

TOPol: Capturing and Explaining Multidimensional Semantic Polarity Fields and Vectors

Gabin Taibi^{1,3}, Lucia Gomez^{2,3},

¹University of Twente

²Bern University of Applied Sciences

³University of Geneva

gabin.taibi@utwente.nl

lucia.gomezteijeiro@bfh.ch

Abstract

Semantic polarity in computational linguistics has traditionally been framed as sentiment along a unidimensional scale. We here challenge and advance this framing, as it oversimplifies the inherently multidimensional nature of language. We introduce TOPol (Topic-Orientation Polarity), a semi-supervised framework for reconstructing and interpreting multidimensional narrative polarity fields given human-on-the-loop (HoTL) defined contextual boundaries (CBs). TOPol begins by embedding documents using a general-purpose transformer-based large language model (tLLM), followed by a neighbor-tuned UMAP projection and topic-based segmentation via Leiden partitioning. Given a CB between regimes A and B, the framework computes directional vectors between corresponding topic-boundary centroids, producing a polarity field that captures fine-grained semantic displacement for each discourse regime change. TOPol polarity field reveals CB quality as this vectorial representation enables quantification of the magnitude, direction, and semantic meaning of polarity shifts, acting as a polarity change detection tool directing HoTL CB tuning. To interpret TOPol identified polarity shifts, we use the tLLM to compare the extreme points of each polarity vector and generate contrastive labels with estimated coverage. Robustness tests confirm that only the definition of CBs, the primary HoTL-tunable parameter, significantly modulates TOPol outputs, indicating methodological stability. We evaluate TOPol on two corpora: US Central Bank speeches upon a macroeconomic breakpoint as CB, where semantic shifts are non-affective, and Amazon product reviews upon rating strata as CB, where sentiment dominates and therefore TOPol interpretation strongly aligns with NRC valence. Results show that TOPol reliably captures both affective and non-affective polarity transitions, those naturally emerging from the data, offering a scalable, generalizable, context-sensitive and interpretable approach to HoTL-guided multidimensional discourse analysis.

Code and Data — https://osf.io/nr94j/?view_only=a787f6e842b64bd4a0bc0344872e1eec

Introduction

Sentiment Polarity scoring has long occupied a central position in Natural Language Processing (NLP), treated as a synonym of Semantic Polarity since its inception, addressed within the scope of Sentiment Analysis, conceptualized as a

scalar indicating the extent to which a text encodes a positive or negative perspective about an object (Mäntylä, Graziotin, and Kuutila 2018). Recent works dealing with Polarity Classification, still framed in the lens of sentiment, however seek to move beyond affective components for capturing dimensions such as sarcasm (Prasanna, Shaila, and Vadivel 2023). While this sentiment-centric framing of polarity has proven powerful, it overlooks the multidimensional nature of semantic orientation.

In response, recent academic efforts are challenging this unidimensional view by developing multi-label and fine-grained affective models (Demszky et al. 2020), and progressively extending polarity modeling beyond sentiment-centric paradigms (Hofmann et al. 2021). These efforts demonstrate that semantic analysis cannot be reduced to single evaluative scales, as such reductions introduce bias by overlooking the multidimensional context and perspectival complexity in which meaning is embedded.

Topic Modeling (TM), the second most used NLP analysis methodology, can capture topical dimensions in text corpora, but it is designed to describe topical diversity rather than semantic orientation, and usually does so in a static manner. Recent advancements in TM explore context-aware (Grootendorst 2022) and dynamic topic reconstruction over time (Adhya and Sanyal 2025). However, these new approaches do not capture the full spectrum of semantic directionality, evidencing the need for methods capturing semantic dynamism in a truly multidimensional manner, a representation solution we conceptualize here as *Semantic Polarity Vector Fields*.

We introduce TOPol (Topic-Orientation Polarity), the first framework for reconstructing and interpreting multidimensional Semantic Polarity Fields. It retrieves the vectorial transformations between topic-aligned discourse subsets by combining tLLM embeddings with manifold learning, and computes polarity vector fields based on cluster centroid displacements. This enables capturing the vectorial structure, magnitude, directionality, and underlying polarity dimensions of semantic change.

