Structural Anatomy of the Dark Web: An Analysis of Hidden Service Connectivity

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Abstract

The Dark Web is frequently conceptualized as a distributed and resilient system. However, the topological structure of its underlying link network is a subject of debate. In this report, we analyze a network of Dark Web hidden services with 7,178 nodes and 24,879 edges. We employ canonical measures of network sciences, centrality analysis and community detection, comparing our findings against Erdős-Renyi and Barabási-Albert null models. Our results reveal a structure of ultra-small world combined with high local clustering. Crucially, we identify an extreme centralization hierarchy that exceeds theoretical scale-free predictions, alongside a strong disassortative mixing pattern. We analyze the roles of specific high-centrality nodes, identifying directory services that act as structural backbones. These findings suggest that the Dark Web's hyperlink structure is functionally oligarchic, relying strongly on central hubs, which renders the network potentially vulnerable to targeted attacks.

1 Introduction

The study of complex networks has changed our understanding of biological pathways, social interactions, or digital information ecosystems such as the World Wide Web. While the surface web has been extensively mapped, revealing scale-free properties and small-world architectures [Albert et al., 1999], the "Dark Web"–specifically hidden services accessible via anonymity networks like Tor–presents a unique case study. These networks are designed for anonymity and resistance to censorship, yet their navigational structure relies on hyperlinks created by users and administrators, which may not follow the decentralized ethos of the underlying protocol.

The primary objective of this report is to characterize the topological structure of a Dark Web hyperlink network. Unlike standard social networks where transitivity is high due to triadic closure, or biological networks shaped by evolutionary constraints, the Dark Web is shaped by a mix of secrecy and the need for *discoverability*. Specifically, we aim to answer the following research questions:

1. **Scale-Free Nature:** Does the Dark Web follow a power-law degree distribution similar to the surface web, or does it exhibit a different structural organization?

2. **Structural Cohesion:** How does its clustering and path length compare to random null models? Is it a "Small World"?

3. **Hierarchy and Control:** Is the network "democratic" or "oligarchic" in terms of centrality distribution? Do specific nodes dominate the information flow?

To address these questions, we perform a comprehensive structural analysis. We employ rigorous statistical fitting for heavy-tailed distributions [Clauset et al., 2009], quantify inequality/heterogeneity using the Gini coefficient, and validate the statistical significance of our findings by generating ensemble null models (Erdős-Rényi and Barabási-Albert).

2 Dataset and Methodology

2.1 Dataset Description

The dataset analyzed in this study represents a snapshot of the Dark Web structure extracted via Tor2web created between 2016 and 2017 [Griffith et al., 2017].

- **Nodes ($V = 7,178$):** Represent distinct hidden services (websites ending in .onion).

- **Edges ($E = 24,879$):** Represent directed hyperlinks from one site to another (i, j), weighted by the number of pages on domain i linking to pages on domain j.

The network provided is fully connected, meaning there are no isolated components that require removal. Consequently, all analyses reported here correspond to the **full network**. Certain metrics requires an undirected graph, so the network was symmetrized by treating all edges as bidirectional, while edge weights were disregarded as this study focuses purely on topological structure.

2.2 Computational Methods and Software

The analysis was conducted using **Python** (v3.10), leveraging the `NetworkX` library for graph algorithms[1]. Rigorous statistical fitting of degree distributions was performed using the `powerlaw` package [Alstott et al., 2014]. Visualization was produced using **Gephi** (v0.10.1).

2.2.1 Degree Distribution Fitting

We tested the hypothesis that the degree distribution follows a Power Law $P(k) \sim k^{-\alpha}$. We employed the **Maximum Likelihood Estimation** (MLE) method. The lower bound cutoff (x_{min}) was determined automatically by minimizing the Kolmogorov-Smirnov distance between the empirical data and the theoretical model. We compared the Power Law fit against Exponential and Log-normal alternatives using the Likelihood Ratio Test (R), where a positive R with $p < 0.05$ indicates a preference for the Power Law.

2.2.2 Centrality and Inequality Quantification

To characterize the hierarchical structure of the network beyond simple connectivity, we computed seven complementary centrality metrics. First, we measured local popularity using **Degree Centrality**. To capture global influence, we employed **Eigenvector Centrality** and its variations: **PageRank** (using a damping factor $\alpha = 0.85$ to model user navigation) and **Katz Centrality**. The latter is particularly relevant as it introduces a distance attenuation factor, resolving the localization issues of Eigenvector centrality in directed networks.

