DSM160 Coursework 2: Retweet Network Analysis

By

Hendrik Matthys van Rooyen

University of London

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CHAPTER 1 BACKGROUND

1.1 RESTRICTIONS

The **Volume** of data in static Twitter (X) retweet networks, while substantial, is finite and represents a snapshot of activity within a specific timeframe. This contrasts with the ever-growing volume of tweets and retweets generated daily on live platforms. Analysing a static dataset simplifies the process to some extent, as the dataset size and scope are fixed, allowing for comprehensive analysis without the need for continuous data updates.

The **Velocity** aspect is notably different in the context of a static dataset. Unlike the real-time nature of Twitter (X), where data changes rapidly, a static dataset remains unchanged, capturing the state of retweet networks at the time of download. This absence of real-time data flow reduces the complexity of analysing data velocity but also means that the dataset may not reflect current trends or the immediate impact of significant events.

Variety remains a challenge, as the dataset includes a range of data types (text, images, videos, and hyperlinks) within tweets. Even in a static dataset, the multifaceted nature of this information requires diverse analytical approaches to extract meaningful insights. However, the static nature of the dataset allows for a more controlled environment to apply natural language processing and multimedia analysis techniques without the need to account for new data types emerging over time.

Veracity in a static dataset is still a concern, as it contains historical inaccuracies, including misinformation, bots, and spam accounts. These elements can affect the quality of the dataset and the reliability of conclusions drawn from it. However, knowing the dataset is static, analysts can apply targeted cleaning and verification techniques to mitigate the impact of such inaccuracies. The absence of new incoming data means that once cleaned, the dataset remains stable for further analysis.

Data quality in static Twitter (X) retweet network datasets significantly influences the reliability and validity of analytical outcomes. Ensuring accuracy and completeness is crucial to avoid skewed insights, especially in studies focusing on retweet dynamics and the identification of influential users. Consistency across the dataset facilitates straightforward analyses, such as tracking retweet chains and comparing user activities. Moreover, the dataset must be relevant and timely, reflecting current social media dynamics to remain applicable for analysis.

Addressing data quality also involves ensuring the dataset is free from biases that could affect the analysis, like overrepresentation of certain topics or user groups. Data preparation and cleaning process is essential before conducting any analysis to maintain high data quality. This preparation enhances the reliability of insights derived from the dataset, enabling more accurate conclusions about Twitter (X) retweet networks and the flow of information within them.

1.2 INFLUENCES ON THE DATA

Misinformation and Disinformation: Given the ease with which information can be spread on social media, it's essential to consider the prevalence and impact of misinformation and disinformation within the network. This includes identifying potential sources of false information and understanding how it might spread through the network.

Bot Activity: Automated accounts, or bots, can significantly influence the dynamics of social media networks by amplifying messages, creating the illusion of more significant support for certain ideas or individuals, and affecting the virality of content. Identifying and analysing the behaviour of bots within the network is crucial for accurate interpretation of the data.

Legislation and Platform Policies: The legal framework and policies of social media platforms regarding content moderation, user behaviour, and data privacy can impact the data collected. It's important to understand how these factors might influence what is visible in the dataset and the general dynamics of the network.

Echo Chambers and Filter Bubbles: Social media platforms often enhance engagement by showing users content that aligns with their views, potentially creating echo chambers or filter bubbles. This phenomenon can affect the spread and reception of information within the network and should be considered when analysing the data.

Influence of External Events: External events (e.g., political elections, natural disasters, public health crises) can significantly impact social media dynamics, influencing the topics discussed, the volume of activity, and the emergence of influential accounts. Understanding the context in which the data was collected is vital for its analysis.

Network Structure and Connectivity: Analysing the structure of the network, including the distribution of connections (e.g., highly connected vs. isolated users), can provide insights into the flow of information and the potential for viral spread.

User Engagement and Content Virality: Different levels of user engagement and the characteristics of content that tends to go viral in the network are important for understanding the mechanisms of information spread and influence.

Demographics and User Behaviour: The demographics of the user base and patterns in user behaviour can offer insights into the reach and impact of information within the network, highlighting potential biases in the data.

CHAPTER 2 THE NETWORKS

2.1 NETWORK FEATURES

Directed Nature: The network is directed because the edges have a direction that represents the flow of information—from the retweeter to the original poster. This directionality is crucial for understanding how information spreads through the network.

Weighted Edges: Edges are weighted, with the weight representing the number of retweets between the original poster and the retweeter. This feature allows for the quantification of interaction intensity between users, highlighting the most influential connections.

Node Attributes:

Each node has several attributes:

- *label*: the name of the Twitter user,
- *size*: a visual representation of the user's influence, calculated as *1 + math.pow(followers_count, 1/3)*, making the node size proportional to the cube root of the follower count, which helps in visualizing the network by reducing the disparity in node sizes while still reflecting differences in user influence,
- *title*: a combination of the user's name and follower count, providing quick information on hover in visual representations,
- *followers*: the number of followers the user has, storing this information for potential analysis.

Edge Processing:

- When an edge (retweet relationship) already exists between two nodes, its weight is incremented, reflecting multiple retweets between the same users.
- Self-loops are removed, as they don't contribute to the flow of information from one user to another.

The directed nature allows for analyzing the flow of information, identifying sources of information, and how it reaches different parts of the network.
The weighted edges enable a more nuanced understanding of the relationships, distinguishing between occasional retweets and more consistent patterns of information sharing.
The inclusion of follower counts as node attributes provides a basis for analyzing the influence of users within the network, which is pivotal for identifying key influencers or hubs in the information dissemination process.

2.2 COMPARATIVE ANALYSIS

Network Size (Nodes and Edges):

- The #BoredApeYachtClub network is the largest with 4,556 nodes and 4,428 edges, suggesting a higher level of activity and possibly more engagement among users compared to the others.
- The #uranium network, although smaller in size with 1,461 nodes and 2,228 edges, shows a high level of interaction relative to its size, indicated by a higher number of edges per node.

Density:

- The #uranium network has the highest density (0.00104), indicating a closer-knit community where users are more directly connected to each other. High density can facilitate information spread but might also indicate an echo chamber effect.
- #Eth and #BoredApeYachtClub also have relatively higher densities compared to #Bitcoin, #chatgpt, and #energy, suggesting tighter networks.

Average (In-)Degree:

- The #uranium network stands out with the highest average in-degree (1.5249), indicating that users in this network tend to be retweeted more on average. This could suggest a higher level of engagement or the presence of influential nodes within the network.

Assortativity:

- #BoredApeYachtClub has a positive assortativity coefficient (0.0992), indicating that nodes tend to connect to others with a similar degree. This can imply a structured community with potential influencers interacting more frequently with each other.
- Negative assortativity in networks like #chatgpt and #Bitcoin suggests a more hierarchical structure where well-connected nodes tend to connect with less connected ones, which can be indicative of information spreading dynamics.

Connectedness and Components:

- All networks are not weakly connected, indicating multiple sub-networks or communities within each network. The number of weakly connected components varies significantly, with #chatgpt having the most (1,786), possibly indicating a more fragmented network.
- The #BoredApeYachtClub has a comparatively lower number of weakly connected components (248), suggesting a more cohesive network despite its size.

Clustering and Centrality:

- The #uranium network has a remarkably higher average clustering coefficient (0.0670) than the others, pointing towards a tendency of nodes to cluster together into tightly knit groups. This can influence information flow, making it faster within clusters but potentially slower between them.
- Centrality measures (closeness and betweenness) are generally low across all networks, indicating no single or small group of nodes dominates information flow

across the entire network. However, the #uranium network's significantly higher average closeness centrality suggests a more efficient information dissemination capability within its structure.

CHAPTER 3 NETWORK USERS

Influential Users Analysis

Across all networks, the top influential users (by in-degree) exhibit a wide range of Follower/Post (F/P) Ratios, suggesting varied levels of engagement and content dissemination. For instance, in the #Bitcoin network, "Bitcoin Archive" leads with a high in-degree of 245 and a significant F/P Ratio, indicating a strong influence within the community. Similar trends are observed in other networks, with "NFT Project Promoter ✨ " and "Ishan Sharma" leading in the #BoredApeYachtClub and #chatgpt networks, respectively, each demonstrating substantial reach and influence.

Comparatively, the #energy and #Eth networks highlight influential users like "Mike Hudema" and "Rollbit Rewards," respectively, who also showcase significant in-degree metrics. These findings indicate that irrespective of the network's theme, there are always a few users who command considerable attention and can potentially shape discussions and opinions within their domains.

Potential Manipulators Analysis

Potential manipulators are identified based on their out-degree metrics, revealing users who extensively retweet content from various sources. For example, "IYIEOW" in the #Bitcoin network has a relatively high out-degree of 20, suggesting potential manipulation or spam-like behaviour. Similar patterns are observed in other networks, albeit with lower out-degree values in networks like #BoredApeYachtClub and #Eth, indicating varying levels of retweeting behaviour that could be considered as potential manipulation or simply active participation.

Virality of Users Analysis

Virality, measured as the ratio of out-degree to the number of followers, highlights users who are not necessarily influential in terms of follower count but are effective in spreading information. "IYIEOW" in the #Bitcoin network and "AI Bot by uCloudify.com" in the #chatgpt network are prime examples, with high virality scores despite relatively lower follower counts. This metric is crucial for identifying users who punch above their weight in terms of information dissemination.

