Debiasing Pretrained Text Encoders by Paying Attention to Paying Attention

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Abstract

Recent studies in fair Representation Learning have observed a strong inclination for Natural Language Processing (NLP) models to exhibit discriminatory stereotypes across gender, religion, race and many such social constructs. In comparison to the progress made in reducing bias from static word embeddings, fairness in sentence-level text encoders received little consideration despite their wider applicability in contemporary NLP tasks. In this paper, we propose a debiasing method for pre-trained text encoders that both reduces social stereotypes, and inflicts next to no semantic damage. Unlike previous studies that directly manipulate the embeddings, we suggest to dive deeper into the operation of these encoders, and pay more attention to the way they pay attention to different social groups. We find that most stereotypes are also encoded in the attention layer. Then, we work on model debiasing by redistributing the attention scores of a text encoder such that it forgets any *preference* to historically advantaged groups, and attends to all social classes with the same intensity. Our experiments confirm that we successfully reduce bias with little damage to semantic representation.

1 Introduction

Natural Language Processing (NLP) is increasingly penetrating real-world processes such as recruitment (Hansen et al., 2015), legal systems (Dale, 2019), healthcare (Velupillai et al., 2018) and Web Search (Nalisnick et al., 2016). Part of this success is attributed to the underlying embedding layer which encodes sophisticated semantic representations of language (Camacho-Collados and Pilehvar, 2018). The wide adoption of modern NLP models in critical domains has also inflicted a more thorough scrutiny. Recent research has uncovered some propensities of NLP models to replicate discriminatory social biases (Bolukbasi et al., 2016; Caliskan et al., 2017; May et al., 2019) which may cause unintended and undesired model behaviors with respect to social groups. Social bias in NLP is mainly caused by unbalanced mentions of attributes near advantaged groups in training data (Zhao et al., 2018a). For example, in most existing text corpora, very few cooks are referred to by male pronouns (e.g. he, him, himself) (Zhao et al., 2017). Accordingly, text encoders or language models trained on such data may use this shortcut to inadvertently dissociate cooks from men, and learn that cooking is a female attribute.

Methods to *debias* static word embeddings such as Word2vec (Mikolov et al., 2013) or GloVe (Pennington et al., 2014) have been applied for various bias types like gender, race and religion (Bolukbasi et al., 2016; Zhao et al., 2018b; Kaneko and Bollegala, 2019; Ravfogel et al., 2020). However, by the time NLP practitioners started casting more attention to the fairness problem of their models, they had already switched to the more powerful sentence-level transformers in the likes of BERT (Devlin et al., 2018), GPT3 (Brown et al., 2020) or T5 (Raffel et al., 2020) which owe their success to the novel self-attention mechanism (Vaswani et al., 2017). This leap in performance in several NLP tasks does not extend to fairness since research discovered social stereotypes in modern text encoders (May et al., 2019; Nadeem et al., 2020; Nangia et al.). To date, debiasing them remains comparatively under-explored.

Mitigating biases in text encoders is difficult for four reasons: (1) They are expensive to retrain, so conventional methods based on Counterfactual Data Augmentation (CDA) to rebalance group-attribute mentions (Zhao et al., 2018a; Webster et al., 2020) become prohibitive as they generate more training data, and all debiasing attempts might be limited to either finetuning or adapting (Houlsby et al., 2019; Lauscher et al., 2021). (2) Static embeddings encode words whereas text encoders need context . Thus, it is not straightforward to use existing debiasing techniques for static embeddings *off-the-shelf* as it is not clear how to generate context for single words. Previous work tackled this problem by either designing bleached sentence templates (May et al., 2019; Kurita et al., 2019) where they fill in the blanks with words of interest, or sampling sentences from large corpora where the words are mentioned (Liang et al., 2020a; Cheng et al., 2020), thus creating context. The former betrays the expressiveness of natural language while the latter suffers from sampling and pre-processing bias (Liang et al., 2020a). (3) The input space of text encoders is the set of all possible sentences, so we cannot debias every single input as it is done with static embeddings. (4) Text encoders are larger in capacity and complexity. This suggests that they can accommodate subtler and more sophisticated forms of stereotype, especially in their attention component, which renders bias imperceptible to existing detection methods as they are not designed to operate on attention.

Despite these difficulties, previous works addressed the problem of reducing bias from modern text encoders with different techniques (Liang et al., 2020a; Webster et al., 2020; Liang et al., 2020b; Cheng et al., 2020; Kaneko and Bollegala, 2021; Lauscher et al., 2021). However, most of them make strong assumptions about the linearity of bias. Moreover, they operate on the embeddings produced by text encoders, and leave their most important block - attention - largely unrectified.

In this paper we explore attention-based debiasing. This approach stems from our observation that attention exhibits a great deal of social biases. We illustrate this finding with examples, propose a novel method to reduce stereotypes from attention blocks, and demonstrate that it is effective in mitigating biases from sentence representations as a whole. Given an input sentence, our method compels the text encoder of interest to redistribute its internal attention scores such that each word in the input allocates the same attention for different social groups. Thus, it learns to forget previously encoded preferences, and generate fair representations, free of stereotypical influence. We also keep semantic information loss at a minimum while debiasing by distilling knowledge from an unaltered teacher text encoder (Hinton et al., 2015; Gou et al., 2021). In this setting, we encourage the debiased model to copy the original attention from its teacher to minimize semantic offset. Unlike most previous work which focus only on gender, we address five bias types in our experiments (gender, race, religion, age and sexual orientation). We conduct likelihood- and inference-based evaluations to measure the intensity of bias in our final debiased models. Experiments demonstrate that the technique we propose effectively reduces bias, and outperforms existing debiasing methods.

2 Related Work

In this section, we discuss related work about debiasing static word embeddings and sentence-level text encoders. It should be noted that bias at data level (Pryzant et al., 2020; Cryan et al., 2020) and in language generation tasks (Sheng et al., 2020; Sap et al., 2020; Dhamala et al., 2021) are also active and complementary areas of research. However, due to space limitations, they will not be discussed further in this paper.

2.1 Bias in Static word embeddings

The work of Bolukbasi et al. (2016) pioneered bias research in NLP by discovering that static word embeddings such as Word2Vec (Mikolov et al., 2013) or GloVe (Pennington et al., 2014) encode significant amounts of *binary* gender bias. They proposed *Hard-Debias*: a method to remove biases by projecting gender-neutral word embeddings onto a gender-free direction. Manzini et al. (2019) extended Hard-Debias to the multiclass setting where they also treat racial and religious stereotypes. In both works, the bias direction is defined by a manually pre-compiled list of stereotyped words. In contrast, Ravfogel et al. (2020) suggest a data-driven approach to learn bias directions with a linear classifier. Debiasing is then conducted by iteratively projecting word embeddings on the null space of the classifier's matrix. On the other hand, fine-tuning is the debiasing approach that attracted the widest adoption, either by using an autoencoder (Kaneko and Bollegala, 2019), attraction-repulsion mechanism (Kumar et al., 2020), or adversarial attacks (Xie et al., 2017; Li et al., 2018; Elazar and Goldberg, 2018). Unlike these post-processing methods, Zhao et al. (2018b) added a new fairness constraint to GloVe loss function, and retrained their fair word embeddings from scratch.

2.2 Bias in Text encoders

Research on biases in sentence representations is dominated by detection rather than correction and mitigation. To date, there are three main approaches to detect stereotypes in text encoders: (1) **representation-based**: where vector relationships between different types of inputs are measured. For example, May et al. (2019) extended the WEAT test (Caliskan et al., 2017) into sentence vector space (SEAT), and compared the cosine similarity between representations of two sets of targets and two sets of attributes. All sentences in SEAT follow a predefined template. (2) **likelihood-based**: These approaches examine how often text encoders prefer stereotypes over anti-stereotypes. Preferences in this case are defined in terms of higher likelihoods as produced by language models using embeddings of the text encoders under study. Two benchmarks are widely used for measuring bias: StereoSet (Nadeem et al., 2020) and Crows-Pairs (Nangia et al.). Both datasets are organized in pairs or triples of minimally-distant sentences which differ only in the word(s) carrying a stereotypical connotation. (3) **inference-based**: These methods employ text encoders in downstream NLP tasks (Blodgett et al., 2020) such as natural language inference (Dev et al., 2020), sentiment analysis (Díaz et al., 2018) or language generation (Sap et al., 2020; Sheng et al., 2020). Bias in such settings is declared as the difference in outcome when the models are tested with the same input sentence, differing only in social groups.

Bias mitigation approaches are mostly inspired by debiasing static embeddings. In projection-based methods, Liang et al. (2020a) contextualize words into sentences by sampling them from existing corpora before applying Hard-Debias. Kaneko and Bollegala (2021) minimize the projection of sentence representations on a *learned* bias subspace, while Qian et al. (2019); Bordia and Bowman (2019); Liang et al. (2020b) add bias-reduction objectives to their loss functions. Another line of research uses CDA (Webster et al., 2020) to balance gender correlations in training data, while Lauscher et al. (2021) use adapters to reduce the large training time that CDA incurs. Finally, Cheng et al. (2020) use contrastive learning, and add a fair filter that minimizes mutual information between stereotypes and anti-stereotypes. In our work, rather than extending approaches from static embeddings, we focus on the self-attention mechanism which is characteristic of many text encoders, and show that fair attention leads to fair representations.

