The Medium Is Not the Message: Deconfounding Document Embeddings via Linear Concept Erasure

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Abstract

Embedding-based similarity metrics between text sequences can be influenced not just by the content dimensions we most care about, but can also be biased by spurious attributes like the text's source or language. These document confounders cause problems for many applications, but especially those that need to pool texts from different corpora. This paper shows that a debiasing algorithm that removes information about observed confounders from the encoder representations substantially reduces these biases at a minimal computational cost. Document similarity and clustering metrics improve across every embedding variant and task we evaluate—often dramatically. Interestingly, performance on out-of-distribution benchmarks is not impacted, indicating that the embeddings are not otherwise degraded.[1]

1 Introduction

Suppose a political scientist is studying U.S. political discourse. They have access to two data sources: Twitter posts from senators and summaries of congressional bills. A natural first step in data exploration is to embed the texts (e.g., with a sentence transformer; Reimers and Gurevych 2019) and then cluster them (e.g., with k-means). However, some clusters will predominantly contain items from one source or the other, because systematic differences between sources dominate the distances that k-means relies on (Fig. 1A).

Text embeddings, generated by pretrained models, capture a wide range of information about text, including topical, semantic, stylistic, multilingual, and syntactic features. These models are typically trained with the goal of "making semantically similar sentences close in vector space" (Reimers and Gurevych, 2019). However, this objective can cause spurious correlations—such as between domain and topic—to be encoded as unintended relationships. As Thompson and Mimno (2018) observe: "collections are often constructed by combining documents from multiple sources, [so the] most prominent patterns in a collection simply repeat the known structure of the corpus."[2] It therefore would seem useful to remove unwanted information from text representations.

Indeed, adjusting embeddings to remove con-

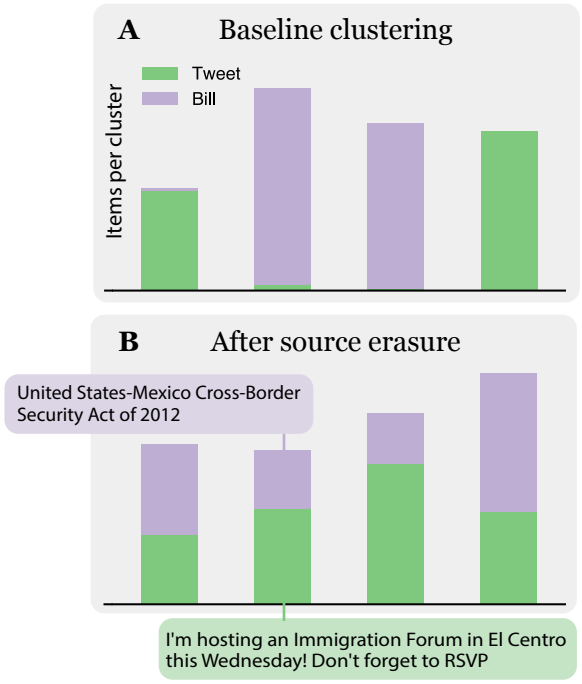

Figure 1: Clustering text embeddings from disparate sources (here, U.S. congressional bill summaries and senators' tweets) can produce clusters where one source dominates (Panel A). Using linear erasure to remove the source information produces more evenly balanced clusters that maintain semantic coherence (Panel B; sampled items relate to immigration). Four random clusters of k-means shown (k=25), trained on a combined 5,000 samples from each dataset.

*Equal supervision.

[1]Code and data available at https://github.com/y-fn/deconfounding-embeddings.

[2]Their analysis focuses on bag-of-words topic models rather than text embeddings, so their vocabulary-based approach does not translate to our setting.

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founding information is exactly what we do in this work. Adapting the algorithm from Belrose et al. (2023) for linear concept erasure, we remove embedding subspaces that are predictive of the confounding variables, which can bias measures of document distance. In the above example from U.S. politics, we residualize out the source information (Twitter or bills), producing adjusted embeddings for which similarity metrics load on the semantic content rather than the source (Fig. 1B). As another practical example, in a multilingual corpus, we residualize out the subspace that is predictive of language, leading to document distance metrics that are driven by content, rather than language.

Extensive tests show that the adjusted embeddings perform significantly better for clustering and similarity search. For example, in a multilingual document search setting, Recall@1 increases from 0.18 to 0.83. Importantly (and surprisingly), there is also no reduction in performance when using the adjusted embeddings on unseen datasets and tasks from a standard retrieval benchmark (Muennighoff et al., 2023; Enevoldsen et al., 2024), suggesting erasure does not harm embedding quality.

The approach is computationally inexpensive, involving only linear transformations on pretrained embeddings. To support practical use, we release a wrapper that streamlines encoding, fitting the deconfounder, and adjusting embeddings. In addition, we provide several evaluation datasets labeled both with confounders (language and source) and semantic content (e.g., topic). In sum, we:

- Formally demonstrate how erasure removes confounding information from document similarities (§2);
- Construct a benchmark of paired data to measure the impact of confounding attributes on embedding performance (§3);
- Evaluate a diverse set of embedding methods, showing that observable features such a text's source can reduce the utility of text embeddings in applied settings (§4);
- Show that applying a linear erasure algorithm to remove observed confounders can effectively mitigate such issues—sometimes dramatically—without degrading other aspects of performance (§5).

2 Background

Many downstream tasks such as nearest-neighbor search, clustering, retrieval, topic discovery etc.

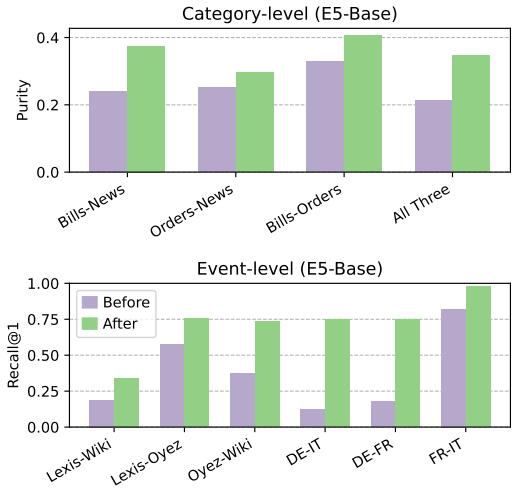

Figure 2: Performance of the multilingual E5-base model before and after erasure. Top: category-level results from the Comparative Agendas Project (metric: purity). Bottom: event-level results from SCOTUS and multilingual Swiss case summaries (metric: recall@1). Detailed results for other models and datasets in Tables 2, 4, 6 and 10.

rely on assessing how "close" two documents are in an embedding space. An effective distance metric should rank pairs by semantic relatedness rather than by superficial attributes like author, language, or publication venue. In practice, however, pretrained embedding models often encode these incidental signals, since they occur frequently during training and help optimize self-supervised objectives. When such signals correlate with content, distance measures become biased and can undermine empirical conclusions.

Embedding text sequences Sentence-level embeddings position semantically similar documents close to each other in a vector space (Kiros et al., 2015; Conneau et al., 2017; Cer et al., 2018; Reimers and Gurevych, 2019). Modern systems typically begin with a transformer encoder pretrained on masked-language modeling, then refine it on hundreds of millions of contrastive pairs drawn from diverse corpora (Reimers and Gurevych, 2019). This approach underpins state-of-the-art performance in retrieval (Asai et al., 2021; Thakur et al., 2021; Zhang et al., 2023), clustering (Aggarwal and Zhai, 2012), and classification (Maas et al., 2011).

Contrastive batches are often drawn from a single source, enabling the model to focus on internal semantics (Nussbaum et al., 2024). A side effect is that different sources may occupy distinct regions

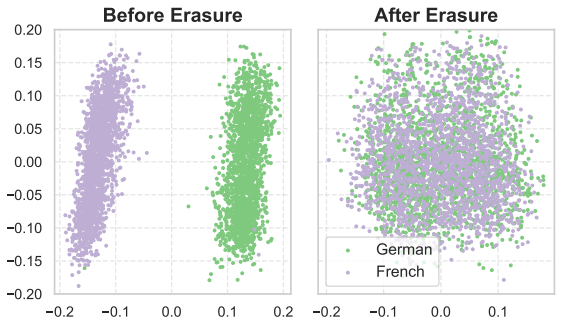

Figure 3: PCA projection of text embeddings before and after LEACE. Data are paired Swiss court case summaries in German (green) and French (purple). We deploy multilingual E5 as the embedding model. The first principal component recovers the two languages almost exactly.

of the embedding space, especially when cross-source positives are scarce. Multilingual models exhibit a similar problem: even when trained with translation pairs (Wang et al., 2024), large amounts of monolingual data tends to push languages apart.

