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DEPARTMENT OF MANAGEMENT SCIENCE & TECHNOLOGY

Μελέτη περίπτωσης:

Cryptocurrency Accounts on BlueSky Platform

Περιεχόμενα

ΠΑΡΑΡΤΗΜΑ ΕΙΚΟΝΩΝ

1. Introduction

1.1 A Dive into the World of Crypto

Cryptocurrency, once the whispered dream of tech enthusiasts and financial rebels, has become one of the most transformative forces in modern finance and technology. Over the past decade, it has evolved from an obscure whitepaper by the elusive Satoshi Nakamoto into a trillion-dollar market reshaping global economies. With Bitcoin, Ethereum, and countless altcoins leading the way, crypto communities have emerged as powerful hubs of innovation, debate, and speculation.

Yet, the heart of the cryptocurrency revolution isn't just its technology - it's the **people**, the communities that drive discussions, share ideas, and collaborate across decentralized platforms. These networks of influencers, traders, developers, and enthusiasts are not limited to traditional social media platforms. They have found new spaces, like **Bluesky**, where decentralized networks mirror the very ethos of cryptocurrency: open, user-controlled, and evolving.

Understanding these networks is critical. Consider these facts:

- The global cryptocurrency market capitalization currently hovers around **$1.5 trillion** (as of recent estimates).
- Platforms like Bitcoin and Ethereum process millions of daily transactions, supported by tens of millions of users worldwide.
- Crypto enthusiasts don't just trade—they engage in **discussions** that define adoption, trends, and sentiment.

However, despite the prominence of these communities, the internal structures of their networks remain largely unexplored. Who acts as a bridge connecting isolated clusters? How do local leaders influence their surroundings? What roles do high-centrality nodes play in spreading ideas across communities?

Driven by these questions, I chose to analyze the cryptocurrency network on Bluesky. By studying its structure -using Gephi tool- I aim to uncover the **hidden influencers**, **local bridges**, and **hubs** that sustain and grow these conversations. Through this analysis, we not only gain insights into how crypto enthusiasts communicate but also uncover patterns that can help us understand the evolution of decentralized platforms and networks themselves. This is not just about a network—it's about understanding the **people** and **connections** behind one of the most revolutionary movements of our time.

2. Data Generation

2.1 Data Collection from Bluesky

My account: theodoraiakovaki.bsky.social

For my network analysis, I chose to analyze my followers' network on BlueSky, specifically focusing on the followers who show an interest in the cryptocurrency market. We are going to fetch my followers, follows and n+1. I decided to analyze this network because the cryptocurrency space is rapidly evolving and is highly active on social platforms, like Twitter and BlueSky. My network is defined by 46 people, currently active and interested in crypto community. The following process focused on key cryptocurrency-related accounts and discussions, using relevant **hashtags, keywords, and interactions** as filters to ensure the dataset represented a focused and meaningful community.

To analyze the cryptocurrency community on Bluesky, I employed a structured methodology to generate and visualize the data, using Gephi, a powerful open-source network analysis tool, and the Bluesky plugin. This process allowed me to extract meaningful insights from user interactions, connections, and influence patterns. The Bluesky plugin for Gephi facilitates the extraction of social network data directly from the Bluesky platform. By leveraging this tool, I collected the following data:

Nodes: Representing user accounts actively discussing cryptocurrency-related topics.

Edges: Connections between users, defined by follows.

Labels: Usernames.

2.2 Network Construction in Gephi

The network was configured as a **directed graph** to show who follows whom.

Graphical representation with ranking and size based on degree

Red color represents low degree nodes.

Black color represents nodes with high degree.

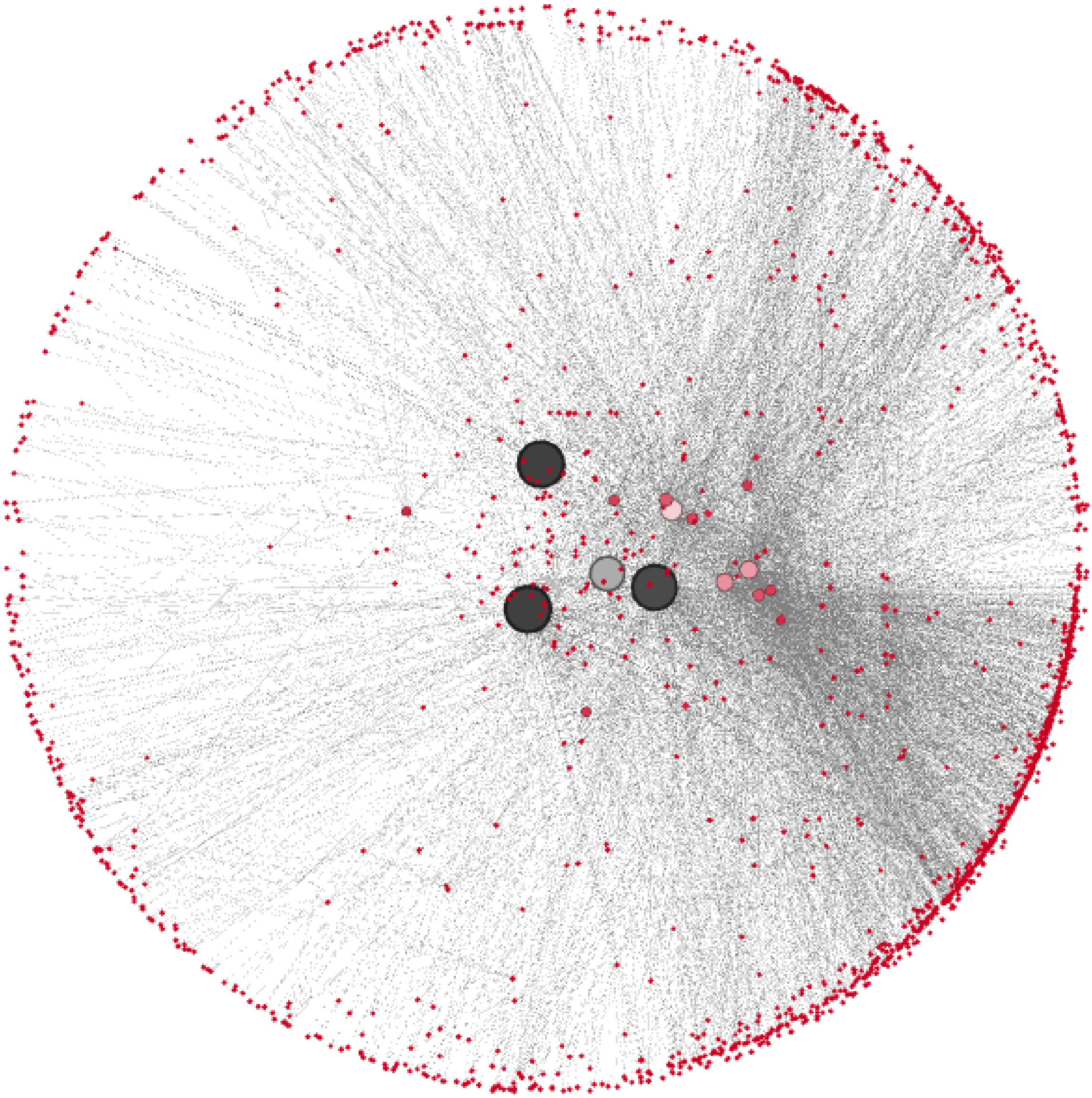


Figure 1: Graphical representation with ranking and size based on degree

Using Yifan Hu layout, we can see that the core part of the graph has several large nodes, which represent individuals or accounts with a **high degree of connectivity**. These could be influencers, popular figures, or hubs within the cryptocurrency community. The periphery is densely populated with smaller nodes, most of which are lightly connected. Many small nodes in the periphery indicate followers who are more passive participants, likely consuming content but not actively engaging with others in the network.

For our analysis, we are going to focus on the central nodes because they are the driving force of my network. These nodes seem to represent the key influencers and information hubs within the cryptocurrency community. By understanding their behavior, interests and connections, we can gain valuable insights into what draws my network to these accounts. Are they sharing technical analysis? Are they discussing specific coins or blockchain technologies? Or are they leaders in crypto-related news?

<u>A graphical representation of my network, with partitioning by modularity and node size scaled by betweenness centrality</u>

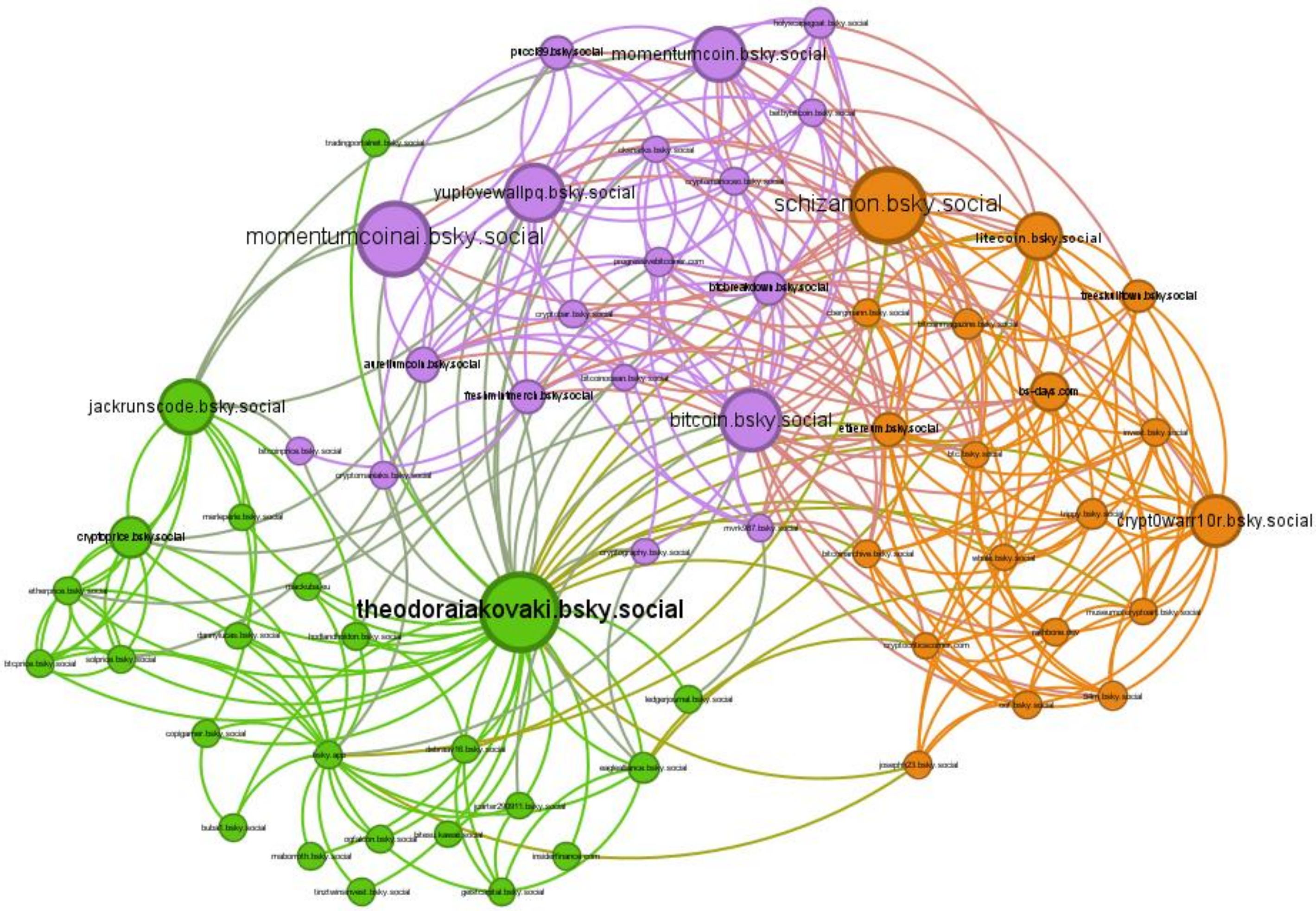


Figure 2: A graphical representation of my network, with partitioning by modularity and node size scaled by betweenness centrality

The graph was provided by Force Atlas 2 layout, which is best for large networks with a lot of interconnections. Using “**Degree Range**” Filter at minimum degree of 10, we are going to remove many low-connection nodes and focus on the central nodes.

Before: 25.088 Nodes, 32.047 Edges

After: 62 Nodes, 331 Edges (0.25% visible)

3. Limitations

One significant challenge was the vast size of the cryptocurrency-related network on Bluesky. Due to technical and resource limitations, I had to set a **crawl limit** of **5,000 nodes** during the data extraction process. This restriction ensured the analysis remained computationally feasible but may have resulted in the exclusion of some potentially relevant user accounts and connections. Given the large volume of extracted data, it was difficult to pinpoint specific, influential accounts within the overall network. To ensure a more focused and meaningful analysis, I applied a **degree range filter** of **10 or more connections** to isolate key accounts. While this approach successfully highlighted nodes with higher connectivity, it may have overlooked some less-connected but contextually significant accounts or users. However, future studies could address these constraints by utilizing advanced tools, extending crawl limits for identifying smaller or emerging communities. Despite these limitations, our goal remained to identify **key communities and influential accounts** driving the conversation and connections within the network.

4. Social Network Analysis

4.1 Basic topological properties

Network diameter: 8

The longest shortest path in the network is 8. A diameter of 8 in a network of 62 nodes suggests that even though it can be some distant profiles, the network is well-connected in terms of distance between most nodes. This happens due to **the shared interest** of the accounts in the investment in crypto.

Average Path Length: 3.083

We can see that it takes 3 steps on average to travel between all pairs of nodes. This means users in my network can reach each other within about three steps. For crypto topics, a shorter path length often indicates faster information spread:

Figure 3: Connection between my account and @bitcoin.bsky.social

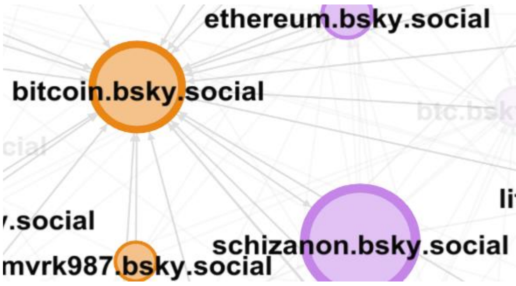


Figure 4: Connection between @bitcoin.bsky.social and @schizanon.bsky.social

For example, I am connected to @schizanon.bsky.social through @bitcoin.bsky.social (2 steps by following the directed edges). These two accounts we can see from the graph representation are of great importance due to their betweenness centrality. We will talk about these profiles later in our analysis.

4.2 Component measures

Calculating the connected components, we can see that there is one connected component, meaning that my network is highly interconnected with the accounts being part of a broader network. This is logical, as we have filtered the nodes to include only those with a minimum degree of 10 to focus on the key ones. The **23 strongly connected components** are distributed within the larger weakly connected component, meaning that while some users form tight sub-groups, they still connect to the overall network indirectly. We can see the graph below that shows communities within the larger network, partitioned by strongly connected component IDs.

