Semantic Diffraction in Conceptual Graphs:

A Structural Approach to Equilibrium and Synthesis Detection

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Abstract

Current approaches to semantic discovery in knowledge graphs and natural language systems rely predominantly on similarity-based measures, embedding spaces, or neural attention mechanisms. While effective at capturing statistical proximity, these methods often conflate similarity with semantic structure, limiting their ability to identify equilibria, conceptual synthesis, and ontologically coherent intermediate concepts.

In this work, we introduce a **Semantic Diffraction Framework**, a novel field-based method for auditing conceptual graphs through structured propagation and interference. Instead of operating directly on embedding similarity, the proposed system defines **structural propagation fields** constrained to non-embedding relations and computes **dual-pole interference patterns** by propagating from opposing conceptual poles. Conceptual equilibria are identified as nodes where propagated intensities from both poles converge under a stability criterion that combines balance and dominance ratios. Equilibria are ranked using an explicit diffraction score combining total propagated intensity with an asymmetry penalty, separating stable mediators from hub-induced artifacts.

To ensure semantic coherence, the framework incorporates an **axis-constrained refine pass**, restricting propagation to shared conceptual axes derived from duality structures, and introduces an explicit **triple-interference synthesis operator** that evaluates candidate synthesis nodes based on their simultaneous alignment with both poles and the detected equilibrium. Ontological rejection rules further exclude candidates that function as poles of dualities, preventing degenerate or structurally inconsistent syntheses.

Crucially, the system operates as a **non-destructive auditor**: it does not mutate the underlying graph but instead annotates nodes with interpretative flags and produces fully traceable logs, enabling longitudinal analysis and reproducibility. Experimental results on evolving conceptual graphs demonstrate that the proposed diffraction-based

approach reliably surfaces semantically meaningful equilibria and synthesis candidates while suppressing hub-induced drift and spurious similarity effects.

This framework establishes semantic diffraction as a distinct paradigm for conceptual discovery, offering a structured alternative to similarity-driven methods and providing a foundation for future integration with mechanistic interpretability and scientific discovery systems.

1. Introduction

Contemporary approaches to semantic discovery in knowledge graphs and language-based systems rely predominantly on similarity-driven mechanisms, such as vector embeddings, clustering, or neural attention. While these techniques are effective at capturing statistical regularities, they often conflate proximity with conceptual role, making it difficult to distinguish between opposition, equilibrium, and synthesis within structured domains of knowledge.

In many conceptual settings, meaning is not defined by similarity alone but by **structural relationships** such as duality, balance, and integration. For example, two opposing concepts may be closely related without being similar, and the concepts that integrate them cannot be reliably identified through interpolation in embedding space. Existing methods lack explicit mechanisms to represent and detect these structural configurations.

This work addresses this limitation by introducing a **Semantic Diffraction Framework**, a field-based approach for auditing conceptual graphs. Instead of operating directly on similarity metrics, the proposed method interprets conceptual structure as a propagating field constrained to explicit semantic relations. By propagating influence from opposing conceptual poles and analyzing their interference, the system identifies candidate equilibria and synthesis concepts in a principled and interpretable manner.

A key design principle of the proposed framework is **non-destructive auditing**. The system does not modify the underlying graph or infer new relations; rather, it evaluates existing structure, records interpretative signals, and produces traceable logs. This design enables reproducibility, longitudinal analysis, and integration with other discovery systems without imposing irreversible structural changes.

The main contributions of this work are the following:

- The introduction of semantic diffraction as a novel paradigm for conceptual discovery based on structured propagation and interference.
- A formal method for detecting stable equilibria through dual-pole interference and stability criteria.
- A synthesis operator based on triple interference with explicit ontological rejection rules.
- A non-destructive auditing architecture that ensures transparency and traceability of semantic decisions.

Together, these contributions position the Semantic Diffraction Auditor as a complementary alternative to similarity-driven methods, particularly suited for domains where conceptual structure and interpretability are central.

2. Related Work

The proposed Semantic Diffraction Framework intersects multiple research areas, including graph-based semantic propagation, embedding-driven concept discovery, knowledge graph reasoning, and mechanistic interpretability. This section reviews the most relevant lines of work and clarifies how the present approach differs from existing methods.

2.1 Graph-Based Semantic Propagation

Graph-based propagation methods have long been used to model relevance, influence, and semantic proximity in structured data. Algorithms such as PageRank and Personalized PageRank (PPR) have been widely applied to knowledge graphs, lexical networks, and citation graphs to estimate node importance or relevance relative to a source.

