Semantic Betweenness Centrality in Cognitive Warfare Networks

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Abstract

This paper introduces Semantic Betweenness Centrality (SBC), a novel family of centrality measures for analyzing complex semantic networks. Unlike classical betweenness centrality, which relies solely on topological shortest paths, SBC evaluates the importance of nodes based on their participation in *semantically optimal* paths – those that are most resilient, scalable, resource-efficient, or rapid in realization. We demonstrate that node centrality is not absolute but context-dependent: a node critical for resilient influence may be insignificant for fast or low-cost strategies.

As a case study, we construct a comprehensive semantic network of cognitive warfare comprising 290 nodes and 310 directed links, modeling pathways from strategic objectives to psychological consequences. The network is built using a "swarm of virtual experts" approach, leveraging Large Language Models (LLMs) to generate diverse, interdisciplinary insights through role-based prompting. While LLMs facilitate rapid, scalable, and semantically rich network expansion, the proposed SBC framework remains methodologically independent and applicable to any domain with semantically annotated paths.

Results show that redefining optimality by semantic criteria leads to dramatic shifts in node rankings, underscoring the limitations of traditional topological metrics. The SBC approach enables goal-oriented analysis of influence structures, with applications in information warfare, strategic communication, and cognitive security. This work advances network analysis by integrating semantic reasoning into structural metrics, offering a multidimensional perspective on influence and control in complex systems.

Keywords: *semantic centrality, SBC, LLM, betweenness centrality, cognitive warfare, information chains, semantic network*

Introduction

Network analysis is a key tool for understanding the structure and dynamics of complex systems, including informational, social, biological, and technical networks. One of the central directions of such analysis is the identification of nodes that play the most important role in the functioning of a network. This role is traditionally assessed using centrality measures – such as degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. These metrics have been successfully applied across diverse fields – from sociology to cybersecurity – to identify influential actors, critical infrastructure elements, or key concepts within cognitive systems.

Particularly powerful is the betweenness centrality measure, which quantifies how many shortest paths between pairs of nodes pass through a given node. It effectively identifies "bridges" in the network – nodes that control the flow of information, influence, or resources. However, this classical metric is based exclusively on the network’s topological structure: it assumes that all paths are equivalent, and only their geometric length matters. In real-world applications, especially within informational and cognitive systems, this assumption is often too restrictive.

In such systems, paths between nodes carry semantic load. For example, in the context of cognitive warfare, chains of influence are evaluated not by their length, but by criteria such as resilience to countermeasures, scalability of impact, resource cost, time of realization, or legitimacy. This means that the most important path may not be the shortest, but, for instance, the most resilient or the most scalable. Consequently, a node lying on such paths becomes strategically central – but only within the context of this specific semantics.

Today, research on centrality is primarily focused on topological or weighted graphs, where edge weights represent distance, time, or cost. For example, Freeman [1] laid the foundation for betweenness centrality; Newman [2,3] provided computational algorithms and generalized it for weighted networks; and Brandes [4] proposed efficient algorithms for its calculation. However, these approaches do not account for the semantic diversity of paths – that is, the fact that different paths can be "optimal" according to different meaningful criteria, even if their topological lengths are identical.

The emergence of Large Language Models (LLMs) has opened fundamentally new possibilities for constructing and analyzing semantic networks. It is now possible to rapidly and automatically generate complex causal-logical structures by integrating knowledge from diverse sources and uncovering hidden connections between abstract concepts [5, 6]. In particular, the approach based on the concept of a "swarm of virtual experts" allows for repeatedly querying an LLM to generate diverse interpretations, which are then aggregated into a single semantic network, ensuring both the depth and completeness of the model [7].

Moreover, LLMs enable not only the construction of networks but also the assessment of qualitative path characteristics – such as their resilience, emotional charge, or cultural legitimacy. This makes it possible to combine formal graph analysis with semantic evaluation, which is critically important for analyzing complex phenomena such as information warfare [8, 9].

In this paper, we propose a new approach to measuring centrality, based on the idea of semantic betweenness. We introduce the concept of Semantic Betweenness Centrality (SBC) – a separate metric for each semantic criterion, which quantifies how frequently a node lies on paths that are optimal with respect to that criterion. This approach allows analyzing the network not from a single, universal perspective, but from multiple context-dependent viewpoints.