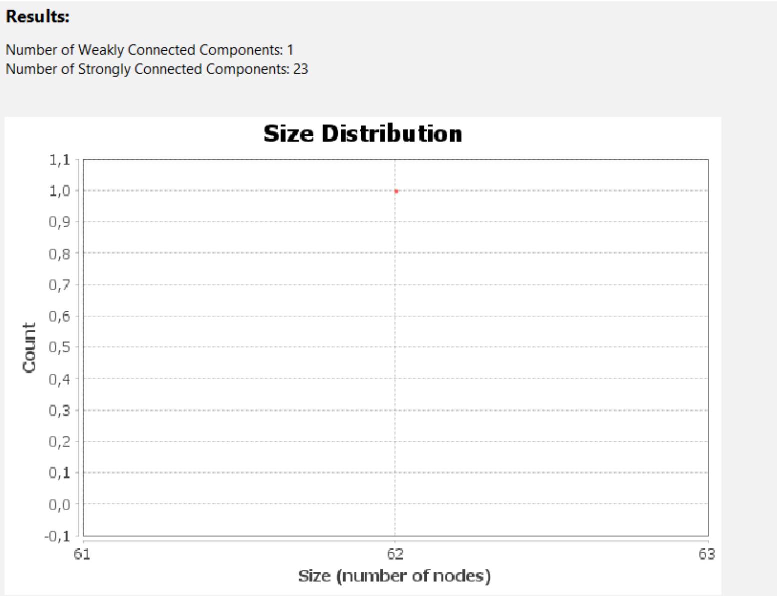


Figure 5: Component Report

On the one hand, we have **green nodes as the dominant color**, suggesting that these nodes belong to one of the largest strongly connected components. These green clusters might represent the most significant communities in terms of size or influence, as they contain prominent, well-connected nodes. They likely indicate active, core groups within the crypto-related network, possibly revolving around similar themes or influences. On the other hand, colors like grey nodes are part of smaller, less connected communities or even isolated groups that have minimal interaction with the rest of the network**. Grey nodes** could signify users or accounts that occasionally interact with the main network but are not deeply integrated. For example, @mackuba.eu, an account that I follow, is interested in web development and algorithms and not only in cryptocurrency market**. A pink node**, @buba1.bsky.social, is connected to the network only because it found my profile through @copigamer.bsky.social, which I follow for tactical updates about crypto prices.

A graphical representation of my network, with partitioning by strong components and node size scaled by betweenness centrality

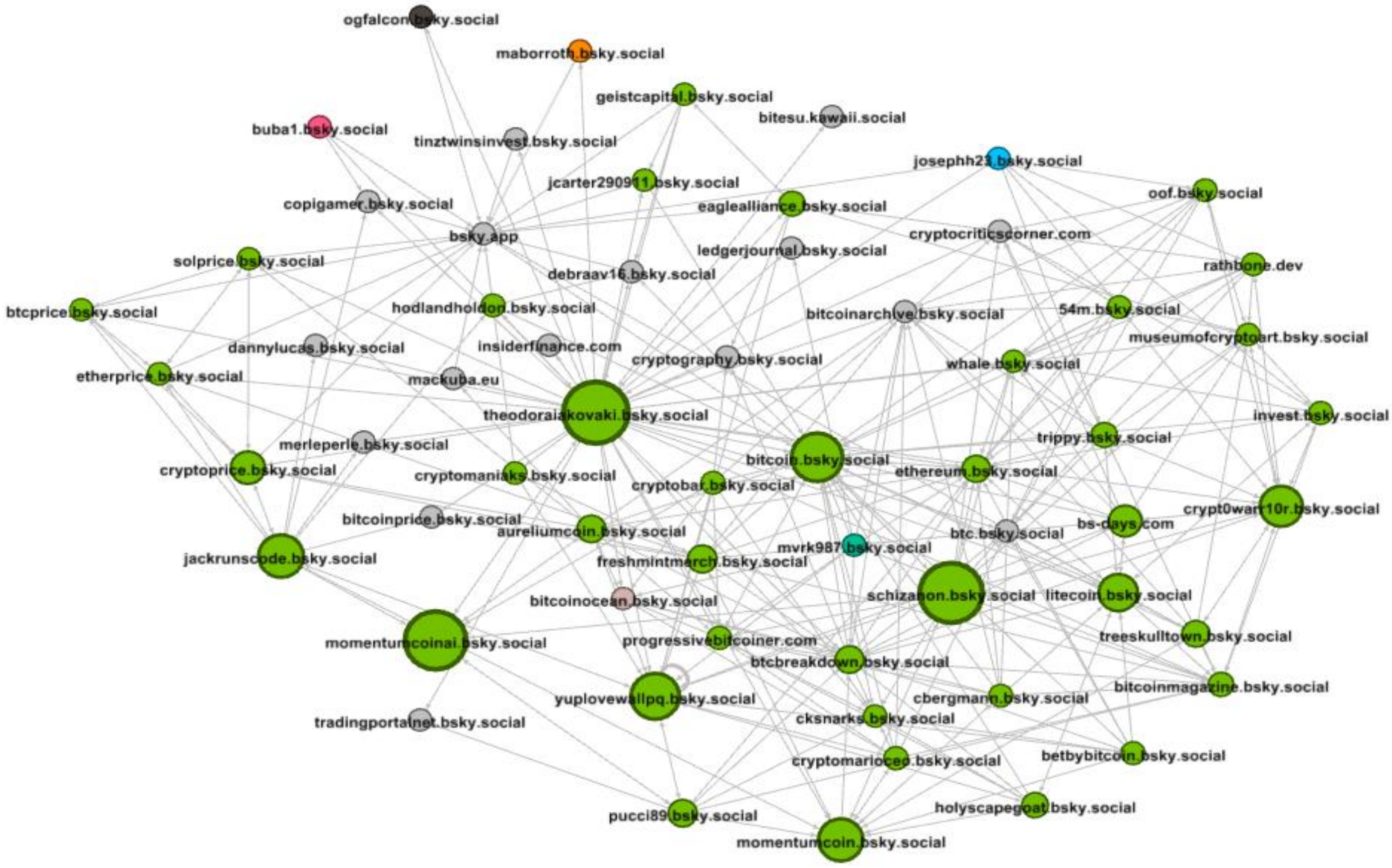


Figure 6: graphical representation of my network, with partitioning by strong components and node size scaled by betweenness centrality

4.3 Degree measures

The average node degree is 5.339. This means that on average, each node representing a user has approximately **5 connections** to other nodes in the network. In the degree distribution plot, we can see that one node has 44 connections. When we look at the graph representation with node rankings, this node is identified as me, which makes sense since we are analyzing my network. It seems like my profile acts as a hub within this network, meaning that I am central to connecting various sub-communities. It also implies that I am a critical node for network cohesion—if I was removed, many other nodes might become disconnected or form smaller, fragmented communities. Next node that we can see that plays a significant role into our network based on degree distribution (28) is the account @bitcoin.bsky.social. This is logical, since it is Bluesky's first bitcoin account and has the most followers (1.9k). As Bluesky's first dedicated Bitcoin account, it holds a position of authority and shares relevant news, updates, and discussions about Bitcoin. This makes it naturally attractive to a wide audience interested in cryptocurrency and Bitcoin on the Bluesky platform, leading to its high degree in the network. With a large follower count of 1.9k, @bitcoin.bsky.social has significant reach, which likely translates into influence across multiple communities within the network. Its high degree indicates that many users in the network, including other influential crypto-related profiles, are connected to or following this account. This could reflect users' interest in receiving timely updates or simply associating with a central authority in the Bitcoin community on Bluesky.

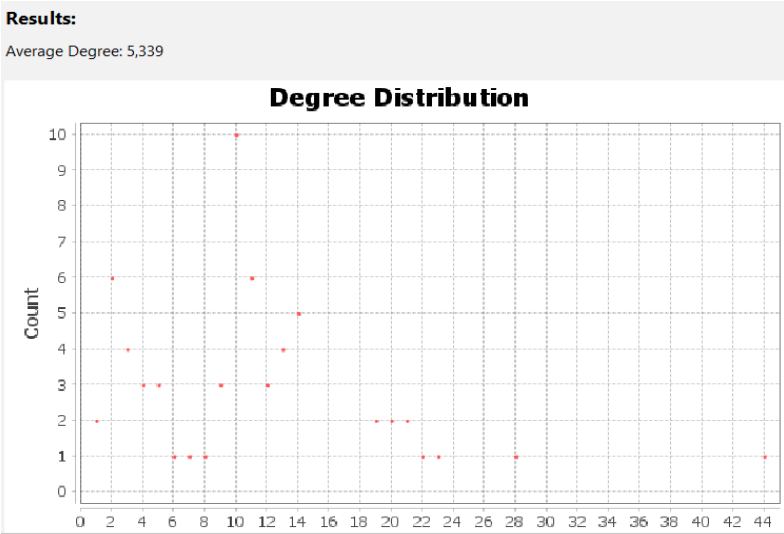


Figure 7: Degree Report

Also, we can see that most of the accounts (10) have node degree equal to 10, acting like secondary hubs. They may not be the primary sources of information, but they still serve as significant pathways for similar levels of interest and connectivity, forming a stable- structured network. We observe that 2 nodes have 1 connection. For example, @bitesu.kawaii.social, which is at bottom, is only followed by me, without following any other from my network. This account is an isolated node in terms of relationships with others in the crypto network. It isn't engaging with or connected to the broader community and has a minimal impact on overall connectivity.

Graphical representation with ranking by Degree

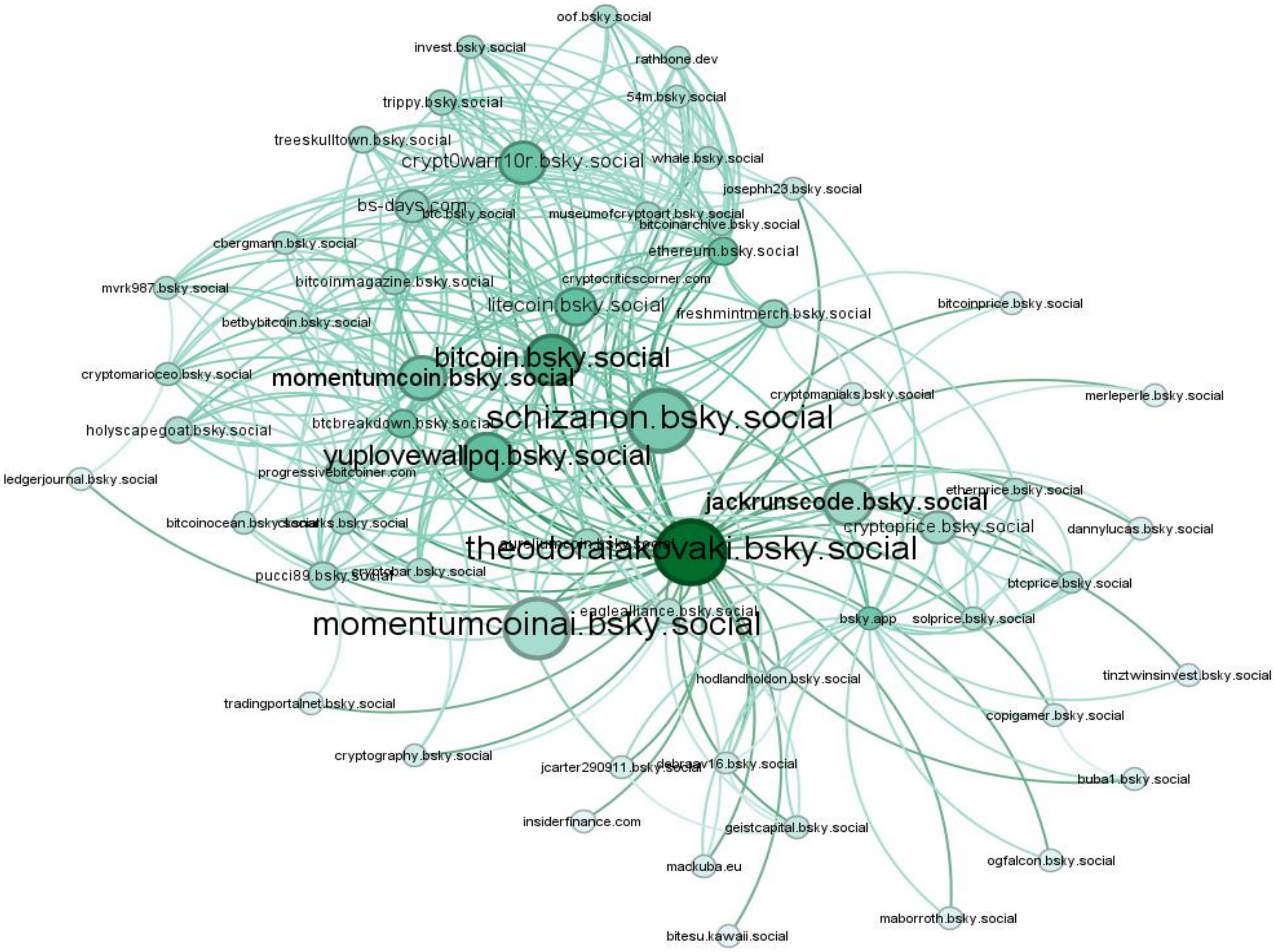


Figure 8: Graphical representation with ranking by Degree

Let’s see the **in-degree and out-degree** differences.

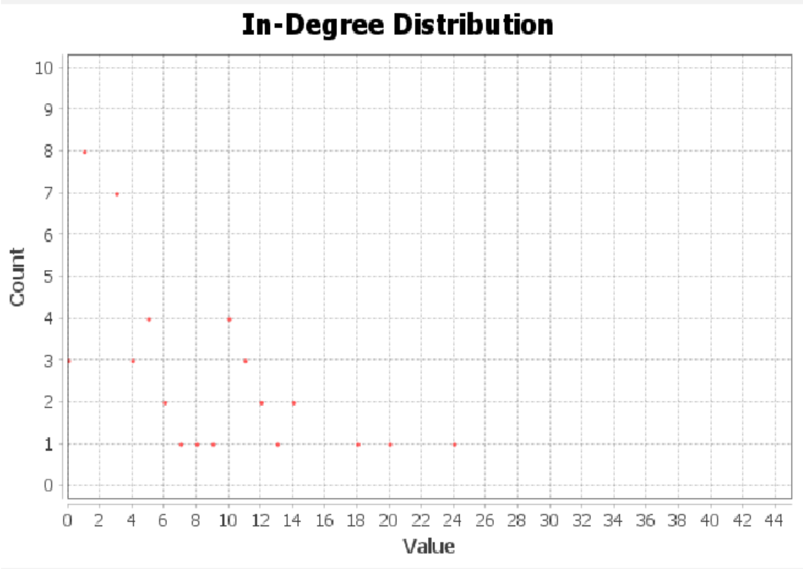


Figure 9: In-Degree Report

The in-degree distribution plot shows how many incoming connections (followers) each node has within the network. It is evident that my account, which plays a crucial role in the degree distribution, has a higher out-degree than in-degree. This is because my network is centered around the accounts I follow, particularly those related to crypto, while I have relatively few followers due to my account being new. An interesting observation is that the account with the highest in-degree is @bitcoin.bsky.social, which has come second in the degree distribution, which is logical as it has the most followers and the widest reach of any Bitcoin-related profile. This node demonstrates a high in-degree but a low out-degree, indicating that it is an influential and central figure within the network—widely followed but not following many accounts in return. Another account with a high in-degree but low out-degree is @bsky.app, which is Bluesky's official account. This is because every new account created on the platform automatically follows @bsky.app by default. Another example is @ethereum.bsky.social, which has a low out-degree but high in-degree. This account is an unofficial Ethereum profile, yet it appears to be followed by the Bitcoin-focused account @btcbreakdown.bsky.social, which has 1.3k followers. Interestingly, @ethereum.bsky.social itself follows only three accounts.

