# Adaptive Axes: A Pipeline for In-domain Social Stereotype Analysis

**Anonymous ACL submission**

## Abstract

Prior work has explored the possibility of using the semantic information obtained from embedding representations to quantify social stereotypes, leveraging techniques such as word embeddings combined with a list of traits (Garg et al., 2018; Charlesworth et al., 2022) or semantic axes (An et al., 2018; Lucy et al., 2022). However, these approaches have struggled to fully capture the variability in stereotypes across conceptual domains for the same social group (e.g., *black* in science, health, and art), in part because the identity of a word and the associations formed during pre-training can dominate its contextual representation (Field and Tsvetkov, 2019). This study explores the ability to recover stereotypes from the contexts surrounding targeted entities by utilizing state-of-the-art text embedding models and **adaptive semantic axes** enhanced by large language models (LLMs). Our results indicate that the proposed pipeline not only surpasses token-based methods in capturing in-domain framing but also effectively tracks stereotypes over time and along domain-specific semantic axes for in-domain texts. Our research highlights the potential of employing text embedding models to achieve a deeper understanding of nuanced stereotypes.

## 1 Introduction

Social stereotypes, representing the associations attributed to social groups (e.g., *White*, *Black*, *Religious*), are deeply embedded in and perpetuated by human languages. These stereotypes are both reflected in everyday language use and contribute to the reinforcement of societal biases. Consequently, a growing topic of interest in NLP is whether and how computational techniques can be used to quantify these associations at scale. Various methodologies have been developed to explore and measure these social biases in language. For instance, by calculating cosine similarities between the embeddings of traits (e.g., *unhealthy*, *weak*) and social groups within word embeddings (Garg et al., 2018; Charlesworth et al., 2022, 2023), researchers can uncover how stereotypes emerge and persist across society. Another related approach involves projecting social group embeddings along opposite semantic dimensions (i.e., semantic axes, such as *beautiful* - *ugly* (An et al., 2018; Lucy et al., 2022)) to reveal tendencies toward particular semantic dimensions, suggesting certain stereotypes.

Social stereotypes are multifaceted and can intersect across different social groups or vary across different domains. For instance, Burnett et al. (2020) investigated how racial stereotypes in the US persist in both academic and non-academic contexts, such as music and sports. Their research demonstrated that the same social group can be associated with different stereotypes depending on the domain. Similarly, Margaret Shih and Trahan (2006) found that Asian American women performed better on a verbal test when their female identity was made salient but performed worse when their Asian identity was emphasized. This finding suggests that domain-specific stereotypes significantly impact performance outcomes. Such complexity underscores the importance of understanding in-domain stereotypes, which are stereotypes specific to particular contexts or domains.

In-domain stereotypes are particularly challenging to analyze due to their contextual specificity and the interplay between different social dimensions. Lucy et al. (2022) attempted to address this by replacing target social group words with neutral words (e.g. “person") and projecting neutral words' contextual embeddings onto semantic axes. However, this approach often resulted in the neutral word's identity dominating the analysis, leading to similar semantic poles across different occupational categories before statistical filtering. In this work, we aim to develop a novel pipeline leveraging off-the-shelf LLMs and text embedding models to explore in-domain stereotypes. Our pipeline first enhances semantic axes in two ways: (1) To address the gap where existing broad semantic axes fail to capture domain-specific variations in stereotypes, we utilize LLMs to generate more comprehensive and relevant axes. This approach allows us to include important contextual nuances, such as *globalization - nationalism* in economic analyses. (2) Employing multiple pruning methodologies to refine existing semantic axes, ensuring inappropriate words are trimmed to avoid semantic confusion. Then, whereas prior work has calculated associations with semantic axes using token embeddings, we explore whether these associations can be better modeled by embedding the context surrounding a target entity mention. Using off-the-shelf text embedding models, we embed the context with target entity masked and adaptive semantic axes to measure group- and domain-specific stereotypes along these axes.

We conduct extensive evaluations using automatic validation metrics and human evaluators, demonstrating that: (1) text embedding models encode semantic axes with greater consistency compared to previous token-based embeddings from BERT; (2) our pipeline captures in-domain stereotypes that better align with human annotations compared to previous approaches; and (3) in a case study of US news discourse, our pipeline effectively captures general stereotypes, contrasts between countries, and changes in associational biases corresponding to real-world events along specific axes of interest. Our results show that this innovative approach allows for a more nuanced and precise understanding of stereotypes within specific domains.

## 2 Background and Related Work

### 2.1 Using NLP for Social Biases Analyses

Social stereotypes are widely encoded within natural languages. Traditional methods for eliciting social stereotypes, such as human surveys (Williams and Best, 1990) or dictionary analysis (Henley, 1989), are limited in scale. The advent of word embedding models, which quantitatively capture word associations, introduced a new approach. Garg et al. (2018) used decade-wise word2vec models trained on *Google Books* (Michel et al., 2011) and the *Corpus of Historical American English (COHA)* (Davies, 2012) to investigate temporal gender and ethnic biases, showing that stereotypes about women correlate with social movements. Similarly, Charlesworth et al. (2022) and Charlesworth et al. (2023) extended this research to 14 social groups, covering periods from 1800 to 1999, and used valence scores to track the positivity/negativity of stereotypes toward different social groups over time.

Semantic axes are a related but alternative approach initially proposed by An et al. (2018). Their framework involves three steps: constructing word embedding models, identifying semantic axes of interest, and projecting targeted words onto these axes to reveal specific associational stereotypes. Semantic axes are advantageous due to their interpretability along human-curated dimensions, allowing for a clear and intuitive comparison of how different groups are perceived along a particular semantic dimension. Lucy et al. (2022) extended this concept to contextualized embedding models, demonstrating their better alignment with human judgments over static embeddings. Both works rely on off-the-shelf knowledge graphs, such as ConceptNet (Speer et al., 2017) and WordNet (Miller, 1995), to construct semantic axes. While these knowledge graphs offer comprehensive synonym pairs, they are grounded in a manually curated, general-purpose ontology that is fixed; in contrast, we aim to capture domain-specific associations.