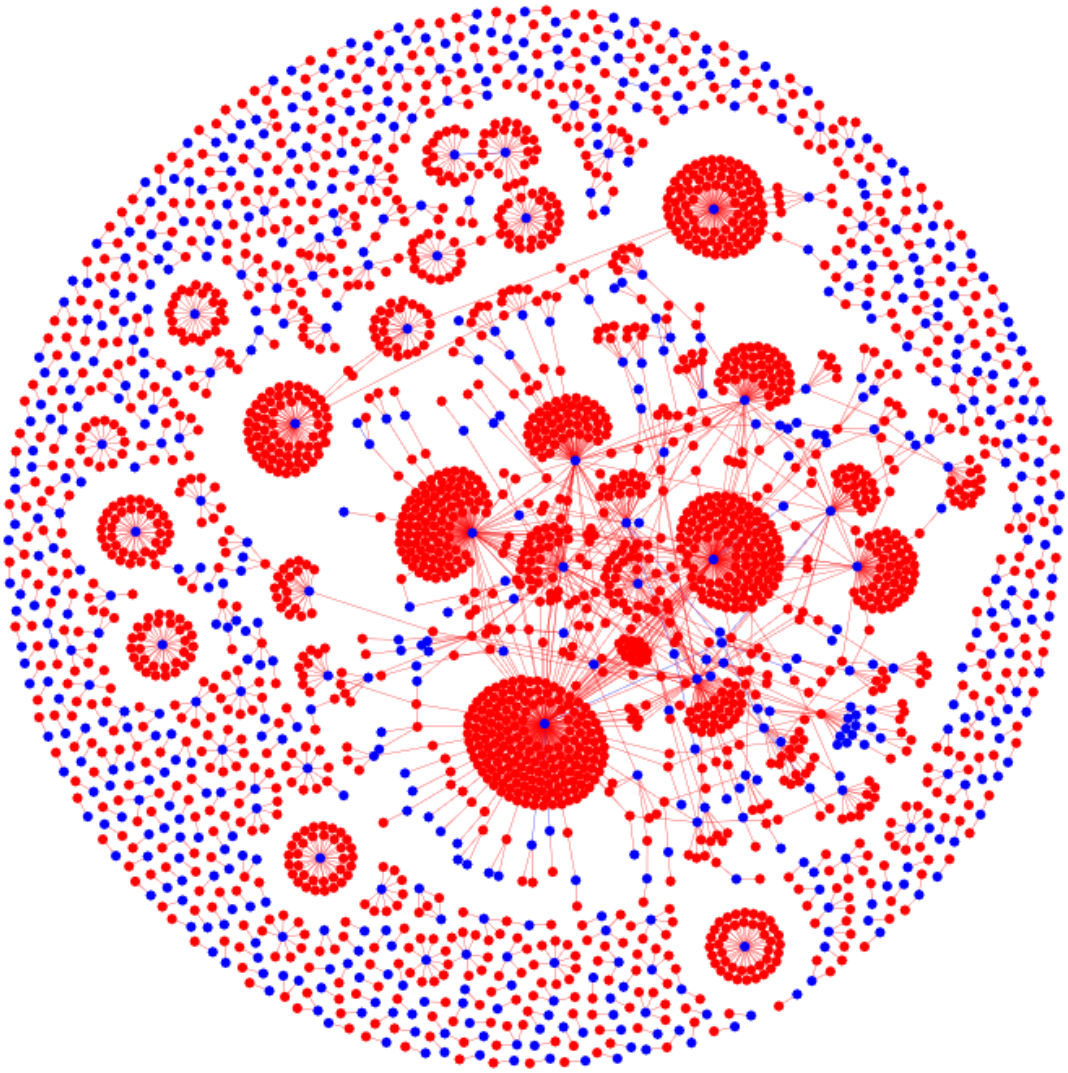
Comparative Insights

- **Influence vs. Virality**: There's a clear distinction between influential users (high in-degree) and viral users (high out-degree/followers ratio). Influential users command large audiences, while viral users are adept at spreading content, regardless of their follower size.
- **Manipulation Indicators**: High out-degree values serve as potential indicators of manipulation or spamming behaviour. However, the context of each network and the content shared by these users would be necessary to make definitive claims about manipulation.
- **Network Dynamics**: Each network exhibits its own dynamics, with the #Bitcoin and #chatgpt networks showing higher levels of engagement and potential manipulation compared to others. This could reflect the nature of discussions within these

communities, which may encourage more active participation or attract more promotional or spam-like activity.

CHAPTER 4 K-CORE VISUALIZATION

4.1 #BITCOIN



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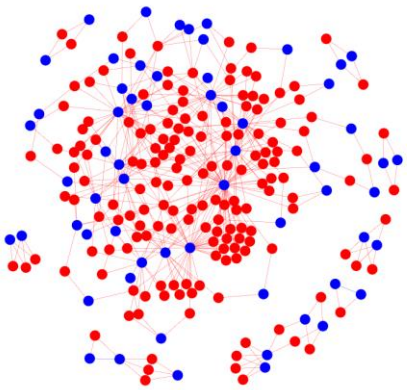
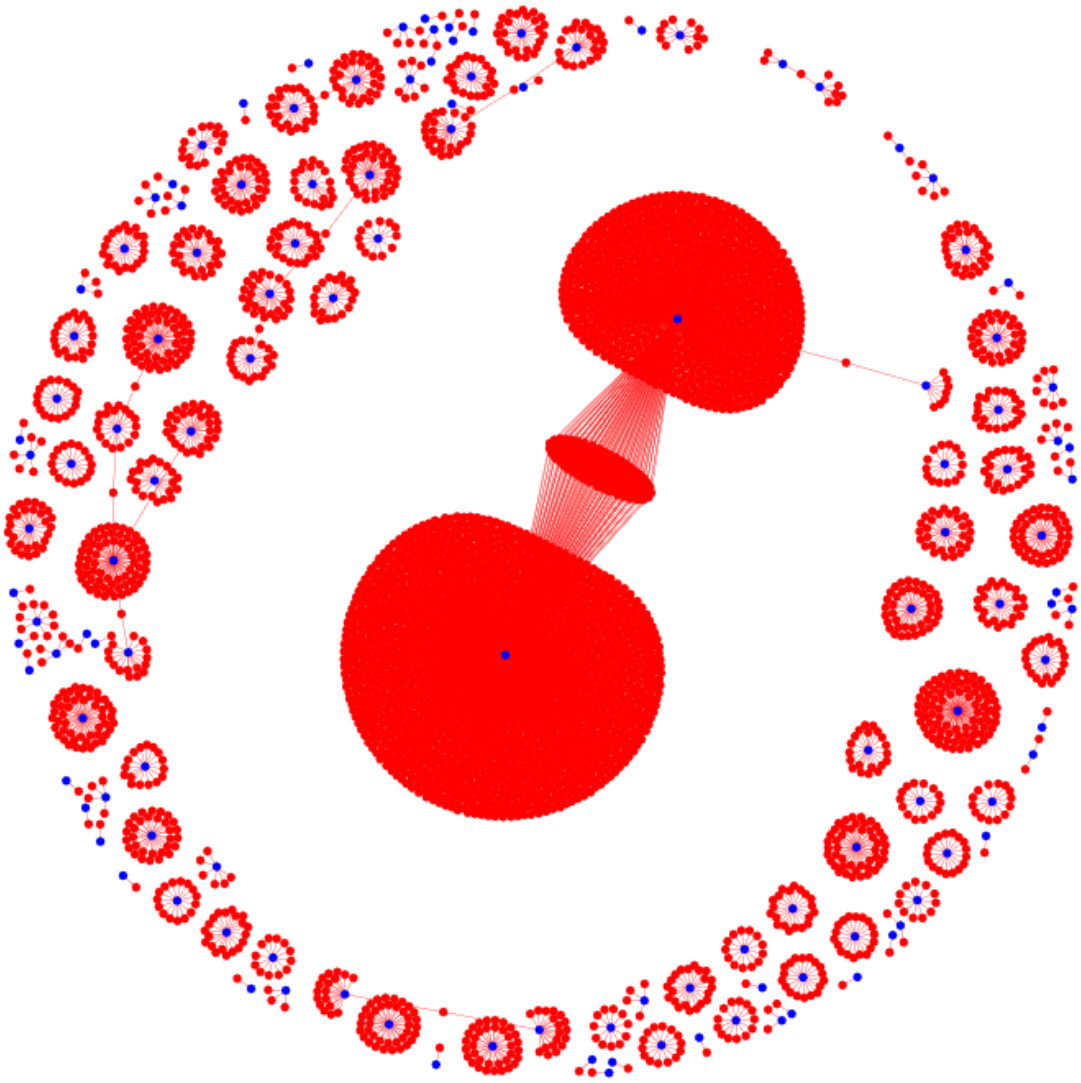


