Does Debiasing Inevitably Degrade the Model Performance

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ABSTRACT

Gender bias in language models has attracted significant attention due to its potential to undermine social justice. However, current debiasing methods often result in performance degradation, whose mechanism is not well understood. We analyzed the causality structure that generates gender bias and discovered the mechanism that debiasing degrades the model performance. According to the analysis, we demonstrate that mitigating the gender bias does not inevitably cause performance degradation. We discover that only mitigating the gender bias caused by the embedding errors will not cause performance degradation. Analyzing the causality structure also enables us to demonstrate that the embedding-errors-induced gender bias can be separately mitigated by a low-cost fine-tuning approach. We develop a self-training fine-tuning approach to correct gender bias induced by the errors of the embedding layer. Our method is able to correct the embedding error when the gender-mutual subspace is unknown and non-Euclidean. Numerical experiments demonstrate the effectiveness of our approach to debiasing and model-performance maintenance. For instance, our method that only fine-tunes the embedding layer is able to achieve similar debiasing effectiveness and better model performance than fine-tuning the whole model.

1 Introduction

It is unclear whether the degradation of model performance is an inevitable consequence of debiasing approaches for correcting gender bias in pre-trained language models. Pre-trained language models have been highly successful in a variety of natural language processing tasks and are widely used in practice. However, several studies have revealed the presence of gender bias in pre-trained models [Bolukbasi et al. 2016, Zhao et al. 2018, Bhardwaj et al. 2021, Vig et al. 2020]. For example, gender bias has been identified in the use of pre-trained models for online advertising [Sweeney 2013], automatic resume filtering systems [Cowgill 2018, Deshpande et al. 2020], and automatic criminal sentencing [Dressel and Farid 2018]. This evidence of bias has raised concerns about the potential risks of using these models in real-world applications, such as recruitment and education. After Dastin 2018 noticed that the automatic resume filtering adopted by Amazon discriminated against female candidates, the system was abandoned. Thus, many studies have explored fine-tuning methods of mitigating gender biases in pre-trained language models. As a result, many researchers have explored fine-tuning methods for mitigating gender bias in pre-trained language models.

However, recent discussions suggest that current debiasing approaches are associated with a decline in model performance [Barikeri et al. 2021, Meade et al. 2022]. It is necessary to examine the possibility and method of easing the dilemma between model performance and gender bias. We discovered that using a method based on causal intervention can effectively reduce model bias and maintain performance. For transformer-structured language models, the source of gender bias is limited to errors in the pre-trained model’s word embedding and transformer architectures.
We demonstrate that intervening in the explicable mechanisms of a language model is possible to reduce bias while preserving performance. Our findings indicate that errors in the word embedding can directly lead to gender bias, and that correcting these errors will not have a significant impact on the performance of the model. Based on this observation, we developed a debiasing method that is able to maintain performance. As the correct embedding is unknown, we developed a gradient-based approach to infer the latent ground truth. We applied this method to debias GPT-2 and found that it effectively reduced bias while maintaining the performance of the model.

Our work is an experiment using the causal-analysis approach to solve the dilemma between gender bias and model performance. Our contributions are summarized as follows. First, We correct the gender bias of the language model by adjusting the word embedding of the language model, which provides a new way to correct the bias. Second, We positioned the two architectures and three mechanisms that originate the gender bias. We demonstrate the possibility of double dividends. Third, We proposed a double-dividend fine-tuning debiasing method equipped with a causality-detection function.

2 Related Work

Current debiasing research can generally be grouped into four categories. However, studies by Barikeri et al. [2021] and Meade et al. [2022] have found that the first three types of methods tend to lead to performance degradation.

Data Augmentation. Data augmentation is a well-established debiasing method for reducing gender bias. Zhao et al. [2018] were the first to use this method by creating a gender-balanced dataset through gender-swapping, to train an unbiased model. Since then, data augmentation has been applied to various NLP tasks, such as knowledge graph building Mitchell et al. [2019] and machine translation Stanovsky et al. [2019].