TOPol advances the NLP representation toolkit by flexibly modeling the change of meaning across human-on-the-loop (HoTL) defined contextual boundaries (CBs). We show that when applied to non-sentiment driven corpora, TOPol reveals novel semantic dimensions such as

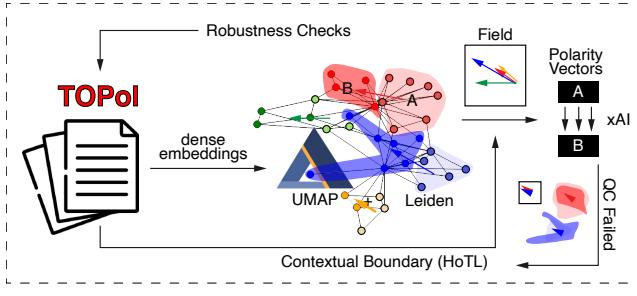


Figure 1: Architecture of TOPol

confidence-doubt or transparency-obfuscation, expanding the analytical vocabulary for interpretive NLP. Conversely, when applied to sentiment-driven corpora, it reconstructs mainly, but not only, sentiment polarity dimensions, such as disappointment-enjoyment, confirming that TOPol vastly extends sentiment analysis into a broader class of multidimensional semantic polarity analysis.

In summary, our contributions can be summarized as follows:

- We identify a critical gap in current semantic polarity modeling: existing NLP tools inadequately represent the multidimensional structure of polarity.
- We propose **Topic-Orientation Polarity** (TOPol), a novel semantic representation framework for reconstructing multidimensional semantic polarity fields and dimensions of change, being flexible to HoTL context-awareness.
- We introduce a contrastive explainability mechanism based on LLMs, which interprets polarity dimensions emerging from vector fields, and demonstrate its efficiency as compared to traditional lexicon based approaches.
- We validate TOPol on sentiment-driven and non-sentiment-driven corpora, demonstrating its ability to recover context-sensitive polarity dimensions across domains and extending the traditional sentiment analysis realm.
- We perform robustness checks for each TOPol core component, showing that polarity field reconstruction is structurally stable under perturbations, while the HoTL CB definition is the key driver of variation in output.

Preliminary

We begin by formalizing the core elements of the TOPol framework, which objective is to model semantic polarity as a vector field induced by shifts in discourse across contextual boundaries.

Definition 1 (Contextual Boundary). A contextual boundary (CB), though it can be extended to more subsets, is here demonstrated as a partition of the corpus into two disjoint subsets \mathcal{D}_A and \mathcal{D}_B , corresponding to regimes A and B , whether derived from the discourse or externally defined. This boundary induces a directional comparison from $A \rightarrow B$.

Definition 2 (Topic Clustering). Given the LLM embedding space \mathcal{Z} , we apply Uniform Manifold Approximation and Projection (UMAP) followed by Leiden clustering to obtain a set of k latent topics $\mathcal{T} = \{T_1, T_2, \dots, T_k\}$, where each $T_i \subseteq \mathcal{Z}$ represents a topic cluster.

Definition 3 (Centroid Pair). For each topic T_i , we compute its contextual centroids:

$$\boldsymbol{\mu}_i^A = \frac{1}{|\mathcal{D}_i^A|} \sum_{\mathbf{z} \in \mathcal{D}_i^A} \mathbf{z}, \quad \boldsymbol{\mu}_i^B = \frac{1}{|\mathcal{D}_i^B|} \sum_{\mathbf{z} \in \mathcal{D}_i^B} \mathbf{z}$$

where $\mathcal{D}_i^A = T_i \cap \mathcal{D}_A$ and $\mathcal{D}_i^B = T_i \cap \mathcal{D}_B$.

Definition 4 (Polarity Vector). The polarity vector for topic T_i is defined as:

$$\mathbf{v}_i = \boldsymbol{\mu}_i^B - \boldsymbol{\mu}_i^A$$

which encodes the semantic displacement of topic T_i across the contextual boundary.

Definition 5 (Semantic Polarity Field). The narrative polarity field is defined as the set of polarity vectors across all topics:

$$\mathcal{V} = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}, \quad \text{with } \mathbf{v}_i = \boldsymbol{\mu}_i^B - \boldsymbol{\mu}_i^A$$

Each vector \mathbf{v}_i is represented in a shared coordinate system and rooted at a common origin, forming a vector field in a normed vector space. This structure captures both the magnitude and direction of semantic displacement for each topic across the contextual boundary from regime A to regime B .