3 Debiasing Method

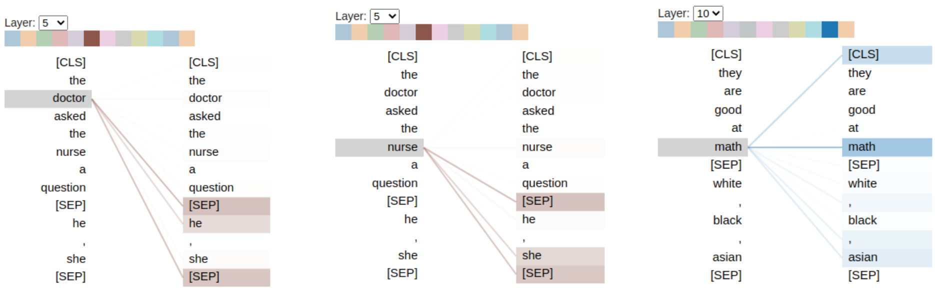
3.1 Motivating example & Intuition

Despite the applicability of our work on any model that is built upon self-attention, we focus in this paper on models based on the encoder side of the transformer architecture, such as BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), or ALBERT (Lan et al., 2019). This owes to the decoder side being usually used in auto-regression tasks, and less often to encode text. Transformers consist of multiple layers, each composed of a self-attention block followed by a feed-forward block to make embeddings. A self-attention block contains multiple heads. Each head transforms the input into attention weights between all pairs of tokens in the input sequence (Vaswani et al., 2017), such that each token learns to attend to its most related tokens, hence the prevalence of attention in defining the *understanding* of natural language. In this work, we hypothesise that undesired social stereotypes are primarily encoded in the self-attention block. In order to verify this hypothesis, we show and analyze some attention maps of BERT in Figure 1[1]. Consider the following sentence *"The doctor asked the nurse a question."* Aiming to analyze how every word representation relates to different social groups, we add a dummy second input consisting of words representing two distinct genders (***he*** and ***she*** after the [SEP] token). Figure 1(a) illustrates that *doctor* pays much more attention to *he* than to *she*[2], while Figure 1(b) reveals that *nurse* attends to *she*. This finding suggests that gender stereotypes are deeply encoded in attention weights. Likewise, in Figure 1(c), *math* is more related to *asian* than to *white* or *black*, conforming to the famous racial stereotype casting asians as really good mathematicians. These examples align with our intuition that social stereotypes are first and foremost encoded in the self-attention block of text encoders before they propagate to their embeddings or predictions in downstream NLP tasks. Consequently, we propose *Att-D*, a finetuning method for reducing undesired biases of text encoders from their attention component, that we describe in the next section.

The intuition of our debiasing strategy is as follows: Given that attention weights conform with undesired biases (e.g., *doctor* attending to ***he***, and

[1] The figures are produced using bertviz tool: https://github.com/jessevig/bertviz

[2] Dark colors correspond to high attention scores, and light colors indicate low attention scores



(a) (b) (c)

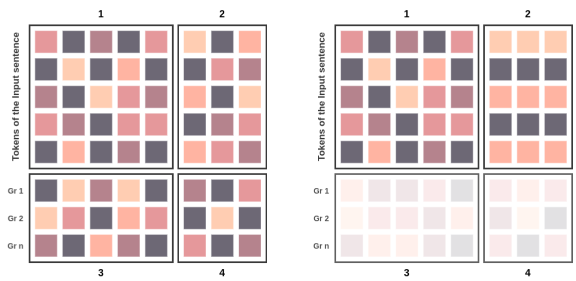
Figure 1: Attention patterns in BERT suggest the existence of potential gender and racial biases

nurse to ***she*** in Figure 1), we aim to equalize the attention scores of every word in the input sentence with respect to social groups. Following the examples of Figure 1, Att-D redistributes the attention scores of *doctor* such that it attends to ***he*** and ***she*** with the same intensity, thus eliminating any preference toward one of the groups. However, alterations to the attention of *doctor* on the remaining words of the input sentence must be kept to a minimum in order not to corrupt the semantic understanding of the original text encoder.

3.2 Debiasing Workflow

Att-D consists of three steps: First, for each input sentence s in the training corpus $\mathbb{S}$, we make an artificial second input s_g consisting of words related to social groups (similar to the examples on Figure 1). Pretrained text encoders expect either one or two inputs before they produce attentions and embeddings (Devlin et al., 2018). In this work, we use both s (as first input) and s_g (as second input) separated by [SEP] token. Consequently, the resulting self-attention includes both s and s_g. The second step of Att-D equalizes the attention weights of all heads in all the layers of the text encoder of interest such that each token in s pays the same amount of attention to tokens of s_g, thus eliminating preferences and stereotypes. Finally, we minimize semantic loss by compelling our model to learn the original semantics from an *unaltered* teacher model by copying its internal attention in a knowledge distillation setting (Hinton et al., 2015).

We schematize the operation of Att-D in Figure 2. Gr_1, Gr_2 and Gr_n in the figure correspond to the tokens of s_g. Both matrices represent one attention head of the text encoder before (left) and after (right) debiasing. The matrices should be read in rows. Each row depicts the attention weights of the corresponding token on all the other tokens of



(a) (b)

Figure 2: Overview of an attention head before (a) and after (b) debiasing

the input $(s + s_g)$[3].

The matrices are conceptually split in four blocks: (1) attentions of s on s, (2) attentions of s on s_g, (3) attentions of s_g on s, and (4) attentions of s_g on s_g. Debiasing consists in making the columns of block 2 equal. In other words, each token in s pays the same amount of attention to all the groups as indicated in the right side of Figure 2. Ideally, debiasing should also preserve the semantics of the original text encoder. That is why block 1 of Figure 2 should be kept unchanged. Both blocks 3 and 4 are irrelevant to the results, since they denote attentions of our artificially inserted second input s_g. Besides, they do not participate in defining neither fairness nor representativeness of text encoders. So, we do not impose any restrictions on them. In the following, we describe each step of Att-D in detail.

3.2.1 Generating augmented inputs

The first step involves identifying bias types that we want to mitigate from pretrained text encoders, such as gender, race, religion. This is achieved by defining a set of tuples $\mathbb{G}$ such that $\mathbb{G} = \{\mathcal{T}_1, \mathcal{T}_2, ..., \mathcal{T}_k\}$ where each $\mathcal{T}_i$ describes social

[3][CLS] token (vector representation of s) is also included for attention calibration. Details in Appendix

Table 1: Examples of group tuples per bias

religion	age
muslim, christian, jewish	old, young
quran, bible, torah	elderly, youth

groups of a given bias type, or their attributes. In the case of binary gender, $\mathcal{T}_i = \{$*"male"*, *"female"*$\}$ or $\mathcal{T}_i = \{$*"he"*, *"she"*$\}$ are both possible definitions (and many others are possible for non-binary cases). Table 1 shows some tuples that we use in Att-D.

During debiasing, we pick a tuple $\mathcal{T}_i$ from $\mathbb{G}$ randomly and construct s_g, a bleached sentence formed by words of $\mathcal{T}_i$. For example, given Table 1, s_g can be *"muslim, christian, jewish"* or *"old, young"*. The input to the text encoder is both the original input sentence s and the artificial one s_g. Pretrained text encoders separate the two halves of the input with a special token [SEP] as illustrated in Figure 1, and compute attention maps for the entire sequence (s + s_g).

3.2.2 Equalizing attentions on social groups

After obtaining attention maps of the augmented input from Section 3.2.1, which is produced by the pretrained text encoder of interest E, we make each token of s pay equal amounts of attention to the tokens of s_g which define social groups. The rationale is to eliminate any inclination for E to prefer a social group to the detriment of others. Suppose $\mathbf{A}^{l,h,s,s_g} = Attn(s, s_g; l, h)$ is the attention matrix at layer l, head h of the encoder E, computed from the input s + s_g. Here, we make the reasonable assumption that s_g contains at least two social groups.[4] In this spirit, equalizing attention vectors of block 2 (as defined in Figure 2) is equivalent to making them equal to a pivot vector. In our method, we consider the attention vector of s on the first social group as the pivot (first column in block 2 of Figure 2), and minimize the mean square error between the pivot and the attention vectors of s on the other groups, one at a time. The equalization loss is given by Equation 1.

$$L_{equ} = \sum_{s \in \mathbb{S}} \sum_{l=1}^{L} \sum_{h=1}^{H} \sum_{i=2}^{||s_g||} ||\mathbf{A}^{l,h,s,s_g}_{:\sigma,\sigma+1} - \mathbf{A}^{l,h,s,s_g}_{:\sigma,\sigma+i}||_2^2 \tag{1}$$

[4]Biases are usually about making one or more groups (dis)advantaged with respect to the others, hence the existence of at least two groups per bias type

where L is the number of layers of the text encoder, H the number of heads, $||s_g||$ the number of social groups in s_g and σ is the position of the special token [SEP] that marks the end of s and the beginning of s_g. As can be seen, $\mathbf{A}^{l,h,s,s_g}_{:\sigma,\sigma+1}$ is the pivot vector containing attention scores of s on the first social group token (whose position is directly after [SEP], i.e., $\sigma + 1$). Equation 1 forces attention scores on subsequent social groups to be the same as on the first one, thus making them all equal.

