Monolingual and Multilingual Reduction of Gender Bias in Contextualized Representations

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Abstract

Pretrained language models (PLMs) learn stereotypes held by humans and reflected in text from their training corpora, including gender bias. When PLMs are used for downstream tasks such as picking candidates for a job, people's lives can be negatively affected by these learned stereotypes. Prior work usually identifies a linear gender subspace and removes gender information by eliminating the subspace. Following this line of work, we propose to use DensRay, an analytical method for obtaining interpretable dense subspaces. We show that DensRay performs on-par with prior approaches, but provide arguments that it is more robust. By applying DensRay to attention heads and layers of BERT we show that gender information is spread across all attention heads and most of the layers. Finally, we demonstrate that we can remove bias multilingually, e.g., from Chinese, using only English training data.

1 Introduction

Word embeddings, which represent the semantic meaning of text data as vectors, are used as input in natural language processing tasks. It has been found that word embeddings exhibit biases such as gender bias, which are present in their training corpora (Bolukbasi et al., 2016; Caliskan et al., 2017; Garg et al., 2018). Contextual word embedding models, such as BERT (Devlin et al., 2018), have become increasingly common and achieved new state-of-the-art results in many NLP tasks. Researchers have also found gender bias in contextualized embeddings (Zhao et al., 2019; May et al., 2019).

A common approach for removing gender information in static embeddings is to identify a linear gender subspace (e.g., a gender direction) and subsequently setting all values on the gender direction to 0. Successful approaches rely on simple principal component analysis (Bolukbasi et al., 2016; Mu and Viswanath, 2018). Bolukbasi et al. (2016) require pairs of gendered words to compute a direction (e.g., "man"-"woman") and Mu and Viswanath (2018) rely on computing a PCA of a set of gender words hoping that the main variation occurs across gender. We propose to use DensRay (Dufter and Schütze, 2019): the main advantage is that DensRay only requires two or multiple groups of gendered words. In contrast to (Bolukbasi et al., 2016), it does not require explicit pairs. Compared to (Mu and Viswanath, 2018), it has explicit supervision with gender labels. We show in §2.5 that this enables DensRay to identify better gender directions.

In summary, our contributions are: i) We adjust DensRay to be usable to debias contextualized embeddings. We evaluate the approach on two tasks – a set of templates we constructed and previously used Association Tests – and show that DensRay performs comparable to prior approaches. ii) We provide arguments why DensRay is more robust and find that applying DensRay preserves language model performance on downstream tasks better. iii) We analyze how gender information is processed in BERT by applying DensRay to attention heads and layers: we conclude that there is no single attention head responsible for processing gender information. In addition we show in a qualitative analysis that token-level gender scores can be obtained. v) We apply our debiasing method to the multilingual-BERT (mBERT) model: we show that English training data can be used to effectively debias Chinese.

2 Methodology

2.1 Debiasing Conceptor

Karve et al. (2019) introduced conceptor debiasing. Given a set of gendered words $V := \{v_1, v_2, \ldots, v_n\}$ and their embeddings E, gender bias can be mitigated by multiplying the debiasing conceptor matrix$\neg C = I - C$, where C is the conceptor matrix that minimizes the objective

$$||E - CE||_F^2 + \alpha^{-2}||E||_F^2 \tag{1}$$

where α is a parameter. C has an analytical solution

$$C = \frac{1}{d}EE^T(\frac{1}{d}EE^T + \alpha^{-2}I)^{-1} \tag{2}$$

Intuitively, C is a soft projection matrix on the linear subspace where embeddings have the maximum bias. Once C is computed a debiased version of embeddings $X \in R^{t\times d}$ can be obtained by matrix multiplication $X(I - C)$.

2.2 Hard Debasing

We will also compare with the hard debiasing method proposed by Mu and Viswanath (2018), which is originally a postprocessing technique for improving word representations. Karve et al. (2019) adopted it as a method for debiasing. Hard debiasing relies upon the assumption that the first principal component of the embedding vectors is a meaningful gender direction. The first principal component of E is the gender direction q.

