highest degree nodes in the project 1inch in the month of March 2022. Other then the unknown names, which could point to large whale wallets or developer wallets that hold a large number of the 1inch coin, the other contract addresses all point to a centralized exchange wallet or a decentralized exchange smart contract that degrees exchanges of the coin. It is interesting to note that for projects Aave and Frax, they include arbitrage bots in their top 10 most influential nodes. This is due to the nature of Aave being a liquidity protocol and Frax being an algorithmic stable coin implementation. Both projets require some level of arbitrage in order to achieve equilibrium. In the case of Aave, it is constantly balance the ratio of liquidity in the liquidity pools and for the case of Frax, it involves pegged the stablecoin to the 1 USD valuation. Unknown Wallets could often point to wallet addresses that are owned by the projects and have not been labelled. Alternatively, they could also belong to institutions or anonymous large holders of the tokens. Additionally, multisig wallets are also used by institutions to hold large amount of the tokens The power law degree distribution is something that is observed in numerous networks [58, 40, 8, 60]. It follows the form of $p(x) = Cx^{\alpha}$, where the dependent variable, the probability for a node

Projects	Input			Output		
	alpha	p	stat	alpha	p	stat
Shibaswap	1.790	<0.001	0.497	2.878	<0.001	0.494
ApeCoin	2.274	<0.001	0.492	2.818	<0.001	0.492
PancakeSwap	2.725	<0.001	0.497	1.691	<0.001	0.498
Decentraland	1.839	<0.001	0.474	1.811	<0.001	0.488
The Sandbox	1.789	<0.001	0.484	1.839	<0.001	0.485
Aave	1.892	<0.001	0.476	1.792	<0.001	0.476
1inch Network	1.942	<0.001	0.450	1.888	<0.001	0.456
Metahero	1.911	<0.001	0.491	1.774	<0.001	0.492
Frax	2.027	<0.001	0.454	1.756	<0.001	0.454
Unus Sed Leo	2.647	<0.001	0.376	3.530	<0.001	0.415

Table 4.4: Power Law Values and Kolmogorov-Smirnov(KS) Test Statistics of Selected Cryptocurrency Project

to have a degree k, varies inversely to the power of the independent variable degree x. The parameter α refers to the coefficient of the power law and typically ranges from $2 \leq \alpha \leq 3$. The complementary cumulative distribution function (CCDF) of the in and out-degree, and the cumulative distribution function (CDF) of the in-degree to out-degree ratio for the selected cryptocurrency projects is shown in Figure 4.2. Table 4.4 shows the corresponding power law coefficient for the projects analyzed along with the Kolmogorov-Smirnov (KS) goodness-of-fit statistics. There is a mix in the results obtained in the approximation of the best-fit power law distribution as some projects' α fall outside the typical range. It is noted that in some cases, scale free networks that follow a power law distribution might might occasionally fall outside of the bounds between 2 and 3 [45, 14].

Table 4.5 shows the power law estimates, diameter and mean distance of the web network graph [8], social network graph [40] and global ERC20 token network [13]. For the social network graphs, the values reported represent the averages for the social network website Flickr, Livejournal and Youtube. In [13], it was worth noting thata number of the ERC20 tokens do not follow a power-law distribution which is contrary to the what is reported in my study. This could be due to the nascent tokens that were studied in 2018 which is the year that the research paper was published compared to 2021 and 2022 where the cryptocurrency sector has grown exponentially since with a higher adoption and maturity

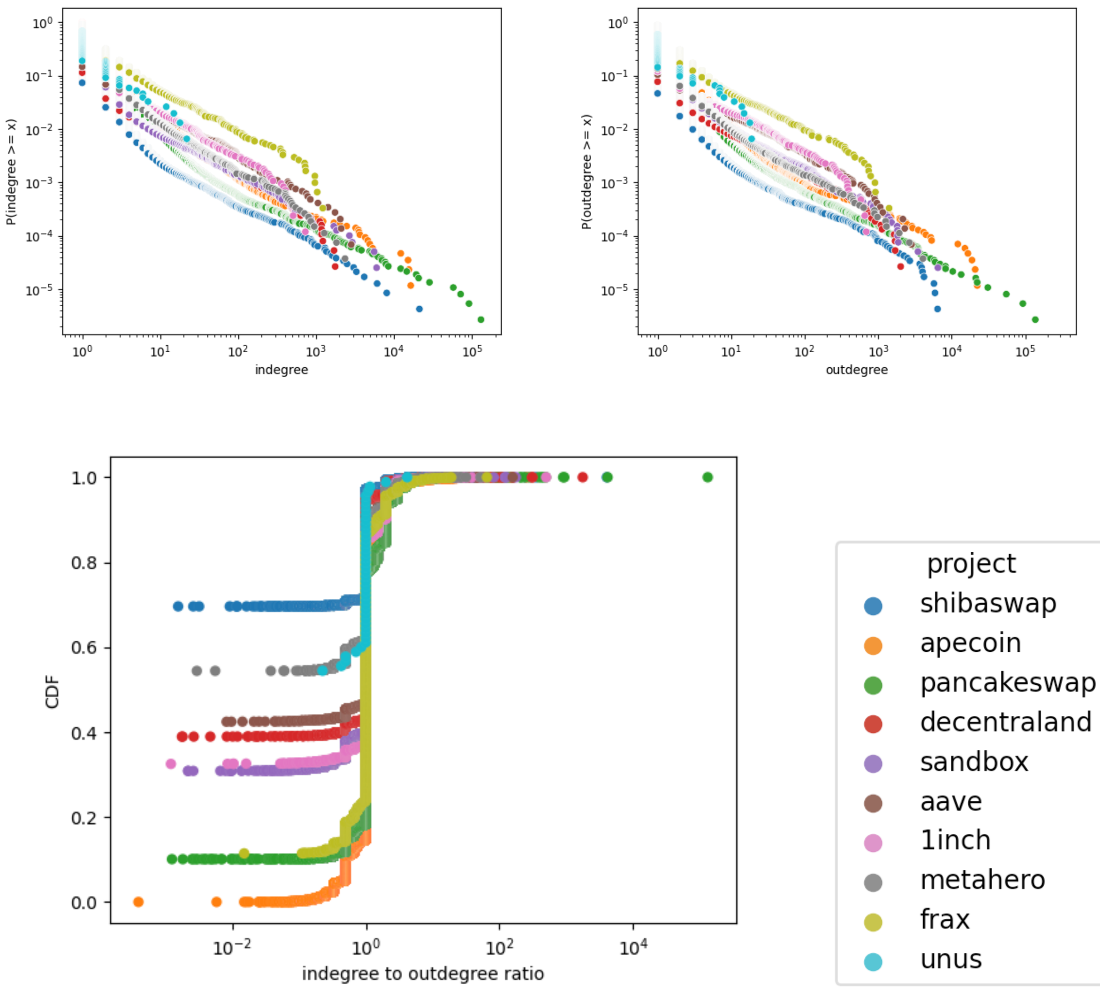

Figure 4.2: Degree Analysis of Selected Projects. CCDF of In and Out Degree and CDF of In-degree to Out-degree Ratio

of users. Power law distributions as shown in the top panel of figure 4.2 shown similar patterns across all the selected projects.

