Proceedings of the
13th International Conference on Applied Informatics
Eger, Hungary, February 19–21, 2026
DOI: 10.17048/icai.2026.257
pp. 257–270

Structural Node Importance Beyond Classical Centrality: A Comparative Study of Entropy-Based *k*-Hop Measures

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Abstract. This paper investigates whether entropy-based k-hop metrics capture aspects of structural node importance that are not emphasized by classical centrality measures. We compare degree and eigenvector centrality with two entropy-based measures, Entropy-Weighted Redundancy (EWR) and Normalized Entropy Density (NED), on three real-world Twitter-derived networks with different sizes and connectivity patterns. Unlike conventional centrality measures, EWR and NED characterize node importance through the informational diversity and redundancy of the induced k-hop neighborhood. The results show that entropy-based rankings differ substantially from classical rankings and highlight structurally distinctive nodes whose local environments exhibit different structural properties. Furthermore, the observed rankings depend on both the underlying network topology and the neighborhood radius. Overall, the study demonstrates that entropy-based k-hop analysis provides a complementary perspective on structural node importance and motivates further comparative evaluation on other classes of networks.

Keywords: complex networks, social network analysis, structural entropy, k-hop neighborhood, entropy-based metrics, node importance, centrality measures, network topology, structural node analysis

2020 *Mathematics Subject Classification:* 05C82, 94A17, 68R10, 91D30

1. Introduction

Identifying important nodes in complex networks is a fundamental problem in network science, with applications in social network analysis, communication systems, and online platforms [5, 10]. Classical approaches to node importance are mainly based on centrality measures. Degree centrality captures immediate connectivity, whereas eigenvector-based approaches assign greater importance to nodes connected to other important nodes [4, 5, 10]. Although these measures are interpretable and widely used [5, 10], they primarily emphasize direct connectivity or recursively defined prominence and may fail to capture the structural heterogeneity of a node's wider environment [3, 16, 17]. This limitation is especially relevant in large social and communication networks, where structurally distinctive actors are not always the most visible hubs [16, 17]. Nodes with only moderate degree may still occupy distinctive positions if they are embedded in neighborhoods with high diversity, low redundancy, or unusual topology [1–3].

Information theory provides a natural framework for addressing this issue. Since Shannon's foundational work, entropy has been used to quantify uncertainty, diversity, and structural complexity [15]. In network analysis, entropy-based approaches have been used to describe graph organization, quantify structural variability, and reveal properties that remain less visible under conventional connectivity-based summaries [3, 16]. Recent studies also suggest that entropy-oriented methods can highlight structurally distinctive nodes and network regions that may not be emphasized by traditional centrality measures [3, 16, 17].

Within this line of research, k-hop-based entropy formulations are particularly attractive because they extend node analysis beyond immediate adjacency [1, 2]. In our previous work, we introduced two hybrid entropy-based metrics for k-hop environment analysis, Entropy-Weighted Redundancy (EWR) and Normalized Entropy Density (NED), to characterize the structural sensitivity of node neighborhoods in complex networks [1, 2]. These metrics distinguish nodes not only by neighborhood size, but also by the informational arrangement and redundancy profile of that neighborhood [1, 2]. Thus, entropy-based structural analysis complements rather than replaces traditional centrality theory and provides an alternative perspective on structural node importance [1–3, 5, 16, 17].

Although the present study focuses on social networks, similar approaches may be investigated in educational and learning-related settings in future work.

In this paper, we investigate whether entropy-based k-hop metrics capture aspects of structural node importance that are not emphasized by classical centrality measures. Using three Twitter-derived networks with different sizes and connectivity patterns, we compare degree centrality, eigenvector centrality, EWR, and NED in order to examine how classical and entropy-based rankings differ. Our working hypothesis is that entropy-guided measures may emphasize nodes whose surrounding environments exhibit different structural characteristics than those highlighted by degree and eigenvector centrality. [1–3].

The main contribution of this work is twofold. First, we provide an empirical comparison between classical and entropy-based node-ranking strategies on real-world Twitter-derived networks with different sizes and connectivity patterns [1, 2, 5, 10]. Second, we investigate whether entropy-based k-hop measures emphasize structurally distinctive nodes and structural characteristics that are not reflected by degree and eigenvector centrality alone. Overall, the study provides a comparative perspective on structural node importance and motivates further evaluation of entropy-based measures on other classes of networks and with additional baseline methods.