2.3 DensRay

DensRay (Dufter and Schütze, 2019) is an analytical method for identifying the embedding subspace of certain linguistic features. It identifies the "gender subspace" using a set of gendered words $V := \{v_1, v_2, \ldots, v_n\}$ and their embeddings $E \in R^{n\times d}$. In contrast to the above approaches it uses a function l for the gender attribute: $l : V \to \{-1, 1\}$; e.g. $l(\text{father}) = 1$, $l(\text{sister}) = -1$. The objective of DensRay is to find an orthogonal matrix $Q \in R^{d\times d}$ such that EQ is a gender subspace.

Let $L_= := \{(v, w) \in V \times V | l(v) = l(w)\}$ and define $L_\neq$ analogously. The DensRay objective in Eq. 3 is to maximize the distance of the word pairs from the same gender group ($L_=$) and minimize the distance of the word pairs from the different gender group ($L_\neq$).

$$\max_q \sum_{(v,w)\in L_\neq} \alpha_\neq ||q^\intercal d_{vw}||_2^2 - \sum_{(v,w)\in L_=} \alpha_= ||q^\intercal d_{vw}||_2^2 \tag{3}$$

where we define $d_{vw} := e_v - e_w$. The objective can be simplified to

$$\max_q q^\intercal (\sum_{(v,w)\in L_\neq} \alpha_\neq ||d_{vw} d_{vw}^\intercal||_2^2 - \sum_{(v,w)\in L_=} \alpha_= ||d_{vw} d_{vw}^\intercal||_2^2) q =: \max_q q^\intercal A q \tag{4}$$

As stated in (Dufter and Schütze, 2019) q is simply the eigenvector of A corresponding to the largest eigenvalue. $\alpha_\neq, \alpha_= \in [0, 1]$ are hyperparameters to balance the different optimization terms.

Let $V_+ := v \in V | l(v) = 1$ with corresponding embedding $E_+ \in R^{n_1\times d}$ and defineV_-, E_- analogously. Also let $K_{+-} = Cov(E_+^\intercal, E_-^\intercal)$, if $n_+ = n_- = n/2$, then matrix A in Eq. 4 can be reformulated into matrix form

$$A = \frac{n}{2}\{\alpha_\neq[(n-2)(K_{++} + K_{+-}) + (E_+ - E_-)(E_+ - E_-)^\intercal] - \alpha_=(n-2)(K_{+-} + K_{+-}^\intercal)\}$$

2.4 Removing Gender Information

Hard debiasing and DensRay yield a gender dimension $q \in R^d$. In a contextualized language model like BERT each layer yields a contextualized embedding matrix $X \in R^{t\times d}$ where t is the length of the sentence. To debias representations we simply zero out the projected values on q for each position, that is we set $X_i^{\text{debiased}} = X_i - (X_i^\intercal q)q$ for each position i.

2.5 Comparison of the Approaches

Figure 1 shows artificially created two dimensional embeddings. The lines show the gender directions identified by hard debiasing and DensRay. In this example the first principal component does not correlate with gender. DensRay is able to handle this as it explicitly uses the labels.

As Conceptor debiasing does not compute a single direction of gender, but always needs to apply the full conceptor matrix, it is not possible to depict the direction in the figure. We argue that DensRay is more interpretable than Conceptor. It allows for example to assign token level gender scores easily. In addition it affects language model performance less than Conceptor debiasing, as we show later.

1 <<< hs : you say that conceptor does not compute a direction , but the figure shows one >>>

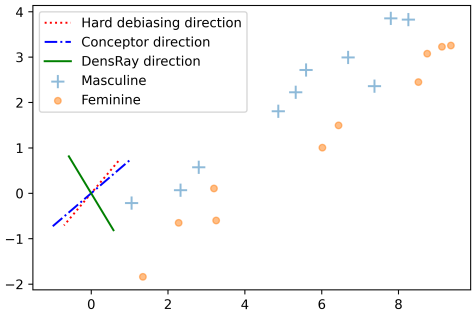


Figure 1: Gender direction for a set of gendered words computed for the three debiasing methods.

