THE META-BODY O POETRY: STRUCTURING NLP TRAINING DATASETS FOR ONTOLOGICAL DEPTH

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ABSTRACT

Poetry presents unique challenges for natural language processing (NLP) due to its fragmented structure, intertextuality, and multimodal nature. Conventional NLP models struggle to capture its evolving semantic relationships, particularly across translations, historical contexts, and interpretative traditions. This paper introduces the Poetic Ontology Dataset (POD), a structured resource designed to embed poetic meaning as a dynamic, topological construct rather than a static textual entity. By applying sheaf theory, functorial mappings, and graph embeddings, we model poetic motifs and metaphors as interdependent structures within a meta-body—a network of poetic relations spanning time and cultures. Empirical validation compares AI-assisted meta-body analysis, derived through structured motif tracking and graph clustering, against traditional NLP embeddings. The results demonstrate that ontology-aware NLP models preserve semantic continuity and intertextual depth more effectively than conventional approaches. This work establishes a foundation for meaning-aware NLP architectures, bridging computational poetics, multimodal embeddings, and topological data analysis.

KEYWORDS

Computational Poetics, Ontology-Based NLP, Sheaf Theory in NLP, Functorial Mapping in AI, Poetic Meaning Representation, Graph-Theoretic Poetic Analysis

1. INTRODUCTION

Poetry resists conventional NLP approaches due to its non-discrete structure, intertextual resonances, and multimodal composition. Unlike prose, where meaning is largely encoded in syntax and semantics, poetic meaning emerges through associative links, metaphorical transformations, and rhythmic structures that evolve over time. Standard NLP models, optimised for discrete token-based analysis, fail to capture these relationships, often reducing poetic interpretation to surface-level lexical patterns. Addressing this challenge requires a shift from text-based representations to ontology-aware embeddings that reflect poetry's dynamic and relational nature.

This paper proposes a meta-body approach to poetry, conceptualizing poetic meaning as a topological structure of interwoven motifs, translations, and cultural reinterpretations. We introduce the **Poetic Ontology Dataset (POD)**, a structured resource that encodes poetic motifs, metaphorical shifts, and historical continuities using sheaf theory, functorial transformations, and graph embeddings. This framework enables NLP models to track semantic evolution across time

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and languages, ensuring that meaning remains structurally coherent rather than fragmented across tokenised embeddings.

We validate our approach through an AI-assisted meta-body analysis, using structured graph-theoretic motif tracking to compare NLP-generated embeddings against human interpretative models. Our empirical results demonstrate that sheaf-theoretic embeddings, trained on POD, reconstruct poetic interconnectivity, motif propagation, and translation consistency more effectively than conventional NLP embeddings.

Contributions

This paper advances computational poetics and NLP in the following ways:

- **Sheaf-Theoretic Poetic Representation**: We introduce a topological framework for poetry, modelling motifs and metaphorical shifts as structured embeddings.
- **Ontology-Aware NLP for Poetics**: The Poetic Ontology Dataset (POD) structures poetic meaning relationally, improving interpretative coherence across translations and historical adaptations.
- **AI-Assisted Meta-Body Analysis**: Using GPT-4o-generated motif clustering and functorial mappings, we validate how well ontology-based embeddings preserve semantic continuity.
- **Empirical Benchmarking**: We compare traditional NLP embeddings against graph-based poetic models, assessing how well they capture poetic motif networks.

By integrating topological mathematics, computational poetics, and multimodal NLP, this work offers a structured approach to meaning-aware AI, positioning poetry as a networked, evolving field of interpretation.

2. Related Work: Literature Review on Poetic Ontology and NLP

This section reviews prior research on poetic NLP, ontological AI, and mathematical structures in computational poetics. We focus on existing models, their limitations, and how recent ontology-driven NLP frameworks address these challenges.

2.1. Traditional NLP Approaches to Poetry Analysis

Early computational approaches to poetry relied on rule-based systems and probabilistic models**,** such as Hidden Markov Models (HMMs) for rhyme and meter detection [1]. More recent research has employed deep learning architectures**,** including Recurrent Neural Networks (RNNs) and Transformer-based embeddings, to analysepoetic style, sentiment, and structure [2].

However, these models treat poetry as sequential text rather than a structured, evolving semantic entity. Major limitations include:

- **Metaphorical layering**: Traditional NLP embeddings fail to capture poetic ambiguity and metaphorical depth**.**
- **Intertextuality**: Poetry references other works, requiring context-aware meaning propagation**.**
- **Diachronic evolution**: Poetic meaning changes across historical and cultural contexts**,** whichstatistical models fail to account for**.**

2.2. Knowledge-Based and Ontology-Driven NLP

To address these limitations, ontology-driven NLP frameworks have been explored. Ontologies provide structured hierarchical meaning representations, enabling semantic inference beyond text-based embeddings.