3.2.3 Preserving semantic information

Text encoders must preserve their ability to represent natural language and keep the same performance on downstream NLP tasks. For this reason, debiasing must ensure that useful information is preserved as much as possible. We minimize semantic information loss in a knowledge distillation setting (Hinton et al., 2015; Gou et al., 2021). We cast the text encoder that we want to debias as the *student* model, and recruit another model to play the role of the *teacher*. We do not apply our debiasing strategy on the teacher since it provides a reference to the original unaltered language representations. We distill semantic information in the form of attention maps from the teacher and instill it in the student. Stated differently, we compel the student to learn from the teacher and reproduce its attention scores for every input sentence in the training corpus $\mathbb{S}$.

As in Section 3.2.2, let $\mathbf{A}^{l,h,s,s_g}$ be the attention of the student model at layer l, head h with s and s_g as input. Likewise, let $\mathbf{O}^{l,h,s,s_g}$ define the same attention matrix, but for the original teacher model. We formalize the preservation of semantic information as a regularizer where we minimize the squared l_2 distance between the student's and the teacher's attention scores.

$$L_{distil} = \sum_{s \in \mathbb{S}} \sum_{l=1}^{L} \sum_{h=1}^{H} ||\mathbf{A}^{l,h,s,s_g}_{:\sigma,:\sigma} - \mathbf{O}^{l,h,s,s_g}_{:\sigma,:\sigma}||_2^2 \tag{2}$$

where L is the number of layers, H is the number of heads, and σ is the position of the [SEP] token. As can be seen from Equation 2, the student learns only to replicate block 1 (as in Figure 2) of the attention matrices. This is because block 1 contains attention scores of the original input sentence s on itself, thus encoding an important aspect of semantics. We force the student not to reproduce the attention distribution on social groups (block 2) from the teacher since these are supposedly biased, and are left to the care of our debiasing objective. We describe the overall training objective as a linear combination of the previously defined losses, with λ as a hyperparameter to control the weight of debiasing over semantic preservation.

$$Loss = L_{distil} + \lambda L_{equ} \tag{3}$$

3.3 Negative Sampling & Layer Selection

The strict application of Att-D as discussed so far may accidentally lead to some undesired spurious phenomena. While learning to equalize attention on social groups that constitute the second half of the input, the text encoder might potentially bear the risk of distributing its attention uniformly on *any* second half of the input, no matter what it is. This is particularly alarming when the text encoder is subsequently employed in double-sentence tasks (Wang et al., 2018) such as semantic textual similarity, paraphrase detection or sentence entailment.

To overcome the above obstacle, we introduce negative sampling. Instead of using words related to social groups in order to generate the artificial second input s_g, we randomly sample words (negative examples) from the vocabulary. In this case, we do not equalize the attentions but compel the student to copy its teacher even for blocks 2, 3 and 4. We do this in order to prevent the text encoder from learning to assign the same attention weight to all tokens of the second input when these do not define social groups. We control the ratio of negative examples with a hyperparameter η.

Another concern when debiasing text encoders is that their layers do not necessarily encode the same information. Bhardwaj et al. (2021) found that BERT layers display widely different reactions when probed with a gender-detection classifier. This means that they do not encode gender stereotype identically. Therefore, it is not clear which layers and/or attention heads are best for debiasing. To investigate this issue, we consider seven settings: debiasing ***all*** layers, ***first 6***, ***first 3***, ***last 6***, ***last 3***, and alternating layers with strides of ***one***[5] or ***two***[6]. We find that debiasing all layers works best. So, unless otherwise specified in this paper, debiasing concerns all the layers.

[5]Layers 2, 4, 6, 8, 10 and 12 of BERT

[6]Layers 4, 8 and 12 of BERT

4 Evaluation

In this section, we first describe our experimental setup, then evaluate Att-D from two viewpoints: *fairness* and *representativeness*. Fairness is traditionally evaluated with two types of metrics: *intrinsic* metrics that measure bias in text representations regardless of their application, and *extrinsic* metrics that quantify bias in downstream tasks that text representations enable. We acknowledge that intrinsic metrics have recently been criticized (Goldfarb-Tarrant et al., 2020; Aribandi et al., 2021; Blodgett et al., 2021). However, we believe that a strong evaluation of bias should include both intrinsic, extrinsic and qualitative methods to draw a complete evaluative picture. Since Aribandi et al. (2021) surmise that StereoSet and Crows-Pairs are more stable than other intrinsic measures of bias (e.g. WEAT (Caliskan et al., 2017) or SEAT (May et al., 2019)), we use them in this work. For extrinsic metrics, we evaluate our method on the tasks of textual inference and hate speech detection. Due to space limitations, we ship the second one to the appendix, in addition to qualitative evaluations (visualizations) and several other experiments/ablation studies[7].

4.1 Debiasing setup

To facilitate comparison, we follow existing literature (Nadeem et al., 2020; Nangia et al.) in defining social groups for each type of bias, although the approach presented here is not restricted to that, and can be leveraged for both other kinds of biases and for a more inclusive definition of the groups. In the experiments, we show results of debiasing based on **(binary) gender** (*male*, *female*), **race** (*white*, *black*, *asian*, *hispanic*), **religion** (*muslim*, *christian*, *jewish*, *buddhist*), **age** (*young*, *old*) and **sexual orientation** (*heterosexual*, *non-heterosexual*). We leverage the definition words from previous work (Liang et al., 2020a) and augment them with our own tuples. The full list can be found in the appendix. We apply our debiasing method on BERT[8] (Devlin et al., 2018), and use the News-commentary-v15 corpus[9] as training data. It contains 223,153 sentences of which we use 80% for training and 20% for development.

[7]We provide code and data as supplementary material

[8]In the appendix, we also apply Att-D on ALBERT, RoBERTa, DistilBERT and SqueezeBERT

[9]http://www.statmt.org/wmt20/translation-task.html

Table 2: Language modeling (lm) and Stereotype scores (ss) of different text encoders on StereoSet

Models	Original BERT		Sent-D		Kaneko		Att-D$^-$		Att-D	
Overall (lm/ss)	83.70	56.04	81.39	54.71	85.58	56.04	80.92	53.37	83.34	**53.04**
gender (lm/ss)	82.35	62.75	76.67	53.33	83.73	58.82	73.33	**51.37**	78.24	53.73
race (lm/ss)	86.28	54.68	85.40	55.09	87.47	56.24	85.03	54.37	86.28	**51.87**
religion (lm/ss)	87.82	56.41	88.46	**51.28**	85.90	57.69	85.90	55.13	88.46	53.85
profession (lm/ss)	80.66	55.50	77.44	55.01	83.87	54.76	77.94	**52.66**	80.96	54.14

Table 3: Bias measurements of different text encoders on Crows-Pairs

Models	BERT	Sent-D	Kaneko	Att-D$^-$	Att-D
Overall	60.48	56.90	57.82	57.23	**55.7**
gender	58.02	51.53	57.63	53.05	57.36
race	58.14	55.23	53.68	53.68	51.15
religion	71.43	60.0	64.76	69.52	64.76
age	55.17	51.72	54.02	54.02	43.68
sexual orientation	67.86	70.24	69.05	66.67	58.33
nationality	62.89	56.6	59.12	61.01	57.86
disability	61.67	65.0	68.33	63.33	60.0

4.2 Evaluations of Fairness

4.2.1 Intrinsic Evaluation

We use the publicly available subsets of two stereotype benchmarks: StereoSet (Nadeem et al., 2020) and Crows-Pairs (Nangia et al.). Both provide likelihood-based diagnostics to measure how often stereotypes are considered more likely than anti-stereotypes by the text encoder of interest. Crows-Pairs is organized in pairs of minimally distant sentences, i.e. sentences that differ only in one word. We pick the following example from the dataset: ***Jews*** *are such greedy people* (Stereotype) versus ***Christians*** *are such greedy people* (Anti-stereotype). Crows-Pairs uses word likelihoods produced by the text encoder to measure how often stereotypes are ranked higher than anti-stereotypes. An ideal *unbiased* text encoder should score 50% in the Crows-Pairs challenge, meaning that it prefers neither stereotypes nor anti-stereotypes. In contrast, StereoSet adds a third absurd sentence to capture the language modeling capabilities of the text encoder in addition to measuring bias. So, an ideal model should have a stereotype score (*ss*) of 50% and a language modeling (*lm*) of 100%.

We compare our method against the original BERT base model to see the effect of debiasing[10]. Also, for accurate comparisons against previous work, we decided to include the baselines whose final debiased models have been published in order to avoid errors of training and/or tuning hyperparameters. Thus, we compare Att-D against Sent-D (Liang et al., 2020a) and the debiasing procedure proposed by Kaneko and Bollegala (2021). We also conduct a simple ablation study by training without negative examples (*Att-D*$^-$). We finetune Att-D and the baselines on language modeling to produce likelihoods. Tables 2 and 3 report the evaluation results on StereoSet and Crows-Pairs respectively.

We found that the original BERT contains significant levels of biases (56.04 in StereoSet and 60.48 in Crows-Pairs). It is important to note that Kaneko and Bollegala (2021) only focused on gender bias, which is clear in Table 2 where only gender stereotype has been reduced. We observe that focusing on one bias type can make text representations even more biased for the other dimensions as can be seen in Kaneko and Bollegala (2021) for race and religion (Table 2), and for sexual orientation and disability (Table 3). In contrast, Att-D always reduces the intensity of stereotyping in BERT (up to 9.53%), and yields the best results overall[11]. We notice that we manage to reduce biases linked to dimensions we did not include in our design such as nationality and disability. We speculate that these bias types are connected to those we worked on mitigating. Therefore, we conjecture that reducing multiple biases at the same time meets better success in mitigating unforeseen stereotypes than working on every bias type separately.