The core idea is that centrality is not an absolute property of a node, but a relative characteristic that depends on the goal of the analysis. A node may be key in chains aimed at achieving sustainable influence, yet remain completely insignificant in chains oriented toward rapid implementation. This makes the proposed approach particularly relevant for analyzing complex information strategies, such as cognitive warfare, where the importance of system elements is determined not only by their position but also by their semantic contribution to achieving specific goals.

The purpose of this paper is to propose a mathematically rigorous model of semantic betweenness centrality, demonstrate its application on an example of a cognitive network, and show how changing the semantic criterion leads to a radical shift in the hierarchy of key nodes. The results confirm that traditional centrality metrics are insufficient for analyzing semantically enriched networks and open the way to creating context-dependent tools for influence analysis.

Forming and Analyzing the Semantic Network

Semantic Networks as a Tool for Analyzing Complex Systems

Modern informational, social, and cognitive systems are characterized by high complexity, multi-level structures, and deep semantic content. To analyze them, semantic networks are increasingly used – graph-based models in which nodes represent concepts, ideas, or entities, and edges represent meaningful, logical, or causal relationships between them.

Unlike traditional topological networks, where only the structure of connections matters, semantic networks account for the semantic nature of paths. This allows modeling not just "who is connected to whom," but "how one idea leads to another," "how a strategy is realized through mechanisms," or "how a goal is achieved through a chain of actions."

In such a network, classical centrality measures – degree, closeness, betweenness – remain important, but insufficient. They do not account for the qualitative properties of paths, which determine their real effectiveness in a specific context.

Constructing the Semantic Network

There are many ways to form semantic networks: manual expert curation, text analysis, knowledge extraction from databases, and automatic document parsing. In this work, we propose one of the possible approaches, which becomes particularly effective when combined with modern technologies – using Large Language Models for the automated expansion of a hierarchical model.

This approach is not universal, but it demonstrates high flexibility, speed, and depth when constructing complex causal structures, especially in cases where it is necessary to quickly generate a large number of ideas that are logically interconnected.

The "Swarm of Virtual Experts" Concept

The key idea is to simulate the collective activity of experts using Large Language Models. Since the same model can generate different responses to the same query, we can "activate" it in different roles, thereby creating an artificial **"swarm of virtual experts"**. This approach can be implemented as follows:

1. Initial Hierarchical Model

We begin with a small but conceptually complete model – a set of key concepts and their interconnections. For example, in general terms, this could be: *Goals → Means → Mechanisms → Consequences*.

2. Systematic Expansion

For each node in this model, a query is submitted to the LLM of the following type:

"For the concept 'X' in the context of 'Y', find up to 3 new concepts (1–3 words) that specify it. Provide the result as pairs: 'X; New concept'."

For example, for the node "Influence Methods" in the context of "information warfare", the model might suggest:

- Influence Methods; Disinformation
- Influence Methods; Emotional Manipulation
- Influence Methods; False News

3. Repeated Querying in Different Roles

To avoid bias and increase diversity, the query is submitted multiple times, but with different assigned "roles":

- "You are a psychologist studying mass behavior."
- "You are a historian of propaganda."
- "You are a strategist of information operations."

This allows obtaining diverse, in-depth, interdisciplinary responses that reflect the multifaceted nature of the phenomenon.

4. Aggregation and Cleaning

All generated pairs are collected, duplicates are removed, and expert filtering is applied (to eliminate illogical or overly distant connections). After this process, a complete semantic network is formed.

5. Result

The output is a directed graph $G = (V, E)$, where:

V is the set of nodes (concepts),

E is the set of directed edges (links of type "general → specific" or "cause → effect").

Such a network can contain hundreds of nodes and connections and serves as a foundation for further analysis.

Example: Semantic Network of Cognitive Warfare

To illustrate the proposed approach, we consider the construction of a semantic network of cognitive warfare. This is not the only possible application, but it effectively demonstrates the power of the method.

The initial model comprises five levels – from the general phenomenon of "Cognitive Warfare" down to specific "Consequences," such as "Collective Amnesia" or "Loyalty to the Aggressor." This model is conceptually complete but includes only the core components.

Using the concept of a "swarm of virtual experts," the model was expanded. For each node, new, more specific concepts were generated. For instance, for "Actors' Objectives," the following concepts were identified: "Destruction of National Identity," "Formation of False Worldviews," "Deconstruction of Mythology," and others.

