Conceptor-Aided Debiasing of Contextualized Embeddings

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Abstract

Pre-trained language models reflect the inherent social biases of their training corpus. Many methods have been proposed to mitigate this issue, but they often fail to debias or they sacrifice model accuracy. We use conceptors—a soft projection method—to identify and remove the bias subspace in contextual embeddings in BERT and GPT. We propose two methods of applying conceptors (1) bias subspace projection by post-processing; and (2) a new architecture, conceptor-intervened BERT (CI-BERT), which explicitly incorporates the conceptor projection into all layers during training. We find that conceptor post-processing achieves state-of-the-art debiasing results while maintaining or improving BERT’s performance on the GLUE benchmark. Although CI-BERT’s training takes all layers’ bias into account and can outperform its post-processing counterpart in bias mitigation, CI-BERT reduces the language model accuracy. We also show the importance of carefully constructing the bias subspace. The best results are obtained by removing outliers from the list of biased words, intersecting them (using the conceptor AND operation), and computing their embeddings using the sentences from a cleaner corpus.

1 Introduction

Pre-trained language models such as BERT (Devlin et al., 2019) and GPT (Radford et al., 2019; Brown et al., 2020) are extremely successful in most natural language processing tasks. However, since the models are trained on text written by humans, the social bias is inherited and represented in the pre-trained parameters of the model (Bolukbasi et al., 2016; Caliskan et al., 2022). For example, gender bias has been found in contextualized embeddings (May et al., 2019; Zhao et al., 2019). Many researchers have thus developed debiasing techniques to improve the social fairness of language models. However, such debiasing often fails to debias effectively and reduces language model performance in downstream tasks (Meade et al., 2022). Furthermore, most debiasing methods fail to follow Bommasani et al. (2020)’s recommendation to reduce bias in all layers.

In this paper, we extend Karve et al. (2019)’s usage of conceptor negation—a soft shrinkage of the principal components of the subspace defined by the list of biased words (Liu et al., 2018)—to debias the contextualized embeddings of BERT and GPT using either post-processing or continued training. In this process, we also show the effect on debiasing performance of choosing different corpora, subspace removal methods, and criteria for selecting the list of bias attribute words that are used to construct the bias subspace.

Specifically, the attribute wordlists at the core of our method, and the methods we build on, are sets of attribute words related to bias. These typically come in opposing pairs (e.g. ‘man’/‘woman’, ‘prince’/‘princess’); Bolukbasi et al. (2016) and others use the first principal component to define
the bias subspace—which can be later subtracted to debias. We similarly construct such subspaces, but use conceptors as a ‘soft’ way to remove them. When generating such wordlists, it is advantageous to remove outliers in the embeddings space. Considering the embeddings are contextualized, we select the contextualized token-level word embeddings using sentences from a specific corpus. Then we stack them to generate a bias subspace in a form of conceptor matrix for the debiasing in the next step. The pipeline is demonstrated in Figure 1.

This work contributes the following:

- Employs debiasing conceptors to debias the contextualized embeddings from language transformer model, BERT and GPT, using post-processing, while retaining useful semantics and robustness in multiple scenarios
- Explores a novel model architecture conceptor-intervened BERT (CI-BERT) which continues training BERT after incorporating conceptors within all of BERT’s layers
- Illustrates how different corpora, bias attribute wordlists, and outlier removal criteria impact debiasing performance
- Demonstrates that conceptor-aided methods can be generalized to different hidden state layers of the language model by using the corresponding conceptor negation matrix generated from that layer

2 Related Work

The Natural Language Processing (NLP) community has long targeted the social bias manifested within language models.

2.1 Bias Manifestation

Multiple demographic biases are common. Gender bias is the most well-studied in academia, given its omnipresence and bi-polarity (Bolukbasi et al., 2016; May et al., 2019; Kurita et al., 2019). Other social biases (e.g. racial, religious, professional) are also widespread in language models and are attracting increasing attention (Nangia et al., 2020; Nadeem et al., 2021; Meade et al., 2022).

Such social bias manifests itself in all layers of the contextualized representations of pre-trained models like BERT and GPT (Bommasani et al., 2020); and Kaneko and Bollegala (2021) shows that debiasing all layers is more effective. Thus, a new challenge is raised on how to adapt current methods or develop novel paradigms to mitigate the bias in each layer.

2.2 Debiasing Techniques and Challenges

Here, we describe a related debiasing method (see Meade et al. (2022) for an overview), each with a typical example(s):

(1) Bias Subspace Projection (BSP): the classic method of bias subspace subtraction is to first capture the bias subspace determined by attribute words in the corpora and then project the bias direction out from the language embeddings. This can be done by post-processing as either hard projection (Bolukbasi et al., 2016; SENTENCEDEBIAS, Liang et al., 2020) or soft projection (Karve et al., 2019). Some variants attain a similar goal by training a linear classifier (INLP, Ravfogel et al., 2020) or fine-tuning the model (Kaneko and Bollegala, 2021).

(2) Counterfactual Data Augmentation (CDA): swapping the bi-polar bias attribute words (e.g. her/him) to rebalance the training dataset and therefore decrease the gender bias (Webster et al., 2020; Barikeri et al., 2021).

(3) Dropout Regularization (DROPOUT): in combination with an additional pre-training, increasing the dropout components inside the transformer-based language models can lead to lower bias (Webster et al., 2020).

(4) SELF-DEBIAS: by using templates deliberately designed to encourage the model to generate toxic output and then modifying the original output distribution of the model by a decoding algorithm, Schick et al. (2021) makes use of the internal knowledge of language model to debias in a post-hoc manner.

Further, it is common to combine multiple such methods. For instance, Zhao et al. (2019) and Liang et al. (2020) combine the techniques of data augmentation and hard debiasing. However, per the discussion in Meade et al. (2022), the methods often neither debias as well as they claim (e.g. CDA, DROPOUT, SENTENCEDEBIAS), nor do they maintain the model’s capability for downstream tasks (e.g. CDA, DROPOUT, INLP). Worse, some techniques like CDA and DROPOUT increase the bias measured on SEAT—a test of language bias which we will describe in Section 4. This dilemma challenges us to develop new methods to further reduce bias while retaining meaningful semantics. Last, the majority of debiasing methods ground the bias
by word list; different lists can lead to different debias performance (Antoniak and Mimno, 2021).

2.3 Conceptors in NLP

Conceptors—a soft projection method supporting conceptual abstraction and logical operations (Jaeger, 2014)—has been used in NLP domains such as debiasing (Liu et al., 2018; Sedoc and Ungar, 2019; Karve et al., 2019), continual learning (Liu et al., 2019a), and semantic information enrichment (Liu et al., 2019b). Conceptor negation is a soft shrinkage of the principal components of a subspace such as stop words or, in our case, of the target words defining the bias directions (Liu et al., 2018).