Despite attempts to construct comparable contrastive pairs, the resulting embeddings still encode confounding information. Platform-specific jargon and style can dominate representations. In addition, language itself may serve as a proxy for topic or geography. For authors and outlets, stylistic markers linked to gender or ideology can act as shortcuts for similarity. Because these attributes correlate with content, they function as *observed confounders* in distance-based analyses.

The document comparison problem. More formally, let $\boldsymbol{X} \in \mathbb{R}^d$ denote the embedding of a random document. For a particular document d_i, we write its realization as $\boldsymbol{x}_i$ and assume $\|\boldsymbol{x}_i\| = 1$. In general, we use bold uppercase letters (e.g., $\boldsymbol{X}$) for random variables and lowercase letters ($\boldsymbol{x}_i$) for their realizations. Erased variables use a tilde ($\tilde{\mathrm{B}}$). Assume a linear decomposition for the embedding:

$$\boldsymbol{X} = \mathrm{B}_z\boldsymbol{Z} + \mathrm{B}_c\boldsymbol{C} + \mathrm{B}_u\boldsymbol{U} + \boldsymbol{\mathcal{E}}, \quad (1)$$

where $\boldsymbol{Z}$ is a random variable representing the *semantic content* of interest (e.g. topic); $\boldsymbol{C}$ the *observed confounders* (source, language, author traits); and $\boldsymbol{U}$ the *unobserved confounders*. B_z,B_c, B_u are loading matrices. $\boldsymbol{Z}$, $\boldsymbol{C}$, $\boldsymbol{U}$ and the noise $\boldsymbol{\mathcal{E}}$ are zero-mean and uncorrelated with one another.

Similarity is measured with the dot product, where x_0 and x_1 are two IID draws of $\boldsymbol{X}$:

$$y_{01} = \boldsymbol{x}_0^\top \boldsymbol{x}_1. \quad (2)$$

Under the model expressed in (1), expanding this dot product creates multiple entangled factors:

$$y_{01} = \boldsymbol{z}_0^\top \Gamma_{zz} \boldsymbol{z}_1 + \boldsymbol{z}_0^\top \Gamma_{zc} \boldsymbol{c}_1 \quad (3)$$
$$+ \boldsymbol{z}_0^\top \Gamma_{zu} \boldsymbol{u}_1 + \boldsymbol{c}_0^\top \Gamma_{zc} \boldsymbol{z}_1 + \ldots, \quad (4)$$

where $\Gamma_{jk} = B_j^\top B_k$. Only the first term reflects the semantic proximity we care about; the others bias any analysis based on y_{01}.

Debiasing and concept erasure. Concept erasure techniques aim to remove a targeted feature (e.g. gender) from an embedding. This is typically achieved by projecting out the corresponding subspace, thereby reducing bias and enabling analysis of model behavior without that feature (Ravfogel et al., 2022; Belrose et al., 2023).

Early debiasing work on word vectors identified a "bias direction" (e.g. race) and removed its projection (Bolukbasi et al., 2016). Later studies showed that the removed signal remained recoverable (Gonen and Goldberg, 2019), motivating stronger linear methods such as Iterative Null-space Projection (INLP, Ravfogel et al., 2020), Linear Adversarial Concept Erasure (LACE, Ravfogel et al., 2022), and LEAst-squares Concept Erasure (LEACE, Belrose et al., 2023). These approaches seek an affine transformation that eliminate all linear correlation with the protected attribute while altering the representations as little as possible.

An important special case of these kinds of concept erasure is *linear concept erasure*, where the goal is to prevent linear adversaries from predicting the information we aim to remove. This is usually achieved in the form of a projection matrix that neutralizes a subspace that is associated with the concept $\boldsymbol{C}$. Following Ravfogel et al. (2022), Belrose et al. (2023) derived sufficient and necessary conditions for achieving *linear guardedness* (Ravfogel et al., 2023), a situation where *no linear classifier* can recover the concept $\boldsymbol{C}$ and achieve a loss lower than that of a trivial predictor that always predicts the majority class. Specifically, they derive a *linear projection matrix* $\boldsymbol{P}^*$ such that:

$$\mathrm{P}^* = \arg\min_{\mathrm{P}\in\mathbb{R}^{d\times d}} \mathbb{E}\left[\|\mathrm{P}\boldsymbol{X} - \boldsymbol{X}\|^2\right] \quad (5)$$
$$\text{subject to } \mathrm{Cov}(\mathrm{P}\boldsymbol{X}, \boldsymbol{C}) = 0. \quad (6)$$

The covariance constraint ensures the erasure of linear information, while the first objective minimizes *distortion* of the representation space. It turns out that this objective has a closed-form solution in the form of

$$\mathrm{P}^* = \mathrm{I} \; - \; \mathrm{W}^\dagger(\mathrm{W}\Sigma_{XC})(\mathrm{W}\Sigma_{XC})^\dagger\mathrm{W} \quad (7)$$

where $\mathrm{W} = \Sigma_{XX}^{-1/2}$ is a whitening matrix, $\mathrm{W}^\dagger$ the pseudoinverse of W, and

$$\Sigma_{XC} = \mathrm{Cov}(\boldsymbol{X}, \boldsymbol{C}), \Sigma_{XX} = \mathrm{Cov}(\boldsymbol{X}), \boldsymbol{\mu} = \mathbb{E}[\boldsymbol{X}].$$

This condition is proved to be sufficient and necessary for achieving *linear guardedness*, i.e., the inability of any linear classifier to recover the attribute $\boldsymbol{C}$ from the embeddings. In other words, Eq. (7) together with $\boldsymbol{b} = \boldsymbol{\mu} - \mathrm{P}\boldsymbol{\mu}$ defines the unique affine map that removes *all* linear correlations with the observed confounder $\boldsymbol{C}$ while modifying the embeddings as little as possible.

For any document, the *adjusted* embedding is $\tilde{\boldsymbol{x}}_i = \mathrm{P}\boldsymbol{x}_i + \boldsymbol{b}$. Applying this LEACE map to the realization of the structural decomposition in (1):

$$\begin{aligned}\tilde{\boldsymbol{x}}_i &= P\big(\mathrm{B}_z\boldsymbol{z}_i + \mathrm{B}_c\boldsymbol{c}_i + \mathrm{B}_u\boldsymbol{u}_i + \boldsymbol{\varepsilon}_i\big) + \boldsymbol{b} \\ &= \tilde{\mathrm{B}}_z\boldsymbol{z}_i + \tilde{\mathrm{B}}_u\boldsymbol{u}_i + \mathrm{P}\boldsymbol{\varepsilon}_i, \end{aligned} \quad (8)$$

where $\tilde{\mathrm{B}}_j = \mathrm{PB}_j$. Note that the middle term vanishes, following from the constraint $\mathrm{Cov}(\tilde{\boldsymbol{X}}, \boldsymbol{C}) = 0$, which ensures that the space spanned by B_c is removed. In turn, the estimand for the document similarity,

$$\begin{aligned}\tilde{y}_{01} \; &= \; \tilde{\boldsymbol{x}}_0^\top\tilde{\boldsymbol{x}}_1 \; = \; \boldsymbol{z}_0^\top\tilde{\Gamma}_{zz}\boldsymbol{z}_1 \; + \; \boldsymbol{z}_0^\top\tilde{\Gamma}_{zu}\boldsymbol{u}_1 \\ &+ \boldsymbol{u}_0^\top\tilde{\Gamma}_{uz}\boldsymbol{z}_1 \; + \; \boldsymbol{u}_0^\top\tilde{\Gamma}_{uu}\boldsymbol{u}_1 + P\boldsymbol{\varepsilon}_i, \end{aligned} \quad (9)$$

is also purged of $\boldsymbol{C}$ (furthermore, in expectation it does not include the cross terms, as they are uncorrelated under our assumptions). Note, however, that the projection alters the geometry of the remaining components. $\tilde{\boldsymbol{x}}$ is now based on $\mathrm{PB}_z\boldsymbol{z}$, which may not be equal to $\mathrm{B}_z\boldsymbol{z}$, depending on the intensity and nature of the dependence between $\boldsymbol{z}$ and $\boldsymbol{C}$. So the LEACE algorithm might also add bias to similarity metrics through its adjustment of this term. Further, the (adjusted) unobserved confounder $\boldsymbol{u}$ remains, and it is unclear how the deconfounding by LEACE would either increase or reduce bias from $\boldsymbol{u}$.

