From Prejudice to Parity: A New Approach to Debiasing Large Language Model Word Embeddings

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arXiv:2402.11512v1 [cs.CL] 18 Feb 2024

Abstract

Embeddings play a pivotal role in the efficacy of large language Models. They are the bedrock on which these models grasp contextual relationships and foster a more nuanced understanding of language and consequently perform remarkably on a plethora of complex tasks that require a fundamental understanding of human language. Given that these embeddings themselves often reflect or exhibit bias, it stands to reason that these models may also inadvertently learn this bias. In this work, we build on the seminal previous work and propose *DeepSoftDebias*, an algorithm that uses a neural network to perform 'soft debiasing'. We exhaustively evaluate this algorithm across a variety of SOTA datasets, accuracy metrics, and challenging NLP tasks. We find that *DeepSoftDebias* outperforms the current state-of-the-art methods at reducing bias across gender, race, and religion.

1 Introduction

Word embeddings are a foundational element in the architecture of large language models (LLMs). They act as the basis for these models to understand and subsequently, generate human-like language. However, it has been shown that these models rely on word embeddings, which themselves may reflect or exhibit bias (Papakyriakopoulos et al., 2020; Dev et al., 2020). Given the exponential increase in the use of large language models on a plethora of downstream tasks, these representations can amplify bias and result in discriminatory actions, especially when it comes to the fields of education, healthcare, and justice. Existing work in this field has looked most commonly into gender bias (Kotek et al., 2023; Bordia and Bowman, 2019; de Vassimon Manela et al., 2021), racial bias (Mozafari et al., 2020; Omiye et al., 2023; Tang et al.), and religious bias (Baligudam, 2022; Kirk et al., 2021).

In this work, we build on the seminal work of (Gonen and Goldberg, 2019), which brought attention to the inherent biases present in traditional GloVe embeddings (Pennington et al., 2014). This study prompted the NLP community to reevaluate the fundamental choices underlying our word representation models. Specifically, we present *DeepSoftBias*: an algorithm that furthers the application of their methodology, by diverging from the conventional GloVe embeddings and delving into the word embeddings produced by the best-performing models on the Massive Text Embedding Benchmark (MTEB) (Muennighoff et al., 2022) leaderboard. By employing these advanced embeddings on the same set of words as used in GloVe embeddings, we seek to investigate whether these state-of-the-art (SoTA) models inherently exhibit reduced bias. Our primary objective is twofold: first, to de-bias the embeddings from these selected models, and second, to rigorously assess the effectiveness of the bias removal process. Our proposed approach, *DeepSoftDebias*, is an innovative methodology to de-bias LLM word embeddings which involves integrating a neural network into the soft debiasing approach developed by (Bolukbasi et al., 2016). This novel amalgamation is driven by the aspiration to enhance the debiasing process and contribute to the ongoing discourse on creating fair and ethically sound language models. To this end, our work answers the following research questions:

RQ1: Compared to traditional methods, does our proposed methodology attain better performance metrics when it comes to debiasing SOTA model embeddings?

RQ2: How do parameters of the model (size, complexity) interact with various SOTA debiasing techniques? What effect do they have on each other?

RQ3: To what extent do various SOTA debiasing techniques influence the performance of models on different downstream tasks?

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RQ4: How does the type of bias (gender, race, religion) affect the effectiveness of the debiasing process?

To answer the above questions, we make the following contributions through this research:

Our Contributions

- We provide, to the best of our knowledge, the first comprehensive study of how various debiasing methods work on SoTA LLM word embeddings
- We present a novel methodology, *DeepSoftDebias*, for debiasing LLM word embeddings, which beats SoTA debiasing methods across multiple bias formats including gender, race, and religion.
- We perform an exhaustive quantitative analysis, establishing SoTA baselines and leveraging multiple evaluation metrics to provide a comparison against accessible SoTA baselines

We illustrate our pipeline in Figure 1. We find that *DeepSoftDebias* not only outperforms the state-of-the-art methods at reducing bias across gender, race, and religion but also does so while preserving the full information of the original embedding (which is an additional improvement on previous methods). Further, we find that model performance on challenging downstream tasks like NER and sentiment analysis remains largely unaffected when we test using our debiased embeddings.

2 Data

This study leverages several datasets to examine and address biases in word embeddings and language models, focusing on the representation and perpetuation of stereotypes within these systems.

2.1 L2-Reddit Corpus

We utilize the L2-Reddit[1] (Rabinovich et al., 2018) corpus, a collection of Reddit posts and comments by both native and non-native English speakers, featuring approximately 56 million sentences from the United States. This dataset serves as the foundation for training the word embeddings, aiming to capture the nuanced and inherently biased linguistic patterns present in social media discourse. The corpus provides a rich linguistic resource for analyzing and understanding the initial biased word embeddings. In our study, we employ the Reddit L2 corpus as the source for our initial Word2Vec (Mikolov et al., 2013) word embeddings. Subsequently, we leverage the vocabulary derived from these word vectors to obtain the word embeddings from the Language Model Models (LLMs).

[1] https://github.com/ellarabi/reddit-l2

2.2 StereoSet

StereoSet (Nadeem et al., 2020) stands out as a critical dataset for measuring stereotype bias in language models, containing around 17,000 sentences across demographic dimensions like gender, race, religion, and profession. It introduces the Context Association Tests (CAT) for evaluating model preferences and biases, providing a structured approach to assess and quantify biases in popular models like BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019), RoBERTa (Liu et al., 2019), and XLNet (Yang et al., 2020). The dataset's creation involved a rigorous crowdsourcing process, ensuring a wide coverage of stereotypes and anti-stereotypes to challenge and evaluate the fairness of NLP systems. In our words we use the stereoset dataset to benchmark our debiasing method against all the other debiasing methods. To accomplish this, we compute the average sentence vector for all sentences and their respective contexts. We then compare these vectors against each other to derive the stereotype score.