The out-degree distribution plot shows how many outgoing connections (following) each node has. Most nodes have low out-degrees, indicating that they don’t follow many accounts within this network. A smaller number of nodes have higher out-degrees, which could represent more active or social accounts that follow many others, possibly for gathering information or engaging widely across the network, like my account (40 accounts followed). Another account with a high out-degree and a low in-degree is @schizanon.bsky.social. This account follows 4.4k other accounts, while is being followed by 884 accounts. This difference make this account have a higher out-degree, even though it is being followed by the first bitcoin

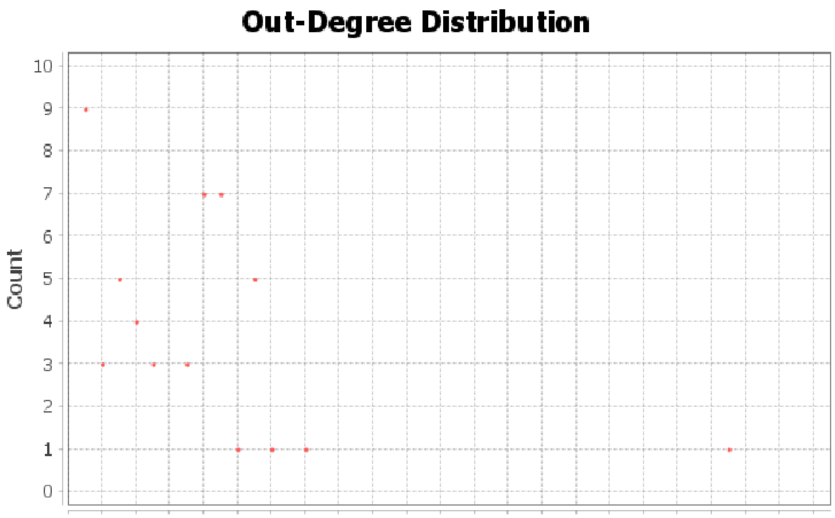


Figure 10: Out-Degree Report

account, which we analyzed above, @bitcoin.bsky.social. @schizanon.bsky.social profile is a connector or hub within the network, actively engaging with and being engaged by the community. Below we can see each graph representation with rankings by in-degree and out-degree.

Graphical representation with ranking by in-degree

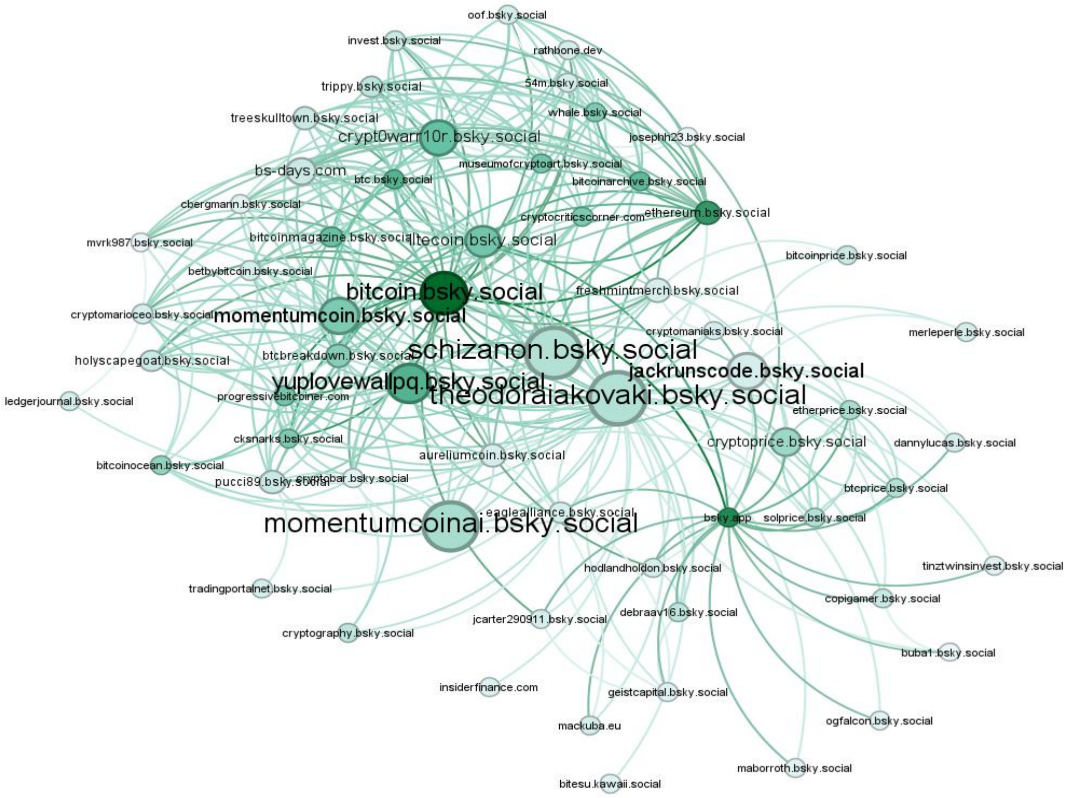


Figure 11: Graphical representation with ranking by in-degree

Graphical representation with ranking by out-degree

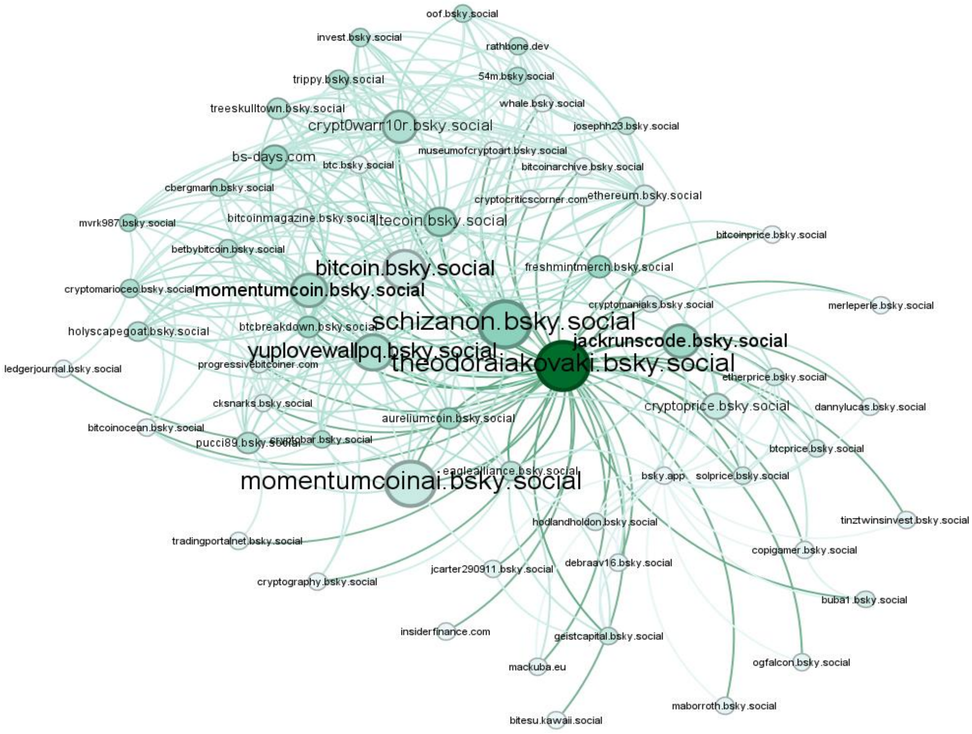


Figure 12: Graphical representation with ranking by out-degree

4.4 Centrality measures

Regarding **Betweenness Centrality,** which shows how important a node is in terms of connecting with other nodes, we can see in the betweenness centrality distribution plot a long tail. Most nodes have very low betweenness centrality, acting primarily as endpoints or part of local clusters. A few nodes have disproportionately high centrality, reflecting their role as critical bridges in the network. My account has one of the highest betweenness centrality values, as I serve as the core of this network, connecting different subgroups.

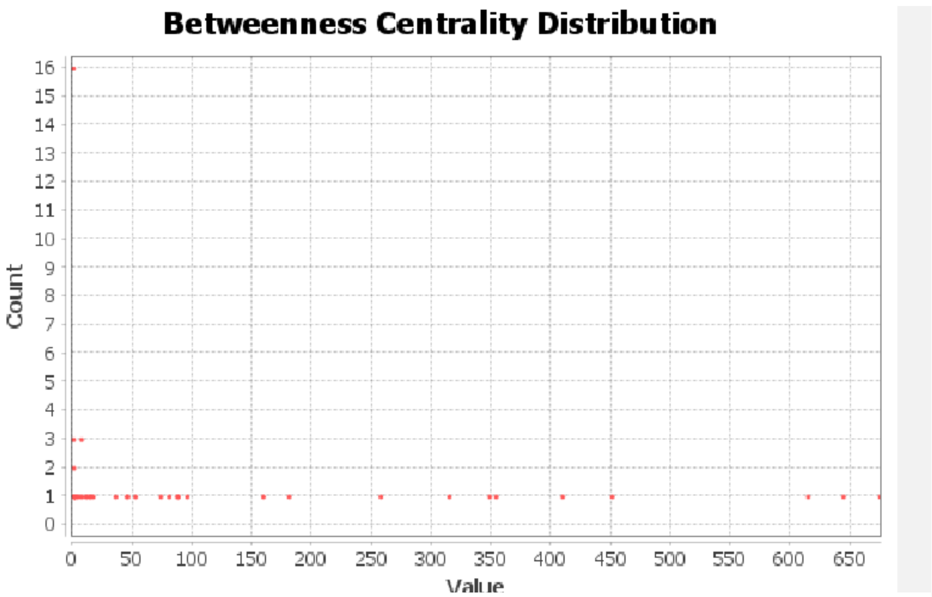


Figure 13: Betweenness Centrality Report

@momentumcoinai.bsky.social has high betweenness centrality too, as it is an active account on Bluesky platform by sharing news for blockchain technology. This profile also labels itself as an experienced crypto advisor. A profile similar to this is @momentuncoin.bsky.social. @schizanon.bsky.social is a profile which strongly supports Bluesky platform and reposts daily other posts about Bitcoin. Its role as a supporter of the Bluesky platform and Bitcoin creates cohesion among users interested in these subjects, further enhancing its connectivity across the network. The presence of a few dominant nodes with high centrality likely reflects the existence of distinct community structures that depend on these nodes for interconnection. Moreover, @bitcoin.bsky.social is pivotal for communication within the network. If my account or @bitcoin.bsky.social were removed, many connections would become weaker or isolated. The nodes with low betweenness centrality are in the periphery of the network, having fewer or no direct interactions beyond their immediate connections.

Graphical representation with ranking and size by Betweenness Centrality

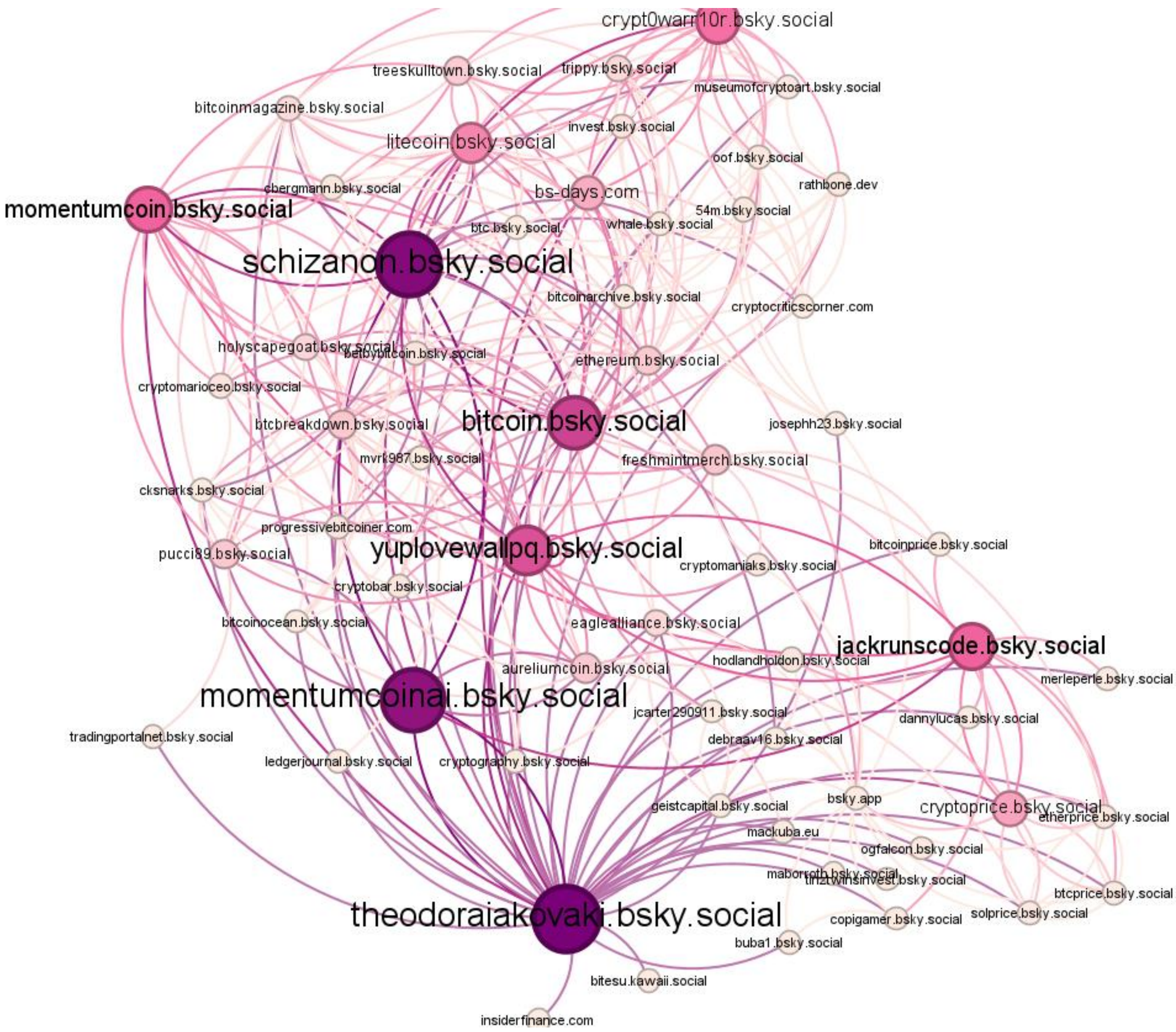


Figure 14: Graphical representation with ranking and size by Betweenness Centrality

Closeness Centrality shows how easily a node can reach other nodes.

All values are between 0 and 1, suggesting that closeness centrality has been normalized, and every node is reachable within the network (as there are no infinite distances). The clustering of values suggests that some nodes are very central (closer to 1), while others are less central (closer to 0).