As a result, a comprehensive network was constructed, consisting of 290 nodes and 310 links (Fig. 1). This network serves as an ontology of cognitive warfare, encompassing not only general categories but also specific mechanisms, tools, and influence scenarios.

Centrality Metrics and Semantic Reinterpretation of Betweenness

To analyze the structural role of nodes in the constructed semantic network, classical centrality metrics are applied. These metrics help identify concepts that play a key role in the system of informational influence. Below, the three most commonly used metrics in this study are presented.

Basic Centrality Metrics

1. Out-Degree Centrality

Measures the number of direct consequences stemming from a given node. For a node v in a directed graph $G = (V, E)$:

$$Cout(v) = |\{u \in V | (v,u) \in E\}|.$$

This metric indicates the sources of influence initiation – concepts that generate many other ideas. For example, concepts such as "Introduction of False Scientific Theories" and "Introduction of False Paradigms" exhibit a high out-degree.

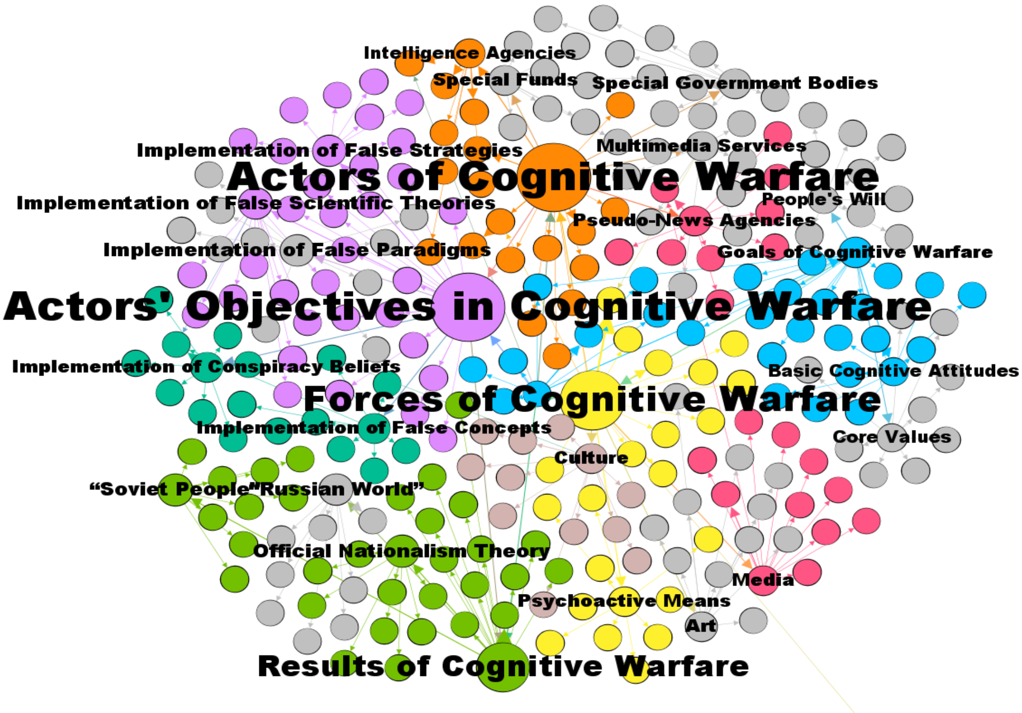

Figure 1. Semantic network "Cognitive Warfare"

2. Eigenvector Centrality

Takes into account not only the number of connections but also the importance of neighboring nodes. It is defined as the principal eigenvector of the adjacency matrix $\boldsymbol{A}$:

$$\boldsymbol{Ax} = \lambda \boldsymbol{x},\ \boldsymbol{C_{eig}(v)=x_v},$$

where λ is the largest eigenvalue and x is the corresponding eigenvector. This metric identifies ideological cores – concepts that are not only central targets but also supported by numerous other chains. For example, "Theory of Official Nationality" has a high $\boldsymbol{C_{eig}}$ value, as it is integrated into many different scenarios.

3. Betweenness Centrality – Classical Version

The most relevant measure for analyzing influence flows is betweenness centrality, which quantifies how often a node lies on the shortest (geodesic) paths between other pairs of nodes.