### 2.2 Text Embedding Models and Social Computing

The development of LLMs has advanced the representation of sentence- or paragraph-level text into fixed-size embeddings, facilitating the retrieval of relevant texts and clustering of similar semantic contents. For instance, SentenceBERT (Reimers and Gurevych, 2019), fine-tuned with natural language inference (NLI) data, and recent LLM-based embedding models fine-tuned using synthetic data (Wang et al., 2024; Meng et al., 2024) have demonstrated extraordinary performances in retrieval and textual similarity tasks, as evidenced by their success on the MTEB leaderboard (Muennighoff et al., 2023).

Despite the potential of text embedding models to significantly enhance social computing across various disciplines, their application in this field remains an open question. For example, Licht (2023) demonstrated the capabilities of multilingual embedding models in political text classification, while Libovický (2023) showed that these models could encode biases related to jobs and occupational locations. In this paper, we investigate

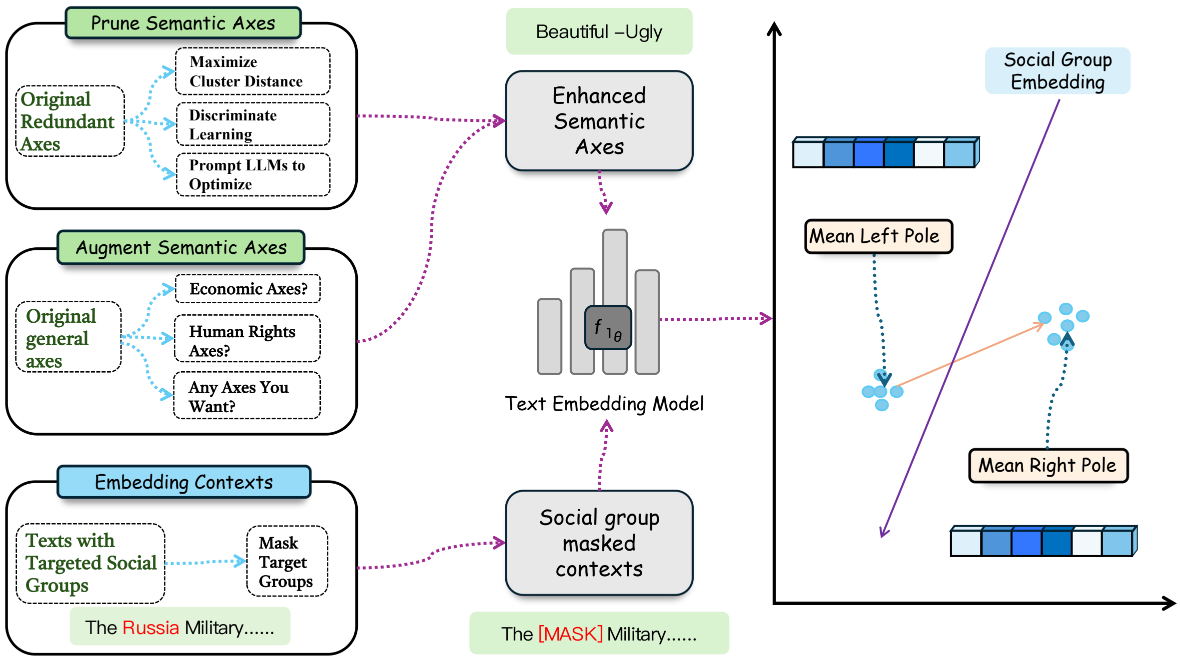


Figure 1: The Adaptive Axes Pipeline. We use text embedding models as our core mechanism for social stereotype analyses, projecting context-only embeddings with the target group masked onto semantic axes. We also develop pruning methods to refine semantic axis seed sets and generate new domain-specific axes with LLMs.

whether sentence representations can effectively recover in-domain stereotypes by encoding contexts, thereby further exploring the potential of text embeddings in social computing.

## 3 Proposed Pipeline – Adaptive Axes

In this section, we describe our Adaptive Axes pipeline. Specifically, the construction of semantic axes relies on three main steps - (1) building embedding models, (2) building semantic axis poles and getting semantic axis vectors, and (3) projecting target vectors on semantic axes to show stereotypes. Our study revisits these steps, aiming to construct a pipeline with high generalizability and accuracy. Our general framework is shown in Figure 1.

### 3.1 Embedding Model Constrution

The construction of semantic axes relies on high-quality embedding models capable of capturing nuanced semantic differences. Previous approaches, such as those by An et al. (2018) and Mathew et al. (2020), utilized static embedding models like `word2vec` or `Glove`, which often fail to capture antonym relations and are unsuitable for contextualized tasks. Lucy et al. (2022) filtered Wikipedia and used up to 1,000 sentences per adjective to obtain average contextualized embeddings, requiring high-quality text instances for effective embedding construction.

In contrast, our study explores whether off-the-shelf text embedding models can effectively construct semantic axes. We propose two key advantages of using text embedding models: (1) models fine-tuned through techniques such as contrastive learning on base models are likely to excel at distinguishing nuanced semantic differences, which is crucial for semantic axes construction; (2) these models can encode short phrases directly without relying on extensive text instances, making semantic axes easily generalizable to any specific phrases. Therefore, we employ text embedding models that perform well on the semantic textual similarity (STS) task of the MTEB leaderboard (Muennighoff et al., 2023) as our backbone models for further analyses. This approach leverages their advanced capabilities to enhance the construction and application of semantic axes in various tasks.

### 3.2 Semantic Axes Enhancement

In this work, we propose to augment existing approaches using semantic axes in two ways. First, we prune axes to improve interpretability and enhance semantic contrast. Second, we go beyond fixed lists of axes by generating new, domain-specific axes tailored to particular contexts.