In semantic applications, PPR-based techniques are typically employed to identify nodes that are *close* to a query concept under the graph topology. However, these approaches generally operate under a single-source paradigm and optimize for proximity or reachability rather than **balanced interaction between multiple conceptual sources**. Moreover, they rarely distinguish between structurally meaningful relations and statistically derived ones, often propagating indiscriminately across all available edges.

The present work builds on the propagation paradigm but departs from prior approaches by (i) explicitly separating structural relations from embedding-based relations, and (ii) interpreting propagation not as proximity, but as a **field whose interference patterns carry semantic meaning**.

2.2 Embedding-Based Similarity and Concept Discovery

Distributional semantic models and neural embeddings constitute the dominant paradigm for concept discovery in natural language processing. Methods based on cosine similarity, vector interpolation, clustering, and analogy operations are commonly used to identify related or intermediate concepts.

While highly effective at capturing statistical regularities, embedding-based methods tend to conflate similarity with conceptual role. Intermediate points in embedding space do not necessarily correspond to equilibria or synthesis concepts, and embedding arithmetic provides limited guarantees of ontological coherence. Furthermore, embedding-driven approaches are typically opaque, offering little insight into *why* a particular concept emerges as relevant.

In contrast, the Semantic Diffraction Framework does not rely on embedding similarity to define semantic structure. Instead, embeddings—when present—are treated as contextual signals and excluded from structural propagation. This allows equilibria and synthesis candidates to emerge from explicit conceptual relations rather than latent statistical correlations.

2.3 Knowledge Graph Reasoning and Path-Based Methods

Reasoning over knowledge graphs has been explored through rule-based inference, path ranking algorithms, and neural graph reasoning models. These methods aim to infer missing relations, rank candidate nodes, or answer structured queries by exploiting graph connectivity.

Most reasoning frameworks, however, focus on **path existence or probability**, rather than on the interaction of multiple semantic influences. Additionally, neural reasoning models often reintroduce embedding-based representations, sacrificing interpretability and structural transparency.

The approach presented here differs in that it does not infer new edges or relations. Instead, it audits the existing graph by analyzing how conceptual influence propagates and interferes within the current structure, preserving both interpretability and ontological constraints.

2.4 Conceptual Spaces and Geometric Semantics

The idea that meaning can be represented geometrically has been explored in cognitive science and philosophy, notably through conceptual spaces and vector-based semantic models. These frameworks emphasize dimensions, regions, and distances as carriers of meaning.

However, most geometric semantic models operate in continuous vector spaces without explicit representation of discrete conceptual relations such as dualities or axes. As a result, the geometry remains implicit and often detached from the underlying conceptual ontology.

The Semantic Diffraction Framework introduces an explicit **geometric interpretation over discrete structures**, where conceptual axes arise from duality relations and geometric constraints are enforced through axis-restricted propagation. This bridges the gap between symbolic structure and geometric reasoning.

2.5 Mechanistic Interpretability and Scientific Discovery Systems

Recent work in mechanistic interpretability and scientific discovery—such as symbolic regression, modular neural networks, and Kolmogorov–Arnold Networks—aims to uncover interpretable structures underlying learned models. These approaches emphasize decomposition, attribution, and structural transparency.

While complementary in spirit, such systems typically operate within neural or symbolic function spaces rather than over evolving conceptual graphs. The Semantic Diffraction Framework is orthogonal to these efforts: it does not learn functions from data, but instead provides a **structural interpretative layer** capable of auditing and organizing conceptual discoveries produced by other systems.

2.6 Summary of Distinctions

In summary, existing approaches either prioritize statistical similarity, path-based reasoning, or neural abstraction. None explicitly model **semantic interference between opposing conceptual poles under structural constraints**, nor do they formalize synthesis as a triple-field interaction subject to ontological rejection rules.

The Semantic Diffraction Framework addresses this gap by introducing a field-based, structurally grounded method for equilibrium and synthesis detection, positioning semantic diffraction as a distinct and complementary paradigm within semantic graph analysis.

3. Method: Semantic Diffraction Auditor

This section presents the Semantic Diffraction Auditor, a structured, non-destructive method for identifying equilibria and synthesis candidates in conceptual graphs through field-based propagation and interference.

3.1 Graph Definition and Relation Types

Let G = (V, E) be a directed conceptual graph, where each node v in V represents a concept and each edge e in E encodes a typed semantic relation. Relations are categorized into two disjoint sets:

- Structural relations, representing explicit conceptual structure (e.g., duality, axis membership, hierarchical relations).
- Embedding relations, representing statistical or similarity-based associations derived from distributional semantics.

The Semantic Diffraction Auditor operates primarily on the structural subgraph, excluding embedding relations from propagation in order to preserve explicit semantic geometry.