Regarding navigational efficiency, we calculated **Closeness Centrality**, which measures the average shortest path distance to all other nodes. Additionally, we computed **Betweenness Centrality** to identify bridge nodes that control information flow, and **Subgraph Centrality** to account for participation in closed loops of all lengths.

To quantify the global heterogeneity of the centrality distributions, we adapted the **Gini Coefficient** from econometrics to network science. For a given centrality measure $X = \{x_1, \ldots, x_V\}$, the coefficient is defined as the relative mean absolute difference [Kunegis and Preusse, 2012]:

[1] The complete reproducibility package, including code and data, is available at: `https://github.com/valexandercapa/darkweb-network-analysis`

$$G = \frac{\sum_{i=1}^{V}\sum_{j=1}^{V}|x_i - x_j|}{2N^2\bar{x}} \quad (1)$$

where $\bar{x}$ represents the mean centrality. A value of $G \approx 0$ indicates a homogeneous topology (e.g., a random graph), while $G \approx 1$ reveals a highly centralized, "winner-takes-all" hierarchy, allowing us to compare the empirical network against the theoretical baselines.

2.2.3 Community Detection and Visualization

Communities were detected using the **Greedy Modularity Optimization** algorithm [Clauset et al., 2004], chosen for its efficiency on networks of this size.

For visualization in Gephi, we employed the **ForceAtlas2** layout algorithm. This force-directed algorithm is specifically designed for scale-free networks. We used a Scaling factor of 200.0 to prevent node overlap and enabled the "Dissuade Hubs" option to push high-degree nodes apart, revealing the structural core. Nodes were colored by their modularity class and sized according to their PageRank score.

2.2.4 Null Models and Statistical Significance

To ensure that our structural findings are not artifacts of the network's size or density, we generated an ensemble of 10 realizations for two types of null models, constrained to have the exact same number of nodes (V) and edges (E) as the real network:

1. **Erdős-Rényi (ER):** A random graph model $G(n, m)$ where edges are placed uniformly at random. This serves as a baseline for a structureless system.

2. **Barabási-Albert (BA):** A preferential attachment model. This serves as a baseline for a standard scale-free network without community structure or assortative constraints. The BA parameter m (number of new edges per node) was set to $m = \text{round}(E/V) = 3$. This choice aligns the null model's density with the empirical network, resulting in an expected average degree of $\langle k \rangle_{\text{BA}} = 2m = 6$, which closely approximates the network's average degree ($\langle k \rangle_{\text{real}} \approx 6.9$).

For each metric, we report the Z-Score, defined as $Z = \frac{X_{\text{real}} - \mu_{\text{null}}}{\sigma_{\text{null}}}$. A magnitude $|Z| > 2$ indicates the result is statistically significant ($p < 0.05$).

3 Results

3.1 Topology

The network exhibits a low density, characteristic of sparse real-world graphs. However, the connectivity patterns reveal an ultra-small world phenomenon.

The average shortest path length of the network is $a \approx 2.37$. This is remarkably short, even when compared to the random null models ($a_{\text{ER}} \approx 4.80$, $a_{\text{BA}} \approx 4.18$). The fact that the real network allows for faster navigation than a random graph suggests an efficient core structure, likely driven by central directories. The Diameter of the network is $d = 5$, further confirming its compactness.

Simultaneously, the average Clustering Coefficient is $C \approx 0.706$. This is orders of magnitude higher than the random expectation ($C_{\text{ER}} \approx 0.0009$, C_{BA}), yielding a massive Z-Score. This indicates high local cohesion: neighbors of a node are highly likely to be connected to each other, forming dense cliques.

The topological features of the network compared with BA and ER null models are presented in Table 1.