The in and out-degree of each node in the projects are analyzed as well. They serve as an indicator to the ratio between accumulation and exchange of the token for other tokens for the various wallets that make up the network. Past studies on the distribution of in and out degree of web networks have helped in identification of better methods to obtain relevant information on the web. Web influencers can be compared to users that accumulate the selected tokens. In web networks, the population that are active and have a high out-degree is different from the population of pages that are popular and have a high in-degree. This is pointed out in [13], where web search techniques that made use of in and out degree were used to separate a small set of popular pages from larger set of active pages. In the bottom panel of figure 4.2, the cryptocurrency project networks show a large number of active nodes with low in to out degree ratios, wallets selling tokens, and a limited number of nodes with a high ratio, wallets accumulating token. For all figures in the research, the colors will follow the legend as in Figure 4.2

Connectivity and Clustering Properties

Projects	Reciprocity	Transitivity	Assortativity
Shibaswap	0.02376518	0.017	-0.3731695
ApeCoin	0.15855831	0.156	-0.4019779
PancakeSwap	0.21824911	0.027	-0.3382954
Decentraland	0.02941913	0.021	-0.1871982
The Sandbox	0.12439462	0.06	-0.3241415
Aave	0.04953409	0.02	-0.2821155
1inch Network	0.04997978	0.02	-0.3610943
Metahero	0.22096085	0.075	-0.4088052
Frax	0.23062227	0.113	-0.3367015
Unus Sed Leo	0.04968944	0.008	-0.3114861

Table 4.5: Summary of Graph Connectivity and Clustering Measures of Selected Cryptocurrency Project

Table 4.5 illustrates the reciprocity, transitivity and assortativity of the selected cryptocurrency projects. The reciprocity coefficient measures the proportion of mutual connections on a direct graph. In other words, it estimates the probability that given an edge $e(v_i, v_j)$, then its reciprocal $e(v_j, v_i)$ also exists. In the table, it can be seen that it most reciprocity levels tends to zero, which indicates that the accumulation and selling of the token are usually made in one direction and exchanges between wallets are uncommon. The transitivity coefficient is a measure of the probability for adjacent nodes of a network to be connected - if there is a link $e(v_i, v_j)$ and a link $e(v_j, v_k)$, what is the probability of there being a link $e(v_i, v_j)$. Once again, the transitivity levels of the projects tend to zero. This indicates that collaboration between wallets is uncommon. Lastly, assortatitvity measures how nodes are connected with respect to a given property. All the projects show negative assortativity levels and most fall within the weakly dissortative range except for Decentraland which is neutral associative. Figure 4.3 shows the CCDF of pageranks and

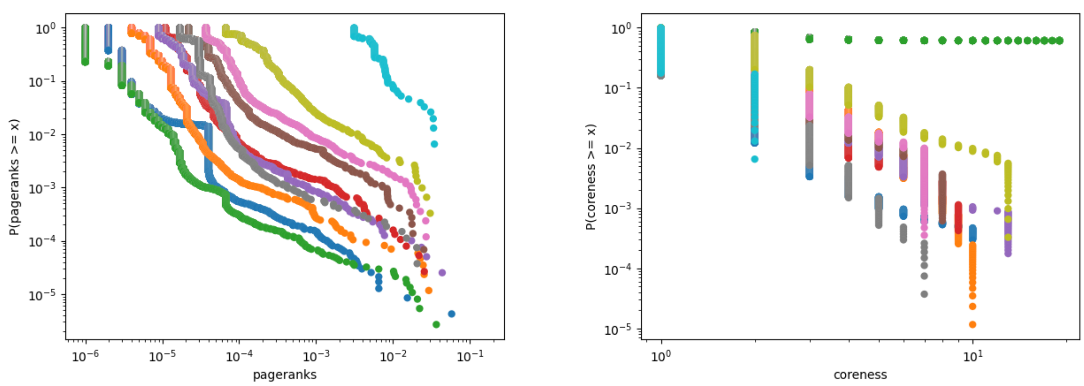

Figure 4.3: CMTG Graphs of Selected Projects from April 2021 to March 2022

coreness value for the cryptocurrency projects considered. The distribution of pageranks [7] estimates the importance of each node. Through the top panel of the figure, we are able to see the emergence of nodes that are more important than others. Coreness, on the other hand, is measure that is used to identify closely interconnected groups within a network. The bottom panel of the figure illustrates that most networks have a core around 10 albeit with low probability except for the Pancakeswap which shows a consistently high probabiltiy of cores greater than 10. Even though it is likely that influencer nodes are high coreness nodes, the inverse might not be true where high coreness nodes are influencers, as seen in [34].

Projects	Nodes	$\|E\|/\|N\|$	ASPL Ratio	ACC Ratio	σ
Shibaswap	236648	1.15	14.55	1913.55	131.55
ApeCoin	85982	1.87	3.18	4736.52	1487.77
PancakeSwap	374334	2.62	5.17	1495.66	289.16
Decentraland	37815	1.27	2.25	1032.60	458.75
The Sandbox	39837	1.48	2.24	688.38	307.54
Aave	14644	1.39	2.26	135.18	59.89
1inch Network	8448	1.47	2.41	137.61	57.14
Metahero	26855	1.27	1.42	474.71	334.12
Frax	3049	2.40	1.08	73.95	68.73
Unus Sed Leo	154	1.05	2.35	0.82	0.35

Table 4.6: Comparison of Small World Properties Among Cryptocurrency Projects

Small World Property

The results in table 4.6 show that all the transaction graphs of all the analyzed cryptocurrencies exhibit small world property except for Unus Sed Leo. Some of the small world properties in the cryptocurrencies are more pronounced than others. Apecoin, by far, showed the highest σ value. The presence of small world property could be due to a the role of smart contracts in the cryptocurrency projects which allows interactions amongst groups of users, thereby becoming common network networks to the users, and also the presence of exchanges that serve as hubs for wallets to buy and sell tokens.

4.1.3 Temporal Topological Properties

In this section, we present the time series analysis of the size of MTG and CMTG graphs and investigate its correlation to the price action of the selected projects. As Apecoin was only introduced at the tail end of February 2022, its time series analysis will be excluding in the following study.

In figure 4.4, we illustrate the number of nodes and number of edges in the MTG graph respectively. Most cryptocurrency projects observe a relatively stable or slight growth in their month over month sizes over the past 12 months from April 2021 to March 2022. As

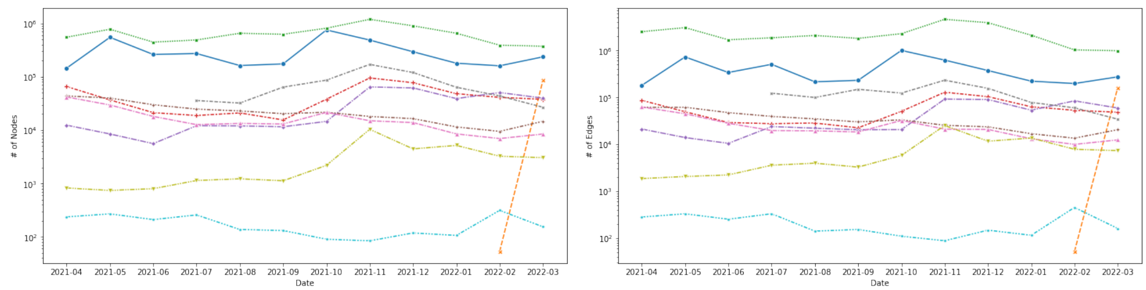

Figure 4.4: Size of MTG Graph (Number of Nodes and Edges) Over Time From April 2021 to March 2022

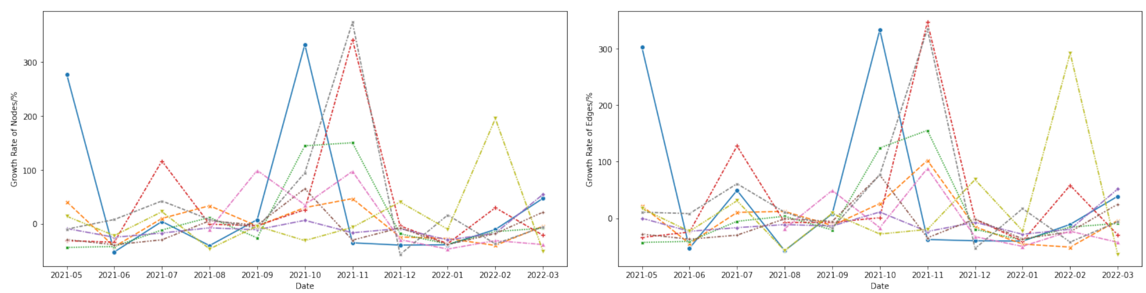

Figure 4.5: Relative Growth Rates of MTG (Number of Nodes and Edges) Over Time From April 2021 to March 2022

the native token for ApeCoin was only introduced in February 2022, it saw a hugh spike in the number of nodes and edges added in its first month. It is noted from the months of September 2021 to November 2021, there was an sharp increase for most projects which coincided with the peak of the price of bitcoin of around $68,000 in the month of November 2021. We can observe that most cryptocurrency projects had the highest addition of nodes and edge during or around this period. This is inpart due to an increase interest in users wanted to buy/sell their respective coins as their coin price increases as well, leading to an increase generating of addresses (nodes) and transactions (edges). This coincides with the huge spikes in growth rate in figure 4.5 where we saw growth rates of nodes and edges as high as 3 times the amount the month before in the cryptocurrency projects ShibaSwap, Decentraland and Metahero.