3.2 Structural Propagation Field

Given a source node s, a structural propagation field is computed by applying a Personalized PageRank (PPR) process over the structural subgraph G_s, which is a subgraph of G where all embedding-type edges are removed.

The propagation field is defined as:

p_s = PPR(G_s, s, alpha)

where alpha is a restart probability in the interval (0, 1). The resulting vector p_s(v) represents the intensity of structural influence propagated from source node s to node v.

This formulation treats conceptual structure as a propagating field rather than as a similarity metric.

3.3 Dual-Pole Interference

Given two opposing conceptual poles a and b, two structural propagation fields are computed independently:

p_a = PPR(G_s, a, alpha)
p_b = PPR(G_s, b, alpha)

A node v is considered a candidate equilibrium if it receives significant influence from both poles. Interference is evaluated by considering both the magnitude and the balance of the propagated intensities.

3.4 Stability Criterion for Equilibrium Detection

Equilibrium candidates are ranked using a balanced interference score that favors both high intensity and pole balance:

$$\text{score}_{eq}(v) = (p_a(v) + p_b(v)) - \lambda \cdot |p_a(v) - p_b(v)|$$

*We refer to this quantity as the **Semantic Diffraction Score**, as it captures both constructive interference (shared intensity) and destructive interference (asymmetry) between the two propagation fields.*

where λ penalizes imbalance between the two propagated fields. To avoid unstable or ambiguous equilibria, we apply two stability checks:

Balance constraint.

$$\text{balance}(v) = \frac{|p_a(v) - p_b(v)|}{p_a(v) + p_b(v)}$$

Dominance ratio. Let v_1 and v_2 be the top-1 and top-2 candidates under scoreeq .

$$D = \frac{\text{score}_{eq}(v_1)}{\text{score}_{eq}(v_2) + \varepsilon}, \quad D \geq \gamma$$

Only candidates satisfying both constraints are considered stable equilibria. If stability is not achieved, a refinement step is triggered.

3.5 Axis-Constrained Refine Pass

To suppress semantic drift caused by structural hubs, the auditor performs an axis-constrained refine pass. The refine pass is triggered only when the initial equilibrium candidate fails the stability criteria described in Section 3.4.

Conceptual axes are derived from explicit duality relations. Structural propagation is recomputed while restricting traversal to edges whose associated axes satisfy the following conditions:

- First, the intersection of axes shared by poles a and b, if this intersection is non-empty.
- Otherwise, the axes associated with the provisional equilibrium candidate.

This step enforces geometric coherence and ensures that equilibria emerge within a consistent conceptual subspace.

3.6 Synthesis via Triple Interference

Once a stable equilibrium eee is identified, the auditor searches for synthesis candidates by evaluating **triple interference** among the structural propagation fields originating from the two poles a,ba, ba,b and the equilibrium eee.

For each candidate node v, a synthesis score is computed as:

$$\mathrm{score}_{\mathrm{syn}}(v) = \big(p_a(v) + p_b(v) + p_e(v)\big) - \lambda\Big(|p_a(v) - p_b(v)| + |p_a(v) - p_e(v)| + |p_b(v) - p_e(v)|\Big)$$

where $p_a(v)$, $p_b(v)$, and $p_e(v)$ denote the propagated structural intensities from poles a, b, and equilibrium e, respectively, and λ penalizes imbalance among the three fields.

3.7 Ontological Rejection Rules

To prevent degenerate syntheses, the auditor applies an ontological rejection rule:

A valid synthesis candidate must not function as a pole of a duality relation within the relevant conceptual axes.

These rejection rules are **not heuristics**, but ontological constraints, ensuring that synthesis represents **integration rather than opposition or structural centrality**.

3.8 Non-Destructive Auditing and Traceability

The Semantic Diffraction Auditor does not modify the underlying graph. Instead, all detected equilibria, synthesis candidates, stability metrics, axis constraints, and drift suspects are recorded as node-level annotations and serialized logs.

This non-destructive design enables:

- reproducibility,
- longitudinal analysis,
- and post-hoc inspection of semantic decisions.

4. Qualitative Results

This evaluation is qualitative by design, as the objective of the proposed auditor is interpretability and structural coherence rather than predictive performance.

We evaluate the proposed Semantic Diffraction Auditor through qualitative analysis on an evolving conceptual graph, focusing on interpretability, coherence of detected equilibria, and the behavior of the synthesis operator. Rather than optimizing for quantitative benchmarks, our goal is to assess whether the system produces **structurally meaningful and ontologically consistent results**, and whether its internal decisions are traceable and inspectable.

4.1 Equilibrium Detection and Stability

Across multiple dual-pole configurations, the auditor consistently identifies equilibrium candidates characterized by balanced propagation intensities from both poles. Logged results show that stable equilibria emerge only when both the dominance ratio between the top-ranked candidates and the balance constraint are satisfied.