Although Karve et al. (2019) show that debiasing conceptors can successfully debias both static embeddings such as Glove, Word2vec, and Fasttext, and contextual embeddings such as ELMo (Peters et al., 2018) and BERT, they state that the performance in BERT is far less consistent and effective than other word representations. We discover that this is the result of their having selected the wrong set of attribute words, which leads to a poor bias subspace. Another difference is that the BERT tokens of attribute words should be averaged if they contain multiple subwords after tokenization (Liang et al., 2020; Kaneko and Bollegala, 2021).

Conceptors offer many advantages for language debiasing. First, debiasing conceptors, as a soft debiasing projection, reduce bias more than hard projection (Bolukbasi et al., 2016) by Karve et al. (2019) and retain enough semantics to provide better performance in downstream tasks (Liu et al., 2018). Further, conceptors can combine subspaces given by different attribute wordlists via logical operations such as AND, and so can simultaneously take multiple different bias types into account, such as gender, race, and ethnicity.

3 Debiasing Sentence Representations

3.1 Bias Subspace Setting

We explore the impact of different choices of attribute wordlists, the corpora used to find their embeddings, and how the wordlists are combined and filtered to remove outliers, on the quality of bias subspace, and hence the debiasing. Different procedures of bias subspace construction yield significantly different debiasing performance.

Corpora To assess the influence of the corpus (e.g., language formality, topic breadth) used to embed bias attribute words, we compare three corpora: (1) the Brown Corpus (Francis and Kucera, 1979), a collection of text samples of mixed genres; (2) the Stanford Sentiment Treebank (SST, Socher et al., 2013), a polarized dataset that scrapes 10,662 movie review sentences; and (3) a Reddit Corpus (Liang et al., 2020), a dataset collected from discussion forums about relationships, electronics, and politics. We use these to provide embeddings for each of the words on the attribute wordlists.

Combining and Filtering Wordlists We compare five ways of using three different wordlists to create bias subspaces.

The three wordlists are gender words originating from different sources: the pronouns wordlist is a set of common terms that are specific to particular genders, such as ‘daughter’ or ‘son’; the extended wordlist, an extension of the former, contains less frequent words such as ‘cowgirls’ or ‘fiances’; and propernouns wordlist is comprised of proper nouns like ‘Tawsha’, ‘Emylee’, etc.

There are five methods of using these three wordlists to generate a bias subspace. We can use each of them individually (their subspaces are named the same as themselves: pronouns, extended, and propernouns, respectively). We can also combine them in two ways: either by concatenating them as a single list generating a corresponding subspace (named all); or by running the conceptor AND operation—a Boolean operation of conceptors that will be described in Section 3.2—on the three corresponding conceptor matrices to generate what can be viewed as an intersection of the three bias subspaces (named and).

Different from Karve et al. (2019), to study the effects of removing outliers from the wordlists, we first project the BERT embeddings of the words in the wordlist to the 2-dimensional UMAP clustering (McInnes et al., 2018) space, shown in Figure 2, and then filter the outliers by percentile based on their $(x, y)$-coordinate. The outliers are defined as the points that fall outside of 1.5 times the interrange (IR), which is the difference between $p$-th and $(1−p)$-th percentile. We iterate $p$ from 0.1 to 1.0 with step size 0.1 to generate different wordlists, and then test how well each debiases. Our goals are to detect the negative effect of outliers on debiasing performance and to explore which percentile here is optimal for debiasing.

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1We fixed the coding issues
3.2 The Mathematics of Conceptors

Similar to Karve et al. (2019), considering a set of vectors \( \{ x_1, \cdots, x_n \} \), \( x_i \in \mathbb{R}^N \) for all \( i \in \{1, \cdots, n\} \), a conceptor matrix \( C \) is a regularized identity map that minimizes

\[
\frac{1}{n} \sum_{i=1}^{n} \| x_i - C x_i \|_2^2 + \alpha^{-2} \| C \|_F^2
\]

where \( \| \cdot \|_F \) is the Frobenius norm and \( \alpha^{-2} \) is a scalar hyper-parameter called aperture \(^2\). It can be shown that \( C \) has a closed-form solution:

\[
C = \frac{1}{n} X X^\top \left( \frac{1}{n} X X^\top + \alpha^{-2} I \right)^{-1}
\]

where \( X = [x_i]_{i \in \{1, \cdots, n\}} \) is a data collection matrix whose \( i \)-th column is \( x_i \). Intuitively, \( C \) is a soft projection matrix on the linear subspace where the typical components of \( x_i \) samples lie.

Conceptors support Boolean operations such as NOT (\( \neg \)), AND (\( \land \)) and OR (\( \lor \)). For two conceptors \( C_1 \) and \( C_2 \), we have

\[
\neg C_1 := I - C_1
\]

\[
C_1 \land C_2 := (C_1^{-1} + C_2^{-1} - I)^{-1}
\]

\[
C_1 \lor C_2 := \neg(\neg C_1 \land \neg C_2)
\]

These logical operations are feasible if \( C_1 \) and \( C_2 \) are created by the sets of equal sizes (Jaeger, 2014). This reveals the potential for debiasing by combining different conceptors learned from different bias subspaces. This is helpful both in combining different wordlists for the same bias (e.g. gender) or different wordlists for different protected classes (e.g. gender and race).

3.3 Debiasing Methods

We propose and explore two kinds of conceptor-aided debiasing methods: conceptor post-processing, and conceptor-intervened continued training. They are abbreviated as P.P. and C.T. respectively in tables hereafter.

**Conceptor Negation and Post-Processing**

First we construct the conceptor negation matrix \( C \) using equation (2) where matrix \( X \) is a stack of the within-sentence contextualized embeddings of the words. The words are determined by attribute wordlists and the sentences are from the specified corpus as mentioned in Section 3.1. Following Kaneko and Bollegala (2021)’s suggestion, if a word crosses multiple sub-tokens, then the contextualized embedding of this word is computed by averaging the contextualized embeddings of its constituent sub-tokens, which is different than the previous conceptor works.

Next, we post-process the sentence embeddings, \( S_{\text{biased}} \), which contain attribute words and target words, by taking the matrix product of \( C \) to subtract the bias subspace, getting debiased results \( S_{\text{debiased}} \). Mathematically, it is expressed as

\[
S_{\text{debiased}} = S_{\text{biased}} \cdot C
\]

Each BERT layer manifests different levels of bias (Bommasani et al., 2020). To maximize the effectiveness of \( C \), we want \( C \) to be generated from the corresponding layer. Therefore, we are the first one to test the debiasing performance by using different conceptor matrices generated by different layers of the language model and to explore whether conceptor post-processing generalizes well on each layer of LLMs and on different LLMs such as BERT and GPT2.

**Conceptor Intervention and Continued Training**

The varying levels of bias across BERT layers suggest the possible utility of an alternate approach to mitigate the bias. Accordingly, we construct a new architecture, Conceptor-Intervened
We use two different metrics to measure the gender bias captured in the sentence representation: The Sentence Encoder Association Test and Gender Co-reference Resolution.