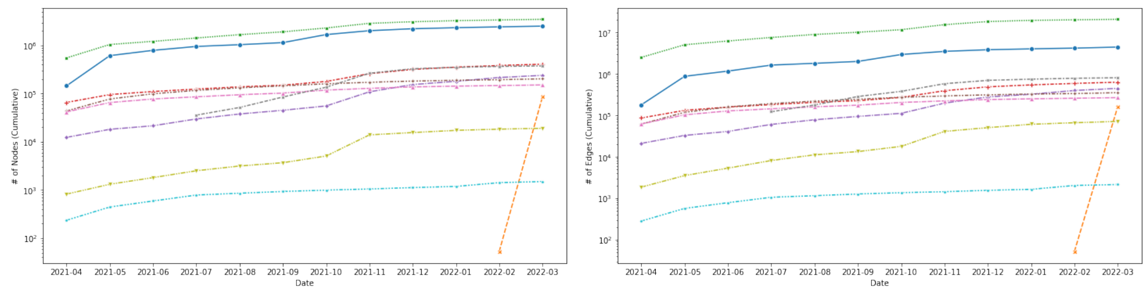

Figure 4.6: Size of CMTG Graph (Number of Nodes and Edges) Over Time From April 2021 to March 2022

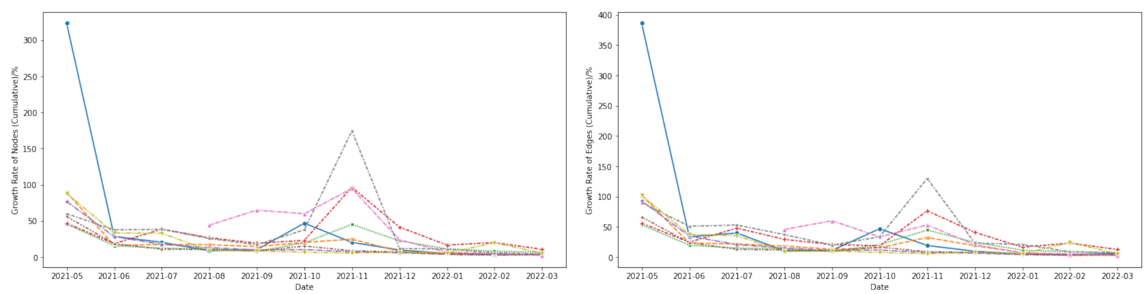

Figure 4.7: Relative Growth Rates of CMTG (Number of Nodes and Edges) Over Time From April 2021 to March 2022

Similarly, we looked at the number of nodes and edges in the CMTG graph over time as shown in Figure 4.6. The charts show a monotonically increasing chart due to the cumulative nature of the CMTG graph. Cumulative growth rate was an overall decrease in growth from the start to the end, showing a decrease in growth rate of the networks at the start of April 2021 to March 2022. Once again, in the periods from September 2021 to November 2021 saw a spike in the growth rate which coincided with the peak of Bitcoin in October 2021.

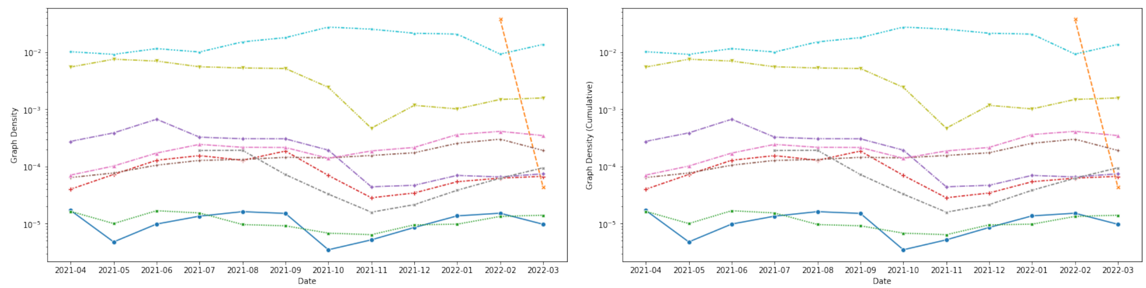

Figure 4.8: Graph Density of MTG and CMTG Over Time from April 2021 to March 2022

Graph density of the transaction graphs were also considered. In figure 4.8, the graph density of the MTG and CMTG graphs are plotted over time. Most cryptocurrency projects show a steady trend in graph density or a slight dip over time. This was once again more significant in the months of September 2021 to November 2021 where most projects saw a dip in their graph densities as the price of bitcoin reached its peak. This can be justified by the increase in new addresses that are created as more users become interested in cryptocurrencies in general and are looking to invest in the market as the price of bitcoin reaches a new high, which in turn reduces the density of the transaction graphs. As the price peaks, the decreasing trend of the graph densities for both graphs slows down or stops completely, and continues overtime on a downward trend as the new accounts created stop transacting or are discouraging after bitcoin peaks and decreases in price, leading to a loss in graph density.

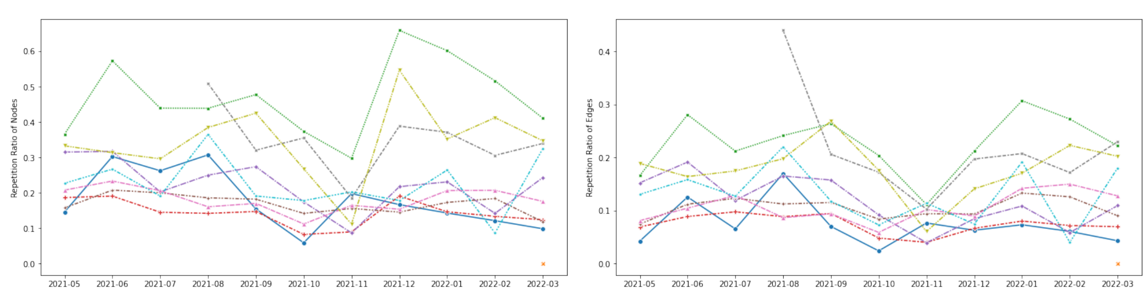

Figure 4.9: Repetition Ratio of MTG (Number of Nodes and Edges) Over Time from April 2021 to March 2022

Lastly, the repetition ratio of nodes and edges in each month compared to its previous month was analyzed on the transaction graphs in figure 4.9. This metric looks at the percentage of accounts that had transacted this month in relation to the accounts that transacted the previous month. If this value is closer to 1, that implies that the network is small as there are no new addresses or new transactions that are being made. Only the MTG graphs are considered because in CMTG, the cumulative nature of the nodes and edges would lead to duplication in the previous months. In figure [], the repetition ratio of the number of nodes and number of edges of the projects chosen are plotted. It is observable that the node repetition ratio for PancakeSwap reaches 0.6 on December 2021 which is a relatively large value for this metric. This could be due to the nature of PancakeSwap as a yield farming protocol where users can deposit their tokens and earn interest through allowing their tokens to be used in DeFi activities within the project such as liquidity providing. Other projects employ different strategies in order to leverage on the protocol and maximise returns for themselves. As a result of repeated calling of the smart contracts of PancakeSwap by the same wallet addresses, the repetition ratio of the nodes are of such a high value. The presence of a robust monthly burning mechanism employed by PancakeSwap is also another reason that might be the case. As PancakeSwap is an inflationary token that has unlimited supply, a burning mechanism is introduced into its tokenomics in order to regulate the supply of the token and maintain a healthy value on its total marketcap. This is seen in how the burn address is part of the top 10 highest degree nodes in appendix A. Similarly, we see the protocol contract "PancakeSwap: SYRUP Token" as the top highest degree node, where users and other cryptocurrency leverage this contract through multiple time calling and recalling of this contract in order to maximise returns on their yield farm by reinvesting their returns back into the existing principal, thereby compounding the value of their returns.