Category-level Data	N_{total}	Categories
CAP Data		
Bills – Orders	1,902	21
Bills – Newspapers	2,613	21
Orders – Newspapers	1,907	21
All Three Sources	3,211	21
Event-level Data	N_{paired}	N_{unpaired}
SCOTUS Cases		
Wikipedia – LexisNexis	2,048	1,518
Wikipedia – Oyez	1,560	1,762
LexisNexis – Oyez	2,048	2,075
SemEval News Articles		
EN – Non-EN	888	0
Swiss Court Cases		
DE – FR	2,048	1,760
DE – IT	2,048	1,760
FR – IT	2,048	1,760

Table 1: Dataset statistics. The data cover a variety of domains and languages.

3 Experimental Setup

Our evaluation settings are designed to approximate real-world use cases and involve datasets from multiple corpora. They are divided into two groups, *category-level* and *event-level* data, both aiming to measure the same thing: the extent to which documents that share a common label have similar embeddings.

The approach is the same across all datasets: create a vector of concept labels $\boldsymbol{c}$ to erase, using known metadata (here, a text's source or language). Then, pass each text item through the embedding model to obtain a matrix $\mathbf{X}$. Fit LEACE on $(\mathbf{X}, \boldsymbol{c})$ to learn the whitening and projection matrices, then apply the transformations back to $\tilde{\mathbf{X}}$.[3]

3.1 Category-level Data

Recalling the motivating example from the introduction, imagine a researcher clusters documents from different sources (like news articles and court cases), with the hope that each cluster contains documents that fall under a coherent topic.

We measure progress on this task by relying on a common set of ground-truth category labels, like "Education", that cover multiple datasets. The goal is that the assigned clusters align with the categories, even if the constituent documents come from different sources.

[3]For the out-of-sample experiments in Section 5, the transformations are applied to novel benchmark data $\mathbf{X}'$.

Datasets. We use datasets from the Comparative Agendas Project (CAP), which provides a coding framework for analyzing policy activities across time and between countries (Jones et al., 2023b).

We use texts from three sources: newspaper articles[4], congressional bill summaries (Wilkerson et al. 2023, taken from Hoyle et al. 2022), and executive orders (Jones et al., 2023a). We evaluate each pair of sources separately, as well as all three simultaneously.

Metrics and Methodology. We measure alignment between ground-truth category labels and assigned clusters with two metrics. Following Poursabzi-Sangdeh et al. (2016), we use purity, which quantifies to what extent each cluster contains items from a single gold category, and the Adjusted Rand Index, a chance-corrected metric that measures the similarity of two clusterings.

The erased concept is the *source* for each of the four settings (Table 1). When generating clusters, we follow a standard practice and apply k-means to the text embeddings for each document (Zhang et al., 2022).[5]

3.2 Event-level Data

Now imagine that a practitioner wants to understand how a common event—a court case, a natural disaster—is portrayed by distinct sources or languages. If they have access to one document discussing the event, how can they best find others?

Datasets. We rely on three paired datasets, which link documents depicting the same event in different sources or languages.

Super-SCOTUS (Fang et al., 2023) contains case summaries from the U.S. Supreme Court sourced from LexisNexis and Oyez. In addition, we scrape case summaries from Wikipedia. This results in 1,518 pairs of LexisNexis and Wikipedia case summaries, 2,075 from LexisNexis and Oyez, and 780 pairs from Wikpedia and Oyez.

SemEval 2022 Task 8 (Chen et al., 2022) assesses the similarity between pairs of multilingual news articles. We obtain 444 pairs of news articles that depict similar events in different languages, namely English and non-English (Spanish, German, and Chinese).

A third dataset is derived from **SwilTra-Bench** (Niklaus et al., 2025), which contains parallel summaries of leading Swiss court decisions from the Federal Supreme Court of Switzerland in German, French, and Italian.

Methodology and Metrics. To accurately simulate real-world conditions, in which only partially paired data is available and the remaining data is unpaired and derived from different sources, we retain up to 1,024 data pairs for each applicable setting. We treat the remainder of the data as unpaired by randomly discarding one example from each pair. Thus, data is considered unpaired either because paired data was unavailable from the original sources or because one item from a pair was randomly removed. In each setting, we pool together the paired and unpaired data and subsequently use this combined dataset to train the LEACE eraser, aiming to remove source-specific information.

We evaluate whether each paired item can retrieve its counterpart from the pooled dataset using **Recall@1 and @10**, the proportion of correct matches that appear in the top k retrieved results.

3.3 Embedding Models

Our experiments use ten embedding models of varying sizes and dimensionality (appendix Table 12). This set includes multilingual and monolingual variants, as well as models with instruction fine-tuning: `MiniLM`[6], `GIST-small`, `GIST-base`, `GIST-large` (Solatorio, 2024), multilingual `E5-small`, `E5-base`, `E5-large` (Wang et al., 2024), `all-mpnet-base-v2` (Song et al., 2020), `Nomic-v2` (Nussbaum and Duderstadt, 2025), and `MXB-large` (Li and Li, 2023; Lee et al., 2024).

4 Primary Results

We first discuss the results on the category-level datasets, then turn to the event-level. In brief, erasure improves embeddings across the board—over all models, metrics, and datasets (when performance is not already saturated). A summary of results for a single model is in Fig. 2.

4.1 Category-level

In all four source pairings from the CAP dataset, erasing source-specific information with LEACE consistently improves clustering quality (Table 2).

[4] https://comparativeagendas.net/project/pennsylvania

[5] We set $k = 21$, the total number of categories in the data. Improvements are robust to different k, see Fig. 10 in appendix.

[6] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2

Model	Bills & News				Orders & News				Bills & Orders				All Three Sources			
	Purity		ARI		Purity		ARI		Purity		ARI		Purity		ARI	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
MiniLM	0.346	**0.507**	0.148	**0.268**	0.329	**0.463**	0.123	**0.228**	0.391	**0.448**	0.169	**0.226**	0.269	**0.411**	0.096	**0.205**
GIST-small	0.380	**0.549**	0.171	**0.328**	0.421	**0.515**	0.200	**0.283**	0.422	**0.513**	0.191	**0.275**	0.330	**0.483**	0.131	**0.259**
E5-small	0.260	**0.414**	0.085	**0.207**	0.289	**0.290**	0.099	**0.101**	0.319	**0.422**	0.123	**0.190**	0.237	**0.356**	0.069	**0.166**
MPNet	0.365	**0.504**	0.162	**0.282**	0.377	**0.444**	0.151	**0.217**	0.461	**0.493**	0.229	**0.256**	0.334	**0.481**	0.130	**0.259**
GIST-base	0.373	**0.534**	0.157	**0.312**	0.380	**0.534**	0.165	**0.309**	0.425	**0.498**	0.188	**0.262**	0.320	**0.470**	0.054	**0.147**
E5-base	0.240	**0.375**	0.072	**0.175**	0.252	**0.297**	0.075	**0.108**	0.328	**0.407**	0.130	**0.173**	0.212	**0.346**	0.130	**0.173**
Nomic-v2	0.324	**0.463**	0.122	**0.250**	0.331	**0.353**	0.127	**0.161**	0.386	**0.442**	0.159	**0.218**	0.249	**0.411**	0.073	**0.196**
MXB-large	0.328	**0.493**	0.134	**0.279**	0.332	**0.524**	0.127	**0.281**	0.420	**0.487**	0.188	**0.263**	0.299	**0.410**	0.112	**0.199**
GIST-large	0.361	**0.492**	0.148	**0.295**	0.375	**0.471**	0.153	**0.258**	0.418	**0.495**	0.195	**0.258**	0.294	**0.434**	0.106	**0.226**
E5-large	0.224	**0.373**	0.066	**0.170**	0.273	**0.283**	0.082	**0.103**	0.327	**0.366**	0.104	**0.152**	0.211	**0.297**	0.055	**0.124**

Table 2: Cluster alignment metrics on the "category-level" Comparative Agendas Project datasets (§3.1), before and after linear concept erasure. Here, the erased concept is the *source* (top row). We set $k = 21$, the total number of categories in the CAP datasets. Erasure substantially improves cluster alignment for every combination of sources across all embedding models. Bolded scores indicate performance improvements after erasure; underlined scores mark the highest value in each column.