The quality of the semantic axis poles is crucial as it directly influences the semantic contrastiveness of the axes, thereby affecting the quality of the semantic axis vectors. An et al. (2018) used 732 predefined single-word antonym pairs from ConceptNet and enhanced both poles by adding the top-$N$ similar words from the embedding model to ensure greater robustness. In contrast, Lucy et al. (2022) utilized WordNet, which consists of 723 axes with each pole averaging 9.63 adjectives. This approach can lead to unwanted meanings across both poles. For example, one example of the semantic axis of WordNet is:

- Left poles: animal, bodily, carnal, corporal, corporeal, fleshly, material, personal, physical, physiologic, physiological, sensual, somatic
- Right poles: intellectual, mental, moral, noetic, psychic, psychical, psychogenic, psychological, rational

We observe that while these axes exhibit some reasonable semantic coherence, they may also be quite broad in their semantic scope. For example, the left pole includes the term "animal," which is quite general, and the right pole includes "psychogenic," which is relatively rare. Additionally, the large number of terms on both poles could make interpretation challenging. To improve the semantic axes, we propose three methods to prune inappropriate words from the semantic axis poles in WordNet:

**Cluster Distance Maximization** We start by independently clustering the embeddings for the two poles. Employing Euclidean distance as our metric, we iterate through all possible combinations to assess the contrasts between the two sets of embeddings. Ultimately, we select the poles with the greatest inter-group distance to construct the pruned axis.

**Using Discriminative Learning** This method utilizes support vector machines (SVMs), a supervised learning algorithm designed for classification tasks, to distinguish between two distinct groups of embeddings by framing it as a binary classification problem. The method involves progressively removing vectors that have minimal influence on the separability of the two embedding clusters, as determined by their effect on the classification margin. This iterative pruning continues until the clusters stabilize, evidenced by a cessation in the growth of the inter-cluster distance. Upon convergence, these refined clusters are employed to establish the final axes.

**LLM Evaluation** We instruct LLMs to analyze the existing exhaustive semantic axes in WordNet. The LLMs are guided to trim both poles in a way that preserves the semantic contrasts of the original seed adjectives. This process ensures that the refined poles retain their distinctiveness and relevance. Our prompt template, which directs the LLMs in this task, is detailed in Appendix A.1. The LLM-generated semantic poles are then used to construct the final semantic axes.

### 3.3 Domain-Specific Axes Augmentation

As highlighted earlier, traditional semantic axes often struggle to adapt to new domain-specific contexts, crucial for analyzing shifts in stereotypes within particular domains. To address this, our study introduces a method to generate domain-specific semantic axes, such as *peaceful protests* versus *military intervention*, using LLMs. We aim to create a specific number of axes, tailored to the needs of each domain, which could be embedded directly using text embedding models. To offer a clear example of this process, our prompt template is presented in Appendix A.2. This approach enables the dynamic creation and adaptation of domain-specific semantic axes, providing a concrete advancement in monitoring subtle shifts in stereotypes.

### 3.4 Stereotype Understanding with Text Embedding Models

Previous studies have typically used token embeddings of target social groups (e.g., static or contextual embeddings of *Black* or *Old*) for stereotype analysis. Although the neutral word approach could extract contextual differences across domains after statistical filtering, the stereotypes derived from contextual differences in Lucy et al. (2022) closely correlate with original token-based stereotypes. This indicates that well-encoded contexts are sufficient for understanding stereotypes, thereby reducing the reliance on social group biases within pre-training data.

Thus, we aim to exploit the context in contextual embeddings, rather than relying solely on token representations, to gain more detailed and domain-specific insights from various text sources. Our method involves extracting the context around specific social groups and masking their appearances in the text to obtain context embeddings, as shown in Figure 1. We then project these embeddings onto constructed semantic axes to identify stereotypes associated with different social groups across various domains.

## 4 Pipeline Validation

In this section, we present a series of experiments validating the effectiveness of our pipeline in two key areas: (1) Do text embedding models encode semantic axes effectively? (2) Does our pipeline capture stereotypes closely aligned with human intuitions? Additionally, we conduct experiments to understand whether target-masked text embedding models could accurately predict affective information in Appendix B.

To address the first question, we use `UAE-large-v1` (Li and Li, 2023), a model fine-tuned with `BERT-large`, and `SFR-Embedding-Mistral` (Meng et al., 2024), based on `Mistral-7B` (Jiang et al., 2023), representing two lines of advanced text embedding models. These models help us evaluate the capability of text embedding models in encoding semantic axes. In the second question, to avoid modeling the specific word of interest directly, we employ attention masks and consistently use 20 tokens around the target token (or all available tokens if fewer than 20) for context modeling.

To introduce more domain-specific semantic axes, our study uses GPT-4 (OpenAI et al., 2024) to generate 13 new axes in the following domains: *politics and governance*, *global trade and economics*, and *culture and education*. These domain-specific axes enable a more precise analysis of stereotypes and their variations across different contexts. Our domain-specific semantic axes are attached in Appendix C.

To effectively classify news articles in the News on the Web corpus (Davies, 2022) into various categories to mine domain-specific stereotypes, we use the zero-shot classification system (Yin et al., 2019) and a list of candidate labels (*global trade and economic*, *politics and governance*, *cultural and education*, and *none of above*) to classify US news articles. We manually annotate 100 random news articles and find a classification accuracy is 82%, sufficient to scale across the corpus.