4.2 Correlation of Transaction Graph Properties to Price Action

After the above transaction graph analysis is conducted, I look at the correlation of the metrics studied with their respective token price. The Pearson's Correlation Coefficient is conducted between the metrics as well as the monthly ending price of the selected projects from April 2021 to March 2022. The below tables summarizes my finding.

MTG Graph Property and Token Price Correlation					
Projects	Node	Edge	Density	RR (Nodes)	RR (Edge)
Shibaswap	0.661	0.641	-0.680	-0.613	-0.507
Apecoin	-	-	-	-	-
Pancakeswap	0.063	0.228	0.204	-0.443	-0.325
Decentraland	0.789	0.802	-0.776	-0.523	-0.817
Sandbox	0.902	0.802	-0.796	-0.671	-0.805
Aave	0.736	0.726	-0.862	0.074	-0.443
1inch	0.788	0.765	-0.839	-0.641	-0.868
Metahero	0.786	0.776	-0.747	-0.759	-0.723
Frax	0.482	0.477	-0.856	0.377	-0.293
Unus	0.180	0.154	-0.033	-0.199	-0.248

Table 4.7: MTG Graph Property and Token Price Correlation

For the metrics analyzed in the MTG, the changes in size of node and edge showed a positive correlation to the price action while density and the repetition ratio for nodes and edges mostly showed a negative correlation with a few exceptions. Unus Sed Leo showed no relation between the metrics studied and its price action in the stipulated time period. PancakeSwap showed similar relationships as well albeit performing slightly better in the metric using repetition ratio. For the other cryptocurency projects, a moderate to strong relationship was discovered between the MTG metrics analyzed as well as their respective price action. It is worth noting that the node repetition ratio metric for Aave performed much worse compared to the rest of the graph properties analzyed.

The metrics analyzed in the CMTG graph showed promising relationships with their respective price action with all metrics showing a relationship except for the size of the CMTG edge in the project Metahero. When it comes to the nature of the relationship, whether the metrics is generally positive or negative, varies within the metrics themselves. As compared to MTG, the node, edge and density metrics for CMTG can either be positive or negative depending on the cryptocurrency projects themselves, highlighting the cumulative nature of the values in the metric. Most metrics show either a moderate to strong relationship with their respective project price action and all projects had at least one metric that performed in the moderate to strong relationship band of correlation.

CMTG Graph Property and Token Price Correlation			
Projects	Node	Edge	Density
Shibaswap	0.543	0.478	-0.445
Apecoin	-	-	-
Pancakeswap	-0.375	-0.368	0.873
Decentraland	0.678	0.644	-0.680
Sandbox	0.668	0.601	-0.741
Aave	-0.634	-0.580	0.753
1inch	-0.450	-0.391	0.704
Metahero	0.285	0.108	-0.511
Frax	0.651	0.631	-0.740
Unus	0.765	0.808	-0.576

Table 4.8: CMTG Graph Property and Token Price Correlation

4.3 Token Price Analysis using Graph Networks

In this section, token price of the selected cryptocurrency projects are analyzed and correlated to another to determine how interconnected their price actions are to one another and later on, employ a minimum spanning tree graph to find tokens that are most and least correlated to another.

4.3.1 Determining Price Correlation

Firstly, we visualize the correlation of the token prices of the projects analyzed through a heatmap. The heatmap is colour coded using a divergent colour scale where strong positive correlations (correlation = 1) are dark green, uncorrelated assets are yellow (correlation = 0) and negatively correlated assets are red (correlation = -1). The monthly token prices of each token was used as the price, and the last 12 months of the different token prices were taken. Additionally, Bitcoin, Ethereum and Binance Coin were also added into the heatmap in order to act as a reference as the token prices are largely related to their much larger 'parent' token.

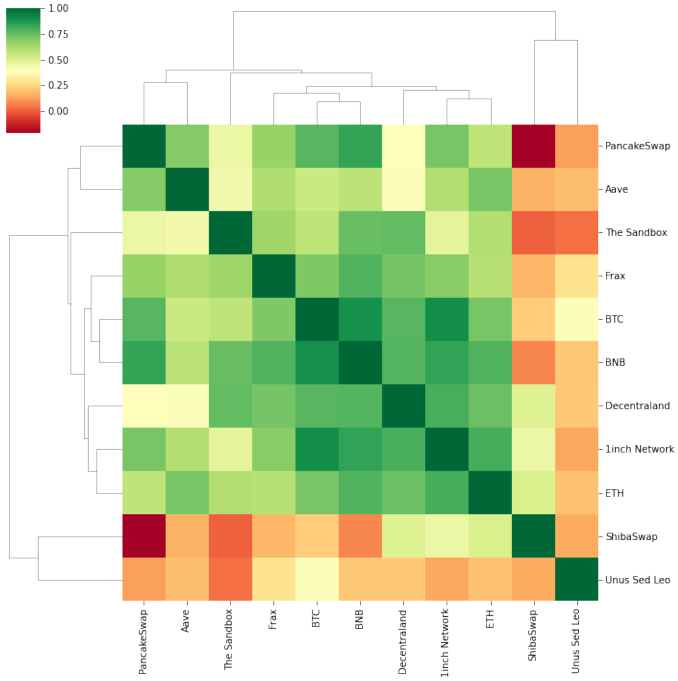

Figure 4.10: Token Price Correlation of Selected Projects and BTC, ETH and BNB

Two cluster emerge from the heatmap - ShibaSwap and Unus Sed Leo are uncorrelated with the other tokens analysed. Shibaswap status as a meme token due to its likeness to the popular Doge coin seems to suggest that it has very little price correlation to the other tokens. This along with its various publicity stunts such as sending half of its token suppy to Vitalik Buterin and aligning itself with reliefs such as the India Covid-19 Relief fund has allowed it to gain widespread popularity amongst investors. The token also has a leg up over the original meme token Doge Coin with its integration of a Dex, DAO and various staking and burning mechanism. Unus Sed Leo Token was founded by iFinex and launched a a bid to make up for the financial shortfall that was caused by the seizing of funds by the governent of the payment processing company Crypto Capital. It includes a unique burn mechanism and buy back scheme in order to make back the money that was lost as such, it is often not used solely as a speculative asset

4.3.2 Constructing Minimum Spanning Tree

Projects	Average Monthly Return/%	Average Monthly Volatility/%
ShibaSwap	23.2	77.8
ApeCoin	-	-
PancakeSwap	-14.0	31.4
Decentraland	5.1	52.9
The Sandbox	15.4	64.0
Aave	-6.9	26.8
1inch Network	-10.5	31.3
Metahero	-	-
Frax	11.1	59.6
Unus Sed Leo	8.0	14.7