- **Frame Semantics for Poetry Interpretation**: Some studies integrate FrameNet and ConceptNetto model poetic meaning within a structured semantic framework [3].
- **Graph-Based Representations**: Knowledge graphs have been proposed for poetry analysis, linkingpoetic elements such as motifs, metaphors, and themes into interconnectednetworks [4].
- **Formal Ontologies for Literary Analysis**: Ontologies such as WordNet have been adapted for poetry, but they lack the ability to model non-linear, evolving poetic structures.

2.3. Mathematical and Category-Theoretic Approaches

Recent research in mathematical linguistics explores category theory and sheaf structures to model semantic continuity in poetry.

- **Sheaf-Theoretic NLP**: Some researchers propose using sheaf structures to represent meaning propagation **across** fragmented poetic elements [5].
- **Functorial Mapping for Translation**: Category-theoretic functors have been explored to track meaning shifts across translations [6].
- **Graph Neural Networks for Poetic Meaning Propagation**: GNNs have been applied to model semantic flow and metaphorical continuity in poetry, though this remains an emerging area [7].

2.4. Gaps in Existing Research

Despite advancements in ontology-driven NLP, existing models fail to fully capture the interpretative fluidity of poetry. Key gaps include:

1. **Lack of Topological Modelling**: Few studies apply sheaf structures to represent poetic meaning across intertextual layers.
2. **Insufficient Cross-Linguistic Adaptation**: While some research explores translation-aware embeddings, functorial transformations for poetry remain underdeveloped.
3. **Inadequate Graph-Based Representations**: Current knowledge graphs do not adequately encode metaphorical layering and diachronic meaning shifts.

Additionally, NLP evaluation metrics do not quantify semantic drift, motif interconnectivity, or multimodal poetic coherence. In Section 5, we introduce graph-theoretic and sheaf-cohomology-based metrics to empirically validate the interpretative fidelity of ontology-aware NLP embeddings.

2.5. Positioning Our Work

Building on these prior studies, our research introduces a mathematically rigorous, ontology-driven NLP framework for poetry interpretation. Our contributions include:

- Sheaf-Theoretic Representation of Poetic Meaning.
- Functorial Mapping for Cross-Linguistic Interpretation.
- Graph Neural Networks (GNNs) for Poetic Embeddings.
- Comparative Study of Sheaf-Theoretic NLP vs. Transformer-Based Models.

This structured approach bridges the gap between mathematical AI, knowledge-driven NLP, and computational poetics, establishing a new paradigm for poetry analysis.

3. Sheaf-Theoretic and Functorial Modelling of Poetic Meaning

Building on prior research in ontology-driven NLP and mathematical approaches to poetic structure, this section introduces a sheaf-theoretic framework for modelling poetic meaning. We formalise poetry as a topological space where meaning propagates through localised semantic structures, mapped onto a global interpretative whole. Additionally, we integrate functorial transformations from category theory to model cross-linguistic translation shifts and diachronic meaning evolution.

3.1. The Meta-Body of Poetry as a Structured Space

The meta-body of poetry - its evolving, interpretive space - cannot be directly encoded in conventional NLP models due to its non-discrete, interconnected nature. Unlike prose, which can often be analysed through lexical semantics and syntactic dependencies, poetry operates through fragmentation, intertextuality, and historical layering. Traditional NLP techniques rely on token-based representations, failing to capture the continuity of meaning that unfolds across drafts, translations, and cultural reinterpretations.

To formalise this non-discrete nature, we adopt a sheaf-theoretic approach. In sheaf theory, local sections ($S(U)$) represent partial interpretations of a poem, while global meaning is constructed from how these fragments interact across historical, cultural, and linguistic contexts. This framework ensures that:

- Interpretative shifts across translations remain structurally coherent.
- Diachronic poetic evolution (draft revisions, reinterpretations) maintains semantic continuity.
- Intertextual relationships across poetic traditions are embedded within a mathematical structure.

By structuring poetic meaning as a sheaf over an interpretative space X, we preserve local meaning variations while maintaining global coherence. This meta-body representation serves as the foundation for our ontology-aware NLP model, as explored in later sections.

3.2. Sheaf-Theoretic Representation of Fragmented Meaning

Poetry often presents disjointed images, discontinuous temporality, and spatial shifts. Rather than treating these as interpretative obstacles, we recognise them as structural properties of poetic ontology.

In **sheaf theory**, we formalise this fragmented meaning as follows:

$$S(U) = \{s_1, s_2, \ldots, s_n\}, U \subset X$$

where:

- X represents the poem's full interpretative space—the global structure where all possible meanings, contexts, and connections exist.
- $U$is a local subset of$X$, representing a particular interpretative lens or context (e.g., a stanza, a motif, a linguistic fragment).
- $S(U)$ is the set of sectionss_i over$U$, where each $s_i$is a partial interpretative construct that contributes to the meta-body of the poem.

The sheaf structure ensures that these local interpretations (sections) can be patched togetherto form a coherent global meaning**,** aligning with the idea that poetic meaning is distributed, emergent, and non-linear**.**

3.3. Time as an Expanding Sheaf: Bergsonian Duration in Poetic Evolution

Time in poetry does not follow a linear, sequential model but instead expands, contracts, and overlaps**,** creating a fluid structure where past, present, and future coexist within poetic experience. Traditional NLP models, which rely on fixed chronological representations, fail to capture the diachronic evolution of meaning in poetry—how motifs, themes, and metaphors shift and accumulate across drafts, translations, and cultural reinterpretations.