### 4.1 Sentence Encoder Association Test

The Sentence Encoder Association Test (SEAT) (May et al., 2019) is an extension of the Word Encoder Association Test (WEAT) (Caliskan et al., 2017). It can measure the bias at the sentence level and can be used in different kinds of bias (Meade et al., 2022).

SEAT uses two types of words: attribute words \( W_a \) (e.g. gender: he/she, man/woman) and target words \( W_t \) (e.g. occupations: doctor, nurse, professors), which we expect to be gender-neutral. That is, the association between \( w_a \) and \( w_t \) and the association between \( w'_a \) and \( w'_t \), where \( w_a \) and \( w'_a \in W_a \) is a pair of opposite attribute words and \( w_t \) and \( w'_t \in W_t \) should be represented with no difference in the language modeling. Extending to sentence level, we put these words into varied, short sentence templates (e.g. “here is a [WORD]”) to evaluate the bias better in sentence representation.

Denote the sentence sets of attribute words as \( A \) and \( A' \), and of target words as \( T \) and \( T' \), then we have equation:

\[
c(A, A', T, T') = \sum_{t \in T} c(t, A, A') - \sum_{t' \in T'} c(t', A, A')
\]

where for each sentence \( s \), we have \( c(s, A, A') \), the difference of the mean cosine similarity of \( s \) concerning sentences from between \( A \) and \( A' \); as

\[
c(s, A, A') = \frac{1}{|A|} \sum_{a \in A} \cos(s, a) - \frac{1}{|A'|} \sum_{a' \in A'} \cos(s, a')
\]

The amount of bias is given by the effect size

\[
d = \frac{\mu \left( \{c(t, A, A')\}_{t \in T} \right) - \mu \left( \{c(t', A, A')\}_{t' \in T'} \right)}{\sigma \left( \{c(a, T, T')\}_{a \in A \cup A'} \right)}
\]

where \( \mu \) and \( \sigma \) denote the mean and standard deviation, respectively. The smaller the absolute value of \( d \) is, the less bias has been detected.

### 4.2 Gender Co-Reference Resolution

As described by Gonen and Goldberg (2019), SEAT can detect only the presence but not the absence of biases. To further understand how the conceptor-aided methods work on debiasing, we adopt an end-task, gender co-reference resolution.

WinoBias (Zhao et al., 2018) provides pairs of gender-balanced co-reference tests where the gender of the pronominal reference should be immune to the co-reference choice. The language model should be neutral to the pronoun (e.g. her/him, she/he) referring to the occupations (e.g. nurse, carpenter, doctor) regardless of whether in pro-stereotypical (PRO) scenarios or anti-stereotypical (ANTI) scenarios. In the PRO subset, gender pronouns apply to occupations that are flavored by the same gender. For instance, in the sentence “The physician called the secretary and told her the cancel the appointment”, “her” to “the secretary” fits...
we only report the result of T2 here.

To evaluate corpora, by testing on the last layer of BERT and another LLM, GPT2, we investigate whether the debiasing techniques are generalized to different scales of BERT and another LLM, GPT2, we use bert-tiny, bert-base-uncased, and gpt2 in our experiment.

5 Debiasing Results

This section aims to answer the following questions:

- What is the best setting for bias subspace generation within conceptor-aided debiasing?
- Given the best setting, can the conceptor post-processing mitigate bias and beat SOTA?
- Does embedding conceptors into BERT and with continued training outperform post-processing?

To facilitate comparison, we include the SOTA debiasing performance from Meade et al. (2022) in the results tables below. To investigate whether the debiasing techniques are generalized to different scales of BERT and another LLM, GPT2, we use bert-tiny, bert-base-uncased, and gpt2 in our experiment.

5.1 Bias Subspace Construction from Corpora, Wordlist Selection, and Combination and Outlier Removal

To evaluate corpora, by testing on the last layer of the “bert-base-uncased” model, we compare the debiasing result of three different corpora: Brown, SST, and Reddit, and then evaluate on SEAT. Table 7 shows that Brown stably provides the best debiasing result even if using different wordlist subspaces. The SST corpus is a close second, while Reddit is by far the worst. The style of the Reddit corpus is most likely least similar to that of the SEAT evaluations.

To evaluate alternate methods of constructing the bias wordlist subspace, we use the five subspaces described in Section 3.1. Among them, and subspace is the most robust; see Table 8, 9 and 10. Combining the pronouns, extended and propernouns subspaces with and represents the distinct concepts (and hence subspaces) of each of the wordlists, both outperforming individual wordlists and outperforming the all subspace, which simply concatenates all the wordlists, giving a less precise subspace definition.

To evaluate wordlist outlier removal, we define the outliers by the UMAP-based filtering method as discussed in section 3.1 and generate different percentages of the words that are used to capture bias. For example, the all subspace has 2071 words within 0.5–1.0 percentile, 2061 in the 0.4 percentile, 1601 in the 0.3 percentile, 430 in the 0.2 percentile, and 82 in the 0.1 percentile (Table 5). We observe that including fewer words often leads to higher debiasing performance, presumably due to the removal of outliers. However, if we set the bias to be extremely small (e.g., 0.1), then it would harm the effectiveness of debiasing because of the inadequate loss being left. (Table 8, 9 and 10). Alternatively, T-SNE clustering (Van der Maaten and Hinton, 2008) has been tried earlier and the result remains similar.

In conclusion, the optimal setting for the “bert-tiny” model is “sst-0.5-and” (SST Corpus; wordlist percentile 0.5; and subspace); similarly, for the “bert-base-uncased” model is “brown-0.4-and” (Brown Corpus; wordlist percentile 0.4; and subspace). Henceforth, we always use these two settings for the conceptor-aided debiasing on these two models respectively unless otherwise stated.

5.2 Post-Processing Debiasing

The debiasing performance of conceptor negation post-processing is excellent. The SEAT score of “bert-base-uncased” model decreases from 0.620 to generally around 0.350–0.400 in Brown Corpus (Table 8), and can be as low as 0.311 if using the setting “brown-0.4-and”, outperforming the debiasing result of CDA, DROPOUT and SENTENCEDEBIASE (Table 1). The success of debiasing is further verified by WinoBias (Table 2), where the skew bias drops from 38.3 to 22.3 without any additional
fine-tuning. Although the stereotype bias increases, it is not only expected since these two biases are trade-offs but also acceptable since now they reach a good balance (de Vassimon Manela et al., 2021). Also, the debiasing conceptors is robust and generalizable; They can mitigate the bias in almost all scenarios, no matter using which corpus, bias subspace, or wordlist threshold (Table 8, 9 and 9); no matter for which BERT model (Table 14, 15 and 15) and even GPT model (Table 18); and no matter in which layer (Table 11, 12 and 17).

| Model                  | F1 Male | F1 Female | Bias |
|------------------------|---------|-----------|------|
| BERT                   | 66.4    | 58.9      | 31.8 |
| + Conceptor P.P.       | 69.5    | 48.1      | 52.8 |
| + Conceptor C.T.       | 41.0    | 39.3      | 57.6 |

Table 2: F1 results of the skew and stereotype biases from Test Set 2 of WinoBias. The model is “bert-base-uncased”.