Removing Gender Subspace. Removing the gender subspace is another popular debiasing method, which was proposed after Bolukbasi et al. [2016] demonstrated the link between word embeddings and gender bias. This method aims to remove the gender subspace in contextualized language models by subtracting the embedding’s projection on a hypothetical gender subspace Ravfogel et al. [2020a], Liang et al. [2020]. However, this method’s effectiveness is limited as it relies on the assumption that the gender subspace is Euclidean, which has been called into question by recent research.

Gender-Equality Regularizer. Several regularization methods have been developed to eliminate gender bias. Some of these methods focus on addressing the imbalance in the training data by adding regularizers Bordia and Bowman [2019], Qian et al. [2019], Lauscher et al. [2020]. Other researchers such as Barikeri et al. [2021] proposed new loss functions for both data augmentation and gender-subspace removal. Additionally, Zhang et al. [2018] proposed a generative adversarial approach for bias mitigation.

Causal Inference. At present, there are some methods to mitigate gender bias in the static word embedding by counterfactual and causal intervention Yang and Feng [2020], Shin et al. [2020]. However, as far as we know, no one has implemented a causality-based debiasing method on the transformer language model.

3 A Causal View on Debiasing Dilemma

3.1 Causal Framework of Gender Bias Origination

Literature has revealed that the gender bias of the language models is oriented from the imbalance of the training data (?). Figure[1] explain the pathways of how the training-data imbalance misleads the embedding and transformer layers and consequently causes gender bias. We theoretically clarify the causal mechanism of how the data imbalance causes model gender biases (Figure). Analyzing the causal diagram enables us to have two discoveries: 1) there exists a pathway, the gender bias oriented by which can be fully mitigated while maintaining the model performance. 2) mitigating gender bias can be achieved by an explainable and controllable fine-tuning approach rather than augmentation.

We discover that the gender bias can be fully mitigated without hurting the model-performance degradation if the bias caused by that the training-data imbalance misleading the fitting of the embedding layers. In the causal diagram Figure[1]a, the pathway from $D \to X \to Y$ denotes the mechanism. The $D \to X$ denotes the mechanism that data imbalance causes incorrect embedding during training while $X \to Y$ denotes the dynamics that the incorrect $X$ causes the model’s gender-biased output. In the misled language model, the gender-mutual words are incorrectly mapped to the embedding vectors that are not perpendicular to the gender subspace Zhao et al. [2018], Bolukbasi et al. [2016]. When the pre-trained model is applied to predict $Y$ according to $W$, the model first converts $W$ to the incorrect embedding vector $X$ and thus leads to a gender-biased prediction $\hat{Y}$. For example, if the word “doctor” is more frequently associated with male words in the training data, it will be mapped to a gender-biased embedding vector. Consequently, gender-bias errors will occur when the words “doctor” is input into the pre-trained model for prediction.
Figure 1: A directed acyclic graph used to indicate how variables of pre-training data (D), occupation word (W), input feature (X), pre-trained knowledge (K), and gender prediction (Y) interact with each other through causal links.

If we are able to correct the parameters of the embedding layer only, we can mitigate the embedding-error-induced model gender bias while avoiding the model-performance degradation according to the literature. However, in the prediction process, the output $Y$ is simultaneously determined by embedding $X$ and transformer $K$. The data imbalance can also mislead the parameter fitting of the transformer layers $K$. If we pursue the mitigation of the embedding-error-induced model, we have to disentangle the effect induced by $X$’s bias from the effect of $K$’s bias.