4.2.2 Extrinsic Evaluation

This approach of measuring bias builds on the intuition of Dev et al. (2020) stating that biased representations lead to invalid inferences, whose ratio quantifies bias. They construct a challenge benchmark for the natural language inference task where every hypothesis should be *neutral* to its premise. For example, suppose that the premise is *The* ***driver*** *owns a van* and the hypothesis is *The* ***man*** *owns a van*. The hypothesis neither entails nor contradicts the premise. If the predictions of a classifier deviate from neutrality, the underlying text encoder is doomed as biased. Suppose that the set contains M instances, and let the predictor's probabilities of the i^{th} instance for entail, contradict and neutral be e_i, c_i and n_i. Following Dev et al. (2020), we report three measures of inference-based bias: (1) Net Neutral (**NN**): $NN = \frac{1}{M}\sum_{i=1}^{M} n_i$; (2) Fraction Neutral (**FN**): $FN = \frac{1}{M}\sum_{i=1}^{M} \mathbf{1}_{n_i = max(e_i, c_i, n_i)}$; (3) Threshold τ (**T:**τ): $T : \tau = \frac{1}{M}\sum_{i=1}^{M} \mathbf{1}_{n_i > \tau}$.

[10] Results of BERT large, ALBERT, RoBERTa, DistilBERT and SqueezeBERT are in the appendix

[11] The closer the stereotype score is to 50%, the better

Table 4: Performance of different models on GLUE tasks. The table shows *accuracy* scores for **sst2**, **rte**, **wnli**, and **mnli** for both matched and mismatched instances; *f1* for **mrpc**; *spearman correlation* for **stsb**; and *matthews correlation* for **cola**

Models	**Single sentence tasks**				**Double sentence tasks**											
	sst2		cola		stsb		mrpc		mnli (m)		mnli (mm)		rte		wnli	
BERT	92.78	-	56.05	-	88.97	-	92.25	-	83.54	-	82.68	-	70.04	-	45.07	-
Sent-D	91.63	-1.15	**59.08**	**+3.03**	89.58	+0.61	90.12	-2.13	**84.97**	**+1.43**	83.51	+0.83	68.95	-1.09	28.17	-16.9
Kaneko	91.97	-0.81	56.50	+0.55	88.44	-0.53	90.69	-1.56	84.48	+0.94	83.66	+0.98	59.93	-10.11	52.11	+7.04
Att-D	**92.66**	**-0.12**	55.22	-0.83	**89.62**	**+0.65**	**91.22**	**-1.03**	84.63	+1.09	**84.19**	**+1.51**	**70.40**	**+0.36**	**53.52**	**+8.45**

Table 5: Inference-based bias measurements. Best scores are highlighted with **bold character**, <u>underlined</u>, or marked with † for **gender**, <u>race</u> and religion† respectively

Model	**Bias type**	**NN**	**FN**	τ**:0.5**	τ**:0.7**
BERT	gender	00.59	00.16	00.15	00.12
	race	75.96	76.57	76.51	74.91
	religion	43.47	43.55	43.45	41.77
Sent-D	gender	00.94	00.38	00.33	**00.24**
	race	59.61	59.28	59.20	56.22
	religion	29.64	29.08	29.02	27.24
Kaneko	gender	00.57	00.14	00.12	00.08
	race	84.24	84.84	84.80	83.26
	religion	69.27†	69.80†	69.72†	67.66†
Att-D	gender	**01.31**	**00.43**	**00.35**	00.21
	race	<u>93.31</u>	<u>93.94</u>	<u>93.90</u>	<u>93.04</u>
	religion	68.51	69.08	68.95	66.97

In this experiment, we finetune text encoders on **MNLI** dataset for natural language inference (Wang et al., 2018). A bias-free model should score 1 (100%) in all three measures. We report our findings in Table 5. Our method outperforms the original model and the baselines. This result shows that Att-D succeeds in mitigating stereotypes in real world inference settings, unlike Sent-D which produces positive results in intrinsic evaluation but comes short of meeting the same success in this experiment. In the next section, we show that these findings are meaningful since the entailment accuracy is not hurt after debiasing.

4.3 Evaluations of Representativeness

We use GLUE benchmark (Wang et al., 2018) to verify whether the debiased text encoder still holds enough semantic information to be applicable in downstream NLP tasks. In essence, GLUE assesses the natural language understanding capabilities of NLP models. So, it constitutes a suitable stack to evaluate the semantic preservation of Att-D. In this experiment, we finetune BERT on seven different tasks from GLUE and show the results in Table 4. We also report the difference in accuracy between original BERT and each of the debiasing baselines. Surprisingly, Att-D not only preserves semantic information, but enhances it in most GLUE tasks as reflected in an increase in accuracy from BERT.

5 Conclusion and Future Work

In this paper, we proposed a finetuning approach to debiasing that trains the text encoder to distribute its attention equally on different social groups. Experiments demonstrate that bias is successfully reduced without harm to semantic representativeness. However, we are aware of the following limitations: (1) our definitions of biases are simplified. There are more social divisions in the real world than the five dimensions we studied. Besides, bias types can be correlated in intricate ways such as the links between *race*, *nationality* and *ethnicity*. Moreover, it is not clear which or how many groups to include. For these reasons, we follow previous work and constrain our experiments to common use-cases. We plan to study the effect that the choice of definition tuples and their order impose overall. (2) We calibrate attention scores of every word in the input. However, some words are inherently charged with a strong inclination toward one group, e.g., *beard* to ***male*** or *pregnant* to ***female***. Such words need not be debiased, which requires compiling expensive lists of related words for every social group and protecting them from attention equalization. In this work, we rely on knowledge distillation to retain as much useful semantic information as possible. (3) Current bias detection experiments have positive predictive ability, which means that they can only detect the presence of bias, not the absence of it. Although contemporary evaluation tools demonstrate the effectiveness of our debiasing method, it is possible that bias is still hiding under shapes and forms that we failed to detect. We plan to address these limitations in future work.

References

Vamsi Aribandi, Yi Tay, and Donald Metzler. 2021. How reliable are model diagnostics? In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1778–1785.

Rishabh Bhardwaj, Navonil Majumder, and Soujanya Poria. 2021. Investigating gender bias in bert. *Cognitive Computation*, pages 1–11.

Su Lin Blodgett, Solon Barocas, Hal Daumé III, and Hanna Wallach. 2020. Language (technology) is power: A critical survey of "bias" in nlp. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5454–5476.

Su Lin Blodgett, Gilsinia Lopez, Alexandra Olteanu, Robert Sim, and Hanna Wallach. 2021. Stereotyping norwegian salmon: an inventory of pitfalls in fairness benchmark datasets. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1004–1015.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. *Advances in neural information processing systems*, 29:4349–4357.

Shikha Bordia and Samuel Bowman. 2019. Identifying and reducing gender bias in word-level language models. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 7–15.

Daniel Borkan, Lucas Dixon, Jeffrey Sorensen, Nithum Thain, and Lucy Vasserman. 2019. Nuanced metrics for measuring unintended bias with real data for text classification. In *Companion proceedings of the 2019 world wide web conference*, pages 491–500.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.

Pete Burnap and Matthew L Williams. 2016. Us and them: identifying cyber hate on twitter across multiple protected characteristics. *EPJ Data science*, 5:1–15.

Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186.

Jose Camacho-Collados and Mohammad Taher Pilehvar. 2018. From word to sense embeddings: A survey on vector representations of meaning. *Journal of Artificial Intelligence Research*, 63:743–788.

Pengyu Cheng, Weituo Hao, Siyang Yuan, Shijing Si, and Lawrence Carin. 2020. Fairfil: Contrastive neural debiasing method for pretrained text encoders. In *International Conference on Learning Representations*.

Jenna Cryan, Shiliang Tang, Xinyi Zhang, Miriam Metzger, Haitao Zheng, and Ben Y Zhao. 2020. Detecting gender stereotypes: Lexicon vs. supervised learning methods. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–11.

Robert Dale. 2019. Law and word order: Nlp in legal tech. *Natural Language Engineering*, 25(1):211–217.

Sunipa Dev, Tao Li, Jeff M Phillips, and Vivek Srikumar. 2020. On measuring and mitigating biased inferences of word embeddings. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 7659–7666.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Jwala Dhamala, Tony Sun, Varun Kumar, Satyapriya Krishna, Yada Pruksachatkun, Kai-Wei Chang, and Rahul Gupta. 2021. Bold: Dataset and metrics for measuring biases in open-ended language generation. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pages 862–872.

Mark Díaz, Isaac Johnson, Amanda Lazar, Anne Marie Piper, and Darren Gergle. 2018. Addressing age-related bias in sentiment analysis. In *Proceedings of the 2018 chi conference on human factors in computing systems*, pages 1–14.

Lucas Dixon, John Li, Jeffrey Sorensen, Nithum Thain, and Lucy Vasserman. 2018. Measuring and mitigating unintended bias in text classification. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, pages 67–73.

Yanai Elazar and Yoav Goldberg. 2018. Adversarial removal of demographic attributes from text data. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 11–21.

Seraphina Goldfarb-Tarrant, Rebecca Marchant, Ricardo Muñoz Sanchez, Mugdha Pandya, and Adam Lopez. 2020. Intrinsic bias metrics do not correlate with application bias. *arXiv preprint arXiv:2012.15859*.

Jianping Gou, Baosheng Yu, Stephen J Maybank, and Dacheng Tao. 2021. Knowledge distillation: A survey. *International Journal of Computer Vision*, 129(6):1789–1819.

