

ΟΙΚΟΝΟΜΙΚΟ  
ΠΑΝΕΠΙΣΤΗΜΙΟ  
ΑΘΗΝΩΝ



ATHENS UNIVERSITY  
OF ECONOMICS  
AND BUSINESS

## DEPARTMENT OF MANAGEMENT SCIENCE AND TECHNOLOGY

# BLUESKY NETWORK ANALYSIS

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Aimilia Dimitra Ktena

8210073

supervised by

Dimitrios Pournarakis

## **Abstract**

This project focuses on analyzing a social network on the Bluesky platform, examining its structure, dynamics, and various key properties. Using data from a selected Bluesky account, the study investigates component measures, degree distributions, and centrality metrics to identify influential users and their roles. Metrics such as network diameter, average path length, clustering coefficients, and triadic closure are explored alongside community structures analyzed through modularity. PageRank is applied to highlight critical nodes driving information flow. This analysis provides insights into the dynamics of the network, how users connect, how information spreads, and how communities are formed within the decentralized Bluesky ecosystem.

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## 1. Introduction

The rise of social media platforms has transformed the way information is disseminated and consumed globally. BlueSky, an emerging decentralized social media platform, provides a space for individuals and organizations to share updates and engage with their audiences in a dynamic and interactive manner.

One account of particular interest is **@palestineday.bsky.social**, which actively informs its audience about the ongoing conflict between Gaza and Israel, advocating for Palestinian rights. This account provides frequent updates and engages users on a highly sensitive geopolitical issue, making it an intriguing case for understanding how politically charged information circulates in online networks.

The choice of this account is motivated by its significance in raising awareness about the humanitarian crisis in Gaza and the broader context of the Palestine-Israel conflict. Through this analysis, I aim to explore how the network surrounding this account operates: identifying the key users who amplify its messages, understanding the flow of information within the network, and uncovering patterns of engagement. By examining these dynamics, this study seeks to provide insights into how digital advocacy fosters awareness, mobilizes communities, and influences discourse on such a polarizing and globally impactful issue.

## 2. Data Presentation

For this project, the data was collected using Gephi's BlueSky plugin, which allows users to fetch and analyze networks directly from the platform. By adding my credentials and connecting to the plugin, I was able to retrieve data related to the account **@palestineday.bsky.social**. The data collection focused on the account's **followers**, **following**, and one level of connections beyond (**n+1**), with a crawl limit of 100 to avoid overloading the network.

The graph creation process was stopped at approximately 40% completion, as the network was already extensive, and further crawling could have unnecessarily complicated the analysis. The resulting network represents the interactions and connections between users surrounding the selected account, providing a clear foundation for the subsequent analysis.

Below are examples of the datasets used to construct the network.

The first table is showing a part of the nodes dataset, representing the individual users within the network:

Data Table									
Nodes	Edges	Configuration	Add node	Add edge	Search/Replace	Import Spreadsheet	Export table	More actions	
									Filter:
did:plc:ilgpnfaxlr5qtlsvoytlyv	palestineday.bsky.social	Palestine, a nation of its people, shall ...	5739	895	6634	5739.0	895.0		
did:plc:mwo3liroe2gwktstlwtoip23	danaekurd.bsky.social	Assistant Professor of Political Science .	114	100	214	114.0	100.0		
did:plc:ln72v57vz2g16uq4xqjuh	npr.org	This is NPR □	114	99	213	114.0	99.0		
did:plc:k6nskatzhyxersjlvtnz4lh	washingtonpost.com	Democracy Skies in Blueness	112	100	212	112.0	100.0		
did:plc:evgc4ukadrede3gwsiwygkpz	ayoub.bsky.social	Brighton-based writer, postdoc resea...	109	99	208	109.0	99.0		
did:plc:ragtjsm2j2vknwk23zp4oxrd	pfrazzee.com	Developer at Bluesky.	107	100	207	107.0	100.0		
did:plc:5wr2hl4l7zcfcxgad13ps	anti-hate.bsky.social	By Anshel Bomberger. I ...	94	112	206	94.0	112.0		
did:plc:2dq4suksjy2uync3s2gvypigj	meganotoole.bsky.social	Award-winning investigative/data jour...	106	100	206	106.0	100.0		
did:plc:nzs3ckkcueviu4o5s2tbfwd	fwcollaborative.bsky.social	The Freedom Writers Collaborative is ...	100	105	205	100.0	105.0		
did:plc:4dalix3anoksehzul6pf5mam	xitnow.org	Join us in calling for a safer, more eq...	93	111	204	93.0	111.0		
did:plc:sj46s4ufqmqeq34ewaam6n4	cendemtech.bsky.social	The Center for Democracy & Technolo...	104	99	203	104.0	99.0		
did:plc:jye22xkeaa3qssabskhfec347	ramilsmail.com	I help good people make good games...	102	100	202	102.0	100.0		
did:plc:qu5u32mm3vetl7txtdktb4za	malachy.bsky.social	I report and run projects on the Visual...	103	99	202	103.0	99.0		
did:plc:oxba7zfwnewwy3tlz2yxm7p	ronnypascale.bsky.social	A very famous comedian. Buy me a ...	99	102	201	99.0	102.0		
did:plc:nzm5w5iwofrnzkcpq3ssh	vleckie.bsky.social	Yemen things Trying to do more here ...	101	100	201	101.0	100.0		
did:plc:vam7lmm4ulanques4fq2ymh	holtie.bsky.social	hotlie the pink tiger NO MINORS pf...	101	100	201	101.0	100.0		
did:plc:otxukm4zw64za2tmgczgn04v	unStopab10.bsky.social	USMC (Ret) he/him just a simple man ...	100	100	200	100.0	100.0		
did:plc:ap6513fejm5532jhzmvxpm	ashantifortson.com	Cartoonist, illustrator, embroiderer, e...	101	99	200	101.0	99.0		
did:plc:vjug65k1dv6syey7kr5fxxn	emilyiliu.me	emilyiliu.me	99	100	199	99.0	100.0		
did:plc:32leysum6sa8q2z77ha4da	kellyscalette.bsky.social	America's Number One Punned-It. L...	99	100	199	99.0	100.0		
did:plc:bxjkgel5jz5mlia25h2hmb	stscl.bsky.social	Understanding the past, present and ...	100	99	199	100.0	99.0		
did:plc:bnqwy3jtwey5ulkfgr2bxg3	rafaelshimunov.bsky.social	Host of Beyond The Pale on WBAI 99...	100	99	199	100.0	99.0		
did:plc:5j3blmrsartsdje6h22qvwi6	unrwd.bsky.social	"Hardship may dishearten at first, but...	76	121	197	76.0	121.0		
did:plc:pbz37tcymp4rymx4srw363	perilresearch.bsky.social	Polarization & Extremism Research & ...	97	100	197	97.0	100.0		
did:plc:m4zukalob5mkjsiqudexsiwg	andrewieber.bsky.social	Asst. Prof. of political science, Tulane...	97	100	197	97.0	100.0		
did:plc:u2rf5ftzl02axpobrh5spnu	isdgloba.bsky.social	Powering solutions to extremism, hat...	98	99	197	98.0	99.0		
did:plc:v4rzweub5b7kr4yfb5x7	simongandrew.bsky.social	Historian of media, pop culture, the M...	98	99	197	98.0	99.0		
did:plc:6ssalrbeuh5tdleq5vn3ck3	toryfib.bsky.social	Care about fixing poverty, protecting ...	95	101	196	95.0	101.0		
did:plc:yhp3tdqnrqz6hbzbz7h7uzsq	thistibithahops.bsky.social	based in Amman - posting about sout...	95	100	195	95.0	100.0		

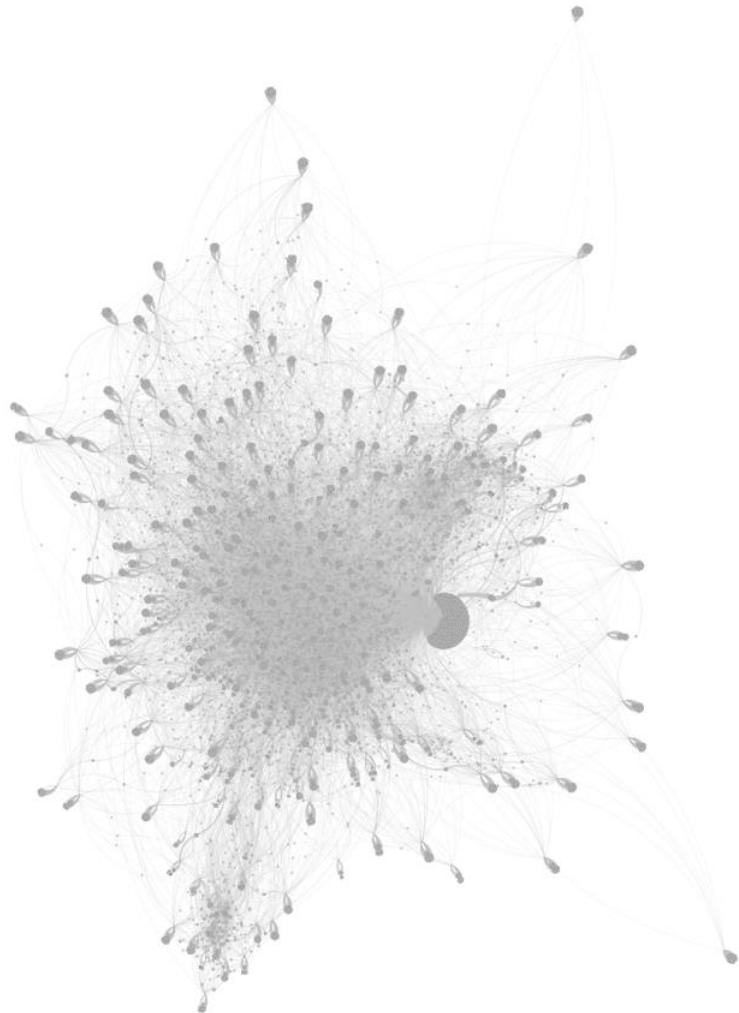
The second table is showing a part of the edges dataset, representing the relationships or interactions between the users in the network:

Data Table					
Nodes	Edges	Configuration	Add node	Add edge	Search/Replace
Source	Target	Type		Id	Weight
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:nbrpw7ydruzxkp5olg2...	Directed		0	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:5rtu7irb6jgrmeluvgzq23g2	Directed		1	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:ukqm6x7boj47yvb4gurd...	Directed		2	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:xedazyy7wsdfi6wzo5gb...	Directed		3	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:djty52fpa3ycoiaeqltg12zg	Directed		4	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:j3em5of2yhdvwvf5ssaf...	Directed		5	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:tbjcatd46cumebfl5mb7a...	Directed		6	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:a2pjivc2qoijpbh2mjdtg7ix	Directed		7	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:lkawfc3ni7da4mv4s3pg...	Directed		8	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:7m6b4iwwf7t5dzy24hh6...	Directed		9	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:6wthauiqjys3y7eztkpsd...	Directed		10	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:n2gxmxieu024dkc5ie2ix...	Directed		11	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:skmvrc4cstxwtt3oct44fp...	Directed		12	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:dmkc3gidgqdqoadidlw...	Directed		13	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:mxc7liuon6iq5gzapmmw...	Directed		14	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:mhkz3blh4pxo3fqh2me...	Directed		15	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:e4im47sn5kpw4ljt2o0kg...	Directed		16	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:c4uehptgeoxt4carvgurfr	Directed		17	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:gq4fo3u6tqzzdkjlwzb23tj	Directed		18	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:s24o32gmddihekek6tu...	Directed		19	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:cgojhmzy7oprirkxfqj45qk7	Directed		20	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:jbvnehrdqu1co4rf5gx5r	Directed		21	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:7gk35tkrugkdcqdteviara	Directed		22	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:cn6pb5ywkb7qicg4rteegjr	Directed		23	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:dfbxu43srqkd2xplm2qb...	Directed		24	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:rddeinqb45gzem3n3zym...	Directed		25	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:belvhj7vlrghqun7poroujo	Directed		26	1.0
did:plc:ilgpnfaxlr5qtlsvoytlyv	did:plc:n4qta7fd3n2754bknqscl...	Directed		27	1.0

### 3. Graphical Representation of the Network

The network surrounding the account **@palestineday.bsky.social** was visualized using various layouts, in order to highlight its structure and relationships.

These are some of the visualizations:



*Figure 1: ForceAtlas 2*

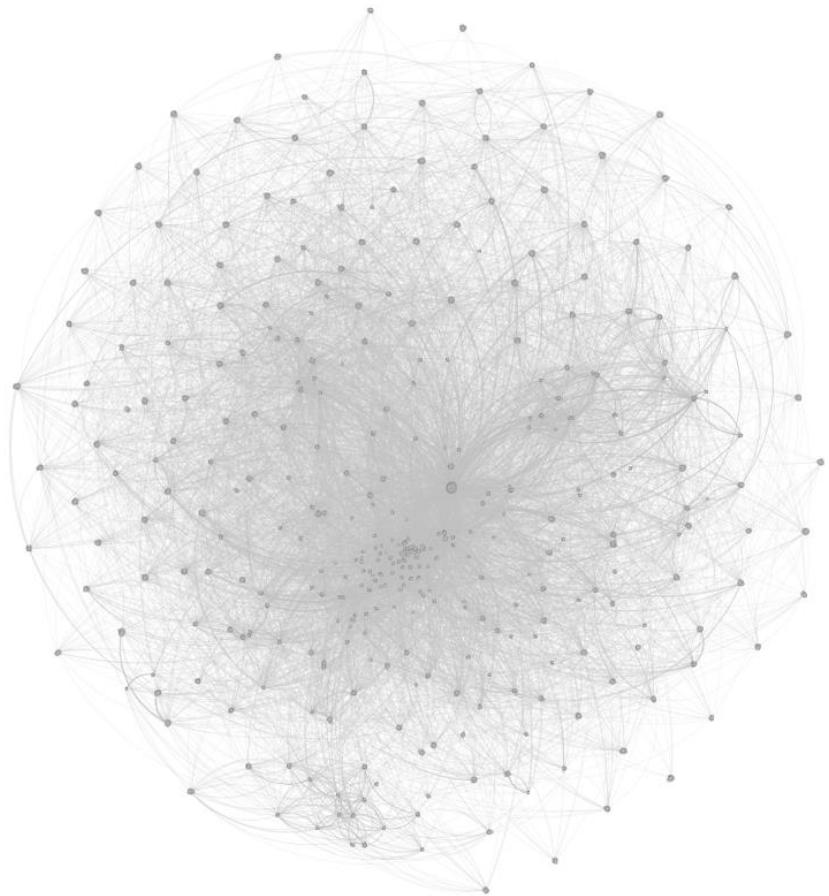


Figure 2: OpenOrd

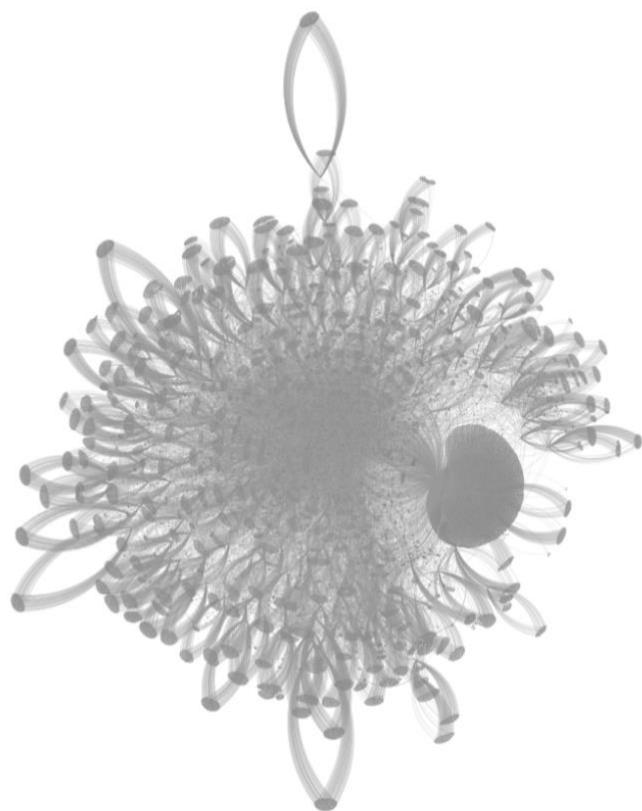


Figure 3: YifanHu

## 4. Basic Topological Properties

Some important properties of the network analyzed are the **number of nodes**, the **number of edges**, the **network diameter**, and the **average path length**. These metrics will provide insights into the structure, size, and connectivity of the network surrounding the account [@palestineday.bsky.social](#).