Methodology

In this section, we describe the proposed TOPol framework, as illustrated in Figure 1. The pipeline reconstructs multidimensional semantic polarity fields and interprets the underlying polarity vectors that encode topic-specific semantic shifts contained in the discourse. TOPol begins by generating dense vector representations for each document in the input corpus using a general-purpose transformer model. Next, it applies UMAP (McInnes, Healy, and Melville 2020) on these embeddings, yielding a non-linearly reduced semantic manifold in which document proximity reflects topical similarity. TOPol then partitions the manifold using the Leiden (Traag, Waltman, and van Eck 2019) community detection algorithm, grouping semantically related documents in latent topics. Each topic cluster, or community, is further subdivided into two (or more) context-specific subsets, denoted A and B , according to the HoTL-defined contextual boundary. For each cluster, TOPol then computes a polarity vector for each Leiden community by calculating the vector displacement between the centroid of documents in regime A and the centroid of documents in regime B . These vectors are then anchored to a shared origin, forming a vector field in a normed vector space, the so-called semantic polarity field for the corpus. Finally, to interpret the polarity dimensions contained in each polarity vector, potentially several per vector, we apply a tLLM-based contrastive explainability procedure. Specifically, for each polarity vector, we provide the tLLM with the document subsets nearest to centroids A and B and prompt it to generate contrastive summaries describing the dominant semantic distinctions between regimes A

and B , along with their estimated coverage and exemplar text captions.

Defining Contextual Boundaries

The process of identifying and defining meaningful CBs is central to TOPol results, as shown afterwards in Experiments section. Therefore, TOPol does not conceive this as an algorithmic tunable parameter but is rather an HoTL decision. CBs define meaningful narrative regimes under comparison, bound to specific research questions, and determine the granularity of the polarity vectors that TOPol detects and explains. CBs may originate from external events or internal shifts in discourse, or a combination of both. In this study, we show the operationalization of CB definition both on external and internal regime detections, on Central Bank speeches and Amazon customer reviews respectively. Also, here we confine CB definition as a 2-set split of a given text corpus, but this can be adapted to cover vectors with as many intermediate steps as desired, or even defined by combining complementary regime splits into multi-category regimes.

Reconstructing Semantic Polarity Fields

The modeling of directional semantic change across the discourse regimes defined by CBs is achieved by reconstructing the semantic polarity field of the corpora under study.

Let $\mathcal{D} = \{d_1, d_2, \dots, d_n\}$ be a corpus of text documents. We obtain dense semantic embeddings $\mathbf{z}_i \in \mathbb{R}^m$ for each document d_i using a general-purpose tLLM pre-trained on large corpora. The output is a set of embeddings $\mathcal{Z} = \{\mathbf{z}_1, \dots, \mathbf{z}_n\}$, where each $\mathbf{z}_i = \text{tLLM}(d_i)$ captures contextual semantic information in a high dimensional space. While the tLLM embedding space is semantically rich, it can result in prohibitive computational costs and may not be well-suited for downstream manifold-based clustering. To address this, we apply UMAP to preserve local topological structures, narrative latent topics, by mapping each \mathbf{z}_i to a low-dimensional representation $\mathbf{u}_i \in \mathbb{R}^d$, obtaining the projection $\mathcal{U} = \{\mathbf{u}_1, \dots, \mathbf{u}_n\} \subseteq \mathbb{R}^d$, where semantically similar documents are located near to each other, preserving discourse topology.

Next, we construct a k -nearest neighbor graph over the projected vectors \mathcal{U} and apply the Leiden community detection algorithm, optimizing modularity and ensuring cluster connectivity. This results in a set of k topic clusters $\mathcal{T} = \{\mathcal{T}_1, \mathcal{T}_2, \dots, \mathcal{T}_k\}$, where each $\mathcal{T}_i \subseteq \mathcal{U}$ represents a geometrically stable, semantically and topologically coherent topic. Given a contextual boundary (CB) defined by a human-on-the-loop (HoTL) operator, we partition each cluster \mathcal{T}_i into two subsets \mathcal{T}_i^A and \mathcal{T}_i^B , corresponding to documents from discourse regimes A and B (see Preliminaries section), though this can be expanded to more than two regimes or to multi-category regimes (see Conclusions).

For each topic \mathcal{T}_i , we compute centroids μ_i^A and μ_i^B for subsets A and B, and the polarity vector for topic \mathcal{T}_i is then: $\mathbf{v}_i = \mu_i^B - \mu_i^A$. These vectors represent the semantic displacement of each topic from regime A to regime B. All polarity vectors \mathbf{v}_i are finally rooted at a common origin for creating a vector field $\mathcal{V} = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ in a normed

vector space, the foundation for subsequent TOPol interpretability. Each vector encodes both magnitude $\|\mathbf{v}_i\|$ and direction of semantic change, allowing the analysis of field properties .