5.3 Conceptor-Intervention Debiasing

We use CI-BERT architecture to continue to train the models to get the new weights. Then we demonstrate the combinations of architectures and weights as an ablation study (Type I, II, and III). Among them, Type III can outperform conceptor post-processing (Table 1), and Type I and II (Table 3). Compared to the SEAT score after post-processing, Type I can outperform it at each layer of “bert-tiny” but underperform it at most layers of “bert-base-uncased” (Table 12 and 17).

In short, using the CI-BERT with the newly trained weights could receive the lowest bias in the model and is promising to beat post-processing. For example, when using the setting “brown-0.4-and”, the lowest SEAT score is 0.280, beating the post-processing result of 0.311 and more than half of the SOTA methods. This is verified again by gender co-reference resolution in Table 2 - in comparison to its post-processing counterpart. CI-BERT continued training lowers the stereotype bias by 22.9 and skew bias by 5.3 from Test Set 2 of WinoBias. This is non-trivial since these two biases are in pair of trade-off and hard to be decreased at the same time (de Vassimon Manela et al., 2021).

To further study the feasibility and robustness of CI-BERT continued training concerning the model property. We experiment on both “bert-tiny” and “bert-base-uncased” models and plot the average SEAT curve along with training steps (Figure 4). Both of them can beat their post-processing counterparts in some steps during the early training stage, then the bias fluctuates and increases again, perhaps due to the model relearning the bias during continued training, or oversaturating the conceptor-based bias projections into its weights.

In comparison, the continual-trained CI-BERT can more stably lower the bias in smaller BERT. We suspect this is related to the model complexity. Since theoretically the debiasing projection of the last layer’s conceptor matrix is built on the last hidden state and therefore generated transitorily from all the prior layers. Currently, we are embedding all layers’ conceptor matrices, which may lead to overlapping and redundant debiasing projection from the prior layers.

5.4 Maintaining Meaningful Semantics

To understand how conceptor debiasing impacts the downstream natural language understanding (NLU) tasks, the GLUE benchmark (Wang et al., 2018)–comprised of nine different tasks–is used to evaluate the model after debiasing. We report the
Table 1: SEAT effect size of gender debiased BERT and GPT model. Effect sizes closer to 0 are indicative of less biased sentence representations (bolded value). Statistically significant effect sizes at $p < 0.01$ are denoted by *.

The final column is the average absolute SEAT score of the first six columns. P.P. stands for post-processing, while C.C. stands for continued training. The full version is in Appendix E and G.

| Model                      | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|----------------------------|--------|---------|--------|---------|--------|---------|-----------|
| BERT ("bert-base-uncased") | 0.931  | 0.090  | -0.124 | 0.937  | 0.783  | 0.858  | 0.629  |
| + Conceptor P.P.           | 0.388  | -0.078 | -0.292 | 0.179  | 0.594  | 0.335  | 0.309  |
| + Conceptor C.T.           | 0.227  | 0.426  | -0.341 | -0.253 | -0.344 | -0.088 | 0.340  |
| + CDA                      | 0.846  | 0.186  | -0.278 | 1.342  | -0.331 | -0.849 | 0.722  |
| + DROPOUT                  | 1.136  | 0.317  | 0.138  | 1.179  | 0.879  | 0.939  | 0.765  |
| + INLP                     | 0.317  | -0.354 | -0.258 | 0.105  | 0.187  | -0.004 | 0.416  |
| + SENTENCEDEBIAS           | 0.350  | -0.298 | -0.626 | 0.458  | 0.413  | 0.462  | 0.434  |
| GPT2 (*gpt2*)              | 0.138  | 0.003  | -0.023 | 0.002  | -0.224 | -0.287 | 0.113  |
| + Conceptor P.P.           | 0.092  | 0.316  | -0.001 | 0.064  | -0.035 | -0.062 | 0.018  |
| + CDA                      | 0.167  | 0.040  | 0.866  | 0.873  | 0.527  | 0.384  | 0.563  |
| + DROPOUT                  | 0.106  | -0.029 | -0.033 | 0.015  | 0.236  | -0.295 | 0.006  |
| + INLP                     | 0.386  | -0.075 | -0.307 | -0.068 | 0.306  | -0.667 | 0.138  |

Table 3: The ablation study of weights and architecture. The model is “bert-base-uncased”. The SEAT score is the average absolute value the same as Table 1.

| Type | CI-BERT | Trained Weights | SEAT |
|------|---------|-----------------|------|
| (Orig.) |         |                 |      |
| I     | ✓       | 0.620           | 0.620|
| II    | ✓       | 0.336           | 0.336|
| III   | ✓       | 0.592           | 0.592|
|       | ✓       | 0.280           | 0.280|

results in Table 4. The conceptor post-processing can retain and even improve the useful semantics (increase the average GLUE score by 1.77) for downstream tasks without damage to the model’s ability, outperforming any other listed SOTA debiasing methods. In comparison, the average GLUE score of conceptor-continued-training is relatively low. Though it is not the lowest among all the methods, this indicates that the continued-training method, while capable of outperforming the post-processing of using the same conceptor setting, may sacrifice NLU abilities. GPT as autoregressive model is largely unaffected by debiasing so it is not necessary to test here (Meade et al., 2022).

| Model                      | Average |
|----------------------------|---------|
| BERT ("bert-base-uncased") | 77.74   |
| + Conceptor P.P.           | ↑1.77   |
| + Conceptor C.T.           | ↑1.03   |
| + CDA                      | ↑0.22   |
| + DROPOUT                  | ↑1.46   |
| + INLP                     | 0.99    |
| + SENTENCEDEBIAS           | ↑0.07   |

Table 4: GLUE validation set results for gender debiased BERT model. The full version is in Appendix E.

It is worth pointing out that by observation, even if being trained on the original BERT architecture, the average GLUE score would still drop about 0.3 point. It shows that the lower GLUE score here is not completely caused by CI-BERT, though the reason is hard to dissect due to training randomness.

6 Conclusion and Future Work

We have shown that conceptor-aided debiasing can successfully mitigate the bias in contextualized embeddings from BERT and GPT. Specifically, conceptor post-processing outperforms many state-of-the-art debiasing methods in both debiasing effectiveness and semantic retention. We also tested a new architecture, conceptor-intervened BERT (CI-BERT), which in combination with continued training, takes all layers’ biases into account and shows the promise to outperform its post-processing counterpart. However, it might be at the cost of increased instability and worse semantic retention.

In all cases, the best conceptor matrices are generally obtained when the bias subspace is constructed using a cleaner corpus, intersection of different related wordlists (e.g. pronouns, roles, and names) by the conceptor AND operation, and removal of outliers from the wordlists.

As language models become larger gender bias seems to increase (Tal et al., 2022), thus we believe that our work should generalize well beyond BERT.