C Hansen, M Tosik, G Goossen, C Li, L Bayeva, F Berbain, and M Rotaru. 2015. How to get the best word vectors for resume parsing. In *SNN Adaptive Intelligence/Symposium: Machine Learning*.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for nlp. In *International Conference on Machine Learning*, pages 2790–2799. PMLR.

Forrest Iandola, Albert Shaw, Ravi Krishna, and Kurt Keutzer. 2020. Squeezebert: What can computer vision teach nlp about efficient neural networks? In *Proceedings of SustaiNLP: Workshop on Simple and Efficient Natural Language Processing*, pages 124–135.

Masahiro Kaneko and Danushka Bollegala. 2019. Gender-preserving debiasing for pre-trained word embeddings. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1641–1650.

Masahiro Kaneko and Danushka Bollegala. 2021. Debiasing pre-trained contextualised embeddings. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1256–1266.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Vaibhav Kumar, Tenzin Singhay Bhotia, and Tanmoy Chakraborty. 2020. Nurse is closer to woman than surgeon? mitigating gender-biased proximities in word embeddings. *Transactions of the Association for Computational Linguistics*, 8:486–503.

Keita Kurita, Nidhi Vyas, Ayush Pareek, Alan W Black, and Yulia Tsvetkov. 2019. Quantifying social biases in contextual word representations. In *1st ACL Workshop on Gender Bias for Natural Language Processing*.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. *arXiv preprint arXiv:1909.11942*.

Anne Lauscher, Tobias Lüken, and Goran Glavaš. 2021. Sustainable modular debiasing of language models. *arXiv preprint arXiv:2109.03646*.

Yitong Li, Timothy Baldwin, and Trevor Cohn. 2018. Towards robust and privacy-preserving text representations. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 25–30.

Paul Pu Liang, Irene Mengze Li, Emily Zheng, Yao Chong Lim, Ruslan Salakhutdinov, and Louis-Philippe Morency. 2020a. Towards debiasing sentence representations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5502–5515.

Sheng Liang, Philipp Dufter, and Hinrich Schütze. 2020b. Monolingual and multilingual reduction of gender bias in contextualized representations. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 5082–5093.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Thomas Manzini, Yao Chong Lim, Yulia Tsvetkov, and Alan W Black. 2019. Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings. *arXiv preprint arXiv:1904.04047*.

Binny Mathew, Punyajoy Saha, Seid Muhie Yimam, Chris Biemann, Pawan Goyal, and Animesh Mukherjee. 2021. Hatexplain: A benchmark dataset for explainable hate speech detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 14867–14875.

Chandler May, Alex Wang, Shikha Bordia, Samuel R Bowman, and Rachel Rudinger. 2019. On measuring social biases in sentence encoders. In *NAACL-HLT (1)*.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Moin Nadeem, Anna Bethke, and Siva Reddy. 2020. Stereoset: Measuring stereotypical bias in pretrained language models. *arXiv preprint arXiv:2004.09456*.

Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. 2016. Improving document ranking with dual word embeddings. In *Proceedings of the 25th International Conference Companion on World Wide Web*, pages 83–84.

Nikita Nangia, Clara Vania, Rasika Bhalerao, and Samuel R Bowman. Crows-pairs: A challenge dataset for measuring social biases in masked language models.

Ji Ho Park, Jamin Shin, and Pascale Fung. 2018. Reducing gender bias in abusive language detection. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2799–2804.

Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in pytorch.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.

Reid Pryzant, Richard Diehl Martinez, Nathan Dass, Sadao Kurohashi, Dan Jurafsky, and Diyi Yang. 2020. Automatically neutralizing subjective bias in text. In *Proceedings of the aaai conference on artificial intelligence*, volume 34, pages 480–489.

Yusu Qian, Urwa Muaz, Ben Zhang, and Jae Won Hyun. 2019. Reducing gender bias in word-level language models with a gender-equalizing loss function. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 223–228.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Shauli Ravfogel, Yanai Elazar, Hila Gonen, Michael Twiton, and Yoav Goldberg. 2020. Null it out: Guarding protected attributes by iterative nullspace projection. *arXiv preprint arXiv:2004.07667*.

Manoel Horta Ribeiro, Pedro H Calais, Yuri A Santos, Virgílio AF Almeida, and Wagner Meira Jr. 2018. Characterizing and detecting hateful users on twitter. In *Twelfth international AAAI conference on web and social media*.

Victor SANH, Lysandre DEBUT, Julien CHAUMOND, Thomas WOLF, and Hugging Face. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter.

Maarten Sap, Saadia Gabriel, Lianhui Qin, Dan Jurafsky, Noah A Smith, and Yejin Choi. 2020. Social bias frames: Reasoning about social and power implications of language. In *Association for Computational Linguistics*.

Emily Sheng, Kai-Wei Chang, Prem Natarajan, and Nanyun Peng. 2020. Towards controllable biases in language generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings*, pages 3239–3254.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

Sumithra Velupillai, Hanna Suominen, Maria Liakata, Angus Roberts, Anoop D Shah, Katherine Morley, David Osborn, Joseph Hayes, Robert Stewart, Johnny Downs, et al. 2018. Using clinical natural language processing for health outcomes research: overview and actionable suggestions for future advances. *Journal of biomedical informatics*, 88:11–19.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355.

Kellie Webster, Xuezhi Wang, Ian Tenney, Alex Beutel, Emily Pitler, Ellie Pavlick, Jilin Chen, Ed Chi, and Slav Petrov. 2020. Measuring and reducing gendered correlations in pre-trained models. *arXiv preprint arXiv:2010.06032*.

Qizhe Xie, Zihang Dai, Yulun Du, Eduard Hovy, and Graham Neubig. 2017. Controllable invariance through adversarial feature learning. *Advances in Neural Information Processing Systems*, 30:585–596.

Ziqi Zhang, David Robinson, and Jonathan Tepper. 2018. Detecting hate speech on twitter using a convolution-gru based deep neural network. In *European semantic web conference*, pages 745–760. Springer.

Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2017. Men also like shopping: Reducing gender bias amplification using corpus-level constraints. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*.

Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2018a. Gender bias in coreference resolution: Evaluation and debiasing methods. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 15–20.

Jieyu Zhao, Yichao Zhou, Zeyu Li, Wei Wang, and Kai-Wei Chang. 2018b. Learning gender-neutral word embeddings. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4847–4853.

A Appendix

A.1 Training Hyperparameters

We used Adam optimizer (Kingma and Ba, 2014) with a learning rate of $5e^{-6}$ for 3 epochs. We keep the betas to their default values (0.9, 0.999) as in PyTorch implementation (Paszke et al., 2017). We set the loss coefficient λ to 2.0 and the negative ratio η to 0.8 meaning that in 80% of the iterations, we use negative examples whose number we set to 5 in each negative iteration. We only finetuned the values of λ, η, the learning rate, and the number of epochs. We conducted the hyperparameter search manually on the development set.

As for GLUE experiments, we follow the experimental setup of (Devlin et al., 2018) and train each task for 3 epochs with a learning rate of $2e^{-5}$ on their respective training data.

A.2 Definition of bias types and social groups used in this paper

While the approach is independent of the definition of social groups and categories (it could work for any kind of grouping, e.g., cuisine styles or sports), in the experiment we focus on groups commonly used in the debiasing literature: binary gender, religion, race, age and sexual orientation. This is to facilitate comparison, but nothing in the approach prevent it from being used with broader and more inclusive groups. This being said, we have not experimented yet with debiasing where a dimension is divided in dozens of categories.

We list the definition tuples that we used in Table 6. We show that Att-D does not incur strict rules for defining social groups, unlike previous work (Bolukbasi et al., 2016; Kaneko and Bollegala, 2019, 2021) that require the definition words to be organized in a predefined format (pairs of words or bag of words for every group), and provided in relatively large quantities. We can see from Table 6 that it is sufficient to define one tuple per bias type (e.g., race) if the tuples are hard to come by. Also, the tuples need not be of the same size (e.g., in religion there is a missing word for *buddhist* group since it is not clear which word to use in that tuple). This desired property owes to the fact that Att-D does not learn subspaces or directions for every bias type as previous works do (Bolukbasi et al., 2016; Kaneko and Bollegala, 2019; Kumar et al., 2020; Kaneko and Bollegala, 2021). In contrast, Att-D uses the tuples in order to equalize the attentions of the input sentence, and make the words therein attend to the groups with the same intensity. These example categories used in experiments are neither complete nor exhaustive, and in some experiments also include terms possibly considered inappropriate but that appear in the corpus and we may still want to debias from (such as using "straight" to define heterosexual).

A.3 Extrinsic bias evaluation on the task of hate-speech detection

Recent studies show that intrinsic metrics of bias do not necessarily correlate with bias measures on concrete real-world applications (Goldfarb-Tarrant et al., 2020). In the body of this paper, we already conducted intrinsic and extrinsic bias evaluations. In this experiment, we validate the efficacy of our debiasing method on a concrete real-world hate speech detection application where an input snippet of text is classified as either offensive (*toxic*, *harmful*, *disrespectful*...) or not. We use hate speech detection because it is well studied in the literature (Burnap and Williams, 2016; Ribeiro et al., 2018; Zhang et al., 2018), and high-quality datasets which are tagged with social groups already exist (Borkan et al., 2019; Mathew et al., 2021).