Revealing TOPol Dimensions

Once the semantic polarity field has been reconstructed, the final step of the TOPol pipeline is to interpret the meaning of each polarity vector \mathbf{v}_i , which captures the semantic displacement of a topic across a contextual boundary. We propose a discovery approach based on contrastive explainability mechanism and which leverages large language models (LLMs) capabilities. For each vector \mathbf{v}_i , we select the top- n nearest documents to the centroids μ_i^A and μ_i^B in the reduced semantic space. Let \mathcal{N}_i^A and \mathcal{N}_i^B denote these local document neighborhoods: $\mathcal{N}_i^A = \text{Top-}n(\mu_i^A)$, $\mathcal{N}_i^B = \text{Top-}n(\mu_i^B)$. \mathcal{N}_i^A and \mathcal{N}_i^B are passed to the LLM, which is prompted to identify salient semantic distinctions between the two sides of the polarity vector. The output of this explainability layer includes: a natural language label set for the poles of each dominant semantic difference between \mathcal{N}_i^A and \mathcal{N}_i^B , a quantitative coverage estimate for each dimensional pole on each subset, and a list of the most representative sentences and keywords for each polar dimension.

Experiments

We conducted extensive experiments for empirical testing and robustness assessment of TOPol performance. This section details the experimental setup and results for the basic formulation and perturbation variations of TOPol on two distinct datasets.

Experimental Setup

Datasets. We evaluate TOPol on two corpora chosen for their contrasting semantic properties: one is nearly sentiment-absent, the other is sentiment-dense. The first is a macroeconomic discourse dataset composed of 2,342 U.S. central bank speeches extracted from the BIS repository. These long-form documents, characterized by low affect and technical language, were filtered from a larger multilingual corpus. and segmented using a PCA-based macroeconomic index. We define a contextual boundary using regime segmentation derived from a PCA-constructed macroeconomic index, selecting the May 2007 breakpoint preceding the Global Financial Crisis. This yielded a final dataset of 600 speeches divided into pre- and post-crisis regimes. The second corpus is a sentiment-saturated dataset: a balanced subset of 10,000 Amazon product reviews, evenly sampled from positive and negative ratings. These short, affect-rich texts offer a natural benchmark for evaluating polarity interpretation.

Due to structural differences between the corpora, we analyze them separately, and chose different contextual boundary logic: a time-based segmentation for the speeches and a sentiment-based split for the reviews.

Transformer Models. While TOPol is model-agnostic and compatible with any transformer-based embedding or

generative model, we deliberately selected two complementary models that balance characteristics, performance and interpretability. For document embedding, we used OpenAI’s *text-embedding-3-small*, a general-purpose model offering strong cross-domain generalization, high throughput, and low computational cost—well suited for large-scale manifold construction.

For the contrastive explainability layer, we opted for Google’s *gemini-2.5-flash*, a state-of-the-art language model distinguished exceptionally high input token limit of 1,048,576—far exceeding that of comparable models such as OpenAI’s *gpt-4o-mini* (128,000 tokens). This extensive context window enables the model to ingest dense document neighborhoods in a single pass, a critical requirement for coherent polarity dimension labeling and high-coverage contrastive interpretation.

Default Hyperparameters In addition to the perturbation experiments discussed later on, we maintained a fixed set of default hyperparameters across all datasets to ensure methodological consistency. The selected hyperparameters reflect informed defaults grounded in the theoretical behavior of UMAP and Leiden algorithms, particularly with respect to preserving local topology and optimizing community granularity. Perturbation scenarios were constructed by applying substantial deviations from these defaults to test the resilience of polarity field reconstruction under extreme yet plausible configurations.

Semi-supervised Reconstruction of Narrative Polarity Vector Field and Shifts

We first evaluate the capacity of TOPol to reconstruct polarity vector fields in a semi-supervised setting, relying on the CB definition and the intrinsic structure of the discourse. This analysis assesses whether the polarity vectors naturally reflect coherent and interpretable semantic shifts without relying on predefined labels or external supervision.