2. Related Work

The identification of important nodes in networks has long been studied through centrality theory. Foundational work established degree-, closeness-, and betweenness-based interpretations of centrality in social networks [9, 10], while eigenvector-type approaches extended node ranking to recursively defined importance [4, 5]. Related link-structure-based models, such as authority and hub formulations, further showed that node importance depends not only on immediate connectivity but also on broader structural context [13].

Although classical centrality measures remain fundamental, they do not capture every aspect of structural relevance. In many real-world networks, highly connected nodes are not necessarily the only actors with important organizational roles. Nodes with moderate degree may still occupy distinctive positions because they connect heterogeneous neighborhoods or lie in locally non-redundant environments. This limitation has motivated broader work on influence estimation and structural role detection, especially in online and social networks [17].

A natural way to address this limitation is through information-theoretic analysis. Since Shannon's foundational work [15], entropy-based ideas have increasingly been adapted to graphs and networks. General graph-entropy frameworks were introduced to quantify structural complexity [6], and later overviews established entropy as a useful perspective for studying structural information in networks [7]. More recently, entropy-based methods have been applied directly to social-network analysis. The Structural Entropy Index of Community (SEIC) was proposed for Twitter communication analysis [3], community-based entropic methods were developed for identifying influential nodes across multiple social networks [16], and structure-entropy formulations were shown to capture macro-level aspects of social-network organization and stability [14].

The present work is most directly connected to recent k-hop-based entropy formulations. In earlier work, hybrid entropy-based metrics for k-hop environment analysis, including Entropy-Weighted Redundancy (EWR) and Normalized Entropy Density (NED), were introduced to characterize the structural sensitivity of node neighborhoods in complex networks [1, 2]. Unlike classical centrality measures, these metrics characterize how the local environment of a node is organized within a broader structural radius by combining informational diversity and redundancy. This makes them suitable for investigating whether structurally distinctive nodes can be emphasized even when they are not highly ranked by degree or eigenvector centrality.

Although the present study focuses on Twitter-derived social networks, similar ideas may also be investigated in educational and learning-related settings in future work [8, 11, 12].

In summary, the present work builds on three main lines of research: classical centrality theory, entropy-based graph and social-network analysis, and recent k-hop-based entropy formulations [1–3, 5–7, 9, 10, 16]. Its specific contribution is an empirical comparison of classical centrality measures and entropy-based k-hop metrics on multiple real-world Twitter-derived networks in order to investigate whether these approaches capture different aspects of structural node importance.

3. Preliminaries and Metrics

Let $G = (V, E)$ be a simple undirected graph, where V is the set of nodes and $E \subseteq V \times V$ is the set of edges. For $v \in V$, let $d(v)$ denote the degree of v. For a fixed integer $k \geq 1$, the k-hop neighborhood of v is

$$N_k(v) = \{u \in V \setminus \{v\} \mid \mathrm{dist}(v, u) \leq k\},$$

and the induced subgraph on $N_k(v)$ is denoted by $G[N_k(v)]$. We write

$$n_k(v) = |N_k(v)|, \quad m_k(v) = |E(G[N_k(v)])|.$$

3.1. Classical Baseline Measures

As baseline measures, we consider raw degree and eigenvector centrality. The degree-based score of node v is

$$C_D(v) = d(v).$$

Let A be the adjacency matrix of G. The eigenvector centrality score $C_E(v)$ is defined by the dominant eigenvector $\mathbf{x}$ of A,

$$A\mathbf{x} = \lambda_{\max}\mathbf{x},$$

where $\lambda_{\max}$ is the largest eigenvalue of A, and $C_E(v)$ is the component of $\mathbf{x}$ corresponding to v.