Metric	**Real Value**	**ER Mean**	**ER Z-Score**	**BA Mean**	**BA Z-Score**
Avg. Clustering (C)	0.7061	0.0009	5614.13	0.0066	1198.08
Transitivity (T)	0.0044	0.0009	35.98	0.0035	4.49
Avg. Path Length (a)	2.3704	4.8053	-1050.92	4.1774	-101.71
Diameter (d)	5.0000	8.9000	-12.33	7.0000	-
Assortativity (r)	-0.4430	-0.0012	-95.48	-0.0429	-62.43
Modularity (Q)	0.3100	0.3419	-23.56	0.3933	-47.41

Table 1: Comparison of the Real Network against ER and BA Null Models ($N = 10$).

3.2 Degree Distribution

Figure 1 illustrates the Complementary cumulative Distribution Function (CCDF) and the Probability Density Function (PDF) of the node degrees. The distribution exhibits a clear heavy tail, characteristic of scale-free networks.

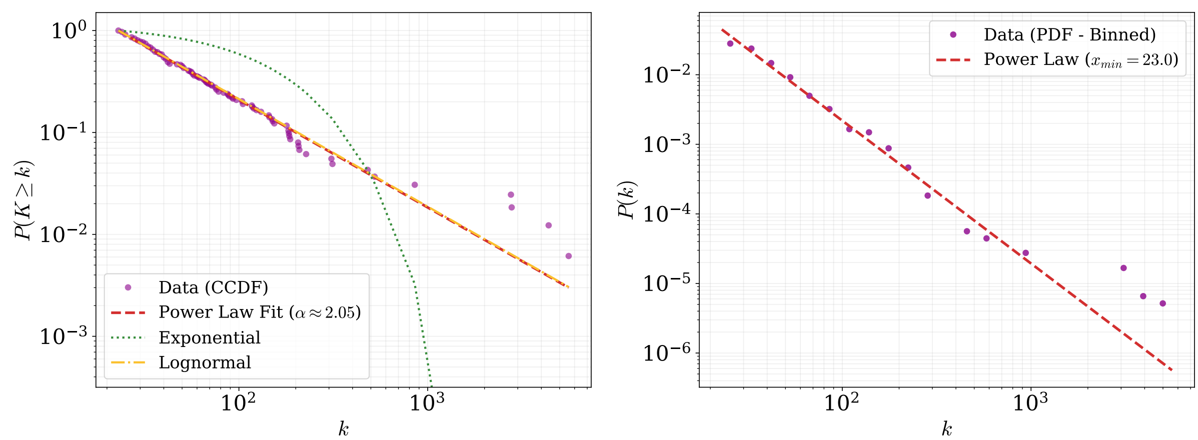

Figure 1: Degree distribution of the Dark Web network (log-log scale). Left: CCDF, the empirical data (purple) is compared against a power law (red), a log-normal (yellow) and an exponential fit (green). Right: PDF, empirical data (purple) compared with the power law fit (red).

The MLE method yielded a power-law exponent $\alpha \approx 2.05$ with a lower bound cutoff at $x_{min} = 23.0$. We compared this fit against alternative distributions using the Likelihood Ratio Test:

- **Power Law vs. Exponential:** $R = 157.54$, $p = 7.05 \times 10^{-5}$. The positive R and low p-value strongly reject the Exponential hypothesis in favor of the Power Law.
- **Power Law vs. Log-normal:** $R = 0.0035$, $p = 0.69$. The test is inconclusive, suggesting that while the tail is heavy, a Log-normal distribution could also explain the data.

3.3 Centrality and Hierarchy

One of the most significant findings of this study is the extreme level of centralization. We quantified this using the Gini coefficient applied to centrality scores.

Metric	Real Value	ER Mean	ER Z-Score	BA Mean	BA Z-Score
HG (Degree)	0.6954	0.2120	386.55	0.3758	221.09
HG (PageRank)	0.5940	0.1769	416.82	0.3290	176.30
HG (Eigenvector)	0.3440	0.2604	34.43	0.5977	-18.84

Table 2: Heterogeneity (Gini Coefficient) comparison with the average coefficient for ten BA and 10 ER.

As shown in Table 2, the real network is almost twice as unequal as the Barabási-Albert model. While the BA model generates hubs through preferential attachment, the Dark Web network exhibits a "winner-takes-all" dynamic that is far more aggressive.

3.3.1 Analysis of Top Nodes

Table 3 highlights the top 5 nodes ranked by different centrality measures. The node labeled `directoryvi6plzm` is the undisputed dominant hub, ranking no.1 in Degree, PageRank, Eigenvector, Betweenness, Closeness, Katz, and Subgraph centrality.