### 4.1 Validation of Semantic Axes Construction

In this section, we first investigate whether text embedding models can capture the meanings of different poles (i.e., antonyms) within semantic axes, following a methodology similar to Lucy et al. (2022). We remove one word from either pole and compute the cosine similarities to the axis constructed from the remaining words. If a semantic axis is consistent, the left-out word should be closer to the pole to which it originally belongs. We average these leave-one-out similarities for each pole to produce a consistency metric, $C$. An axis is considered "consistent" if both poles have $C \geq 0$.

| **Models** | **Average $C$** | **Number of Consistent Axes** |
|---|---|---|
| GLOVE | 0.101 | 503 |
| BERT-prob$^{z}$ | 0.133 | 512 |
| UAE-large-v1 | 0.120 | 603 |
| SFR-Embedding-Mistral | **0.153** | **712** |
| **Pruning Methods** | **Average $C$** | **Number of Consistent Axes** |
| Cluster Distance Maximization | 0.148 | 641 |
| Using Discriminative Learning | 0.106 | 522 |
| LLM Evaluation | 0.107 | 537 |

Table 1: Top: The results of different models' consistency $C$ and the number of consistent semantic axes. A higher consistency or number of consistent axes represents a better encoding of semantic contrasts.
Bottom: The results of the pruned semantic axes based on `UAE-larve-v1`.

For a fair comparison, we first use the same data as Lucy et al. (2022) to evaluate semantic axes derived from different models. The results, shown in Table 1, indicate that contemporary text embedding models embed semantic axes much better than corpus-curated semantic axes using the original BERT. These findings suggest that using off-the-shelf sentence encoders to embed semantic axes is a rational approach, leading to a larger number of consistent axes and comparable consistency with the best results reported by Lucy et al. (2022). We then further prune the semantic axes only based on `UAE-large-v1` due to the large computational requirements of `SFR-Embedding-Mistral`, with the results presented in the second half of Table 1. Only the method of maximizing the cluster distance leads to positive improvements, thus we use the pruned axes in further analyses.

To evaluate the relevance of our novel domain-specific axes, we propose that they should have a relatively high variance in that domain of texts compared to general semantic axes used in prior work. We project entity-masked context embeddings from different domains onto semantic axes and rank axes according to their cosine similarity variances. We use the average percentile ranking by variance of these entity embeddings for the domain-specific axes as a quantitative measure to evaluate

| Domains | Average Variance Ranking |
|---|---|
| Politics and Governance | 6.4% |
| Global Trade and Economics | 9.7% |
| Cultural and Education | 10.3% |

Table 2: The average variance ranking measures the in-domain average percentile rank by mean variance for our evaluation set of augmented semantic axes compared to WordNet-based axes. Lower numbers indicate better performance. Our domain-specific axes generally fall within the top 10% when ranked by variance, suggesting they capture significant variation in the domain-specific representation of entities.

| Model | Average Ranking |
|---|---|
| Random Baseline | 2.4 ($\pm$0.227) |
| Token-based Embedding | 1.925 ($\pm$0.217) |
| Entity-masked Context Embedding (ours) | 1.675 ($\pm$0.177) |

Table 3: Human-evaluated rankings for three types of pipelines, where the ranking ranges from 1 to 3, with lower numbers indicating better performance. Confidence intervals are shown in parentheses.

whether these axes are meaningful in that domain. The results are shown in Table 2, indicating that entity embeddings along these domain-specific axes show high in-domain variance, suggesting they can capture meaningful domain-specific variation.

### 4.2 Validation of the Pipeline

Previous sections validate the text embedding model's capacity to encode semantic axes. In this section, we validate the practical step - how can our pipeline understand domain-specific stereotypes compared to previous models?

We construct an annotation task in which for each run we obtain three sentences which include `China/Chinese`, `Mexico/Mexican`, or `Canada/Canadian` in the **political** and **cultural** domains from the News on the Web corpus (Davies, 2022). Then these sentences go through three pipelines - **ADAPTIVE AXES**, contextualized token-based semantic axes (Lucy et al., 2022), and a randomized baseline model which samples five seed words from semantic poles. We recruited 20 participants from the crowdsourcing platform Prolific to rank the three models in $3 \times 2 = 6$ questions. A Kendall's $W$ metric is calculated to understand to what extent participants agree on the rankings of these three models. Our interface is shown in Appendix A.3.

The final results of the averaged ranking are shown in Table 3, indicating that in most cases ADAPTIVE AXES helps to capture domain-specific semantic associations with the highest ranking and a reasonable inter-annotator agreement (Kendall's $W = 0.58$).

## 5 Case Study #1

In this section, we turn to real-world case studies with ADAPTIVE AXES to ask one research question: how are different countries generally framed across various domains in US news discourse?

### 5.1 Data

This study uses the US news subset of the NOW corpus (Davies, 2022) ranging from June 2010 to August 2023 and further filters news articles with target countries and citizens nouns (e.g. France and French) in the news title to avoid scrolling news without extensive target information. We cover four countries (China, Russia, Germany, and Canada), in which China and Russia are frequently framed as competitors with the US, and Germany and Canada are often depicted as allies. The detailed number of news articles for each category of each country is attached in Appendix D.

### 5.2 Results

**Observation #1: ADAPTIVE AXES can model general social stereotypes** In Table 4, we list the top 3 semantic axes associated with different countries in different domains. Although quantitative evaluation is hard to conduct, most semantic axes retrieved from our pipeline align well with general stereotypes. For example, in the *politics and governance* domain, the word *electoral* is closely correlated with Germany and Canada. In contrast, the opposite side of *electoral* - *authoritarian* is mostly used to depict China and Russia. Another meaningful difference here is in the *global trade and economic* domain - in which our pipeline correctly captures the stereotypes about China being the "world factory" and having a mass amount of workers (Zhang, 2006). The axes "antimonopoly" and "market economy" also correctly capture the economic impressions of Germany (Marktanner, 2014; Yamazaki, 2019). These associations suggest that modeling contexts does robustly uncover meaningful associational differences across social groups and domains.