3.2. Entropy in the k-Hop Environment

Following the local-degree variant of the k-hop entropy framework, the entropy-based metrics are computed from the degree distribution inside the induced subgraph $G[N_k(v)]$. For each $u \in N_k(v)$, let $d_{N_k(v)}(u)$ denote the degree of u within $G[N_k(v)]$. If

$$\sum_{u \in N_k(v)} d_{N_k(v)}(u) > 0,$$

we define

$$p_u(v) = \frac{d_{N_k(v)}(u)}{\sum\limits_{w \in N_k(v)} d_{N_k(v)}(w)}, \quad u \in N_k(v),$$

and the Shannon entropy of the k-hop environment of v by

$$H_k(v) = -\sum_{u \in N_k(v)} p_u(v) \log_2 p_u(v).$$

If $N_k(v) = \varnothing$ or $G[N_k(v)]$ has no edges, then $H_k(v) = 0$.

3.3. *k*-Hop Redundancy / Density

The redundancy component is defined as the edge density of the induced k-hop neighborhood:

$$R_k(v) = \begin{cases} \dfrac{m_k(v)}{\binom{n_k(v)}{2}}, & \text{if } n_k(v) \geq 2, \\ 0, & \text{if } n_k(v) < 2. \end{cases}$$

3.4. Entropy-Weighted Redundancy (EWR)

The Entropy-Weighted Redundancy of node v at radius k is

$$\mathrm{EWR}_k(v) = H_k(v)\, R_k(v).$$

3.5. Normalized Entropy Density (NED)

The Normalized Entropy Density of node v at radius k is

$$\mathrm{NED}_k(v) = \begin{cases} \dfrac{H_k(v)}{n_k(v)}\, R_k(v), & \text{if } n_k(v) > 0, \\ 0, & \text{if } n_k(v) = 0. \end{cases}$$

Thus, $\mathrm{NED}_k(v)$ normalizes the entropy-redundancy score by the size of the induced k-hop neighborhood.

3.6. Datasets

The empirical evaluation was conducted on three Twitter-derived networks with different sizes and connectivity patterns. The Zandberg Twitter network represents a relatively small political communication network related to the Polish electoral context. In contrast, the Foursquare-based Twitter network and the Twitter network are substantially larger anonymized social networks obtained from the publicly available *Foursquare and Twitter Networks* dataset available on Kaggle.

The Foursquare-based network contains 44,832 nodes and 1,664,402 edges, whereas the Twitter network contains 48,089 nodes and 16,303,641 edges.

In all datasets, nodes correspond to user accounts and edges represent social relationships between users. Following common practice in structural network analysis, edge directions were ignored and the networks were converted into simple undirected graphs. This representation enables direct comparison between connectivity-based centrality measures and entropy-based k-hop metrics without introducing additional asymmetries associated with directed interactions.

The Zandberg Twitter network is not fully connected; its largest connected component contains 463 nodes out of the total 609 nodes. In contrast, the Foursquare-based Twitter network and the Twitter network are connected. The analysis was performed on the complete graphs and was not restricted to the largest connected component.

The three networks exhibit markedly different structural characteristics. The Zandberg network is sparse and relatively small, allowing qualitative interpretation of several publicly identifiable actors. The Foursquare-based network exhibits a highly heterogeneous connectivity pattern, whereas the Twitter network is considerably denser and provides a contrasting environment in which the behavior of entropy-based measures can be examined under different connectivity regimes. These differences make the three datasets suitable for investigating whether entropy-based rankings emphasize structural characteristics that differ from those highlighted by degree and eigenvector centrality.

4. Analysis

This section presents the empirical analysis of the three Twitter-derived datasets. For each network, we compare the rankings obtained from degree centrality, eigenvector centrality, EWR, and NED for $k = 2$ and $k = 3$, with the aim of investigating whether entropy-based measures emphasize structural characteristics differently from classical centrality measures.

4.1. Zandberg Twitter Network

We first consider the *Zandberg Twitter network*, the most interpretable dataset in this study because several accounts are publicly identifiable. The network is related to the Polish political landscape in an election-related context and contains 609 nodes and 843 edges; its largest connected component has 463 nodes, so the graph is not fully connected. Both degree and eigenvector centrality identify @ZandbergRAZEM and @___Lewica as the most prominent actors. By contrast, EWR and NED place @pawel_baka among the highest-ranked nodes despite its lower visibility under degree and eigenvector centrality. Interestingly, this account belonged to the spokesperson of the Razem party. Although the present analysis does not validate functional influence, this observation illustrates that entropy-based rankings may emphasize actors whose structural characteristics differ from those highlighted by connectivity-based measures. The relatively small differences between the $k = 2$ and $k = 3$ rankings suggest that the entropy-based rankings are fairly stable with respect to the neighborhood radius.