Rank	Degree	PageRank	Eigenvector	Betweenness
1	directoryvi6plzm (0.78)	directoryvi6plzm (0.11)	directoryvi6plzm (0.45)	directoryvi6plzm (0.48)
2	visitorfi5kl7q7i (0.61)	visitorfi5kl7q7i (0.08)	visitorfi5kl7q7i (0.39)	visitorfi5kl7q7i (0.23)
3	skunksworkedp2cg (0.39)	cratedvnn5z57xhl (0.05)	skunksworkedp2cg (0.26)	skunksworkedp2cg (0.15)
4	cratedvnn5z57xhl (0.38)	skunksworkedp2cg (0.05)	cratedvnn5z57xhl (0.25)	cratedvnn5z57xhl (0.14)
5	gxamjbnu7uknahng (0.12)	gxamjbnu7uknahng (0.02)	gxamjbnu7uknahng (0.07)	gxamjbnu7uknahng (0.10)

Table 3: Top 5 Nodes by Centrality Measures.

This node consistency indicates a robust "backbone". However, we observe interesting deviations. For instance, node `cratedvnn5z57xhl` ranks 4th in Degree (0.38) but jumps to 3rd in PageRank (0.05), suggesting that although it has fewer connections than `skunksworkedp2cg`, the connections it does have come from highly important neighbors. Conversely, `skunksworkedp2cg` has a high degree but lower PageRank influence.

Furthermore, the Subgraph Centrality values for these top nodes are astronomical (order of 10^{48}), confirming their participation in an immense number of closed loops, which reinforces the high clustering coefficient found globally.

A complete list of the 25 top nodes by different centrality measures are presented in Appendix A.

3.4 Mixing Patterns and Community Structure

The network is strongly **disassortative**, with a degree assortativity coefficient of $r \approx -0.44$. This contrasts sharply with the neutral mixing found in the null models ($r \approx 0$). This negative correlation implies that high-degree nodes tend to connect with low-degree nodes, a signature typical of technological networks (e.g., servers connecting to clients) or directory-based structures, rather than social networks where "rich nodes" tend to associate with other "rich nodes".

The Modularity ($Q \approx 0.31$) is significantly higher than in random models ($Q \approx 0$), confirming the existence of distinct functional communities.

4 Discussion

4.1 The Star-Like Directory Structure

The results present a topological paradox: a very high Clustering Coefficient (0.70) combined with a very low Transitivity (0.004). In many social networks, these two metrics correlate. However, in this Dark Web dataset, this discrepancy points to a structural motif: **local stars**.

Small groups of nodes form dense clusters (high clustering), but these clusters are linked via central hubs that do not close triangles with each other (low global transitivity). Supported by the strong disassortativity ($r = -0.44$), this confirms that the network is organized around central authorities (directories) that point to many sites, but those sites do not link back to the directory or to each other.

4.2 Beyond Scale-Free: The Oligarchy

The comparison with the Barabási-Albert (BA) model is particularly important in this case. The BA model assumes that popularity is proportional to current degree (rich gets richer). However, the Gini coefficients for the Dark Web network (0.69) are significantly higher than the BA baseline (0.37).

This implies that standard preferential attachment is insufficient to explain the concentration of power in the Dark Web. There are likely external mechanisms that artificially inflate the degree of specific nodes, creating an artificial oligarchy that dominates navigation.

We also note the anomaly in Eigenvector Centrality heterogeneity (HG Eigenvector). The Dark web network (0.34) is *less* unequal than the BA model (0.60). In BA models, hubs connect to other hubs (rich club effect), amplifying eigenvector scores. In our disassortative Dark Web, hubs avoid connecting to other hubs, which distributes the Eigenvector influence more evenly across the network, despite the high degree inequality.

4.3 Network Visualization

The visualization in Figure 2 corroborates these statistical findings.