One main disadvantage here is that no matter what kind of semantic axis is used, all semantic axes capture the co-occurrences of different words or contexts rather than the direct causal associa-

| Countries | Domains | Top Semantic Axes | | |
|---|---|---|---|---|
| China | Global Trade and Economic | overseas | industrious, untiring | factory-made, mass-produced |
| | Politics and Governance | socialized | authoritarian | asymmetric |
| | Culture and Education | ethnical | self-conscious | authoritarianism |
| Germany | Global Trade and Economic | overseas | antimonopoly | market economy |
| | Politics and Governance | electoral | democratic | nationalistic |
| | Culture and Education | historical | labor-intensive | ethnical |
| Russia | Global Trade and Economic | overseas | ploughed | state control |
| | Politics and Governance | authoritarian | corrupt | rebellious |
| | Culture and Education | dictatorial | culture exclusivity | blue-collar |
| Canada | Global Trade and Economic | overseas | profitable | blue-chip, valuable |
| | Politics and Governance | soft power | electoral | nationalistic |
| | Culture and Education | north | time-honored | multiculturalism |

Table 4: Top semantic axes associated with different countries in each domain.

| Contrastive Groups | Domains | Semantic Axes |
|---|---|---|
| China vs. Canada | Trade | inequality, warlike |
| China vs. Germany | Politics | foresighted, left-wing |
| Canada vs. Germany | Culture | emotionless, native |

Table 5: Contrastive semantic axes associated with the former social groups. The semantic axes represent the more salient associations with the former country relative to the latter.

tions. For example, in the economic and trade domain, all countries have close associations with the *'overseas'* axis, which represents one general property of trade rather than domain-specific stereotypes, suggesting that although our approach can capture more general domain shifts in stereotypes, any identified associations still need to be interpreted with caution.

**Observation #2: ADAPTIVE AXES can (partially) capture contrastive stereotype changes across social groups** Will this pipeline generalize to contrastive stereotypes? For example, what are the main differences in semantic associations between China and Canada in the domain of trade and economics? To answer this question, we calculate the two groups' top semantic axes and corresponding scores, respectively, and use the differences to represent their contrastive axes.

The top two semantic axes associated with example contrastive groups are shown in Table 5. These results suggest that our pipeline, by contrast to semantic axis scores, can at least partially represent the crucial differences between groups. For example, between China and Canada, the pipeline successfully captures the tension between the US and China - emphasizing the inequality of trade dynamics and finally leading to trade wars in 2017 (Kwan, 2020). Additionally, the *left-wing* in China vs. Germany around politics represents a general description of Chinese politics (Chen et al., 2012), and the *native* in Canada vs. Germany contrast, which captures the closer cultural alignment between the US and Canada than Germany. These results suggest that domain-specific contexts could capture contrastive differences between various countries.

# 6 Case Study #2

One main theoretical advantage of our pipeline is that it can embed any new intended semantic axes which are words or phrases easily. Further, we show that these domain-specific axes represent relatively big variances among all axes for in-domain texts. In this section, we dive into a case study in which we use new LLM-curated axes and quantify temporal changes along the new axes. Do these new axes quantify social framing well? How do these axes correspond to real-world events?

## 6.1 Background and Data

In March 2018, the USA announced the sanctions against China based on Section 301 of the US Trade Act due to dissatisfaction with China's "unfair trade practices" (Kwan, 2020). One of the central claims behind this is that China was implementing trade protectionism despite its claimed free trade. In this perspective, we create two new semantic axes *open markets, free trade - trade barriers, protectionism*, and *market economy, capitalism - planned economy, socialism* which directly fits this scenario to show the US news discourse changes. We use the data from the NOW corpus classified as economic and trade in the last section.

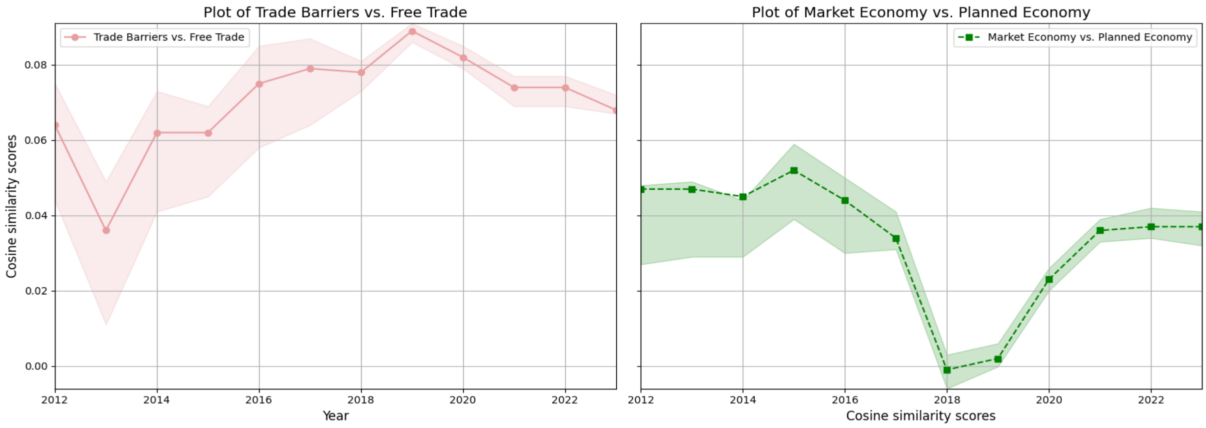


Figure 2: The cosine similarity score changes for two LLM-curated semantic axes. Left: a higher score means inclining to *trade barriers*. Right: a higher score means inclining to *market economy*. The color-filled parts represent 95% confidence intervals.

### 6.2 Results

**Observation #3: ADAPTIVE AXES can model temporal social stereotype changes** The results from 2011 to 2023 are shown in Figure 2. The score trend clearly captures the trade tensions between China and the US. The inclination toward trader barriers side experienced a sudden jump at the point of 2018, accurately corresponding to the timeline when the US exerted sanctions on Chinese goods. The relatively high scores inclining to trade barriers after 2018 also correspond to the fact that the trade tensions between China and the US have been constant since then. The results of the second axis also suggest the changes in framing over time. China's economic system has long been considered a hybrid between a market economy and a planned economy with an inclination toward the planned side (Miranda, 2018). Similarly, we witnessed a quick drop and then a gradual rise after 2018, which also aligns with the trade tensions timeline and the claims about 'the Chinese government manipulating the economy' during that time. These results, as a whole, suggest that our pipeline, which uses contexts as the center, could transfer to human-curated well-constructed semantic axes well and capture real-world social dynamics.