### Number of Nodes

The network consists of **33.440 nodes**, each of which represents a user connected to our profile of interest. As we said previously, these nodes include followers, users the account follows, and connections within the n+1 level. The large number of nodes reflects the extensive reach and influence of the account within its network.

### Number of Edges

There are **50.363 edges** in the network, representing the connections or relationships between the nodes. This is a directed graph, where each edge has a defined direction: a "source" node (the origin of the connection) and a "target" node (the destination). These edges capture user relationships such as following or interacting, showing how information or influence flows through the network.

### Network Diameter

The network diameter is **15**, meaning the longest shortest path between any two users in the network spans 15 steps. This relatively large value indicates that while the network is extensive, there are users who may be significantly distant from one another. This suggests that the network has a somewhat decentralized structure, characterized by clusters of users that may not always be directly connected.

### Average Path Length:

The average path length of the network is **5,106**, indicating that, on average, it takes just over five steps to connect two users. This reflects a moderately connected network: while accounts engage a large number of users, information or influence may require multiple intermediary connections to reach distant parts of the network. The relatively short average path length—in comparison to the previously calculated diameter—highlights the presence of bridging nodes or hubs that enhance overall connectivity.

**Nodes:** 33440  
**Edges:** 50363  
**Directed Graph**

**Parameters:**  
Network Interpretation: directed  
  
**Results:**  
Diameter: 15  
Radius: 0  
Average Path length: 5.106174063612982

## 5. Component Measures

Component measures are metrics that are used to evaluate specific aspects of a network's structure, providing insights into its connectivity, fragmentation, and key substructures. These measures help to identify groups of nodes that interact closely as well as the overall cohesion of the network.

### 5.1 Connected Components

A connected component in a graph is a subgraph where every two nodes are connected by a path, and no nodes outside the subgraph are connected to it. Connected components illustrate the extent to which nodes in a network are grouped or isolated.

For the `@palestineday.bsky.social` network:

- There is **1 weakly connected component**, meaning that all **33.440 nodes** are indirectly connected to one another when edge directions are ignored. This indicates that the network forms a single cohesive structure, even in its weakly connected form.
- However, there are **29.588 strongly connected components**, representing smaller clusters of nodes where each node is mutually reachable by directed paths. This result highlights that, while the network as a whole is interconnected, many of these connections are unidirectional, resulting in a large number of small, strongly connected clusters.

#### Parameters:

Network Interpretation: directed

#### Results:

Number of Weakly Connected Components: 1

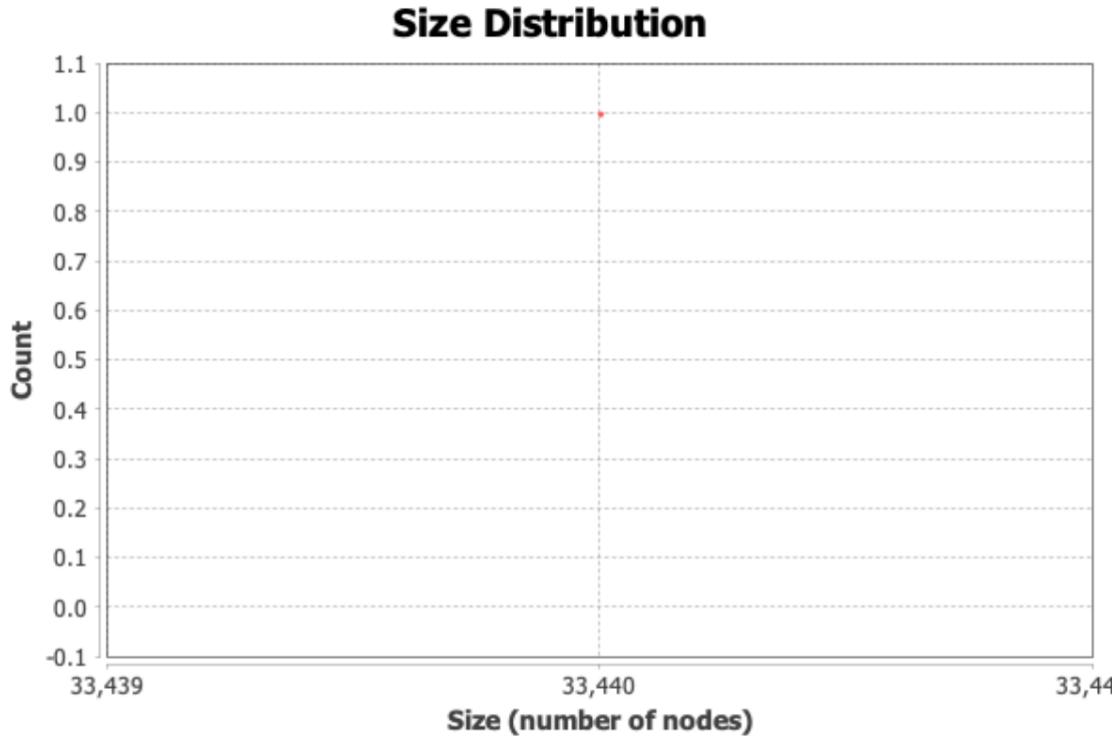
Number of Strongly Connected Components: 29588

### 5.2 Component Size Distribution

The size distribution of components highlights the variation in the number of nodes within each connected component. In our case:

- The weakly connected component contains all **33.440 nodes**, forming the largest and only weakly connected component.
- For strongly connected components, the size distribution shows that most components are extremely small, consisting of just one or two nodes, representing isolated users or minimal clusters with reciprocal connections.

The component size distribution is visualized in the following figure:

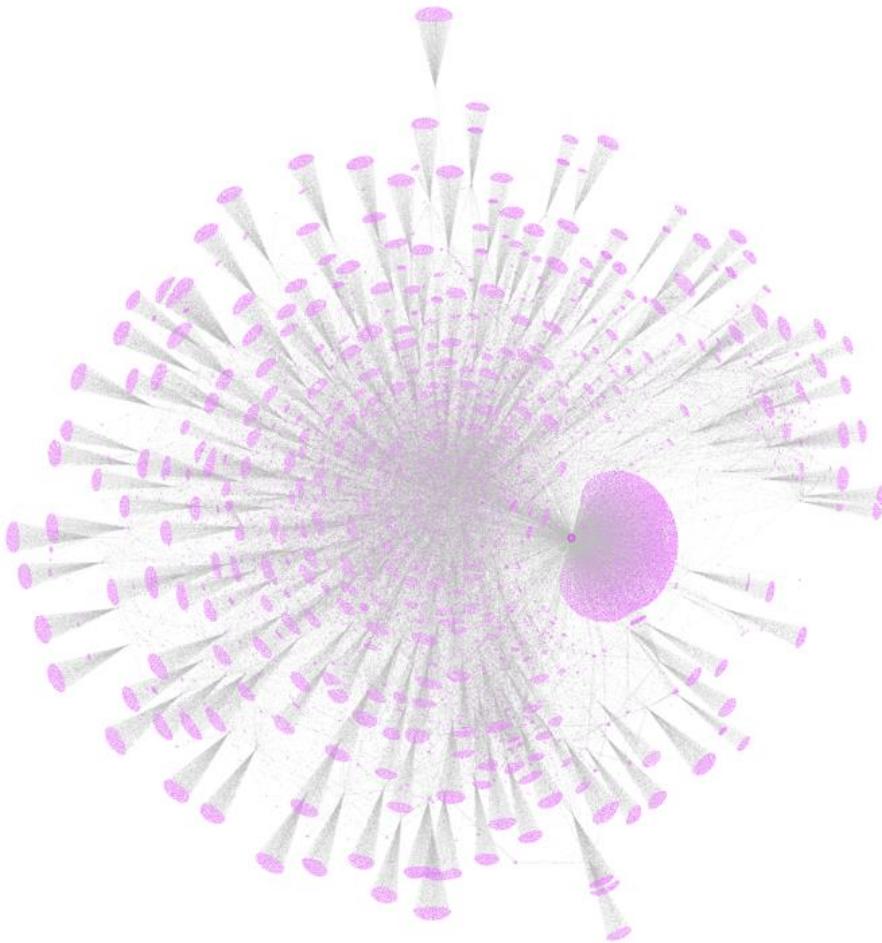


### 5.3 Giant Component

The giant component represents the largest connected subgraph in a network, encompassing nodes and edges that are all reachable through paths. In our network, applying the **giant component filter** revealed that the entire graph is the giant component, containing all **33.440 nodes**. This indicates that every user in the network is indirectly connected, forming a single weakly connected structure.

This result aligns with earlier findings of a single weakly connected component in the network. It highlights the cohesive nature of the network, where all nodes are connected through at least one path, despite the network's sparsity (density = 0.000). The account **@palestineday.bsky.social** acts as a central hub, linking users and creating an interconnected system.

Below is a visualization of the giant component.



## 6. Degree Measures

In network analysis, degree measures serve as a means to quantify the connectivity of nodes within a network and to analyze its overall structure. These measures include metrics such as degree, in-degree, out-degree, and weighted degree. By examining these properties, we can gain valuable insights into the relationships between nodes and identify key players in the network.

At this point in the analysis, when running the initial degree-based statistics on the full graph, it became that many of the key measures, such as weighted degree, were relatively small, averaging only **1.506**. Given the enormous size of the network, this result suggested that many nodes contributed minimally to the network's structure, likely due to their low degree. To enhance the focus of the analysis and better highlight the role of more connected nodes, a decision was made to narrow the graph by applying a degree filter.

For this part of the analysis, we retained nodes with a degree of **2 or higher**, resulting in a smaller subgraph with:

- **Nodes: 7.621** (22.79% of the original graph)
- **Edges: 24.544** (48.73% of the original graph)

This filtered graph provides a clearer picture of the network's core structure, enabling a more meaningful analysis of degree measures and connectivity.

## 6.1 Average Degree Distribution

The average degree of a network quantifies the typical number of connections per node, offering insight into how densely nodes are connected. For the filtered graph, the **average degree** is **3.221**, indicating that, on average, each node is connected to approximately **three** other nodes, reflecting a moderate level of connectivity within the filtered network.

Below is a snapshot of the average degree calculation:

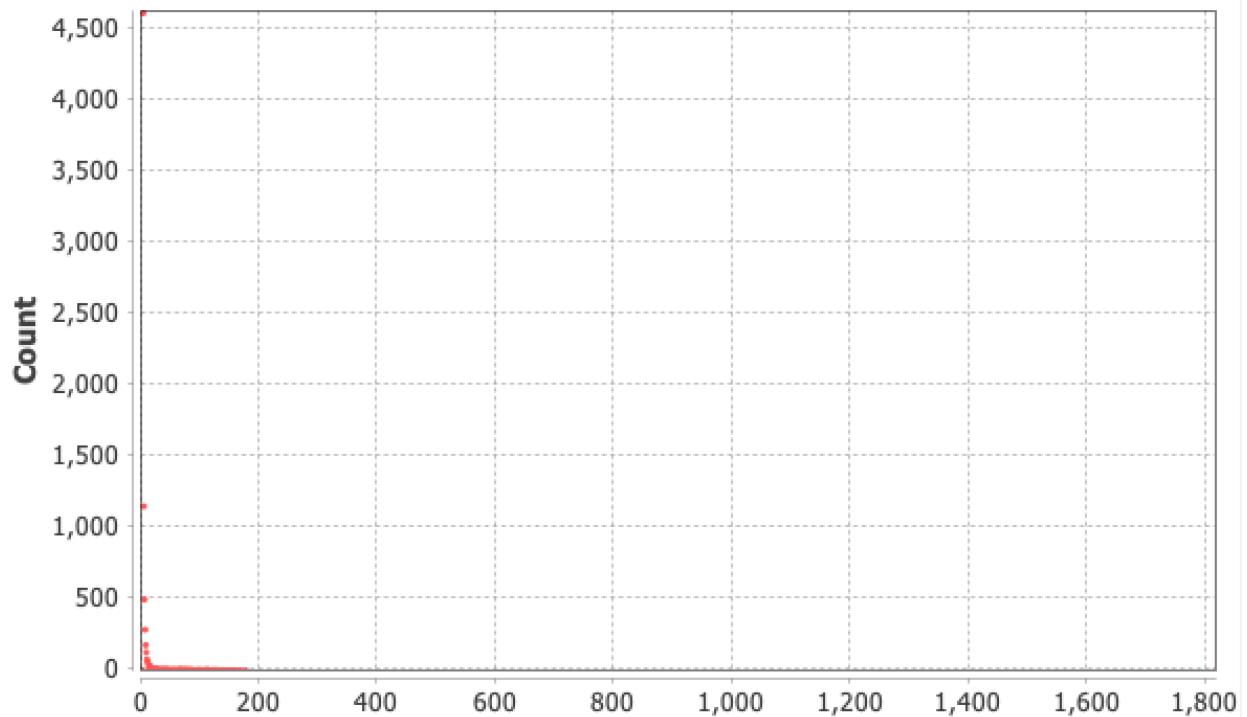
**Results:**  
**Average Degree: 3.221**

## 6.2 Degree Distribution

Degree distribution describes the frequency of nodes with specific degrees in the network. The degree of a node is the number of edges connected to it, reflecting its level of connectivity. This metric provides insights into the network's structure and identifies the presence of influential nodes or hubs.