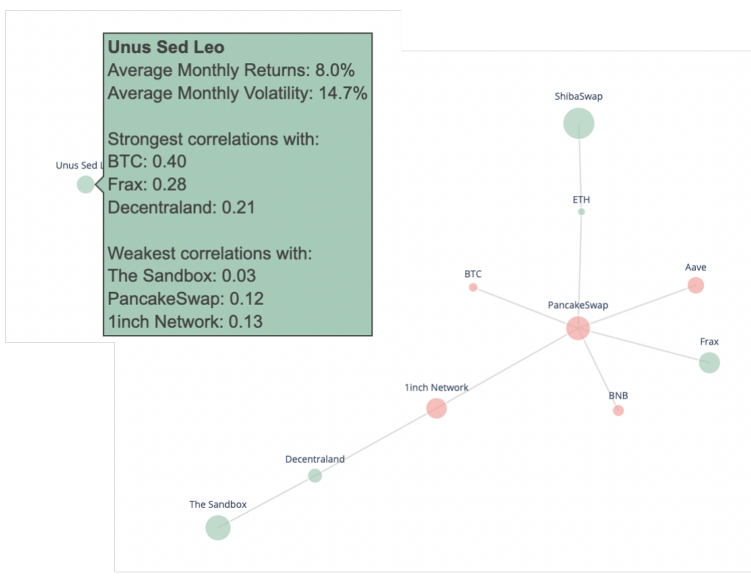

Figure 4.11: Minimum Spanning Tree of Selected Projects and BTC, ETH and BNB

The average monthly returns and average monthly volatility are further calculated to determine the average return of investments and the dispersion of returns if users had invested in the closing monthly price of the token for the past 12 months. The minimum spanning tree is subsequently constructed based on the correlation matrix determined using the heatmap. From the minimum spanning tree, we can see the Unus Sed Leo is separate from the main branch which contains the other tokens that were considered. Bitcoin and Ethereum ShibaSwap return the highest average monthly return out of the other projects. It also has the highest average monthly volatility.The Tokens PancakeSwap, Aave and 1inch had negative average monthly returns and all showed lower average monthly volatility within the 20-30 percentages. Unus Sed Leo is an outlier in the MST and had the lowest average monthly volatility. Projects that showed higher average monthly volatility also showed positive and higher average monthly return.

Chapter 5

DISCUSSION & CONCLUSION

In this work, I investigated the static and temporal graph properties of selected cryptocurrency projects from the Ethereum and Binance Smart Chain, and related those graph properties to existing social networks as well as their respective token price actions.

I find that many of the cryptocurrency projects obey a power law and exhibit small world properties that are similar to the graph properties of the network that we see around us today. The existence of more central entities in the graph through centralized exchanges or contract addresses that act as a decentralized exchange function as hubs where a lot of the transaction occur in order for swapping of tokens to occur, much like we see in the web or social networks, which exist sites or influencers that tends to lead to a high concentration of traffic to these few prominent places.

By Investigating the temporal graph properties, we are able to see how the cryptocurrency project graph properties change over time. This is especially pertinent when compared to its respective price action. Through a Pearson's Correlation Coefficient, we are able to quantify how useful those indicators are to determining how the price action of the token will change in relation to its graph properties. Individual price action of the cryptocurrency projects showed varied strength of relationship to its graph properties. In general, all cryptocurrency projects were found to exhibit some correlation to the change of the size of its network, as more user adoption generally leads to more activity and a higher utility of the token and (in theory), and higher price.

Lastly, the tokens price of all the cryptocurrency projects analyzed were investigated in relation to one another using a minimum spanning tree. Through the construction of this graph visualization, we are able to detect tokens that are unrelated to one another and potentially use such insights to diversify our portfolio.

Through the proposal of the GAPNET framework, I was once again able to investigate the graph properties of the cryptocurrency projects, static and temporal, and seeing how it relates to their price action, while also investigating the price action themselves in relation to one another. Further research may refine the understanding of the static properties of cryptocurrency projects with a sampling method that takes into its years of inception, rather than taking one month's worth of transactions as the sample, which could lead to bias due to the existence of marketing campaigns or unaccounted market events that lead to spikes in transactions of the selected projects. Additionally, the time frame chosen for the selected projects was chosen during a bull market. It would be interesting to investigate whether such graph metrics perform better during a bull or bear market. By applying the GAPNET framework, I have gained many new observations and insights into the selected cryptocurency projects which could aid in understanding the cryptocurreny projects before participating in them.

BIBLIOGRAPHY

[1] Binance Academy. A guide to pancakeswap, Mar 2022.

[2] Ammar Ahmed, Zohair Raza Hassan, and Mudassir Shabbir. Interpretable multi-scale graph descriptors via structural compression. *Information Sciences*, 533:169–180, 2020.

[3] Nansen Ai. Surface the signal in blockchain data, 2022.

[4] Binance Binance Academy. What is decentraland (mana)?, Nov 2021.

[5] Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10), 2008.

[6] Aleksandar Bojchevski and Stephan Günnemann. Deep gaussian embedding of graphs: Unsupervised inductive learning via ranking. 2017.

[7] Sergey Brin and Lawrence Page. The anatomy of a large-scale hypertextual web search engine. *Computer Networks and ISDN Systems*, 30(1-7):107–117, 1998.

[8] Andrei Broder, Ravi Kumar, Farzin Maghoul, Prabhakar Raghavan, Sridhar Rajagopalan, Raymie Stata, Andrew Tomkins, and Janet Wiener. Graph structure in the web. *Computer Networks*, 33(1-6):309–320, 2000.

[9] HongYun Cai, Vincent W. Zheng, and Kevin Chen-Chuan Chang. A comprehensive survey of graph embedding: Problems, techniques, and applications. *IEEE Transactions on Knowledge and Data Engineering*, 30(9):1616–1637, 2018.

[10] William Campbell, Charlie Dagli, and Clifford Weinstein. Social network analysis with content and graphs, 2013.

[11] S. Casale-Brunet, P. Ribeca, P. Doyle, and M. Mattavelli. Networks of ethereum non-fungible tokens: A graph-based analysis of the erc-721 ecosystem. *2021 IEEE International Conference on Blockchain (Blockchain)*, 2021.

[12] David Chaum. Computer systems established, maintained, and trusted by mutually suspicious groups, 1982.

[13] Ting Chen, Yuxiao Zhu, Zihao Li, Jiachi Chen, Xiaoqi Li, Xiapu Luo, Xiaodong Lin, and Xiaosong Zhange. Understanding ethereum via graph analysis. *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, 2018.

[14] Krzysztof Choromański, Michał Matuszak, and Miekisz Jacek. Scale-free graph with preferential attachment and evolving internal vertex structure. *Journal of Statistical Physics*, 151(6):1175–1183, 2013.

[15] Nicolas Christin. Traveling the silk road: A measurement of a large anonymous online marketplace. 2012.

[16] Coinmarketcap. A deep dive into metahero: Coinmarketcap, Nov 2021.

[17] E. W. Dijkstra. A note on two problems in connexion with graphs. *Numerische Mathematik*, 1(1):269–271, 1959.

[18] Cem Cagri Donmez, Doruk Sen, Ahmet Fatih Dereli, M. Bilal Horasan, Cagri Yildiz, and Nergis Feride Kaplan Donmez. An investigation of fiat characterization and evolutionary dynamics of the cryptocurrency market. *SAGE Open*, 11(1):215824402199480, 2021.

[19] Claudio Gallicchio and Alessio Micheli. Graph echo state networks. In *The 2010 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8, 2010.

[20] Adem Efe Gencer, Soumya Basu, Ittay Eyal, Robbert van Renesse, and Emin Gün Sirer. Decentralization in bitcoin and ethereum networks. *Financial Cryptography and Data Security*, page 439–457, 2018.

[21] Shaurya Malwa Godbole and Omkar. Frax stablecoin backing to feature layer 1 tokens, real-world loans, Apr 2022.

[22] Yashu Gola. Bored ape yacht club is a huge mainstream hit, but is wall street ready for nfts?, Jan 2022.

[23] William L. Hamilton, Rex Ying, and Jure Leskovec. Representation learning on graphs: Methods and applications, 2017.

[24] Bernhard Haslhofer, Roman Karl, and Erwin Filtz. O bitcoin where art thou? insight into large-scale transaction graphs., 2016.

[25] Messari io. Crypto research, data, and tools, 2022.

[26] Hyunyoung Kil, Seog-Chan Oh, Ergin Elmacioglu, Wonhong Nam, and Dongwon Lee. Graph theoretic topological analysis of web service networks. *World Wide Web*, 12(3):321–343, 2009.

[27] Thomas N. Kipf and Max Welling. Semi-supervised classification with graph convolutional networks, 2016.

[28] Thomas N. Kipf and Max Welling. Variational graph auto-encoders, 2016.

[29] Certik Leaderboard. Certik blockchain security leaderboard, 2022.

[30] Eli Tan Ledesma and Lyllah. Bored ape yacht club's apecoin surges 90% on second day of trading, Mar 2022.