4.2 #BOREDAPEYACHTCLUB



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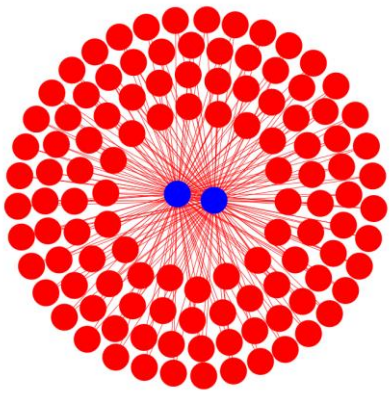
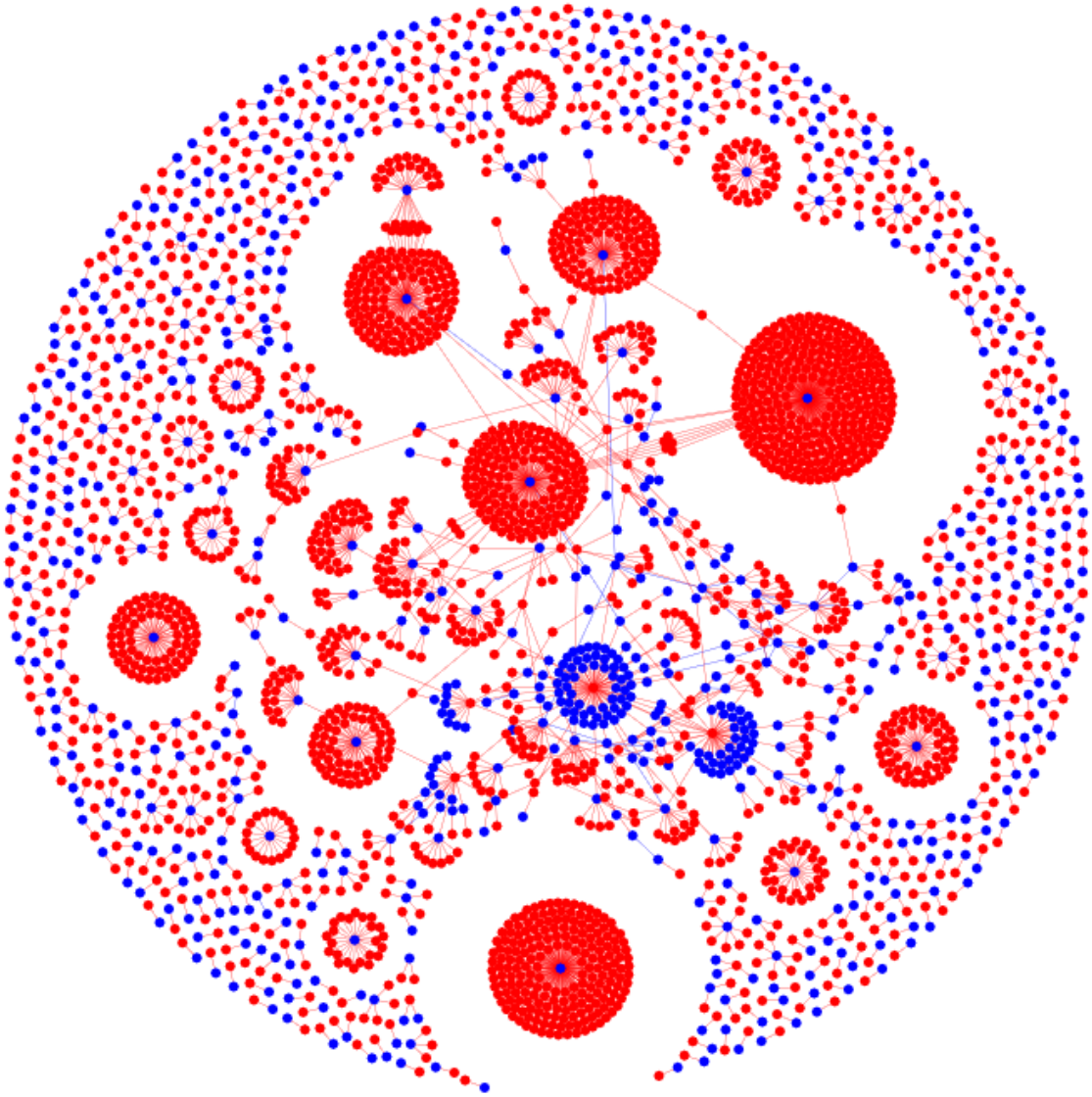


4.3 #CHATGPT



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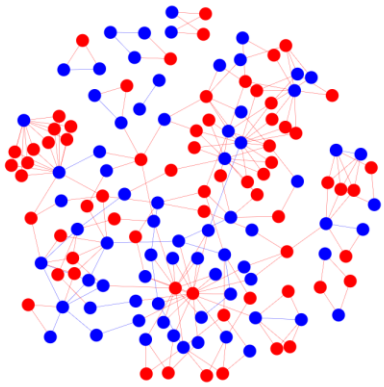
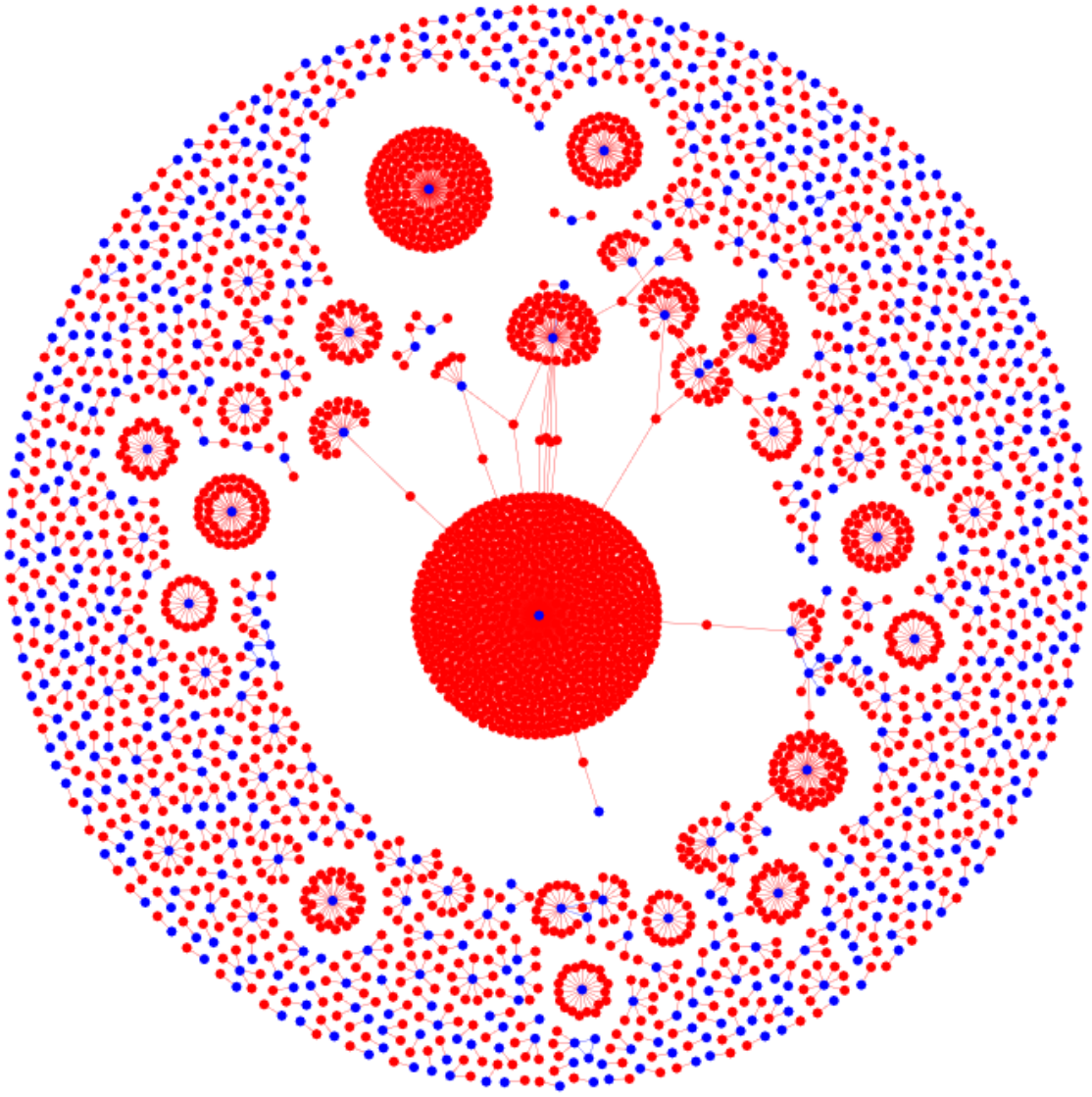