Below is a graphical representation of the degree distribution:

## Degree Distribution

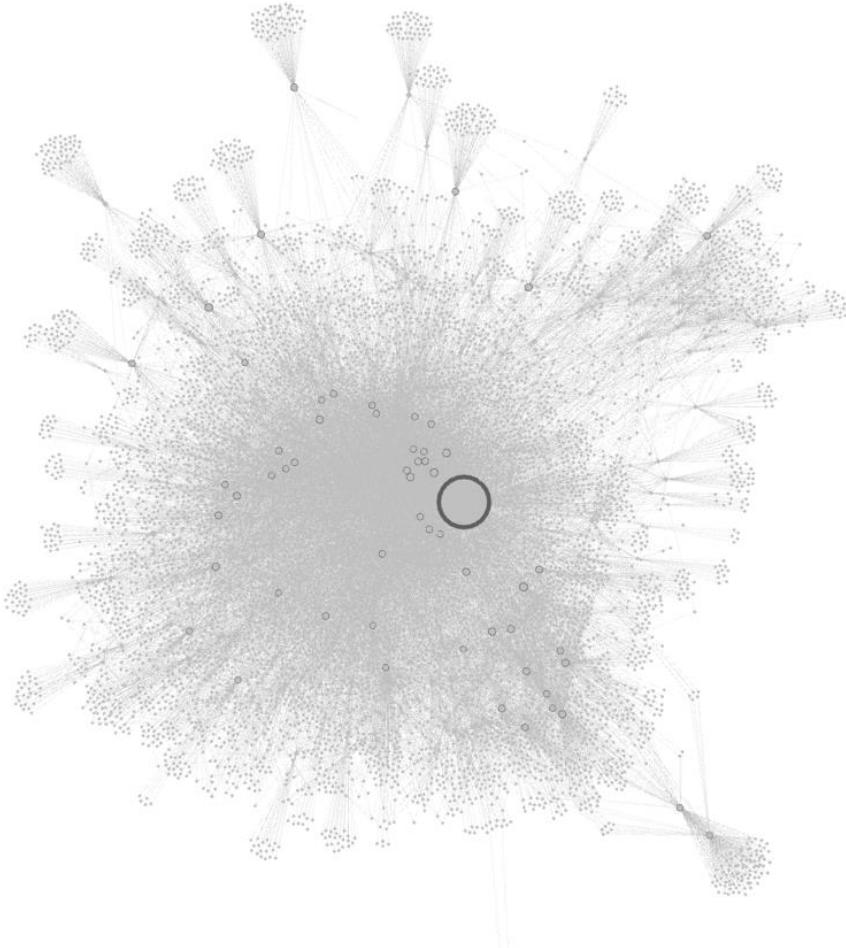


For the filtered graph, we could conclude that the degree distribution has an **uneven structure**, with the majority of the nodes having a low degree, while only a few nodes exhibit significantly higher connectivity. This pattern is characteristic of a **scale-free network**, where a small number of nodes, also referred to as “hub nodes”, play a central role in maintaining the network's structure.

The most prominent node in the network is **@palestineday.bsky.social**, which has the highest degree of **1.815**, indicating its central role as the main hub of the network.

Id	Label	Interval	Degree
did:plc:il...	palestineday.bsky.social		1815
did:plc:....	phillipetches.bsky.social		175
did:plc:l...	jamilag.bsky.social		165
did:plc:l...	johnnyrondo.bsky.social		164
did:plc:z...	bsky.app		156
did:plc:f...	senara130.bsky.social		155
did:plc:....	ralphdouglas.bsky.social		153
did:plc:....	klo12345.bsky.social		152
did:plc:....	vleckie.bsky.social		150

In addition to analyzing the distribution, the network is visually represented below, with node sizes scaled by their degree. The Yifan Hu layout was applied to optimize spacing and minimize overlap, making the structure clear. The largest node, **@palestineday.bsky.social**, as shown, is highlighted as the most influential hub in the network.

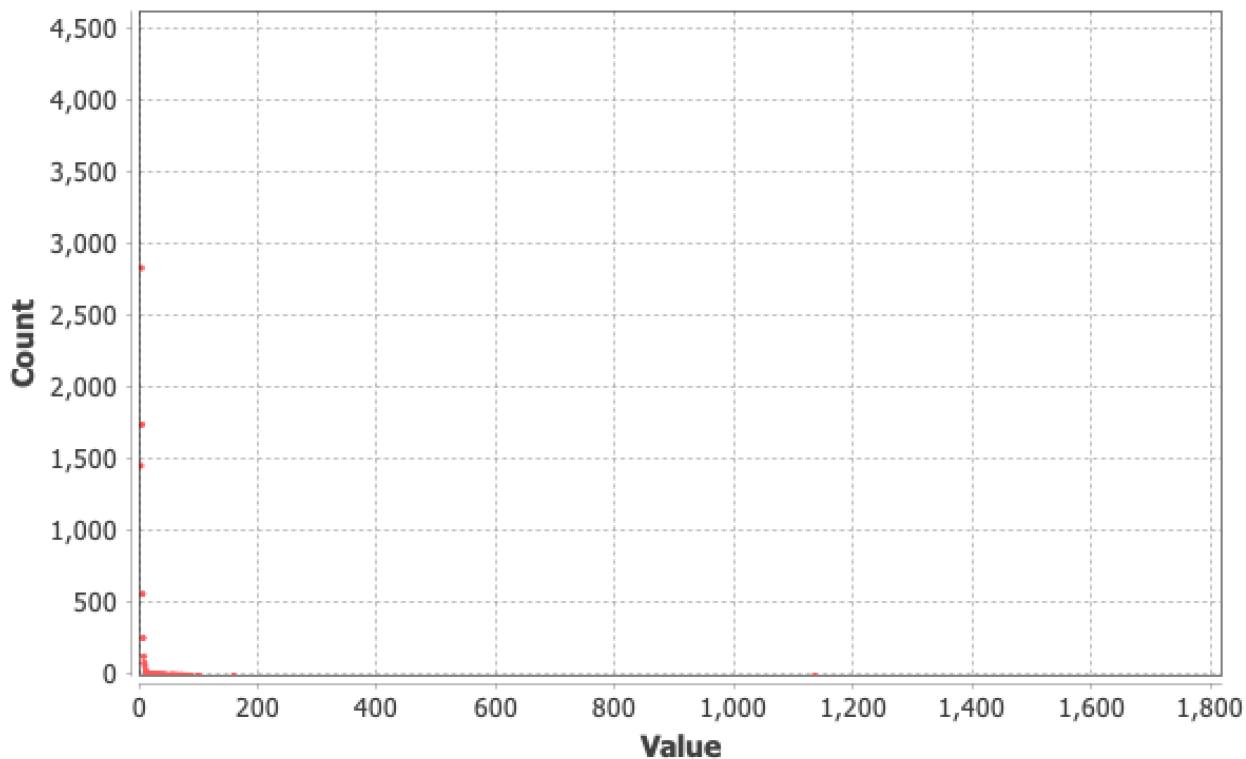


### 6.3 In-Degree Distribution

In-degree distribution refers to the distribution of the in-degree values of nodes in a directed network. The in-degree of a node is the number of incoming edges it has, indicating how many other nodes are connected to it. This measure provides us with valuable insights about the flow of information/influence within the network.

Below is a graphical representation of the in-degree distribution:

## In-Degree Distribution



In our network, most nodes have a low in-degree, meaning they receive connections from only a few other nodes. However, we can observe that there are also nodes, including **@palestineday.bsky.social** with an in-degree of **1.131**, which exhibit significantly higher in-degree values, highlighting their centrality and importance in the network.

<b>Id</b>	<b>Label</b>	<b>Interval</b>	<b>In-De...</b> ▾
did:plc:i...	palestineday.bsky.social		1131
did:plc:...	bsky.app		156
did:plc:...	meganotoole.bsky.social		97
did:plc:l...	joanmg.bsky.social		96
did:plc:...	malachy.bsky.social		95
did:plc:t...	ghaffarzishan.bsky.social		84
did:plc:...	phillipetches.bsky.social		82
did:plc:...	amelle.bsky.social		81
did:plc:...	vleckie.bsky.social		81

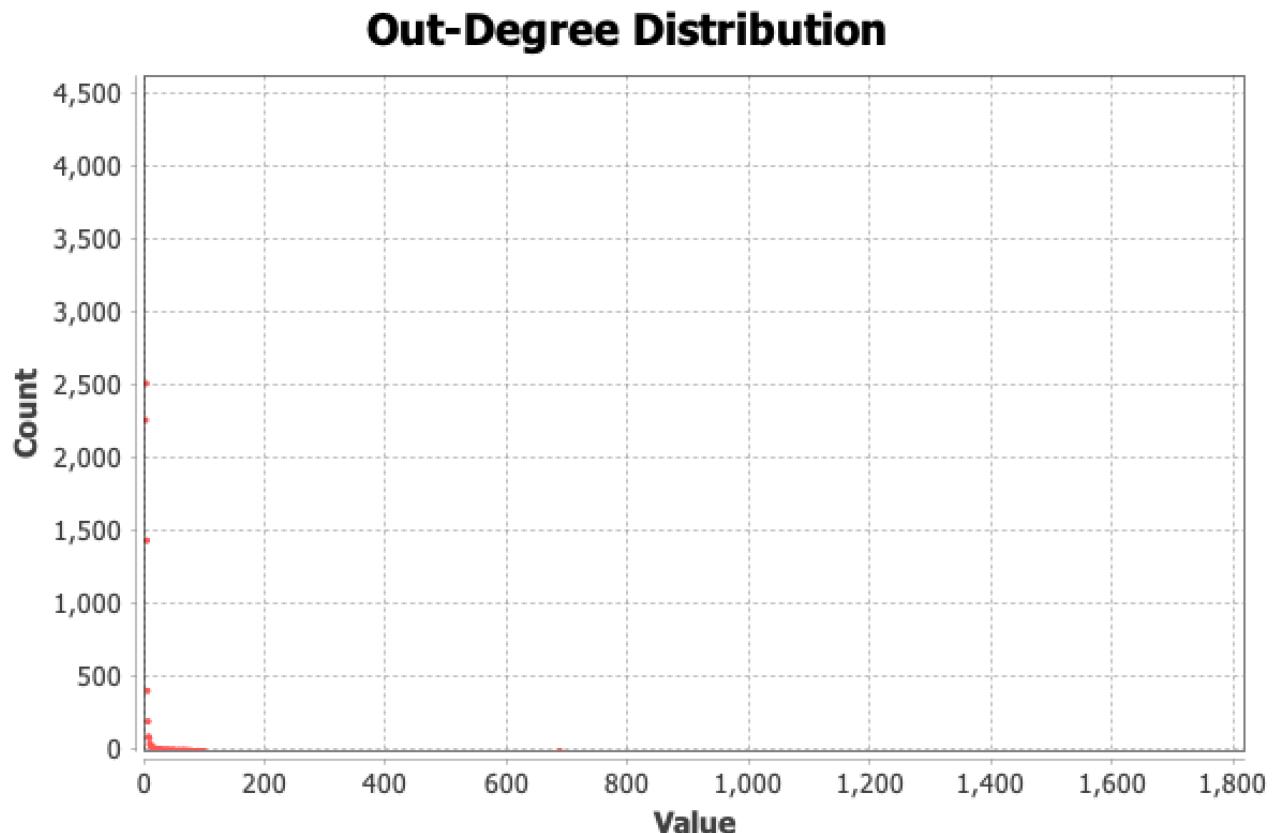
The majority of nodes fall within the in-degree range of **0 to 100**, while only a few have much higher values. This skewed distribution reflects the hierarchical structure of the network, where dominant central hubs, such as **@palestineday.bsky.social**, plays a critical role in connecting and influencing the rest of the network.

The graphical representation of the network, where the size of the nodes is scaled based on their in-degree, closely resembles the earlier visualization where node sizes were based on their overall degree.

## 6.4 Out-Degree Distribution

The out-degree distribution is the metric that describes the number of outgoing edges or connections from nodes in a directed network. It provides insights into how nodes distribute their connections and interact with others in the network. Nodes with high out-degree are typically seen as central or influential in disseminating information, while nodes with low out-degree may represent peripheral or less active participants.

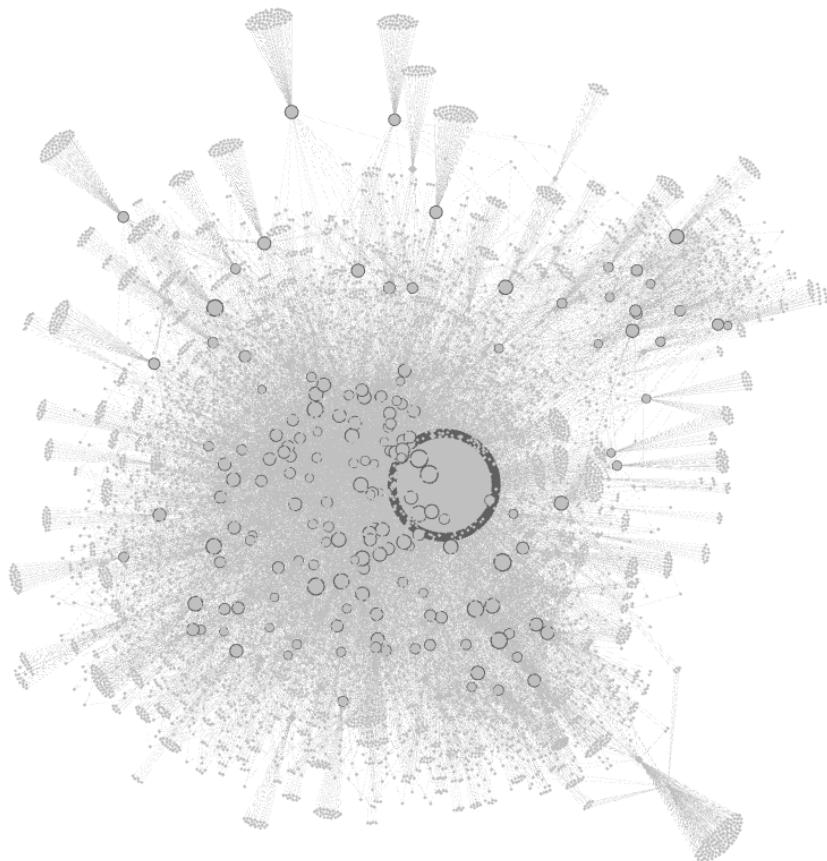
Below is a graphical representation of the out-degree distribution:



In our network, the out-degree distribution reveals a clear hierarchy. The most prominent node, which once again is **@palestineday.bsky.social**, has an out-degree of **684**, significantly higher than any other node. The remaining nodes exhibit much smaller and relatively uniform out-degree values, with the next highest being 96, 93, and 91, followed by a gradual decrease. This distribution indicates that while **@palestineday.bsky.social** is once again the dominant connector, the other nodes maintain a more balanced level of outgoing interactions.

Id	Label	Interval	Out-...
did:plc:i...	palestineday.bsky.social	684	
did:plc:l...	jamilag.bsky.social	96	
did:plc:...	wasenshi.bsky.social	96	
did:plc:...	phillipetches.bsky.social	93	
did:plc:...	investorkb.bsky.social	91	
did:plc:...	klo12345.bsky.social	89	
did:plc:...	andrewleber.bsky.social	88	
did:plc:l...	johnnyrondo.bsky.social	87	
did:plc:...	mrrg.bsky.social	87	
did:plc:f...	senara130.bsky.social	85	

The graphical representation below uses the Yifan Hu layout, with node sizes scaled by their out-degree.



## 6.5 In- Degree vs Out- Degree

Comparing the in-degree and out-degree representations of the network reveals the highly centralized nature of the **@palestineday.bsky.social** account. In both cases, the node **@palestineday.bsky.social** stands out as the central hub, with the highest in-degree, as well as out-degree values. This dual prominence underscores the vital role of this node as the primary **receiver and distributor** of influence in the network.