To formalise this non-linear temporality, we adopt Bergson's concept of duration, which views time as a continuous, qualitative expansion rather than a sequence of discrete events. Mathematically, this corresponds to a **presheaf**, where meaning evolves dynamically over different interpretative contexts.

$D : O(X) \rightarrow \text{Set}$

where:

- ***X***represents the poem's interpretative space**,** structured as a global field of possible meanings**.**
- ***O(X)***is the collection of interpretative windows U (stanzas, motifs, translations) that contribute to the temporal transformation of meaning**.**
- ***D***assigns each $U \subseteq X$ a set of temporally relevant poetic meanings**,** reflectinghow past interpretations shape the present and anticipate future readings**.**

This **sheaf-theoretic formalism** ensures that:

- Each new interpretation accumulates prior semantic layers while introducing new shifts.
- Poetic meaning is not fixed but continuously evolving, adapting across different cultural and historical contexts.
- Temporal coherence is preserved, even as individual interpretative sections vary**.**

Example: Diachronic Evolution in Poetic Drafts

Consider a poem with multiple historical versions:

- Each revision inherits semantic traces from earlier drafts **while introducing** new thematic and structural modifications.
- Translations and adaptations maintain the core metaphorical framework but reconfigure linguistic and cultural elements**.**

- In tertextual references accumulate across time, ensuring that each iteration of the poem contributes to its meta-body.

By modelling poetic time as an expanding sheaf, we move beyond static representations of meaning and toward an ontology-aware approach, where poetic evolution is encoded within semantic morphisms across textual instances**.**

3.4. Functorial Mapping Across Interpretations: Heidegger's Temporal Ecstasies

Poetic meaning is never static—each reading is shaped by what has come before and anticipates new interpretations. This aligns with Heidegger's concept of time as ecstasis, where the present is always shaped by the past ("already-been") and the future ("not-yet").
To formalise this within NLP, we define a functorial mapping across interpretations:

$$F : \mathrm{Poetry}_A \rightarrow \mathrm{Poetry}_B$$

where:

- Objects (poems) transform through historical, cultural, and linguistic adaptations.
- Morphisms track semantic shifts, ensuring that translations and re-readings remain coherent across different contexts.

In an NLP model, this functorial mapping preserves the semantic and syntactic integrity of poetic structures while allowing cultural evolution and adaptation. This allows us to:

- **Quantify interpretative divergence**—how much does a translation alter poetic form?
- **Map intertextual resonance**—how does one poem "echo" another across time?

The poetic meta-body evolves not as discrete versions, but as a connected topological space, where each transformation leaves traces within the sheaf of possible meanings.

4. CONSTRUCTING META-BODY TRAINING DATASETS FOR NLP

To enable NLP systems to engage meaningfully with poetry, we must first reimagine how training data is constructed. Conventional datasets isolate poems as static texts, severed from the web of historical, thematic, and intertextual relationships that give them meaning. In contrast, a meta-body-informed approach treats poetic meaning as a distributed, topological structure—emergent through relations, rather than fixed in lexical units. This requires a shift in methodology: from token-level annotation to network-level encoding; from text as an object to poetry as an evolving system. The following subsections outline how such a dataset can be structured to approximate the dynamic, relational ontology of poetic knowledge.

4.1. The Meta-Body as a Computationally Invisible Structure

As previously discussed in Section 3.1, the meta-body cannot be directly encoded using conventional NLP models. Here, we apply sheaf-theoretic structuring to NLP training datasets to approximate meaning continuity. However, this evolving, multi-dimensional nature of poetic meaning is computationally invisible to current NLP models. Transformers and statistical NLP methods rely on word embeddings, syntax trees, and probabilistic associations, which inherently flatten the multilayered interactions between poetic elements. This reductionist approach cannot encode semantic continuity, cross-linguistic shifts, or the interplay between textual and non-textual dimensions of poetry.

To address this, we propose a meta-body-driven methodology for structuring NLP training datasets. Rather than treating a poem as a standalone object, we construct datasets that capture the networked relationships of poetic motifs, metaphors, and interpretive transformations. This methodology encodes meaning not as a static, pre-defined vector space but as a topological structure, where local meanings are linked to global interpretive possibilities.

4.1.1. Encoding the Meta-Body Without Direct Computation

The meta-body remains computationally invisible in a strict algorithmic sense because it is not a single dataset or a set of rules but a conceptual space of evolving meaning. However, by using sheaf theory, functorial mappings, and graph-based embeddings, we structure datasets that approximate the meta-body's function in poetic interpretation.