4.4 #ENERGY



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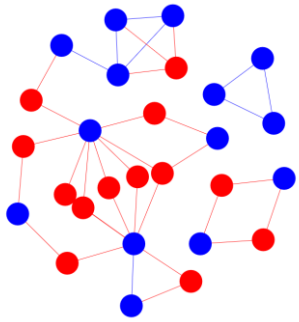
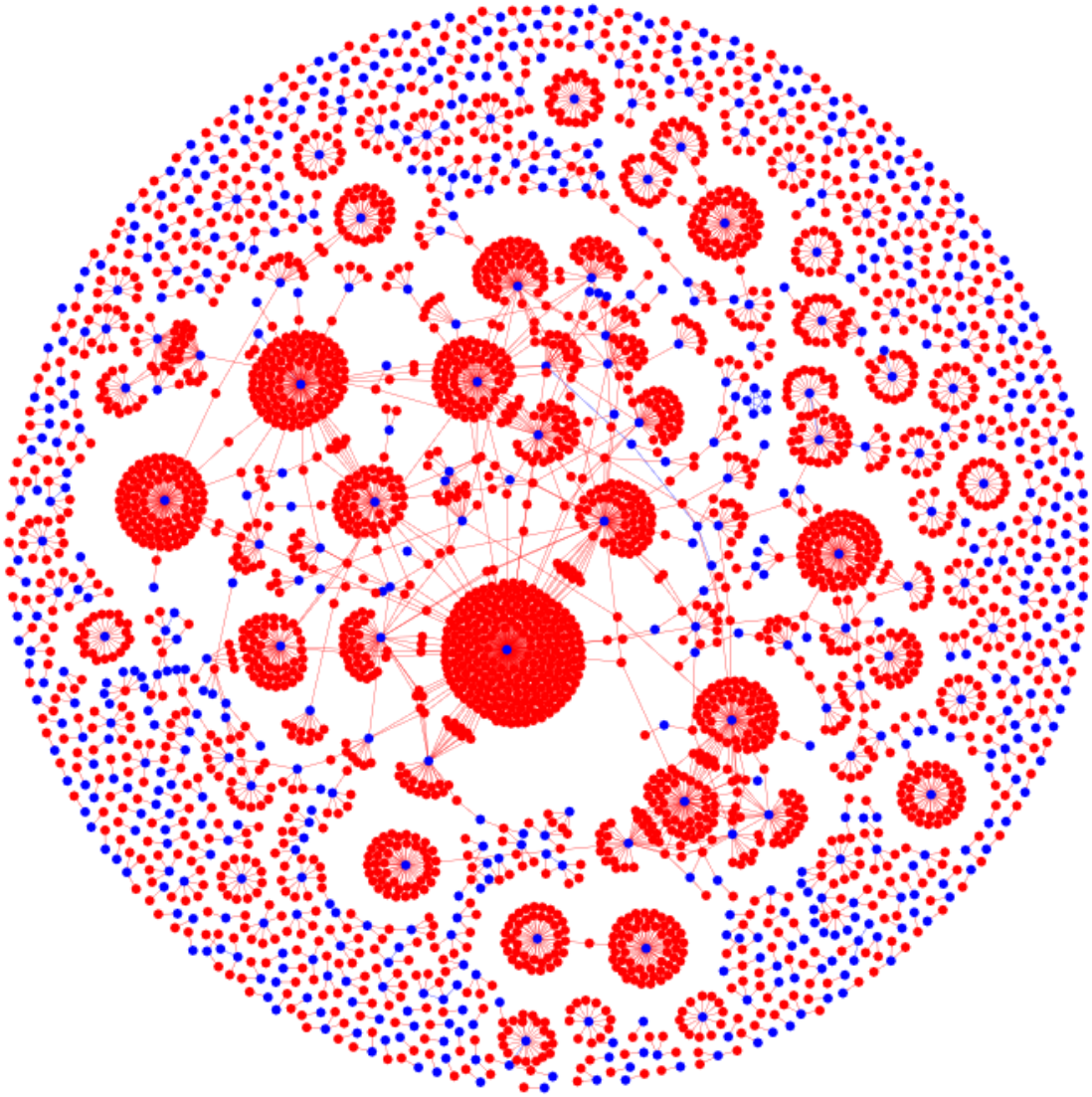


4.5 #ETH



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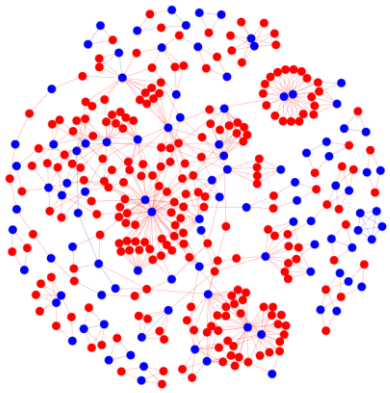
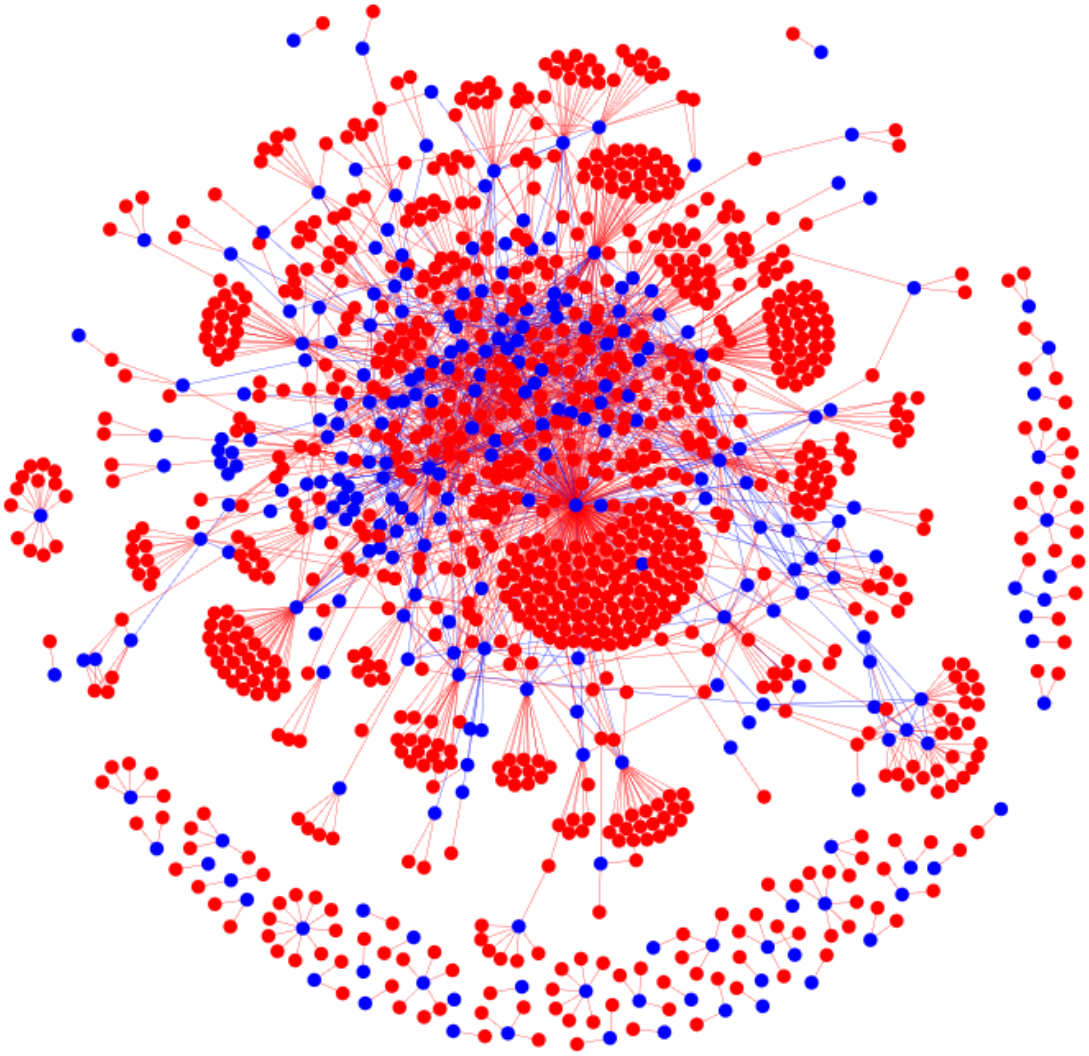


4.6 #URANIUM



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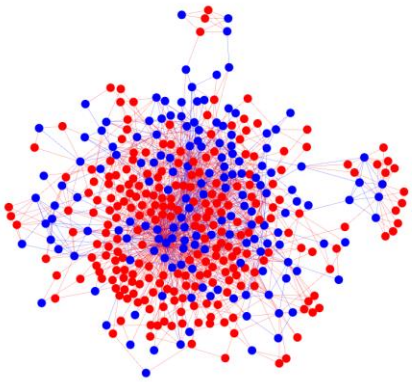
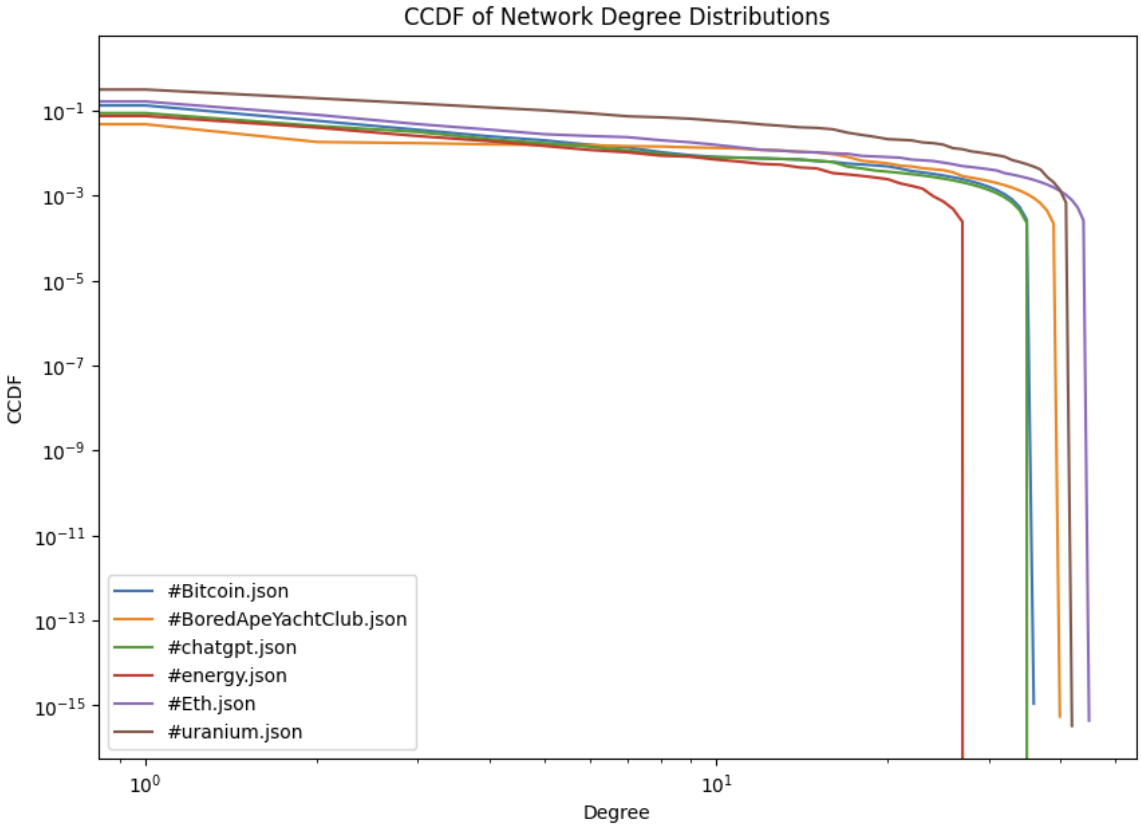