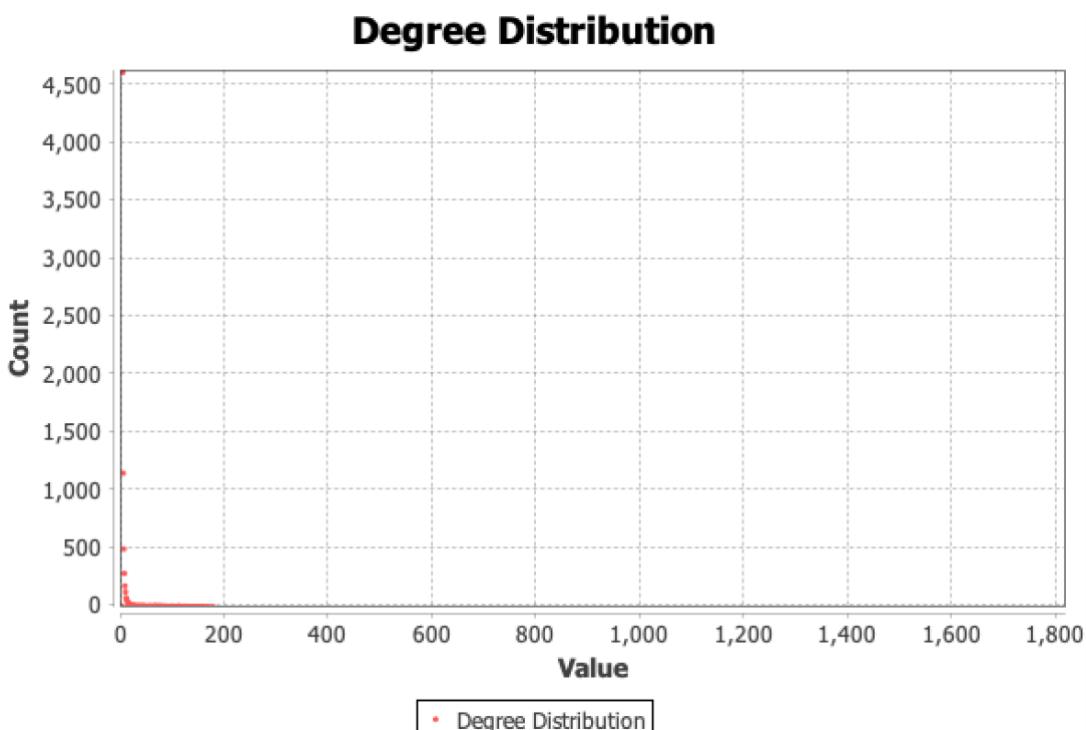
However, beyond this dominant node, the remaining nodes display relatively uniform out-degree values, with no other significant hubs. Similarly, the in-degree representation shows only minor variations among the other nodes. This suggests a network structure where the majority of nodes have limited interactions, either sending or receiving relatively few connections.

This configuration is characteristic of a network centered around a single influential hub.

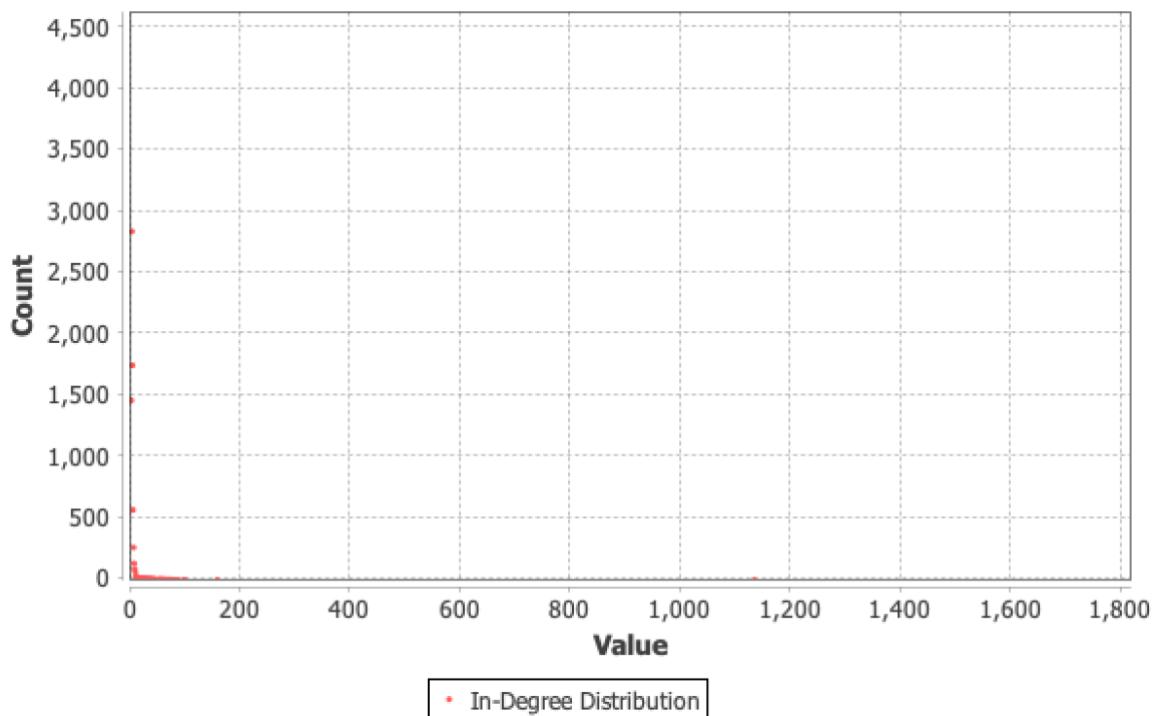
## 6.6 Weighted Degree Distribution

The weighted degree distribution measures the total weight of edges connected to a node, considering the strength or frequency of the connections. Unlike the traditional degree distribution, which simply counts the number of edges, the weighted degree accounts for the intensity of interactions. This metric can provide valuable insights into the structure of the network and help identify nodes with stronger relationships or influence.

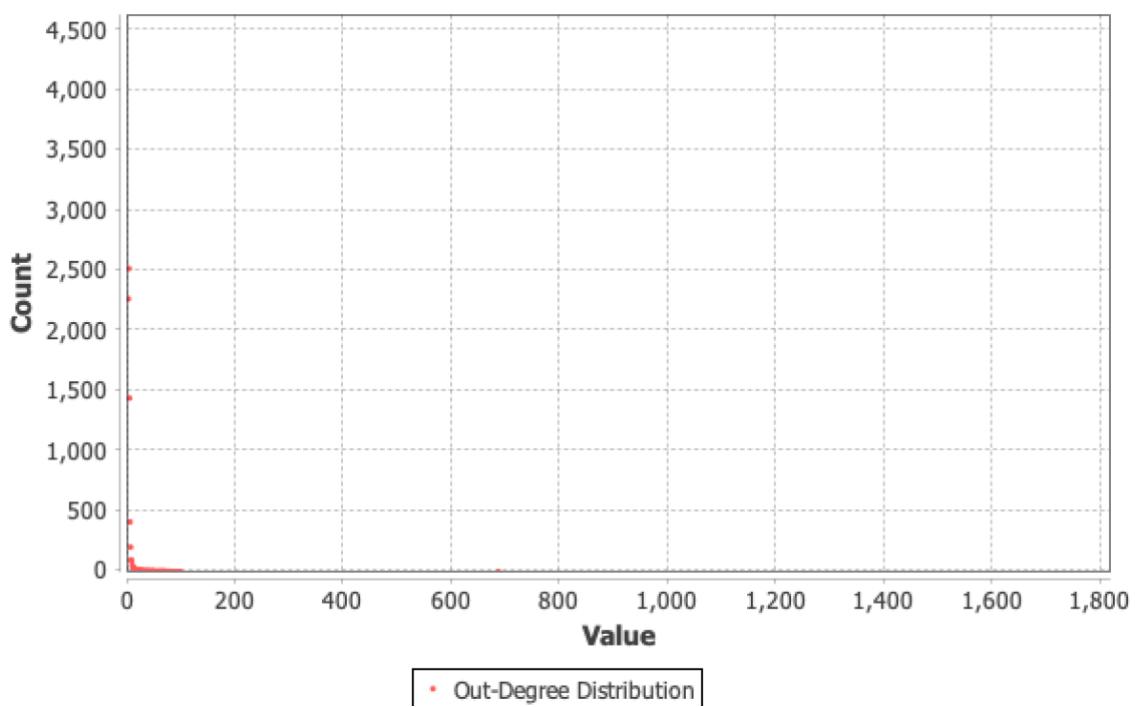
In our network, the analysis reveals no difference between weighted and non-weighted degree distributions, indicating that all edges in the network are treated equally, with no variation in their weights to reflect interaction strength or frequency. As a result, the weighted degree distribution mirrors the traditional degree distribution, which is shown in the following figures:



## In-Degree Distribution



## Out-Degree Distribution



The lack of edge weight differentiation suggests that the connections in this network are uniform in terms of their strength or interaction frequency. Despite this, **@palestineday.bsky.social** remains the most central node in the network, with the highest weighted degree, reflecting its role as the primary hub for connections.

# 7 Centrality Measures

Centrality measures are important metrics in network analysis that evaluate the importance and influence of nodes within a network. These measures provide insights into the roles that nodes play in the overall structure of the network, such as serving as hubs, connectors, or influencers. Key centrality measures include **degree centrality**, **betweenness centrality**, **closeness centrality**, and **eigenvector centrality**, each offering a unique perspective on node significance.

## 7.1 Degree Centrality

Degree centrality measures the number of connections a node has to other nodes in the network, offering insight into the importance of nodes based on their connectivity. Nodes with high degree centrality are considered influential because they connect to many others, playing an important role in spreading information and maintaining network cohesion. In this section, we will analyze the degree, in-degree, and out-degree of nodes to enhance our understanding of their centrality within the filtered @palestineday.bsky.social network.

### 7.1.1 Degree

Starting off with degree, in the filtered graph, **@palestineday.bsky.social** has the highest degree, confirming its role as the primary hub of the network. Beyond this node, there is a gradual decrease in the degree values, with most nodes having relatively smaller degrees, despite the fact that we have already filtered out our graph, by retaining nodes with a degree of 2 or more. This reflects a centralized network structure where the majority of interactions are concentrated around the central node.

Id	Label	Degree
did:plc:i...	palestineday.bsky.social	1815
did:plc:...	phillipetches.bsky.social	175
did:plc:l...	jamilag.bsky.social	165
did:plc:l...	johnnyrondo.bsky.social	164
did:plc:...	bsky.app	156
did:plc:f...	senara130.bsky.social	155
did:plc:...	ralphdouglas.bsky.social	153
did:plc:...	klo12345.bsky.social	152
did:plc:...	vleckie.bsky.social	150
did:plc:...	mrrg.bsky.social	147
did:plc:...	henriqueura4.bsky.social	147
did:plc:...	amelle.bsky.social	144
did:plc:...	nettlesongmorning.bsky.social	143
did:plc:...	lutherkingon.bsky.social	143
did:plc:...	maryahannun.bsky.social	142
did:plc:...	andrewleber.bsky.social	139
did:plc:...	sana25.bsky.social	139
did:plc:...	katsikajules.bsky.social	138

### 7.1.2 In-Degree

In-degree measures the number of incoming connections a node receives. The @palestineday.bsky.social node also has the highest in-degree in the filtered graph, underscoring its centrality as a receiver of connections.

Id	Label	Degree	In-Degree
did:plc:i...	palestineday.bsky.social	1815	1131
did:plc:...	phillipetches.bsky.social	175	82
did:plc:l...	jamilag.bsky.social	165	69
did:plc:l...	johnnyrondo.bsky.social	164	77
did:plc:...	bsky.app	156	156
did:plc:f...	senara130.bsky.social	155	70
did:plc:...	ralphdouglas.bsky.social	153	70
did:plc:...	klo12345.bsky.social	152	63
did:plc:...	vleckie.bsky.social	150	81
did:plc:...	mrrg.bsky.social	147	60
did:plc:...	henriqueura4.bsky.social	147	73
did:plc:...	amelle.bsky.social	144	81
did:plc:...	nettlesongmorning.bsky.social	143	72
did:plc:...	lutherkingon.bsky.social	143	78
did:plc:...	maryahannun.bsky.social	142	65
did:plc:...	andrewleber.bsky.social	139	51
did:plc:...	sana25.bsky.social	139	65
did:plc:...	katsikajules.bsky.social	138	78
did:plc:...	ninaczacha.bsky.social	136	68

Interestingly, **2.264** nodes in the filtered graph have an **in-degree of 0**, meaning they do not receive any incoming connections but may still play a role in the network as outgoing connectors. These nodes highlight the structure of a centralized network where most interactions flow toward a few key nodes.

Id	Label	Degree	In-De... ▲
did:plc:...	wasenshi.bsky.social	96	0
did:plc:...	lillypodmore.bsky.social	21	0
did:plc:...	kapalo.bsky.social	20	0
did:plc:...	hifaaa823.bsky.social	17	0
did:plc:...	julietthotel.fellas.social	16	0
did:plc:...	mohammedhilles.bsky.social	14	0
did:plc:...	eugenedebs12.bsky.social	14	0
did:plc:...	theeyespynews.bsky.social	13	0
did:plc:...	stephenferrisart.bsky.social	13	0
did:plc:...	shahedshaat.bsky.social	12	0
did:plc:...	manarhammoudeh.bsky.social	12	0
did:plc:...	esyst.bsky.social	12	0
did:plc:...	amiralshanti.bsky.social	11	0
did:plc:...	chollos10.bsky.social	11	0
did:plc:...	lanahelles.bsky.social	10	0

### 7.1.3 Out-Degree

Out-degree measures the number of outgoing connections from a node.

Similarly, **@palestineday.bsky.social** exhibits the highest out-degree, further establishing its role as the main distributor of connections. However, **1,460 nodes** in the filtered graph have an out-degree of **0**, meaning they do not send any connections to other nodes but receive connections instead.

Id	Label	Degree	Out-Degree
did:plc:...	jeremycorbyn.bsky.social	17	0
did:plc:...	ilhanmn.bsky.social	18	0
did:plc:l...	bdsmovement.bsky.social	19	0
did:plc:...	theintercept.com	19	0
did:plc:...	jvp.bsky.social	19	0
did:plc:...	aoc.bsky.social	19	0
did:plc:...	owenjones.bsky.social	20	0
did:plc:...	intifada.bsky.social	20	0
did:plc:...	theonion.com	22	0
did:plc:...	theguardian.com	26	0
did:plc:...	ipsc.bsky.social	27	0
did:plc:...	mondoweiss.net	28	0
did:plc:...	middleeasteye-rss.bsky.social	36	0
did:plc:j...	mehdirhasan.bsky.social	36	0
did:plc:...	eyeonpalestine.bsky.social	44	0
did:plc:...	palestinestudies.bsky.social	52	0

This asymmetry between in-degree and out-degree distribution underscores the hierarchical structure of the network. Nodes with a high out-degree are likely to be broadcasters of information, while those with a high in-degree act as key receivers. In contrast, nodes with either zero in-degree or zero out-degree reveal selective interaction patterns, where connections are focused on specific functions such as sending or receiving.

## 7.2 Betweenness Centrality

Betweenness centrality quantifies the extent to which a node acts as a bridge or mediator in the network, lying on the shortest paths between other nodes. Nodes with high betweenness centrality play a critical role in the flow of information and structural stability, as their removal would significantly disrupt connectivity within the network.

In our network, **5,805 nodes**, which is almost 76% of the filtered graph, have a betweenness centrality value of **0**, indicating that the majority of nodes do not serve as intermediaries for information flow.