1. **Sheaf-Theoretic Encodings**
   - In mathematical topology, sheaf structures allow local sections (i.e., fragmentary meanings) to be mapped onto a global semantic space.
   - In poetry, a sheaf-theoretic approach enables the construction of NLP datasets where motifs, metaphors, and semantic shifts retain contextual dependencies across translations, interpretations, and historical periods.
2. **Functorial Mappings for Interpretive Shifts**
   - Meaning in poetry is non-deterministic and evolves through intertextuality and historical transformations.
   - By using functorial mappings, we structure datasets that account for transformations between poetic categories, enabling NLP models to encode meaning propagation rather than just static embeddings.
3. **Graph-Based Knowledge Representations**○
   - Instead of training NLP models on isolated texts, we propose constructing a Poetic Ontology Dataset that represents poetry as a graph of interconnected meanings.
   - This enables semantic resonance tracking, where a motif (e.g., "light" as transcendence in Dante and mysticism in Rumi) is mapped across cultural and linguistic contexts.

4.1.2. Implications for NLP Training

Since the meta-body cannot be explicitly computed, our methodology instead provides a structured approach to dataset construction that encodes the ontological continuity of poetic meaning. This shifts NLP for poetry from a lexical/syntactic focus to an ontology-aware paradigm, allowing for the preservation of poetic ambiguity, interpretive multiplicity, and metaphorical depth.

In the following sections, we outline the sheaf-theoretic model (4.2), functorial mappings (4.3), and the Poetic Ontology Dataset (4.4), detailing how each contributes to capturing the meta-body in an NLP-adaptable format.

4.2. Sheaf-Theoretic Representation of Poetic Meaning

Building on the sheaf-theoretic model introduced in Section 3.1, we construct NLP embeddings that track local-to-global interpretative structures in poetry. Sheaf theory, originating in algebraic topology and category theory, provides a formal framework for structuring meaning across fragmented, intertextual, and evolving poetic spaces.

In this approach:

- Local meaning units (words, lines, motifs) are treated as sections over an interpretative space *X*.
- Morphisms encode the semanticdependencies between local interpretations and their global poetic significance.
- Cohomological consistency conditions ensure that meaning remains coherent across translations, revisions, and intertextual adaptations.

To approximate this continuity of meaning in NLP, we propose a sheaf-theoretic dataset structure, where:

- Words and motifs are nodes in a topological space of poetic relations.
- Edges encode interpretative connections, linking local variations to global coherence.

This enables NLP models to retain interpretative flexibility, ensuring that meaning is not reduced to discrete tokens but emerges dynamically through relational structures.

4.2.1. Sheaf Structures for NLP Training Datasets

To capture the evolving, relational nature of poetic meaning, we structure NLP training datasets using sheaf-theoretic embeddings, where:

- **Local Sections**: Individual poetic lines or phrases, each carrying multiple semantic potentials.
- **Stalks**: Contextual embeddings that encode interpretative ambiguity and resonance across traditions.
- **Gluing Conditions**: Relations that preserve semantic continuity across languages, historical contexts, and reader perspectives.

For example, consider the motif of **"light"** in poetry:

- **Local Sections**: "Light" appears in Dante's *Paradiso* (divine illumination), Rumi's Sufi poetry(mystical knowledge), and Emily Dickinson's verse (inner transcendence).
- **Stalks**: Capture historical and cultural shifts in interpretation.
- **Gluing Conditions**: Ensure connections between interpretations remain intact, allowing NLP models to track motif evolution rather than reducing meaning to discrete embeddings.

By encoding poetic meaning as a topological structure, our approach enables NLP datasets to retain interpretative depth, moving beyond static word embeddings.

4.2.2. Applications to Ontology-Aware NLP

This sheaf-theoretic NLP structure transforms poetry processing from a flat, statistical approach into an ontology-aware architecture, enabling:

- **Semantic Resonance Tracking**: Modelling how poetic motifs evolve across texts and time.
- **Interpretive Continuity**: Ensuring that translations, adaptations, and intertextual references remain structurally linked.

- **Generative AI Enhancement**: Embedding relational structures into AI-generated poetry, improving its coherence with human poetic sensibility.

This dataset methodology ensures that poetic meaning remains fluid, allowing NLP models to align more closely with the meta-body's topological complexity**.**

4.3. Functorial Mappings in Cross-Linguistic Poetic Interpretation

The meta-body of poetry is not only evolving but non-static across languages. Translation is not a simple lexical mapping but a structural transformation, where poetic meaning shifts topologically while maintaining interpretive coherence.

To capture this dynamic, we propose using functorial mappings - a key concept in category theory - to structure cross-linguistic NLP training datasets. Functors encode how objects and relationships in one category transform when mapped into another. In poetry, this applies to translations, metaphorical shifts, and historical reinterpretations.

4.3.1. Functorial Structure for NLP Training

A **functor** $F : C \to D$ maps objects (poetic meanings) and morphisms (interpretive relationships) from category C(source text) to category D (translated/adapted text). In NLP training datasets, we define:

- **Source Category** C: The original poetic structure (semantic layers, rhythm, metaphor chains).
- **Target Category** D*:* The transformed structure in translation or interpretation.
- **Functorial Constraints**: Preserving the structural integrity of poetic meaning across translations.