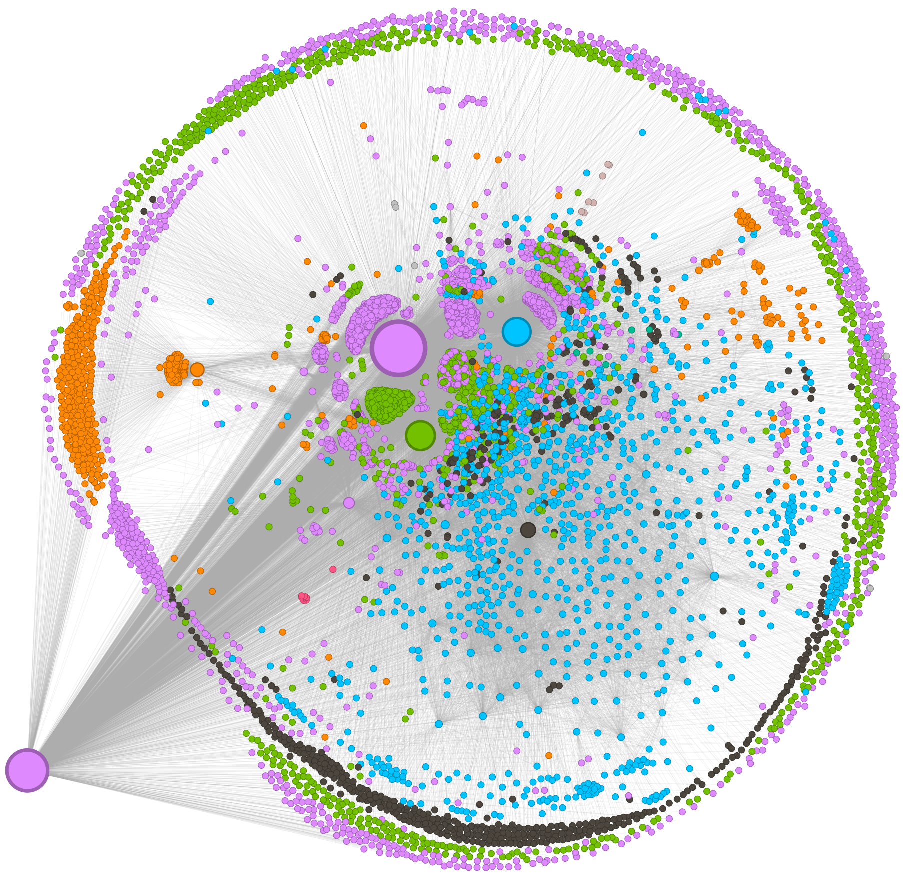

Figure 2: ForceAtlas2 visualization of the network generated in Gephi. Nodes are colored by modularity class (partition) and sized according to their PageRank score. The structure highlights the "star-like" hubs connecting the periphery. Note the presence of bridge nodes (high-ranking nodes located between distinct communities) which facilitate the low average path length.

The visual layout reveals a core-periphery structure where large hubs (high PageRank) act as bridges between distinct colored communities, validating the high modularity and centralization scores.

5 Conclusion

This report analyzed the structural properties of a Dark Web hyperlink network consisting of 7,178 nodes. Our analysis leads to three main conclusions:

1. **Efficiency:** The network is an ultra-small world ($a = 2.37$), allowing for information propagation speeds that exceed theoretical random models and standard scale-free networks.

2. **Organization:** It is not a random mesh but a highly structured, disassortative system likely organized around central directories. The Power Law fit ($\alpha \approx 2.05$) confirms its heavy-tailed nature.

3. **Vulnerability:** The extreme centralization suggests that while the network is efficient, **it is likely fragile to targeted attacks on its main hubs** (such as `directoryvi6plzm`), contrary to the typical assumption of Dark Web resilience.

Future work could focus on the temporal evolution of these hubs to determine if this oligarchy is stable or shifting over time, and also regarding on the direction and weights of the edges.

References

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A Top 25 nodes by centrality

Table 4: Degree, PageRank, and Betweenness.