Analyzing the causal diagram Fig. 1 confirms that the effects of the biases of $X$ and $K$ can be disentangled. When a gender-mutual word $W$ is inputted to predict $Y_0$, a biased model $M$ will output a gender-biased prediction $\hat{Y}_M$. Here, $Y_0$ refers to the probability that the output word is male when there is no gender bias and $Y_0 = 0.5$. We use total effect ($TE$) to denote the size of the gender bias caused by both the errors in $X$ and $K$:

$$TE = |E[\hat{Y}_M|W = w] - E[Y_0|W = w]|$$

$$= E[Y|X = x, K = k] - E[Y|X = x_0, K = k_0],$$

where $x, k$ are the current value of parameter $X, K$ and $x_0, k_0$ are the correct value of the parameters. Note that both $X$ and $K$ are the parts of the model $M$ and thus determine TE. In the following theorem, we rigorously explain and prove the two gender biases can be disentangled.

**Theorem 3.1.** The incorrect $X$ misled during the training process is able to be adjusted alone without affecting $K$.

**Proof.** The total effect can be decomposed into the sum of two parts, the Total Direct Effect (TDE) [Pearl, 2013] and the Natural Indirect Effect (NIE) [Pearl, 2013], as follow

$$TE = \{E[Y|X = x, K = k] - E[Y|X = x_0, K = k_0]\}^{TDE} + \{E[Y|X = x_0, K = k_0] - E[Y|X = x_0, K = k_0]\}^{NIE}$$

According to the above theorem, the TDE is purely caused by gender-biased embedding. Further, the size of TDE is monotonic to the gap between the gender-biased embedding vectors and the correct one. The $X$ minimizing TDE is also the embedding vectors avoiding the gender bias. Thus, if we are able to figure out the $X$ that minimizes TDE, we only correct the embedding-error-induced gender bias and will not degrade the model performance.

**Remark:** The above theoretic analysis also implies why the current fine-tuning methods of debiasing for the pre-trained model in literature cause performance degradation. We argue that the current literature aims at minimizing TE rather than TDE, which causes the risk of model-performance degradation. The current fine-tuning approach mainly modifies
the objective function of the training process by including the gender-equality regularizer. Then, according to the modified objective function, the whole model is fine-tuned. While the whole TE is included in the objective function, the parameters of K can change during the fine-tuning process, which can cause a change in the model performance. While the literature has confirmed that adjusting the embedding-error-induced bias will not cause performance degradation. The degradation in literature has to come from adjusting the transformer-error-induced bias.

4 Causality-Detection Debiasing for Double Dividend

According to the theoretical analysis, we discover that the embedding-error-induced gender bias is able to be mitigated by a fine tuning approach. The above analysis implies that we shall explore a fine-tuning approach that only minimize TDE but not influence the parameters in the latter transformer layers. The fine-tuning approach enables us to only calibrate the parameters in the embedding layer while maintain all other parameters in the transformer layers. Here, we propose a Debiasing Approach with Maintaining Performance (DAMP) and apply it in GPT-2 model. The key of DAMP is to find the correct token embedding X through TDE without any other impact, as shown in Figure 2. So as to complete the task of correcting deviation without affecting the performance of the model.

There are three challenges of developing the fine-tuning approach for mitigate the embedding-error-induced gender bias. First, there lacks an systematical approach to systematically sample sufficient $\hat{Y}$, which is critical for calculating TDE. To estimate the TDE, it is necessary to generate templates to generate sufficient samples of $\hat{Y}$. In contrast, literature mostly focus on the performance in several particular templates. The sampling method is absent from the previous studies. Second, there is currently no established method to disentangle TDE from TE. Third, it is hard to directly reduce TDE through projection or other geometric approach because that the word embedding spaces of GPT-2 and other transformer language models are non-Euclidean. Thus, our DAMP method respectively solve the three challenges. Sequentially, the DAMP method includes three steps:

**Step 1.** Develop the approach of generating the templates for sufficiently sampling $\hat{Y}$

**Step 2.** Disentangle the TDE from TE by preventing the fine-tuning process from affecting K, the parameters of transformer layers.

**Step 3.** Develop the gradient approach to minimize the TDE value in order to correct the parameters of the embedding effects, so that the token embedding of input word is gender unbiased.