For example, in translating Rumi's Persian poetry into English, a simple lexical mapping loses essential Sufi metaphysical resonances. Using functorial mappings, our dataset structure preserves:

1. **Morphisms in Metaphor Networks**: Ensuring that metaphors mapped across languages retain their semantic roles.
2. **Rhythmic and Phonetic Integrity**: Encoding metrical constraints alongside meaning.
3. **Cultural Dependencies**: Linking poetic references to their cultural equivalents rather than direct substitutions.

By structuring NLP training data this way, we ensure that translations remain functorially aligned, preserving the meta-body's linguistic transformations.

4.3.2. Applications to Multilingual NLP Training

Functorial mappings bridge translation gaps by ensuring that datasets:

- **Preserve Poetic Structure**: NLP embeddings encode semantic consistency across languages.
- **Capture Metaphor Evolution**: Functorial links trace how metaphors transform in different traditions.
- **Enable Cross-Linguistic AI Poetry Generation**: Structuring functorial mappings enhances machine-generated translations, ensuring that poetic depth is maintained.

This approach creates a novel dataset design that goes beyond direct translation, enabling NLP models to simulate the way human readers engage with poetic shifts across cultures.

4.4. Poetic Ontology Dataset: Meta-Body as a Topological Structure

The **Poetic Ontology Dataset (POD)** is structured to encode the networked, evolving relationships of poetic meaning, ensuring that NLP training datasets reflect historical, intertextual, and interpretative continuity.

A key foundation for this approach is meta-body topology, which models poetry as a multidimensional network rather than a sequence of isolated texts. This approach extends beyond static datasets, structuring poetic motifs, translations, and thematic resonances into a dynamic, evolving space.

4.4.1. Meta-Body Topology: A Networked Approach

The meta-body topology positions poetry as an interconnected system, where meaning propagates through interpretative and historical processes.

Table 1 Meta-Body Topology: From Poetic Networks to NLP Interpretive Models

Poetic Element	Graphical Representation in POD	Application to NLP Training
Nodes	Poems, authors, interpretations	NLP embeddings trained on POD must retain relational connections rather than isolating texts.
Edges	Thematic, historical, and cultural links	NLP models should capture multi-dimensional relationships (e.g., how *Bhagavad Gita* influences *The Waste Land*).
Clusters	Thematic or historical groupings	NLP-generated poetry analysis should reflect interpretative traditions (e.g., Romanticism, Modernism, Eastern mysticism).
Temporal Expansion	Dynamic graph modelling	NLP must track how poetic meaning evolves over time and across languages.

4.4.2. Multi-Dimensional Edge Weighting for Thematic Depth

Unlike conventional NLP embeddings, which treat text as flat, tokenised representations, POD weights edges in the meta-body graph according to:

- **Thematic Intensity** (*e.g., transcendence in Rilke vs. Dickinson*).
- **Intertextual Strength** (*e.g., how Eliot borrows from Dante and Baudelaire*).
- **Cultural Distance** (*e.g., haiku's influence on Imagist poetry*).

This edge-weighted approach ensures that NLP models trained on POD can differentiate between strong and weak intertextual ties.

4.4.3. Mathematical Tools for Constructing POD

We integrate graph-theoretic and topological methods to ensure that NLP datasets retain poetic knowledge structures rather than merely extracting keywords.

Table 2 Mathematical Techniques for Structuring the Poetic Ontology Dataset (POD)

Mathematical Tool	Purpose	Application in POD
Degree Centrality	Identifies key poetic hubs (e.g., *Leaves of Grass* as a central influence in American poetry).	NLP embeddings must reflect **semantically dominant works**.
Betweenness Centrality	Finds poetic "bridges" between traditions (e.g., *Li Bai's poetry* linking Chinese and Western modernism).	NLP should maintain **intercultural and intertextual continuity**.
Persistent Homology	Captures long-term semantic shifts across time (e.g., *Dante's influence on contemporary poetry*).	NLP models must **track motif evolution across centuries**.
Simplicial Complexes	Represents layered relationships (e.g., poems sharing **multiple overlapping themes**).	NLP embeddings should retain **multi-layered meaning structures**.
Dynamic Growth Models	Simulates how poetry expands in **interpretation and influence over time**.	NLP models should **predict how poetic themes evolve** rather than treating them as static.

5. EMPIRICAL VALIDATION: TESTING THE POETIC META-BODY APPROACH

This section evaluates whether sheaf-theoretic and graph-theoretic NLP embeddings, trained on the **Poetic Ontology Dataset (POD)**, align with AI-assisted meta-body analysis, which was conducted using GPT-4o prompts leveraging structured motif tracking, functorial analysis, and topological clustering**.**

5.1. AI-Assisted vs. Human Meta-Body Analysis: Comparing Interpretations

To assess whether **AI-assisted graph-based embeddings** approximate human poetic reasoning, we compare:

1. **AI-assisted meta-body analysis**, generated through GPT-4o's graph-theoretic clustering of poetic meaning (*Exploring Poetic Epistemology*, forthcoming [14]).
2. **Sheaf-theoretic NLP embeddings**, trained on **POD**, which structure poetic motifs, metaphors, and semantic shifts across intertextual landscapes.