Multidimensional Profiling. Having extracted the semantic displacement across contextual boundaries in the form of centroid drift vectors, we next assess the statistical and structural significance of the resulting polarity field. The first step involves comparing the polarity field induced by the HoTL-defined CB with those obtained under random CBs. This procedure provides a baseline to evaluate whether the observed semantic displacement is meaningful or could arise by chance.

Random CBs are generated by randomly permuting the CB assignment column, effectively decoupling the documents from their original regime labels while preserving topic composition. Figures 2a and 2b illustrate two-dimensional projections of polarity vector fields computed from the HoTL-defined CB (left) and a randomly generated CB (right) for both the U.S. central bank speeches and Amazon review datasets. In both datasets, the vector fields generated under the HoTL CB exhibit greater coherence and alignment than those under random CBs (Table 1 and 2). In the Amazon dataset, the vector field aligns strongly with the primary semantic axis that separates positive and negative sentiment across dense product-specific clusters (Figure 2b).

In contrast, the speech dataset reveals more heterogeneous and dispersed polarity shifts, suggesting multiple semantic dimensions underlie the observed transitions (Figure 2a).

To generalize this comparison, we perform $N = 1000$ simulations of random CBs and compute two key metrics: (1) the average magnitude of polarity drifts, a proxy for the overall strength of semantic displacement:

$$\bar{m} = \frac{1}{k} \sum_{i=1}^k \|\mathbf{v}_i\|$$

and (2) the average pairwise cosine similarity among drifts which reflects the alignment of directional change across topics:

$$\bar{s} = \frac{1}{\binom{n}{2}} \sum_{i=1}^n \sum_{j=i+1}^n \frac{\mathbf{v}_i \cdot \mathbf{v}_j}{\|\mathbf{v}_i\| \|\mathbf{v}_j\|}$$

where $\frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|}$ is the cosine similarity measure between two vectors \mathbf{x} and \mathbf{y} . A high overall drifts cosine similarity suggests a low-dimensional, coherent polarity shift, whereas a low value indicates the presence of diverse and potentially orthogonal polarity dimensions.

The significance of the observed polarity shift is assessed via a non-parametric test. Specifically, the p -value is computed as:

$$p = \frac{1 + \sum_{i=1}^N \mathbb{I}_{\bar{m}_i \geq \bar{m}_{\text{HoTL}}}}{N + 1}$$

where \bar{m}_{HoTL} is the average drift magnitude under the HoTL-defined CB, and \bar{m}_i are those obtained from random CBs.

For the U.S. central bank speeches, the average cosine similarity among polarity vectors is $\bar{s} = 0.12$, likely indicating a dispersed, multidimensional semantic change, as we hypothesized before. In contrast, the Amazon reviews exhibits a higher cosine similarity of $\bar{s} = 0.66$, suggesting a more uniform, sentiment-aligned polarity shift. In both cases, the observed average magnitude significantly exceeds that of the random CBs, yielding p -values of 0.000999, strongly confirming that the detected semantic displacements are non-random.

These results validate the relevance of the HoTL-defined contextual boundaries, revealing semantically coherent polarity transitions. In particular, they indicate that while sentiment dominates the semantic change in Amazon product reviews, central bank speeches exhibit richer, multidimensional polarity shifts. This motivates the need to further interpret the underlying polarity dimensions, which we address in the following section.

Explaining Polarity Vectors’ Dimensionality To interpret the latent dimensions captured by each TOPol polarity vector, we employed *gemini-2.5-flash* as a contrastive explainability model. Its extended context window allowed us to include a substantial number of document neighborhoods around each cluster centroid—regardless of individual text length—which proved particularly valuable for the longer central bank speeches. The model was then