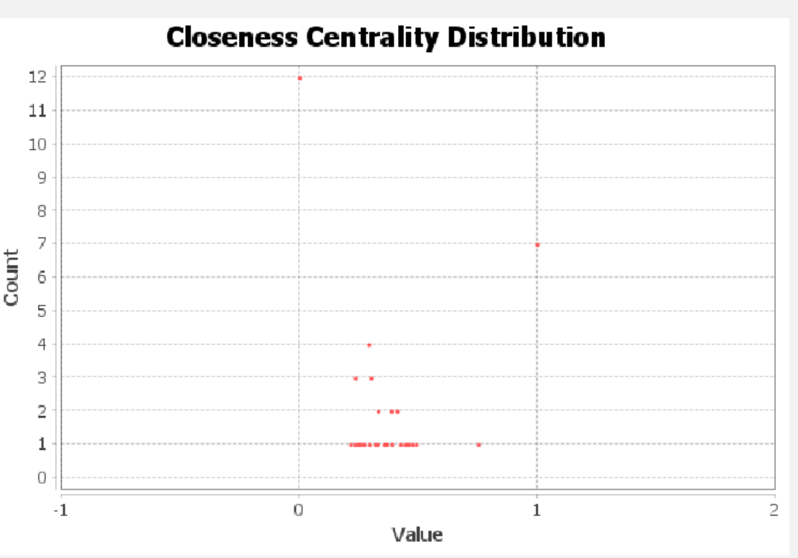


Figure 15: Closeness Centrality Report

Account @mackuba.eu seems to have a high Closeness Centrality, but a low Betweenness Centrality. This implies that it is geographically-structurally central, even if it does not necessarily facilitate connections between other nodes. Nodes with high closeness centrality are generally good at disseminating information quickly because they can reach others in fewer steps. In this case, mackuba.eu is likely connected to multiple "core" parts of the network, like my account. However, it does not serve as a critical broker between disparate groups. Also, @crypt0war10r.bsky.social can efficiently reach many other nodes in the network, though not as efficiently as nodes with high closeness centrality. It is not the most central node structurally, but it still has a relatively short average path length to others. This node also is moderately important in connecting different subgroups. It is traversed in some of the shortest paths between other nodes, but it is not the primary bridge node. Nodes with middle values for both centralities often act as **secondary hubs**. They provide additional stability to the network, ensuring subgroups remain integrated even if a high-betweenness node is removed. This profile is interested in crypto arts. @schizanon.bsky.social who has high betweenness centrality, have a bit lower closeness centrality. The node plays a key structural role in ensuring that information flows across disconnected parts of the network. Without it, the network could experience reduced efficiency in communication. Although it is crucial for bridging the network, it is not as directly connected to all other nodes compared to those with high closeness centrality. The average path length from this node to all others is slightly longer. It connects clusters that are relatively far apart in terms of the network's structure, explaining its slightly lower closeness centrality.

The account @ledgerjournal.bsky.social has low values in both closeness and betweenness centrality. The node is in the periphery of the network and less active than others (posting every 2 months). Also, this profile targets a specific audience — researchers, academics, and professionals in the blockchain and cryptocurrency space. This result in fewer followers or connections within my network. Even with low metrics, @ledgerjournal.bsky.social adds value to my network by providing depth through its academic focus. Its low metrics are reflective of its targeted audience rather than a lack of importance.

Graphical representation with ranking by Closeness Centrality and size by Betweenness Centrality

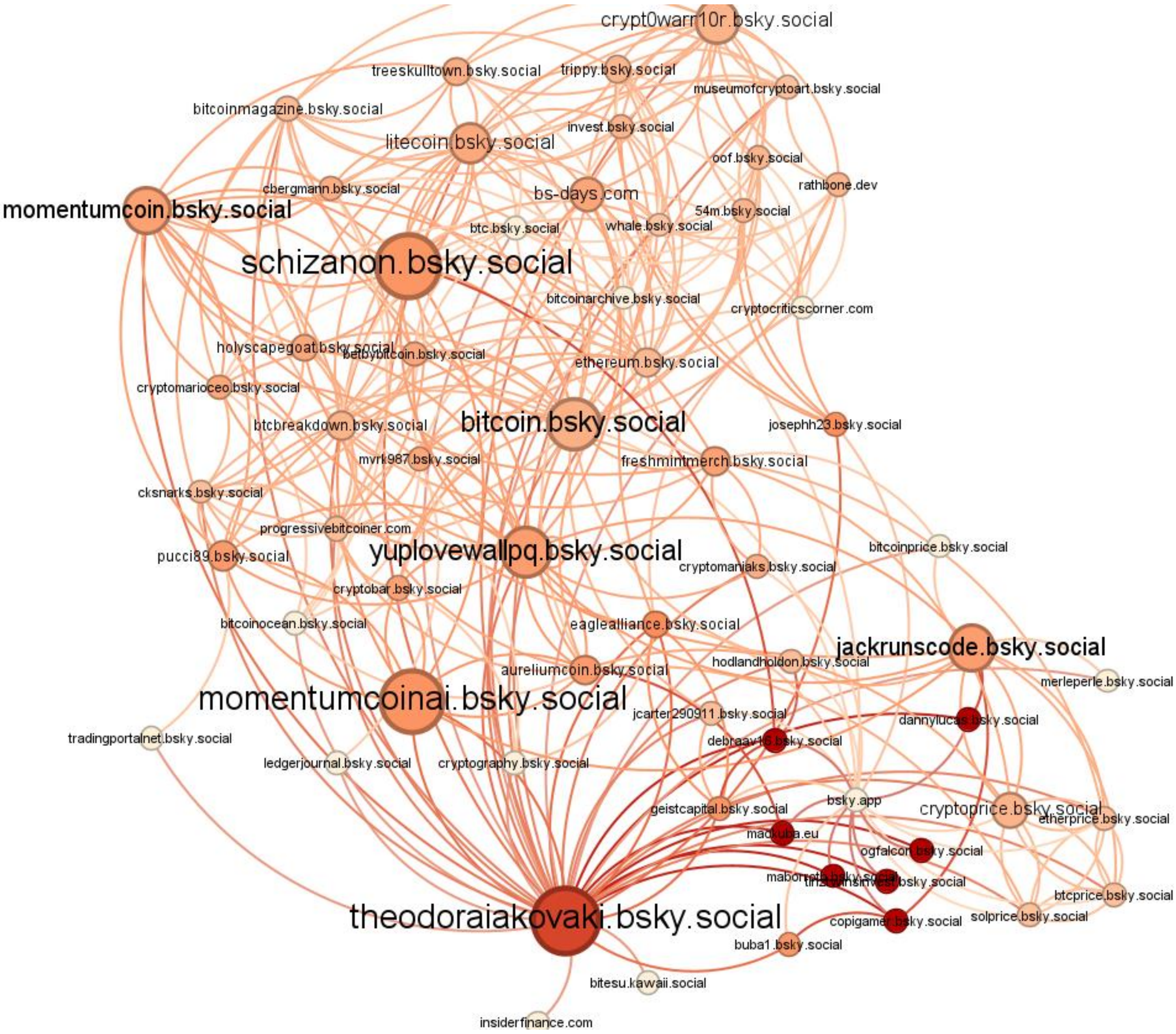


Figure 16: Graphical representation with ranking by Closeness Centrality and size by Betweenness Centrality

Eigenvector centrality measures the influence of a node in a network by considering not just the number of connections a node has, but also the quality or influence of its neighbors. Nodes with high eigenvector centrality are connected to other nodes that are themselves central, making them more influential in the overall network structure. Most nodes in the network have eigenvector centrality values close to zero. This suggests that the majority of nodes are not significantly connected to influential nodes, and therefore have limited influence in the network. There are only a few nodes with high eigenvector centrality values.

These nodes play critical roles in the network, as they are connected to other influential nodes. For example, @bitcoin.bsky.social appears prominently in the graph, suggesting it has a high eigenvector centrality, consistent with its role as a key influencer in the Bitcoin-related network. Account @ethereum.bsky.social also has moderately high eigenvector centrality, aligning with its position as key intermediary and active participant in the crypto-related discussions.

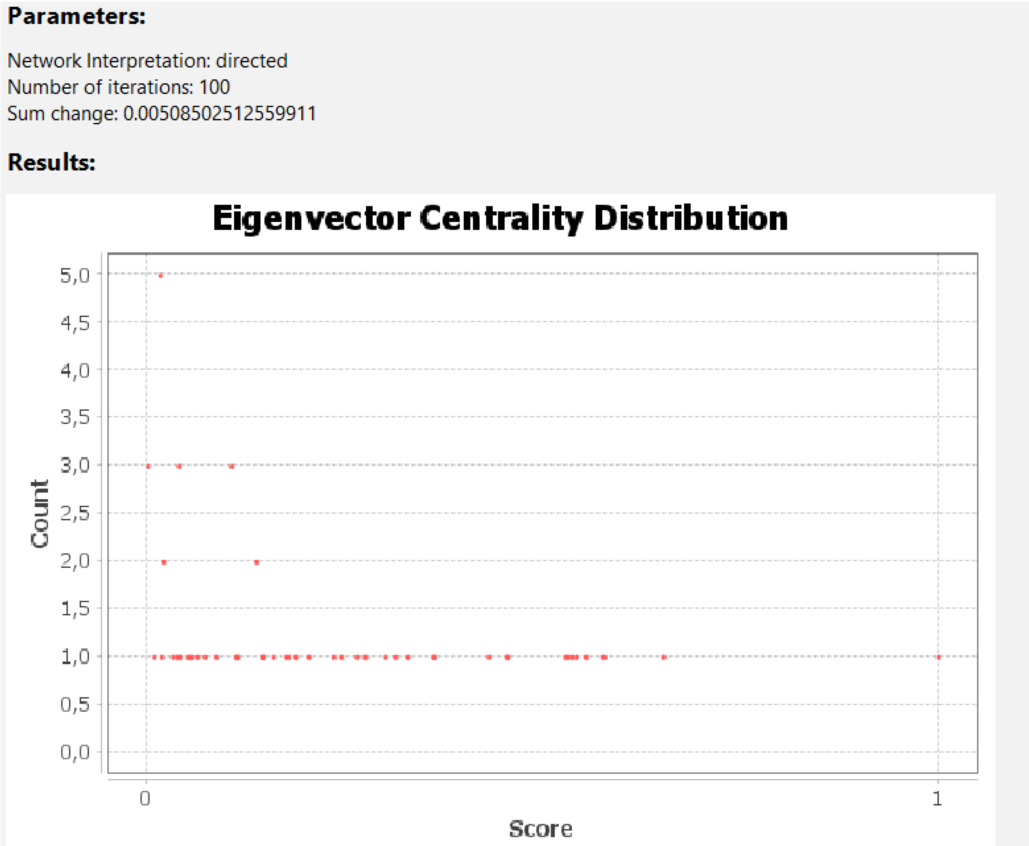


Figure 17: Eigenvector Centrality Report

<u>Graphical representation with ranking by Eigenvector Centrality and size by Betweenness Centrality</u>

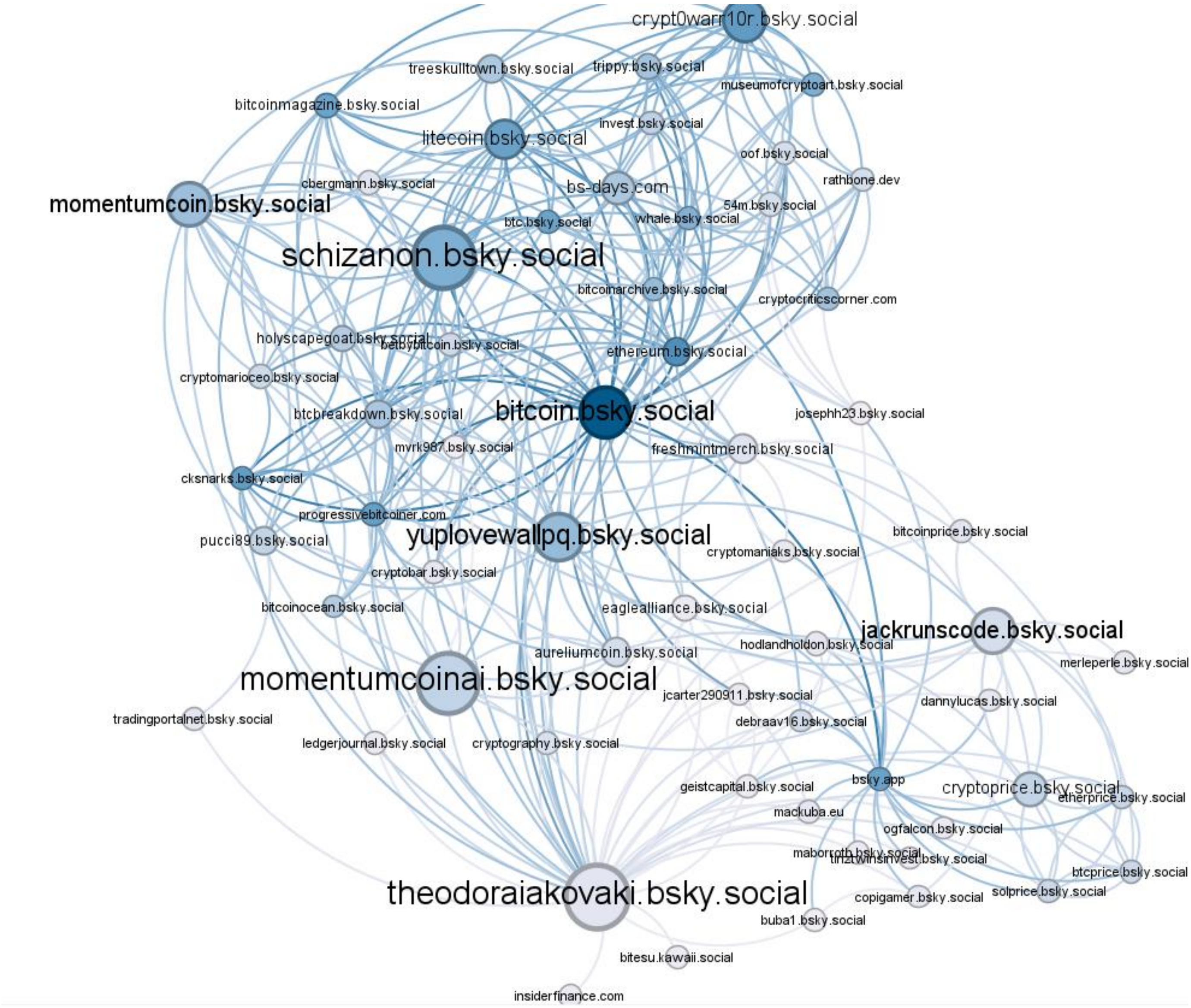


Figure 18: Graphical representation with ranking by Eigenvector Centrality and size by Betweenness Centrality

Here's a summary table for the profiles discussed so far, including their **Degree**, **Betweenness Centrality**, **Closeness Centrality**, and **Eigenvector Centrality** values. Since exact numeric values are not provided in the images, I will use relative rankings (High, Medium, Low) based on the discussions.

Profile	Degree	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Notes
@bitcoin.bsky.social	High	High	High	High	Most central and influential in the network; key Bitcoin account with extensive reach.
@ethereum.bsky.social	High	Low	Medium	High	A key player in the network, having influence given its connection to Ethereum, one of the largest blockchain platforms.
@schizanon.bsky.social	High	High	High	High	Strong supporter of Bluesky, active in reposting Bitcoin content.
@crypt0war10r.bsky.social	Medium	Medium	Medium	Medium	Balanced metrics; neither a major hub nor a bridge, but still well-connected.
@momentumcoinai.bsky.social	Medium	High	High	Medium	Active account sharing blockchain news; acts as a bridge in the network.

@btcbreakdown.bsky.social	Medium	Low	Medium	Medium	Focused on Bitcoin-related discussions. While not a primary connector, it remains reasonably well-integrated within the Bitcoin cluster.

4.5 Clustering effects

The average clustering coefficient is calculated for the **undirected version of my network.** This approach helps to uncover structural groupings rather than focusing on interaction directionality.

The **average clustering coefficient** represents the mean of the local clustering coefficients of all nodes in the network. The clustering coefficient of a node A is defined as the probability that two randomly selected friends of A are friends with each other. The value **0.219** that my network is relatively sparse, with only a moderate level of interconnectedness among nodes. This means that most nodes form smaller, localized clusters.