## 7 Discussion

In this paper, we develop a new pipeline centering around text embedding models to encode augmented semantic axes and news discourse contexts around target social groups altogether, then project context embeddings to semantic axes embeddings for understanding the internal stereotypes.

Understanding social stereotypes is a multifaceted process. Recent research has delved into how intersectional social stereotypes — those arising at the intersection of different social groups — have evolved in various text sources (Charlesworth et al., 2024). In this work, we identify that text sources are themselves multifaceted, encompassing diverse social domains such as culture, politics, and economics, and diverse repositories such as Google Books, COHA, and Common Crawl (Charlesworth et al., 2023). This diversity leads to a complex amalgamation of social stereotypes within word embedding models. We deconstruct the complexity of these text sources by categorizing them into different domains and utilize our pipeline to demonstrate the framings of social groups vary widely across these domains. Our findings advance the discussion of nuanced stereotype understanding by highlighting the intricate and fine-grained nature of text sources.

Our pipeline extends the advantages of existing semantic axes by using text embedding models to encode arbitrary semantic axes, and the semantic accuracy of text embedding models makes axes more consistent in understanding semantic nuances. However, our pipeline still focuses on the co-occurrences within texts. For example, the *overseas* in the trade domain. Additionally, Canada is also closely associated with *north/northern* ranked by cosine similarity scores, indicating the general geographical positions rather than stereotypes. This implies the necessity to effectively retrieve stereotype languages targeting specific social groups. We leave this for future work.

## Limitations

We identify two main limitations of this work.

**Consistency Metric for Semantic Axes** In this work, we use the consistency metric, which measures whether two poles of each semantic axis are well-separated from each other. Although Lucy et al. (2022) showed that models with higher consistency would generally have better human voting preferences, there still lacks one clear metric to evaluate whether one semantic axis is meaningful in both semantic spaces and sociocultural scenarios. Thus, the evaluation in this work only represents the capability of embedding models to separate contrastive semantic terms in vector space. A better and more comprehensive way to construct semantic axes is still needed.

**Framing vs. Stereotypes** In this work, we use the word 'stereotype' to describe the associations retrieved from semantic axes. We note that there is a potentially ill-defined boundary between stereotypes and the adjacent concept of framing. "Framing" can occur at the level of individual instances, while "stereotype" necessarily refers to a more generalized set of associational biases or rather the large-scale accumulation of instances of framing. In our human annotation task, we evaluate the relevance of associated axes with reference to three concrete sentences, which is therefore potentially better described as framing. Nevertheless, we maintain the vocabulary of stereotyping throughout since our ultimate goal is the extraction of large-scale, generalizable associational biases.

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# A Prompt Templates and Interfaces

In this section, we show the prompt templates and the annotation interface we use throughout our study.

## A.1 The Prompt Template for Pruning Semantic Axes

```
Background:
Semantic axes are essential in the analysis of interpretable embeddings, aiding in the visualization and understanding of relationships between various concepts. These axes are defined by pairs of contrasting groups of terms, representing opposite ends of a spectrum. For effective analysis, it's important that these axes are clear, concise, and focused.

Task:
You are tasked with refining a list of semantic axes. Each axis is currently represented by a pair of contrasting term groups. Your objectives are to:
1. You will see one seed adjective, which represents the central word of this semantic axis. Each seed adjective has a list of synonyms and a list of antonyms.
2. You should read and understand the semantic contrasts and eliminate uncommon or irrelevant terms that do not contribute to the core meaning of each group.
3. Ensure the seed adjective exists in the final optimized axis.

Instructions:
1. You will get a seed adjective, a list of left poles, and a list of right poles.
2. Do not introduce new axes or significantly change the existing ones beyond recognition.
3. Make sure the revised axes maintain their original intent but are articulated in a more succinct manner.
4. Return the axes in the same format: the seed adjective as one word, and left and right poles as two lists of strings.
5. Only return the optimized axes without any rationales.
6. Ensure that each side of the semantic axis distinctly represents one pole of a concept without any overlap of contrasting terms.

Example:
Original axes:
seed_adjective = "heavy"
left_pole = ['dense','doughy','heavier-than-air','heavy','hefty','massive','ponderous','soggy']
right_pole = ['airy','buoyant','floaty','light','lighter-than-air','lightweight','low-density']

Optimized axes:
seed_adjective = "heavy"
left_pole = ['dense', 'heavy', 'massive', 'ponderous']
right_pole = ['airy', 'light', 'buoyant']

Now do this:
Original axes:
seed_adjective = "{seed_adjective}"
left_pole = {left_pole}
right_pole = {right_pole}

Optimized axes:
```

Figure 3: The prompt template to prune the existing semantic axes.

## A.2 The Prompt Template for Generating Domain-specific Semantic Axes

Background: Semantic axes are utilized to interpret concept spaces, particularly within distinct domains. They facilitate the visualization and understanding of relationships between diverse terms by positioning them on contrasting ends of a conceptual continuum. These axes typically consist of opposing groups of terms that epitomize the extremities of a recognizable spectrum within a particular field.

Task: Create domain-specific semantic axes tailored to the {*domain*} sector.