2.3 CrowS-Pairs

CrowS-Pairs (Nangia et al., 2020), designed to assess social biases in masked language models (MLMs), comprises 1,508 examples covering nine bias types, including race, religion, and age. It contrasts sentences related to historically disadvantaged and advantaged groups in the U.S., with annotations from crowd workers highlighting the degree of stereotyping. Despite its noise and reliability issues, CrowS-Pairs remains a valuable resource for evaluating the bias in major language models, providing a nuanced metric that quantifies preference for stereotypical versus non-stereotypical expressions. In our study, we obtain debiased word embeddings for sentences by computing the average sentence vector for both less and more stereotypical or anti-stereotypical directions. We then compare these embeddings against each other to calculate the Crows Metric score.

3 Methodology

In this research, we delve into the domain of debiasing word embeddings, presenting both an established and a newly proposed methodology for mitigating biases in word vector representations.

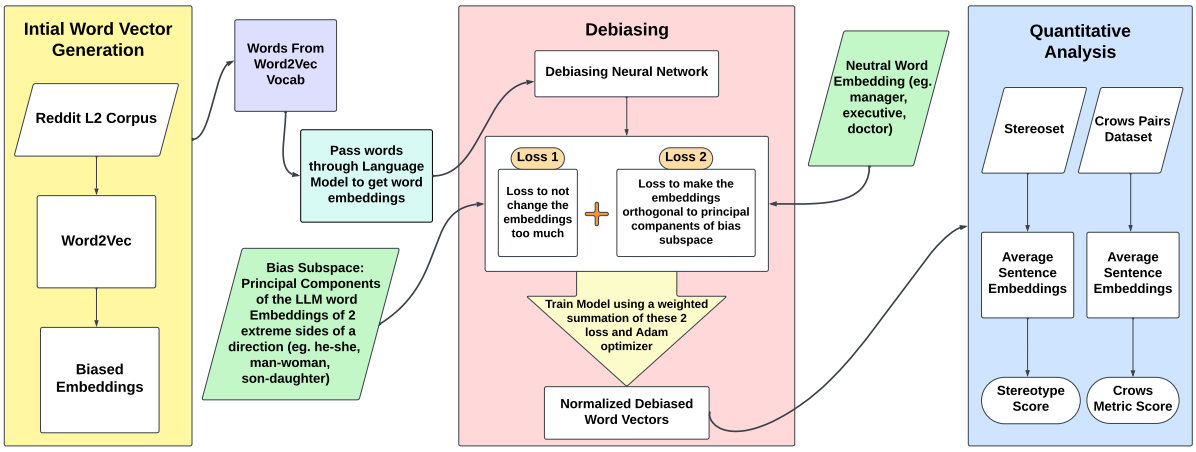

Figure 1: A step-by-step visualization of the pipeline for *DeepSoftDebias*. Our pipeline has 3 major components, Initial Word Vector Generation, Debiasing, and Quantitative Analysis. The Debiasing stage leverages the *DeepSoftDebias* network.

These biases span across gender, racial, and religious lines and are encoded inadvertently within language models.

3.1 Bias Identification and Data Structure

To quantitatively assess bias in word embeddings, we measure the projection of word vectors onto a gender-specific axis, defined by the vectorial difference between the terms 'he' and 'she.' The magnitude of this projection serves as an indicator of bias. We use a structured vocabulary with its associated vector representations from the Word2Vec model to facilitate the identification of biases. For a comprehensive evaluation, we utilize additional data files that include definitive sets of gender-associated word pairs, analogy templates that list occupational roles often linked with specific genders, and a set of neutral terms used as evaluation targets. These resources are crucial for the systematic identification and rectification of biases in word embeddings.

3.2 Soft Debiasing: The baseline approach

The initial method as seen in the paper (Manzini et al., 2019) leverages a method called soft debiasing. We recap its algorithm in Algorithm 1. Soft debiasing involves learning a projection of the embedding matrix that preserves the inner product between biased and debiased embeddings while minimizing the projection onto the bias subspace of embeddings mentioned in 3.1 that should be neutral. Given embeddings W and N which are embeddings for the whole vocabulary and the subset of bias-neutral words respectively, and the bias subspace B obtained in Section 2.1, soft debiasing seeks a linear transformation A that minimizes the following objective:

$$\left\|(AW)^T(AW) - W^TW\right\|_F^2 + \lambda \left\|(AN)^T(AB)\right\|_F^2$$

Minimizing the first term preserves the inner product after the linear transformation A, and minimizing the second term minimizes the projection onto the bias subspace B of embeddings. R is a tunable parameter that balances the two objectives.

Algorithm 1: Transformation Matrix Approach

Input: Biased word embeddings ($\text{emb}_{\text{biased}}$), Bias Subspace (BiasSpace), Neutral word embeddings ($\text{emb}_{\text{neutral}}$)

Output: Debiased word embeddings

Perform Singular Value Decomposition (SVD) on $\text{emb}_{\text{biased}}$ to obtain singular values (s) and left singular vectors (u);
Precompute $t1 = s \cdot u^T$ and $t2 = u \cdot s$;
Compute norm1 as $\|t1 \cdot (T^T \cdot T - I) \cdot t2\|_F$;
Compute norm2 as $\|\text{emb}_{\text{neutral}}^T \cdot T^T \cdot \text{BiasSpace}\|_F$;
Total loss is a weighted combination of norm1 and norm2;
Optimize transformation matrix using SGD;
Output debiased word embeddings after recomputing using T and normalizing;

3.3 *DeepSoftDebias*: Our proposed approach

In the original approach introduced by (Bolukbasi et al., 2016), a transformation matrix is utilized and optimized by an optimizer to enable a direct mapping between input and output embeddings. To enhance performance, we propose *DeepSoftDebias*. In this approach, we replace the transformation matrix with a neural network, leveraging its capability to represent a sequence of transformation matrices. This adaptation enables the algorithm to handle more complex functions mapping between input and output embeddings. We use the same loss functions as mentioned in the section 3.2. Furthermore, we transition from stochastic gradient descent (SGD (Robbins and Monro, 1951)) to the Adam (Kingma and Ba, 2017) optimizer, resulting in enhanced efficiency, speed, and optimization quality. We describe our full algorithm in Algorithm 2. While these modifications were implemented, the fundamental aspects of the method remain unaltered, ensuring minimal alterations in embeddings and preserving orthogonality with the bias space. Unlike the baseline, which relies on singular value decomposition (SVD) and incurred information loss, *DeepSoftDebias* preserves the full information of the original matrix. Moreover, unlike the baseline, *DeepSoftDebias* can handle large embedding dimensions of more than 4.5k. We demonstrate the effectiveness of *DeepSoftDebias* on various datasets and tasks, and show that it outperforms the state-of-the-art methods in terms of accuracy and efficiency. Figure 2 presents a visualization of our approach to downstream testing.