2.6 Adapting DensRay to Contextualized Language Models

We now describe how we adapt DensRay to contextualized language models. Given a set of gendered words V, we extract sentences containing a word in V from a corpus. We run a contextualized language model with M layers on a set of sentences that each contains one of the gender words, i.e., $t_1, \ldots, t_j, \ldots, t_n$ (where $t_j \in V$). For each t_j in each sentence we compute the contextualized representations $e_j^m, 1 \leq m \leq M$, one for each layer. We then use the vectors e_j^m in Eq. 4. to compute a gender direction q_m for the mth BERT layer.

3 Experiments

3.1 Setup and Data

In the experiments, we downcase all text and use the BERT models "bert-base-uncased" and "bert-large-uncased". We implemented all experiments using the transformers library (Wolf et al., 2019).

To compute the rotation matrices by DensRay, we need the labels of a gendered word list and a corpus. For the word list, we get 23 masculine words and 23 feminine words from the "family" category,[1] of the Google analogy test set (Mikolov et al., 2013). As the input corpus, we collect text data from Wikipedia that contains 5,000 (resp. 10,000) occurrences of words in the gendered list for the BERT base (resp. large) model. We carefully balance the occurrences such that the number of male and female samples are equal. We set $\alpha_{\neq} = \alpha_{=} = 0.5$, as we have balanced the training samples from the corpus.

We applied DensRay to all BERT layers for debiasing. We compare with the hard debiasing method (Mu and Viswanath, 2018) and the debiasing conceptor (Karve et al., 2019) to eliminate gender bias as adapted to contextualized embeddings by (Karve et al., 2019). In the experiments, we found that hard debiasing applied to all BERT layers yields better results than only applying it to the contextual embeddings (i.e., the last layer). In contrast, when applying debiasing conceptor to all layers, language modeling performance (as measured by perplexity) is extremely poor. We therefore applied the debiasing conceptor only to the last BERT layer.

[1] http://download.tensorflow.org/data/questions-words.txt

3.2 Evaluation

3.2.1 OCCTMP

We use two evaluation datasets to measure gender bias: Association tests (Section 3.2.2) and OCCTMP.

OCCTMP is a new evaluation dataset based on occupation templates that we created specifically to evaluate contextualized language models. It has the added advantage that results are easier to interpret than those for Association tests.

To construct OCCTMP, we start with 320 occupation names[2] provided by Bolukbasi et al. (2016). Each occupation name is converted into the format "[MASK] is an *occupation*." We measure gender bias as the average difference between the log probability of BERT predicting [MASK] as "he" vs. "she"

$$\text{diff} = \frac{1}{|\mathcal{T}|}\sum_{T\in\mathcal{T}}(\log p_{max} - \log p_{min}),$$
$$\text{where } p_{max} = \max\{p(\text{he}|T), p(\text{she}|T)\};\ p_{min} = \min\{p(\text{he}|T), p(\text{she}|T)\}$$

where $\mathcal{T}$ is the set of 320 templates. We find that for most experiments and templates, the probability of "he" is higher than "she", which qualitatively indicates that gender bias can be identified using the OCCTMP templates. We also find that in most cases the sum of the two probability is higher than 0.7; thus, this evaluation task is a good fit for BERT because it has learned that a pronoun is likely to occur in the masked position. Our templates can be easily extended to other languages as we later show for Chinese.

3.2.2 Association Tests

Association tests originated in sociological research. Greenwald et al. (1998) proposed the Implicit Association Test (IAT) to quantify societal bias. In IAT, response times were recorded when subjects were asked to match two concepts. For example, subjects were asked to match black and white names with "pleasant" and "unpleasant" words. Subjects tended to have shorter response times for concepts they thought associated.