Let σ_{st} denote the number of shortest paths between nodes *s* and *t*, and let $\sigma_{st}(v)$ denote the number of such paths that pass through node *v*. Then:

$$C_B(v) = \sum_{\substack{s,t \in V \\ s \neq t \neq v}} \frac{\sigma_{st}(v)}{\sigma_{st}}.$$

This metric identifies "bridges" within the network – concepts that connect different levels or domains of influence. For instance, "Introduction of False

Paradigms" exhibits a high C_B, as it links overarching objectives with specific instruments.

Semantic Reinterpretation of Betweenness

In the context of cognitive networks, the shortest path is not always the most significant. The importance of a path is determined not only by its length but also by its semantic properties, which define its effectiveness within a specific strategy. In particular, the following criteria are introduced:

– Resistance to counteraction (R) – the degree to which a chain is difficult to neutralize.
– Scalability of influence (S) – whether the path operates at the local, national, or global level.
– Resource intensity (C) – the amount of resources required for implementation.
– Chain length (L) – the number of transitions (as in the classical case).

This implies that, instead of counting shortest paths, one can compute paths that are optimal according to a given semantic criterion.

Let a set of paths from node s to node t be defined for each pair of nodes $s, t \in V$. For each criterion $q \in \{R, S, C, L\}$, the set of optimal paths can be defined:

$$P_{st}^{(q)} = \left\{ p \in P_{st} \mid q(p) = opt_q\left(\left\{ q(p') \mid p' \in P_{st} \right\}\right) \right\},$$

where opt_q denotes the optimization operation with respect to criterion q:

– maximization for R and S,

– minimization for C and L.

To determine opt_q, the following steps are performed:

– Collect the values of criterion q for all paths between s and t,

– Identify the optimal value (minimum or maximum – depending on q),
– Select all paths that achieve this optimal value.

Let:
– $\sigma_{st}^{(q)} = \left| P_{st}^{(q)} \right|$ be the number of shortest paths between nodes s and t that are optimal with respect to criterion q,

– $\sigma_{st}^{(q)}(v)$ be the number of such paths that pass through node v.

Then, the semantic betweenness centrality with respect to criterion q is defined as:

$$C_B^{(q)}(v) = \sum_{\substack{s,t \in V \\ s \neq t \neq v}} \frac{\sigma_{st}^{(q)}(v)}{\sigma_{st}^{(q)}}.$$

This formula is a direct generalization of classical betweenness, but instead of geodesic paths, semantically optimal paths are used.

Each such $C_B^{(q)}$ corresponds to a specific logic of influence; for example:

- $C_B^{(R)}$ indicates which nodes are most important for stable, resilient chains;
- $C_B^{(S)}$ identifies nodes critical for large-scale, extensive operations;
- $C_B^{(C)}$ highlights nodes utilized in cost-effective, resource-efficient scenarios;
- $C_B^{(L:)}$ reveals nodes that control the fastest, most direct pathways.

Set of Centralities

Since there may be numerous semantic criteria for path optimality – such as resilience, scalability, time, risk, legitimacy, emotional charge, cultural depth, ethical acceptability, and others – each such criterion gives rise to a distinct centrality measure.

In other words, there is no single, universal centrality. The meaning of centrality is determined by the research objective. For example:

- if the goal is to identify the fastest paths to "Collective Amnesia," then the key measure will be $C_B^{(L:)}$;
- if the goal is to identify the most resilient paths, then $C_B^{(R)}$;
- if the goal is to identify the least resource-intensive paths, then $C_B^{(C)}$;
- if the goal is to identify the most emotionally charged paths, then $C_B^{(emotion)}$.

This implies that the number of possible centralities is limited only by the number of ways in which "optimality" of a path can be interpreted.

Thus, centrality is not merely a property of a node, but also a reflection of the analytical objective.

Empirical Analysis: Variability of Node Centrality Depending on the Semantics of Paths

Building upon the theoretical framework outlined in the previous section, we proceed to an empirical analysis aimed at demonstrating how the same node can occupy different positions within the hierarchy of key concepts depending on which semantic optimality criterion is used to define semantic betweenness centrality (SBC).

To this end, the complete set of chains leading from the initial state "Cognitive Warfare" to the target state "Collective Amnesia" was used. These chains were identified by traversing the graph (e.g., using the DFS algorithm) in the extended semantic network containing 290 nodes and 310 links.