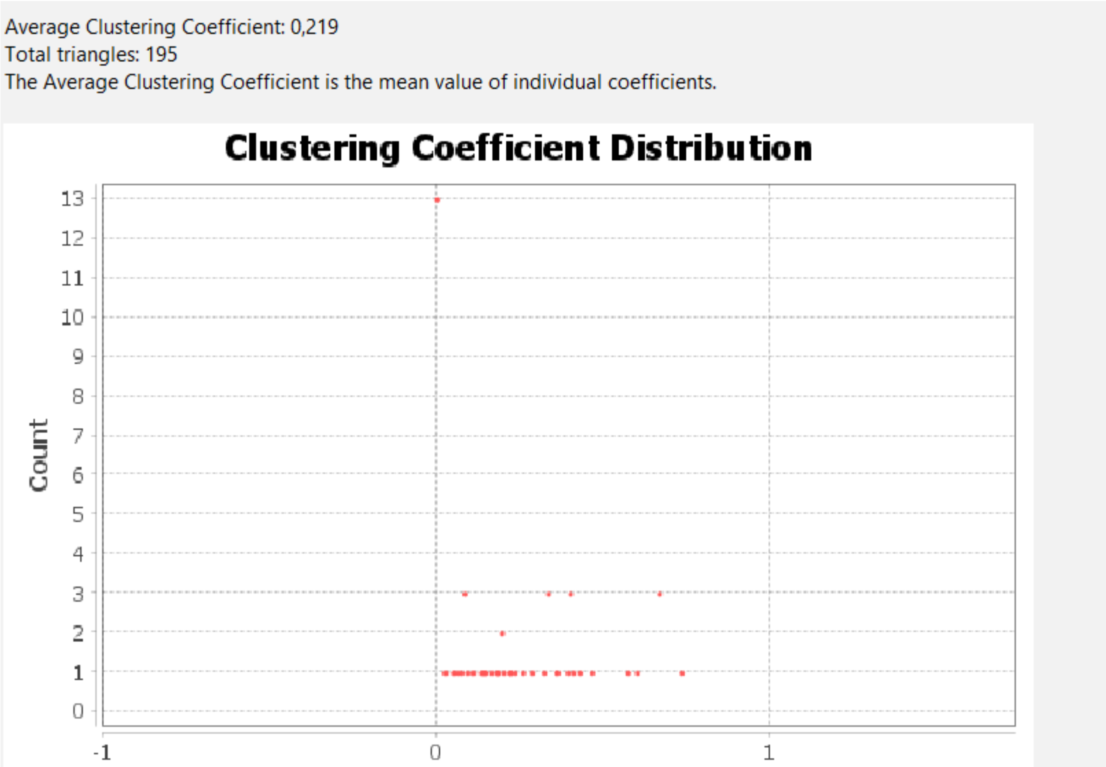


Figure 19: Clusterig Coefficient Report

This value reflects the number of closed triplets in the graph. A triangle exists when three nodes are all mutually connected.

The presence of 195 triangles supports the interpretation of smaller, localized clusters in the network. In my network, there are **195 unique triangles**, which suggests the presence of some clusters or subgroups where users are tightly interconnected. This complements the clustering coefficient by quantifying the specific instances of such structures.

@bitcoin.bsky.social: This node has seems to be highly connected in terms of triadic closure, forming numerous triangles. This indicates that it plays a central role in the network, acting as a hub where many tightly knit clusters intersect. Its high number of triangles suggests strong local clustering, meaning its connections are frequently connected to one another, forming cohesive subgroups.

My account also is a large and prominent node in terms of size, indicating high connectivity and participation in triangles. It serves as a critical connector between clusters or communities, though its importance differs in terms of eigenvector centrality. This means that it is primarily linked to nodes that are not globally central or influential in the broader network. The hub itself has a low clustering coefficient, but it contains many triangles. High triangle counts and low clustering coefficients are typical in **hub-and-spoke structures**, where highly connected nodes link many others but don't form tightly interconnected groups.

@ethereum.bsky.social: This account also indicates a dark blue color, showing strong involvement in forming triangles. It is likely connected to multiple influential nodes, reinforcing its importance in the network.

Graphical representation with ranking by Clustering Coefficient and size by Betweenness Centrality

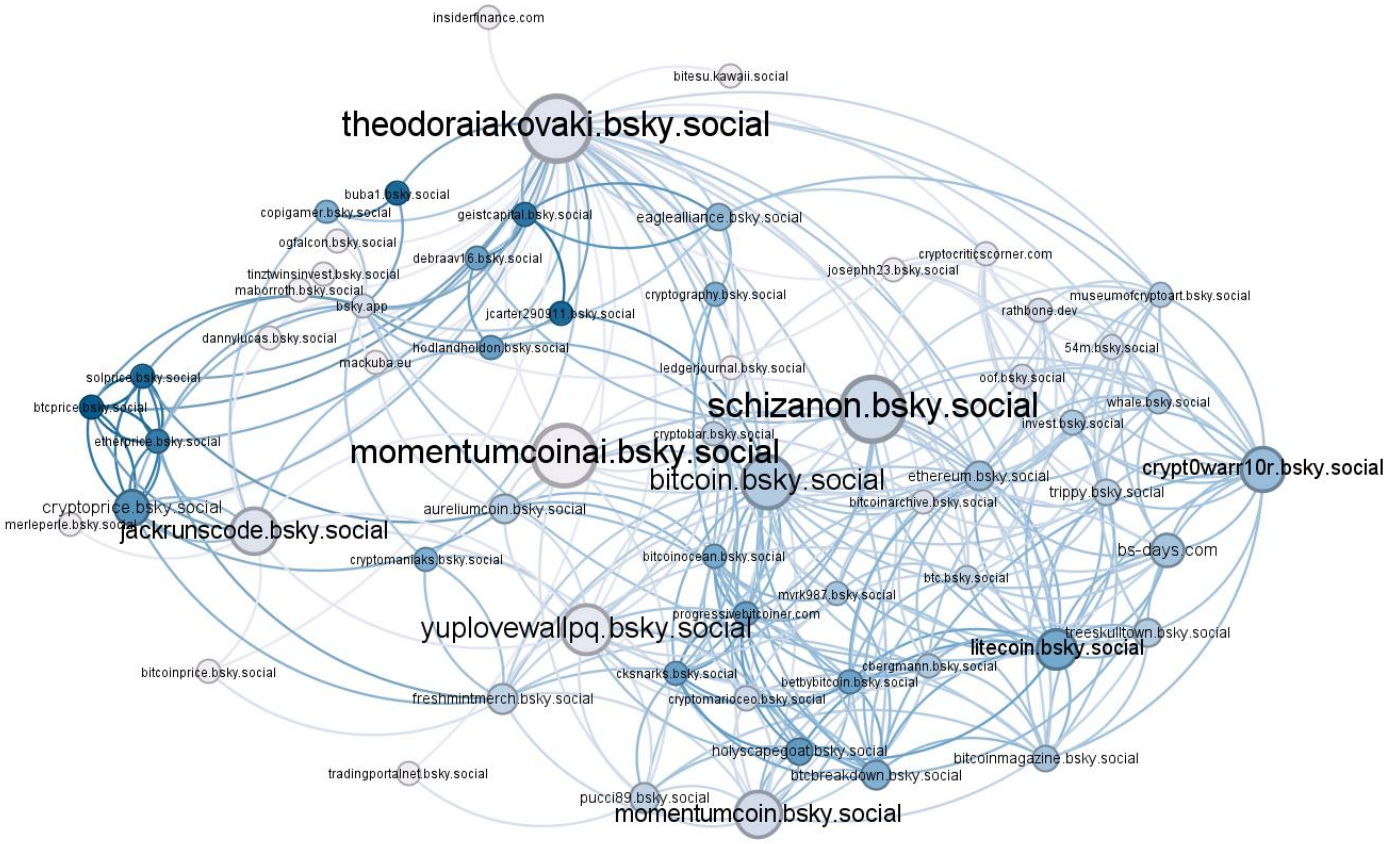


Figure 20: Graphical representation with ranking by Clustering Coefficient and size by Betweenness Centrality

Nodes like **@schizanon.bsky.social** or **@crypt0war10r.bsky.social** have lower clustering coefficients despite their prominence in other measures such as betweenness or degree centrality. This suggests these nodes function as **bridges** between otherwise disconnected groups, linking communities without being embedded in densely connected clusters themselves.

Nodes like **@btcprice.bsky.social** and **@solprice.bsky.social** have visibly high clustering coefficients. They seem to be involved in fostering localized information flow and collaboration. Peripheral nodes tend to have fewer connections and are less embedded in the larger web of triangles. However, the smaller groups they belong to are likely highly interconnected.

<u>Graphical representation with ranking by Number of triangles and size by Betweenness Centrality</u>

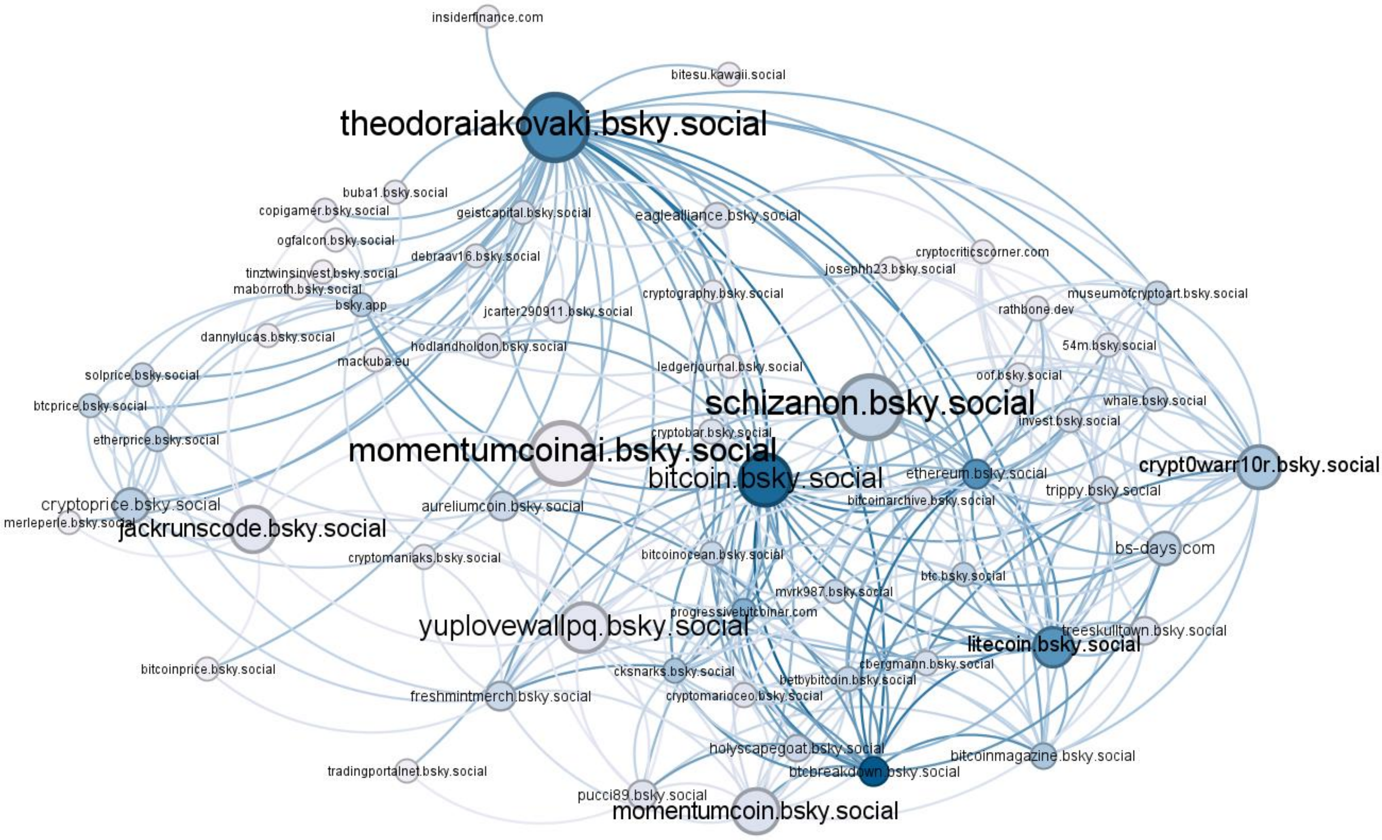


Figure 21: Graphical representation with ranking by Number of triangles and size by Betweenness Centrality

4.6 Bridges and local bridges

Betweenness centrality measures the extent to which a node lies on the shortest paths between pairs of other nodes. Nodes with high betweenness often serve as *connectors* between clusters.

Bridging centrality extends this by considering not only how often a node acts as a bridge but also the **structural importance of its connections** to disconnected or weakly connected components.

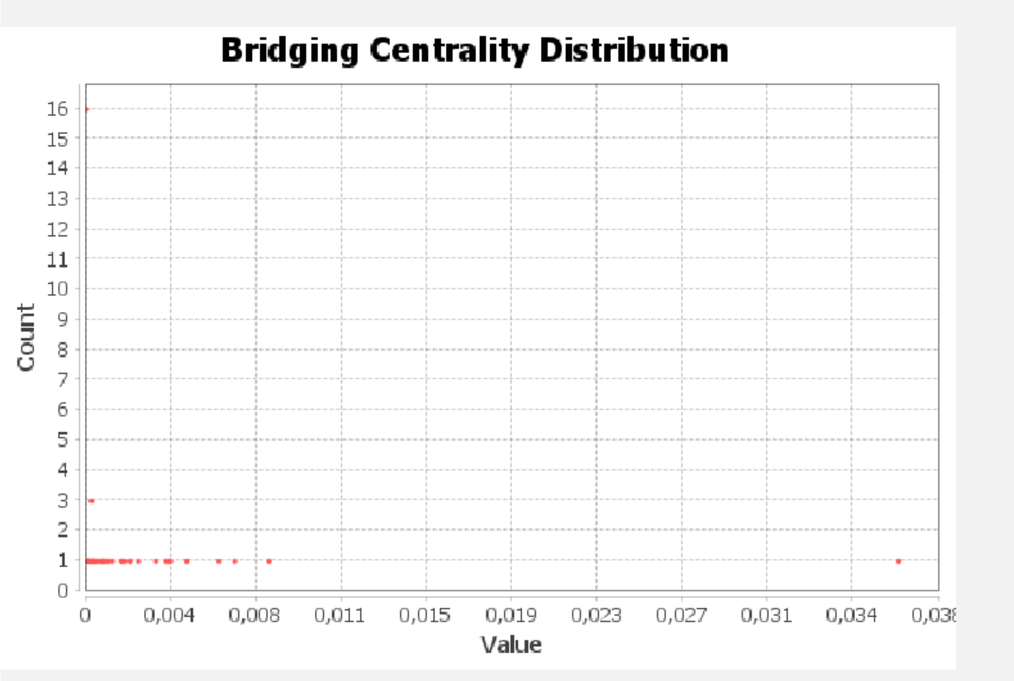


Figure 22: Bridging Centrality Report

<u>Graphical representation with ranking by Betweenness Centrality and size by Bridging Centrality</u>