[31] Lyllah Ledesma. Pancakeswap's cake rallies 27% on binance announcement, Mar 2022.

[32] Yitao Li, Umar Islambekov, Cuneyt Akcora, Ekaterina Smirnova, Yulia R. Gel, and Murat Kantarcioglu. Dissecting ethereum blockchain analytics: What we learn from topology and geometry of the ethereum graph? *Proceedings of the 2020 SIAM International Conference on Data Mining*, page 523–531, 2020.

[33] Jiaqi Liang. Evolutionary dynamics of cryptocurrency transaction networks v1. 2018.

[34] Ying Liu, Ming Tang, Tao Zhou, and Younghae Do. Core-like groups result in invalidation of identifying super-spreader by k-shell decomposition. *Scientific Reports*, 5(1), 2015.

[35] R.N. Mantegna. Hierarchical structure in financial markets. *The European Physical Journal B*, 11(1):193–197, 1999.

[36] coin marketcap. Cryptocurrency prices, charts and market capitalizations, 2022.

[37] Sarah Meiklejohn, Marjori Pomarole, Grant Jordan, Kirill Levchenko, Damon McCoy, Geoffrey M. Voelker, and Stefan Savage. A fistful of bitcoins. *Proceedings of the 2013 conference on Internet measurement conference*, 2013.

[38] Robert Meusel, Sebastiano Vigna, Oliver Lehmberg, and Christian Bizer. Graph structure in the web — revisited. *Proceedings of the 23rd International Conference on World Wide Web*, 2014.

[39] Milkshake. Partnershibs unite! payment gateway onboard at welly's, john richmond, and sorbillo., Mar 2022.

[40] Alan Mislove, Massimiliano Marcon, Krishna P. Gummadi, Peter Druschel, and Bobby Bhattacharjee. Measurement and analysis of online social networks. *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement - IMC '07*, 2007.

[41] Alex Moskov. What is the sandbox: A guide to the growing crypto metaverse, Mar 2022.

[42] Amir Pasha Motamed and Behnam Bahrak. Quantitative analysis of cryptocurrencies transaction graph. *Applied Network Science*, 4(1), 2019.

[43] Satoshi Nakamoto. Bitcoin: A peer-to-peer electronic cash system, 2008.

[44] glass node. Glassnode on-chain market intelligence, 2022.

[45] J.-P. Onnela, J. Saramäki, J. Hyvönen, G. Szabó, D. Lazer, K. Kaski, J. Kertész, and A.-L. Barabási. Structure and tie strengths in mobile communication networks. *Proceedings of the National Academy of Sciences*, 104(18):7332–7336, 2007.

[46] Symeon Papadopoulos, Yiannis Kompatsiaris, Athena Vakali, and Ploutarchos Spyridonos. Community detection in social media. *Data Mining and Knowledge Discovery*, 24(3):515–554, 2011.

[47] Marton POSFAI and Albert-Laszlo BARABASI. *Network science*. Cambridge University Press, 2016.

[48] Marcel Resovsky, Denis Horvath, Vladimír Gazda, and Marianna Sinicakova. Minimum spanning tree application in the currency market - nbs201, Jul 2013.

[49] Dorit Ron and Adi Shamir. Quantitative analysis of the full bitcoin transaction graph. *Financial Cryptography and Data Security*, page 6–24, 2013.

[50] Anwar Said, Muhammad Umar Janjua, Saeed-Ul Hassan, Zeeshan Muzammal, Tania Saleem, Tipajin Thaipisutikul, Suppawong Tuarob, and Raheel Nawaz. Detailed analysis of ethereum network on transaction behavior, community structure and link prediction. *PeerJ Computer Science*, 7, 2021.

[51] Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and Gabriele Monfardini. The graph neural network model. *IEEE Transactions on Neural Networks*, 20(1):61–80, 2009.

[52] Luca Serena, Stefano Ferretti, and Gabriele D'Angelo. Cryptocurrencies activity as a complex network: Analysis of transactions graphs. *Peer-to-Peer Networking and Applications*, 15(2):839–853, aug 2021.

[53] Andrey Sergeenkov. What is shibaswap?, Dec 2021.

[54] the Premerger Notification Office Staff, DPIP Staff, CTO, Emma Fletcher, and Emma Fletcher. Reports show scammers cashing in on crypto craze, Jun 2022.

[55] Dapp Statistics. Dapp statistics, May 2022.

[56] Michael Steketee, Atsushi Miyaoka, and Maura Spiegelman. Social network analysis. *International Encyclopedia of the Social amp; Behavioral Sciences*, page 461–467, 2015.

[57] Robert Stevens. What is 1inch exchange? beginner's guide, Jun 2021.

[58] Friedhelm Victor and Bianca Katharina Lüders. Measuring ethereum-based erc20 token networks. *Financial Cryptography and Data Security*, page 113–129, 2019.

[59] Steve Walters. Unus sed leo: Bitfinex token - what you need to know!!, Jun 2021.

[60] Jiajing Wu, Jieli Liu, Yijing Zhao, and Zibin Zheng. Analysis of cryptocurrency transactions from a network perspective: An overview. *Journal of Network and Computer Applications*, 190:103139, 2021.

[61] Yunyi Xie, Jiajun Zhou, Jinhuan Wang, Jian Zhang, Yunxuan Sheng, Jiajing Wu, and Qi Xuan. Understanding ethereum transactions via network approach. *Graph Data Mining*, page 155–176, 2021.

[62] Wenchao Yu, Cheng Zheng, Wei Cheng, Charu C. Aggarwal, Dongjin Song, Bo Zong, Haifeng Chen, and Wei Wang. Learning deep network representations with adversarially regularized autoencoders. *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery amp; Data Mining*, 2018.

[63] C.T. Zahn. Graph-theoretical methods for detecting and describing gestalt clusters. *IEEE Transactions on Computers*, C-20(1):68–86, 1971.

[64] Ziwei Zhang, Peng Cui, and Wenwu Zhu. Deep learning on graphs: A survey, 2018.

[65] Lin Zhao, Sourav Sen Gupta, Arijit Khan, and Robby Luo. Temporal analysis of the entire ethereum blockchain network. *Proceedings of the Web Conference 2021*, 2021.