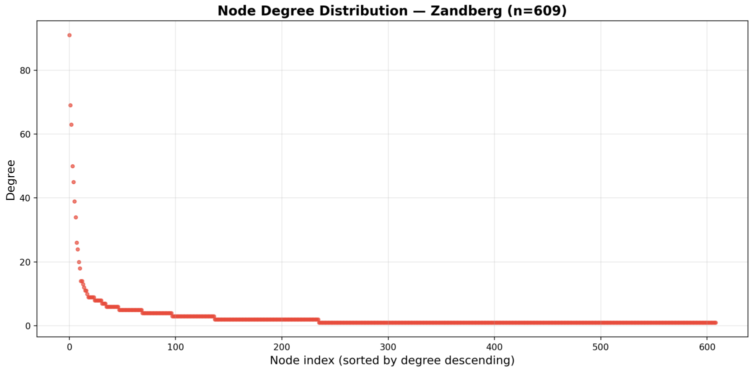

Figure 1. Sorted degree sequence of the Zandberg Twitter network.

Figure 1 shows the sorted degree sequence of the Zandberg Twitter network. Only a few nodes occupy hub-like positions, whereas the majority of nodes have low degree, indicating a heterogeneous interaction structure.

Tables 1–3 summarize the top-10 rankings of the Zandberg Twitter network under the classical and entropy-based measures. Table 1 shows that @ZandbergRAZEM and @Lewica are the most prominent actors according to degree and eigenvector centrality. By contrast, Tables 2 and 3 place @pawel_baka at or near the top of the entropy-based rankings. The strong overlap between Tables 2 and 3 indicates that the entropy-based rankings are relatively stable with respect to the neighborhood radius in this network.

Table 1. Top 10 nodes by classical measures in the Zandberg Twitter network.

Rank	Degree		Eigenvector	
	Node	Value	Node	Value
1	@ZandbergRAZEM	91	@Lewica	1.0000
2	@PolskieRadio24	69	@PiotrNo66983662	0.7954
3	@CzerwonyKat	63	@ZandbergRAZEM	0.7630
4	@Lewica	50	@rorek	0.7513
5	@Amigant	45	@CzerwonyKat	0.5009
6	@rorek	39	@PolskieRadio24	0.4939
7	@partiarazem	34	@wlodekczarzasty	0.4132
8	@PiotrNo66983662	26	@Amigant	0.2780
9	@wlodekczarzasty	24	@AMZukowska	0.2233
10	@marianapiorkows	20	@GiertychRoman	0.1357

Table 2. Top 10 nodes by entropy-based measures ($k = 2$) in the Zandberg Twitter network.

Rank	EWR ($k = 2$)		NED ($k = 2$)	
	Node	Value	Node	Value
1	@pawel_baka	1.5850	@pawel_baka	0.5283
2	@maggiepython	1.3333	@BuurtBelangen	0.5000
3	@SurowKarol	1.2027	@kasiababis	0.5000
4	@Lewica_News	1.1232	@BNDeStem	0.5000
5	@DemSocjalizm	1.0863	@mkljczk	0.5000
6	@adamidmark	1.0610	@Bartek19953	0.5000
7	@BuurtBelangen	1.0000	@21lupus	0.5000
8	@damian_krawczuk	1.0000	@_surdackiH	0.5000
9	@boch_adam	1.0000	@RazemInt	0.5000
10	@jakubkaldunski	1.0000	@BatugWojciech	0.5000

Table 3. Top 10 nodes by entropy-based measures ($k = 3$) in the Zandberg Twitter network.

Rank	EWR ($k = 3$)		NED ($k = 3$)	
	Node	Value	Node	Value
1	@pawel_baka	1.5850	@pawel_baka	0.5283
2	@jakubkaldunski	1.0000	@mkljczk	0.5000
3	@Europiara	1.0000	@Bartek19953	0.5000
4	@SWasilkowski	1.0000	@Strykasia	0.5000
5	@BNDeStem	1.0000	@JablonskiDoktor	0.5000
6	@mkljczk	1.0000	@s_urbanowicz	0.5000
7	@Bartek19953	1.0000	@wziolek_sj	0.5000
8	@RazemInt	1.0000	@1972tomek	0.5000
9	@Strykasia	1.0000	@jzpinski	0.5000
10	@JablonskiDoktor	1.0000	@CDA_Breda	0.5000