For each chain, the following semantic criteria were defined:

- Length (L) – the number of transitions in the chain (the shorter, the better).
- Resistance to countermeasures (R) – a score from 1 to 5 indicating how difficult it is to neutralize the chain.
- Resource intensity (C) – a score from 1 to 5, where 1 denotes low resource consumption and 5 denotes high.
- Scalability of impact (S) – 1 (local), 2 (national), 3 (global).

For each criterion $q \in \{L, R, C, S\}$, a set of optimal paths $P^{(q)}$ was defined – those paths achieving the best value according to criterion q (minimum L, maximum R, minimum C, maximum S). Subsequently, for each node v, the Semantic Betweenness Centrality (SBC) value with respect to criterion q was computed.

Below (Tab. 1) are the computation results for four key nodes that frequently appear in paths leading to "Collective Amnesia".

Table 1: *SBC* and node rankings under different criteria

NODE	SBC_L	RANK SBC_L	SBC_R	RANK SBC_R	SBC_C	RANK SBC_C	SBC_S	RANK SBC_S
Implementation of False Scientific Theories	0.88	2	0.32	18	0.75	3	0.40	12
Official Nationalism Theory	0.15	47	0.92	1	0.15	47	0.89	2
Art	0.65	8	0.50	8	0.60	7	0.70	5
Reduction of Critical Thinking	0.40	15	0.25	25	0.80	4	0.30	18

Analysis of Results

The obtained data clearly demonstrate the relative nature of centrality:

1. ***"Official Nationalism Theory":***

- Ranks first in resilience (R) – this is the most important node within long-term, hard-to-eliminate chains.
- Has a high rank in scalability (S) – second place, as the impact spreads at national/global levels.
- However, it is not cost-efficient (low SBC_C) and not rapid (low SBC_L) – unsuitable for time-sensitive or low-budget operations.

2. ***"Implementation of False Scientific Theories":***

- Second place in terms of length (L) – one of the fastest pathways to the target.
- Third place in terms of resource intensity (C) – an economically efficient mechanism.
- However, low in stability (R) – such chains can be easily neutralized by fact-checking.

3. ***"Art":***

- Universal node – consistently high scores across all criteria.
- Particularly strong in scale (S) – influence through art has broad reach.

4. ***"Reduction of Critical Thinking":***

- Most efficient in terms of resource intensity (C) – ranked fourth.
- However, weak in terms of stability and scalability – not critical for strategic operations.

This example convincingly demonstrates that node centrality is not a universal characteristic, but rather depends on the objective of the analysis. What is crucial for achieving a rapid effect may be insignificant for sustained, long-term aggression, and vice versa.

This approach enables adaptation of the analytical strategy to a specific threat – whether we are countering rapid disinformation, prolonged ideological aggression, or economic sanctions in the field of education.

Conclusions

This paper proposes a novel approach to analyzing node centrality in semantic networks, based on a rethinking of the classical betweenness centrality measure. Instead of identifying key nodes by the number of shortest paths passing through them, we consider centrality as a value dependent on the semantic properties of paths – such as resilience to counteractions, scalability of influence, resource intensity, or time required for implementation. This allows us to define semantic betweenness centrality (SBC) for each individual path optimality criterion, thereby formalizing the idea that a node's importance is determined not merely by its topological position, but by its role within the context of a specific strategy or objective.

It is demonstrated that the same node can occupy either leading positions or significantly lower ranks in the centrality hierarchy, depending on the chosen semantic criterion. This result highlights the relative nature of centrality in complex information systems and indicates the limitations of traditional metrics in cases where the analysis requires consideration of content-specific aspects of interaction. The proposed approach provides a flexible toolkit for context-dependent analysis, applicable across diverse domains – from cognitive warfare and information operations to social networks and organizational management.

The novelty of this work lies in generalizing the concept of centrality by introducing a set of independent SBC (Semantic Betweenness Centrality) metrics, each corresponding to a specific logic of system functioning. This approach enables the development of multidimensional influence models, allowing analysts to set priorities according to the research objective – whether identifying the most resilient chains, the most resource-efficient pathways, or those with the broadest reach.

Future research directions include expanding the set of semantic criteria, automating their identification using large language models, and developing tools for visualizing and comparing centrality vectors for strategic analysis. The obtained results are significant for understanding the structural role of concepts in complex information systems and can be applied to enhance the effectiveness of countermeasures against destructive influences, particularly in the context of cognitive aggression.

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