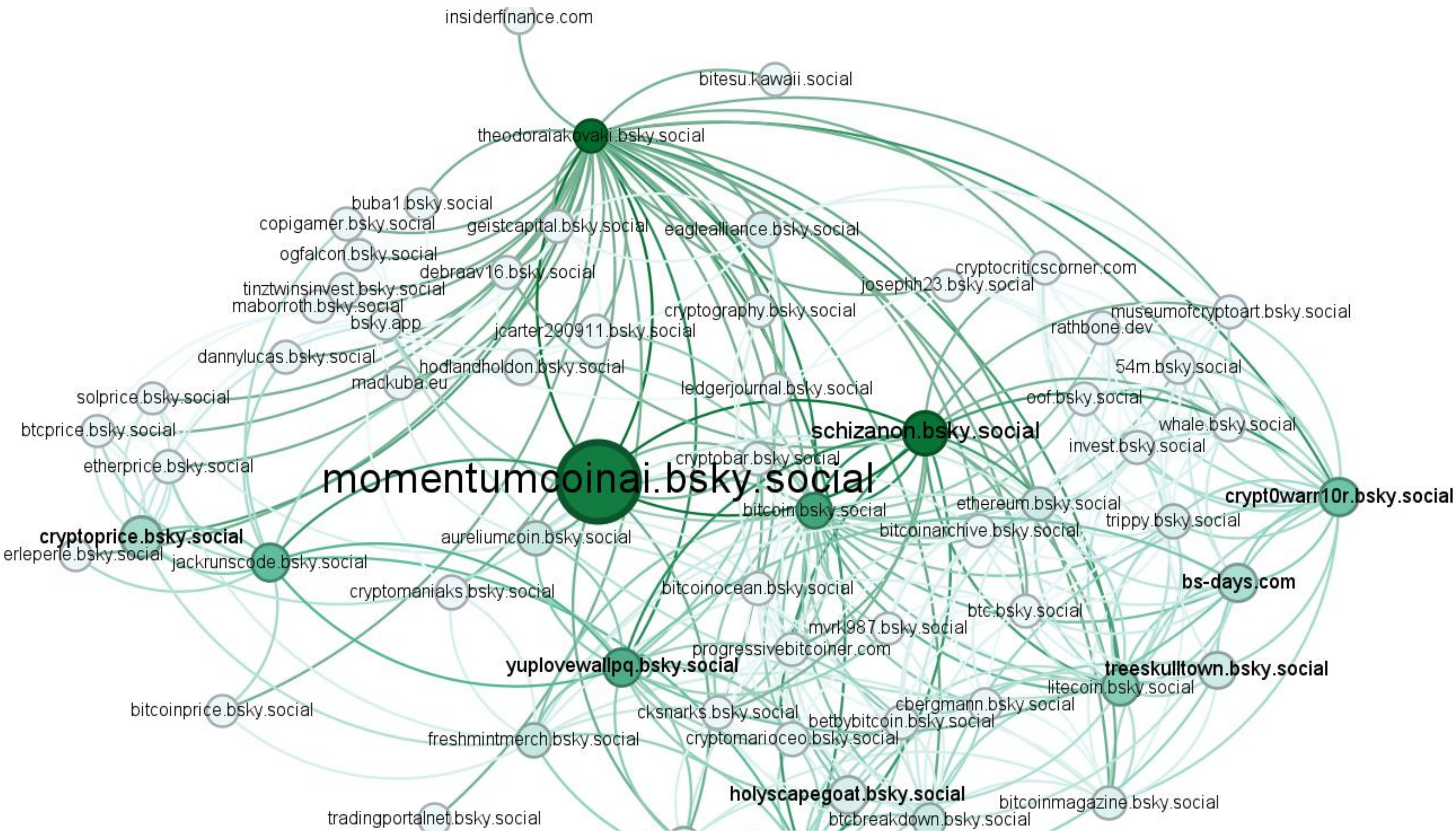


Figure 23: Graphical representation with ranking by Betweenness Centrality and size by Bridging Centrality

There is a single outlier node on the far right of the distribution, with a bridging centrality of ~0.038. This node acts as a key bridge, connecting disparate parts of the graph. The majority of nodes (near the left) have negligible bridging centrality values, showing they primarily belong to **localized sub-communities** without acting as bridges. The outlier with the highest bridging centrality is essential for network cohesion. Removing this node could disrupt connections between distinct communities or sub-communities. The small bridging centrality values for most nodes reinforce their role as **non-bridge nodes.** They primarily serve within their immediate communities rather than connecting different regions of the graph.

We already have stand out some profiles that form hubs and influential nodes. Let's see them more analytically.

Bridges connect separate clusters, and their removal increases the number of connected components in the graph. Characteristics of **bridge nodes:**

- Nodes that are **central in sparse regions** of the graph.
- Nodes that link otherwise **disconnected clusters**.

Nodes like @momentumcoinai.bsky.social (large size + high betweenness) serve as critical bridges. They connect distinct regions or communities, especially in blockchain-related discussions. These nodes are likely to lie on global shortest paths across the graph. Removing them would cause fragmentation or increase the shortest path length between clusters.

Active Bitcoin Advocate: @schizanon.bsky.social — Plays a **central role** in reposting Bitcoin content and is well-connected across the network. A **strong bridge** between different parts of the network.

My account has high betweenness centrality, high degree, and moderate clustering coefficient. Nodes with high betweenness centrality tend to be well-connected across the graph and link multiple communities, acting like a local bridge.

Local bridges are nodes that connect different groups within a network, facilitating communication between those groups. These nodes are not necessarily the most connected or influential, but they play a key role in connecting otherwise disconnected clusters. They are critical for maintaining short distances between nodes.

@bitcoin.bsky.social: This account is highly connected to many nodes, even less densely ones, and plays a major role in information flow and influence within the network. As a **key Bitcoin account**, it has an extensive reach. Its high values across all centrality measures suggest that it serves **local** bridge role.

@yuplovewallpq.bsky.social: This account also plays a **bridging role**, linking different communities or sub-networks within the broader crypto-focused network. It is also influential beyond just bridging and also contribute to fast information spread, as it has high closeness and eigenvector centrality.

While not as influential or central as other nodes, @crypt0war10r.bsky.social still plays a **moderate bridging role** in the network. Its **balanced centrality metrics** mean it connects various parts of the network without being the most dominant node. It's positioned between Bitcoin-related discussions and other blockchain-related content, acting as a **local bridge**.

For @litecoin.bsky.social, a high degree implies that it interacts directly with many nodes in the network, connecting different groups with cryptocurrency interests.

@jackrunscode.bsky.social connects multiple **localized clusters** where the neighbors might not otherwise have direct links. Removing it would **break intra-community connectivity** and force neighbors to take longer, indirect paths.

4.7 Gender and Homophily

This visualization, generated using the **Circular Layout Plugin** in Gephi, is a useful tool for analyzing **homophily** in the network. Here's an analysis of what this layout conveys based on the parameters used:

1. **Group nodes by Modularity Class**: Nodes are grouped into communities based on modularity, reflecting shared connections.

2. **Order nodes by Degree**: Within each group, nodes are arranged by their degree, showing the most connected nodes closer to the center of their respective axis.

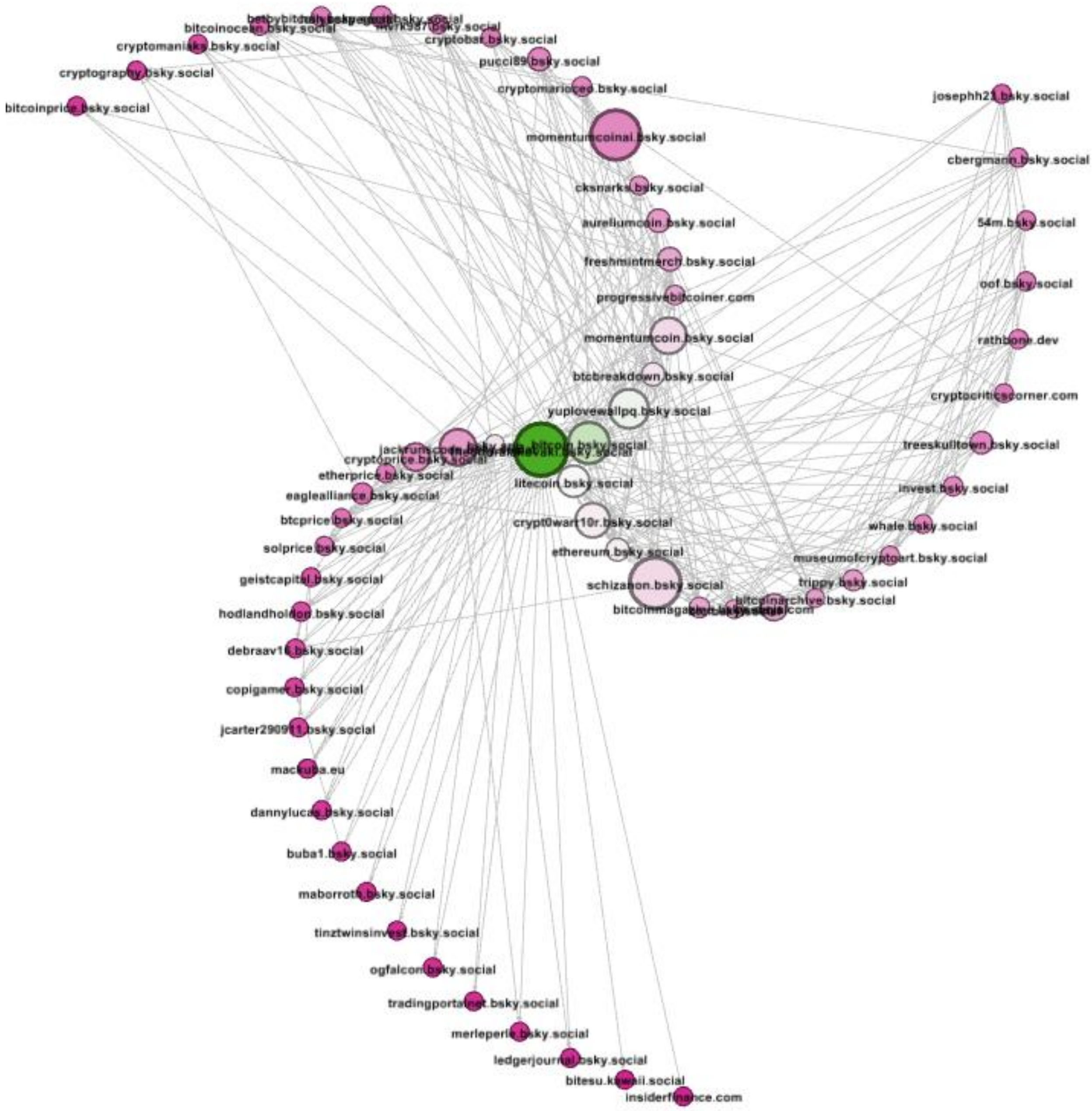


Figure 24: Graphical representation of homophily

If nodes in the same cluster are more connected, it suggests a higher degree of **homophily** in that group. This indicates that nodes with similar attributes or behaviors, like cryptocurrency-related topics, tend to form stronger ties with each other. Larger nodes, representing more central nodes, could be seen as influencers within the network. These nodes act as bridges between otherwise disconnected clusters, which could suggest that their centrality doesn't rely on homophily but rather on influence or authority. Let's see what is the thing that “unites” those profiles:

1. Price-analysis team: These nodes share a common interest in **price analysis** of cryptocurrencies, and their connections are formed around this shared focus (etherprice, btcprice, solprice etc.) They serve as **specialist nodes** contributing niche content about price trends of specific coins, which attract connections from both other specialized nodes and general influencers.
2. News and Updates team: This cluster forms around accounts sharing **general cryptocurrency news, updates, and critiques**. Nodes like @cryptomagazine.bsky.social, @cryptocritics.bsky.social and @btc.bsky.social suggest a focus on both informing the audience and analyzing trends or developments in the crypto space. Unlike the price-analysis group, which is more specialized, this cluster serves a **broader informational purpose**, attracting users across various subtopics in the cryptocurrency ecosystem.
3. Meme and Image-Oriented team: This cluster forms around accounts specializing in visual and meme-based content. Nodes like @yuplovewallpq.bsky.social and @btcbreakdown.bsky.social frequently post cryptocurrency memes, infographics, or quick visual analyses aimed at making complex topics more accessible or entertaining. Memes and images have a higher potential for **virality**, which helps this cluster spread ideas and information widely within and beyond the network.

The central nodes such as **@bitcoin.bsky.social** and **my account** show strong clustering with nodes sharing the same topic or interest (cryptocurrency, Bitcoin, etc.). These high-degree nodes are probably acting as connectors across different clusters, which implies that although there may be some **homophily** (same-topic connections), these central nodes act as bridges that link different subgroups.

Also, from the homophily visualization we can see better the nodes with **higher influence or importance** within their respective groups, like **@momentumcoinai.bsky.social** and **@schizanon.bsky.social.** These nodes aggregate and disseminate information about cryptocurrency images and news respectively. Each central hub on these teams is:

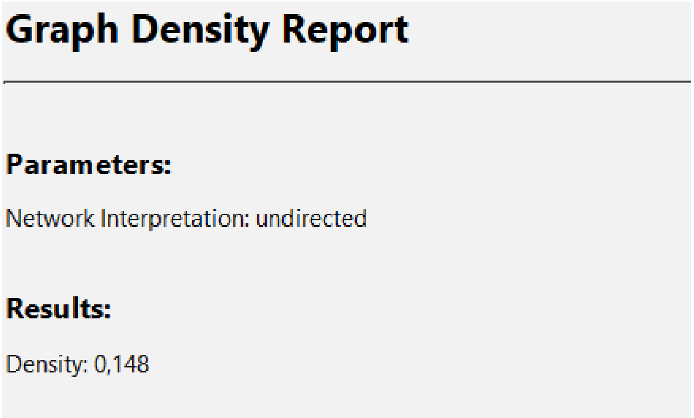
Price Cluster: Financial analysts and price-oriented influencers.

News Cluster: Content distributors and thought leaders.

Meme/Image Cluster: Community builders and network engagers.

4.8 Graph density

Graph Density measures the proportion of actual edges in a graph compared to the maximum possible edges. A value of **1** means the graph is fully connected (a complete graph), while a value close to **0** means the graph is sparse.


Graph Density Report

Parameters:

Network Interpretation: undirected

Results:

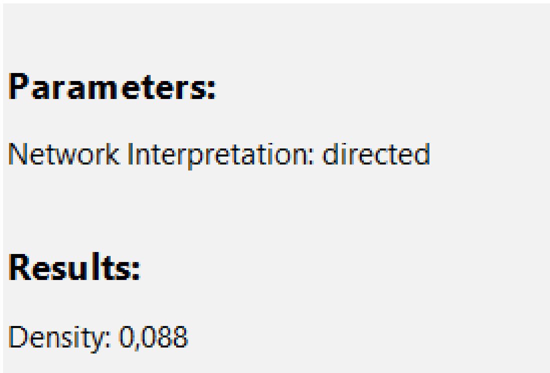
Density: 0,148

Figure 25: Graph Density Report - undirected

In the undirected version of the graph, the density is 0.148. Only **14.8% of the possible connections** between nodes exist in the graph. This indicates that the network is relatively sparse, which is typical for social and communication networks. Sparsity often results from the presence of well-defined **clusters or communities**. Nodes within a community are highly connected, but there are relatively fewer connections between communities. In my network case, the presence of 23 SCCs and visually distinct clusters in the Radial Axes Layout strongly supports this. Sparse graphs depend heavily on **bridges** and **local bridges** for connectivity. Without these, the graph could easily fragment into disconnected components. The flow of information rely on key-nodes (like those with high betweenness or degree centrality).

In the directed version of the graph, a density of **0.088** means that only **8.8% of the possible directed edges** exist in the graph.

Since this is lower than the undirected density (**0.148**), it highlights the asymmetry in the connections—many potential pairs of nodes have only one-way connections or no connection at all. We can see from the Homophily section, that connections **between clusters** are rarer, which depend on bridge nodes to facilitate cross-cluster interactions. In the Degree measures section, we have identified nodes with high **out-degree** (broadcasters) and **in-degree** (information aggregators).


Parameters:

Network Interpretation: directed

Results:

Density: 0,088

Figure 26: Graph Density Report - directed

Sparse graphs with low density are common in **real-world social networks** because:

1. People (or accounts) tend to interact with a limited subset of others (e.g., shared interests or niches).
2. Nodes within communities often share similar attributes, which leads to dense intra-community connections but sparser inter-community connections.