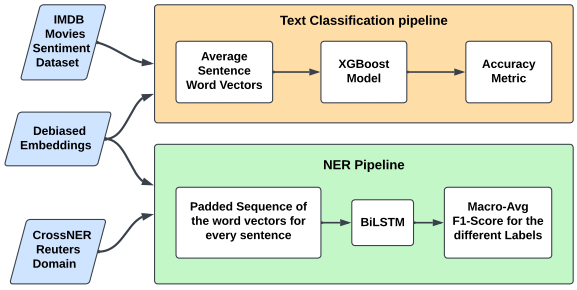

Figure 2: A step-by-step visualization of our downstream testing process to effectively evaluate *DeepSoftDebias*

4 Effects of LLM Size and Dependency of Network Size

The debiasing performance of word embeddings depends on the size of the embeddings and the depth of the debiasing neural network, rather than the number of parameters of the language model. We observe in 11 Smaller models, such as bge-small (Xiao et al., 2023) and DeBERTa-v3-base (He et al., 2023) or DeBERTa-v3-large, can be debiased effectively by a single-layer neural network. Larger models, such as Llama-2 (Touvron et al., 2023), Alpaca (Taori et al., 2023) and Yi-6b (01.ai, 2024) need a more complex debiasing neural network. For embedding dimensions around 2000, a two-layer neural network is sufficient, while for larger embedding dimensions, a three-layer neural network is required to achieve good debiasing results. Additionally, the debiasing neural network and the optimization algorithm need to be hyperparameter-tuned, such as adjusting the learning rate, to get optimal results. The hyperparameters may vary depending on the model size, the embedding dimension, and the debiasing task. Therefore, a systematic search for the best hyperparameters is necessary to ensure the effectiveness of the debiasing process.

Algorithm 2: Neural Network Approach

Input: Biased word embeddings ($\text{emb}_{\text{biased}}$), Bias Subspace (BiasSpace), Neutral word embeddings ($\text{emb}_{\text{neutral}}$)

Output: Debiased word embeddings

Initialize neural network NN with input dimension as embedding dimension and output dimension as embedding dimension;

Pass $\text{emb}_{\text{biased}}$ through NN to obtain transformed embeddings;

Compute T^T as the matrix multiplication of the transpose of outputs of NN and the outputs;

Compute norm1 as $\|(T^T \cdot T - I)\|_F$;

Compute norm2 as $\|\text{emb}_{\text{neutral}}^T \cdot T^T \cdot \text{BiasSpace}\|_F$;

Total loss is a weighted combination of norm1 and norm2;

Optimize NN using an Adam optimizer;

Output normalized embeddings obtained after passing $\text{emb}_{\text{biased}}$ through NN;

5 Results

The results obtained are described in the following subsections.

5.1 Mean Average Cosine Similarity (MAC)

MAC (Manzini et al., 2019) is a metric used to quantify semantic associations between word classes and attributes. MAC takes word embeddings, targets (representing classes), and attributes as inputs. By computing the mean cosine distance between target words and attribute sets, MAC offers a concise measure of semantic proximity. This metric provides valuable insights into the contextual semantics encoded within word embeddings. Table 1 shows that the word embeddings debiased in the direction of race and gender have comparable increases in their average MAC of 0.64, whereas word embeddings debiased in the direction of religion have an increase in MAC of around 0.61. We see that our debiasing procedure categorically moves MAC scores closer to 1.0. This indicates an increase in cosine distance. Further, the associated P-values indicate these changes are statistically significant. This demonstrates that our approach for multiclass debiasing decreases bias in the word embeddings. We provide visual representations of the efficiency of *DeepSoftDebias* at removing gender bias, racial bias, and religion bias in Appendix A.

5.2 Stereotype Score

Our research focuses on evaluating and mitigating stereotypical bias in natural language inference tasks using the Stereoset dataset. This dataset comprises pairs of sentences differing only in the substitution of words related to social groups like gender, race, or religion. The objective is to predict their relationship as same, entailment, or contradiction. We introduce a method aimed at reducing bias in word embeddings, with SS values closer to 50 indicating decreased bias. Table 2 presents *DeepSoftDebias*'s results alongside existing approaches on the Stereoset dataset. Notably, *DeepSoftDebias* achieves the lowest SS across all social groups, demonstrating its effectiveness in bias reduction. Particularly impressive is *DeepSoftDebias*'s performance in the gender and race categories, where it significantly outperforms existing methods. For instance, with the SFR-Embedding-Mistral (Jiang et al., 2023) model, *DeepSoftDebias* achieves an SS of 50 for gender and 50.409 for race using the Llama-2-7b model. Additionally, *DeepSoftDebias* attains a score of 51.282 (or 48.717) for the zephyr-7b-beta(Tunstall et al., 2023) (or Alpaca-7b(Taori et al., 2023)) group. We present an illustration of these scores in Figure 6.

5.3 Crows-Pairs Dataset

Our study evaluates social bias in natural language generation tasks using the CrowS Pairs dataset, comprising pairs of sentences differing in their degree of bias. By ranking these sentences according to bias level, we quantify the effectiveness of various methods in reducing bias in word embeddings. But as our work is based on word embeddings instead of getting the log-likelihood of the next token from the language model, we compute the average sentence vector for the common parts shared between two sentences. Next, we compare the similarity of this average sentence vector with the uncommon part (i.e., the modified tokens) using word embeddings. By doing so, we capture the semantic differences between stereotypical and non-stereotypical components within the sentence pairs. The rest of the metric remains the same.