Based on IAT, Caliskan et al. (2017) proposed the Word Embedding Association Test (WEAT). It uses word similarities between targets and attributes instead of the response times to get rid of the requirement for human subjects. Consider two sets of target words X_1, X_2 with equal size $|X_1| = |X_2|$, and two sets of attribute words A_1, A_2. The null hypothesis in the WEAT statistical test is: there is no difference in the similarity between X_1, X_2 and A_1, A_2. In the prior literature, it has been argued that if the null hypothesis cannot be rejected, there is no significant gender bias. The WEAT test statistic is defined as

$$s(X_1, X_2, A_1, A_2) = \sum_{x\in X_1} s(x, A_1, A_2) - \sum_{x\in X_2} s(x, A_1, A_2),$$
$$\text{where } s(x, A_1, A_2) = \text{mean}_{a\in A_1} cos(\vec{x}, \vec{a}) - \text{mean}_{a\in A_2} cos(\vec{x}, \vec{a})$$

in which $cos(\vec{x}, \vec{a})$ denotes the cosine similarity between embedding vector $\vec{x}$ and $\vec{a}$. Intuitively, $s(x, A_1, A_2)$ measures the association of a word with the attributes, so the test statistic measures the differential association of the two target sets with the attributes.

Let $\{(X_{1i}, X_{2i})\}_i$ denote all the partitions of $X_1 \cup X_2$. The one-sided p-value of the permutation test is defined as

$$p = Pr_i[s(X_{1i}, X_{2i}, A_1, A_2) > s(X_1, X_2, A_1, A_2)]$$

The effect size d-value is a normalized measure of how separated the two distributions of associations between the target and attribute are. It is defined as

$$d = \frac{s(X_1, X_2, A_1, A_2)}{\text{std}_{x\in X_1\cup X_2} s(x, A_1, A_2)}.$$

[2] https://github.com/tolga-/debiaswe/blob/master/data/professions.json

To extend WEAT to contextual embeddings, Karve et al. (2019) extracted contextual embeddings from the template "[MASK] is *word*". May et al. (2019) proposed the Sentence Embedding Association Test (SEAT), for which they designed more complex templates to extract word embeddings.

In these association tests, we measure the effect size d-value and the one-sided p-value of the permutation test. A d-value closer to zero indicates less gender bias. We also prefer a high p-value (at least 0.05) that aims to not reject the null hypothesis, i.e., we do not reject that there is no gender bias. We use the three categories C6: career/family, C7: math/arts, C8: science/arts, following Karve et al. (2019)'s WEAT setup and May et al. (2019)'s SEAT setup.

3.2.3 Model Performance

It is crucial that debiasing methods do not harm the downstream performance of BERT models. Thus we test the perplexity of language modeling on Wikitext-2 (Merity et al., 2016), a subset of Wikipedia with 2 million words. We also test on GLUE (Wang et al., 2018). For all the tests we follow the same setup as (Wolf et al., 2019).[3]

4 Results

4.1 Debiasing Results

Table 1 gives results on OCCTMP. Two OCCTMP examples are given in Table 4. We see that DensRay can mitigate the gender bias in BERT: bias between predicting he/she drops to around two third (e.g., for bert-base from 1.98 to 0.36). The table indicates that DensRay outperforms the other two method on OCCTMP. While the probabilities of debiasing conceptor predictions are significantly lower then the other two methods, which indicates that debiasing conceptor will affect the performance of the model. Table 2 shows the results on association tests. The debiasing performance of the three methods are comparable.

model	prob(he)	prob(she)	sum	diff	var
bert-base	0.66	0.19	0.85	1.98	1.39
bert-base-hard	0.35	0.42	0.77	0.42	0.09
bert-base-conceptor	0.18	0.11	0.28	0.68	0.26
bert-base-densray	0.48	0.37	0.86	**0.36**	0.07
bert-large	0.63	0.19	0.82	1.82	1.30
bert-large-hard	0.40	0.23	0.63	0.69	0.30
bert-large-conceptor	0.43	0.18	0.61	1.03	0.53
bert-large-densray	0.47	0.31	0.77	**0.49**	0.13