Admittedly, common social biases have also been shown to exist in hate speech detection models, for example in associating toxicity to frequently attacked groups (such as "muslim" or "gay") even if the text itself is not toxic (Dixon et al., 2018; Park et al., 2018). In this experiment, we adopt the bias definition of Borkan et al. (2019) which casts bias as a skewing in the hate speech detector scores based solely on the social groups mentioned in the text. In other words, we consider a model to exhibit unintended social stereotypes if the model's performance varies across groups. We use the bias measures proposed by Borkan et al. (2019) which are based on the Area Under the Receiver Operating Characteristic Curve (ROC-AUC, or AUC) metric. AUC measures the probability that a randomly chosen negative example (not offensive) receives a lower toxicity score than a randomly chosen positive example (offensive), meaning that a perfect model should always have an AUC score of 1.0. Stated differently, all negative examples have lower toxicity scores than positive examples. While AUC is used to measured the general performance of classifiers, Borkan et al. (2019) propose three extensions of AUC to measure bias. We summarize them in the following:

Subgroup (Sub) AUC: where AUC is computed only on the group under consideration and not on all the examples of the test benchmark, i.e. only positive and negative examples of the target group are considered. This metric represents the model's performance on a given group. A higher value means that the model is good at distinguishing between toxic and non-toxic texts specific to the group.

Background Positive Subgroup Negative (BPSN) AUC: where AUC is calculated on the negative examples of the target group, and the positive examples of the background (all other groups except the group under consideration). This metric computes whether the model *discriminates* against the target group with respect to the others. This

Table 6: Full list of definition tuples for bias types and social groups used in this work

gender		religion			
male	*female*	*muslim*	*christian*	*jewish*	*buddhist*
man	woman	muslim	christian	jewish	buddhist
boy	girl	muslims	christians	jews	buddhists
father	mother	islam	christianity	judaism	buddhism
brother	sister	mosque	church	synagogue	temple
grandfather	grandmother	quran	bible	torah	
son	daughter	imam	priest	rabbi	monk
gentleman	lady	mohammad	jesus	moses	buddha
he	she				
his	her				
himself	herself				

race				age		sexual orientation	
white	*black*	*asian*	*hispanic*	*old*	*young*	*heterosexual*	*non-heterosexual*
white	black	asian	hispanic	old	young	straight	gay
				elderly	youth	straight	lesbian
				adult	child	heterosexual	homosexual
				senior	junior	heterosexual	bisexual
				adult	teenager		

value is reduced when non-toxic examples of the group have *higher* toxicity scores than actually toxic examples of the background.

Background Negative Subgroup Positive (BNSP) AUC: where AUC is calculated on the positive examples of the target group, and the negative examples of the background. This metric computes whether the model *favors* the target group with respect to the others. This value is reduced when toxic examples of the group have *lower* toxicity scores than non-toxic examples of the background.

In this experiment, we finetune the text encoder under study on hate speech detection task using the training set of HateXplain dataset (Mathew et al., 2021). We also use the test portion of HateXplain for the evaluation, which contains posts from Twitter[12] and Gab[13] annotated with their ground-truth toxicity scores and the social groups and communities they target. Fundamentally, the three metrics described above give bias scores per group. In order to combine the per group scores in one overall measure, we apply the Generalized Mean of Bias (GMB) introduced by the Google Conversation AI Team as part of their Kaggle competition[14], and later used by Mathew et al. (2021) in their own evaluations. The formula of GMB is as the following:

$$GMB(b) = \left(\frac{1}{|b|}\sum_{g=1}^{|b|} b_g^p\right)^{1/p} \qquad (4)$$

where b is an array of AUC scores per group, and b_g is the AUC score of group g. We follow Mathew et al. (2021) and set p to -5. We compute the GMB of all three metrics: Subgroup, BPSN and BNSP. As for Subgroup, we also add the standard deviation as it gives valuable information about how much the performance of the hate speech detection model varies across groups. We report our results in Table 7, in addition to classic performance measures.

We observe that Att-D provides competitive results across the four bias metrics, and largely outperforms the baselines. Especially with *GMB-BNSP*, where bias scores of the original model are very low (i.e. it is throttled by social biases), we observe the best improvements overall, and by a large margin compared to existing debiasing methods. Also, the variance in model performance is lowest with Att-D, which confirms that the corresponding hate speech detection model has less stereotypes about different social groups. Finally, the general performance (Accuracy, F1 score and AUC) of the hate speech detection model after debiasing is not hurt.

A.4 Visualizing debiasing results

In this experiment, we aim to visualize the effects of debiasing on attention weights. We only fo-

[12] https://twitter.com

[13] https://gab.com

[14] https://www.kaggle.com/c/jigsaw-unintended-bias-in-toxicity-classification/overview/evaluation

Table 7: AUC-based bias measures on hate speech detection task

Models	Performance			Bias			
	Acc↑	F1↑	AUC↑	STD-Sub↓	GMB-Sub↑	GMB-BPSN↑	GMB-BNSP↑
BERT	0.783	0.823	0.870	0.119	0.698	**0.800**	0.379
Sent-D	0.791	0.825	0.870	0.121	0.689	0.725	0.583
Kaneko	0.797	0.833	0.872	0.112	0.705	0.789	0.512
Att-D	0.789	0.829	0.866	**0.085**	**0.808**	0.793	**0.726**

cus on binary gender bias for two reasons: First, it is easier to visualize binary variables on a 2D plane than multiclass variables (such as race, religion...). Second, gender is the most well studied bias type (Bolukbasi et al., 2016; Caliskan et al., 2017; May et al., 2019), so linguistic resources and vocabularies for gender exist and are well documented. We use the vocabulary words compiled by (Kaneko and Bollegala, 2019) and categorized into three non-overlapping subsets: (1) **Male-definition** Ω^M whose corresponding words are exclusively male-gendered such as *father*, *king* or *uncle*. (2) **Female-definition** Ω^F which is a set of inherently female words (*mother*, *queen*, *aunt*...). (3) **Gender-stereotype** Ω^S which is constituted of words that are not gendered by definition, but that carry a strong gender stereotype such as *doctor* being attributed to ***male*** or *nurse* to ***female***.

For every word $w \in \Omega^M \cup \Omega^F \cup \Omega^S$, we extract sentences from the News-commentary-v15 corpus where w is mentioned. We denote this set as S^w. Then, for every sentence $s \in S^w$, we append the dummy input *"man, woman"* as explained in Sections 3.1 and 3.2.1. The augmented input s' is then fed to the text encoder of interest (BERT base in this experiment), and we collect the attention scores of w on the second-half tokens ***man*** and ***woman***. Finally, for every word $w \in \Omega^M \cup \Omega^F \cup \Omega^S$, we take the mean of its attention scores in S^w. By the end of this procedure, we have for every word w its attention score on the words ***man*** (a_m^w) and ***woman*** (a_f^w) as computed on the News-commentary-v15 corpus which includes overall 223,153 sentences. We take the difference $a_m^w - a_f^w$ which indicates the preference of the text encoder to consider w as male (positive difference) or female (negative difference). The absence of gender bias is reflected in difference scores near zero.

We plot the results in Figure 3 where the x-axis represents the differences $a_m^w - a_f^w$, and the y-axis random values to separate the words vertically. Stereotype words (green dots) should have values near 0, which is not the case in Figure 3(b). This means that BERT has a strong preference for one of the genders, and is thus heavily biased. In contrast, our method brings the attention of stereotype words near 0, meaning that they prefer neither male nor female connotations. Moreover, the spread of stereotype words in Figure 3(d) is narrower than male- or female-oriented words, which is desired since these are inherently gendered and must pick a side. This result strengthens the claim that Att-D preserves semantic information, and is less severe in reducing bias from gendered words as it is on gender-neutral words. The difference in spread is less apparent in the original BERT model. We also note that debiasing the embeddings of BERT rather than the attention mechanism as in (Kaneko and Bollegala, 2021) (Figure 3(c)) is not enough since bias information is still lurking (and perhaps made worse for some words) in the attention component. Thus, we conclude that working on attention directly constitutes our best option for debiasing to date.

A.5 Effect of the choice of layers

Transformer-based text encoders consist of many layers. It is not clear which layers to choose for debiasing since bias information is spread out across all of them. In this experiment, we try different debiasing settings in which we select different layer combinations of BERT to work on: ***all*** layers, ***first 6***, ***first 3***, ***last 6***, ***last 3***, and alternating layers with strides of ***1*** (layers 2, 4, 6, 8, 10 and 12) or ***2*** (layers 4, 8 and 12). We apply the debiasing method proposed in this paper, and report both language modeling and stereotype scores of StereoSet benchmark in Table 8.