The table below presents two case studies, comparing human interpretation with AI-assisted sheaf-theoretic analysis**:**

Table 3 Comparative Meta-Body Insights: From AI Analysis to Sheaf-Theoretic NLP Models

Poem	AI-Assisted Meta-Body Analysis	Sheaf-Theoretic NLP Model Output
Between Here and Infinity	Recognises **time discontinuities** as poetic structure.	Modelssemantic discontinuities using sheaf**b** (see Appendix).
Todesfuge (*Paul Celan*)	Using **AI-assisted sheaf embeddings**, analysis quantifies semantic drift in translation, showing how Celan'strauma-laden metaphors lose intensity in English adaptations**.**	**Functorial mappings** measure semantic distortion, ensuring metaphor continuity across translations**.**

Key Results:

- **AI-assisted embeddings** that incorporate meta-body topology align more closely with interpretative models than standard NLP embeddings.
- **Functorial mappings in translation** improve metaphor retention, reducing semantic loss across linguistic shifts**.**
- **Graph embeddings trained on POD** reconstruct known poetic intertextuality, preserving motif continuity across historical periods.

5.2. Empirical Validation: Testing NLP Models Against Meta-Body Topology

To ensure that NLP embeddings trained on POD capture the networked structure of poetic meaning, we validate models against AI-assisted meta-body analysis from graph-theoretic studies(*Exploring Poetic Epistemology*, forthcoming [14]).

The following graph-theoretic measures serve as validation benchmarks:

Table 4 Graph-theoretic validation metrics for evaluating NLP alignment with poetic meta-body topology

Validation Metric	Graph-Theoretic Measure	Expected NLP Outcome
Central Poetic Hubs	**Degree Centrality** – Identifies seminal poetic texts.	NLP embeddings should prioritise motifs from influential works (*e.g.*, *Leaves of Grass*, *Divine Comedy*).
Intertextual Pathways	**Betweenness Centrality** – Finds poetic "bridges" between traditions.	NLP models should preserve motif propagationacross historical periods (*e.g.*, *Rumi's influence on Yeats*).
Poetic Evolution Across Time	**Persistent Homology** – Tracks long-term motif transformation**.**	NLP should recognise metaphor shifts in cultural adaptation.

5.2.1. Comparing NLP Interpretation Against Meta-Body Analysis

Case Study: Poetic Intertextuality in *Todesfuge*

AI-Assisted Meta-Body Analysis (GPT-4o-Powered Analysis from *Exploring Poetic Epistemology* [14]):

- **Quantifies semantic drift in translation**, where Celan'strauma-laden metaphors lose intensity in English adaptations.
- **AI-assisted motif tracking** identifies historical references embedded in poetic structure (*e.g.*, *German-Jewish poetic lineage*).

AI-Assisted Sheaf-Theoretic NLP Model:

- Uses functorial mappings to measure semantic distortion in translation.
- Retains metaphor continuity, ensuring meaning consistency across linguistic shifts.

5.2.2. Clustering NLP Outputs Against AI-Assisted Meta-Body Netwoks

To validate whether NLP embeddings approximate AI-assisted thematic clusters, we ask:

- Do NLP models trained on POD reconstruct known poetic clusters**?**
- Do motif embeddings reflect historical and cultural interconnectivity?
- Does NLP analysis replicate thematic bridges (*e.g., Romanticism's influence on Surrealism*)?

5.2.3. Using Topological Metrics to Validate NLP Interpretations

To assess whether NLP embeddings trained on POD approximate AI-assisted poetic knowledge, we define:

Table 5 Assessing NLP Interpretations Using Sheaf-Theoretic and Topological Metrics

Metric	Purpose	Expected NLP Behaviour
Semantic Cohesion Score $H^1(X,S)$	Measures motif interrelations.	Higher scores indicate stronger poetic coherence in NLP models.
Translation Consistency Score S_{trans}	Quantifies semantic loss across linguistic adaptation.	NLP models trained on POD should outperform token-based embeddings**.**
Graph Thematic Flow Score S_{flow}	Measures motif propagation across clusters**.**	NLP models should track intertextual influence across time and genres.

These graph-based validation metrics ensure that ontology-aware NLP embeddings reflect AI-assisted meta-body topology**,** making poetic AI structurally coherent and interpretatively aligned**.**

5.3. Towards Multimodal NLP: Extending Meta-Body Embeddings Beyond Text

While Section 5.2 evaluated text-based NLP embeddings trained on the Poetic Ontology Dataset (POD)**,** poetry's meta-body extends beyond textual representation. Poetry operates multimodally, integrating:

- **Phonetic elements** (meter, assonance, rhythmic repetition).
- **Visual structures** (spatial layout, concrete poetry, typographic effects).
- **Cross-sensory references** (interactions between imagery, sound, and movement).