Id	Label	Betweenness Centrality ^
did:plc:...	wasensihi.bsky.social	0.0
did:plc:...	palestinestudies.bsky.social	0.0
did:plc:...	eyeonpalestine.bsky.social	0.0
did:plc:...	middleeasteye-rss.bsky.social	0.0
did:plc:j...	mehdirhasan.bsky.social	0.0
did:plc:...	mondoweiss.net	0.0
did:plc:...	ipsc.bsky.social	0.0
did:plc:...	theguardian.com	0.0
did:plc:...	theonion.com	0.0
did:plc:...	lillypodmore.bsky.social	0.0
did:plc:...	owenjones.bsky.social	0.0
did:plc:...	intifada.bsky.social	0.0
did:plc:...	kapalo.bsky.social	0.0
did:plc:l...	bdsmovement.bsky.social	0.0

Once again, the node **@palestineday.bsky.social** has the highest betweenness centrality value at **22.916.761**, further solidifying its role as the dominant hub in the network. However, also other nodes scored significant betweenness centrality values, such as **@enas305.bsky.social**, with a score of **1.659.866** and **@toddappel.bsky.social** with **1.642.812**, demonstrating their importance as intermediaries in the network.

Id	Label	Betweenness Centrality ^
did:plc:...	palestineday.bsky.social	22916761.622134
did:plc:...	enas305.bsky.social	1659866.800388
did:plc:...	toddappel.bsky.social	1642812.753212
did:plc:f...	senara130.bsky.social	1457310.746743
did:plc:i...	burneraccount.bsky.social	1299569.360532
did:plc:...	nettlesongmorning.bsky.social	1287105.277269
did:plc:...	saharzuhir92.bsky.social	1191062.297518
did:plc:...	henriqueura4.bsky.social	1107856.127839
did:plc:...	sonofnoor2.bsky.social	925862.032346
did:plc:...	michaeleastwriter.bsky.social	912845.149363
did:plc:l...	johnnyrondo.bsky.social	859947.470429
did:plc:...	geofffhughes.bsky.social	827981.431954
did:plc:...	fabriziol.bsky.social	779848.47674
did:plc:...	charleskeener.bsky.social	720307.263431
did:plc:...	jessrabbit.bsky.social	705072.115476

A deeper look into these accounts provides additional context for their centrality. For example, the account **@enas305.bsky.social** identifies herself as a mother from Gaza running a donation campaign to help children affected by the ongoing conflict, which likely accounts for her high level of engagement and connections within the network. Such nodes not only

serve as bridges in the digital space but also play crucial roles in amplifying humanitarian narratives.



I am Inas from Gaza, a mother of five children and the wife of an injured man.  
Your donation is hope for us amidst the darkness 🇵🇸

However, the normalized betweenness centrality values reveal a highly skewed distribution, with a mean of approximately  $1.17 \times 10^{-11}$ .

These statistics were calculated using Python, as shown in the following code snippet.

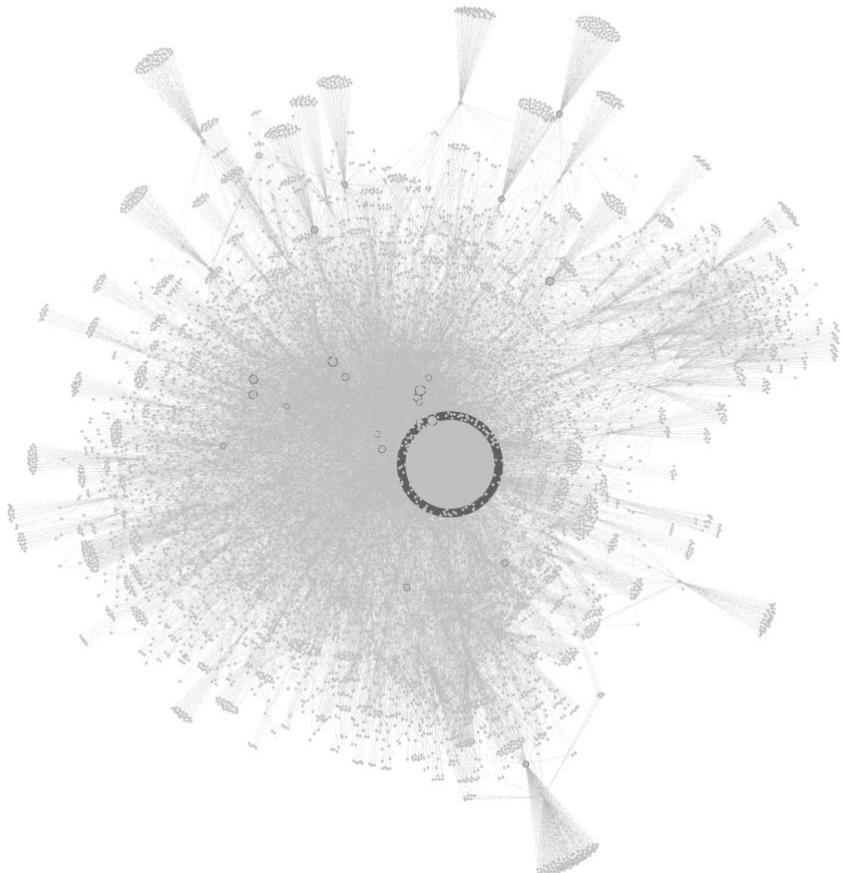
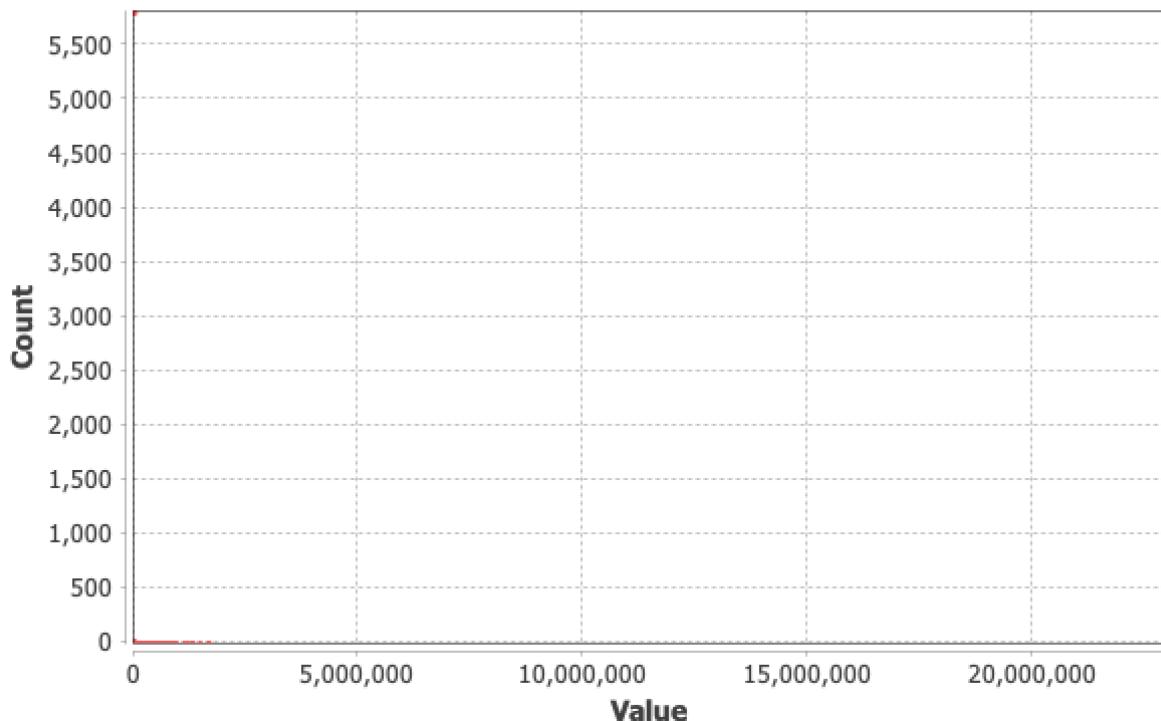
```
description = df['Normalized Betweenness Centrality'].describe()
description
✓ 0.0s
count      5.805000e+03
mean       1.173183e+11
std        8.930424e+12
min        0.000000e+00
25%        0.000000e+00
50%        0.000000e+00
75%        4.710996e+07
max        6.804141e+14
Name: Normalized Betweenness Centrality, dtype: float64
```

Python

The histogram of betweenness centrality values further illustrates the heavily skewed distribution, with only a few nodes exhibiting high scores while the vast majority remain at zero. This is consistent with the hierarchical nature of the network, centered around a few key players.

Below is the distribution of betweenness centrality as well as a the network graph which highlights the nodes with larger betweenness centrality values.

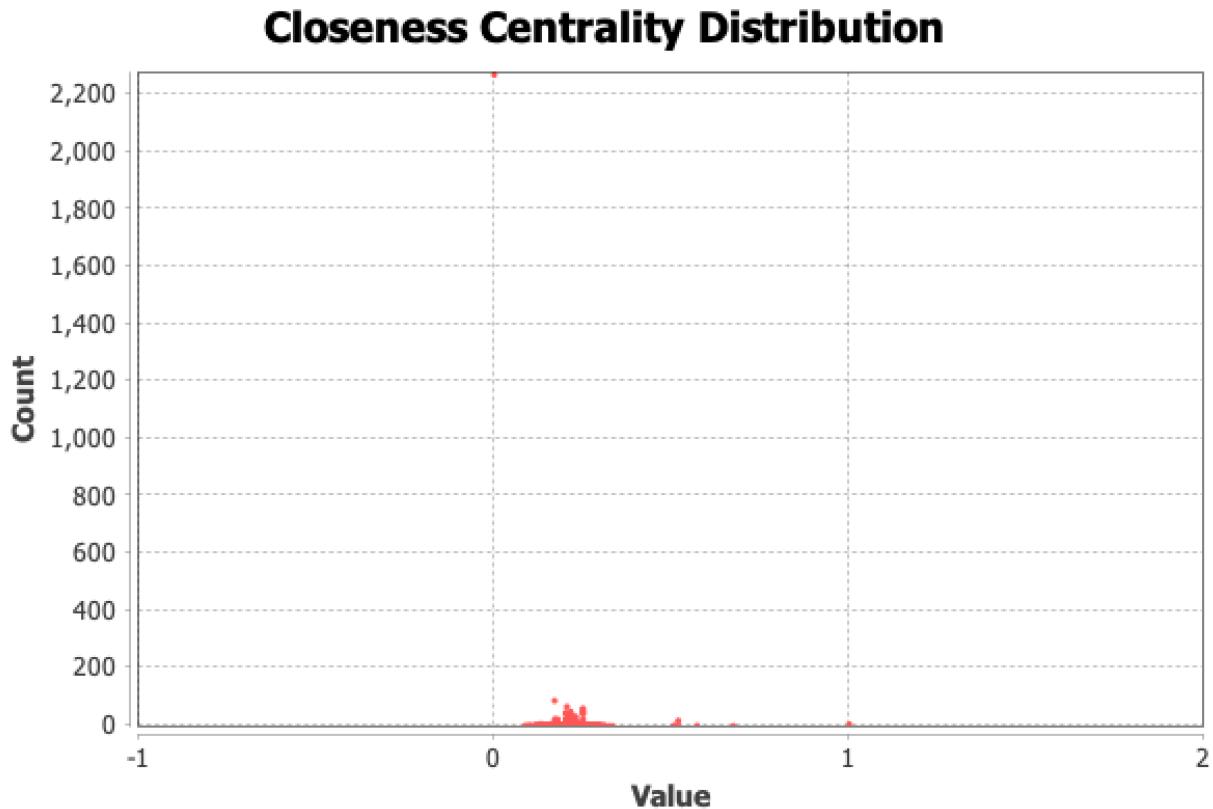
## **Betweenness Centrality Distribution**



## 7.3 Closeness Centrality

Closeness centrality is a measure of a node's proximity to all other nodes in a network. It reflects the average distance between a node and all others, with higher values indicating that the node is closer to the rest of the network. Nodes with high closeness centrality are well-connected and positioned to transfer information or resources quickly, whereas nodes with low values are less impactful in terms of information dissemination.

In our network, the closeness centrality distribution highlights an uneven nature.



After running some calculations, the mean of the closeness centrality is approximately **0.1646**, with a minimum value of 0.0 and a maximum value of 1.0. This indicates that while a few nodes are highly central and can quickly reach all others in the network, the majority of nodes are less central or entirely disconnected.

These statistics were once again calculated using Python, as shown in the following code snippet:

```
description = df['Closeness Centrality'].describe()
description
✓ 0.0s
```

	count	mean	std	min	25%	50%	75%	max
count	5806.000000	0.164626	0.106238	0.000000	0.000000	0.205711	0.228564	1.000000

Name: Closeness Centrality, dtype: float64

To be more specific, the top-ranking nodes such as @rafaelshimunov.bsky.social, @aljazeera.com, and @malachy.bsky.social achieve a perfect closeness centrality score of 1.0, suggesting they are positioned as highly accessible hubs within the network. These nodes' high scores could be attributed to their roles as influential individuals, organizations, or information broadcasters, ensuring strong connectivity across the network.

For instance, **@rafaelshimunov.bsky.social** identifies himself as the "Host of Beyond The Pale on WBAI 99.5 FM NYC, Board alum of Jews for Racial & Economic Justice, and Co-founder of the Jewish Vote." His advocacy and active participation in social justice and political movements likely contribute to his centrality in the network.

Id	Label	Closeness Centrality
did:plc:...	rafaelshimunov.bsky.social	1.0
did:plc:...	aljazeera.com	1.0
did:plc:...	malachy.bsky.social	1.0
did:plc:...	nytimes.com	1.0
did:plc:...	washingtonpost.com	1.0
did:plc:...	cendemtech.bsky.social	1.0
did:plc:...	stsuci.bsky.social	1.0
did:plc:...	rafacavada.bsky.social	0.674419
did:plc:...	trishgreenhalgh.bsky.social	0.571429
did:plc:...	ncse.bsky.social	0.571429
did:plc:r...	kincaidrick.bsky.social	0.518519
did:plc:...	pjmcoble.bsky.social	0.518519



## Rafael Shimunov

@rafaelshimunov.bsky.social

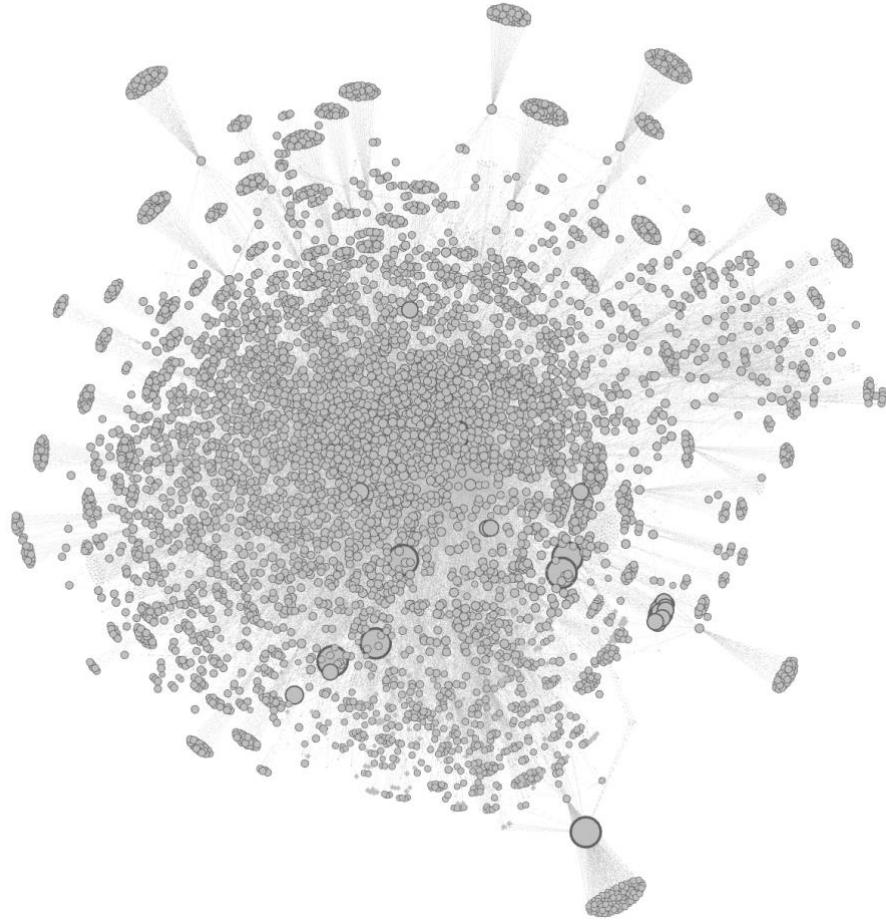
11K followers 149 following 56 posts

Host of Beyond The Pale on WBAI 99.5 FM NYC, Board alum Jews for Racial & Economic Justice. Co-founder of the Jewish Vote. Art at Art V War. Queens is the Future. @rafternoon on IG

On the other hand, several nodes exhibit a closeness centrality value of 0.0, such as "reuters.com," "muhammadsmiry.bsky.social," and "samhusseini.bsky.social." These nodes are entirely disconnected from the network or poorly linked, suggesting limited influence or engagement. This pattern of a few highly central nodes and many disconnected ones aligns with the hierarchical and star-like structure observed earlier, where the central hubs serve as the backbone of the network while the peripheral nodes remain relatively isolated.