Instructions:
1. Format the semantic axes as [('Term1A', 'Term1B', 'Term1C', ...), ('Term2A', 'Term2B', 'Term2C', ...)], where each tuple forms one semantic axis with two contrasting poles.
2. Tailor the axes specifically to the {0} domain, reflecting its unique concepts and terminology.
3. Utilize nouns or adjectives for constructing the axes, steering clear of verbs to maintain clarity and uniformity.
4. Employ phrases or compound terms to accurately represent complex domain-specific concepts when necessary.
5. Develop a comprehensive array of axes to cover a wide range of domain-specific concepts, ensuring that each axis is distinct and relevant without any overlapping meanings.
6. Important: Each line of your output should represent one individual axis, clearly distinguishing between contrasting concepts.
7. Ensure that each side of the semantic axis distinctly represents one pole of a concept without any overlap of contrasting terms.

Example 1 (General Semantic Axis):
[('heavy', 'dense'), ('light', 'airy')]

Example 2 (Domain-Specific for Political Science):
[('left-wing'), ('right-wing')]
[('liberal', 'radical'), ('conservative', 'traditional')]
......

Now, create optimized semantic axes for the domain of {*domain*}, following these guidelines and ensuring each line in your output represents one distinct semantic axis:

Output:

Figure 4: The prompt template to generate domain-specific semantic axes.

### A.3 The Annotation Interface of Human Judgments

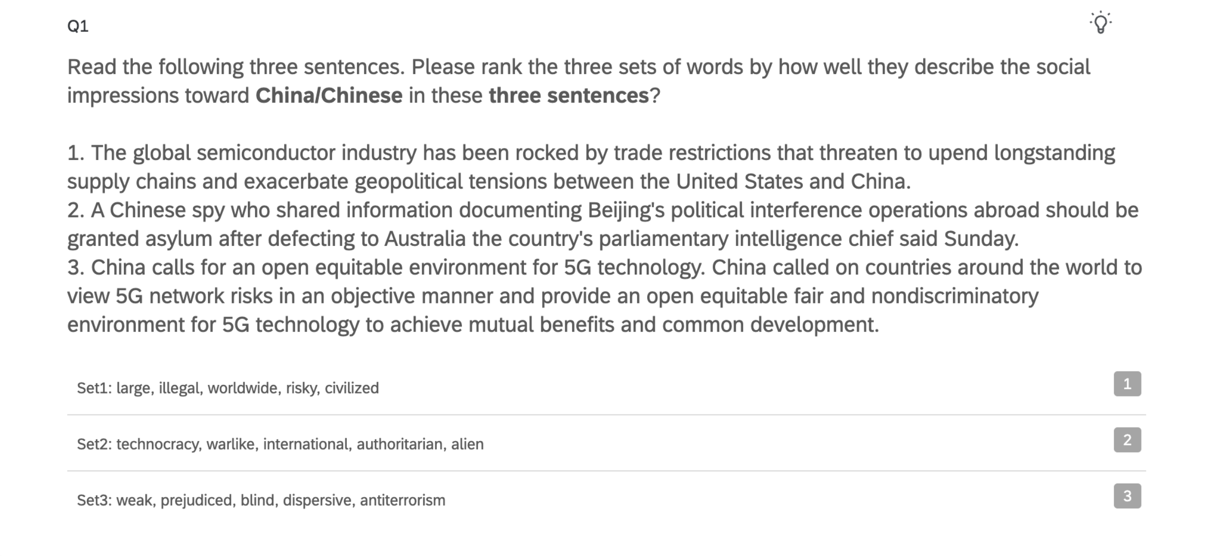


Figure 5: This is the interface we use for human annotators to rank the framing from various pipelines. The annotators are asked to rank 1/2/3 in this task.

## B The Evaluation of Affective Information Understanding

In this section, we conduct a side experiment to evaluate whether entity-masked context embedding could recover affective information better than token-based embeddings. Given this study is not directly associated with stereotypes, we attach the experimental procedure in the Appendix.

### B.1 Background about Affective Lexicons

Russell (2003) classified word meaning into three factors - *valence* (positiveness – negativeness / pleasure – displeasure), *arousal* (active - passive), and *dominance* (dominant - submissive) and this has long been the general principle to construct affective lexicons. For example, Mohammad (2018) constructed a comprehensive VAD lexicon with scores for 20,000 English words ranging from 0 to 1 using best-worst scaling.

### B.2 Can Large Language Models Generate Human-aligned Affective Information?

To verify whether LLMs can generate sentences with accurate valence scores for target words, we first need to evaluate whether LLMs can generate human-aligned affective information. To achieve this, we design a multi-LLM-in-the-loop strategy to guarantee that our annotations are not closely inclined to one specific LLM's values and emotional understandings. We use six seed annotations to elicit LLMs' emotional reasoning capacities, then we ask multiple LLMs (QWen1.5-72B (Bai et al., 2023), GPT-4 (OpenAI et al., 2024), LLaMA2-70B-Instruct (Touvron et al., 2023), DeepSeek-Chat-V2 (DeepSeek-AI et al., 2024), Mistral-7B (Jiang et al., 2023)) to generate affective values for all semantic units. Finally, we prune the highest and the lowest values for each semantic unit and average to get the multi-LLM-collaboration affective scores. Our prompts are detailed in Figure 6.

To validate whether our newly generated affective scores accurately reflect human-level affective understanding, we randomly choose 50 semantic units not in the original VAD lexicon and ask three individual annotators to perform similar reasoning procedures to what LLMs do. We average these three annotations to get human-annotated affective scores for three dimensions. Then, we calculate Pearson's correlation coefficient to show whether multi-LLM collaboration generates human-aligned affective values.

Our results are shown in Table 6. The correlation for *arousal* is the highest at 0.86, and the lowest is *dominance* at 0.78. The statistical significance suggests that multi-LLM could approximate human-level affective annotations really well. Similarly, Nilsson et al. (2024) reported results of using LLMs to automatically annotate implicit motives, suggesting that LLMs could generate as accurate as humans and 99% cheaper. Our results further contribute to this field and show the great potential of using LLMs for quantifying affective information.

| Affective Dimensions | Correlation |
|---|---|
| Valence | $0.82^{**}$ |
| Arousal | $0.86^{**}$ |
| Dominance | $0.78^{**}$ |

Table 6: The Pearson correlation score between LLM judgments and human judgments. The asterisks represent statistical significance.