In the *Bills–Newspapers* comparison, all ten models show marked improvements, with gains in ARI ranging from +0.104 (E5-large) to +0.157 (GIST-small), and purity increases as high as +0.169 (GIST-small). Although the magnitude of improvement varies, this pattern persists in the *Orders–Newspapers* comparison. While most models benefit substantially, multilingual models such as E5-small and E5-large show only marginal gains, suggesting that source signal may be less distinct in this pairing.

The *Bills–Orders* setting yields more moderate improvements, yet the gains remain consistent across model scales. Finally, the *All Three Sources* setting demonstrates that LEACE generalizes to more complex source distributions. Smaller-sized models, such as MiniLM and GIST-small, gain over +0.130 in purity and +0.100 in ARI. Even larger models such as GIST-large and MXB-large improve substantially after concept erasure.

Overall, these results demonstrate the robustness of LEACE across diverse source combinations and embedding models, confirming its ability to reduce spurious relationships between items while preserving task-relevant semantic structure.

4.2 Event-Level

At the event level, we present the results with Recall@10 and Recall@1, because only one document is deemed relevant for each query.

U.S. Supreme Court Case Summaries Applying LEACE consistently improves retrieval performance on the SCOTUS summary data (Table 10). In both *Wikipedia* pairings, improvements are large and especially pronounced for the E5 family. For instance, on *LexisNexis-Wikipedia*, E5-small gains +0.177 in Recall@1 and E5-base +0.153.

Performance before erasure on *LexisNexis–Oyez* is already high, likely because the two have more stylistic elements in common—both being technical summaries based on the original court opinion. Nonetheless, we still observe more modest but consistent gains. E5-small and E5-base increase Recall@1 by +0.226 and +0.183, respectively, although GIST-base and MXB-large exhibit improvements of only about +0.08.

Overall, LEACE not only improves representation consistency across heterogeneous legal sources, but also enhances alignment even when initial model performance is already strong.

Swiss Federal Supreme Court Case Summaries Turning now to multilingual data, we observe that LEACE can be extremely effective, even with already-multilingual embeddings (Table 4).

For all settings on the Swiss court case summary data, nearly every model sees higher recall after applying LEACE. The improvements tend to be largest with different language families: German-Italian and German-French. On *DE-IT*, gains in Recall@1 can reach +0.651 (E5-large); on *DE-FR*, +0.570 (E5-base). As French and Italian are closer, baseline retrieval is already strong, with some models already having near-perfect Recall@10. This reflects the tendency of related languages to lie closer in embedding space, as shown in prior work on genealogical structure (Östling and Kurfalı, 2023) and cross-lingual language representations (Sharoff,

Model	LexisNexis & Wikipedia				LexisNexis & Oyez				Oyez & Wikipedia			
	Recall@10		Recall@1		Recall@10		Recall@1		Recall@10		Recall@1	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
MiniLM	0.487	**0.606**	0.231	**0.313**	0.890	**0.899**	0.651	**0.693**	0.850	**0.924**	0.623	**0.747**
GIST-small	0.563	**0.656**	0.261	**0.325**	0.918	**0.943**	0.702	**0.778**	0.762	**0.844**	0.478	**0.599**
E5-small	0.421	**0.673**	0.176	**0.353**	0.830	**0.939**	0.563	**0.789**	0.689	**0.951**	0.398	**0.752**
MPNet	0.566	**0.666**	0.259	**0.337**	0.926	**0.943**	0.724	**0.775**	0.856	**0.911**	0.565	**0.678**
GIST-base	0.646	**0.757**	0.308	**0.412**	0.939	**0.963**	0.727	**0.819**	0.880	**0.950**	0.628	**0.773**
E5-base	0.414	**0.660**	0.188	**0.341**	0.830	**0.940**	0.575	**0.758**	0.650	**0.942**	0.371	**0.737**
Nomic-v2	0.530	**0.701**	0.254	**0.384**	0.950	**0.966**	0.770	**0.820**	0.903	**0.978**	0.658	**0.819**
MXB-large	0.537	**0.703**	0.249	**0.376**	0.928	**0.958**	0.720	**0.805**	0.883	**0.960**	0.654	**0.819**
GIST-large	0.657	**0.770**	0.305	**0.414**	0.954	**0.967**	0.787	**0.834**	0.947	**0.971**	0.760	**0.826**
E5-large	0.479	**0.720**	0.209	**0.381**	0.864	**0.949**	0.636	**0.791**	0.765	**0.964**	0.489	**0.792**

Table 3: Document similarity search results on paired "event-level" U.S. Supreme Court Summaries (3.2), before and after linear concept erasure. Here, the erased concept is the document's *source*. Erasure improves recall for every setting and model.

2020). Still, increases in metrics abound, primarily in the smaller models like MiniLM. Taken together, LEACE removes source-specific signals even in complex multilingual legal domains.

SemEval News Articles To avoid bludgeoning the reader with positive results, we briefly outline the results on our other multilingual dataset: all ten models again benefit from erasure (Table 6 in the appendix).

4.2.1 Qualitative Analysis

To investigate which semantic features contribute most and least to changes before and after LEACE, we conducted a qualitative analysis using pairs of legal case summaries sourced from Wikipedia and LexisNexis, employing multilingual E5 as the embedding model.

We observe that when baseline similarity is already high due to shared style or genre, LEACE encounters fewer residual confounders to remove, thus yielding relatively smaller improvements. Conversely, when baseline similarity is lower owing to clear stylistic or domain differences, LEACE proves particularly effective, as it targets and removes pronounced confounding signals, leading to greater gains.

Our examination of legal case summaries provides insights into these dynamics. Summaries that experience the largest changes after applying LEACE are generally shorter, focus primarily on legal rulings, and lack factual idiosyncrasies. Without LEACE-based deconfounding, these summaries present substantial challenges for similarity-based text retrieval because of their limited semantic overlap regarding specific facts and rules (see also Fan et al. 2025). We provide examples in Appendix F.1.

On the other hand, summaries that display minimal change tend to incorporate both factual details and judgments, offer broader contextual framing, discuss subsequent impacts, and frequently integrate direct quotations from court decisions. An example can be found in Appendix F.2.

These findings underscore LEACE's distinctive advantage in scenarios where domain experts can clearly identify and specify features irrelevant to downstream similarity tasks, highlighting its potential value within human-in-the-loop frameworks that leverage expert knowledge to detect and eliminate confounding factors. They also show LEACE is less useful when relevance relies on higher-order discourse features such as blending facts, judgments, and framing, which it cannot account for.

5 Erasure helps, but can it hurt?

The results from the previous section appear conclusive: linear concept erasure effectively removes spurious information from embeddings that distorts similarities. At the same time, we must ask whether erasure might also degrade embeddings in subtle ways that our evaluations fail to detect. Although LEACE is designed to minimize unwanted distortions, the trained eraser may inadvertently remove "desirable" information that may support other tasks.

In this section, we address this question through additional evaluations on out-of-distribution (OOD) benchmarks. These experiments test whether apply-

Model	DE & IT				DE & FR				FR & IT			
	Recall@10		Recall@1		Recall@10		Recall@1		Recall@10		Recall@1	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
MiniLM	0.009	**0.086**	0.003	**0.023**	0.026	**0.102**	0.008	**0.030**	0.146	**0.545**	0.040	**0.260**
GIST-small	0.020	**0.211**	0.004	**0.063**	0.041	**0.246**	0.011	**0.075**	0.315	**0.771**	0.101	**0.461**
E5-small	0.093	**0.930**	0.027	**0.543**	0.167	**0.937**	0.051	**0.563**	0.853	**1.000**	0.455	**0.968**
MPNet	0.016	**0.149**	0.006	**0.048**	0.053	**0.155**	0.021	**0.050**	0.157	**0.646**	0.052	**0.346**
GIST-base	0.034	**0.296**	0.008	**0.092**	0.076	**0.378**	0.024	**0.142**	0.440	**0.873**	0.167	**0.565**
E5-base	0.380	**0.987**	0.124	**0.749**	0.457	**0.989**	0.178	**0.748**	0.987	**1.000**	0.821	**0.979**
Nomic-v2	0.958	**0.994**	0.600	**0.765**	0.944	**0.996**	0.596	**0.767**	1.000	1.000	0.968	**0.979**
MXB-large	0.027	**0.356**	0.012	**0.117**	0.087	**0.427**	0.033	**0.168**	0.366	**0.910**	0.125	**0.632**
GIST-large	0.045	**0.298**	0.014	**0.090**	0.116	**0.385**	0.039	**0.152**	0.415	**0.880**	0.144	**0.551**
E5-large	0.503	**0.995**	0.175	**0.826**	0.722	**0.998**	0.300	**0.852**	0.988	**1.000**	0.831	**0.983**

Table 4: Document similarity search results on paired "event-level" multilingual Swiss Court Case Summaries (3.2), before and after linear concept erasure. Here, the concept is the document's *language*. Once again, erasure significantly improves recall of the paired item in all cases. The only exception is one instance where retrieval performance is already perfect before erasure. In some cases, erasure even allows smaller models to outperform their larger counterparts.

ing an eraser trained for a specific domain unintentionally harms general-purpose semantic representations. While our main experiments in the previous section focused on domain-specific differences, real-world deployment of embedding models often requires robust cross-domain performance. We thus benchmark our models against diverse evaluation datasets from MTEB (Muennighoff et al., 2023) to assess whether erasers trained to isolate certain information also degrade performance in unrelated tasks.