Table 3 presents *DeepSoftDebias*'s results alongside existing approaches on the CrowS Pairs dataset. Notably, *DeepSoftDebias* achieves scores closest to 50 across all social groups, indicating a significant reduction in social bias. The metric used here can be defined as:

$$\text{Metric score: } \frac{(\text{stereo_score} + \text{antistereo_score}) \times 100}{N} \tag{1}$$

where stereoscore is the number of stereotypical samples that agree with their label direction and antistereoscore is the number of anti-stereotypical samples that agree with their label direction. Particularly noteworthy is *DeepSoftDebias*'s superior performance in the gender and religion categories. For instance, with the Yi-6B model, *DeepSoftDebias* achieves a score of 49.62 for gender and 50.48 for religion with the falcon-7b model. Similarly, using the SFR-Embedding-Mistral model, *DeepSoftDebias* achieves a score of 49.03 for race biasing the SFR-Embedding-Mistral model. These results underscore the effectiveness of *DeepSoftDebias* in mitigating social bias in word embeddings. We depict the variation of these scores in Figure 8.

6 DownStream Results

6.1 Sentiment Classification

In our study, we employ downstream testing to assess the utility of embeddings debiased using *DeepSoftDebias* across two key natural language processing tasks: text classification and named entity recognition (NER). Utilizing the IMDB Sentiment Classification dataset(İlhan Tarımer et al., 2019) for

Model	Variant	Topic	BMAC	NSMAC	SS	CMS	CSS	CAS
Yi	Yi-6B		0.148	0.964	55.372	**49.620**	58.970	37.250
Alpaca	Alpaca-7B		0.612	0.816	53.306	48.850	57.690	37.250
BAAI	bge-base-en-v1.5		0.471	**0.997**	**50.000**	48.090	42.310	58.820
BAAI	bge-large-en-v1.5		0.404	0.983	49.174	50.380	50.640	51.960
Zephyr	Zephyr-7B-beta	Gender	0.393	0.981	52.893	46.950	59.620	29.410
Mistral	e5-mistral-7b-instruct		0.343	0.971	52.893	48.090	55.770	38.240
Llama 2	Llama-2-7b-hf		0.182	0.964	48.347	44.660	57.690	26.470
Salesforce	SFR-Embedding-Mistral		0.343	0.971	**50.000**	45.420	50.000	40.200
Falcon	falcon-7b		0.011	0.964	51.240	48.850	60.900	32.350
Yi	Yi-6B		0.111	0.964	46.209	64.150	66.170	53.660
Alpaca	Alpaca-7B		0.655	0.938	52.357	41.280	41.540	46.340
BAAI	bge-base-en-v1.5		0.496	0.992	**49.590**	44.770	46.250	36.590
BAAI	bge-large-en-v1.5		0.404	0.990	50.922	40.890	40.690	51.220
Zephyr	Zephyr-7B-beta	Race	0.419	0.992	49.283	42.250	41.330	60.980
Mistral	e5-mistral-7b-instruct		0.380	**0.999**	50.922	52.520	52.680	60.980
Llama 2	Llama-2-7b-hf		0.175	0.990	**50.410**	45.930	46.680	46.340
Salesforce	SFR-Embedding-Mistral		0.381	0.994	51.639	**49.030**	50.750	39.020
Falcon	falcon-7b		0.010	0.985	50.922	46.710	46.900	53.660
Yi	Yi-6B		0.147	0.984	52.564	47.620	48.480	33.330
Alpaca	Alpaca-7B		0.676	0.823	51.282	80.000	82.830	33.330
BAAI	bge-base-en-v1.5		0.497	0.990	46.154	59.050	61.620	16.670
BAAI	bge-large-en-v1.5		0.406	0.985	**51.282**	60.000	61.620	33.330
Zephyr	Zephyr-7B-beta	Religion	0.465	0.996	**51.282**	48.570	50.510	16.670
Mistral	e5-mistral-7b-instruct		0.436	0.985	52.564	52.380	51.520	66.670
Llama 2	Llama-2-7b-hf		0.202	1.003	44.872	64.760	66.670	33.330
Salesforce	SFR-Embedding-Mistral		0.437	0.988	**51.282**	40.950	39.390	66.670
Falcon	falcon-7b		0.009	**0.998**	**48.718**	**50.480**	51.520	33.330

Table 1: Quantitative analysis for *DeepSoftDebias* using BiasedMAC (BMAC), New SoftMAC (NSMAC), StereotypeScore (SS), Crows Metric Score (CMS), Crows Stereotype Score (CSS), Crows Antistereotype Score (CAS). The best performance is highlighted in **bold**.

Stereotype Score (SS)			
Stereoset	**Gender**	**Race**	**Religion**
FineDeb	53.27	50.82	**50.39**
CDA	59.61	56.73	58.37
INLP	57.25	57.29	60.31
Self-Debias	59.34	54.30	57.26
Sentence Debias	59.37	57.78	58.73
DeepSoftDebias	**50.00**	**50.41**	51.28

Table 2: StereoSet evaluation. Closer to 50 is better for SS. The best performance is highlighted in **bold** while the next best is underlined).

Crows Pairs Metric Score (CMS)			
Crows Pairs Dataset	**Gender**	**Race**	**Religion**
FineDeb	54.58	65.24	44.76
CDA	56.11	56.70	60.00
INLP	51.15	67.96	60.95
Self-Debias	52.29	56.70	56.19
Sentence Debias	52.29	62.72	63.81
DeepSoftDebias	**50.38**	**49.07**	**50.48**

Table 3: Crows Pairs evaluation. Metric score for every demographic. Closer to 50 is better for the metric (**best**; next best).

text classification, featuring labeled movie reviews as positive or negative, we compute the average sentence vectors using both original and debiased embeddings. Training XGBoost (Chen and Guestrin, 2016) classifiers on these vectors, we compare their accuracy on the test set, recognizing accuracy as a straightforward metric for binary classification tasks like sentiment analysis. Notably, our results reveal a performance improvement when debiasing in the gender and religion directions, whereas a slight decrease in performance is observed in the case of race debiasing. We provide a visual representation of these results in Figure 9.