### B.3 Validation of Affection Understanding

If embedding contexts leads to robust affective understanding, contextual text representations should approximate valence scores, which measure the intrinsic attractiveness or averseness of a word, at least as accurately as target token representations. In this study, we first demonstrate that LLMs can generate human-aligned valence, arousal, and dominance scores. We then randomly sample 1,000 words from our semantic axes and prompt LLMs to generate two sentences under two scenarios: (1) a sentence reflecting the general use of the word, and (2) a sentence reflecting a human-curated valence score, randomly sampled from the other half of the (0,1) range to represent a non-general use of the word. For example, for the word *abandon*, the two sentences are:

(1) The feeling of being **abandoned** by someone you love can be utterly devastating, filling your heart with sorrow and despair. *(Valence - 0.05)*

(2) When you decide to **abandon** a toxic relationship, it marks the beginning of a positive transformation and personal growth. *(Valence - 0.7)*

in which the same word in different sentences conveys different affections. We manually checked the generated 1,000 sentences and removed 87 inappropriate sentences.

We get the target word's token embedding and the contextual embedding around the target word. Then, two kernel ridge regression models will be fitted on 700 training sentences. We use the adjusted $R^2$ to determine which better predicts the affective annotations on the remaining 213 sentences. Our results are shown in Table 7, indicating that well-trained text embedding models could predict affective annotations better than token-based embeddings, which are not intended for in-domain use. These results also partially correspond to Field and Tsvetkov (2019) and further reveal the potential of using text embedding models to understand specific social stereotypes.

## C Domain-specific Semantic Axes

**Global Trade and Economics:**
Free Trade, Open Markets - Protectionism, Trade Barriers
Market Economy, Capitalism - Planned Economy, Socialism

```
### Background:
In social psychology, research has expanded on the understanding of human emotions and perceptions through various dimensions, notably including valence, arousal, and dominance. These dimensions are instrumental in constructing lexicons that quantify the emotional and perceptual connotations of words. Valence reflects the intrinsic positivity or negativity of the emotional tone a word conveys. Arousal refers to the level of alertness, wakefulness, and activation caused by stimuli in an individual. Dominance relates to the extent of control or influence one entity or process exerts over others within a particular context or interaction.

### Task Description:
Your objective is to extrapolate values for new words or phrases based on given lexicon entries. These entries list words along with their respective scores for valence, arousal, and dominance, providing a quantitative insight into their emotional and perceptual significance.

### Instructions:
1. Utilize reasoning over the provided scores to generate corresponding values for new words or phrases.
2. Scores for valence, arousal, and dominance range from 0 to 1, where 0 represents the minimum and 1 the maximum possible value for each dimension.

### Example Lexicon Entries:
| Word          | Valence | Arousal | Dominance |
|---------------|---------|--------|------------|
| able          | 0.939   | 0.510  | 0.769      |
| abusive       | 0.125   | 0.903  | 0.567      |
| belligerent   | 0.344   | 0.680  | 0.594      |
| cunning       | 0.604   | 0.685  | 0.683      |
| sentimental   | 0.583   | 0.378  | 0.312      |
| unsympathetic | 0.163   | 0.620  | 0.281      |

### Task:
Generate valence, arousal, and dominance values for the phrase: **"{}"**.

**Format for Response:**
Provide your response in the following format to ensure clarity and facilitate straightforward information extraction:

- **Phrase**: The word or phrase being analyzed.
- **Valence**: [Your estimated value], with a brief explanation.
- **Arousal**: [Your estimated value], with a brief explanation.
- **Dominance**: [Your estimated value], with a brief explanation.
```

Figure 6: The prompt to use multiple LLMs to annotate affective dimensions automatically.

| Regression | | | |
|---|---|---|---|
| Model | Valence Score | | |
| | general | non-general | total |
| BERT-Large | 0.62 | 0.39 | 0.44 |
| UAE-Large-V1 | 0.64 | 0.58 | 0.60 |

Table 7: The Pearson correlation between predicted valence scores and silver valence scores.

Globalization, International Integration - Localization, Economic Self-sufficiency
Economic Liberalization, Deregulation - State Intervention, Regulation
Innovation, Technological Advancement - Traditionalism, Preservation
**Politics and Governance**
Authoritarianism, Totalitarianism - Democracy, Republic
Centralization, Federal Authority - Decentralization, Local Autonomy
Political Transparency, Political Openness - Political Secrecy, Political Opaqueness
Individual Rights, Personal Freedom - Collective Good, Social Responsibility
Progressivism, Social Reform - Conservatism, Tradition
**Cultural and Education**
Cultural Homogeneity, Monoculture - Cultural Diversity, Multiculturalism
Cultural Openness, Inclusivity - Cultural Exclusivity, Preservation
Global Culture, Cross-Cultural Exchange - Local Culture, Indigenous Practices

## D Numbers of News Articles

| Country Name | Total Number of News Articles | Categories | The Number of In-category News Articles |
|---|---|---|---|
| China | 63431 | Politics and Governance | 10550 |
| | | Global Trade and Economics | 4940 |
| | | Culture and Education | 7402 |
| | | None of the Above | 40539 |
| Canada | 17694 | Politics and Governance | 1046 |
| | | Global Trade and Economics | 1294 |
| | | Culture and Education | 3804 |
| | | None of the Above | 11550 |
| Germany | 17256 | Politics and Governance | 2233 |
| | | Global Trade and Economics | 909 |
| | | Culture and Education | 3026 |
| | | None of the Above | 11088 |
| Russia | 52377 | Politics and Governance | 28770 |
| | | Global Trade and Economics | 1644 |
| | | Culture and Education | 3906 |
| | | None of the Above | 18057 |

Table 8