4.2. Foursquare

The second dataset is the *Foursquare-based Twitter dataset.* Degree and eigenvector centrality show strong overlap, indicating a relatively consistent notion of prominence. In contrast, the entropy-based rankings differ both from the classical rankings and from one another. EWR ($k = 2$) is notably distinct from NED ($k = 2$) and from the $k = 3$ rankings, whereas NED ($k = 2$), EWR ($k = 3$), and NED ($k = 3$) show substantial overlap. In particular, @Uma appears prominently in the entropy-based rankings but not in the classical ones, while @Tom exhibits the opposite behavior. The presence of @Kevin only in EWR ($k = 2$) further illustrates that different metrics and neighborhood radii may emphasize different structural characteristics.

Figure 2 shows the sorted degree sequence of the Foursquare-based Twitter dataset. The sequence is highly skewed, with a small number of highly connected

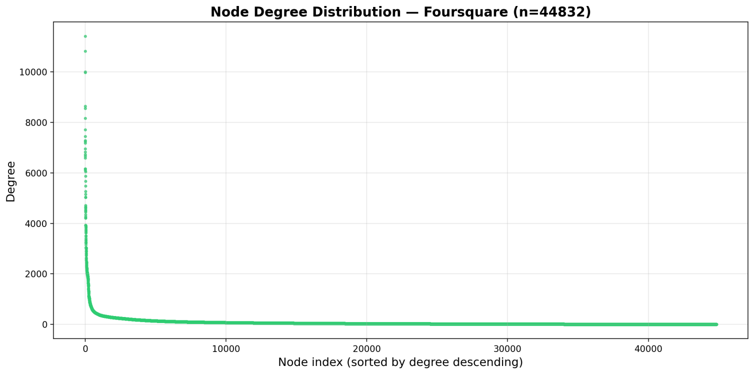

Figure 2. Sorted degree sequence of the Foursquare-based Twitter dataset.

nodes and a long tail of low-degree nodes. This indicates a heterogeneous network structure in which connectivity is concentrated in relatively few actors. Such a pattern provides a useful setting for comparing classical and entropy-based rankings.

Tables 4–6 summarize the top-10 rankings of the Foursquare-based Twitter dataset under the classical and entropy-based measures. The classical rankings in Table 4 exhibit substantial overlap, indicating a relatively stable notion of prominence. In contrast, the entropy-based rankings in Tables 5 and 6 differ considerably from the classical rankings and partly from one another. A notable example is @Uma, which appears prominently in the entropy-based rankings but not in the classical ones, whereas @Tom is highly ranked by degree and eigenvector centrality but absent from the entropy-based top lists. Overall, these results indicate that entropy-based rankings may emphasize structural characteristics that are not highlighted by degree and eigenvector centrality.

Table 4. Top 10 nodes by classical measures in the Foursquare-based Twitter dataset.

Rank	Degree			Eigenvector Centrality		
	Node	ID	Value	Node	ID	Value
1	@Tom	4105	11415	@Tom	4105	1.0000
2	@Alice	4297	10817	@Charlie	4326	0.9731
3	@Bob	4231	10007	@Alice	4297	0.9621
4	@Charlie	4326	9975	@Bob	4231	0.9614
5	@David	48	8639	@David	48	0.9384
6	@Emma	4289	8553	@Frank	4142	0.9297
7	@Frank	4142	8169	@Emma	4289	0.9257
8	@Grace	39	7712	@Grace	39	0.9204
9	@Hannah	4299	7449	@Ivan	4208	0.9005
10	@Ivan	4208	7287	@Jack	4146	0.8899

Table 5. Top 10 nodes by entropy-based measures ($k = 2$) in the Foursquare-based Twitter dataset.