Table 1: BERT debiasing results on OCCTMP. *bert-base* and *bert-large* are the original models without debiasing. *prob(he)* is the average probability predicted for *he* as the [MASK] in OCCTMP. We also show the average sum probability $sum = prob(he) + prob(she)$ and *var*, the variance of *diff*, for reference.

		bert-base				bert-large			
		WEAT		SEAT		WEAT		SEAT	
category	model	d	p	d	p	d	p	d	p
C6	without debiasing	0.66	0.08	1.04	$<10^{-2*}$	1.57	$<10^{-2*}$	0.50	$<10^{-2*}$
	hard debiasing	0.15	0.38	**-0.08**	0.67	0.80	0.06	0.07	0.35
	debiasing conceptor	**0.07**	0.46	0.77	$<10^{-2*}$	1.33	$<10^{-2*}$	**0.06**	0.37
	densray	0.62	0.12	0.36	0.02^{*}	**0.76**	0.07	0.13	0.22
C7	without debiasing	0.60	0.11	0.17	0.15	-0.40	0.75	0.38	0.01^{*}
	hard debiasing	**-0.07**	0.56	**-0.06**	0.64	-0.51	0.83	0.38	0.01^{*}
	debiasing conceptor	0.54	0.14	-0.25	0.93	-0.32	0.73	**-0.60**	0.99
	densray	0.09	0.45	-0.47	0.99	**0.06**	0.05	-0.73	0.99
C8	without debiasing	0.78	0.08	0.81	$<10^{-2*}$	-0.60	0.87	-0.30	0.95
	hard debiasing	-0.29	0.68	**-0.10**	0.71	0.78	0.06	**-0.03**	0.56
	debiasing conceptor	0.62	0.14	0.50	$<10^{-2*}$	**0.12**	0.39	0.30	0.94
	densray	**0.03**	0.47	0.41	0.01^{*}	0.20	0.33	-0.66	0.99

Table 2: BERT debiasing results on association tests. * shows significant gender bias.

[3] https://huggingface.co/transformers/

4.2 Model Performance

Table 3 shows that DensRay debiasing gets comparable results with the original models on Wikitext-2 and GLUE tasks. In most tasks on bert-base and all tasks on bert-large, DensRay performs better than hard debiasing, so DensRay affects model performance less.

model	Wikitext-2	CoLA	SST-2	MRPC	STS-B	RTE	WNLI	GLUE avg
bert-base	3.77	49.15	92.09	85.86	82.66	62.82	52.11	70.78
bert-base-hard	3.95	45.53	**91.74**	82.48	**82.60**	63.54	**56.34**	70.37
bert-base-conceptor	4.46	**48.31**	91.43	84.08	81.37	59.57	**56.34**	70.18
bert-base-densray	**3.81**	48.04	**91.74**	**84.89**	82.43	**63.90**	53.52	**70.75**
bert-large	3.29	47.93	94.90	89.30	87.60	70.10	65.10	75.82
bert-large-hard	3.85	47.45	93.95	85.01	82.33	67.12	63.02	73.15
bert-large-conceptor	4.13	**49.44**	93.87	87.67	83.44	62.45	56.34	72.20
bert-large-densray	**3.35**	48.91	**94.02**	**88.84**	**85.63**	**67.78**	**64.48**	**74.94**

Table 3: Language modelling perplexity and GLUE tasks performance.

4.3 Examples

In Table 4 we show two OCCTMP examples. In the first sentence, hard debiasing reverses male bias and creates female bias. The sum probabilities of ”he” and ”she” on the debiasing conceptor are around 0.5, indicates that the pronoun is not likely to occur in the masked position.

sentence	model	prob(he)	prob(she)	sum	diff
[MASK] is a professor.	bert-base	0.84	0.13	0.97	1.86
	bert-base-hard	0.37	0.55	0.92	0.40
	bert-base-conceptor	0.28	0.23	0.51	0.20
	bert-base-densray	0.53	0.37	0.90	0.36
[MASK] is a dancer.	bert-base	0.22	0.72	0.94	1.19
	bert-base-hard	0.27	0.64	0.91	0.86
	bert-base-conceptor	0.20	0.33	0.53	0.50
	bert-base-densray	0.42	0.52	0.94	0.21

Table 4: OCCTMP examples with prediction probabilities.