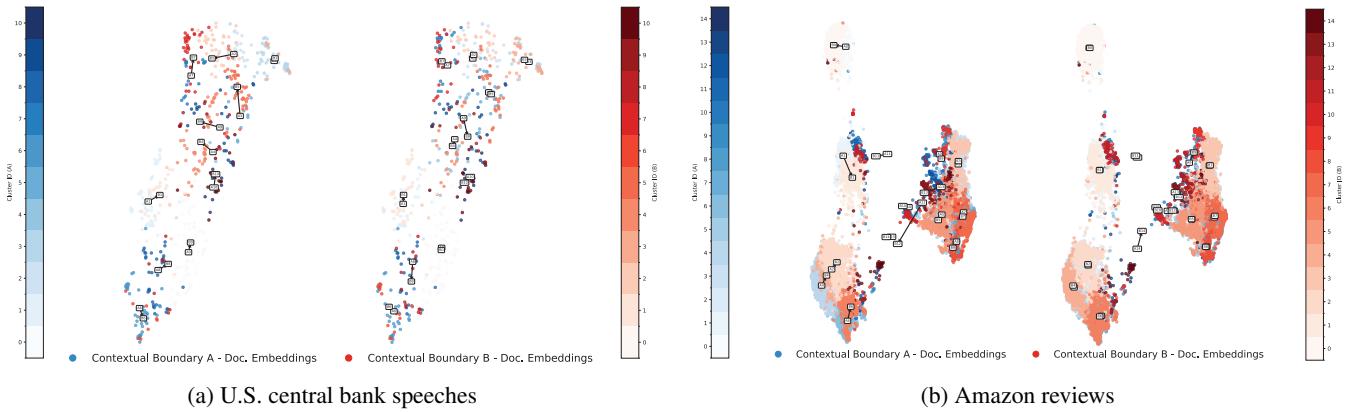


Figure 2: TOPol cluster projections under HoTL-defined (left) and randomized (right) contextual boundaries. Blue and red points correspond to documents from regimes A and B, respectively. White squares indicate cluster centroids; arrows represent semantic drift vectors between regime-specific centroids.

prompted to (i) assign a descriptive label to each polarity dimension, (ii) extract and count supporting and contradicting sentences, and (iii) identify distinguishing keywords for each direction of the shift. Additional constraints and examples were provided to minimize hallucinations and ensure that the model would return an empty response when no coherent signal was present. The ratio of supporting to contradicting sentences served as a proxy for interpretability reliability.

The approach uncovered polarity dimensions that reflect deeper shifts in reasoning and rhetorical strategy. For example, in the cluster 0 of the U.S. central bank speech corpus, the transition from *Amorphous Debate to Empirically Grounded Practice* captures a move from speculative, politically entangled discourse toward data-driven institutional reasoning—suggesting increased epistemic confidence and technocratic closure. In cluster 10, the three dimensions (*Program-Level Reform to Macroeconomic Fiscal Strategy*, *Proactive Adjustment to Impending Crisis*, and *Technical Details to Societal Values*) span broader cognitive and rhetorical shifts: from program-specific reforms to systemic fiscal narratives, from incrementalism to anticipatory crisis framing, and from technical descriptions to moral appeals grounded in equity and collective responsibility. These transitions illustrate how macroeconomic polarity fields reflect shifts in cognitive abstraction, temporal orientation, and normative positioning.

In contrast, polarity dimensions in the Amazon review dataset were more sentiment-saturated and literal. Examples include transitions such as *Criticism to Praise*, *Informality to Formality*, or *Product Dysfunction to Product Effectiveness*, each supported by dense clusters of emotionally charged sentences.

Overall, the polarity fields reconstructed by TOPol reveal domain-specific structures of semantic change: in economic discourse, they span epistemological orientation, anticipatory reasoning, and normative framing—reflecting the multidimensional nature of policy communication and consistent with the low average pairwise cosine similarity ob-

served across polarity vectors. In contrast, polarity fields in Amazon reviews exhibit tighter directional alignment, matching the sentiment-defined contextual boundary and producing polarity vectors that the LLM consistently explains in evaluative terms. These findings support TOPol’s interpretability design and demonstrate the method’s robustness across boundary types and data domains.

Benchmark with Sentiment-Centric Representations

To assess how the polarity fields reconstructed by TOPol compare to a sentiment-aligned baseline, we benchmarked our method against traditional sentiment-centric representations. This section thus serves to isolate the sentiment component of the reconstructed polarity field, by examining whether sentiment is present, and to what extent it contributes to the observed shifts.

We first implemented transformer-based sentiment analysis using two models: a general-purpose model (DistilBERT (Sanh et al. 2020)) and a domain-specific model (FinBERT (Araci 2019)). For each document, sentiment was scored on a continuous scale using the normalized class probability difference:

$$\text{sentiment} = \frac{p_{\text{positive}} - p_{\text{negative}}}{p_{\text{positive}} + p_{\text{neutral}} + p_{\text{negative}}},$$

where p denotes class probabilities. This provides a general sentiment signal that is widely used in applied settings.