Rank	EWR ($k = 2$)			NED ($k = 2$)		
	Node	ID	Value	Node	ID	Value
1	@Kevin	31106	2.3072	@Uma	40102	0.5000
2	@Laura	44011	2.2980	@Victor	43638	0.5000
3	@Mike	42036	2.0403	@Wendy	42264	0.3333
4	@Nina	21647	1.8982	@Xavier	38481	0.3333
5	@Oscar	36293	1.8683	@Yara	24008	0.3333
6	@Paul	21648	1.7988	@Zane	41146	0.3176
7	@Quinn	39322	1.7869	@Adam	32205	0.2241
8	@Rachel	44064	1.7869	@Bella	36512	0.2241
9	@Steve	38127	1.7184	@Chris	43078	0.2241
10	@Tina	42150	1.6820	@Diana	33438	0.2241

Table 6. Top 10 nodes by entropy-based measures ($k = 3$) in the Foursquare-based Twitter dataset.

Rank	EWR ($k = 3$)			NED ($k = 3$)		
	Node	ID	Value	Node	ID	Value
1	@Uma	40102	0.9756	@Victor	43638	0.0181
2	@Xavier	38481	0.8316	@Uma	40102	0.0127
3	@Ethan	26933	0.8019	@Xavier	38481	0.0121
4	@Yara	24008	0.6838	@Oliver	41184	0.0079
5	@Noah	14627	0.5650	@Liam	41186	0.0079
6	@Victor	43638	0.5618	@Lucas	26935	0.0070
7	@Oliver	41184	0.5509	@Noah	14627	0.0061
8	@Liam	41186	0.5509	@Ethan	26933	0.0060
9	@Lucas	26935	0.5204	@Wendy	42264	0.0039
10	@Wendy	42264	0.4938	@Yara	24008	0.0038

4.3. Twitter

The third dataset is the *Twitter dataset*. In this considerably denser network, degree and eigenvector centrality exhibit relatively little overlap in their top-10 rankings, suggesting that these measures emphasize different aspects of node prominence. Their highest-ranked nodes are also absent from the entropy-based rankings, indicating that the entropy-based measures emphasize different structural characteristics. At the same time, EWR ($k = 2$) and NED ($k = 2$) are highly similar, whereas the $k = 3$ rankings introduce partly different nodes. In particular, nodes such as @Luke and @Caleb appear in EWR ($k = 3$), while NED ($k = 3$) retains nodes already highlighted at $k = 2$, including @Lucas and @Matthew. This illustrates that the rankings produced by EWR and NED are influenced by the choice of neighborhood radius.

Figure 3 shows the sorted degree sequence of the Twitter dataset.

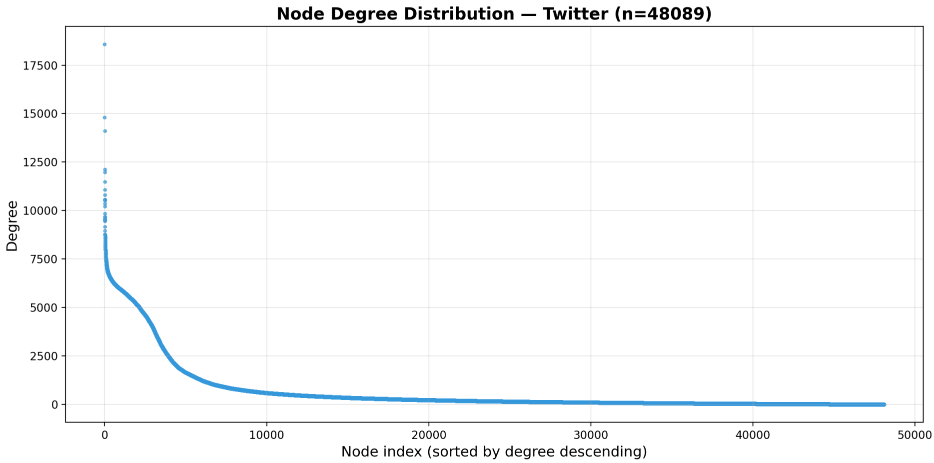

Figure 3. Sorted degree sequence of the Twitter dataset.

Tables 7–9 summarize the top-10 rankings of the Twitter dataset under the classical and entropy-based measures. The classical rankings in Table 7 show relatively little overlap, indicating that degree and eigenvector centrality emphasize different aspects of node prominence in this dense network. By contrast, Table 8 shows strong agreement between EWR and NED for $k = 2$, whereas Table 9 introduces partly different nodes at $k = 3$. In particular, nodes such as @Luke and @Caleb appear in EWR ($k = 3$), while NED ($k = 3$) retains nodes already highlighted at lower radius, including @Lucas and @Matthew. Taken together, these results indicate that entropy-based rankings may emphasize structural characteristics that are not highlighted by degree and eigenvector centrality.