Rank	Degree		PageRank		Betweenness	
1	directoryvi6plzm	0.7778	directoryvi6plzm	0.1129	directoryvi6plzm	0.4769
2	visitorfi5kl7q7i	0.6092	visitorfi5kl7q7i	0.0830	visitorfi5kl7q7i	0.2267
3	skunksworkedp2cg	0.3882	cratedvnn5z57xhl	0.0540	skunksworkedp2cg	0.1480
4	cratedvnn5z57xhl	0.3847	skunksworkedp2cg	0.0514	cratedvnn5z57xhl	0.1416
5	gxamjbnu7uknahng	0.1190	gxamjbnu7uknahng	0.0203	gxamjbnu7uknahng	0.1018
6	torvps7kzis5ujfz	0.0730	zlal32teyptf4tvi	0.0173	zlal32teyptf4tvi	0.0821
7	zlal32teyptf4tvi	0.0670	torvps7kzis5ujfz	0.0108	torvps7kzis5ujfz	0.0440
8	hwikis25cffertqe	0.0436	hwikis25cffertqe	0.0049	hwikis25cffertqe	0.0110
9	w363zoq3ylux5rf5	0.0431	w363zoq3ylux5rf5	0.0047	pdizimmrq5mwjkun	0.0063
10	wikitorcwogtsifs	0.0316	fhostingesps6bly	0.0038	vj5wxqmjaes2bae5	0.0057
11	fhostingesps6bly	0.0291	auutwvpt2zktxwng	0.0033	w363zoq3ylux5rf5	0.0053
12	y4yhci7273s2yeqk	0.0288	wikitorcwogtsifs	0.0032	wikiwarixvouhwyn	0.0037
13	auutwvpt2zktxwng	0.0287	hdwikicorldcisiy	0.0029	n6pbizsbykwxmydz	0.0036
14	hdwikicorldcisiy	0.0261	y4yhci7273s2yeqk	0.0027	besthqdirnimrgpj	0.0035
15	mijpsrtgf54l7um6	0.0258	wikiwarixvouhwyn	0.0025	nqigfqrxnkwcqmiq	0.0032
16	wikiwarixvouhwyn	0.0256	nqigfqrxnkwcqmiq	0.0024	tt3j2x4k5ycaa5zt	0.0030
17	zqktlwi4fecvo6ri	0.0255	mijpsrtgf54l7um6	0.0024	hdwikicorldcisiy	0.0030
18	32b5oz2bbtn6gqj3	0.0249	32b5oz2bbtn6gqj3	0.0024	auutwvpt2zktxwng	0.0029
19	nqigfqrxnkwcqmiq	0.0249	zqktlwi4fecvo6ri	0.0023	kpynyvym6xqi7wz2	0.0025
20	ntcixulmms4275vi	0.0215	soupkso3la22ltl3	0.0022	32b5oz2bbtn6gqj3	0.0024
21	kpvz7ki2lzvnwve7	0.0210	kpvz7ki2lzvnwve7	0.0021	wikitorcwogtsifs	0.0023
22	soupkso3la22ltl3	0.0209	ntcixulmms4275vi	0.0019	mcretro35qepy5cy	0.0019
23	wikihiddkz5w3hfg	0.0202	n6pbizsbykwxmydz	0.0019	fhostingesps6bly	0.0019
24	torwikignoueupfm	0.0201	godnotaba36dsabv	0.0019	hiddenwk7qnvvpfo	0.0014
25	n6pbizsbykwxmydz	0.0183	hiddeninasdyooih	0.0019	4hohkxjvlt5fjzqv	0.0013

Table 5: Eigenvector and Closeness Centrality.