4.9 Modularity

Let’s see exactly the communities provided by Modularity report. Modularity is a scalar measure used in network science to assess the strength of the division of a network into communities (or modules). A community, in this context, is a group of nodes that are more densely connected to each other than to nodes in other communities. Gephi calculates Modularity based on **The Louvain method**. Also, we will check for cliques. In a clique, all nodes are connected to one another. There are no isolated nodes or edges that are missing between any two nodes in the clique.

Modularity Report

Parameters:

Randomize: On
Use edge weights: On
Resolution: 1.0

Results:

Modularity: 0,228
Modularity with resolution: 0,228
Number of Communities: 3

Figure 27: Modularity Report

The modularity score of **0.228** indicates that while there is some degree of community structure, the division of the network into distinct groups is not particularly strong. A higher modularity score (closer to 1) would indicate well-defined, highly separate groups. This happens due to the nodes behavior. Some nodes, like my account, act as bridges, creating links across multiple communities, which makes the groups less distinct. Also, there is an overlap of communities, since nodes from different communities share significant connections with one another, blurring the boundaries between groups. The undirected density of **0.148** and directed density of **0.088** show that the graph has a moderate number of edges, which can cause communities to blend together.

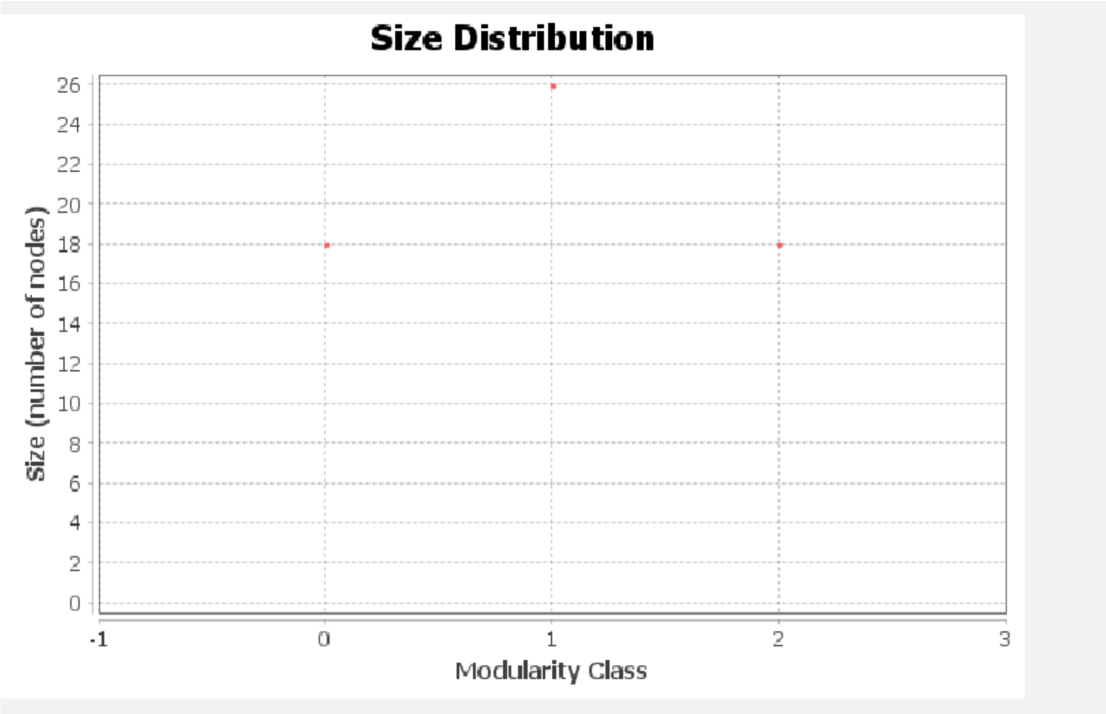


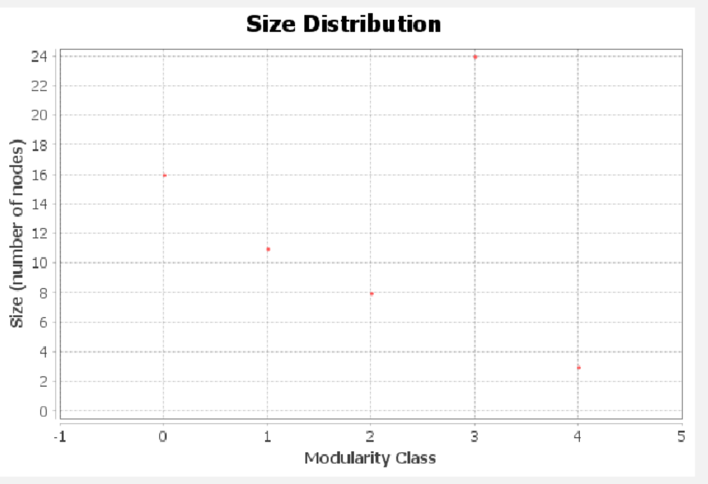
Figure 28: Modularity Distribution with Resolution 1.0

As we can see from the report, There are **3 distinct communities** detected in the network:

- Community 1: Largest, with **~26 nodes**.
- Community 2: Medium-sized, with **~18 nodes**.
- Community 3: Medium-sized, with **~18 nodes**.

Community 1 dominates in size and represents the central or most influential cluster. Community 2 and 3 represent a cohesive but slightly less influential group.

Changing the resolution to 0.8, we observe the algorithm has detected five communities instead of three, with a slightly lower modularity score of 0.213. The slight drop in modularity (from 0.228 to 0.213) indicates that the five-community partitioning explains the structure of the network slightly less effectively than the three-community partitioning.



Parameters:

Randomize: On
Use edge weights: On
Resolution: 0.8

Results:

Modularity: 0,213
Modularity with resolution: 0,121
Number of Communities: 5

Figure 29: Modularity Report with Resolution 0.8

Community structure:

Community 1: Largest, with **~24 nodes**.

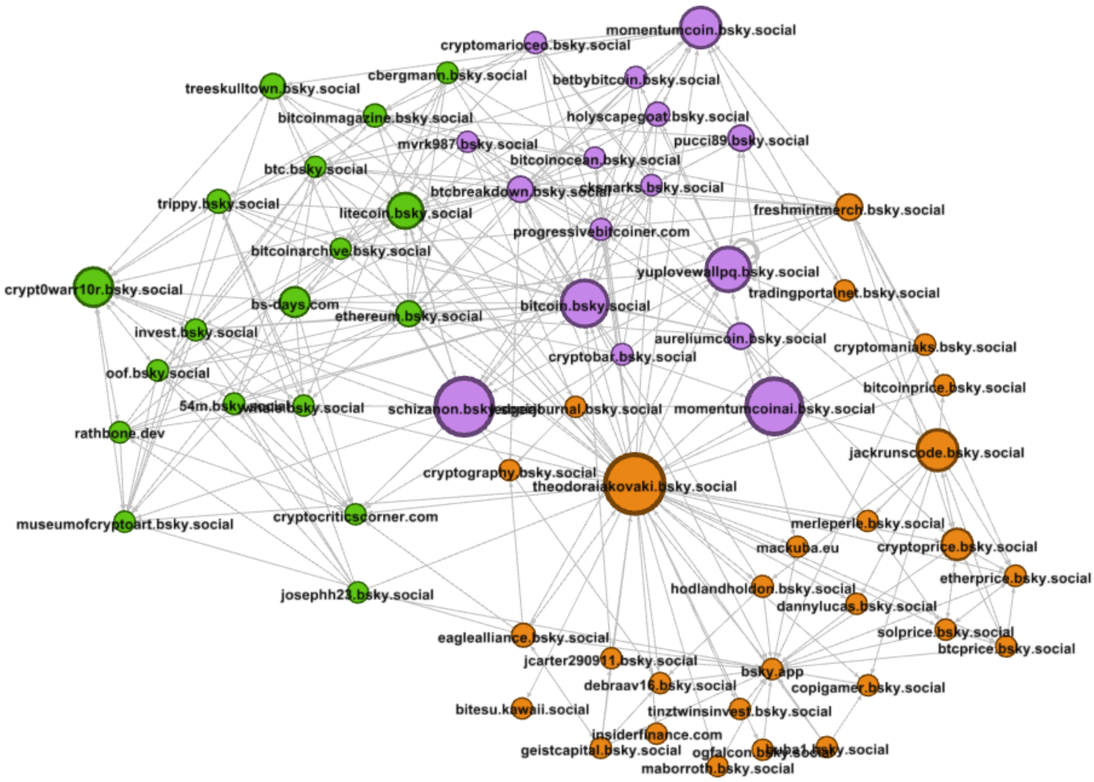
Community 2: Medium-sized, with **~16 nodes**.

Community 3: Medium-sized, with **~12 nodes**.

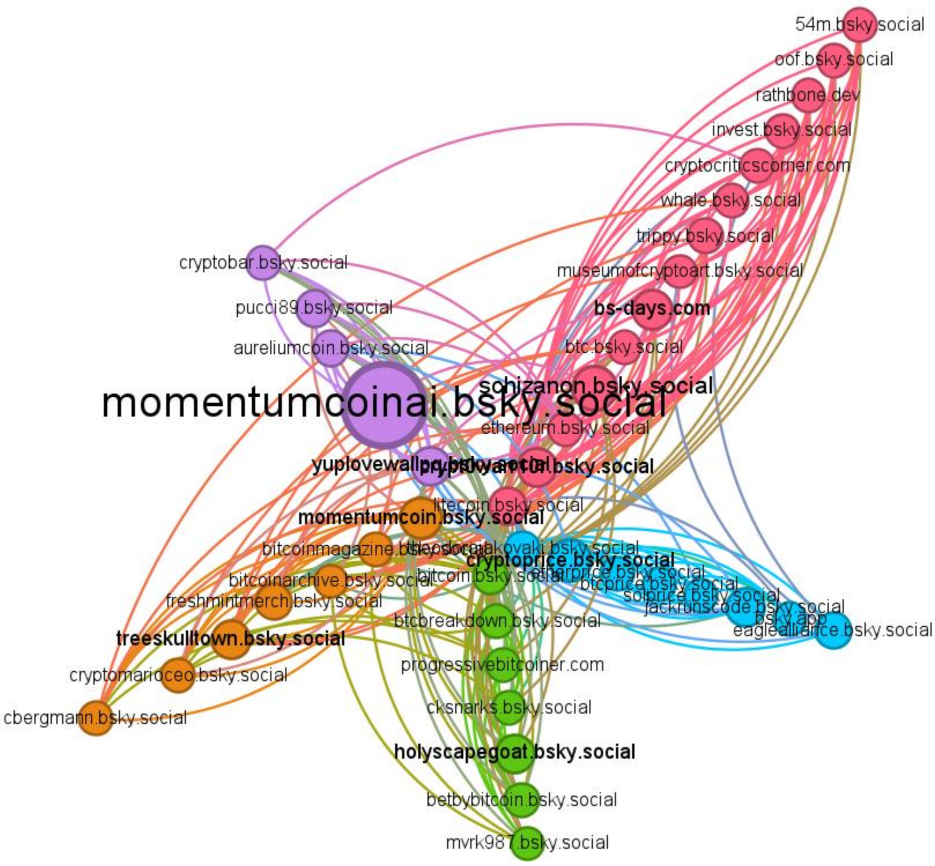
Community 4: Small, with **~8 nodes**.

Community 5: Smallest, with **~3 nodes**.

<u>Graphical representation with partition by Modularity (Resolution=0.1)</u>



<u>Graphical representation with partition by Modularity (Resolution=1.0)</u>



At 3 Communities, the network was divided into broad themes (news, images, price analysis), as we have seen in the Section of Homophily. This is useful for high-level categorization.

At 5 Communities, the granularity highlights **nuanced divisions**, which may uncover specialized roles or behaviors within the larger groups. **Blue community** (Community 1) becomes more fragmented, indicating the presence of tightly connected sub-groups within the larger cluster. @crypt0war10r.bsky.social and @litecoin.bsky.social are the key hubs in this group, as we have explained in Bridges section. **Orange community** (Community 1 in the 3-community view) splits into smaller, localized clusters. **Pink and green nodes** emerge as distinct smaller clusters, indicating specialized roles. Let's see each role:

1. Purple community: It has 2 key nodes, with profiles focused on Bitcoin.

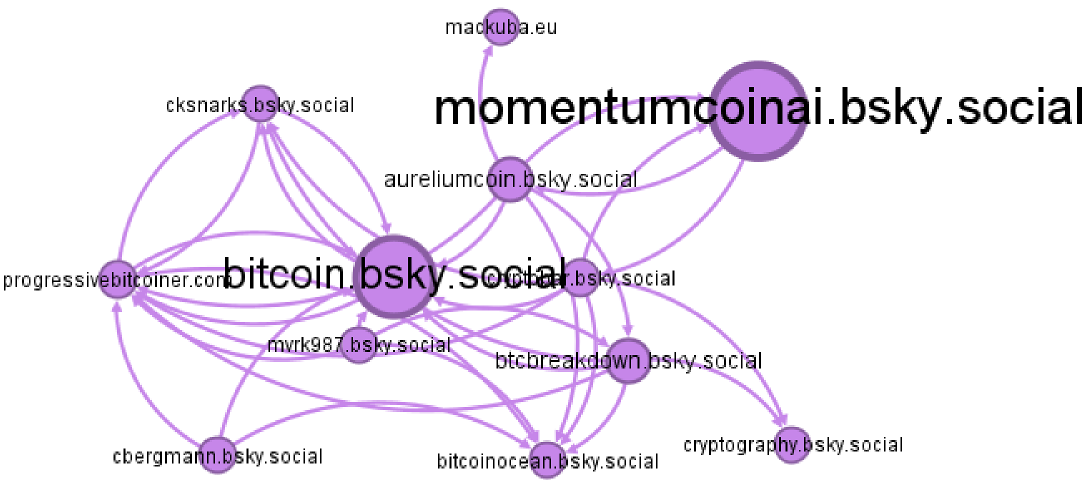


Figure 30: Purple Community

2. Green community: Focus on crypto prices. A particularly interesting feature of this community is the **clique** formed between the nodes representing key cryptocurrency price trackers: **cryptoprice**, **btcprice**, and **etherprice**. These three nodes form a tightly interconnected group, where each node is connected to every other node in the clique. This structure reflects a high degree of mutual exchange of information related to cryptocurrency prices. @jackrunscode.bsky.social connects this clique with the other accounts.