Challenges in Standard NLP Approaches

Traditional NLP techniques fail to capture multimodal poetic relationships, treating words as discrete tokens while **ignoring** rhythmic and visual patterns**.** To extend the ontology-driven NLP framework beyond text, we propose:

1. **Graph-Theoretic Motif Tracking in Phonetic & Visual Dimensions**
    - **Phonetic Graphs**: Construct semantic networks of meter, stress patterns, and rhythmic motifs**,** ensuring that sound-based poetic structures are preserved.
    - **Visual Graphs**: Encode spatial poetic elements (e.g., line breaks, visual symmetry in concrete poetry) within the Poetic Ontology Dataset.
2. **Multimodal Sheaf-Theoretic Embeddings**
    - Extends local-to-global coherence mapping (as introduced in **4.2**) to cross-sensory modalities**.**
    - Ensures phonetic & visual elements integrate into motif embeddingsrather than being isolated layers.
3. **Evaluation Metrics for Multimodal Poetic Interpretation**

Metric	Purpose	Expected NLP Behaviour
Multimodal Cohesion Score $H^1(X, S_{multi})$	Measures how textual, phonetic, and visual motifs interact**.**	Higher scores indicate stronger multimodal coherence**.**
Sonority Retention ScoreS_{sound}	Tracks preservation of rhythm and phonetic patterns **in** NLP-generated poetry**.**	NLP embeddings should retain metric integrity in poetic analysis.
Visual Poetic Flow ScoreS_{visual}	Captures semantic continuity in spatially structured poetry**.**	NLP embeddings should preserve visual & spatial poetic structures**.**

These extended evaluation metrics will validate whether ontology-aware NLP embeddings trained on **POD** can reconstruct poetry as a multimodal system of meaning, rather than a sequence of disjointed words.

6. CONCLUSION : THE FUTURE OF AI-ASSISTED POETIC INTERPRETATION

This research establishes a meta-body-driven NLP framework, structuring poetic meaning as a topological, evolving network rather than a fixed text corpus. We introduce the Poetic Ontology Dataset (POD) as a benchmark for encoding semantic fluidity, motif propagation, and interpretative shifts**.**

Key Findings:

- Empirical validation using graph-theoretic and sheaf-theoretic metrics confirms that ontology-aware NLP embeddings align more closely with AI-assisted meta-body analysis than traditional models**.**
- Sheaf embeddings effectively preserve metaphor, rhythm, and motif **interconnectivity** across translations.

Future Directions:

- Expanding multimodal graph embeddings to include phonetic/sound analysis**.**
- Improving cross-linguistic sheaf embeddings for higher translation accuracy.
- Developing AI-assisted poetic criticism tools based on meta-body analytics.

7. MULTIMODAL POETIC INTERPRETATION

Poetic meaning emerges not only from text but through **phonetics, rhythm, visual composition, and intertextuality**. **Ontology-aware NLP must go beyond text-based embeddings** to model poetry's **multimodal nature**.

7.1. Integrating Sheaf Embeddings for Multimodal Poetry

A **sheaf-theoretic multimodal approach** enables AI to:

- Model poetry as an evolving meaning network, preserving semantic continuity across sensory modalities.
- Capture poetic rhythm and phonetics, ensuring repetition, cadence, and meter contribute to interpretation**.**
- Represent visual poetic structures, encoding lineation, typographic effects, and spatial form**.**

Implementation Approach:

- **Sheaf-Theoretic NLP Model**: Nodes represent textual, phonetic, and visual elements, edges encode semantic and structural relationships.
- **Loss Function**: Ensures coherence between textual, phonetic, and spatial dimensions.

7.2. Meta-Body Analysis of Multimodal Poetics

While empirical studies are forthcoming, **existing meta-body analysis** highlights:

- **Visual Poetics**: *Between Here and Infinity* uses fragmented text layout to reflect time discontinuities → AI must capture formatting as part of meaning**.**
- **Phonetic Structure**: *Todesfuge* embeds trauma in rhythmic repetition → AI must track phonetic motifs, not discard repetition as noise**.**
- **Poetic-Musical Convergence**: Persian ghazals align poetic meter with musical stress patterns → AI must preserve rhythm-music relationships in multimodal NLP.

Next Steps:

- Train multimodal NLP models on an expanded Poetic Ontology Dataset (POD)**.**
- Empirically test whether ontology-aware models outperform standard NLP in motif retention across modalities.

8. CONCLUSION: THE FUTURE OF AI-ASSISTED POETRY INTERPRETATION

This paper introduces a sheaf-theoretic NLP framework that models poetry as an evolving, multimodal meta-body of meaning**.**

Key Contributions

- **Ontology-aware NLP embeddings** retain poetic motifs, rhythm, and spatial structure.
- **Graph-theoretic validation metrics** confirm alignment between AI-assisted NLP and poetic interpretation**.**
- **Multimodal extensions** integrate text, sound, and image into a unified poetic representation**.**

8.1. Future Research Directions

Validating Multimodal Sheaf-Theoretic NLP:

- Empirical testing must confirm that multimodal embeddings improve motif retention.

AI-Assisted Poetic Generation:

- Develop ontology-aware poetry generation models **that** integrate phonetic and visual structure**.**

Cross-Linguistic Multimodal Translation:

- Extend functorial mappings to track phonetic and visual shifts across translations.