CHAPTER 5 FREQUENCY DISTROBUTIONS



In-degree KS Test Comparisons:

Comparison	KS Statistic	p-value
#Bitcoin.json vs #BoredApeYachtClub.json	1.0	1.71e-22
#Bitcoin.json vs #chatgpt.json	1.0	7.89e-20
#Bitcoin.json vs #energy.json	1.0	7.98e-19
#Bitcoin.json vs #Eth.json	1.0	8.61e-24
#Bitcoin.json vs #uranium.json	1.0	6.12e-22
#BoredApeYachtClub.json vs #chatgpt.json	1.0	3.94e-21
#BoredApeYachtClub.json vs #energy.json	1.0	4.94e-20
#BoredApeYachtClub.json vs #Eth.json	1.0	1.75e-25
#BoredApeYachtClub.json vs #uranium.json	1.0	1.91e-23
#chatgpt.json vs #energy.json	1.0	9.17e-18
#chatgpt.json vs #Eth.json	1.0	2.56e-22
#chatgpt.json vs #uranium.json	1.0	1.26e-20
#energy.json vs #Eth.json	1.0	3.92e-21
#energy.json vs #uranium.json	1.0	1.45e-19
#Eth.json vs #uranium.json	1.0	7.97e-25

Out-degree KS Test Comparisons:

Comparison	KS Statistic	p-value
#Bitcoin.json vs #BoredApeYachtClub.json	0.6666666666666666	1.89e-01
#Bitcoin.json vs #chatgpt.json	1.0	7.40e-07
#Bitcoin.json vs #energy.json	0.8	1.00e-02
#Bitcoin.json vs #Eth.json	0.8888888888888888	1.43e-04
#Bitcoin.json vs #uranium.json	0.9166666666666666	5.93e-08
#BoredApeYachtClub.json vs #chatgpt.json	0.6666666666666666	1.89e-01
#BoredApeYachtClub.json vs #energy.json	0.6666666666666666	2.86e-01
#BoredApeYachtClub.json vs #Eth.json	0.6666666666666666	2.36e-01
#BoredApeYachtClub.json vs #uranium.json	0.6666666666666666	1.17e-01
#chatgpt.json vs #energy.json	1.0	3.23e-04
#chatgpt.json vs #Eth.json	1.0	6.80e-06
#chatgpt.json vs #uranium.json	1.0	5.11e-10
#energy.json vs #Eth.json	0.8	1.40e-02
#energy.json vs #uranium.json	0.8	2.72e-03
#Eth.json vs #uranium.json	0.8888888888888888	5.18e-06

In-Degree KS Test Comparisons:

All the in-degree KS (Kolmogorov-Smirnov) test comparisons show a KS statistic of 1.0, which suggests a perfect non-overlap between the distributions; they are completely different. Given that all the p-values are extremely small and effectively zero (way below the typical alpha level of 0.05), we can reject the null hypothesis that the distributions are the same for all pairs compared. This indicates that the in-degree distributions of these networks are significantly different from each other.

Out-Degree KS Test Comparisons:

The out-degree comparisons show a mix of KS statistics:

- For some comparisons, the KS statistic is 1.0, indicating completely different out-degree distributions, and the p-values are very low (significantly less than 0.05), which confirms the differences are statistically significant. This is the case for any network when compared with #chatgpt.json, which suggests that the #chatgpt.json network's out-degree distribution is distinctively different from all the others. Referring to the network graphs, this is also clear in that #chatgpt is the only graph in which there are clear clusters of blue around red, indicating that there is a single account retweeting multiple others.
- For other comparisons, the KS statistic varies (0.666, 0.8, 0.888, 0.916), which suggests less pronounced differences in the out-degree distributions. However, the p-values in these comparisons vary:
- Some are not statistically significant (e.g., the comparison between #Bitcoin.json and #BoredApeYachtClub.json has a p-value of 0.189, suggesting we cannot reject the null hypothesis for these two networks at a 95% confidence level).
- Others have small p-values (significantly less than 0.05), which suggests statistically significant differences despite the lower KS statistics (e.g., the comparison between #Bitcoin.json and #Eth.json with a p-value of about 0.000143).

In summary, there is clear statistical evidence that the in-degree distributions across these six networks are significantly different. For the out-degree distributions, the differences are more nuanced, with some networks showing significant differences and others not. The degree of difference and the significance level, as indicated by the KS statistics and p-values, could be influenced by several factors, such as the network's size, the presence of influential users, and the network's overall connectivity pattern.

CHAPTER 6 ADENDUMS

6.1 ADENDUM A: NETWORK COMPARRISON METRICS

Metrics for #Bitcoin.json Network:

Metric	Value
number_of_nodes	3712
number_of_edges	2592
density	0.00018816380007247792
average_in_degree	0.6982758620689655
average_out_degree	0.6982758620689655
assortativity	-0.05026603710410164
is_weakly_connected	False
number_of_weakly_connected_components	1317
share_of_users_retweeting	0.16702586206896552
share_of_users_being_retweeted	0.5942887931034483
average_clustering	0.0004969393436637296
average_closeness_centrality	0.00018878398270440086
average_betweenness_centrality	7.631181369616067e-10

Metrics for #BoredApeYachtClub.json Network:

Metric	Value
number_of_nodes	4556
number_of_edges	4419
density	0.0002129373793523504
average_in_degree	0.9699297629499561
average_out_degree	0.9699297629499561
assortativity	0.09891922444294174
is_weakly_connected	False
number_of_weakly_connected_components	248
share_of_users_retweeting	0.02787532923617208
share_of_users_being_retweeted	0.9427129060579456
average_clustering	0.0
average_closeness_centrality	0.0002129373793523504
average_betweenness_centrality	0.0

Metrics for #chatgpt.json Network:

Metric	Value
number_of_nodes	4394
number_of_edges	2702
density	0.00013997938749123057
average_in_degree	0.6149294492489759
average_out_degree	0.6149294492489759
assortativity	-0.17778440965428274
is_weakly_connected	False
number_of_weakly_connected_components	1786
share_of_users_retweeting	0.16090122894856623
share_of_users_being_retweeted	0.5359581247155212
average_clustering	0.0028519862364141993
average_closeness_centrality	0.0001428508397939424
average_betweenness_centrality	4.210994060121535e-09

Metrics for #energy.json Network:

Metric	Value
number_of_nodes	4141
number_of_edges	2574
density	0.00015014226767321484
average_in_degree	0.6215889881671094
average_out_degree	0.6215889881671094
assortativity	-0.10589026836971625
is_weakly_connected	False
number_of_weakly_connected_components	1583
share_of_users_retweeting	0.14489253803429122
share_of_users_being_retweeted	0.6042018836029944
average_clustering	0.0016198152354293539
average_closeness_centrality	0.00015111429088134287
average_betweenness_centrality	7.891999135049297e-10

Metrics for #Eth.json Network:

Metric	Value
number_of_nodes	3852
number_of_edges	3320
density	0.0002238093812803137
average_in_degree	0.8618899273104881
average_out_degree	0.8618899273104881
assortativity	-0.08870375495640873
is_weakly_connected	False
number_of_weakly_connected_components	786
share_of_users_retweeting	0.16329179646936656
share_of_users_being_retweeted	0.7437694704049844
average_clustering	0.006218933215045522
average_closeness_centrality	0.00022549393781548914
average_betweenness_centrality	1.7334633661986432e-09

Metrics for #uranium.json Network:

Metric	Value
number_of_nodes	1461
number_of_edges	2198
density	0.0010304445257048559
average_in_degree	1.5044490075290897
average_out_degree	1.5044490075290897
assortativity	-0.16736264251618194
is_weakly_connected	False
number_of_weakly_connected_components	271
share_of_users_retweeting	0.17932922655715264
share_of_users_being_retweeted	0.728952772073922
average_clustering	0.06702394908386806
average_closeness_centrality	0.004276639567080905
average_betweenness_centrality	2.0597117244166442e-05

6.2 ADENDUM B: TOP USER ANALYSIS METRICS

Analysis for #Bitcoin.json Network:

Top Influential Users (by in-degree):

User	Followers	Posts	In-Degree
Bitcoin Archive	1205577	39116	245
Bitcoin Magazine	2824027	28052	157
Michael Saylor	2934189	4123	130
GAMB	18481	1038	97
Crypto Rover	441543	18909	81
Aptos NFT | MINT IS LIVE	86262	670	68
Altcoin Daily	1334160	21303	62
Bitcoin News	25938	48668	61
Dan Held	656922	69620	58
Memeing ฿itcoin	33533	865	49

Potential Manipulators (by out-degree):

User	Followers	Posts	Out-Degree
IYIEOW	1091	19838	20
Coin on the co฿	3002	110388	13
Alessandro Tosin	921	27134	10
Franek Schmidt	196	18348	8
Nerio Ramirez	141	864	7
Adam Moody	2248	242487	6
Syafwan TwentyNine	912	92769	6
Dennis Parker	35745	150226	5
Jennifer Eliogu	605	56123	5
Richard McDonald	624	12518	5