5.1 Data and Methods

We focus on two sentence embedding models: MiniLM and E5-base-v2 (Wang et al., 2022). Each model is paired with two trained concept erasers: the CAP eraser, trained to remove the source from the *Bill–Newspapers* pair, and the Legal eraser, trained on *LexisNexis–Wikipedia*. This results in four models-eraser combinations per task.

We apply these combinations to retrieval and semantic texutal similarity (STS) tasks from MTEB (Muennighoff et al., 2023): (1) Legal Retrieval tasks, (2) News Retrieval tasks (Thakur et al., 2021), and (3) STS News tasks. These benchmarks differ in domain, structure, and evaluation metrics, offering a comprehensive perspective on erased embedding behavior in out-of-domain settings. For each benchmark, we compare the performance of the original model embeddings to the same embeddings after applying the trained LEACE erasers.

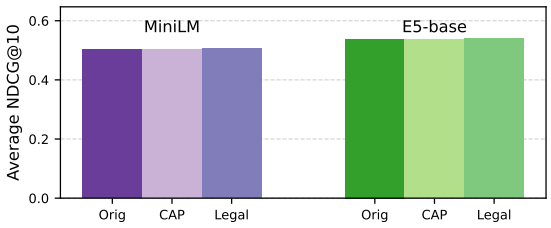

Figure 4: An eraser trained on embeddings from one dataset does not degrade embeddings from a different dataset. Erasers fit to the CAP and SCOTUS data (§3) are applied to embeddings (MiniLM and E5-base-v2) from five legal retrieval tasks. Each triplet of same-color bars compares the average NDCG@10 for the base and erased embeddings.

5.2 MTEB Results

We report a selection of results here, again emphasizing that our hope is not to improve benchmark results, but to *avoid making them worse* (full results in Appendix C).

Retrieval. On both the legal and news retrieval tasks, the trained erasers do not harm performance (as measured by the average NDCG@10). See Fig. 4 for legal retrieval; per-task performance (Fig. 6) and news retrieval (Fig. 7) are in the appendix. Given the domain overlap, we had hypothesized that the Legal eraser might improve legal retrieval somewhat, but only one task sees a marginal improvement (AILACasedocs), from 0.197 to 0.218 (Table 7 in appendix). That said, the results are still positive overall, indicating that

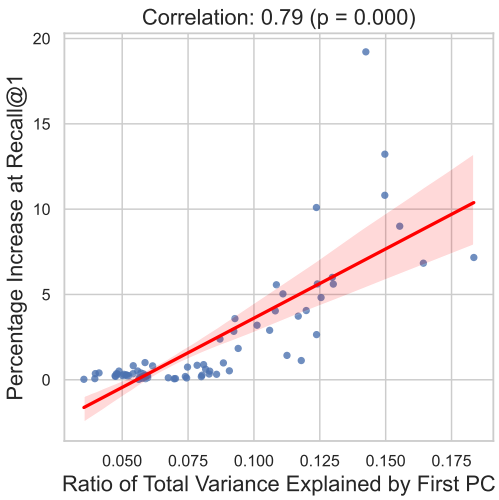

Figure 5: Relationship between variance explained by PC1 in the original embeddings and Recall@1 improvement after LEACE. Each point corresponds to a dataset setting in the event-level evaluation.

both the CAP and Legal erasers operate robustly in OOD retrieval tasks with both small and large models.

Semantic Textual Similarity. We evaluate the four model–eraser combinations on eight well-established STS benchmarks, covering both monolingual and crosslingual settings in the news domain (Fig. 8 and Table 9 in the appendix). The evaluation metric is the Spearman correlation between embedding cosine similarities and ground-truth semantic similarity. LEACE does not degrade performance over tasks, with most scores either unchanged or showing negligible increases.

Across the retrieval and semantic similarity evaluations, LEACE consistently preserves the quality of the embedding space while effectively removing targeted conceptual signals. These results reinforce its utility as a lightweight and reliable method for concept erasure.

6 Additional Findings

Relating LEACE to PCA Why does LEACE work in these settings? Here, we consider its relationship to Principal Component Analysis (PCA).

Taking the embeddings of the German-French Swiss court summaries, the first principal component (PC1) forms two clearly separable clusters corresponding directly to the text's language (Fig. 3). After applying LEACE, the clusters collapse into a single, overlapping distribution, an indication that language identity is no longer linearly separable in the embedding space.

To better understand when LEACE is effective, we investigate how the structural characteristics of the original embedding space relate to observed performance improvements. Specifically, we hypothesize that LEACE provides greater performance gains when the removable concept is prominently encoded within the embedding space.

To test this, we apply PCA to the original embeddings from each event-level dataset (SCOTUS, SemEval, Swiss Court Cases) and record the proportion of total variance explained by PC1. A high proportion of explained variance suggests that PC1 encodes a dominant direction in the embedding space, which will tend to correspond to the concept targeted by LEACE (i.e., the source or language, per Fig. 3). Indeed, Fig. 5 shows a strong positive correlation ($r = 0.79$, $p < 0.001$) between the proportion of variance explained by PC1 and the percentage improvement in Recall@1. This result indicates that LEACE is more effective when the removable concept aligns with dominant directions in the embedding space.

Given these findings, one might ask why not use PCA for erasure instead, following Bolukbasi et al. (2016). We observe positive but less consistent results than LEACE on our tasks, along with a strong degradation in MTEB performance (Appendix E).

A new task: bitext mining Erasure improves already multilingual models on with multilingual tasks, so can it help with *bitext mining*—retrieving translation pairs via similarity search? Our further experiments show that improvements are not uniformly strong, but we do achieve state-of-the-art results on a few leaderboard tasks from Enevoldsen et al. (2025), and erasure never reduces performance (details in Appendix A).

7 Conclusion

For applied practitioners working with large text collections from multiple sources or languages—a common scenario—our results offer a clear recommendation: apply linear erasure to document embeddings before use to remove confounding information. While there may be cases where it is less effective, the method does not appear to harm representations (see below) and incurs only minimal computational cost.

Limitations

The primary limitation of our method is its dependence on per-document metadata or labels. If an undesirable low-level pattern in the data distribution is suspected but not known—say, an unreported change in how a corpus was collected over a long time period—then the user must first apply some possibly-unsupervised labeling method. Although confounder labels are available for many tasks, reliance on such labels constrains the broader applicability of our proposed methods. We explored approaches that automatically generate features; however, these did not lead to measurable improvements in downstream retrieval or similarity comparison tasks. Other works have developed unsupervised techniques to debias or erase neural representations (Kim et al., 2019; Seo et al., 2022; Yang et al., 2025). We leave a deeper exploration of such methods in our context for future work. One direction is to integrate sparse autoencoders (e.g., Movva et al., 2025; Paulo et al., 2025) that extract features whose utility can be interpreted and validated by human experts.

Another shortcoming arises when metadata is available but the categories are too numerous relative to the total number of items. For example, in the paired *within*-language (en–en) SemEval Task 8 news articles, the data originate from dozens of sources, many of which are represented by only a handful of articles. In contrast to removing the language label in the multilingual data (Table 6), removing the source label does not improve retrieval results over the baseline. A possible direction for future work is to first merge similar sources into broader categories (e.g., local vs. national newspapers) before applying label erasure.

A final limitation was first noted by Huang et al. (2024), who used LEACE as a baseline in multilingual retrieval contexts. While they similarly removed language information, their results were mixed, suggesting that LEACE may not be effective in all settings. One hypothesis is that our tasks, though realistic, differ from the standard benchmark data on which models are typically trained, leading to saturated in-domain performance that does not transfer well out-of-domain. Another possibility is that retrieval setups—with their distinct (short query, document) structure, as opposed to our (document, document) structure—may be less amenable to erasure. We plan to explore these hypotheses to help explain such discrepancies.