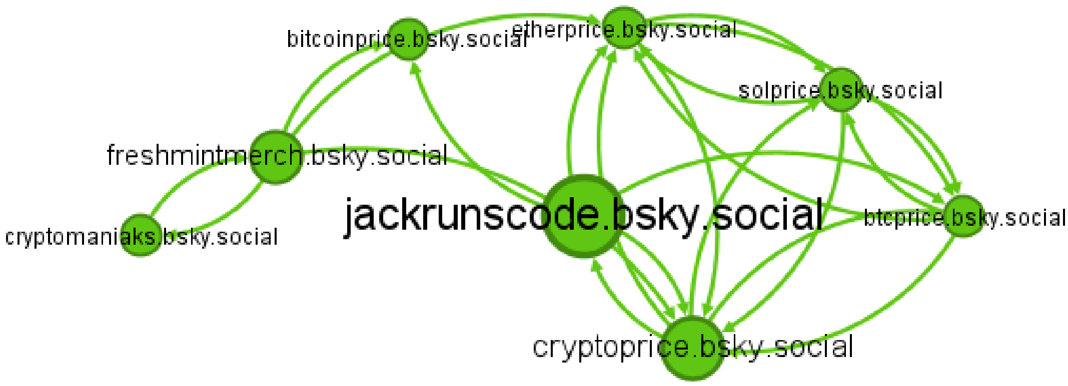


Figure 31: Green Community

3. Blue community: It stays unchangeable and more imaged-oriented.

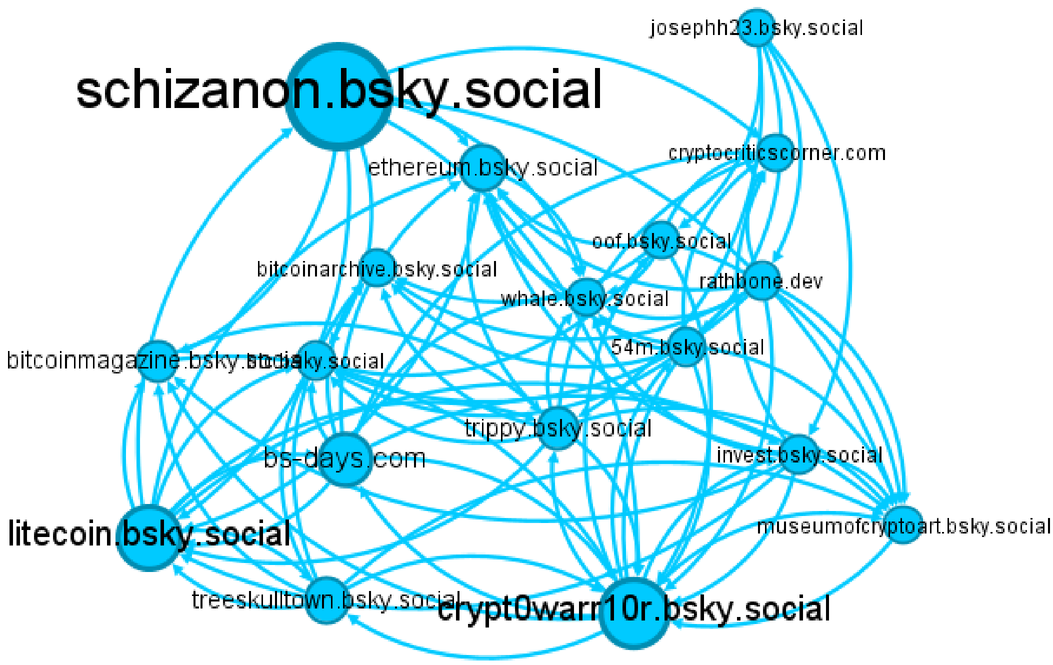


Figure 32: Blue Community

4. Pink community: Main key node is my account, connected with profiles that are not specialized only in the crypto community.

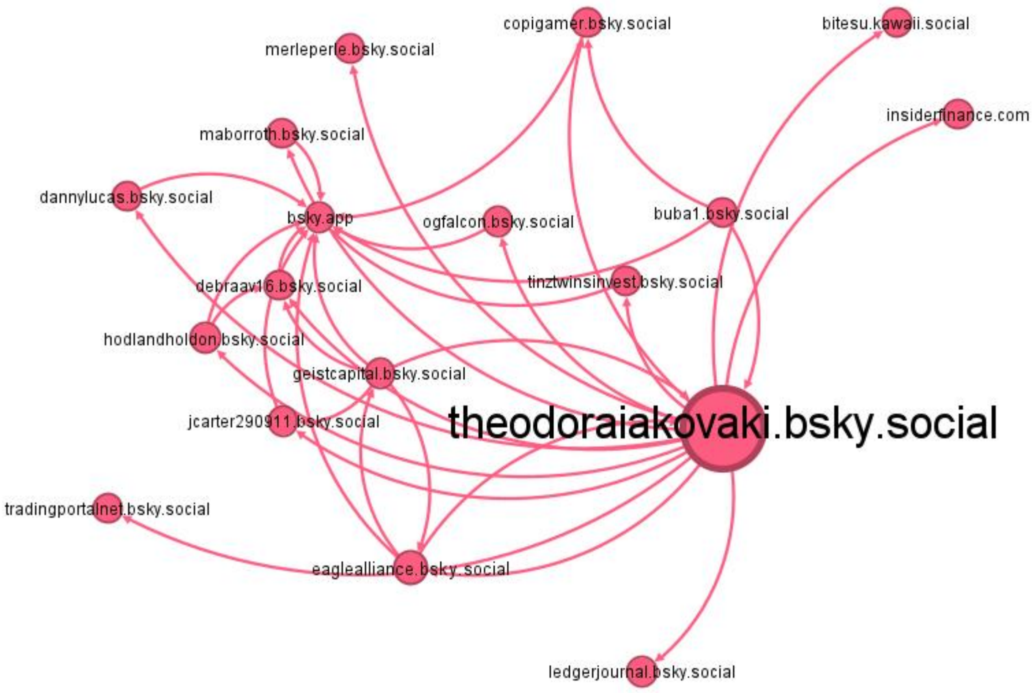


Figure 33: Pink Community

5. <u>Orange community:</u> Sub-community of purple, interested in Bitcoin but also in other social news.

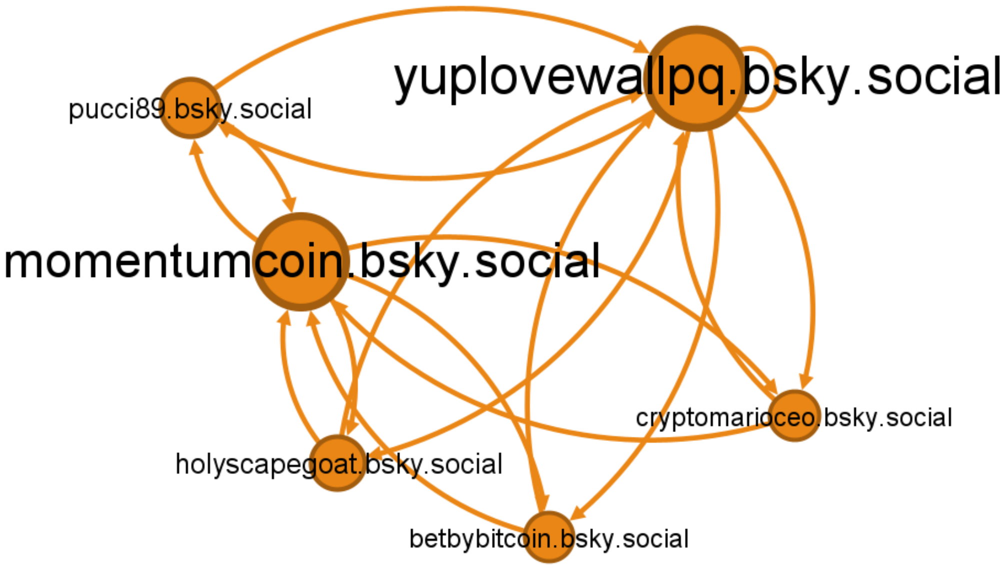


Figure 34: Orange community

The difference in modularity highlights a trade-off: higher modularity often aggregates communities, whereas lower modularity reveals **more precise clusters**. Also, key nodes are clearly visible.

4.10 PageRank

PageRank calculates the importance of a node compared to others in the network.

Epsilon: 0.001
The precision level of the PageRank computation ensures that the results are highly accurate. A low epsilon indicates the algorithm converged to a very precise value.

Probability: 0.85
This parameter reflects that the likelihood of following links (connections) within the network is standard. It models real-world behavior where a user follows links most of the time but occasionally restarts at a random node.

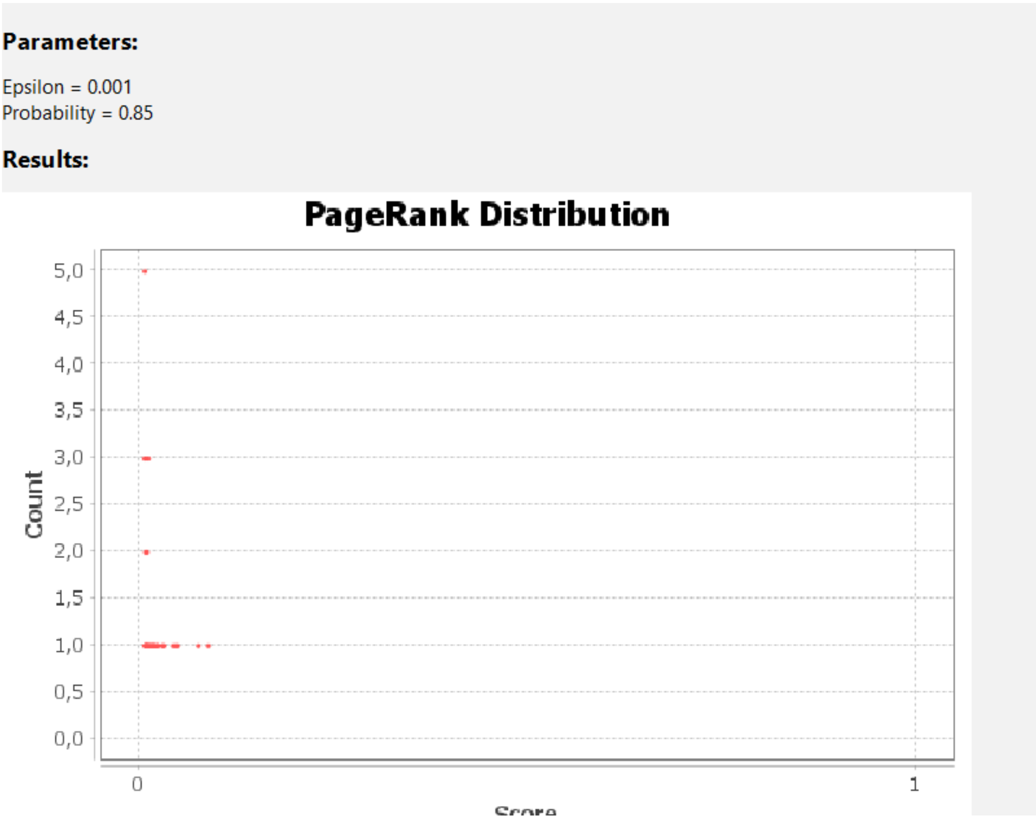


Figure 35: PageRank Report

Graphical representation with ranking by PageRank

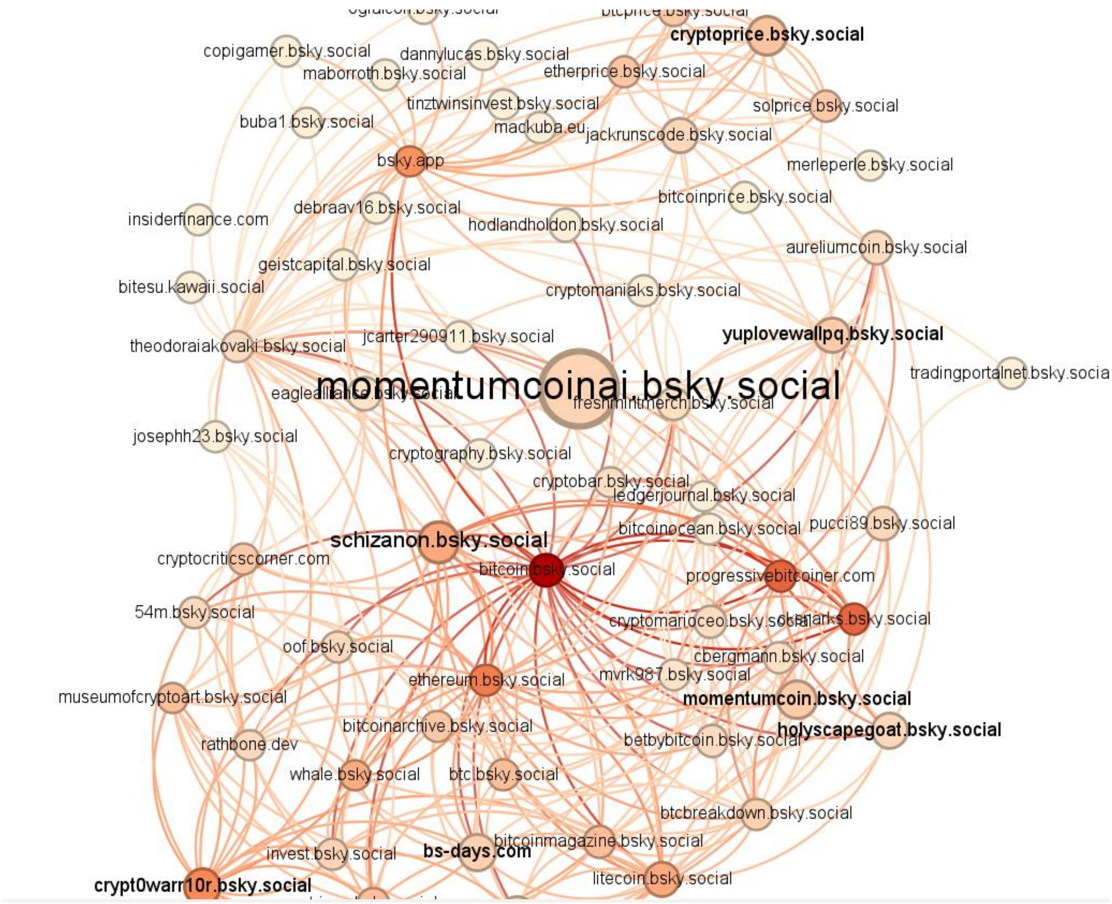


Figure 36: Graphical representation with ranking by PageRank

A few accounts have **significantly higher PageRank scores**, while the majority of nodes have very low scores (close to 0). This reflects that a small subset of nodes dominates the influence within the network. Specifically, @bitcoin.bsky.social, @bsky.app, @crypt0war10r.bsky.social are the profiles that we have highlighted previously in our analysis. @bsky.app is the official account of Blue Sky platform, so it is logical to attract engagement. Accounts like @bitcoin.bsky.social and @crypt0war10r.bsky.social have many incoming connections (high PageRank) and serve as key sources of information. They are likely followed or cited frequently, amplifying their visibility and influence across the network.

A node with high Page Rank does not mean that it works as a bridge. As we can see, the @bsky.app may attract followers, but those followers also connect to each other without relying on this account.

5. Conclusions

This study set out to analyze the cryptocurrency community on the Bluesky platform, focusing on its network structure, key influencers, and community dynamics. By leveraging social network analysis techniques and utilizing Gephi as the primary tool, the research employed to extract meaningful insights from a network of 62 key nodes and their connections. The analysis revealed the critical roles of central nodes, community structures, and bridges in sustaining the cryptocurrency discourse on decentralized platforms.

Influential nodes in the network act as hubs for information dissemination and engagement. Their behavior, interests, and connections drive their centrality in the community. These accounts often share a mix of technical analyses, updates on specific coins or blockchain technologies, insights into broader cryptocurrency trends and engagement content like crypto memes. By engaging with these varied topics, they attract a diverse audience and maintain relevance across subgroups. Many influential nodes provide in-depth analyses of cryptocurrency markets, including price trends, volatility indicators, and investment strategies. This content appeals to both novice and experienced users seeking actionable insights. A significant portion of the shared content revolves around blockchain advancements, including discussions about new protocols, smart contract capabilities, and decentralized applications. These posts foster technical discussions and knowledge sharing. The most viral nodes are engaged in Bitcoin discussions.

The findings of this study have practical implications for understanding and leveraging decentralized networks. Identifying influential nodes can guide efforts to strengthen community engagement and foster collaboration. Understanding network dynamics helps predict trends and sentiments within cryptocurrency communities. This research opens pathways **for further exploration**. Comparing the Bluesky cryptocurrency network with those on platforms like Twitter or Discord could reveal unique patterns in user engagement.

6. References

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