Top Viral Users (by out-degree/followers ratio):

User	Followers	Posts	Virality Score
IYIEOW	1091	19838	0.018
Coin on the co฿	3002	110388	0.0043
Lambo Raul. Gonzalez |||	1326	6902	0.003
Adam Moody	2248	242487	0.0027
Camarada Sobrinho ∞/21M |13%|	1288	7511	0.0023
RunCMC	1026	105277	0.0019
Harry D. Bean	1040	88197	0.0019
0xCruel.NFT	2086	15010	0.0019
Crypto Cuddler	1050	18691	0.0019
Sandra Ki	1078	1455	0.0019

Analysis for #BoredApeYachtClub.json Network:

Top Influential Users (by in-degree):

User	Followers	Posts	In-Degree
NFT Project Promoter✨	59557	2354	1767
Degen Ape Trader	25765	917	966
ALTAVA	110664	1247	87
OKX	2766739	15932	71
Hakibot.eth | Biscuit The General #Ape1045	5279	455	57
BrianLopez.eth	6849	2088	49
Captain JR	41331	16415	46
🍩 GG	5753	4768	40
Otter	8631	2968	39
MetaZig.eth ᴱᵐ 🍌	11041	25053	38

Potential Manipulators (by out-degree):

User	Followers	Posts	Out-Degree
kel	182	26721	2
isaa🕊️	666	17040	2
⚡Luck89 💚🌿🍀	1160	52446	2
🌸 °freetag°	63	6763	2
cani🐾freetag	217	4986	2
CAPE KELOCK ELONN	351	64747	2
DEE DEEW	263	4873	2
al || freetag	384	13248	2
madu wangi ✨ mau $100	511	18987	2
A L E X A	2425	39728	2

Top Viral Users (by out-degree/followers ratio):

User	Followers	Posts	Virality Score
⚡Luck89 💚🌿🍀	1160	52446	0.0017
ruyu freetag	1322	113519	0.0015
nitaa WIN🍀	1865	50180	0.0011
chir☆🟡	1002	78250	0.001
BIGWIN TODAY🌷🌷chaaa🍀harum wangi🍀	2006	15288	0.001
GD	1012	3447	0.00099
mutemute dicini	1015	84666	0.00099
aca	1017	26739	0.00098
Shia ❤️	1020	44416	0.00098
mobi 🥇	1024	83782	0.00098

Analysis for #chatgpt.json Network:

Top Influential Users (by in-degree):

User	Followers	Posts	In-Degree
Ishan Sharma	136398	7474	294
Whistle	10023	1820	197
John Vianny	1357	3100	155
BEP-AI | Bot Engineering Protocol	3876	3	126
DataChazGPT 🤯 (not a bot)	62327	15079	103
Aptos Insiders	82093	2607	68
Megh Updates 🎉™	180867	13746	58
BAHA MACHACHARI🤯	47741	259474	51
Alethea AI	46331	4903	33
Artik 🦑	33543	615	29

Potential Manipulators (by out-degree):

User	Followers	Posts	Out-Degree
AI Bot by uCloudify.com	1569	219589	82
FolivorAI	159	8120	49
Frédéric Guariento	157	24124	19
Data Governance Framework	8143	341710	14
Galactic Ditto	1006	280741	9
S L A T T 💚 🌿	547	74665	9
Security News	44768	3079877	7
Shah	33	1414	7
ApeBot - Domains	1803	179865	6
Riya	8	685	6

Top Viral Users (by out-degree/followers ratio):

User	Followers	Posts	Virality Score
AI Bot by uCloudify.com	1569	219589	0.052
Galactic Ditto	1006	280741	0.0089
ApeBot - Domains	1803	179865	0.0033
Olivia	1047	99958	0.0019
종이나무 papertree	1111	476645	0.0018
Wellington Torrejais da Silva 🇧🇷 - 💙🧡	1148	133458	0.0017
Data Governance Framework	8143	341710	0.0017
Fintech Bot	1187	219567	0.0017
CK	1211	17699	0.0017
Amy.M.Anderson	1223	9571	0.0016

Analysis for #energy.json Network:

Top Influential Users (by in-degree):

User	Followers	Posts	In-Degree
Mike Hudema	205753	34880	702
Emerging Pakistan	47572	14085	150
Dr Paul Dorfman	7602	21640	63
Francis Dubé	578	1017	48
Larenz Tate	616236	7504	42
Asiko Energy Holdings Limited	40	91	42
Power The Future	42762	2988	35
Robert Bryce	14627	15289	32
alok kumar	25088	900	26
Gurbaksh Singh Chahal	510128	141506	26

Potential Manipulators (by out-degree):

User	Followers	Posts	Out-Degree
Kirill Klip ⛏ #Gold & #rEVolution	7964	530346	4
Michelangelo/TechMentor_Wanted	280	30966	4
Joe Gambiste	17505	2140043	3
Ruth Magin	648	37911	3
International Trading	453	59893	3
Low Carbon Agriculture	4146	6899	3
Sufiy	3077	633126	3
senile♠	46	6423	3
MasalaRepublic	129	47989	3
TheGretaEffect-EarthWins	15293	150921	3

Top Viral Users (by out-degree/followers ratio):

User	Followers	Posts	Virality Score
patty	1072	107838	0.0019
Vinod Menon	1284	11130	0.0016
Peter u308 Au	1496	5445	0.0013
rhodogal	1522	143221	0.0013
Powerstar	1740	4052	0.0011
Martin Baxter	1957	16311	0.001
TheGreatKoppite	2963	76881	0.001
Steve Fall 💙	1001	74646	0.001
Khushi...	1004	63013	0.001
Galactic Ditto	1006	280741	0.00099

Analysis for #Eth.json Network:

Top Influential Users (by in-degree):

User	Followers	Posts	In-Degree
Rollbit Rewards	69260	1266	283
KOOSH	19608	10352	116
MOON KING B-ROOTS	36514	37381	92
Agresivoo 🖤	143711	757	80
MrShinyBird 🦩✨	38956	4500	77
Dubai Saitama 🖤💚🖤🤍	15120	11333	74
SHIBONK $SBONK	28656	498	73
SHIBONK $SBONK	45654	45	69
Pikamoon	14219	77	61
Oron	34385	1169	57

Potential Manipulators (by out-degree):

User	Followers	Posts	Out-Degree
Darkzi	8693	45004	8
zAYneUdeLe	23	883	7
Goyo	9	443	7
Felicity	13	4648	6
JKS	474	43120	5
Yamamoto	46	5421	5
Gigi_Normand	79	5491	5
ApeBot - Web3 domains	1376	125774	5
rizalkojenk	126	60	5
UneekOne	133	6010	5

Top Viral Users (by out-degree/followers ratio):

User	Followers	Posts	Virality Score
ape_nft	1089	18873	0.0037
ApeBot - Web3 domains	1376	125774	0.0036
CryptoPumpers.io 🇺🇸	1412	4968	0.0028
Beggar's Club	1300	1449	0.0023
ApeBot - Domains	1802	179821	0.0022
ItsParaJay	1234	20194	0.0016
Ijen	1342	12723	0.0015
Anna🐺 #Saitama #SaitaRealty Queen💖	2130	44355	0.0014
S0luti0n 🐺🇵🇸 #SaitaRealty #Saitama #Crypto	1440	23194	0.0014
c.	2177	6251	0.0014

Analysis for #uranium.json Network:

Top Influential Users (by in-degree):

User	Followers	Posts	In-Degree
John Quakes	69402	76005	306
📐triANGLE Investor	9114	14385	87
Uranium Corgi	14778	9919	85
Kevin Bambrough	37355	15512	69
Worldwide Exchange	28350	9951	52
Amir Adnani 🇺🇸	65539	1949	51
Patrick Downes #NuclearEnergy advocate	5452	26863	46
I believe in U	1059	1370	45
Beta Beaker	1066	3779	44
Art Hyde	14232	2474	43