Appendix A
CRYPTOCURRENCY PROJECT GRAPHS

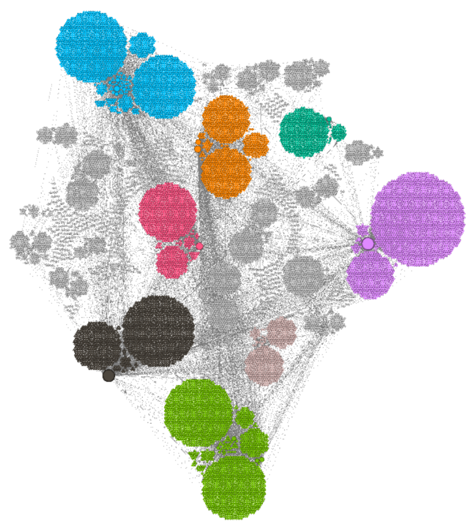

Figure A.1: Aave March 2022 Monthly Transaction Graph

Figure A.2: Apecoin March 2022 Monthly Transaction Graph

Figure A.3: Decentraland March 2022 Monthly Transaction Graph

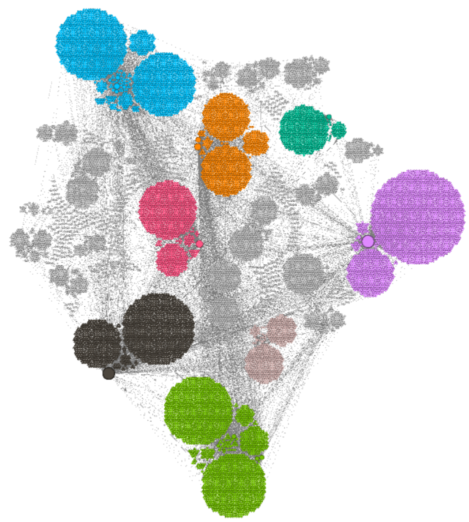

Figure A.4: Aave March 2022 Monthly Transaction Graph

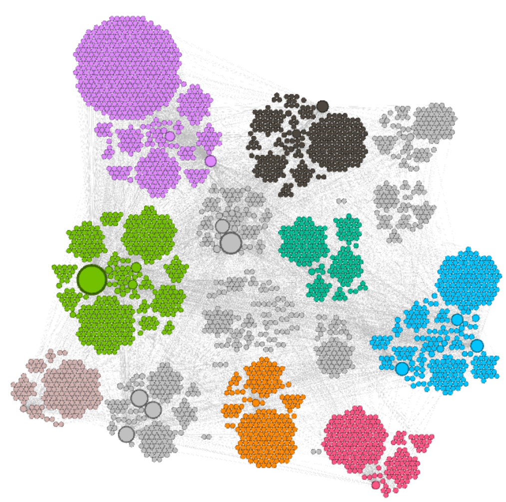

Figure A.5: Frax March 2022 Monthly Transaction Graph

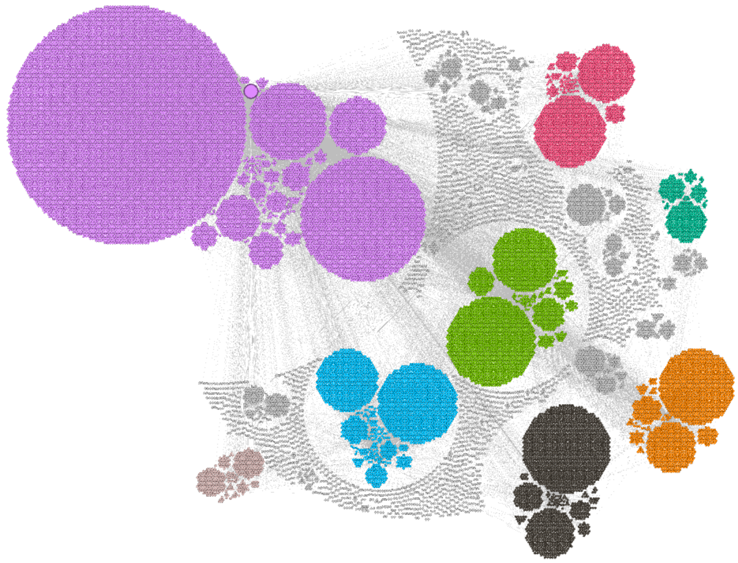

Figure A.6: Metahero March 2022 Monthly Transaction Graph

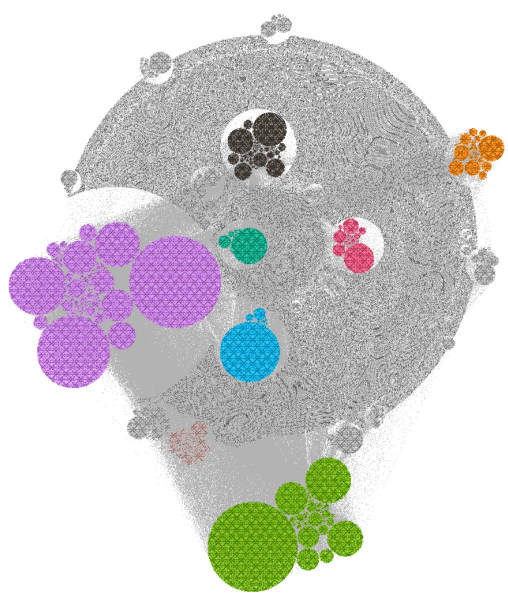

Figure A.7: Pancakeswap March 2022 Monthly Transaction Graph

Figure A.8: The Sandbox March 2022 Monthly Transaction Graph

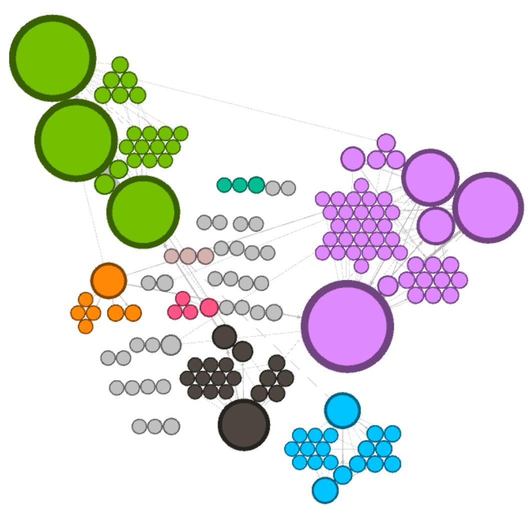

Figure A.9: Unus Sed Leo March 2022 Monthly Transaction Graph

Appendix B

CRYPTOCURRENCY PROJECT TOP 10 HIGHEST DEGREE NODES

Rank	Contract	Name	Type
1	0x28c6c06298d514db089934071355e5743bf21d60	Binance 14	Exchange Wallet
2	0x95a9bd206ae52c4ba8eecfc93d18eacdd41c88cc	Unknown	Unknown
3	0x811beed0119b4afce20d2583eb608c6f7af1954f	Uniswap V2: Shib	Contract Address
4	0x74de5d4fcbf63e00296fd95d33236b9794016631	AirSwap	Contract Address
5	0xB4a81261b16b92af0B9F7C4a83f1E885132D81e4	Shiba Inu: xSHIB Token	Token Contract
6	0x6262998ced04146fa42253a5c0af90ca02dfd2a3	Crypto.com	Exchange Wallet
7	0x46340b20830761efd32832a74d7169b29feb9758	Crypto.com 2	Exchange Wallet
8	0xcf6daab95c476106eca715d48de4b13287ffdeaa	Uniswap v2 Pair	Contract Address
9	0x2f62f2b4c5fcd7570a709dec05d68ea19c82a9ec	Uniswap V3: SHIB	Contract Address
10	eth:0xe66b31678d6c16e9ebf358268a790b763c133750	ZeroExProxy	Contract Address

Table B.1: Shibaswap Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0x74de5d4fcbf63e00296fd95d33236b9794016631	AirSwap	Contract Address
2	0xac4b3dacb91461209ae9d41ec517c2b9cb1b7daf	Uniswap V3: APE 7	Contract Address
3	0xb011eeaab8bf0c6de75510128da95498e4b7e67f	UniswapV2Pair	Contract Address
4	0xf79fc43494ce8a4613cb0b2a67a1b1207fd05d27	Uniswap V3: APE 4	Contract Address
5	0x95a9bd206ae52c4ba8eecfc93d18eacdd41c88cc	Unknown	Unknown
6	0x025c6da5bd0e6a5dd1350fda9e3b6a614b205a1f	AirdropGrapesToken	Contract Address
7	0x618e2fb404f135d7cc9d498a989ac2ca5cd217be	DividendDistributor	Contract Address
8	0xe66b31678d6c16e9ebf358268a790b763c133750	ZeroEx Proxy	Contract Address
9	0x7ef865963d3a005670b8f8df6aed23e456fa75e0	TransparentUpgradeableProxy	Contract Address
10	0xb07fe2f407f971125d4eb1977f8acee8846c7324	Uniswap V3: APE-USDC 2	Contract Address

Table B.2: Apecoin Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0x009cF7bC57584b7998236eff51b98A168DceA9B0	PancakeSwap: SYRUP Token	Token Contract
2	0x0000000000000000000000000000000000000000	Burn Address	Burn address
3	0xa80240eb5d7e05d3f250cf000eec0891d00b51cc	CakeVault	Contract Address
4	0xceba60280fb0ecd9a5a26a1552b90944770a4a0e	GnosisSafeProxy	Multisig Wallet
5	0x0ed7e52944161450477ee417de9cd3a859b14fd0	PancakePair	Token Contract
6	0x73feaa1ee314f8c655e354234017be2193c9e24e	PancakeSwap: Main Staking Contract	Contract Address
7	0x804678fa97d91b974ec2af3c843270886528a9e6	PancakePair	Token Contract
8	0x1b2a2f6ed4a1401e8c73b4c2b6172455ce2f78e8	IFOPool	Unknown
9	0xa39af17ce4a8eb807e076805da1e2b8ea7d0755b	PancakePair	Token Contract
10	0x21835332cbdf1b3530fae9f6cd66feb9477dfc02	GnosisSafeProxy	Multisig Wallet