Table 7. Top 10 nodes by classical measures in the Twitter dataset.

Rank	Degree			Eigenvector Centrality		
	Name	ID	Value	Name	ID	Value
1	@Oliver	4639	18577	@James	7812	1.0000
2	@Jack	4374	14804	@Henry	4367	0.9914
3	@Harry	4368	14105	@Leo	7383	0.9815
4	@George	4741	12110	@Alfie	7123	0.9800
5	@Noah	268	11968	@Joshua	7994	0.9798
6	@Charlie	4919	11474	@Freddie	10998	0.9786
7	@Jacob	5427	11079	@Archie	11468	0.9770
8	@Thomas	4303	10817	@Theo	12062	0.9756
9	@Oscar	2091	10567	@Isaac	11947	0.9756
10	@William	9155	10565	@Alexander	7873	0.9744

Table 8. Top 10 nodes by entropy-based measures ($k = 2$) in the Twitter dataset.

Rank	EWR ($k = 2$)			NED ($k = 2$)		
	Name	ID	Value	Name	ID	Value
1	@Lucas	41893	1.0000	@Lucas	41893	0.5000
2	@Mason	46367	1.0000	@Mason	46367	0.5000
3	@Ethan	33250	1.0000	@Ethan	33250	0.5000
4	@Logan	38746	0.8962	@Logan	38746	0.2241
5	@Daniel	45437	0.8962	@Daniel	45437	0.2241
6	@Matthew	29604	0.8962	@Matthew	29604	0.2241
7	@Aiden	43465	0.8155	@Samuel	26985	0.1600
8	@Joseph	43466	0.8155	@David	39059	0.1600
9	@Samuel	26985	0.8000	@Aiden	43465	0.1359
10	@David	39059	0.8000	@Joseph	43466	0.1359

Table 9. Top 10 nodes by entropy-based measures ($k = 3$) in the Twitter dataset.

Rank	EWR ($k = 3$)			NED ($k = 3$)		
	Name	ID	Value	Name	ID	Value
1	@Carter	10347	0.2324	@Lucas	41893	0.000124
2	@Owen	6358	0.2204	@Matthew	29604	0.000062
3	@Dylan	6635	0.2150	@Ryan	45838	0.000011
4	@Luke	42707	0.1979	@Caleb	7171	0.000011
5	@Gabriel	7155	0.1966	@Nathan	45412	0.000010
6	@Anthony	7596	0.1964	@Carter	10347	0.000009
7	@IsaacJr	12018	0.1863	@Adrian	31762	0.000008
8	@Grayson	21728	0.1794	@Christian	10149	0.000008
9	@Wyatt	11173	0.1778	@Aaron	11911	0.000008
10	@Caleb	7171	0.1764	@Luke	42707	0.000007

5. Conclusion and Future Work

This paper investigated whether entropy-based k-hop metrics emphasize structural characteristics that are not highlighted by classical centrality measures. Using three Twitter-derived networks with different sizes and connectivity patterns, we compared degree centrality and eigenvector centrality with two entropy-based measures, Entropy-Weighted Redundancy (EWR) and Normalized Entropy Density (NED). Across all analyzed datasets, the results showed that entropy-based rankings often differ substantially from classical rankings and may emphasize structural characteristics that are not highlighted by degree or eigenvector centrality alone.

The empirical analysis further showed that the behavior of EWR and NED depends on both the underlying network topology and the neighborhood radius. In the Zandberg network, the entropy-based rankings were relatively stable across $k =$

2 and $k = 3$, whereas in the larger datasets the differences between configurations were more pronounced.

Overall, the results indicate that entropy-based rankings provide a complementary perspective to connectivity-based measures, particularly when different structural characteristics of node neighborhoods are of interest. Future studies should extend the empirical analysis to other network classes and additional baseline measures, investigate the influence of the neighborhood radius for a wider range of k values, and perform quantitative comparisons using Spearman correlation, Kendall's τ, top-k overlap, and Jaccard similarity. These investigations may contribute to a more comprehensive characterization of structural node importance in complex networks.

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