In practice, this leads to a clear separation between:

- **stable equilibria**, where a single candidate dominates with comparable influence from both poles, and
- **unstable configurations**, where multiple candidates compete or propagation remains skewed toward one pole.

Importantly, unstable cases do not force a selection. Instead, they trigger the refine pass or yield no equilibrium, demonstrating that the system prefers **semantic precision over completeness**.

4.2 Effect of Axis-Constrained Refinement

The axis-constrained refine pass plays a crucial role in suppressing semantic drift. Qualitative inspection of audit logs shows that, prior to refinement, high-degree structural hubs occasionally appear among top candidates due to their connectivity. After refinement, propagation is effectively restricted to a coherent conceptual subspace defined by shared axes.

This results in equilibria that are not only balanced but also **geometrically aligned** with the duality under analysis. The refinement mechanism thus functions as a semantic lens, narrowing the field of interpretation without introducing external supervision.

4.3 Emergence of Meaningful Synthesis Candidates

When stable equilibria are detected, the synthesis operator evaluates candidates via triple interference among both poles and the equilibrium. In multiple audited cases, synthesis candidates correspond to intuitively meaningful integrative concepts rather than interpolations or lexical averages.

For example, in configurations involving rotational or directional dualities, the auditor proposes synthesis nodes such as *"angle"* or *"angular displacement"*, which integrate both opposing poles through the detected equilibrium. These candidates consistently rank highest in synthesis score while maintaining balanced influence from all three propagation fields.

Notably, synthesis candidates are often not explicitly labeled as "synthesis" nodes in the graph; instead, they emerge naturally from structural interference, highlighting the method's ability to surface latent integrative concepts.

4.4 Ontological Rejection and Absence of Degenerate Syntheses

The synthesis rejection rule—excluding candidates that act as poles of a duality—was activated conservatively in the evaluated runs. In the analyzed logs, no synthesis candidates were rejected, indicating that the system does not trivially promote duality poles to synthesis roles.

This behavior suggests two desirable properties:

1. The synthesis operator is sufficiently constrained to avoid obvious structural errors.
2. The underlying graph structure already enforces a strong separation between oppositional and integrative roles.

The absence of rejected syntheses is therefore interpreted not as a failure of the rule, but as evidence of **structural consistency** in the evaluated conceptual graph.

4.5 Drift Detection and Diagnostic Transparency

Beyond final selections, the auditor records *drift suspects*: high-scoring candidates that fail to share conceptual axes with the poles or equilibrium. These suspects are not selected but are logged for inspection.

Qualitative analysis shows that such candidates often correspond to:

- generic concepts,
- structurally peripheral nodes,
- or nodes connected via incidental paths.

By externalizing these near-misses rather than silently discarding them, the system provides a transparent diagnostic layer that supports debugging, refinement of the graph, and theoretical analysis.

4.6 Non-Destructive Auditing and Reproducibility

A key qualitative result is the system's non-destructive behavior. All equilibria, synthesis candidates, stability metrics, axis filters, and drift suspects are recorded as annotations and serialized logs without modifying the underlying graph.

This design enables:

- reproducible re-analysis,
- longitudinal tracking of conceptual evolution,
- and comparison of alternative propagation or refinement strategies.

As a result, the Semantic Diffraction Auditor functions not as a generative model, but as an **interpretative instrument** over structured semantic spaces.

5. Conclusion

This work introduced a Semantic Diffraction Framework for auditing conceptual graphs through structured propagation, interference, and geometric constraints. By separating explicit conceptual structure from statistical similarity, the proposed method enables the detection of equilibria and synthesis candidates that are both semantically meaningful and ontologically coherent.

Unlike traditional similarity-based approaches, the framework models meaning as a field that propagates through structural relations and interacts via interference patterns. This perspective allows equilibria to emerge from balanced influence between opposing poles and enables synthesis to be identified through triple-field interaction rather than interpolation or averaging.

As such, semantic diffraction should be understood not as a competing learning paradigm, but as an interpretative instrument that audits and organizes conceptual discoveries produced by other systems.

The non-destructive nature of the auditor ensures full traceability and reproducibility, making it suitable as an interpretative layer for evolving knowledge systems. Rather than generating new content, the system provides insight into the latent structure already present in a conceptual graph, supporting both theoretical analysis and practical refinement.

Future work will explore quantitative evaluation strategies, extensions to additional structural patterns, and integration with scientific discovery and mechanistic interpretability systems. More broadly, semantic diffraction opens a new direction for structured semantic analysis, emphasizing geometry, balance, and integration over proximity alone.