Table B.3: Pancakeswap Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0x77696bb39917c91a0c3908d577d5e322095425ca	Unknown	Unknown
2	0x74de5d4FCbf63E00296fd95d33236B9794016631	AirSwap Router	AirSwap Contract Address
3	0x28c6c06298d514db089934071355e5743bf21d60	Binance 14	Exchange Wallet
4	0x8661ae7918c0115af9e3691662f605e9c550ddc9	Uniswap V3: MANA	Uniswap Contract Address
5	0x1bec4db6c3bc499f3dbf289f5499c30d541fec97	SushiSwap: MANA	SushiSwap Contract Address
6	0x6262998ced04146fa42253a5c0af90ca02dfd2a3	Crypto.com	Exchange Wallet
7	0xdfd5293d8e347dfe59e90efd55b2956a1343963d	Binance 16	Exchange Wallet
8	0x11b1f53204d03e5529f09eb3091939e4fd8c9cf3	Uniswap V2: MANA	Uniswap Contract Address
9	0x21a31ee1afc51d94c2efccaa2092ad1028285549	Binance 15	Exchange Wallet
10	0x4f6742badb049791cd9a37ea913f2bac38d01279	Celsius Network: Wallet 5	Exchange Wallet

Table B.4: Decentraland Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	Uniswap V2: SAND 21	Contract Address
2	0x74de5d4FCbf63E00296fd95d33236B9794016631	Unknown	Contract Address
3	0x40ec5b33f54e0e8a33a975908c5ba1c14e5bbbdf	Polygon (Matic): ERC20 Bridge	Contract Address
4	0x5859ebe6fd3bbc6bd646b73a5dbb09a5d7b6e7b7	Uniswap V3: Factory	Contract Address
5	0xe66B31678d6C16E9ebf358268a790B763C133750	ZeroEx Proxy	Contract Address
6	0x28c6c06298d514db089934071355e5743bf21d60	Binance 14	Exchange Wallet
7	0x0eb04462d69b1d267d269377e34f60b9de1c8510	Gnosis Safe Multisig Wallet	Multisignature Wallet
8	0x2faf487a4414fe77e2327f0bf4ae2a264a776ad2	FTX Exchange	Exchange Wallet
9	0x21a31ee1afc51d94c2efccaa2092ad1028285549	Binance 15	Exchange Wallet
10	0xdfd5293d8e347dfe59e90efd55b2956a1343963d	Binance 16	Exchange Wallet

Table B.5: The Sandbox Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0xa57bd00134b2850b2a1c55860c9e9ea100fdd6cf	MEV BOT	Arbitrage Bot
2	0x56178a0d5f301baf6cf3e1cd53d9863437345bf9	Unknown	Unknown
3	0xc697051d1c6296c24ae3bcef39aca743861d9a81	BPool	Token Contract
4	0xddfabcdc4d8ffc6d5beaf154f18b778f892a0740	Coinbase 3	Exchange Wallet
5	0x4da27a545c0c5b758a6ba100e3a049001de870f5	Aave: Staked Aave	Token Contract
6	0x4f6742badb049791cd9a37ea913f2bac38d01279	Celsius Network: Wallet 5	Exchange Wallet
7	0xd75ea151a61d06868e31f8988d28dfe5e9df57b4	SushiSwap: AAVE	Token Contract
8	0x28c6c06298d514db089934071355e5743bf21d60	Binance 14	Exchange Wallet
9	0x2faf487a4414fe77e2327f0bf4ae2a264a776ad2	FTX Exchange	Exchange Wallet
10	0xfa103c21ea2df71dfb92b0652f8b1d795e51cdef	MEV Bot	Arbitrage bot

Table B.6: Aave Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0xe267018c943e77992e7e515724b07b9ce7938124	PancakePair	Token Contract
2	0xc590175e458b83680867afd273527ff58f74c02b	Unknown	Unknown
3	0x53f78a071d04224b8e254e243fffc6d9f2f3fa23	Unknown	Unknown
4	0xe107b56ddf1c9c51d3ab33a2724c0ce5502bd323	PancakeSwap V2: HERO-BUSD	Token Contract
5	0x8c5493fec412e205d5fc2c909b4ce619e1136dc9	PancakeSwap V2: BSC-USD-HERO	Token Contract
6	0xf842a922edb51fe7ca464823bff7fd906366ee4b	BiswapPair	Token Contract
7	0xa38c28f8049d95a0ef025cfbd3a2bff6ab2692c9	Unknown	Unknown
8	0x0d0707963952f2fba59dd06f2b425ace40b492fe	Gate.io	Exchange Wallet
9	0xc076de70bcd095f45b6f6d76c53130a954006581	Unknown	Unknown
10	0x4cf8800ccc0a56396f77b1e7c46160f5df0e09a5	Unknown	Unknown

Table B.7: Metahero Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0xc63b0708e2f7e69cb8a1df0e1389a98c35a76d52	Uniswap V3: FRAX-USDC	Token Contract
2	0xe1573b9d29e2183b1af0e743dc2754979a40d237	Uniswap V2: FXS-FRAX 2	Token Contract
3	0xe06f8d30ac334c857fc8c380c85969c150f38a6a	SushiSwap: SUSHI-FRAX	Token Contract
4	0x8aff5ca996f77487a4f04f1ce905bf3d27455580	MEV Bot	Arbitrage Bot
5	0xec8c342bc3e07f05b9a782bc34e7f04fb9b44502	SushiSwap: FRAX	Token Contract
6	0x220bda5c8994804ac96ebe4df184d25e5c2196d4	Unknown	Token Contract
7	0xc2a856c3aff2110c1171b8f942256d40e980c726	Uniswap V3: FRAX-USDT	Token Contract
8	0x97e7d56a0408570ba1a7852de36350f7713906ec	Uniswap V3: DAI-FRAX	Token Contract
9	0xd632f22692fac7611d2aa1c0d552930d43caed3b	FRAX Finance: FRAX3CRV-f Token	Token Contract
10	0x9fae36a18ef8ac2b43186ade5e2b07403dc742b1	Uniswap V2: SYN-FRAX	Token Contract

Table B.8: Frax Top 10 Highest Degree Nodes in March 2022

Rank	Contract	Name	Type
1	0x523a36ad73c402e456f49b04f0fe8eba5a8c85cd	Uniswap V2: LEO	Token Contract
2	0x2faf487a4414fe77e2327f0bf4ae2a264a776ad2	FTX Exchange	Exchange Wallet
3	0xc208d313012124c7403d94ec1e0c5fdd740dc659	Unknown	Unknown
4	0x876eabf441b2ee5b5b0554fd502a8e0600950cfa	Bitfinex 3	Exchange Wallet
5	0x74de5d4fcbf63e00296fd95d33236b9794016631	Airswap Router	Contract Address
6	0x758a5f59b3ebe8a5cb9e6a09b5b876d2414042cd	Uniswap V3: LEO	Token Contract
7	0x0d0707963952f2fba59dd06f2b425ace40b492fe	Gate.io	Exchange Wallet
8	0xe66b31678d6c16e9ebf358268a790b763c133750	ZeroEx Proxy	Contract Address
9	0x220bda5c8994804ac96ebe4df184d25e5c2196d4	Unknown	Unknown
10	0x6cc5f688a315f3dc28a7781717a9a798a59fda7b	OkEx	Exchange Wallet

Table B.9: Unus Sed Leo Top 10 Highest Degree Nodes in March 2022

VITA

Jerome Wong is a graduate student at the University of Washington working on his thesis for his Master of Science in Industrial Engineering under the Industrial & Systems Engineering Department. He is also interning at CertiK as a data scientist.

He welcomes your comments to `jerome95@uw.edu` or `jerome.wong@certik.com`.