Future research is recommended on improving the robustness and effectiveness of CI-BERT. Lastly, we can ensemble this work with other debiasing techniques to further mitigate the bias. For example, we can follow the insight of Liang et al. (2020), in combinations with Counterfactual Data...
Augmentation (CDA) to rebalance the corpora before generating the conceptor bias subspace, which may lead to better debiasing performance.

Limitations

We list several limitations of our work below.

1) We only test the binary bias (e.g. male/female or young/old). It is widely recognized that terms in gender, race, etc. can be multi-polar. But we only test them in pairs via SEAT and WinoBias.

2) Our result is limited to English, and both corpora and wordlist tend towards North American social biases. The whole of our experiment is conducted in English. In addition, Brown and SST Corpora are collected entirely in the North American environment. So are the wordlists. Therefore, it is expected that they skew towards North American social biases. When such models are debiased under the North American environment, it is necessary to understand how effective they are when transferred to other cultures.

3) Our work only focuses on BERT models. Although this should generalize to other large language models (LLM), we have not shown this in the paper. Further study on proving the effectiveness of transforming the conceptor-aided debiasing method to other LLMs is needed.

Ethical Considerations

Definition and recognition of bias is subtle. For example, we have used simple traditional binary definitions of male and female to examine gender bias. This, of course, ignores a much wider variety of gender identities, thus introducing an implicit bias to the analysis. Similarly, studies on racial bias rely on possibly problematic definitions of race. Core to our debiasing method is the selection of the wordlists. Each wordlist carries its own implicit definitions of gender, race, and other important dimensions. Care should be used to assure that they represent the desired categories. To this end, it is often useful to involve people from the communities whose language is being debiased to better represent their values and belief systems.

One should also be careful in the use of debiasing. Removing signals about race or gender is often beneficial in reducing discrimination or in producing better translations. It may also remove key features of models needed for analyses. For example, removing gender or race ‘signal’ from the model may severely hamper the use of that model gender studies or work on critical race theory. “White-washing” models are not always a benefit; sometimes one wants to see the bias inherent in a corpus.

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A  Attribute Wordlist

The examples and sources of the three attribute wordlists are provided below. Due to space limitations, we would only list up to 50 words for each list.

A.1 Pronouns Wordlist

Words (in total 22): son, mother, daughter, him, brother, girl, uncle, hers, grandfather, his, boy, her, father, she, sister, man, female, aunt, woman, grandmother, he, male.

They are the concatenation of W7_terms and W8_terms from WEAT list3.

A.2 Extended Wordlist

Words (randomly 50 of 388): paramour, abbesses, headmistress, stepson, gods, congressman, gents, uncle, hers, wizard, cowgirls, fiancées, adulteress, sororal, ladies, sons, uncles, actors, beards, heiress, fellas, salesman, princess, empress, masters, chairwomen, miss, horsewomen, actor, mr., strongwoman, barons, andrology, busboy, prince, hens, womb, masseuse, lady, testosterone, daughter, girl, stateswoman, businessmen, women, fraternities, aunts, boys, abbot, heroine, . . .

They are the concatenation of lists: WinoBias extra gendered words4, GN-GloVe male’s name5, and female’s name6.

A.3 Propernouns Wordlist

Words (randomly 50 of 7578): Broddie, Tony, Tawsha, Emylee, Orelle, Gerrilee, Katusha, Georges, Reine, Hayley, Deloria, Richmond, Wilfrid, Neille, Florie, Riva, Sandro, Cooper, Thom, Pate, Nikolletta, Rodrigue, Pat, Chuck, Theressa, Brett, Kasper, Elist, Storm, Yule, Babba, Thomasina, Anson, Margery, Abra, Benedict, Cy, Gertrud, Morly, Julina, Melly, Quinta, Paolo, Brynne, Maurene, Alexis, Ramsey, Sianna, Phebe, Alfred, . . .

They are the concatenation of lists: CMU male’s name7 and female’s name8.

A.4 Outlier Filtering

Table 5 shows the number of remaining words per percentile after being filtered on UMAP-clustering space.

| Percentile | Pronouns | Extended | Propernouns | All |
|------------|----------|----------|-------------|-----|
| 0.5-1.0    | 22       | 388      | 7578        | 7988|
| 0.4        | 22       | 388      | 5443        | 6902|
| 0.3        | 11       | 372      | 4942        | 5140|
| 0.2        | 7        | 364      | 3194        | 3289|
| 0.1        | 4        | 67       | 1067        | 1087|

Table 5: The number of remaining words per percentile after filtering on UMAP-clustering space. The model is “bert-base-uncased”.

B  Model Checkpoints

We use the Hugging Face Transformers package (Wolf et al., 2019) in our experiments. The models and their checkpoint names are given in Table 6.

| Model      | Checkpoint       |
|------------|------------------|
| BERT-TINY  | prajjwal1/bert-tiny|
| BERT       | bert-base-uncased |
| GPT2       | gpt2             |

Table 6: The package’s model and checkpoint name in our experiment.

C  Continued Training Details

The conceptor-intervened model is trained for one epoch by setting the per device train batch size as 8 and prediction loss only as true. Following the training procedure in Devlin et al. (2019), we train by tasks Masked Language Model (MLM) and Next Sentence Prediction (NSP) simultaneously. The training corpus is the Wikipedia dump from datasets library (Lhoest et al., 2021).

D  GLUE Details

Before being evaluated on GLUE, each model is trained for three epochs with the following settings: batch size 32, maximum sequence length 128, and learning rate $2e^{-5}$; the same as Meade et al. (2022).

E  Full Bert-Base-Uncased Model Results

- Table 7 shows the gender debiasing result by different types of the corpus, using the last layer of “bert-base-uncased” as a benchmark.
• Table 8, and 9, 10 show the post-processing gender debiasing result of different percentiles of wordlist on three different corpora: Brown, SST, and Reddit, respectively.

• Table 11 and 12 show the post-processing and conceptor-intervened gender debiasing result of each layer on two different corpora: Brown and SST, respectively.

• Table 13 contains GLUE results for gender debiased model.

F Full Bert-Tiny Model Results

• Table 14, 15, and 16 show the post-processing gender debiasing result of different percentiles of wordlist on three different corpora: Brown, SST, and Reddit, respectively.

• Table 17 shows the post-processing and conceptor-intervened gender debiasing result of each layer on the SST corpus.