4.4 Analyses

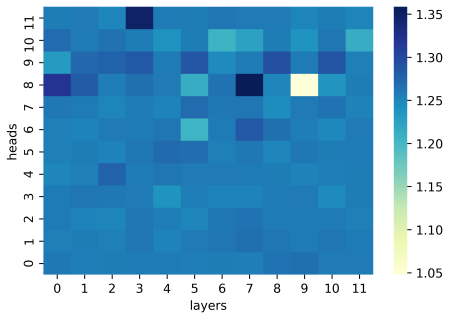
4.4.1 Debiasing on Attention Heads and Layers

We now apply DensRay to the attention heads in BERT to debias on OCCTMP. The heatmap Figure 2(a) shows that the debiasing effect of one single attention head is not apparent, with diff scores all in [1.0,1.4]. Due to the lack of dimensions and the distribution of gender features in the attention heads, we chose to apply DensRay on layers as a debiasing method. We conclude that there is no single attention head that is responsible for processing gender information.

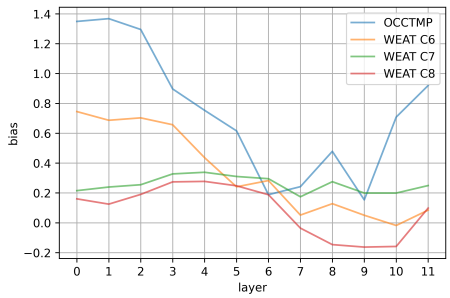
So far we have also applied DensRay to all BERT layers simultaneously.Figure 2(b) illustrates the effect of debiasing a single layer on our templates and the three WEAT categories. We see that the debiasing effect is stronger in layers 7–10 than in the other layers in bert-base model. It is shown that gender information is extracted and processed on BERT layers, especially the upper layers.

4.4.2 Quantifying Gender Bias with DensRay

DensRay can be used to quantify gender bias for sentences and tokens. We use the distance to the origin of the gender subspace as the measurement. In BERT, we use the average bias score of tokens to quantify the whole sentence. Table 5 compared DensRay with the log probability score (Kurita et al., 2019), which can quantify gender bias on specific templates ’[TARGET] is a [ATTRIBUTE].’ we regard zero as a balance point without bias. Contrary to the log probability score, a positive DensRay score represents the level of female bias. These examples show that DensRay is more versatile, it can quantify the bias both token and sentence level.



(a) attention heads



(b) layers

Figure 2: (a): DensRay debiasing on each single attention head in bert-base, measured by diff on OCCTMP. (b): DensRay debiasing on each single layer, bias is measured by diff on OCCTMP and d-value on WEAT.

DensRay						Avg.	log probability score
[MASK]	is	a	professor	.			
-0.69	-0.97	-0.9	-0.15	0.45		-0.45	0.63
[MASK]	is	a	nurse	.			
2.43	1.34	1.7	1.93	0.5		1.58	-5.44
The	professor	asked	me	.			
-1.25	-0.55	-0.08	0.59	0.35		-0.19	-
The	professor	asked	the	nurse	.		
-1.3	-0.25	0.24	1.28	2.19	0.45	0.43	-

Table 5: Examples for quantifying bias on bert-base model.

4.4.3 Number of Training Samples

In the experiments, we collected training samples for DensRay by considering occurrences of the same word in the corpus across different sentences. This greatly enriches training samples. We also collected equally many masculine and feminine words for data balancing. Now we analyze the impact of these processes. DensRay is essentially a supervised learning method. It is difficult to extract useful features in the case of insufficient or unbalanced labels. As shown in Figure 3, the debiasing results improve with an increased number of training samples.