6.2 Named Entity Recognition (NER)

In our research, we examine the performance of debiased embeddings in the domain of named entity recognition (NER) using the Reuters subset of the CrossNER (Liu et al., 2020) dataset. This dataset comprises news domain sentences annotated with four entity types: person, location, organization, and product. Employing a simple Bidirectional Long Short-Term Memory (BiLSTM) model, we inputted padded arrays of embeddings for each sentence and trained the model on the dataset. We evaluate the models' performance on the test set using the macro-averaged F1-score, a metric that balances precision and recall, crucial for accurate entity identification and classification. To mitigate potential bias towards more frequent entity types,

Model	Variant	Bias Direction	Biased Text Class. Acc.	Debiased Text Class. Acc.	Biased NER Macro F1 Avg.	Debiased NER Macro F1 Avg.
Mistral	e5-mistral-7b-instruct	Gender	0.809	0.810	0.385	0.433
Zephyr	Zephyr-7B-beta		0.806	0.810	0.368	**0.429**
Salesforce	SFR-Embedding-Mistral		0.807	0.821	0.373	0.428
Yi	Yi-6B		0.748	**0.782**	0.378	0.423
Alpaca	Alpaca-7B		0.745	0.729	0.349	0.391
BAAI	bge-large-en-v1.5		0.831	0.822	0.456	0.421
BAAI	bge-base-en-v1.5		0.831	0.822	0.453	0.392
Mistral	e5-mistral-7b-instruct	Race	0.811	0.817	0.362	**0.435**
Zephyr	Zephyr-7B-beta		0.806	**0.814**	0.393	0.443
Salesforce	SFR-Embedding-Mistral		0.810	0.818	0.382	0.413
Yi	Yi-6B		0.748	0.782	0.378	0.423
Alpaca	Alpaca-7B		0.751	0.729	0.358	0.373
BAAI	bge-large-en-v1.5		0.832	0.821	0.473	0.424
BAAI	bge-base-en-v1.5		0.830	0.813	0.457	0.433
Mistral	e5-mistral-7b-instruct	Religion	0.808	0.815	0.385	0.437
Zephyr	Zephyr-7B-beta		0.805	0.812	0.389	**0.444**
Salesforce	SFR-Embedding-Mistral		0.808	0.817	0.389	0.440
Yi	Yi-6B		0.750	**0.769**	0.384	0.439
Alpaca	Alpaca-7B		0.751	0.726	0.364	0.389
BAAI	bge-large-en-v1.5		0.830	0.816	0.457	0.419
BAAI	bge-base-en-v1.5		0.830	0.817	0.459	0.421

Table 4: Downstream testing results with embeddings debiased using *DeepSoftDebias*. The first two columns represent results for downstream performance on sentiment analysis. The second two columns represent results for downstream performance on NER. The best performance is highlighted in **bold**.

Debiasing Direction	Biased	Baseline	Baseline + Adam	DeepSoftBias + SGD	DeepSoftBias + Adam
Gender	0.390	0.623	0.799	0.893	0.982
Race	0.404	0.656	0.824	0.984	0.987
Religion	0.406	0.623	0.812	0.966	0.983

Table 5: Ablations to characterize various design decisions in the development of *DeepSoftDebias*. We start with the transformation matrix, then make incremental additions till we reach the proposed architecture of the *DeepSoftDebias* network.

we adopt macro-averaging, allotting equal importance to each entity type. Remarkably, our findings indicate a slight performance boost when using debiased embeddings in all three directions compared to biased embeddings. We provide a visual representation of these results in Figure 10.

7 Ablation Experiments

In our study, we conduct ablation experiments to assess the effectiveness of various debiasing techniques in the realm of natural language processing. These techniques encompassed five distinct scenarios: the utilization of debiased embeddings, the application of the original soft debiasing method, the integration of the original debiasing method with the Adam optimizer, the incorporation of new neural networks trained with the debiasing method alongside the SGD optimizer, and finally, our proposed approach, which combines neural networks trained with the debiasing method and the Adam optimizer.

Through rigorous experimentation across three biasing directions, we systematically analyze the performance of each method. Our results reveal a consistent trend of incremental improvements as we transitioned from one method to the next. Notably, *DeepSoftDebias*, emerged as the standout performer, boasting the highest mean average cosine similarity score across all evaluated scenarios. In addition, our analysis revealed that substituting the transformation matrix with our neural network approach resulted in the most significant enhancement in the efficacy of the debiasing method. This observation underscores the pivotal role played by neural networks in maximizing the effectiveness of the debiasing techniques. We present a visualization of the results of our Ablation experiments in Table 5.

This empirical evidence underscores the robustness and efficacy of our proposed approach in mitigating bias within natural language processing systems. By combining state-of-the-art debiasing techniques with advanced optimization strategies, we have unlocked a powerful methodological frame-

work for enhancing the fairness and accuracy of language models.

8 Discussion

In this section, we summarise the answers to our research questions.

8.1 RQ1

We find that *DeepSoftDebias outperforms state-of-the-art methods, and does so without negatively affecting downstream task performance.* We make this conclusion after exhaustive testing on several models, and datasets and evaluating several metrics.

8.2 RQ2

We find that *size and complexity do affect the ability of debiasing models.* Specifically, we make the following observations about *DeepSoftDebias*:

- A single layer neural network can effectively de-bias embeddings with dim ≤ 1024.
- A two-layer neural network can effectively debias embeddings with dim ≤ 2048.
- A two-layer neural network with an increased layer size can effectively de-bias embeddings with dim ≤ 4096.
- A three-layer neural network can effectively debias embeddings with dim ≤ 4450.

As a step for future work, we are curious to investigate scaling patterns to a further extent.

8.3 RQ3

While debiasing techniques in general can affect the downstream performance of models, we test *DeepSoftDebias* on multiple challenging downstream tasks and report that *our proposed approach, to a large extent, does not negatively influence the performance of different downstream tasks. Remarkably, we see an improvement when using our debiased embeddings for some downstream tasks.*

8.4 RQ4

We find that while *DeepSoftDebias* is *effective at reducing bias across gender, race, and religion.* We conclude this after testing on multiple embeddings, and multiple datasets and evaluating on multiple performance metrics. As a step for future work, we are curious to investigate whether our proposed approach works towards other forms of bias as well.