In summary, the above three steps together enable a self-training fine-tuning approach to correct the errors in the embedding layer, which cause the language model’s gender bias and are oriented by the training-data imbalanced. In the rest of this section, we provide the details of each step.

### 4.1 Get Gender Prediction

Given a language model $M$ and a sequence of tokens $w_1, \ldots, w_k$, we define $p_M(w_{k+1}|w_1, \ldots, w_k)$ as the probability assigned by the language model to the token $w_{k+1}$ being the next token in the sequence. In general, the language model cannot directly provide the gender judgment of a certain professional vocabulary $w$. However, by designing a reasonable template as input for the model, we can get the model’s prediction of the next word, and indirectly obtain the
model’s gender prediction $\hat{Y}$ for $w$. For example, when the template is "The nurse said that" and the options are the pronouns "he" and "she", we can observe the gender prediction $Y$ of "nurse" from the word selection of the model. We can calculate the distribution of $\hat{Y}$ using the following equation:

$$p(Y = \text{male}|t) = \frac{p_M(\text{he}|t)}{p_M(\text{he}|t) + p_M(\text{she}|t)},$$

$$p(Y = \text{female}|t) = \frac{p_M(\text{she}|t)}{p_M(\text{he}|t) + p_M(\text{she}|t)}.$$  

Here, we propose an automatically template generating approach enabling the gradient search of our DAMP method. Our templates, denoted by $t$, are designed to meet two requirements:

- **Intermediary**: The context should link the occupation and gender. To achieve this, we require the text to contain the target occupation words and have a probability of the pronoun "he" and "she" greater than some threshold $s$.

- **Neutrality**: The text should not contain information suggestive of gender. To achieve this, we require the text to be composed of gender-neutral words, specifically, we require $t$ to have no intersection with a list of gendered words $V_{gender}$ provided by Zhao et al. [2018].

Further, we propose a template generation algorithm that utilizes the text generation capabilities of GPT-2. Our algorithm starts by fixing the beginning of the template to include the target occupation word, and then uses GPT-2 to continue generating the template through top-k sampling. The sampling continues until the predicted probability of selecting "he" and "she" as the next word is greater than the threshold. To ensure efficiency, we set a maximum length for the top-k sampling at 15 words. If this maximum length is reached without satisfying the probability threshold, the sampling process is restarted from the beginning. Algorithm 1 explains the detailed workflow of the template generation process.

**Algorithm 1** Templates Generation

**Input**: Occupation word $w$, GPT-2 model $p_M$

**Output**: A template for gender prediction

Initialize $t = \text{the w'}$

repeat

- Get the next words $w' \sim p_M(w'|t)$
- if $w' \notin V_{gender}$ then
  - Add $w'$ at the end of $t$
- end if

- if $\text{len}(t) > 15$ then
  - Set $t = \text{the w'}$
- end if

until $p_M(\text{he}|t) > s, p_M(\text{she}|t) > s$

return: $t$

### 4.2 Calculation of TDE

With gender predicting the distribution of $Y$, we can calculate the $TDE$ of $X$ on $Y$. For gender-neutral occupations, we know prior that they are independent of the gender prediction. To simplify the process, we use a uniform distribution to substitute for $\hat{Y}_k|do(X = x_0)$. Combined the Eq.4.1, we have

$$|TDE_t| = |\frac{1}{2} - p_1| = |\frac{1}{2} - p_2|,$$

$$p_1(t) = \frac{p_M(\text{he}|t)}{p_M(\text{he}|t) + p_M(\text{she}|t)},$$

$$p_2(t) = \frac{p_M(\text{she}|t)}{p_M(\text{he}|t) + p_M(\text{she}|t)}.$$  

for given template $t$. To avoid the influence of the template itself on the results, we select enough templates $t_1, ..., t_n$ and use the average TDE for every template as the final TDE:

$$TDE = \frac{1}{n} \sum_{i=1}^{n} TDE_{t_i}.$$  

(3)
Table 1: The perplexity results of the original and different debiased GPT-2 models. If the perplexity score is lower, the model performs better. We show the lowest results of perplexity in bold.

