Disagreeing but Cohesive?
An Embedding Approach to Climate Discourse Dynamics

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This study aims to understand the climate **discourse dynamics** on Reddit by

1) **creating a novel vector space** that **encodes** the **complex interactions** among a representative set of **discourse features** (topical, affective, ideological, and referential),

2) **quantifying discourse cohesion**,

3) **examining** the association between **cross-positional engagement** and **discourse cohesion**.

We find climate discourse mainly clusters around **shared topics and structures**, maintaining **cohesion** even when affective and ideological differences arise. **Politeness**, **continuity**, and **on-topic** exchanges foster substantive **cross-positional engagement**, with **disagreement** occurring within **common semantic** and **topical frames** rather than through fragmentation or disengagement.

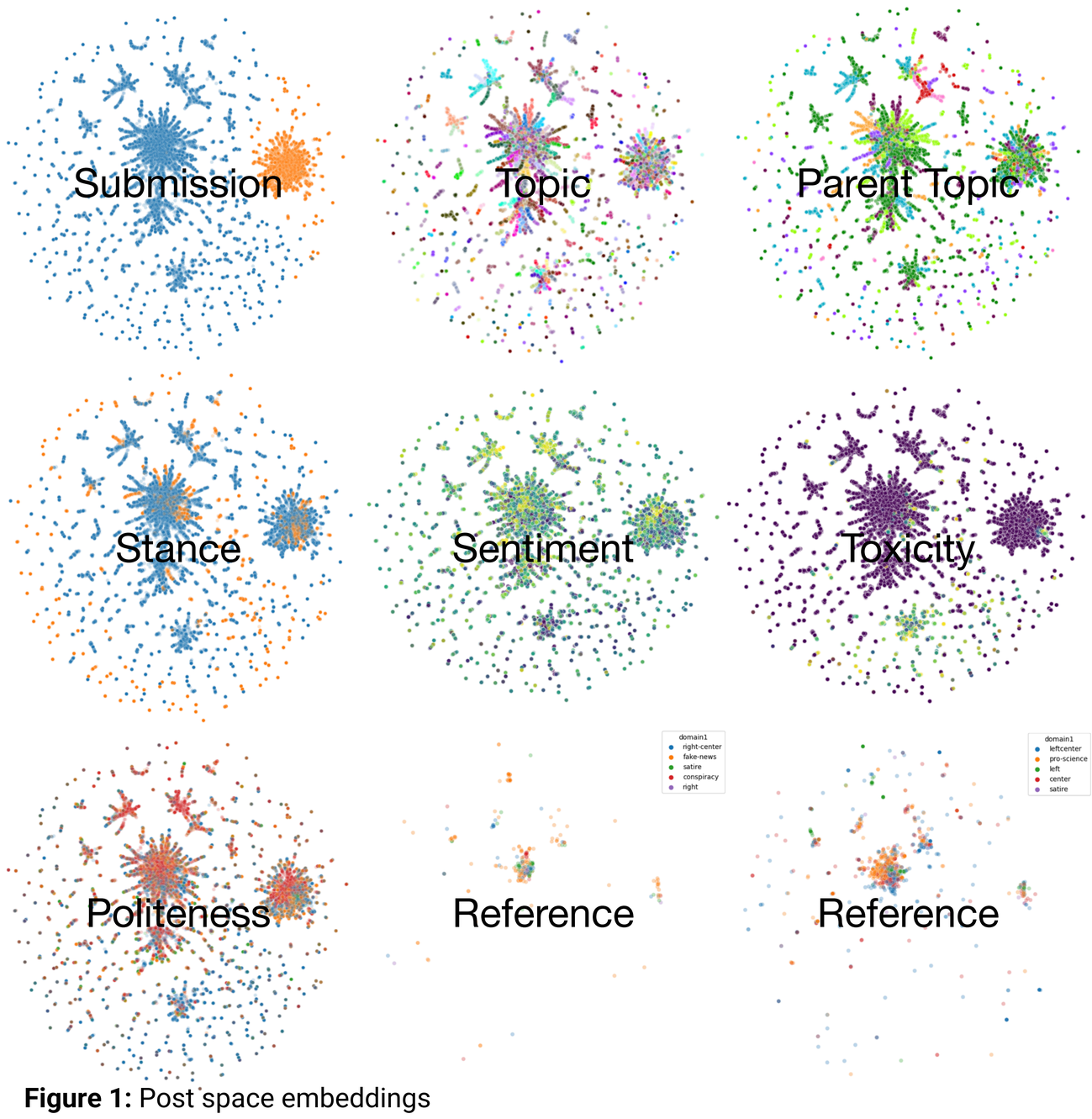

Figure 1: Post space embeddings

Post Space

- The post-embedding space is **topic-driven,** clearly **distinguishing original submissions from comment**. Within each topical cluster, the **local structure varies**, shaped by the dynamics of individual threads and their interactional patterns.
- The interwoven stance patterns indicate **engagement across opposing viewpoints** within threads. Sentiment, toxicity, politeness, and political positions are more diffusely distributed, permeating discussions rather than forming distinct clusters, while domains tightly cluster around a shared core.

Data & Methods

231,042 comments of 36,384 threads from Reddit's subreddit r/climate using the Reddit Pushshift dump.

Methods:

- Identify **discourse features** of each post, including topic[1], stance (climate contrarian/ non-contrarian)[2], reference domain (domain type/political position[3]), sentiment[4], toxicity[5], politeness[6], and **disagreement**[7] using fine-tuned or pre-trained (BERT) models.
- Construct structure-aware **feature embeddings** with the GloVe[8] model and obtain **post embeddings** by averaging the feature vectors of each post. A graph-based weighting scheme is applied to account for the relationship of each post to others when computing the co-occurrence matrix.
- Explore **discourse cohesion** by analyzing cosine-similarity–based **continuity**, **relatedness**, **spread**, and **depth**, and assess feature **diversity** using the entropy of individual feature distributions.
- Measure **cross-positional engagement** by calculating the proportion of thread-level disagreements.
- Examine the association between discourse cohesion and cross-positional engagement through **regression** analyses.

Table 1: Logistic regression results examining the association between disagreement and discourse cohesion of the relational interaction between posts.

	Post-level disagreement
Standardized between-post similarity	0.326
Positive variables of feature diversity (toxicity, toxicity_prev, sentiment_prev, contrarian, contrarian_prev, stance_diff, domain_left, domain_right)	Yes
Negative variables of feature diversity (sentiment, politeness, politeness_prev, topic_diff)	Yes
Pseudo R-squared	0.078
N	231,042

Table 2: OLS regression results examining the association between thread-level discourse cohesion and cross-positional engagement (threads containing more than ten comments).

	Thread-level cross-positional engagement
Standardized continuity	0.095
Standardized relatedness	-0.032
Standardized spread	-0.009
Standardized depth	-0.038
Positive variables of feature diversity distribution (contrarian, toxicity, sentiment)	Yes
Negative variables of feature diversity distribution (topic, politeness)	Yes
Adjusted R-squared	0.277
N	5,370

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