9 Conclusion

In this paper, we propose *DeepSoftDebias*, an approach that leverages neural networks to reduce bias in large language model embeddings. We perform an exhaustive series of tests using multiple performance metrics, state-of-the-art datasets, and downstream tasks to ensure that our debiasing technique is robust, efficient, and accurate. In the future, it would be interesting to see how this method translates to multilingual datasets since bias is language and culture-specific. We hope that this research paves the way for future endeavors that look to make large language models fair, ethical, and bias-free.

10 Limitations

While we do perform exhaustive analysis to test our proposed methodology, our study is monolingual and covers datasets only in English. Consequently, our downstream tasks are also tested only in English. Further, we were unable to test on API-based models at this time.

11 Ethics Statement

We understand that bias can be defined in various ways, and it's not necessarily ideal for a language model to treat all users exactly the same without considering demographics. There are situations where certain topics require careful handling to avoid perpetuating harmful stereotypes against marginalized communities. Using specific bias metrics might suggest they encompass all negative social impacts across different groups, but we recognize that existing metrics may not capture all nuances in treatment across demographics. Therefore, any benchmark for bias needs to continually evolve to better understand and address these issues as they affect different communities.

The definitions of morality and bias are shaped by cultural perspectives, resulting in diverse interpretations among individuals. Consequently, we do not claim that this work provides an objective or exhaustive measure of any of these concepts.

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Frequently Asked Questions (FAQs)

1. **Is this method effective at removing all kinds of bias?**
   We acknowledge that bias has multiple forms that vary by different social factors, language, culture, and various other factors. We evaluated *DeepSoftDebias* on gender bias, racial bias, and religious bias and it has proved effective at reducing all of them. We hope that in the future, this method will prove effective in reducing other kinds of biases as well.

2. **Why isn't GPT analyzed in this paper?**
   Given that GPT is an API-based model, we were unable to test it at this time. We hope that one day, this method can be tested even on API-based LLMs.

3. **Is the proposed approach open-sourced?**
   Yes, we plan to make all our code available on a GitHub repository.

Appendix

This section provides supplementary material in the form of additional examples, implementation details, etc. to bolster the reader's understanding of the concepts presented in this work.

A MAC Scores of *DeepSoftDebias*

Figures 3, 4, and 5 illustrate how *DeepSoftDebias* reduces bias in LLM embeddings.

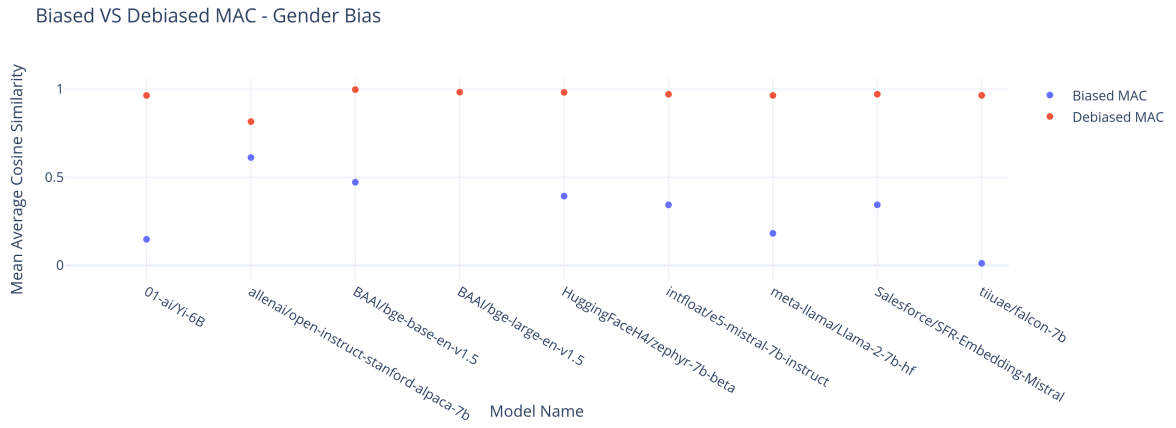

Figure 3: A visual representation of how *DeepSoftDebias* reduces gender bias in large language model embeddings.

B Stereoset Scores of *DeepSoftDebias*

Figures 6 and 8 provide an illustration of word vectors debiased using *DeepSoftDebias* and their stereoset scores and Crows Metric scores respectively.

C Downstream Testing Results

Figures 9 and 10 present an illustration of the results of various downstream tasks and their performance evaluation.

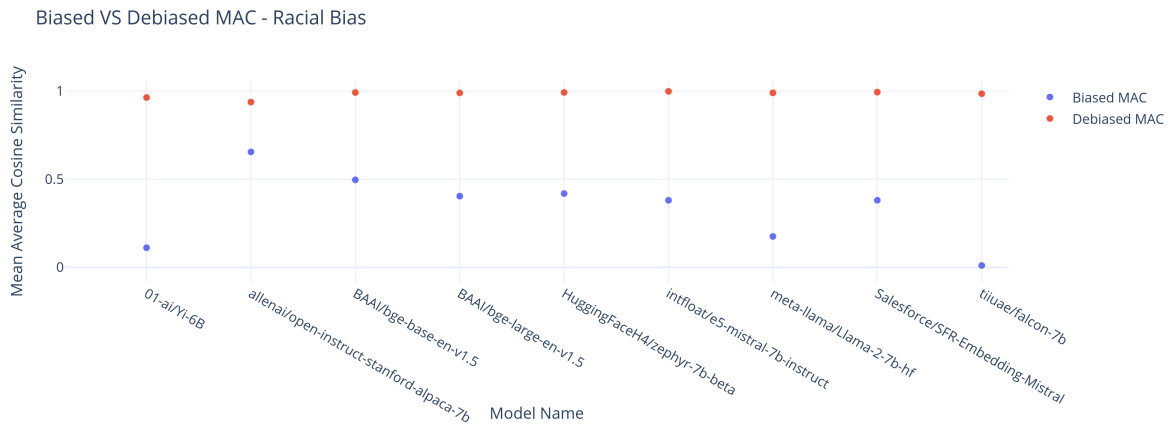

Figure 4: A visual representation of how *DeepSoftDebias* reduces racial bias in large language model embeddings.