G Full GPT2 Model Results

• Table 18 shows the post-processing gender debiasing result of different percentiles of wordlist on Brown corpus.
Table 7: SEAT effect size of gender debiasing. The impact of different corpora on bert-base-uncased models. Effect sizes closer to 0 are indicative of less biased sentence representations (bolded value). Statistically significant effect sizes at $p < 0.01$ are denoted by *. Note that the “conceptor-X (subspace)” indicates the conceptor negation matrix is generated by the X-layer of the language model in combinations with the subspace of the specific attribute attribute wordlist. The top-3 best performance is colored in orange.
Table 8: SEAT effect size of gender debising. The impact of different percentiles of wordlist (using UMAP clustering) on Brown Corpus, bert-base-uncased models. The top-3 best performance is colored in orange.
| Model                              | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|-----------------------------------|--------|---------|--------|---------|--------|---------|-----------|
| BERT ("bert-base-uncased")        | 0.931  | 0.090   | -0.124 | 0.937   | 0.783  | 0.858   | 0.620     |
| (Wordlist Percentile 0.3-1.0)     |        |         |        |         |        |         |           |
| + Conceptor-12 (pronouns)         | 0.627* | -0.104  | -0.416 | 0.520*  | 0.636* | 0.628*  | 0.132     | 0.488     |
| + Conceptor-12 (extended)         | 0.688* | 0.024   | -0.293 | 0.138   | 0.559* | 0.375   | 0.274     | 0.346     |
| + Conceptor-12 (propornouns)      | 0.680* | -0.050  | -0.405 | 0.614*  | 0.585* | 0.790*  | 0.099     | 0.521     |
| + Conceptor-12 (all)              | 0.624* | -0.093  | -0.480 | 0.442*  | 0.538* | 0.663*  | 0.147     | 0.473     |
| + Conceptor-12 (and)              | 0.619* | -0.069  | -0.428 | 0.280   | 0.414  | 0.539*  | 0.229     | 0.391     |
| (Wordlist Percentile 0.4)         |        |         |        |         |        |         |           |
| + Conceptor-12 (pronouns)         | 0.619* | -0.113  | -0.526 | 0.449*  | 0.606* | 0.584*  | 0.137     | 0.483     |
| + Conceptor-12 (extended)         | 0.688* | 0.024   | -0.293 | 0.138   | 0.559* | 0.375   | 0.274     | 0.346     |
| + Conceptor-12 (propornouns)      | 0.704* | -0.086  | -0.227 | 0.590*  | 0.682* | 0.716*  | 0.119     | 0.501     |
| + Conceptor-12 (all)              | 0.622* | -0.087  | -0.508 | 0.277   | 0.519* | 0.578*  | 0.188     | 0.432     |
| + Conceptor-12 (and)              | 0.646* | -0.034  | -0.427 | 0.200   | 0.438* | 0.401   | 0.262     | 0.358     |
| (Wordlist Percentile 0.3)         |        |         |        |         |        |         |           |
| + Conceptor-12 (pronouns)         | 0.550* | -0.035  | -0.396 | 0.344   | 0.682* | 0.744*  | 0.161     | 0.459     |
| + Conceptor-12 (extended)         | 0.687* | 0.023   | -0.299 | 0.129   | 0.559* | 0.382   | 0.273     | 0.347     |
| + Conceptor-12 (propornouns)      | 0.706* | -0.088  | -0.230 | 0.602*  | 0.683* | 0.720*  | 0.115     | 0.505     |
| + Conceptor-12 (all)              | 0.652* | -0.117  | -0.378 | 0.504*  | 0.536* | 0.657*  | 0.146     | 0.474     |
| + Conceptor-12 (and)              | 0.595* | 0.027   | -0.375 | 0.171   | 0.519* | 0.600*  | 0.239     | 0.381     |
| (Wordlist Percentile 0.2)         |        |         |        |         |        |         |           |
| + Conceptor-12 (pronouns)         | 0.730* | 0.090   | -0.110 | 0.523*  | 0.714* | 0.758*  | 0.132     | 0.488     |
| + Conceptor-12 (extended)         | 0.687* | 0.023   | -0.299 | 0.129   | 0.559* | 0.382   | 0.273     | 0.347     |
| + Conceptor-12 (propornouns)      | 0.755* | -0.057  | -0.346 | 0.584*  | 0.659* | 0.733*  | 0.098     | 0.522     |
| + Conceptor-12 (all)              | 0.699* | -0.094  | -0.492 | 0.456*  | 0.620* | 0.688*  | 0.112     | 0.508     |
| + Conceptor-12 (and)              | 0.579* | -0.004  | -0.261 | 0.270   | 0.503* | 0.634*  | 0.245     | 0.375     |
| (Wordlist Percentile 0.1)         |        |         |        |         |        |         |           |
| + Conceptor-12 (pronouns)         | 0.903* | 0.198   | -0.464 | 0.030   | 0.434  | 0.492*  | 0.200     | 0.420     |
| + Conceptor-12 (extended)         | 0.631* | -0.107  | -0.012 | 1.008*  | 0.615* | 0.794*  | 0.092     | 0.528     |
| + Conceptor-12 (propornouns)      | 0.655* | -0.130  | -0.166 | 0.895*  | 0.641* | 0.877*  | 0.059     | 0.561     |
| + Conceptor-12 (all)              | 0.597* | -0.164  | -0.223 | 0.791*  | 0.698* | 0.909*  | 0.056     | 0.564     |
| + Conceptor-12 (and)              | 0.542* | -0.039  | -0.184 | 0.589*  | 0.457* | 0.929*  | 0.163     | 0.457     |
| + CDA                              | 0.846* | 0.186   | -0.278 | 1.342*  | 0.831* | 0.849*  | 0.120     | 0.722     |
| + DROPOUT                          | 1.136  | 0.317   | 0.138  | 1.179*  | 0.879* | 0.939*  | 0.144     | 0.765     |
| + INLP                             | 0.317  | -0.354  | -0.258 | 0.105   | 0.187  | -0.004  | 0.416     | 0.204     |
| + SENTENCEDEBIAS                   | 0.350  | -0.298  | -0.626 | 0.458*  | 0.413  | 0.462*  | 0.186     | 0.434     |

Table 9: SEAT effect size of gender debising. The impact of different percentiles of wordlist (using UMAP clustering) on SST Corpus, bert-base-uncased models. The top-3 best performance is colored in orange.
| Model | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|-------|--------|---------|--------|---------|--------|---------|----------|
| BERT ("bert-base-uncased") | 0.931 | 0.090 | -0.124 | 0.937* | 0.783* | 0.858* | 0.620 |
| + Conceptor-12 (pronouns) | 0.619* | -0.092 | -0.235 | 0.816* | 0.756* | 0.962* | 0.040 | 0.580 |
| + Conceptor-12 (extended) | 0.630* | -0.061 | -0.157 | 0.676* | 0.711* | 0.806* | 0.113 | 0.507 |
| + Conceptor-12 (propernouns) | 0.792* | 0.151 | 0.068 | 0.964* | 0.765* | 0.934* | 0.008 | 0.612 |
| + Conceptor-12 (all) | 0.613* | -0.010 | 0.004 | 0.803* | 0.735* | 0.917* | 0.106 | 0.514 |
| + Conceptor-12 (and) | 0.593* | 0.004 | 0.092 | 0.838* | 0.652* | 0.961* | 0.097 | 0.523 |
| + Conceptor-12 (extended) | 0.936 | -0.187 | 0.130 | 0.187 | 0.601 | 0.838 | 0.186 | 0.434 |
| + Conceptor-12 (all) | 0.949 | 0.121 | -0.472 | -0.035 | 0.814* | 0.910* | 0.134 | 0.486 |
| + Conceptor-12 (propernouns) | 0.948 | 0.107 | -0.094 | 0.949* | 0.783* | 0.842* | 0.005 | 0.625 |
| + Conceptor-12 (all) | 0.949 | 0.105 | -0.061 | 0.899* | 0.782* | 0.846* | 0.013 | 0.607 |
| + Conceptor-12 (and) | 0.936 | 0.130 | -0.579 | 0.601 | 0.914* | 0.835* | 0.070 | 0.541 |
| + CDA | 0.846 | 0.186 | -0.278 | 0.342 | 0.831* | 0.849 | 0.120 | 0.722 |
| + DROPOUT | 1.136 | 0.317 | 0.138 | 1.179* | 0.879* | 0.939* | 0.144 | 0.765 |
| + INLP | 0.317 | -0.354 | -0.258 | 0.105 | 0.197 | -0.004 | 0.416 | 0.204 |
| + SENTENCEDEBIAS | 0.350 | -0.298 | -0.626 | 0.458* | 0.413 | 0.462* | 0.186 | 0.434 |