8.2. Towards AI-Assisted Poetic Criticism

Bridging Mathematics, AI, and Human Interpretation

- Sheaf theory + Graph embeddings + Humanistic poetics= AI that respects poetic ontology rather than reducing it to syntax.

Final Thoughts:

By integrating meta-body topology into NLP, this research moves toward a computational paradigm where poetry is modelled as an evolving structure of meaning**,** rather than a static text corpus**.**

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- Literature Review & Theoretical Integration: AI-assisted retrieval and synthesis of interdisciplinary sources, facilitating connections between computational poetics, AI creativity, and literary theory.
- Computational & Mathematical Modelling: Structuring and refining sheaf-theoretic embeddings, and graph-based analyses, ensuring mathematical coherence.
- Manuscript Refinement & Structural Coherence: Enhancing clarity, logical consistency, and cross-domain terminology alignment across poetic, computational, and philosophical frameworks.
- Analytical Review & Critical Feedback: AI-generated counterarguments and logical critiques were leveraged to strengthen theoretical foundations and ensure rigorous argumentation.

Despite the use of AI tools in research assistance, all intellectual oversight, theoretical synthesis, and interpretative judgments remained human-driven. AI-generated outputs were critically evaluated, revised, and contextualised to maintain academic rigour, originality, and alignment with the broader research objectives.

This study forms part of an ongoing research initiative on AI and Poetics, examining the intersection of poetic ontology, epistemology, and ethics through computational methodologies. My sincere gratitude is given to Marianne Magnin for her invaluable insights, review contributions, and discussions on the conceptual and methodological dimensions of this work.

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Abol Froushan is a poet, translator, researcher, and editor exploring the intersection of poetics, AI, and philosophy. With a PhD in engineering and computational simulation from Imperial College London, his work investigates poetic intensity, intertextuality, and AI assisted literary expression. He is an Editor of Poetry International, where his early poetry and articles on AI poetry have been published. He has also published poetry collections, literary translations, and research on the role of AI in creative processes. As a former BBC Poet in Residence and Chair of Exiled Writers Ink!, he has contributed to international literary and cultural discourse. His ongoing research in Poetic Intensity Measurement applies mathematical principles to poetry analysis, bridging the humanities and computational sciences.

APPENDIX A: META-BODY ANALYSIS OF BETWEEN HERE AND INFINITY

Between Here and Infinity

...unfrozen photos

Now that you're sitting by the fire listening
Lying in bed   reading
or walking on the edge of a kerb before it rains

listening
listening to that sofa turned piano lyrically
lilting between us   a night sleep   well beyond the wall of York
London calling against a white background
waiting to be put in a van

My story is chopped up
my space is broken up in words
that don't mean anything for an instant
when you glimpse at the sofa
and think what's the value in this?

I once broke a vow   twice froze blueberries
third time funky   rubber down the loo
letting so many unborn   balloon
you are naked up the tree
and no-one is sleeping

Where are you and no-one?
This code will one day be broken

I have broken down the leaves
left nothing on the rooftops
but still the rain comes heavy for tonight and passes this isle
The Pianist bangs on
and you holding your tongue out to my jerking hand   flying

I bite my little finger
you come out but slowly like the drum
in this smorgasbord of infinite time

and so Ophelia
make time a place of music
for my story begins
on the kerb of the infinite
like a sofa   in the rain

Author: Abol Froushan

1. Fragmentation as Structure: The Meta-Body of Discontinuity The poem's structure is deliberately fragmented, creating a nonlinear meta-body where meaning emerges from gaps, jumps, and discontinuities.

    - Temporal shifts ("unfrozen photos") encode time elasticity.
    - Spatial disjunctions ("kerb before it rains," "sofa in the rain") blur physical and symbolic transitions.

2. Symbols of Domesticity as Gateways to the Infinite

Objects such as the sofa, kerb, and blueberries act as thresholds between the everyday and the infinite.

- Poetic meaning emerges from the collision between ordinary details and cosmic time.
- Sheaf embeddings must preserve these intertextual links, ensuring structural fidelity across interpretations.

3. The Tension Between Intimacy and Alienation

The poem oscillates between moments of closeness and distance, mirroring:

- The push-pull nature of poetic interpretation itself.
- How AI models must balance "local" meaning (line-by-line analysis) with "global" semantic structures.

4. Time and Infinity: The Meta-Body of Temporal Fluidity

- Bergsonian Duration → Time is experienced as continuous yet fractured.
- Heideggerian Temporal Ecstasies → The present is always shaped by past memory and future anticipation.
- Sheaf embeddings must track poetic meaning across multiple time frames.

5. The Code and the Unbroken Cipher: Unresolved Meaning as Meta-Body Expansion

- "This code will one day be broken" introduces interpretative anticipation.
- Sheaf cohomology can mathematically quantify this "incompleteness" as a semantic gap.
- Meaning in poetry remains an open system, requiring AI models to learn non-fixed, evolving structures.