The results show that it is safest to equalize attention heads of all layers of the text encoder under study, since it produces the best scores both in terms of language modeling and stereotype. Our

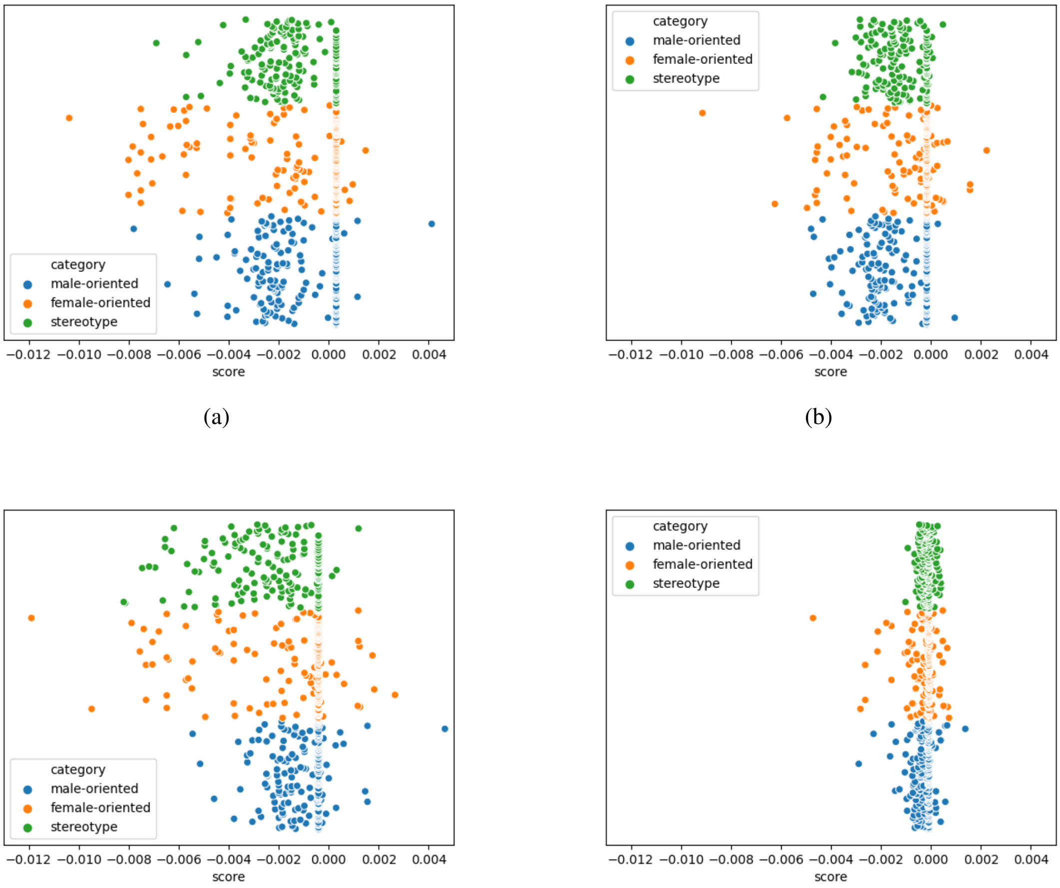


Figure 3: Scatter plots of attention scores on male - female direction. (a) Original BERT, (b) BERT debiased by Sent-D (c) BERT debiased by (Kaneko and Bollegala, 2021), (d) BERT debiased by Att-D

Table 8: Language modeling (lm) and Stereotype scores (ss) of different layer combinations on StereoSet. Underlined depicts the best language modeling score, while **bold** shows the best stereotype score

Models	**first 3**		**first 6**		**last 3**		**last 6**		**1-stride**		**2-stride**		**all**	
Overall (lm/ss)	83.17	54.28	78.80	54.04	82.51	54.13	81.92	54.33	82.70	54.42	82.68	54.04	83.34	**53.04**
gender (lm/ss)	78.04	55.29	71.96	55.69	78.43	56.08	77.65	55.69	76.47	55.29	78.43	54.51	78.24	**53.73**
race (lm/ss)	87.11	54.05	83.16	54.16	85.71	54.05	85.40	54.57	85.76	54.26	86.38	52.91	86.28	**51.87**
religion (lm/ss)	87.82	**51.28**	87.82	57.69	85.90	52.56	88.46	57.69	88.46	53.85	86.54	60.26	88.46	53.85
profession (lm/ss)	79.67	54.51	74.91	**53.03**	79.67	53.77	78.49	53.28	80.47	54.39	79.23	54.64	80.96	54.14

Table 9: Effect of negative examples on GLUE tasks. The table shows *accuracy* scores for **sst2**, **rte**, **wnli**, and **mnli** for both matched and mismatched instances; *f1* for **mrpc**; *spearman correlation* for **stsb**; and *matthews correlation* for **cola**

Models	Single sentence tasks sst2	cola	Double sentence tasks stsb	mrpc	mnli (m/mm)	rte	wnli
BERT	**92.78**	56.05	88.97	**92.25**	83.54 / 82.68	70.04	45.07
Att-D	92.66	55.22	**89.62**	91.22	**84.63 / 84.19**	**70.40**	**53.52**
Att-D^{-}	92.32	**56.25**	89.12	80.44	84.59 / 83.96	58.12	39.44

findings go in tandem with those of (Liang et al., 2020b; Kaneko and Bollegala, 2021; Bhardwaj et al., 2021) who found that reducing bias from all layers usually is the best option.

A.6 Effect of negative examples on representativeness

We remind that the introduction of negative examples to training serves in forcing the text encoder not to rely on a dangerous shortcut which is distributing its attention uniformly on all the tokens constituting the second half of the input, no matter what the input is. This is particularly important in double-sentence tasks where the text encoder is given two input sentences. In addition to Tables 2 and 3 which highlighted the effect of negative sampling on the final stereotype scores, the primary goal of using negative examples remains the preservation of the text encoder's representativeness. In Table 9, we report the performance of *Att-D* and *Att-D*$^{-}$ with and without negative examples respectively on GLUE tasks. Unsurprisingly, the lack of negative examples does not damage the performance of single-sentence tasks since these ignore the second half of the input altogether. However, in double-sentence tasks where both halves are used for prediction, Table 9 shows that negative sampling plays a pivotal role in preserving the semantics of text encoders, and bypassing the side effects inflicted by attention equalization.

A.7 Word-Level vs Sentence-Level Debiasing

As previously explained in the paper, Att-D calibrates the attention weighs of all tokens of the input sentence on group-related words. Since we used BERT-based models in our experiments, the first token in the input is the special [CLS] token, which is considered by the NLP community as a vector representation for the entire input sentence. In the current version of Att-D, we also calibrate the attention weighs of the special [CLS] token on groups, in addition to calibrating the other tokens of the sentence. One can see this notion as a combined word-level and sentence-level debiasing. In this experiment, we motivate this design choice by comparing it to word-level and sentence-level debiasing separately. For word-level, we exclude the [CLS] token from the attention equalization process, whereas in sentence-level we only calibrate the attention of [CLS]. We use all the bias evaluations run so far to understand the difference in performance. Tables 10, 11, 12, 13 and 14 report the results of StereoSet, Crows-Pairs, inference, hate speech and GLUE experiments respectively. We denote word-level debiasing by **No [CLS]**, and sentence-level debiasing by **Only [CLS]** in the tables. The combination of both is referred to as **Att-D**, and is the variant that we promote in this paper. We observe that while the three settings are good at reducing bias from text encoders, Att-D is superior than word-level and sentence-level debiasing since it capitalizes on the benefits of both. It enjoys the fine granularity of reducing bias from every word, while it also mitigates biases that manifest at sentence-level.

A.8 Static vs Random ordering of group-related words

In the preprocessing step of our method (as explained in Section 3.2.1), we use a preset ordering of group-related words of a given bias type to form the second input. For example, if we have the groups *Muslim*, *Christian*, *Jew* and *Buddhist* defining the religion bias type, Att-D constructs the second input using the same preset ordering of groups across all samples of the training data. Continuing the example above, Att-D appends the following artificial sentence "muslim, christian, jew, buddhist". In this experiment, we change the ordering of groups in a random way. Tables 10, 11, 12, 13 and 14 also report the bias scores of Att-D (static ordering) and Att-D with random ordering.

Although the semantic performance of Att-D with random ordering is better, we notice that it suffers from a stronger presence of bias than in its static counterpart. In Table 13, Att-D with random ordering has an AUC score of 0 in one of the groups, which made the GMB extremely small. We suspect that the relatively poor fairness of random ordering owes to the fact that the model might be confused by different orderings throughout the iterations. A more serious analysis of the impact of group order on the overall performance (fairness

Table 10: Language modeling (lm) and Stereotype scores (ss) on StereoSet of different variants of Att-D

Models	Att-D		No [CLS]		Only [CLS]		Random Order	
Overall (lm/ss)	83.34	**53.04**	80.37	53.71	81.70	55.51	82.91	54.75
gender (lm/ss)	78.24	53.73	76.86	**52.94**	75.88	54.51	79.02	55.69
race (lm/ss)	86.28	**51.87**	84.10	53.01	85.24	55.09	86.75	54.57
religion (lm/ss)	88.46	**53.85**	84.62	60.26	85.26	56.41	87.18	56.41
profession (lm/ss)	80.96	**54.14**	76.63	**54.14**	78.99	56.24	79.17	54.51

Table 11: Bias measurements of different variants of Att-D on Crows-Pairs

Models	Att-D	No [CLS]	Only [CLS]	Random Order
Overall	55.7	56.1	**55.5**	58.36
gender	57.36	50.76	**50.0**	53.82
race	**51.15**	54.84	53.1	57.75
religion	**64.76**	69.52	65.71	67.62
age	43.68	56.32	44.83	**54.02**
sexual orientation	**58.33**	71.43	63.1	64.29
nationality	57.86	**53.46**	65.41	62.28
disability	60.0	61.67	**58.33**	65.0

and semantics) of Att-D motivates the direction of future work.