As a projection-based debiasing method, the premise of DensRay debiasing is that the gender direction should be correct. Unbalanced samples will lead to incorrect gender direction biased towards either the male or the female, resulting in reversing the gender bias during debiasing. For example, if there are more masculine samples, then the embeddings will be biased towards feminine after debiasing. The figure also shows that a balanced training sample improves the debiasing performance.

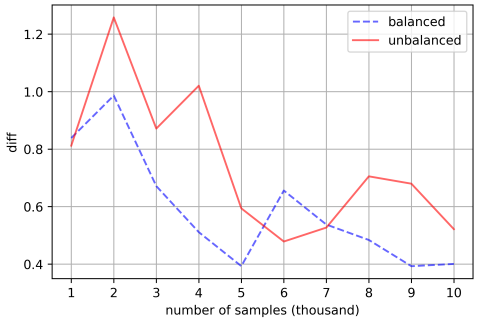


Figure 3: DensRay debiasing results on OCCTMP with different number of samples and unbalanced/balanced data.

4.4.4 Balancing Gender Bias

In this experiment, we zero out the dimensions of gender subspace to remove gender bias. Here we explore some other ways.

We explored three other ways to remove bias: 1) replace the first dimension of the gender subspace with the mean value of the first dimension of the training samples. 2) standardize the first dimension. 3) replace the first dimension with a small random variable sampled from Gaussian distribution. All of them did not perform well. We further checked the mean and found that the mean of the different layers is not stable around zero, which is a problem worthy of further exploration. We also tried to delete more dimensions. However removing more dimensions does not improve the debiasing results significantly while harming the model performance.

4.5 Multilingual Debiasing

We now show that, in a multilingual contextualized language model like mBERT, we can use DensRay for zero-shot debiasing. Specifically, we train a DensRay model on English and use it to debias Chinese. We use bert-base-multilingual-uncased from (2019). We use the same setup as for bert-base-uncased in our previous experiments. As before, we compute the rotation matrices using the English gendered words from the "family" category of the Google analogy test set (2013).

Since Chinese is a language that does not mark gender, we can construct the OCCTMP templates by directly translating from the English templates. We use the following form: "[MASK]是一个*occupation*。" We translate the occupation name based on Tencent Translation[4] and make some manual adjustments to the translation. After removing duplicates, 302 Chinese templates remain.

Table 6 gives results for the Chinese templates. Two examples are given in Table 6. We see that DensRay trained with English can mitigate gender bias in mBERT: the diff score drops from 1.39 to 1.33 on Chinese templates.

model	prob(he)	prob(she)	sum	diff	var
bert-multi-en	0.51	0.14	0.65	1.66	0.81
bert-multi-densray-en	0.33	0.12	0.46	1.33	0.65
bert-multi-cn	0.24	0.07	0.31	1.39	0.60
bert-multi-densray-cn	0.12	0.04	0.17	1.22	0.47

Table 6: Results of OCCTMP on mBERT after applied DensRay. Models with *-en* are tested on English templates, and those with *-cn* are tested on Chinese templates.

sentence	model	prob(他)	prob(她)	sum	diff
[MASK]是一个客座教授。	bert-multi-en	0.68	0.16	0.84	1.45
[MASK] is an adjunct professor.	bert-multi-densray-en	0.51	0.18	0.70	1.04
	bert-multi-cn	0.52	0.11	0.63	1.55
	bert-multi-densray-cn	0.30	0.08	0.38	1.31
[MASK]是一个管理员。	bert-multi-en	0.53	0.17	0.70	1.14
[MASK]is an administrator.	bert-multi-densray-en	0.35	0.13	0.48	0.99
	bert-multi-cn	0.68	0.16	0.84	1.45
	bert-multi-densray-cn	0.51	0.18	0.69	1.04

Table 7: Sanity check on the Chinese templates, where 他 means *he* and 她 means *she*. Corresponding English translations are shown blow the Chinese.