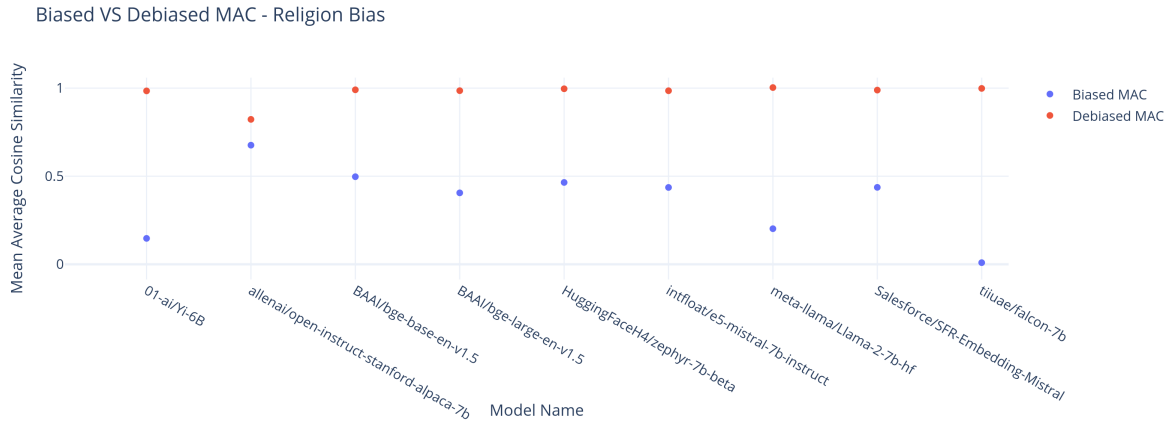

Figure 5: A visual representation of how *DeepSoftDebias* reduces religion bias in large language model embeddings.

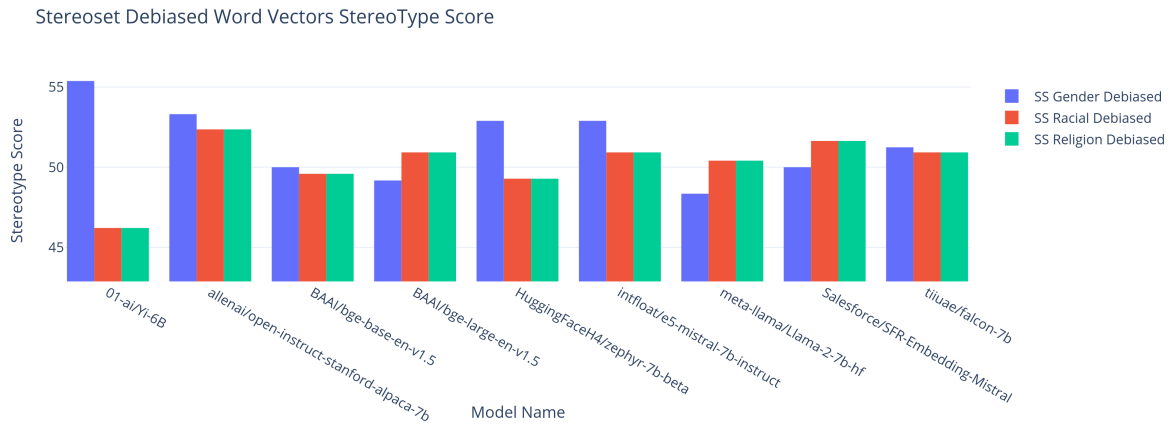

Figure 6: A visual representation of word vectors debiased using *DeepSoftDebias* and their stereotype scores across gender, race and religion respectively.

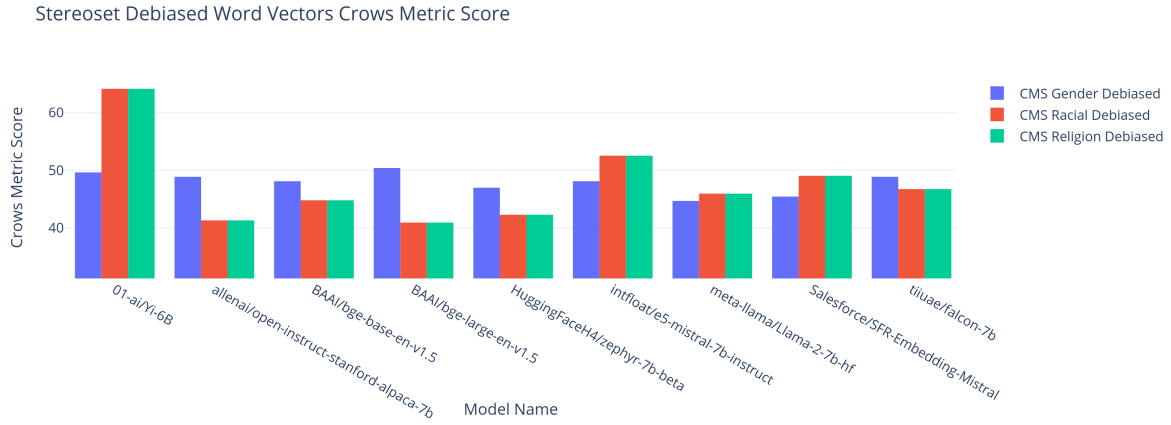

Figure 7: A visual representation of word vectors debiased using *DeepSoftDebias* and their Crows Metric score across gender, race and religion respectively.