In parallel, we implemented a lexicon-grounded benchmark using the NRC-VAD Lexicon (Mohammad 2025), applying the community integration method introduced earlier. Each NRC-VAD term was embedded and projected into the discourse manifold using UMAP model, followed by Leiden clustering to form NRC-VAD communities \mathcal{C}_i . For each community, we computed the average Valence, Arousal, and Dominance (VAD) scores:

$$\bar{\mathbf{v}}_i = \frac{1}{|\mathcal{C}_i|} \sum_{w_j \in \mathcal{C}_i} \text{VAD}(w_j) = (\bar{v}_i, \bar{a}_i, \bar{d}_i).$$

We then assigned each polarity vector endpoint μ_i^A and μ_i^B

to its closest VAD community centroid, using cosine similarity:

$$\mathcal{C}_A = \arg \min_{\mathcal{C}_j} \left(\frac{\mu_i^A, \nu_j}{\|\mu_i^A\| \|\nu_j\|} \right)$$

and

$$\mathcal{C}_B = \arg \min_{\mathcal{C}_j} \left(\frac{\mu_i^B, \nu_j}{\|\mu_i^B\| \|\nu_j\|} \right),$$

where ν_j denotes the centroid of community \mathcal{C}_j . The resulting displacement in VAD space is:

$$\Delta \mathbf{v}_i^{\text{VAD}} = \bar{\mathbf{v}}_b - \bar{\mathbf{v}}_a = (\Delta v_i, \Delta a_i, \Delta d_i),$$

yielding a lexicon-anchored, three-dimensional polarity shift per topic.

The results on the Amazon reviews align with expectations outlined in earlier sections. Since sentiment is the contextual boundary, both transformer-based sentiment scoring and NRC-VAD projection reliably detected a sharp, interpretable polarity vector field. Polarity vectors seem to be uniformly aligned and sentiment-dominant, confirming the narrow semantic structure of the Amazon polarity field and validating TOPol’s approach of considering sentiment as one dimension among many others.

In contrast, for the U.S. central bank speech dataset, both FinBERT and DistilBERT failed to detect a consistent sentiment shift across the HoTL-defined boundary ($\text{sentiment}_{\text{FinBERT}}(\mathcal{D}_B) - \text{sentiment}_{\text{FinBERT}}(\mathcal{D}_A) \approx 0$). NRC-VAD projections also yielded weak signals. These results confirm the absence of sentiment-focus change, consistent with the low cosine similarity among polarity vectors and the multidimensional, topic-specific interpretability found in earlier analyses. However, while the global sentiment gap across the boundary is clearly undetectable, the topic-oriented analysis revealed localized affective shifts within specific clusters, suggesting that emotional framing may play a secondary, context-dependent role. The limited presence of sentiment, or its absence altogether, is itself informative, and indicates that the discourse boundary does not (or only partly), reflect affective change.

Evaluation via Methodological Perturbations

To assess the stability and reliability of the semantic polarity fields reconstructed by TOPol, we conducted a series of methodological perturbation experiments. These controlled variations target key components of the pipeline while holding all other parameters constant. By comparing the resulting polarity vector fields and their statistical properties against the default configuration, we evaluate the robustness of the framework under representational and structural shifts in the embedding and clustering space.

Perturbation of Polarity Field Space Our first robustness check increases the UMAP projection dimensionality from $d = 50$ to $d = 75$. This allows TOPol to capture more semantic variance and latent structure, but at the cost of eventually introducing noise and reducing interpretability. The trade-off between expressiveness and stability is dataset-specific and best tuned through HoTL-guided experiments.

CB	\bar{m}			\bar{s}		
	min	mean	max	min	mean	max
Default setup						
HoTL	0.13	0.29	0.43	-0.09	0.12	0.40
Random	0.11	0.17	0.23	-0.20	-0.01	0.18
Robustness Check 1						
HoTL	0.13	0.30	0.43	-0.09	0.13	0.40
Random	0.11	0.17	0.25	-0.26	-0.01	0.26
Robustness Check 2						
HoTL	0.12	0.32	0.45	-0.013	0.11	0.41
Random	0.11	0.17	0.25	-0.28	0.10	0.18
Robustness Check 3						
HoTL	0.13	0.26	0.35	-0.16	0.19	0.46
Random	0.11	0.14	0.15	-0.15	0.00	0.26

Table 1: Drift magnitude (\bar{m}) and pairwise cosine similarity (\bar{s}) under HoTL and random contextual boundaries for the U.S. central banker speech corpus.