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A Bitext Mining Results

Our gains on multilingual tasks with already multilingual embeddings motivate us to ask whether erasure can benefit already "saturated" leaderboard tasks that cover multiple languages. To this end, we focus on *bitext mining*: given pairs of sentences in different languages, the goal is to retrieve a specific sentence in the target language given a "query" sentence in the source language (typically a translation; F_1 is the standard metric). We collect all 28 tasks available through the MTEB package at the time of writing (Muennighoff et al., 2023) and use `E5-large-instruct`, one of the best-performing models on the leaderboard.

In several cases, there is a marked increase, yielding state-of-the-art scores on three tasks that appear on the public leaderboard (even with a different base model class, Table 5 in appendix). Generally, though, the improvements are much smaller than those in our main experiments, with over half of the 28 tasks showing less than a 0.01 change (although no tasks decrease more than -0.01). First applying LEACE is therefore a simple step when bitext mining; even if it may not always help, it is unlikely to hurt.

	F_1		
	Before	After	Δ
SynPerChatbotSumS	0.283	0.500	0.217
SAMSumFa	0.811	0.943	0.132
SynPerChatbotRAGSumS	0.560	0.680	0.120
RomaTales	0.201	0.263	0.062
SRNCorpus	0.500	0.551	0.051
NusaX*	0.853	**0.892**	0.039
NollySenti*	0.807	**0.839**	0.032
NusaTranslation*	0.851	**0.876**	0.025
LinceMT	0.487	0.506	0.019
Bornholm*	0.560	0.578	0.018
IN22Conv	0.626	0.637	0.011
Phinc	0.855	0.867	0.011
Number of tasks with $\lvert\Delta\rvert < 0.01$			*15*

Table 5: F_1 on MTEB Bitext Mining Tasks before and after erasing the language ID, for `E5-large-instruct`. Gains are substantial in a few cases, sometimes improving over the reported state-of-the-art on MTEB (tasks with * appear on the public leaderboard, improvements over SotA in **bold**).

B SemEval English & Non-English News Results

The results on testing LEACE on the SemEval 2022 Task 8 dataset are presented in Table 6. All models benefit from LEACE, with consistent improvements in both Recall@10 and Recall@1. The E5-small model shows the strongest gains overall: +0.202 (Recall@10) and +0.236 (Recall@1). High-performing large models like E5-large and MXB-large achieve further enhancements of up to +0.156 in Recall@1. Smaller models also gain notable increases. For instance, MiniLM gains +0.183 (Recall@10) and +0.127 (Recall@1), respectively. These improvements highlight LEACE's utility in reducing source bias and improving semantic alignment in multilingual event representations. Nomic-v2, which already has high scores before LEACE, showed modest increases, likely due to saturation. In general, LEACE proves effective even under high-resource, multilingual scenarios.

	`Recall@10`		`Recall@1`	
Model	Before	After	Before	After
MiniLM	0.350	**0.533**	0.150	**0.277**
GIST-small	0.497	**0.636**	0.247	**0.372**
E5-small	0.614	**0.816**	0.318	**0.554**
MPNet	0.557	**0.664**	0.262	**0.347**
GIST-base	0.564	**0.694**	0.301	**0.402**
E5-base	0.777	**0.859**	0.466	**0.601**
Nomic-v2	0.892	**0.906**	0.637	**0.651**
MXB-large	0.527	**0.691**	0.250	**0.390**
GIST-large	0.624	**0.734**	0.332	**0.428**
E5-large	0.747	**0.866**	0.436	**0.592**

Table 6: Results on SemEval English & Non-English News Articles

C MTEB Evaluation Results

We report the full evaluation results of the CAP and Legal erasers on three MTEB benchmark groups: Legal Retrieval, News Retrieval, and STS News Tasks. Each setting involves comparing model performance before and after LEACE-based erasure, across two embedding models (MiniLM and E5-base), as shown in Table 7, Table 8, and Table 9 and Fig. 6, Fig. 7 and Fig. 8.

D Sources of MTEB Tasks

We list below the original sources for the datasets used from the MTEB benchmark (Muennighoff et al., 2023; Enevoldsen et al., 2025):

- Legal retrieval tasks: **AILACasedocs** and **AILAStatutes** (Bhattacharya et al., 2020), **LegalBenchConsumerContractsQA** (Wang et al., 2025; Koreeda and Manning, 2021),

Task	MiniLM			E5-base		
	Before	After (CAP)	After (Legal)	Before	After (CAP)	After (Legal)
AILACasedocs	0.197	0.197	0.218	0.292	0.290	0.292
AILAStatutes	0.205	0.196	0.205	0.186	0.191	0.193
ConsumerContractsQA	0.656	0.659	0.654	0.720	0.712	0.720
CorporateLobbying	0.864	0.865	0.863	0.915	0.914	0.913
LegalSummarization	0.590	0.591	0.592	0.577	0.576	0.578

Table 7: Legal Retrieval Results on MTEB evaluated using NDCG@10. Each model (MiniLM, E5-base-v2) is tested with and without LEACE erasure, using both CAP and Legal erasers.

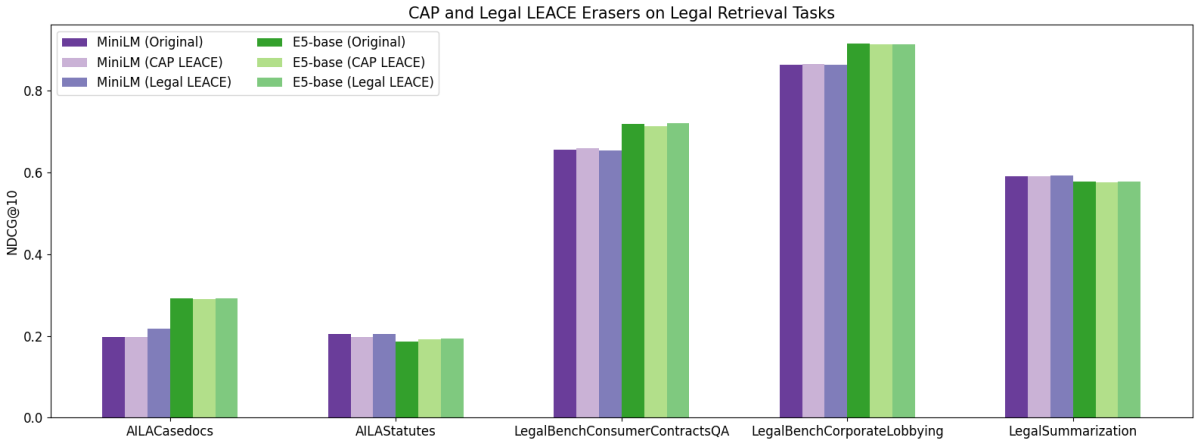

Figure 6: Performance of CAP and Legal erasers across three news retrieval tasks. Each group of bars compares the base and LEACE-erased models for MiniLM and E5-base-v2 embeddings.

LegalBenchCorporateLobbying (Guha et al., 2023; Holzenberger and Van Durme, 2021; Lippi et al., 2019; Ravichander et al., 2019; Wang et al., 2023; Wilson et al., 2016; Zheng et al., 2021; Zimmeck et al., 2019), **LegalSummarization** (Manor and Li, 2019).

- News retrieval tasks: **BelebeleRetrieval** (Bandarkar et al., 2024), **NanoClimateFeverRetrieval** (Diggelmann et al., 2021), **mFollowIRCrossLingualInstructionRetrieval** (Weller et al., 2025).

- STS news tasks: **IndicCrosslingualSTS** (Ramesh et al., 2022), **STS12** (Agirre et al., 2012), **STS13** (Agirre et al., 2013), **STS15** (Biçici, 2015), **STS17** (Cer et al., 2017), **STS22** (Chen et al., 2022), **STSBenchmark** and **STSBenchmarkMultilingualSTS** (May, 2021).

E Additional PCA Analysis

We create a baseline by removing PC1 from the embedding space, and evaluate it in the event-level setting using the SCOTUS dataset (Table 10). Overall, the baseline occasionally helps and can even marginally outperform LEACE in a few cases, but its effectiveness appears unstable, heavily dependent on the particular setting and model used (although it is effective for the E5 family for most configurations). Furthermore, in some cases, it performs worse than applying no erasure at all. There is also a final catch: removing the learned PC1 from OOD embeddings *does* dramatically degrade performance on MTEB tasks (Table 11), unlike LEACE (Fig. 9).