Table 10: SEAT effect size of gender debising. The impact of different percentiles of wordlist (using UMAP clustering) on Reddit Corpus, bert-base-uncased models. The top-3 best performance is colored in orange.
| Model | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|-------|--------|--------|--------|--------|--------|--------|----------|
| (Layer 0) | | | | | | | |
| BERT ("bert-base-uncased") | 0.921 | 0.194 | 0.251 | -0.172 | -0.110 | 0.366 | 0.336 |
| + Conceptor-0 (and) | 0.147 | -0.087 | -0.266 | -0.653 | -0.405 | -0.324 | 0.022 |
| + Conceptor-Intervened | 0.147 | -0.087 | -0.266 | -0.653 | -0.405 | -0.324 | 0.022 |
| (Layer 1) | | | | | | | |
| BERT ("bert-base-uncased") | 1.245 | 0.292 | 0.469 | 1.101 | 0.110 | 1.261 | 0.746 |
| + Conceptor-1 (and) | 0.473 | 0.205 | -0.210 | -0.093 | -0.095 | 0.396 | 0.501 |
| + Conceptor-Intervened | 0.241 | -0.038 | -0.274 | 0.291 | -0.751 | -0.107 | 0.462 |
| (Layer 2) | | | | | | | |
| BERT ("bert-base-uncased") | 1.149 | 0.216 | 0.431 | 1.021 | 0.474 | 1.231 | 0.754 |
| + Conceptor-2 (and) | 0.180 | -0.047 | -0.450 | -0.105 | 0.133 | 0.133 | 0.579 |
| + Conceptor-Intervened | -0.108 | 0.115 | -0.965 | 1.388 | -1.146 | 0.329 | 0.079 |
| (Layer 3) | | | | | | | |
| BERT ("bert-base-uncased") | 1.186 | 0.214 | 0.152 | 0.770 | 0.262 | 1.049 | 0.606 |
| + Conceptor-3 (and) | 0.404 | -0.046 | -0.675 | 0.102 | -0.325 | -0.024 | 0.343 |
| + Conceptor-Intervened | 0.158 | 0.081 | -0.959 | 1.348 | -1.093 | 0.409 | 0.069 |
| (Layer 4) | | | | | | | |
| BERT ("bert-base-uncased") | 0.975 | 0.106 | 0.552 | 0.890 | 0.542 | 0.724 | 0.632 |
| + Conceptor-4 (and) | 0.597 | 0.068 | -0.249 | 0.251 | -0.016 | -0.315 | 0.383 |
| + Conceptor-Intervened | 0.060 | 0.121 | -0.986 | 1.676 | -0.840 | 0.943 | 0.139 |
| (Layer 5) | | | | | | | |
| BERT ("bert-base-uncased") | 1.002 | 0.184 | 0.628 | 0.914 | 0.376 | 1.053 | 0.693 |
| + Conceptor-5 (and) | 0.634 | 0.064 | 0.118 | 0.225 | -0.160 | 0.429 | 0.421 |
| + Conceptor-Intervened | -0.046 | 0.043 | -1.038 | 1.378 | -0.790 | 0.659 | 0.034 |
| (Layer 6) | | | | | | | |
| BERT ("bert-base-uncased") | 0.753 | 0.118 | 0.539 | 1.048 | 0.597 | 1.042 | 0.683 |
| + Conceptor-6 (and) | 0.327 | 0.041 | 0.176 | 0.104 | 0.150 | 0.174 | 0.521 |
| + Conceptor-Intervened | -0.210 | 0.004 | -0.965 | 1.242 | -0.739 | 0.475 | 0.077 |
| (Layer 7) | | | | | | | |
| BERT ("bert-base-uncased") | 0.719 | 0.155 | 0.341 | 0.935 | 0.562 | 0.721 | 0.572 |
| + Conceptor-7 (and) | 0.235 | -0.019 | -0.038 | 0.206 | 0.173 | 0.223 | 0.416 |
| + Conceptor-Intervened | -0.246 | -0.082 | -0.821 | 1.112 | -0.671 | 0.248 | 0.042 |
| (Layer 8) | | | | | | | |
| BERT ("bert-base-uncased") | 0.983 | 0.163 | 0.313 | 1.157 | 0.766 | 0.789 | 0.695 |
| + Conceptor-8 (and) | 0.235 | 0.005 | -0.136 | 0.389 | 0.379 | 0.135 | 0.482 |
| + Conceptor-Intervened | -0.125 | -0.193 | -0.940 | 0.796 | -0.606 | 0.084 | 0.238 |
| (Layer 9) | | | | | | | |
| BERT ("bert-base-uncased") | 0.922 | 0.224 | 0.503 | 1.293 | 0.780 | 0.996 | 0.786 |
| + Conceptor-9 (and) | 0.234 | 0.019 | -0.005 | 0.485 | 0.694 | 0.686 | 0.432 |
| + Conceptor-Intervened | -0.151 | -0.246 | -0.599 | 0.836 | -0.455 | -0.095 | 0.389 |
| (Layer 10) | | | | | | | |
| BERT ("bert-base-uncased") | 0.686 | 0.082 | 0.226 | 0.894 | 0.904 | 0.965 | 0.626 |
| + Conceptor-10 (and) | 0.294 | -0.091 | -0.153 | 0.078 | 0.703 | 0.545 | 0.315 |
| + Conceptor-Intervened | -0.253 | -0.298 | -0.569 | 0.753 | -0.462 | -0.099 | 0.221 |
| (Layer 11) | | | | | | | |
| BERT ("bert-base-uncased") | 0.665 | -0.015 | -0.344 | 0.602 | 0.919 | 0.891 | 0.573 |
| + Conceptor-11 (and) | 0.197 | -0.114 | -0.399 | -0.157 | 0.557 | 0.277 | 0.289 |
| + Conceptor-Intervened | -0.314 | -0.269 | -0.635 | 0.769 | -0.430 | 0.096 | 0.154 |
| (Layer 12) | | | | | | | |
| BERT ("bert-base-uncased") | 0.931 | 0.090 | -0.124 | 0.937 | 0.783 | 0.858 | 0.620 |
| + Conceptor-12 (and) | 0.388 | -0.078 | -0.292 | 0.179 | 0.594 | 0.335 | 0.309 |
| + Conceptor-Intervened | -0.334 | -0.117 | -0.698 | 0.459 | -0.230 | 0.178 | 0.284 |
| (CIX) | | | | | | | |
| 0.646 | 0.166 | -0.278 | 1.342 | 0.831 | -0.049 | 0.129 |
| (CPU) | | | | | | | |
| 1.136 | 0.317 | 0.138 | 1.179 | 0.879 | 0.939 | 0.144 |
| (INLP) | | | | | | | |
| 0.317 | -0.354 | -0.258 | 0.105 | 0.187 | -0.004 | 0.416 |
| (SENTENCE) | | | | | | | |
| 0.350 | -0.298 | -0.626 | 0.458 | 0.413 | 0.462 | 0.186 |