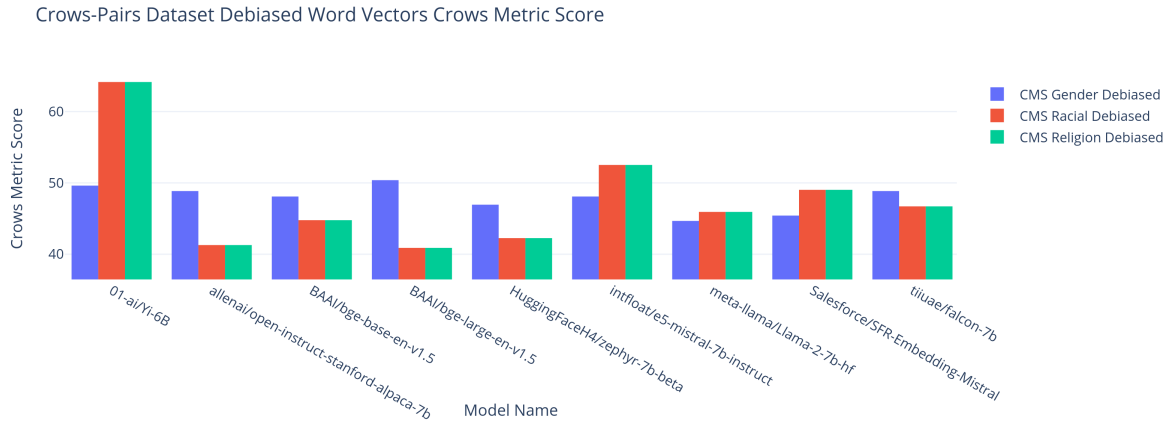

Figure 8: A visual representation of word vectors debiased using *DeepSoftDebias* and their Crows Metric scores across gender, race and religion respectively.

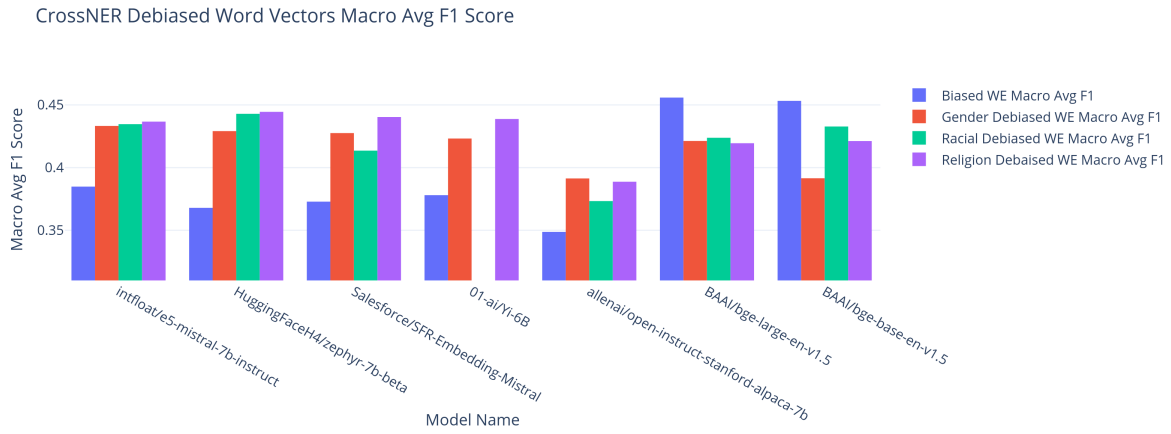

Figure 9: An illustration of the results of downstream testing on NER. We compare the performance of biased and debaised embeddings in the directions of gender, race, and religion respectively.

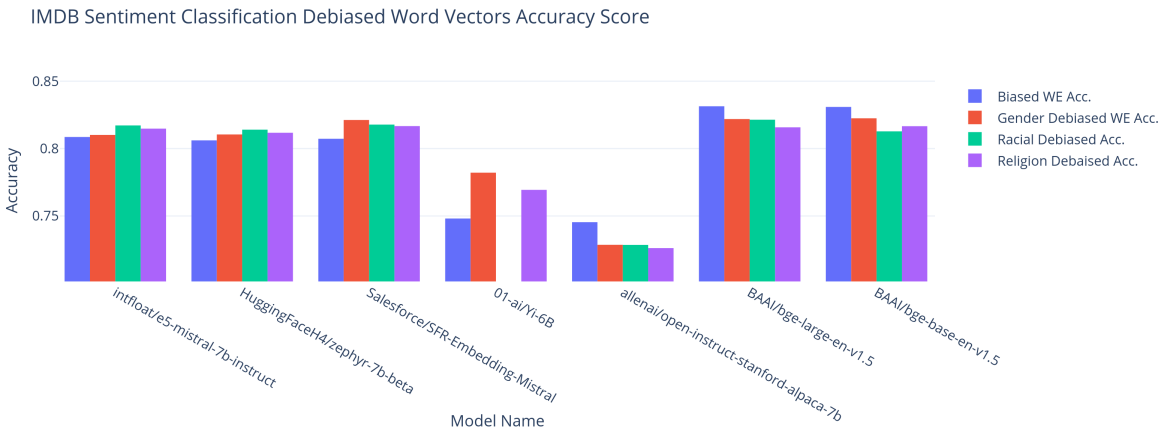

Figure 10: An illustration of results of downstream testing on sentiment analysis. We compare the performance of biased and debaised embeddings in the directions of gender, race, and religion respectively.

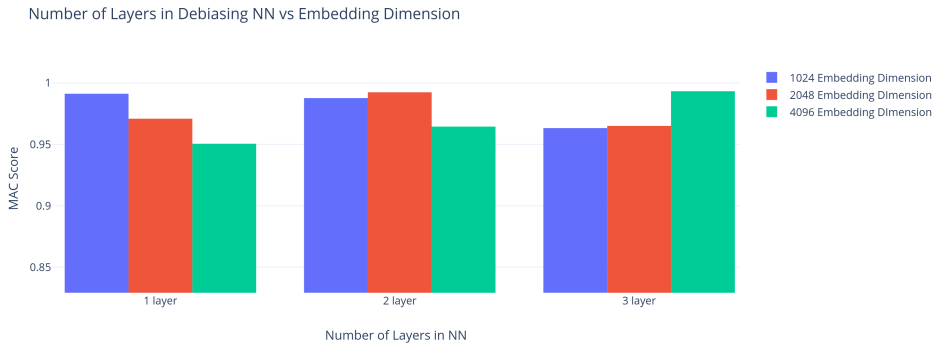

Figure 11: An illustration analysis of number of layers in debiasing neural network vs. embedding dimension. We can see the varying performance of the 3 different sizes according to the embedding dimension of the LM it is used with.