As shown in Tables 1 and 2, this perturbation results in marginal variations in both drift magnitude and cosine similarity. For U.S. central bank speeches, average drift magnitude slightly increases, while cosine similarities remain stable or even slightly improve, suggesting that higher dimensionality preserves coherence. Similarly, in Amazon reviews, drift magnitudes remain consistently high, and pairwise cosine similarities are preserved. These findings suggest that the semantic polarity field structure reconstructed by TOPol is robust to moderate increases in projection dimensionality.

In the second robustness check, we increase the UMAP neighborhood size from $k = 100$ (default) to $k = 150$, expanding the local connectivity radius for manifold construction. This yields smoother topological structures and denser, more aggregated topic clusters. However, larger neighborhoods may also blur finer semantic boundaries, potentially reducing sensitivity to local discourse variation.

We see in Tables 1 and 2 that under this condition, drift magnitudes and cosine similarities remain highly stable. Notably, the Amazon reviews dataset exhibits consistent average cosine similarities. These outcomes indicate that TOPol’s polarity field representation is not overly sensitive to changes in local neighborhood radius, retaining interpretability across topological granularity scales.

Perturbation of Detected Communities The final robustness check lowers the Leiden resolution parameter from $r = 1.5$ to $r = 1.0$, effectively increasing cluster size and consequently reducing their number. This produces coarser topic segmentations, which can enhance robustness by smoothing over noisy boundaries, though it may also dilute finer semantic distinctions and obscure localized polarity shifts.

According to Tables 1 and 2, this perturbation yields a slight reduction in average drift magnitudes and more pronounced degradation in cosine similarity. This suggests that overly coarse topic granularity can obscure the mul-

CB	\bar{m}			\bar{s}		
	min	mean	max	min	mean	max
Default setup						
HoTL	0.21	0.33	0.49	0.21	0.66	0.91
Random	0.04	0.08	0.12	-0.15	0.00	0.18
Robustness Check 1						
HoTL	0.21	0.33	0.59	0.24	0.65	0.91
Random	0.04	0.08	0.13	-0.15	0.01	0.12
Robustness Check 2						
HoTL	0.24	0.33	0.51	0.23	0.66	0.92
Random	0.04	0.08	0.14	-0.15	0.01	0.14
Robustness Check 3						
HoTL	0.21	0.32	0.43	0.45	0.74	0.93
Random	0.04	0.07	0.14	-0.19	-0.01	0.11

Table 2: Drift magnitude (\bar{m}) and pairwise cosine similarity (\bar{s}) under proposed (HoTL) and random contextual boundaries for the Amazon Reviews corpus.

tidimensional polarity structure and reduce interpretability. Nonetheless, the method continues to distinguish proposed from random CBs, indicating that even at lower resolution, meaningful polarity fields persist.

Conclusions

This paper introduced TOPol, a semi-unsupervised framework for modeling and interpreting multidimensional polarity fields across discourse regimes defined by HoTL contextual boundaries. Our empirical results demonstrate that TOPol not only reconstructs coherent and interpretable polarity vector fields, but also reveals latent semantic dimensions of change that go beyond sentiment.

Evaluation across two structurally different corpora showed that TOPol adapts to both high-context, jargon-heavy language and short, sentiment-rich text. The framework remains robust under methodological variations. These findings suggest that while the HoTL-defined CB remains the principal driver of semantic displacement, the topology of the polarity field is stable across moderate representational variations.

Our experiments further reveal that sentiment-aligned polarity dimensions constitute only a part of the semantic shifts captured by TOPol, with the proportion of affective dimensions varying significantly across datasets. This underscores the broader potential of the framework for tracking non-affective, epistemic, or rhetorical polarity transitions, such as transparency–obfuscation or confidence–uncertainty.

Current limitations include the exclusion of topic clusters that are unbalanced or entirely absent from one regime, which may lead to underutilized polarity vectors or topic-level dropout. Additionally, the non-deterministic nature of LLMs makes this part of the framework difficult to reproduce, and their outputs may be prone to hallucinations despite prompting safeguards. Future work will address these constraints.

Finally, while the current implementation focuses on binary regime comparisons, the general structure of TOPol naturally extends to more complex applications. Future extensions will explore sequential or parallel contextual boundaries, enabling multi-point temporal analysis or multidimensional polarity fields over 2D discourse partitions. These directions open new possibilities for modeling evolving narratives and ideological shifts in various domains.

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¹<https://openreview.net/forum?id=r7DXpvpuQv>