Table 11: SEAT effect size of gender debiasing from CI-BERT, Type I. The conceptor-intervened performance of different layer’s conceptors on SST Corpus, bert-base-uncased models. The setting is “brown-0.4-and”. The layer(s) of CI-BERT that outperform the conceptor post-processing of the same layer(s) are colored in orange.
Table 12: SEAT effect size of gender debiasing from CI-BERT, Type I. The conceptor-intervened performance of different layer’s conceptors on SST Corpus, bert-base-uncased models. The setting is “sst-0.9-extended”. The layer(s) of CI-BERT that outperform the conceptor post-processing of the same layer(s) are colored in orange.
Table 13: GLUE validation set results for gender debiased BERT model. Following Meade et al. (2022), we use tasks, we report the accuracy. All scores are averaged among three runs. The model is “bert-base-uncased”. The top-3 best performance is colored in orange.

| Model                      | CoLA  | MNLI  | MRPC  | QNLI  | QQP   | RTE   | SST   | STS-B | WNL | Average |
|----------------------------|-------|-------|-------|-------|-------|-------|-------|-------|------|---------|
| BERT                       | 55.89 | 84.50 | 88.39 | 91.38 | 91.03 | 63.54 | 92.58 | 88.51 | 43.66 | 77.74   |
| + Conceptor P.P.           | 57.54 | 84.66 | 89.30 | 91.03 | 91.05 | 65.34 | 92.66 | 89.07 | 54.93 | 71.77   |
| + Conceptor C.T.           | 47.06 | 83.46 | 87.20 | 90.73 | 90.97 | 58.98 | 91.67 | 88.21 | 52.11 | 67.71   |
| + CDA                      | 55.90 | 84.73 | 88.76 | 91.36 | 91.01 | 66.31 | 92.43 | 89.14 | 38.03 | 70.22   |
| + DROPOUT                   | 49.83 | 84.67 | 88.20 | 91.27 | 90.36 | 64.02 | 92.58 | 88.47 | 37.09 | 71.46   |
| + INLP                      | 56.06 | 84.81 | 88.61 | 91.34 | 90.92 | 64.98 | 92.51 | 88.70 | 32.86 | 70.99   |
| + SENTENCEDEBIAS           | 56.41 | 84.80 | 88.70 | 91.48 | 90.98 | 63.06 | 92.32 | 88.45 | 44.13 | 79.07   |

Table 14: SEAT effect size of gender debiasing. The impact of different percentiles of wordlist (using UMAP clustering) on Brown Corpus, bert-tiny models. The top-3 best performance is colored in orange.
Table 15: SEAT effect size of gender debiasing. The impact of different percentiles of wordlist clustering on SST Corpus, bert-tiny models. The top-3 best performance is colored in orange.
Table 16: SEAT effect size of gender debiasing. The impact of different percentiles of wordlist (using UMAP clustering) on Reddit Corpus, bert-tiny models. The top-3 best performance is colored in orange.

| Model | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|-------|--------|---------|--------|---------|--------|---------|-----------|
| BERT ("bert-tiny") | 1.735* | 0.797* | 1.294* | 1.243* | 0.837* | 1.293* | 1.200 |
| (Wordlist Percentile 1.0)* | 1.676* | 0.389* | 1.218* | 1.095* | 0.557* | 1.008* | 0.210 0.990 |
| + Conceptor-2 (pronouns) | 1.578* | 0.507* | 1.248* | 1.220* | 0.656* | 1.351* | 0.107 1.093 |
| + Conceptor-2 (extended) | 1.713* | 0.776* | 1.184* | 1.315* | 0.538* | 1.193* | 0.080 1.120 |
| + Conceptor-2 (all) | 1.660* | 0.379* | 1.248* | 1.185* | 0.486* | 1.125* | 0.186 1.014 |
| + Conceptor-2 (and) | 1.550* | 0.180 | 1.010* | 1.146* | 0.197 | 1.088* | 0.338 0.862 |

Table 17: SEAT effect size of gender debiasing from CI-BERT, Type I. The conceptor-intervened performance of different layer’s conceptor matrix on SST Corpus, bert-tiny models. The layer(s) of CI-BERT that outperform the conceptor post-processing of the same layer(s) are colored in orange.

| Model (Layer 0) | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|----------------|--------|---------|--------|---------|--------|---------|-----------|
| BERT ("bert-tiny") | 1.536* | 0.640* | 0.959* | 1.307* | 0.263 | 0.814* | 0.920 |
| + Conceptor-0 (and) | 0.903* | 0.103 | 0.249 | 0.825* | 0.039 | 0.568* | 0.489 0.431 |
| + Conceptor-Intervened | 0.803* | 0.135 | 0.249 | 0.825* | 0.039 | 0.568* | 0.489 0.431 |

| Model (Layer 1) | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|----------------|--------|---------|--------|---------|--------|---------|-----------|
| BERT ("bert-tiny") | 1.702* | 1.019* | 1.102* | 1.250* | 0.313 | 1.094* | 1.080 |
| + Conceptor-1 (and) | 1.241* | -0.067 | 0.588* | 0.939* | -0.340 | 0.477* | 0.471 0.609 |
| + Conceptor-Intervened | 0.928* | 0.022 | -0.427 | 0.708* | -0.753 | 0.542* | 0.517 0.563 |

| Model (Layer 2) | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Abs. |
|----------------|--------|---------|--------|---------|--------|---------|-----------|
| BERT ("bert-tiny") | 1.735* | 0.797* | 1.294* | 1.243* | 0.837* | 1.293* | 1.200 |
| + Conceptor-2 (and) | 1.542* | 0.148 | 0.486* | 0.806* | -0.549 | 0.245 | 0.571 0.629 |
| + Conceptor-Intervened | 1.026* | -0.079 | -0.264 | 0.862* | -0.500 | 0.239 | 0.705 0.495 |
Table 18: SEAT effect size of gender debising. The impact of different percentiles of wordlist (using UMAP clustering) on Brown Corpus, gpt-2 models. The top-3 best performance is colored in orange.