E.1 Event-Level Results on SCOTUS Case Summaries

Table 10 reveals the results of applying the baseline, which removes the first principal component (PC1) from the embedding space, in the event-level setting on the SCOTUS dataset. While it sometimes improves over the original embeddings and occasionally outperforms LEACE (especially for the E5 family), its performance is inconsistent across models and configurations, and it can underperform

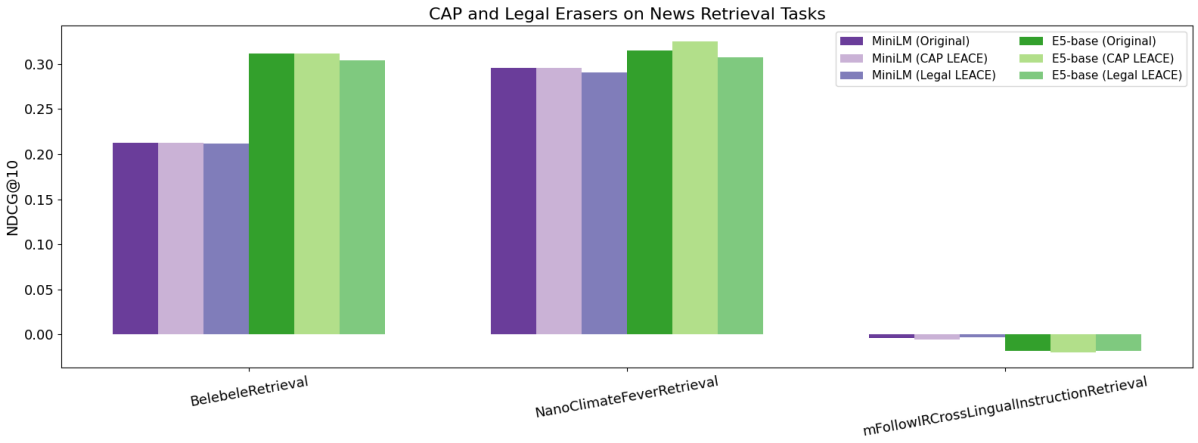

Figure 7: Performance of CAP and Legal erasers across three news retrieval tasks. Each group of bars compares the base and LEACE-erased models for MiniLM and E5-base-v2 embeddings.

Task	MiniLM			E5-base		
	Before	After (CAP)	After (Legal)	Before	After (CAP)	After (Legal)
`BelebeleRetrieval`	0.212	0.212	0.211	0.312	0.311	0.303
`NanoClimateFeverRetrieval`	0.296	0.296	0.291	0.315	0.325	0.307
`mFollowIR (CrossLingual)`	-0.004	-0.005	-0.003	-0.018	-0.019	-0.018

Table 8: News Retrieval Results on MTEB evaluated using NDCG@10. Each model (MiniLM, E5-base-v2) is evaluated before and after applying LEACE, using both CAP and Legal erasers.

even relative to no erasure.

E.2 MTEB Evaluation Results

Table 11 shows the results of applying the baselines, derived from both CAP and SCOTUS datasets, on the MTEB legal retrieval tasks. In all cases, this PC1 removal leads to a drastic performance drop for both MiniLM and E5-base models. As observed in the comparison between the two approaches in Fig. 9, in contrast, LEACE erasures maintain retrieval quality, highlighting its robustness.

F Examples for Qualitative Analysis

We provide here examples for legal case summaries that experience the largest and least changes after applying LEACE.

F.1 Examples with The Largest Changes

- *Riggins v. Nevada, 504 U.S. 127 (1992), is a U.S. Supreme Court case in which the court decided whether a mentally ill person can be forced to take antipsychotic medication while they are on trial to allow the state to make sure they remain competent during the trial.*

- *Benton v. Maryland, 395 U.S. 784 (1969), is a Supreme Court of the United States decision concerning double jeopardy. Benton ruled that the Double Jeopardy Clause of the Fifth Amendment applies to the states. In doing so, Benton expressly overruled Palko v. Connecticut.*

- *Rutan v. Republican Party of Illinois, 497 U.S. 62 (1990), was a United States Supreme Court decision that held that the First Amendment forbids a government entity from basing its decision to promote, transfer, recall, or hire low-level public employees based upon their party affiliation.*

F.2 An Example with The Least Changes

- *Cuomo v. Clearing House Association, L.L.C., 557 U.S. 519 (2009), was a case decided by the United States Supreme Court. In a 5–4 decision, the court determined that a federal banking regulation did not pre-empt the ability of states to enforce their own fair-lending laws. The Court determined that the Office of the Comptroller of the Currency is the sole regulator of national banks but it does not have the authority under the National Bank Act to pre-empt state law enforcement against national banks. The case came out of an inter-*

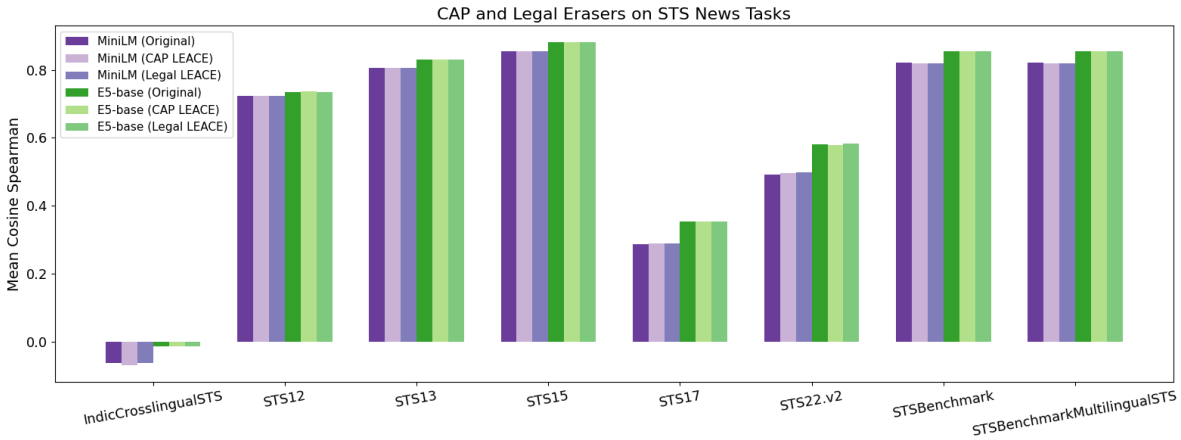

Figure 8: Performance of CAP and Legal erasers across eight STS news tasks. Each group of bars compares the base and LEACE-erased models for MiniLM and E5-base-v2 embeddings.

Task	MiniLM			E5-base		
	Before	After (CAP)	After (Legal)	Before	After (CAP)	After (Legal)
IndicCrosslingualSTS	-0.063	-0.070	-0.062	-0.013	-0.012	-0.013
STS12	0.724	0.724	0.723	0.735	0.736	0.735
STS13	0.806	0.806	0.806	0.830	0.830	0.830
STS15	0.854	0.854	0.854	0.882	0.882	0.882
STS17	0.288	0.289	0.288	0.354	0.355	0.353
STS22.v2	0.492	0.496	0.499	0.581	0.578	0.583
STSBenchmark	0.820	0.820	0.820	0.855	0.855	0.855
STSBenchmarkMultilingualSTS	0.820	0.820	0.820	0.855	0.855	0.855

Table 9: STS News Results on MTEB evaluated using the mean cosine Spearman score. Each model (MiniLM, E5-base-v2) is evaluated before and after LEACE, using both CAP and Legal erasers.

pretation of the US Treasury Department's Office of the Comptroller of the Currency which had blocked an investigation by New York into lending practices. The OCC claimed that the 1864 National Bank Act bars states from enforcing their own laws against national banks. Justice Scalia stated in the opinion that while the OCC has "visitorial powers," the right to examine the affairs of a corporation, that does not mean that it has the exclusive right to enforcement. "A sovereign's 'visitorial powers' and its power to enforce the law are two different things. Contrary to what the [OCC's] regulation says, the National Bank Act pre-empts only the former." Scalia noted that states "have always enforced their general laws against national banks—and have enforced their banking-related laws against national banks for at least 85 years." The case is notable for the justices composing the 5-4 majority, which included the liberal justices (John Paul Stevens, David Souter, Ruth Bader Ginsburg, and Stephen Breyer) along with the conservative Scalia, who authored the opinion. Justice Clarence Thomas, joined by Justices Samuel Alito, Anthony Kennedy, and Chief Justice John Roberts, wrote a dissent. The case is further notable for the suggested relationship of this OCC decision to the 2008 financial crisis.