Id	Label	Closeness Centrality
did:plc:j... reuters.com		0.0
did:plc:... muhammadsmiry.bsky.social		0.0
did:plc:... samhusseini.bsky.social		0.0
did:plc:... summerlee.bsky.social		0.0
did:plc:... unhabitayouth.bsky.social		0.0
did:plc:... icrs.bsky.social		0.0
did:plc:... jujuskiswim.bsky.social		0.0
did:plc:... communalpress.bsky.social		0.0
did:plc:... meowlenin.bsky.social		0.0
did:plc:... lsto.bsky.social		0.0
did:plc:... nicholasdanfort.bsky.social		0.0
did:plc:... esmat.bsky.social		0.0

Additionally, the graph representation below visually illustrates the closeness centrality values across the network. The size of each node is proportional to its closeness centrality, with larger nodes representing higher closeness centrality scores.

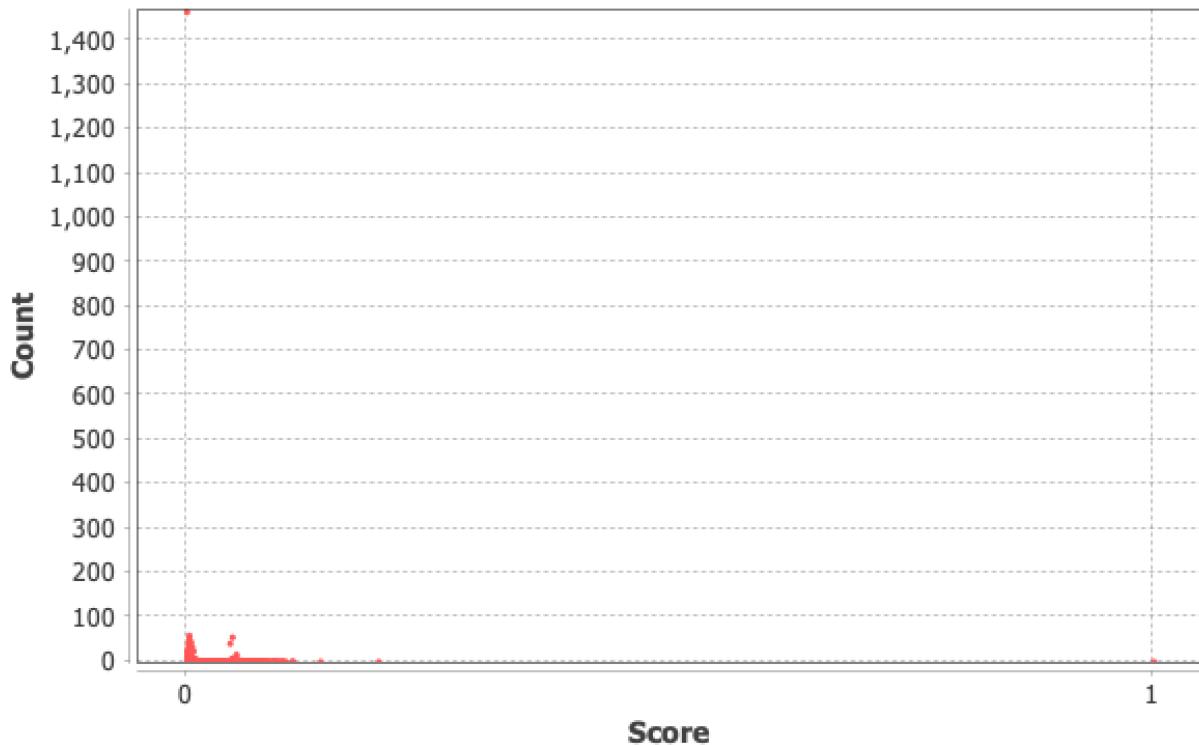


## 7.4 Eigenvector Centrality

Eigenvector centrality is a measure of the importance of a node within a network, based on its connections to other highly connected nodes. This metric goes beyond simply counting connections and considers the quality and influence of those connections. In mathematical terms, eigenvector centrality is derived from the eigenvector of the adjacency matrix of the network and corresponds to the largest eigenvalue. A node's eigenvector centrality is proportional to the sum of the centralities of its neighbors, weighted by the strength of the connections.

Below is a graphical representation of the eigenvector centrality distribution:

## Eigenvector Centrality Distribution



In our network, the eigenvector centrality distribution reveals a highly centralized structure. The descriptive statistics for eigenvector centrality were calculated using a Python script. The following code was used:

```
description = df['Eigenvector Centrality'].describe()
description
✓ 0.0s
count    5807.000000
mean      0.010559
std       0.021919
min      0.001042
25%      0.002106
50%      0.003165
75%      0.006567
max      1.000000
Name: Eigenvector Centrality, dtype: float64
```

The descriptives show that while the majority of nodes have very low eigenvector centrality values, there is one standout node with a perfect eigenvector centrality score of 1.0, which is the account **@palestineday.bsky.social**. This highlights its pivotal role as the primary hub in the network. The mean eigenvector centrality is approximately 0.0106, with most nodes concentrated around low values.

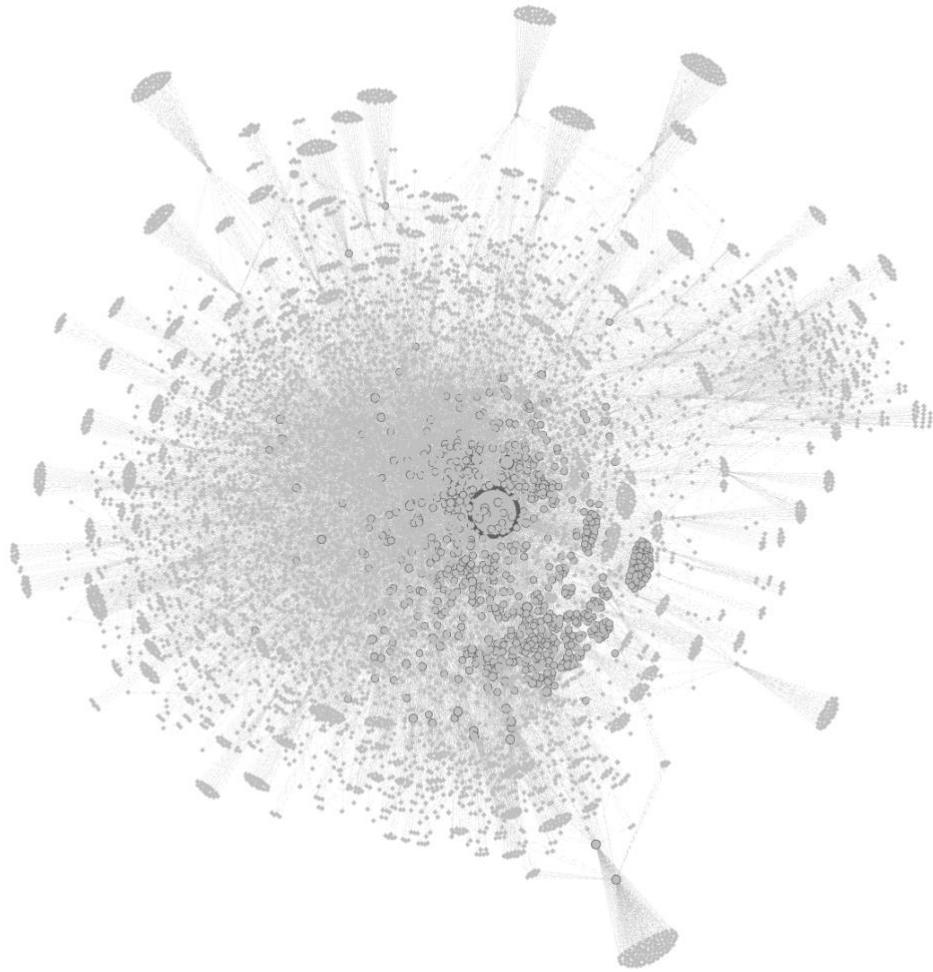
Below we see the top eigenvector centrality nodes of the data laboratory:

Id	Label	Eigenvector Centrality
did:plc:ilgpngfaxlr5qt...	palestineday.bsky.social	1.0
did:plc:nbrpw76ydruz...	drraghad2004.bsky.social	0.047049
did:plc:5rtu7irb6jgrme...	greenaquamarine.bsky.social	0.044758
did:plc:ukqm6x7boj4...	mfuentesal.bsky.social	0.044758
did:plc:xedazyy7wsd...	rafacavada.bsky.social	0.049609
did:plc:tbjcatd46cum...	sonarfm.bsky.social	0.046739
did:plc:7m6b4iwwf7t...	hoypalestina.bsky.social	0.052928
did:plc:6wthauiuqiy3...	lepapillonblue.bsky.social	0.049658
did:plc:n2gxmxueo24...	spookyconnections.bsky.social	0.050537
did:plc:skmvcc4cstxw...	msf.ca	0.062882
did:plc:mxc7liuon6iq...	youranoncentral.bsky.social	0.052321
did:plc:mhzk3blh4pfx...	economist.com	0.048568
did:plc:c4cuehptgeox...	eworcmeedanrd.bsky.social	0.044758
did:plc:gq4fo3u6tqzz...	dame.bsky.social	0.050763
did:plc:s24o3i2gmddi...	us.theconversation.com	0.059569
did:plc:jbvnehrdqoul...	reuters.com	0.064025
did:plc:cn6pb5ywkt...	prospectmagazine.co.uk	0.045783
did:plc:dfbxu43srqkd...	themoscowtimes.com	0.051588

Followed by the bottom eigenvector centrality nodes of the list:

Id	Label	Eigenvector Centrality
did:plc:yft77fiikjhjqo...	circadies.bsky.social	0.0
did:plc:v4jcoirpjw3olc...	samaaziz.bsky.social	0.0
did:plc:ycgvprf3l5yrlb...	chornayakoshka.bsky.social	0.0
did:plc:n3zygsqihsh...	ashleyfay.bsky.social	0.0
did:plc:io77fpf37lo3l6...	darkjuju.bsky.social	0.0
did:plc:2j7pwwwkuhb...	dudaatam.bsky.social	0.0
did:plc:pa6p67ejvsb6...	abdulraheemit.bsky.social	0.0
did:plc:yhzo3gusmbi...	bluwhalien.bsky.social	0.0
did:plc:d6zueyf3e5q3...	twitchy-witch.bsky.social	0.0
did:plc:hdsfkq3lj7o6...	ashiqlone.bsky.social	0.0
did:plc:ieewzocspibb...	wajahatfarooqbt786.bsky.social	0.0
did:plc:ld2oyrcowlsc...	kevvypaz729.bsky.social	0.0
did:plc:umhc5ax5dvx...	randiiiv.bsky.social	0.0
did:plc:uwwgrkvjnchu...	madeindex.bsky.social	0.0
did:plc:tqafu3iz2tuwv...	mariamfromgaza.bsky.social	0.0

Additionally, a graphical representation of the network, where the size of each node corresponds to its eigenvector centrality value, visually emphasizes the discrepancy between the central node and the rest of the network:



## 8. Clustering Effects

Clustering effects in networks describe the tendency for nodes to form tightly-knit groups, or clusters, that exhibit a higher density of connections among themselves than with nodes outside the group. This phenomenon highlights the presence of communities within a network, where members are more likely to interact with one another, fostering stronger relationships and shared interests. Clusters can significantly influence the dynamics of the network, affecting information flow, collaboration, and overall connectivity.

### 8.1 Clustering Coefficient

The clustering coefficient of a node measures how well its neighbors are interconnected, with values ranging from 0 (no clustering at all) to 1 (fully connected neighbors).

The **average clustering coefficient** of our network is **0.07**, indicating once again a sparse structure with limited local clustering overall. While most nodes exhibit low clustering coefficients, a few nodes have coefficients closer to 1, reflecting fully interconnected neighborhoods.

Label	Clustering Coefficient	Label	Clustering Coefficient
mfuentesal.bsky.social	0.0	edinh.bsky.social	1.0
eworcmeedanrd.bsky.social	0.0	jonathanlorddc.bsky.social	1.0
g-abdi84.bsky.social	0.0	ryanbohl.bsky.social	1.0
zulfah.bsky.social	0.0	brunofeuerheerd.bsky.social	1.0
abdultahir786.bsky.social	0.0	cosmofa.bsky.social	1.0
charlestieszen.bsky.social	0.0	farrahfazal.bsky.social	1.0
thegentyytc.bsky.social	0.0	mc2x.bsky.social	1.0
mauiwong.bsky.social	0.0	bluwhalien.bsky.social	1.0
geekpie.bsky.social	0.0	mauricio2001.bsky.social	1.0
mariondublin.bsky.social	0.0	helplubnafamily.bsky.social	1.0
drjillstein.bsky.social	0.0	matt72423.bsky.social	1.0
khaili4nj.bsky.social	0.0	shirinj.bsky.social	1.0
kellyscaletta.bsky.social	0.0	futureexpat25.bsky.social	1.0
sunburycross.bsky.social	0.0	bangtanxot7.bsky.social	1.0
lisabisa.bsky.social	0.0	lorenoheer.bsky.social	1.0
contrapunktus.bsky.social	0.0	quarkrotto.bsky.social	1.0
melissahedgewitch.bsky.social	0.0	maysaashuja.bsky.social	1.0
		ibbd.bsky.social	1.0

This low average clustering coefficient is consistent with the network's sparse nature and its reliance on a few central hubs for connectivity. Peripheral nodes generally have limited local interconnections, contributing to the overall low clustering value.