Rank	Eigenvector		Closeness	
1	directoryvi6plzm	0.4463	directoryvi6plzm	0.7890
2	visitorfi5kl7q7i	0.3883	visitorfi5kl7q7i	0.6961
3	skunksworkedp2cg	0.2562	skunksworkedp2cg	0.6170
4	cratedvnn5z57xhl	0.2493	cratedvnn5z57xhl	0.6005
5	gxamjbnu7uknahng	0.0662	gxamjbnu7uknahng	0.5148
6	torvps7kzis5ujfz	0.0541	torvps7kzis5ujfz	0.5038
7	w363zoq3ylux5rf5	0.0480	hwikis25cffertqe	0.4964
8	hwikis25cffertqe	0.0468	w363zoq3ylux5rf5	0.4962
9	zqktlwi4fecvo6ri	0.0382	zqktlwi4fecvo6ri	0.4906
10	wikitorcwogtsifs	0.0381	wikitorcwogtsifs	0.4900
11	y4yhci7273s2yeqk	0.0381	kpynyvym6xqi7wz2	0.4898
12	mijpsrtgf54l7um6	0.0347	nqigfqrxnkwcqmiq	0.4890
13	32b5oz2bbtn6gqj3	0.0338	wikiwarixvouhwyn	0.4883
14	wikiwarixvouhwyn	0.0330	kpvz7ki2lzvnwve7	0.4882
15	auutwvpt2zktxwng	0.0329	n6pbizsbykwxmydz	0.4869
16	nqigfqrxnkwcqmiq	0.0329	grams7enufi7jmdl	0.4868
17	kpynyvym6xqi7wz2	0.0321	fhostingesps6bly	0.4867
18	hdwikicorldcisiy	0.0311	54ogum7gwxhtgiya	0.4864
19	kpvz7ki2lzvnwve7	0.0309	tfwdi3izigxllure	0.4861
20	soupkso3la22ltl3	0.0305	xfnwyig7olypdq5r	0.4860
21	ntcixulmms4275vi	0.0305	wikitjerrta4qgz4	0.4858
22	wikihiddkz5w3hfg	0.0296	tt3j2x4k5ycaa5zt	0.4857
23	fhostingesps6bly	0.0291	uj3wazyk5u4hnvtk	0.4857
24	torwikignoueupfm	0.0280	torbox3uiot6wchz	0.4856
25	dirnxxdraygbifgc	0.0257	2kka4f23pcxgqkpv	0.4856

Table 6: Top 25 Nodes: Subgraph Centrality and Katz Centrality.

Rank	Subgraph		Katz	
1	directoryvi6plzm	1.17×10^{49}	directoryvi6plzm	0.4268
2	visitorfi5kl7q7i	8.82×10^{48}	visitorfi5kl7q7i	0.3644
3	skunksworkedp2cg	3.84×10^{48}	skunksworkedp2cg	0.2400
4	cratedvnn5z57xhl	3.64×10^{48}	cratedvnn5z57xhl	0.2343
5	gxamjbnu7uknahng	2.57×10^{47}	gxamjbnu7uknahng	0.0663
6	torvps7kzis5ujfz	1.71×10^{47}	torvps7kzis5ujfz	0.0522
7	w363zoq3ylux5rf5	1.35×10^{47}	w363zoq3ylux5rf5	0.0443
8	hwikis25cffertqe	1.28×10^{47}	hwikis25cffertqe	0.0434
9	zqktlwi4fecvo6ri	8.53×10^{46}	wikitorcwogtsifs	0.0354
10	wikitorcwogtsifs	8.51×10^{46}	y4yhci7273s2yeqk	0.0350
11	y4yhci7273s2yeqk	8.49×10^{46}	zqktlwi4fecvo6ri	0.0349
12	mijpsrtgf54l7um6	7.04×10^{46}	mijpsrtgf54l7um6	0.0320
13	32b5oz2bbtn6gqj3	6.69×10^{46}	32b5oz2bbtn6gqj3	0.0313
14	wikiwarixvouhwyn	6.38×10^{46}	auutwvpt2zktxwng	0.0312
15	auutwvpt2zktxwng	6.33×10^{46}	wikiwarixvouhwyn	0.0309
16	nqigfqrxnkwcqmiq	6.32×10^{46}	nqigfqrxnkwcqmiq	0.0307
17	kpynyvym6xqi7wz2	6.02×10^{46}	kpynyvym6xqi7wz2	0.0294
18	hdwikicorldcisiy	5.65×10^{46}	hdwikicorldcisiy	0.0294
19	kpvz7ki2lzvnwve7	5.59×10^{46}	kpvz7ki2lzvnwve7	0.0288
20	soupkso3la22ltl3	5.44×10^{46}	soupkso3la22ltl3	0.0284
21	ntcixulmms4275vi	5.43×10^{46}	ntcixulmms4275vi	0.0283
22	wikihiddkz5w3hfg	5.14×10^{46}	fhostingesps6bly	0.0282
23	fhostingesps6bly	4.97×10^{46}	wikihiddkz5w3hfg	0.0276
24	torwikignoueupfm	4.59×10^{46}	torwikignoueupfm	0.0261
25	dirnxxdraygbifgc	3.87×10^{46}	n6pbizsbykwxmydz	0.0244