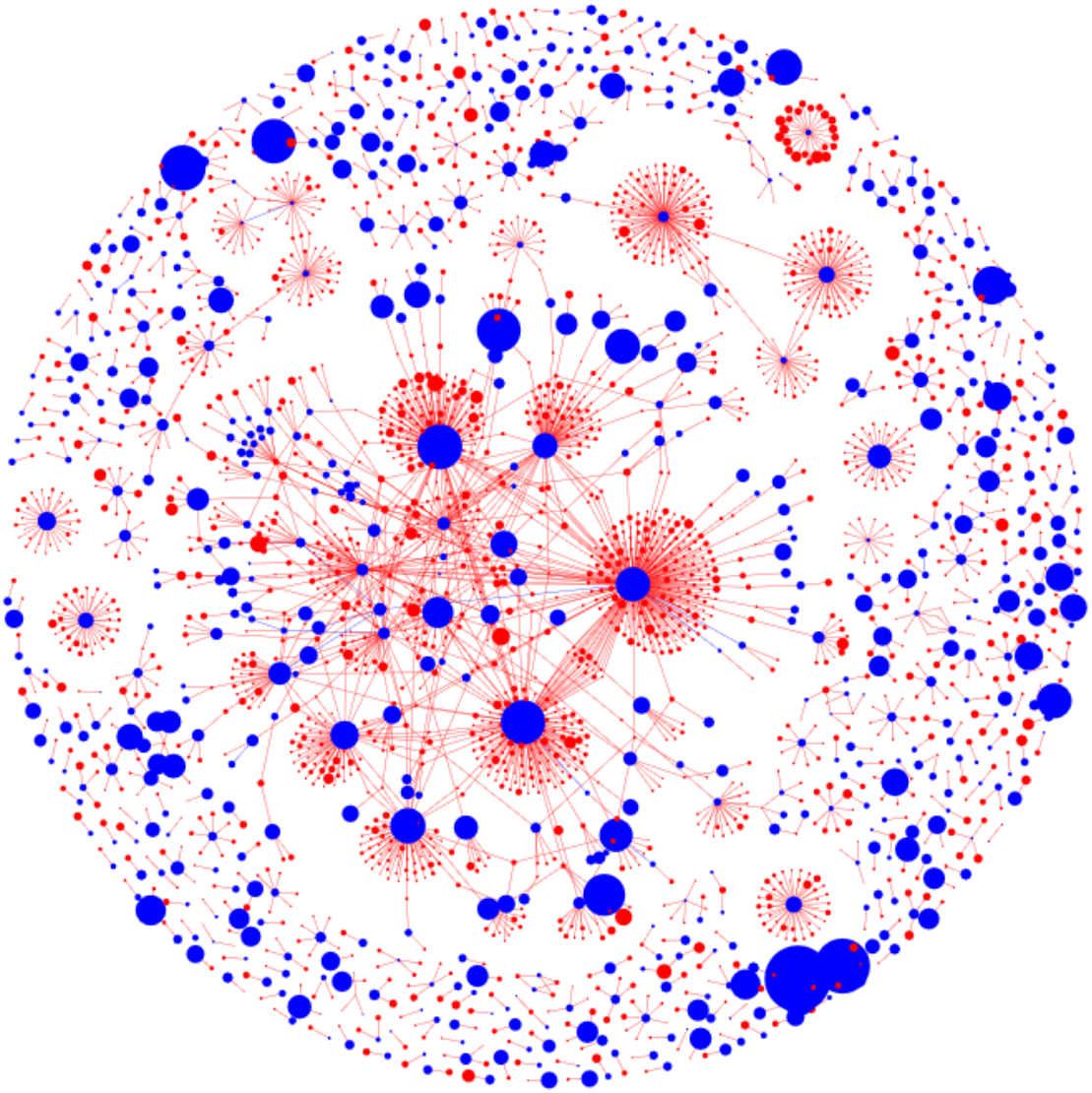
Potential Manipulators (by out-degree):

User	Followers	Posts	Out-Degree
DW Black Uranium/ Geo/Engr #Resister, #BidenHarris	3941	24392	48
Uranium and Commodities watcher	3247	37191	44
alex g.	151	35433	42
UraniumCaesar ☸	964	11800	33
LadyLisaCan2	2127	246980	28
Joe Gambiste	17509	2139962	27
Eduardo #uranium 🇧🇷	2200	15438	25
Big Mike & his 🌶🧄s #Uranium $GLO $TCF	3842	30692	21
goldbug	659	24252	19
bebold007	453	18709	19

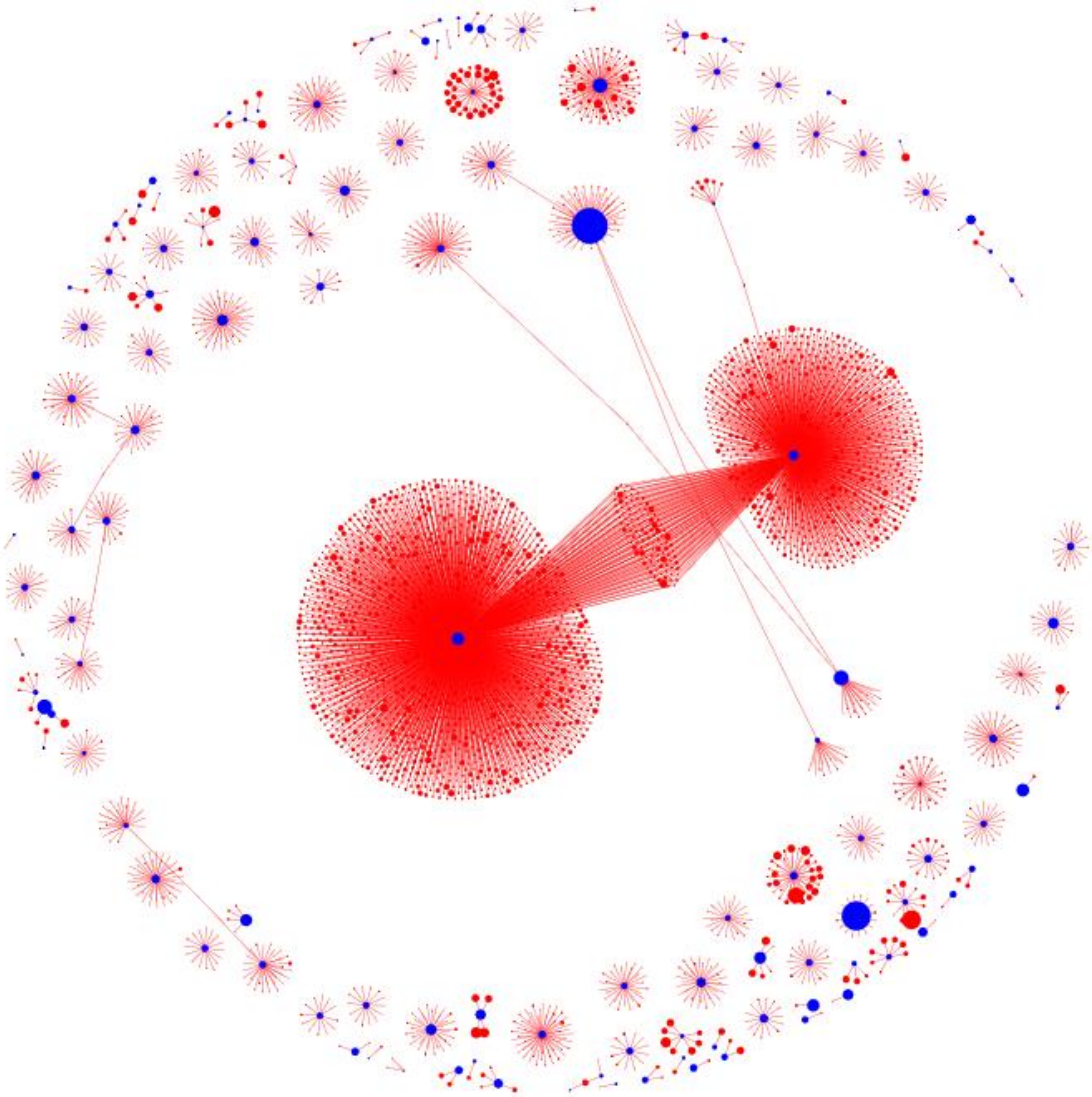
Top Viral Users (by out-degree/followers ratio):

User	Followers	Posts	Virality Score
Inflation-Battle253	1159	23476	0.015
Uranium and Commodities watcher	3247	37191	0.014
LadyLisaCan2	2127	246980	0.013
DW Black Uranium/ Geo/Engr #Resister, #BidenHarris	3941	24392	0.012
Eduardo #uranium 🇧🇷	2200	15438	0.011
Pucci Mon	1784	36386	0.0062
Big Mike & his 🌶🧄s #Uranium $GLO $TCF	3842	30692	0.0055
Steve Mueller	2730	19462	0.0044
Brandon Weber	1173	1726	0.0043
long U bull	2561	23450	0.0039

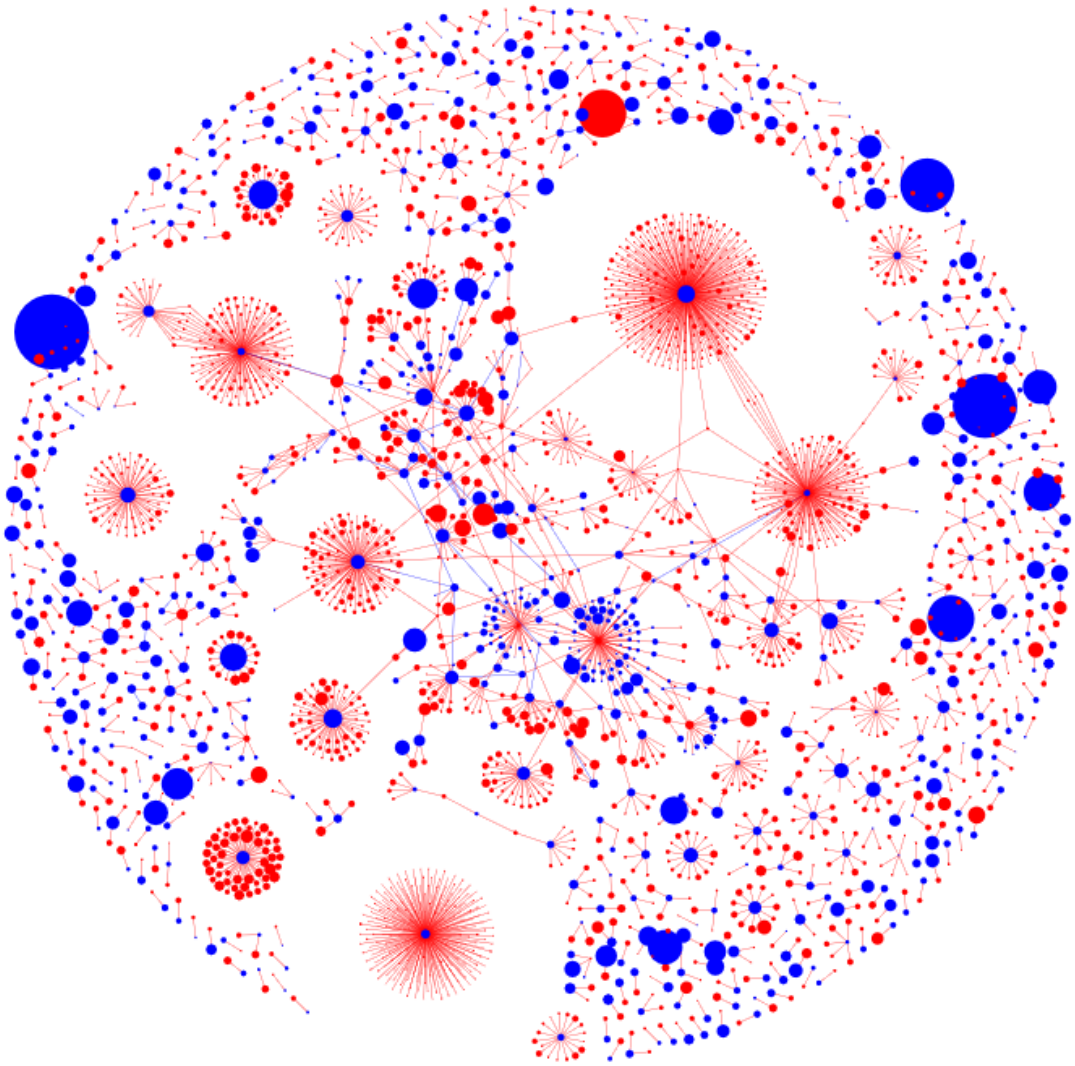
6.3 ADENDUM C: FOLLOWER REPRESENTAATIVE NETWORK GRAPHS #Bitcoin