A.9 Effect of Att-D on other transformer-based text encoders

We evaluate five widely used sentence-level text encoders: BERT (Devlin et al., 2018), ALBERT (Lan et al., 2019), RoBERTa (Liu et al., 2019), DistilBERT (SANH et al.) and SqueezeBERT (Iandola et al., 2020). For each model, we evaluate both its base and large variants (except for DistlBERT and SqueezeBERT since these are not available in HuggingFace's transformers library[15]), original and debiased; which gives a total of sixteen evaluated models. We use Crows-Pairs dataset (Nangia et al.) to quantify the intensity of undesired stereotypes encoded therein. As a reminder, ideal stereotype scores according to Crows-Pairs benchmark should be close to 50, i.e. models preferring neither stereotypes nor anti-stereotypes. Tables 15, 16, 17 and 18 show the bias results for BERT, ALBERT, RoBERTa and DistillBERT/SqueezeBERT respectively.

All five models exhibit substantial levels of bias, and in each of the bias types with differing intensities (religion, sexual orientation and disability being the bias categories with the most severe stereotyping). Also, we find that the large variants are more biased than their base counterparts mainly because large models, with their larger capacity and greater number of parameters, can capture more

[15] https://huggingface.co/transformers/index.html

Table 12: Inference-based bias measurements on different variants of Att-D. Best scores are highlighted with **bold character**, underlined, or marked with † for **gender**, race and religion† respectively

Model	Bias type	NN	FN	τ:0.5	τ:0.7
Att-D	gender	01.31	00.43	00.35	00.21
	race	93.31	93.94	93.90	93.04
	religion	68.51†	69.08†	68.95†	66.97†
No [CLS]	gender	00.85	00.36	00.30	00.20
	race	76.14	76.24	76.19	74.26
	religion	40.80	40.04	39.98	37.78
Only [CLS]	gender	**02.35**	**01.60**	**01.38**	**00.90**
	race	81.63	81.52	81.50	80.37
	religion	44.40	44.01	43.95	42.76
Random Order	gender	01.54	00.51	00.39	00.23
	race	54.71	54.92	54.89	52.49
	religion	26.94	26.67	26.59	24.58

intricate and more sophisticated aspects of training data, exposing them to learn more bias. This finding corresponds well to results of previous work (Nangia et al.; Nadeem et al., 2020). The tables also show that Att-D is effective in mitigating bias from BERT, ALBERT, RoBERTa, DistilBERT and SqueezeBERT, and produces a reduction of up to 25%. We note that Att-D succeeds in debiasing all models, with varying effectiveness across bias types. We also note that Att-D meets the best success with ALBERT as reductions are greater on this particular text encoder. We believe this is because ALBERT is composed of a single transformer layer (Lan et al., 2019) with substantially less parameters than BERT or RoBERTa; which makes debiasing easier since there is no interference between different attention layers. Finally, we see from the tables that Att-D sometimes contributes to adding a bit of bias. We observe that this phenomenon is rare, and happens especially with bias types we did not include in our design[16]. We assume that not explicitly compelling the text encoder to equalize attention heads corresponding to these overlooked bias types gave it green light to adjust these attentions in a way to facilitate solving the optimization problem; even if it entails adding bias. We plan to include all bias types present in Crows-Pairs dataset to our debiasing design as a future work.

[16] In the current version of this work, we remind that we only consider five bias types: gender, race, religion, age and sexual orientation

Table 13: AUC-based bias measures on hate speech detection task on different variants of Att-D

Models	Performance			Bias			
	Acc↑	F1↑	AUC↑	STD-Sub↓	GMB-Sub↑	GMB-BPSN↑	GMB-BNSP↑
Att-D	0.789	0.829	0.866	**0.085**	**0.808**	0.793	**0.726**
No [CLS]	0.791	0.830	0.871	0.114	0.710	**0.797**	0.530
Only [CLS]	0.765	0.805	0.838	0.142	0.660	0.766	0.636
Random Order	0.784	0.822	0.861	/	/	0.764	/

Table 14: GLUE performance of different variants of Att-D. The table shows *accuracy* scores for **sst2**, **rte**, **wnli**, and **mnli** for both matched and mismatched instances; *f1* for **mrpc**; *spearman correlation* for **stsb**; and *matthews correlation* for **cola**

Models	Single sentence tasks		Double sentence tasks				
	sst2	cola	stsb	mrpc	mnli (m/mm)	rte	wnli
Att-D	92.66	55.22	**89.62**	91.22	**84.63** / 84.19	70.40	**53.52**
No [CLS]	91.51	40.85	88.94	91.62	84.49 / 84.02	68.95	40.85
Only [CLS]	92.43	55.23	89.43	90.04	84.42 / 84.67	**71.84**	23.94
Random Order	**93.23**	**59.07**	88.85	**91.94**	83.75 / **84.86**	**71.84**	30.99

Table 15: Bias reduction in BERT base and large measured on Crows-Pairs dataset. Each cell is organized as follows: o $\rightarrow$ d +/-diff where o is the stereotype score of the original model, d is that of the debiased model using attention-based debiasing, and $diff$ is the difference in stereotype score. Negative values correspond to reduction in bias (desired) where positive values mean addition of bias (undesired).

Models	BERT base		BERT large	
Overall	60.48 → 55.70	-04.78	59.68 → 56.96	-02.72
race	58.14 → 51.15	-06.99	60.08 → 53.49	-06.59
gender	58.02 → 57.36	-00.66	55.34 → 53.05	-02.29
socioeconomic	59.88 → 51.16	-08.72	56.40 → 57.56	+01.16
nationality	62.89 → 57.86	-05.03	52.20 → 57.23	+05.03
religion	71.43 → 64.76	-06.67	68.57 → 66.67	-01.90
age	55.17 → 43.68	+01.15	55.17 → 54.02	-01.15
sexual orientation	67.86 → 58.33	-09.53	65.48 → 67.86	+02.41
physical appearance	63.49 → 61.90	-01.89	69.84 → 65.08	-04.76
disability	61.67 → 60.00	-01.67	76.67 → 65.00	-11.67

Table 16: Bias reduction in ALBERT base and large measured on Crows-Pairs dataset. Each cell is organized as follows: o → d +/-diff where o is the stereotype score of the original model, d is that of the debiased model using attention-based debiasing, and $diff$ is the difference in stereotype score. Negative values correspond to reduction in bias (desired) where positive values mean addition of bias (undesired).

Models	ALBERT base		ALBERT large	
Overall	56.76 → 51.99	-04.77	60.48 → 53.58	-06.90
race	51.36 → 48.84	-00.20	59.11 → 50.97	-08.14
gender	54.20 → 53.44	-00.76	56.11 → 48.47	-04.58
socioeconomic	60.47 → 61.05	+00.58	54.07 → 50.00	-01.16
nationality	51.57 → 57.86	+06.29	62.26 → 60.38	-04.07
religion	59.05 → 60.00	+00.95	76.19 → 61.90	-14.29
age	65.52 → 42.53	-08.05	54.02 → 54.02	-00.00
sexual orientation	75.00 → 38.10	-13.10	71.43 → 63.10	-08.33
physical appearance	46.03 → 41.27	+04.76	58.73 → 57.14	-01.59
disability	86.67 → 61.67	-25.00	73.33 → 58.33	-15.00

Table 17: Bias reduction in RoBERTa base and large measured on Crows-Pairs dataset. Each cell is organized as follows: o → d +/-diff where o is the stereotype score of the original model, d is that of the debiased model using attention-based debiasing, and $diff$ is the difference in stereotype score. Negative values correspond to reduction in bias (desired) where positive values mean addition of bias (undesired).

Models	RoBERTa base		RoBERTa large	
Overall	53.98 → 51.39	-02.59	61.27 → 56.83	-04.44
race	47.09 → 50.39	-02.52	61.43 → 53.49	-07.94
gender	54.96 → 45.80	-00.76	51.91 → 51.91	-00.00
socioeconomic	56.40 → 55.81	-00.59	66.28 → 59.88	-06.40
nationality	45.28 → 43.40	+01.88	56.60 → 55.35	-01.25
religion	56.19 → 60.00	+03.81	59.05 → 62.86	+03.81
age	64.37 → 56.32	-08.05	71.26 → 62.07	-09.19
sexual orientation	69.05 → 48.81	-17.86	71.43 → 59.52	-11.91
physical appearance	66.67 → 60.32	-06.35	68.25 → 66.67	-01.58
disability	71.67 → 65.00	-06.67	66.67 → 70.00	+03.33

Table 18: Bias reduction in DistilBERT and SqueezeBERT measured on Crows-Pairs dataset. Each cell is organized as follows: o → d +/-diff where o is the stereotype score of the original model, d is that of the debiased model using attention-based debiasing, and $diff$ is the difference in stereotype score. Negative values correspond to reduction in bias (desired) where positive values mean addition of bias (undesired).

Models	DistilBERT		SqueezeBERT	
Overall	56.83 → 51.26	-05.57	57.43 → 54.71	-02.72
race	53.29 → 47.87	-01.16	55.04 → 56.01	+00.97
gender	54.58 → 46.56	-01.14	52.67 → 48.47	-01.14
socioeconomic	55.81 → 58.14	+02.33	57.56 → 51.16	-06.40
nationality	54.09 → 50.94	-03.15	53.46 → 61.01	+07.55
religion	70.48 → 57.14	-13.34	74.29 → 60.95	-13.34
age	59.77 → 48.28	-08.05	55.17 → 48.28	-03.45
sexual orientation	70.24 → 55.95	-14.29	70.24 → 57.14	-13.10
physical appearance	55.56 → 63.49	+07.93	52.38 → 52.38	-00.00
disability	61.67 → 56.67	-05.00	70.00 → 61.67	-08.33