Below is a graphical representation of the network, where node sizes are proportional to their clustering coefficients. Larger nodes indicate higher clustering coefficients, making it easier to identify regions of higher local interconnectedness.



## 8.2 Triangles

Triangles in a network represent groups of three nodes, each directly connected to the other two. These structures are indicative of local clustering, as they show that nodes are not only connected to a common neighbor but also directly connected to each other. The prevalence of triangles within a network often sheds light on its cohesiveness, density, and the extent to which clusters of nodes are interconnected.

In the directed graph of our network, edges have specific directions, which naturally constrains the formation of triangles. To conduct a comprehensive analysis of triangles, it was necessary to convert the graph from a directed representation to an undirected one. This transformation eliminates the directional constraints of edges, allowing us to identify all possible triangles between nodes. The process was performed using a Python script, ensuring an accurate transformation of the graph into an undirected version. This included exporting the edges of the directed graph, creating an undirected edges file, and importing the updated file into Gephi for further analysis.

Below is the Python script that was used for this purpose:

```
edges_df = pd.read_csv('edges.csv')
nodes_df = pd.read_csv('nodes.csv')

G_directed = nx.from_pandas_edgelist(edges_df, source='Source', target='Target', create_using=nx.DiGraph())
G_undirected = G_directed.to_undirected() #Convert to an undirected graph

edges_undirected_df = nx.to_pandas_edgelist(G_undirected)
edges_undirected_df.to_csv('edges_undirected.csv', index=False)
print(f'Number of edges in the undirected graph: {G_undirected.number_of_edges()}')

✓ 0.1s
```

Number of edges in the undirected graph: 21356

Python

Once the undirected graph was imported into Gephi, the Clustering Coefficient metric was used to analyze triangle structures. The results revealed a total of **6.505** triangles in the network, with an average clustering coefficient of **0.180**. This suggests moderate clustering activity, aligning with the sparse yet hierarchical structure of the network which were identified in earlier chapters.

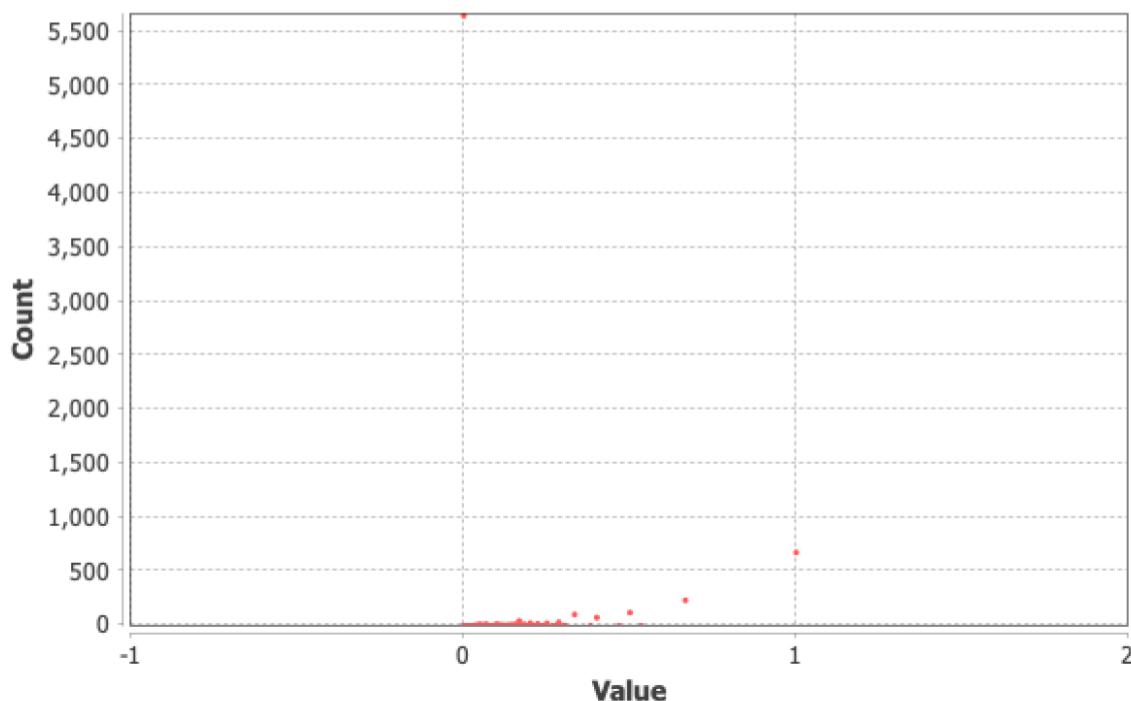
## Results:

Average Clustering Coefficient: 0.180

Total triangles: 6505

The Average Clustering Coefficient is the mean value of individual coefficients.

### Clustering Coefficient Distribution

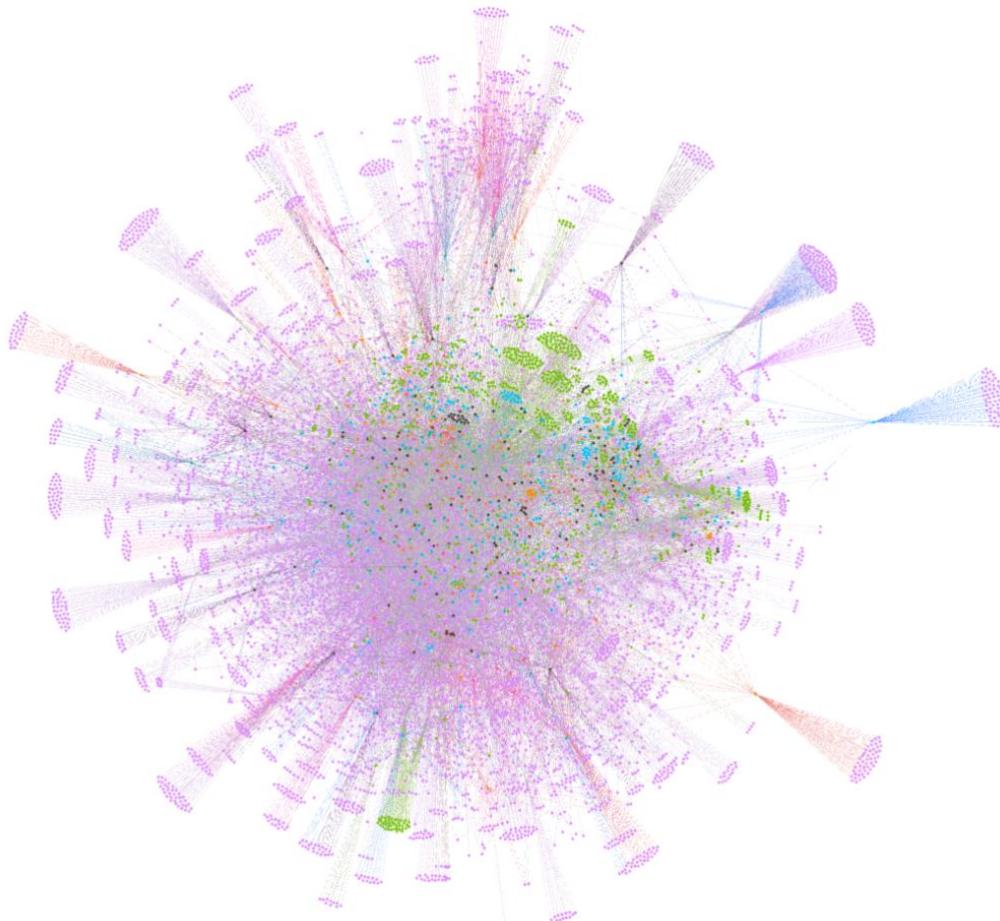


The node with the highest number of triangles is **@palestineday.bsky.social**, with an overwhelming **5.754** triangles, far surpassing other nodes. This node, as throughout the whole analysis, acts as the central hub of the network. The nature of this hub profile is centered on its activism and advocacy for raising awareness of the situation in Gaza, connecting with a wide range of other nodes in the network. Its central position enables it to form numerous triangles with other key accounts, further solidifying its influence and connectivity within the network.

Other nodes with relatively high triangle counts include **@jamilag.bsky.social** and **@klo12345.bsky.social**. Many of the “top” nodes represent individuals or platforms engaged in spreading information, news, or activism related to humanitarian causes, particularly in Gaza. These nodes contribute to forming local clusters within the network, connecting smaller subgroups to the central hub.

Label	Number of triangles
palestineday.bsky.social	5754
bsky.app	188
jamilag.bsky.social	173
klo12345.bsky.social	146
toddappel.bsky.social	136
maryahannun.bsky.social	135
andrewleber.bsky.social	117
joanmg.bsky.social	116
brittle77.bsky.social	116
aljazeera.com	114
amelle.bsky.social	109
ninaczacha.bsky.social	109

Below, we provide a visual representation of the network, with nodes colored according to their triangle counts:



### 8.3 Triadic Closure

Triadic closure is a key concept in network theory, describing the process by which three nodes that are already partially connected form new connections to create a triangle. In other words, it refers to how likely it is for nodes with mutual neighbors to connect and complete a triangle. To calculate this metric, we first needed to transform the network from a directed graph to an undirected graph, as we did before in the triangles analysis.

Using a Python script, we firstly calculated the **global** triadic closure of the network, representing the proportion of closed triangles in relation to all possible triangles of the network, resulting in a value of **0.0086**.

```
nodes_df = pd.read_csv("nodes.csv")
edges_df = pd.read_csv("edges_undirected.csv")

G = nx.Graph()
for index, row in nodes_df.iterrows():
    G.add_node(row["Id"], **row.to_dict())

for index, row in edges_df.iterrows():
    G.add_edge(row["source"], row["target"])

global_triadic_closure = nx.transitivity(G)
print(f"Global Triadic Closure: {global_triadic_closure}")

✓ 0.6s
```

Python

Global Triadic Closure: 0.008567345747167814

Furthermore, we computed the local clustering coefficient for each node, which indicates the extent to which a node's neighbors are interconnected. This was achieved with the following Python script:

```
local_clustering = nx.clustering(G)

local_clustering_df = pd.DataFrame(local_clustering.items(), columns=["Node", "Clustering Coefficient"])
local_clustering_df = local_clustering_df.sort_values(by="Clustering Coefficient", ascending=False)

✓ 0.1s
```

	Node	Clustering Coefficient
623	did:plc:qiafot5ftuh5hcqs4apfkxc3	1.0
7232	did:plc:kh7js2apwqsxxfr73ed3ztlj	1.0
580	did:plc:b7pjaoptfxqf5imv7ua547p	1.0
581	did:plc:f6zmavbjhqh5g2qltobbfnc	1.0
582	did:plc:pjvpykaxphs43wzol3irvvzz	1.0
...	...	...
3813	did:plc:oml3ytrbycbqi3drmhngbtjv	0.0
1614	did:plc:ci4fabkk4kuobrrvthzcxsd42	0.0
1615	did:plc:r6wxaadynk3m7sqsyn3r3vrf	0.0
1616	did:plc:zd2xrecgi2uw12q44op2rani	0.0
7620	did:plc:bmndmtg2b6blslyjdh4yp7r	0.0

On the **local level**, the results revealed:

- **681 nodes** had a clustering coefficient of **1.0**, meaning their neighbors were fully connected.
- **5.658 nodes** had a clustering coefficient of **0.0**, indicating no connections among their neighbors.

These findings align with the hierarchical and sparse structure of the network, where a small subset of nodes forms highly clustered subgroups, while the majority exhibit minimal clustering.

## 9. Bridges and Local Bridges

Bridges and local bridges are key structural elements in the analyzed network. Bridges are edges whose removal would disconnect the graph into more components, while local bridges increase the shortest path length between connected nodes.

In our network, we identified **1.875 bridges** and **13.181 local bridges**, , using the NetworkX Python library.

The presence of **1.875 bridges** underscores the sparse nature of the network, where a few critical edges connect different clusters or communities. These bridges are likely concentrated around key nodes previously identified as central hubs, such as @palestineday.bsky.social, ensuring the network remains a unified entity despite its sparsity. Conversely, the large number of **13.181 local bridges** indicates strong local organization, with these edges sustaining short paths and efficient communication within individual clusters.

The disparity between the number of bridges and local bridges reflects the sparse, hierarchical and modular structure of the network. While the global connectivity of the network relies on relatively few critical edges- bridges, the abundance of local bridges ensures local robustness and connectivity within clusters. This dual nature highlights the network's reliance on both global connections and local interactions for its overall stability.

```
import networkx as nx
import pandas as pd

edges_df = pd.read_csv("edges.csv")
G = nx.Graph()
for _, row in edges_df.iterrows():
    G.add_edge(row["Source"], row["Target"])

✓ 0.0s
```

```
bridges = list(nx.bridges(G))
print("Number of Bridges:", len(bridges))
✓ 0.0s
```

Number of Bridges: 1875

```
local_bridges = list(nx.local_bridges(G))
print("Number of Local Bridges:", len(local_bridges))
✓ 1m 54.8s
```

Number of Local Bridges: 13181

## 10. Gender

Gender is an important demographic characteristic that can influence the dynamics of social networks, affecting patterns of interaction, engagement, and influence. However, the data that was retrieved via the Bluesky plugin in Gephi does not include explicit demographic information, such as gender. While it may be possible to infer gender from usernames and bios, or even external research, such assumptions would lack reliability and validity as they rely on subjective interpretation.

Furthermore, given the nature of this analysis, which focuses on a socio-political topic the relevance of gender to the network's structure and interactions may not be as critical as other factors we have already mentioned. Therefore, gender analysis has not been included in this report, as it would neither provide reliable results nor significantly enhance our understanding of the network's dynamics.

## 11. Homophily

Homophily refers to the tendency of nodes in a network to form connections with others who share similar characteristics. This phenomenon often results in the formation of homogeneous groups, where nodes with shared attributes are more likely to connect, and cross-group interactions are limited. To examine this phenomenon, we tested for homophily across several key attributes, including degree-based metrics (e.g., in-degree, out-degree, degree) and centrality measures (e.g., betweenness centrality, degree centrality).

The analysis involved calculating the Jaccard similarity for each pair of connected nodes based on their attribute values. Homophily relationships were recorded if nodes exhibited a similarity score greater than zero. Below is the Python script used for this analysis:

```

G = nx.Graph()
for _, row in nodes_df.iterrows():
    G.add_node(row["Id"], degree=row["Degree"])

for _, row in edges_df.iterrows():
    G.add_edge(row["Source"], row["Target"], weight=row.get("Weight", 1))

# Define the Jaccard similarity function based on node attributes
def jaccard_similarity(G, u, v, attribute):
    """Calculate Jaccard similarity based on a node attribute."""
    set_u = set([G.nodes[u][attribute]])
    set_v = set([G.nodes[v][attribute]])
    if len(set_u | set_v) > 0:
        return len(set_u & set_v) / len(set_u | set_v)
    return 0

attribute = "degree"
count = 0
similarity_count = 0

for u, v in G.edges:
    similarity = jaccard_similarity(G, u, v, attribute)
    count += 1
    if similarity > 0:
        similarity_count += 1

if count == 0:
    print("No edges found in the graph for analysis.")
else:
    print(f"There are {similarity_count} homophily relationships based on {attribute} out of {count} edges checked.")

✓ 0.4s

```

Python

There are 22 homophily relationships based on degree out of 21356 edges checked.