5 Related Work

5.1 Quantifying Gender Bias

A typical way to measure gender bias is the **association tests**. The origin WEAT is used on static embeddings. To extend WEAT to contextual embeddings, some template-based processes (Karve et al., 2019; Kurita et al., 2019; Tan and Celis, 2019) were constructed to obtain the word embeddings from the context. SEAT further improved the templates and computed the similarities between the sentences instead of words. (Guo and Caliskan, 2020) proposed CEAT (Contextual Embedding Association Test), which samples the occurrences from the corpus to get the embeddings, and measure the bias by a random-effects

[4]https://fanyi.qq.com/

model. However, we find that it is difficult to obtain a stable result on CEAT due to the vary contexts, so in this paper we still use WEAT and SEAT as experiments. Besides, (Kurita et al., 2019) proposed a template-based log probability bias score to measure the association between targets and attributes in BERT. Since it can only be applied on specific templates, we compare this method with DensRay as a measurement of gender bias in §4.4.2.

An alternative way to measure gender bias is to evaluate on **downstream tasks**. For coreference resolution, (Zhao et al., 2018) designed Winobias and (Rudinger et al., 2018) designed Winogender schemas. (Webster et al., 2018) released GAP, a balanced corpus of Gendered Ambiguous Pronouns, which measures gender bias as the ratio of F1 score on masculine to F1 score on feminine. However the ratio is very close to 1 (Chada, 2019; Attree, 2019) making it hard to compare debiasing systems. For sentiment analysis, Equity Evaluation Corpus (EEC) (Kiritchenko and Mohammad, 2018) was designed to measure gender bias by the difference in emotional intensity predictions between gender-swapped sentences. Since the measurements of gender bias in these data sets are not intuitive, we chose to experiment on association tests in this paper.

5.2 Debiasing Methods

Many methods to remove gender bias have been proposed. The most common way is to define a gender direction (or, more generally, a subspace) by a set of gendered words and debias the word embeddings in a post-processing projection. (Bolukbasi et al., 2016) propose (i) *hard debiasing*: use the gendered words to compute the difference embedding vector as the gender direction; and (ii) *soft debiasing*, a machine learning based method that combines the inner-products objective of word embedding and an objective to project the word embedding into an orthogonal gender subspace. It has been found to work better than soft debiasing. (Dev and Phillips, 2019) explored partial projection and some simple tricks to improve the hard debiasing method. (Zhao et al., 2019) applied the data augmentation and debiasing method of (Bolukbasi et al., 2016) to mitigate gender bias on ELMo (Peters et al., 2018). (Karve et al., 2019) proposed the debiasing conceptor, which shrinks each principal component of the covariance matrix of the embeddings to achieve a soft debiasing. They also introduced a simple and intuitive hard debiasing method proposed by (Mu and Viswanath, 2018), which identified the gender subspace by PCA and projected the first principal component off.

The debiasing conceptor and the (Mu and Viswanath, 2018) hard debiasing produce gender direction by gendered word list mixed with male and female words. In contrast, the (Bolukbasi et al., 2016) hard debiasing used two groups of gendered words for definition and another two groups for alignment, to identify the gender direction by male-female pairs. The method we use, DensRay, is similar to the (Bolukbasi et al., 2016) hard debiasing in this aspect. However, DensRay uses only one male and one female word list, and it can be solved efficiently in a closed form. So it would be more stable to be applied to contextual models than the (Bolukbasi et al., 2016) hard debiasing.

6 Conclusion

We introduced DensRay debiasing on BERT. Our experiments show that this method can effectively mitigate gender bias on OCCTMP and the Association Tests, while maintained the performance of BERT on language modeling and GLUE tasks. We applied DensRay to BERT attention heads, we showed that gender information is processed discretely in all attention headers, there is no single attention head responsible for processing gender information. We also used DensRay to obtain interpretable gender scores, to quantify bias on token and sentence level for all representations. Finally, we demonstrated that we can remove bias multilingually, we used only English training data to effectively debias Chinese. As to further research, we plan to investigate other linguistic features on multilingual spaces by DensRay.

2 <<< hs: three parts of the paper should be in sync:
(i) the abstract
(ii) the contributions at the end of the introduciton
(iii) the conclusino
make sure to check that during final editing >>>

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