G Embedding model information

We list characteristics of the embedding models in Table 12.

H Use of AI Assistants

We used AI assistants, including ChatGPT and Claude, for editing (e.g. grammar, spelling, and word choice), debugging code, and visualizing results.

Model	LexisNexis & Wikipedia						LexisNexis & Oyez						Oyez & Wikipedia					
	Recall@10			Recall@1			Recall@10			Recall@1			Recall@10			Recall@1		
	Before	After	Baseline	Before	After	Baseline	Before	After	Baseline	Before	After	Baseline	Before	After	Baseline	Before	After	Baseline
MiniLM	0.487	**0.606**	0.478	0.231	**0.313**	0.231	0.890	**0.899**	0.883	0.651	**0.693**	0.646	0.850	**0.924**	0.869	0.623	**0.747**	0.670
GIST-small	0.563	**0.656**	0.547	0.261	**0.325**	0.254	0.918	**0.943**	0.920	0.702	**0.778**	0.701	0.762	**0.844**	0.776	0.478	**0.599**	0.500
E5-small	0.421	0.673	**0.675**	0.176	0.353	**0.356**	0.830	**0.939**	**0.939**	0.563	**0.789**	**0.789**	0.689	**0.951**	0.950	0.398	0.752	**0.753**
MPNet	0.566	**0.666**	0.552	0.259	**0.337**	0.257	0.926	**0.943**	0.925	0.724	**0.775**	0.722	0.856	**0.911**	0.862	0.565	**0.678**	0.574
GIST-base	0.646	**0.757**	0.636	0.308	**0.412**	0.309	0.939	**0.963**	0.936	0.727	**0.819**	0.725	0.880	**0.950**	0.917	0.628	**0.773**	0.701
E5-base	0.414	**0.660**	**0.660**	0.188	0.341	**0.344**	0.830	**0.940**	0.939	0.575	**0.758**	0.755	0.650	**0.942**	**0.942**	0.371	0.737	**0.738**
Nomic-v2	0.530	0.701	**0.703**	0.254	**0.384**	0.382	0.950	**0.966**	0.948	0.770	**0.820**	0.767	0.903	0.978	**0.981**	0.658	**0.819**	0.818
MXB-large	0.537	**0.703**	0.627	0.249	**0.376**	0.321	0.928	**0.958**	0.933	0.720	**0.805**	0.729	0.883	**0.960**	0.919	0.654	**0.819**	0.737
GIST-large	0.657	**0.770**	0.641	0.305	**0.414**	0.300	0.954	**0.967**	0.954	0.787	**0.834**	0.787	0.947	**0.971**	0.944	0.760	**0.826**	0.772
E5-large	0.479	**0.720**	0.717	0.209	0.381	**0.388**	0.864	**0.949**	**0.949**	0.636	**0.791**	0.790	0.765	**0.964**	0.963	0.489	**0.792**	**0.792**

Table 10: Event-Level Results on SCOTUS Case Summaries

Task	MiniLM			E5-base		
	Before	After (CAP)	After (Legal)	Before	After (CAP)	After (Legal)
AILACasedocs	0.197	0.039	0.044	0.292	0.027	0.042
AILAStatutes	0.205	0.082	0.092	0.186	0.081	0.079
ContractsQA	0.656	0.018	0.029	0.720	0.022	0.028
CorporateLobbying	0.864	0.012	0.016	0.915	0.012	0.004
LegalSummarization	0.590	0.011	0.012	0.577	0.018	0.006

Table 11: Legal Retrieval Results on MTEB evaluated using NDCG@10. Each mode (MiniLM, E5-base-v2) is evaluated before and after applying baseline model (PC1 removal), using both CAP and Legal erasers.

Models	#Dims	#Params	Multilingual	IFT
MiniLM	384	22.7M		
GIST-small	384	33.4M		
E5-small	384	118M	✓	
MPNet	768	109M		
GIST-base	768	109M		
E5-base	768	278M	✓	
Nomic-v2	768	475M	✓	✓
MXB-large	1,024	335M		✓
GIST-large	1,024	335M		
E5-large	1,024	560M	✓	

Table 12: Embedding Models. We examine mono- and multilingual models spanning multiple parameter sizes and embedding dimensions.

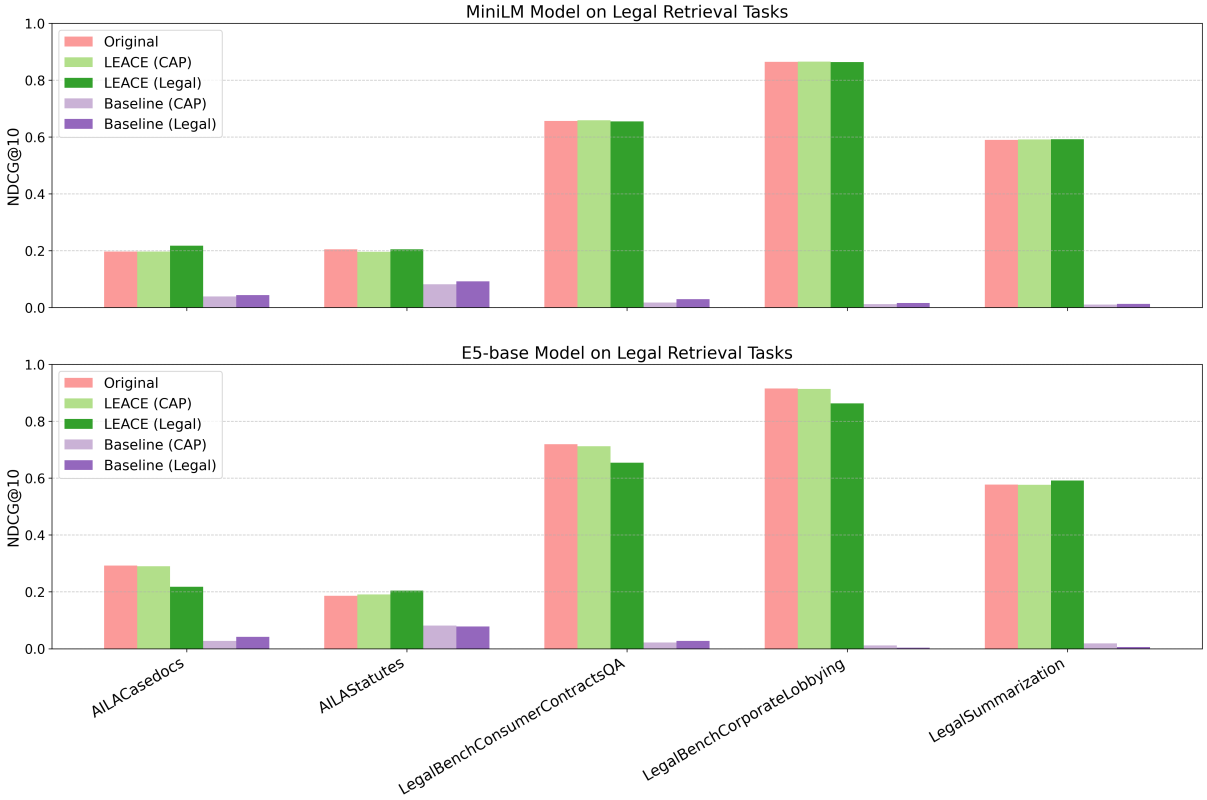

Figure 9: Comparison of average NDCG@10 scores across five MTEB legal retrieval tasks. Each group of bars compares the original, LEACE-erased and baseline models for MiniLM and E5-base-v2 models.

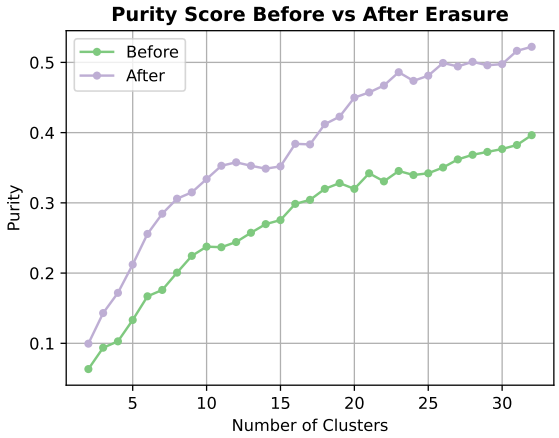

Figure 10: Purity score before vs. after LEACE erasure under different cluster counts, using data from CAP news articles and congressional bills.