Despite testing multiple attributes, the results revealed low levels of homophily across all metrics. For instance, some examples:

Based on **Degree**, only 22 homophily relationships were found out of 21.356 edges. **Betweenness Centrality** resulted in 112 homophily relationships, which remains a very small fraction of the total edges.

These low scores suggest that the network lacks strong clustering based on these structural attributes. This indicates that nodes in this network do not preferentially connect with others sharing similar properties like degree or centrality. Instead, connections appear to be influenced by other factors, possibly reflecting the heterogeneous and sparse nature of the network. This reinforces earlier findings of a centralized structure dominated by a few influential hubs.

## 12. Graph Density

Graph density measures how densely connected a graph is, quantifying the ratio of actual edges to the maximum possible edges in the network. It provides an indication of how tightly the nodes in the graph are interconnected. A graph density of 1 represents a complete graph, where every node is connected to every other node, while a graph density close to 0 indicates a sparse network with very few connections relative to the potential maximum.

In the @palestineday.bsky.social network, the graph density is calculated to be **0.000**, which confirms that this is an extremely sparse network. This value reflects the hierarchical and centralized structure of the network, as observed in earlier analyses, where a small number of

key nodes, such as our main account @palestineday.bsky.social, dominate the connections, while the majority of nodes remain relatively isolated or peripheral. The low density aligns with the presence of numerous weakly connected nodes and emphasizes the limited overall interconnectivity in the network.

## Graph Density Report

### Parameters:

Network Interpretation: directed

### Results:

Density: 0.000

## 13. Community structure (modularity)

Community structure, or modularity, refers to the grouping of nodes in a network into coherent and densely interconnected sub-groups or communities. Modularity is a metric that quantifies the quality of this community structure, with higher values indicating stronger clustering of nodes within communities.

## Modularity Report

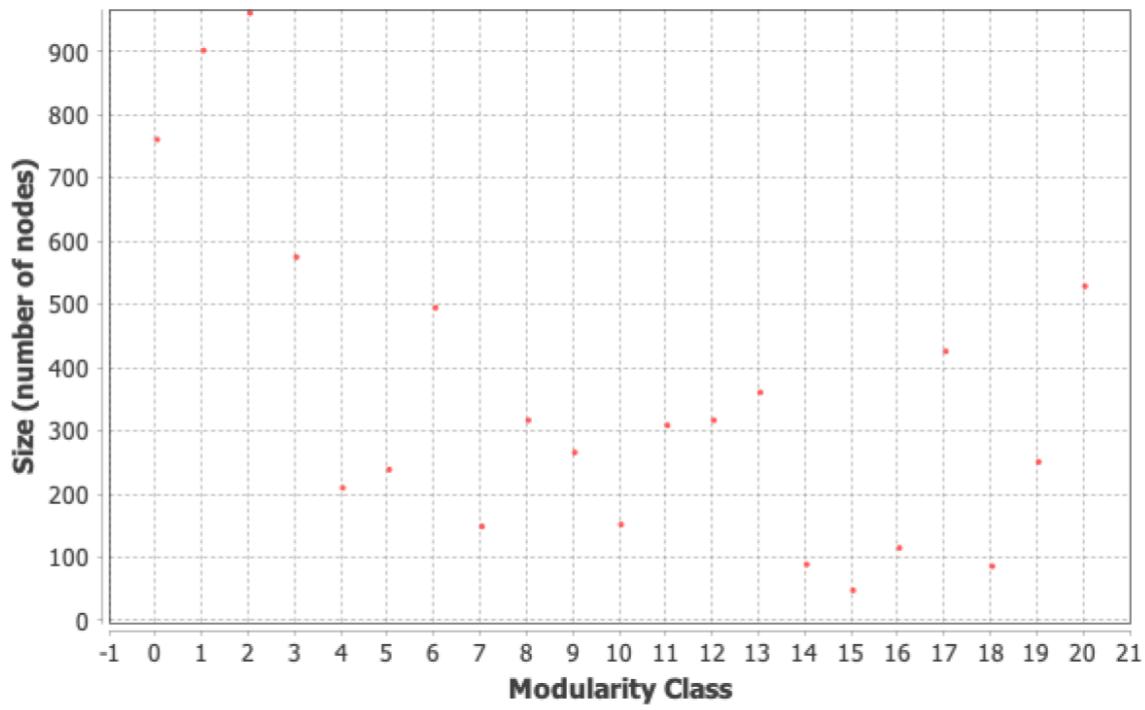
### Parameters:

Randomize: On  
Use edge weights: On  
Resolution: 1.0

### Results:

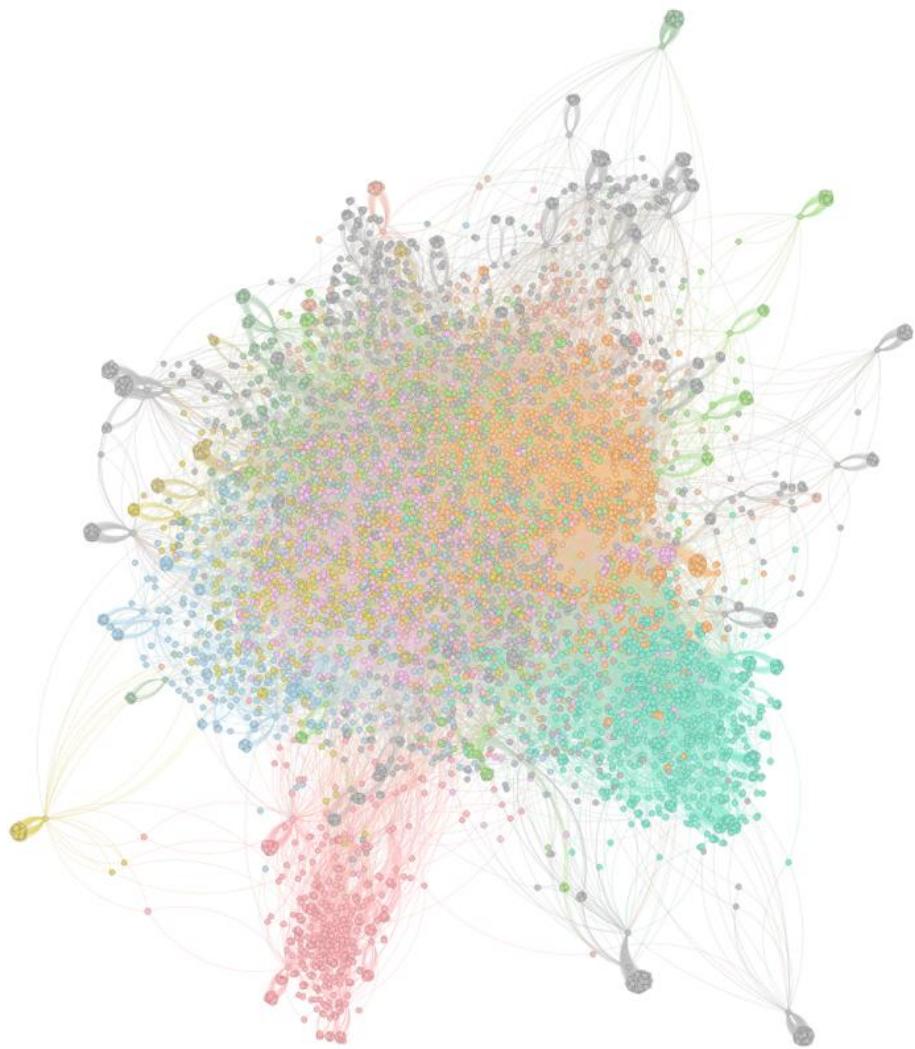
Modularity: 0.445  
Modularity with resolution: 0.445  
Number of Communities: 21

## Size Distribution



The modularity analysis of this network, conducted at a resolution of 1.0, yielded a modularity score of **0.445** and identified **21** distinct communities. This modularity score reflects a moderate community structure, consistent with the sparse nature of the graph and its reliance on a few central hubs. The relatively low number of communities indicates that the network's clusters are broad and hierarchical, with a few key nodes dominating the structure, such as @palestineday.bsky.social.

Below is a graphical representation of the network, where nodes are colored according to their modularity class. This visualization highlights the distinct communities and how nodes are clustered within them:

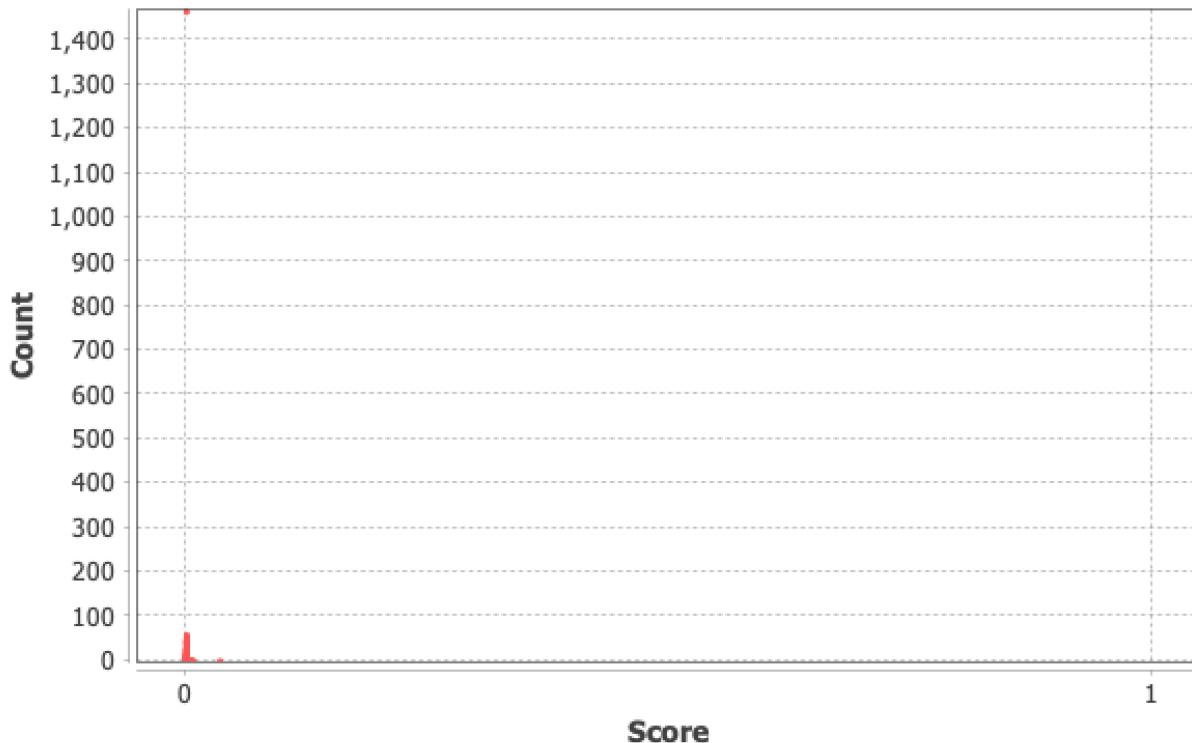


## 14. PageRank

PageRank is a measure of node importance in a network, based on the idea that a node is considered influential if it has many incoming links from other influential nodes. The PageRank calculation for this network was performed with a probability factor of 0.85 and a convergence threshold (epsilon) of 0.001.

The PageRank distribution shows a heavily skewed pattern, with most nodes having very low PageRank values:

## PageRank Distribution



The node @palestineday.bsky.social, has the highest PageRank value of **0.0349**, clearly identifying it as the most influential node in the network, for yet another time. While other nodes exhibit relatively higher PageRank values compared to the rest, their scores are significantly smaller in comparison to this central hub.

The screenshot below from the Data Laboratory illustrates the nodes with the highest PageRank values, highlighting the concentration of influence within the network.

Label	PageRank
palestineday.bsky.social	0.034868
jessrabbit.bsky.social	0.007179
ribboncaged.bsky.social	0.00675
lutherkingon.bsky.social	0.005987
giannaro.bsky.social	0.005387
johnnyrondo.bsky.social	0.004537
bsky.app	0.00443
karmelete06278695.bsky.social	0.004345
fmarianoc.bsky.social	0.004343
rightuare.bsky.social	0.003655

Based on the above, there are a few observations we could make:

**Highly Skewed Distribution:** The minimum PageRank value in the network is very close to 0, and more than half of the nodes have values near this minimum. This shows that most nodes have little influence in the overall network structure. Also, the maximum PageRank value (0.0349) is significantly higher than the mean, indicating a small number of influential hubs dominating the network.

**Centralization:** The central role of @palestineday.bsky.social aligns with its dominance in previous centrality measures, confirming its importance in connecting and influencing the network.

**Influence Spread:** Nodes like @jessrabbit.bsky.social and @lutherkingon.bsky.social, while less influential than the central hub, still hold significant positions in the network. Their relatively high PageRank values suggest that they are well-connected to other influential nodes, reinforcing their role in information dissemination. Upon further examination, these profiles actively engage with content related to the Palestinian conflict, which aligns with the observed network structure and helps explain their prominence.

## Lutherkingon

@lutherkingon.bsky.social

1K followers 1.6K following 863 posts

De Podemos, antirracista y antifascista. # 7 2 9 1 😢  
Abstenerse de entrar en mi bluesky, fachas, mediocridades y pijiprogres.

## 15. Conclusion

The analysis of the @palestineday.bsky.social network reveals a **highly centralized and sparsely connected structure**, where **information dissemination is dominated by a single influential hub**. The account @palestineday.bsky.social, which serves as a key digital advocacy platform supporting the Palestinian cause, emerges as the primary node in the network, exhibiting the highest degree, betweenness centrality, eigenvector centrality, and PageRank. This highlights its central role in aggregating and distributing information related to the Palestinian struggle, human rights violations, and ongoing developments in the region.

The structure of this network is characteristic of activist-driven digital movements, where a small number of highly influential accounts shape discourse and direct engagement. The low clustering coefficient and weak triadic closure indicate that interactions are mostly one-to-one, with limited tightly-knit community formations. Rather than forming dense clusters of discussion, users in this network appear to engage primarily by consuming and redistributing information from key figures, reinforcing a broadcast-like dissemination model rather than reciprocal engagement.

Despite its low modularity and limited number of communities, the network does exhibit sub-groups of engagement, likely reflecting different activist groups, media platforms, and individuals engaging with pro-Palestinian content. The presence of a high number of bridges

and local bridges further suggests that while the network is not densely interconnected, certain edges play a crucial role in keeping sub-communities linked, ensuring that information circulates effectively even in a sparse environment.

However, the heavy reliance on a small number of central nodes presents a structural vulnerability. Should @palestineday.bsky.social or a few other influential nodes be removed, a significant portion of the network's ability to spread information would be compromised. This demonstrates the fragile yet powerful nature of digital advocacy, where visibility and reach are concentrated in a handful of key figures.

## 16. Final Thoughts

This study underscores the role of social networks as tools for digital activism, where pro-Palestinian advocacy finds a space to mobilize, inform, and engage users. The findings suggest that networks supporting political or humanitarian causes tend to adopt a hub-and-spoke model, where a central entity amplifies information to a large but less-connected audience. The results also highlight the challenges of sustaining engagement and structural resilience in a network where dependency on a few key players remains high.

Ultimately, the @palestineday.bsky.social network functions as a critical conduit for advocacy and information flow, leveraging social media's ability to transcend traditional barriers to political discourse. However, its structural limitations raise important questions about long-term sustainability, resistance to censorship, and the role of decentralized platforms in shaping modern activism.