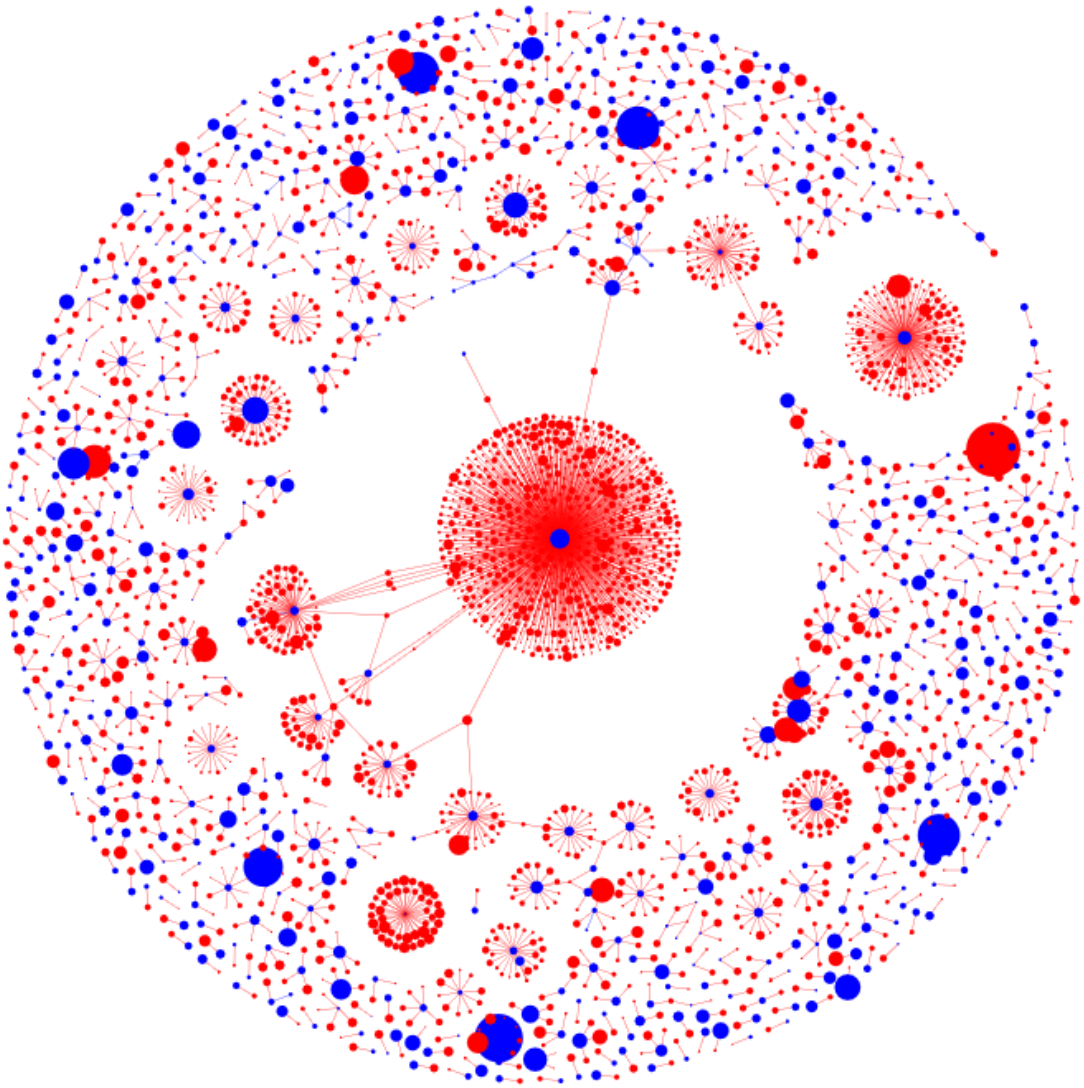
#BoredApeYachtClub



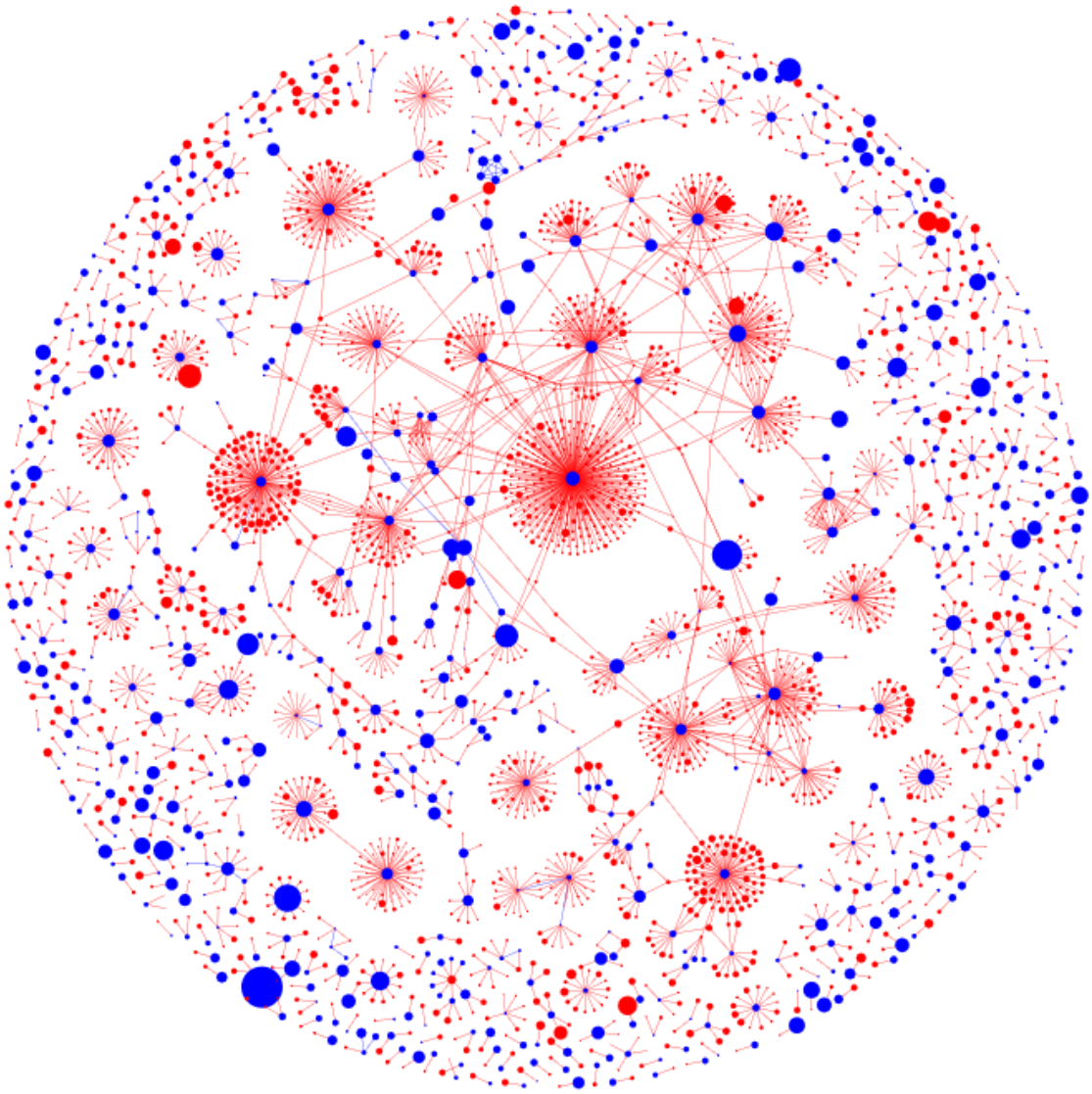
#chatgpt



#energy



#Eth



#uranium