|        | vanilla | INLP  | SD     | GEL    | DAMP(ours) |
|--------|---------|-------|--------|--------|------------|
| small  | 25.1711 | 6.73E+16 | 2.67E+11 | 1.09E+46 | 26.2769   |
| medium | 18.4633 | 1.68E+15 | 157.6118 | 2.05E+32 | 36.9222   |
| large  | 16.4447 | 21.0505 | 16.4732 | 17.133  | 16.5336   |
| xl     | 14.7881 | 17.6801 | 15.2138 | 15.451  | 14.9612   |

4.3 Gradient Descent

According to our previous discussion, as a debiasing method with minimal side effects, we should adjust the embeddings for occupational words in order to minimize the TDE, that is
\[
\min_{d_{o(x=\hat{x})}} |TDE|.
\]
(4)

Due to the limitations of pre-trained knowledge, the variable \(\hat{x}\) in optimization problem 4 has a limited range of values. As noted by Ethayarajh [2019], word representations tend to occupy a narrow cone in the vector space. Therefore, it is important to ensure that the selected features meet the constraint
\[
||\hat{x} - x||^2 < r,
\]
(5)

Due to the uncertainty of the specific value of \(r\), we utilize the Sequential Unconstrained Minimization Technique (SUMT) to find a solution to the problem at hand. To do this, we design the following loss function:
\[
L = \sum_{i} p_1(t_i) \log p_1(t_i) + p_2(t_i) \log p_2(t_i)
\]
\[
+ \alpha ||\hat{x} - x||^2,
\]
(7)

Next, we use an optimizer based on gradient descent to minimize the loss function \(L\). In summary, we use algorithm 2 to obtain unbiased embeddings for gender-neutral occupation words \(w\).

**Algorithm 2** DAMP Debiasing Method

**Input:** word \(w\) and pre-trained LM \(p_M\)

**Output:** unbiased embedding \(\hat{x}\) for \(w\)

Extract the pre-trained embedding \(\hat{x}_0 = x\) of \(w\).

Generate the template \(t_1, \ldots, t_n\).

for \(k = 1\) to \(m\) do

Initialize \(TDE = 0\)

for \(i = 1\) to \(n\) do

\(p_1 = \frac{p_M(\text{he}|t_i)}{p_M(\text{he}|\text{he}) + p_M(\text{she}|\text{he})}\)

\(p_2 = \frac{p_M(\text{she}|t_i)}{p_M(\text{he}|\text{he}) + p_M(\text{she}|\text{he})}\)

\(L_{TDE} = L_{TDE} + \frac{1}{n} (1 + p_1 \log p_1 + p_2 \log p_2)\)

end for

\(L_{k-1} = L_{TDE} + \alpha ||e_{k-1} - e_0||^2\)

\(\hat{x}_k = \hat{x}_{k-1} - \alpha \frac{\partial L_{k-1}}{\partial e_{k-1}}\)

Set \(\hat{x}_k\) as the embedding of \(w\) in \(p_M\).

end for

return \(\hat{x}_m\)

For the overall model, we use Algorithm 1 to reduce gender bias for each gender-neutral occupation in the occupation vocabulary. We then replace the embeddings of occupation words with the debiased embeddings, to create a bias-free language model.

In practice, the token representations of different occupation words may share the same tokens due to Byte Pair Encoding (BPE). For example, in GPT-2, the token representation of "jeweler" is [16927, 263] and the token representation of "entertainer" is [8204, 263]. They both contain the same token [263]. In this scenario, we use the average value of the debiased embeddings corresponding to the token as the final token embedding.
Table 2: Scores of different debiasing methods on 9 test tasks of GLUE. We bold the result with the highest average result.

|            | CoLA | MNLI | MRPC | QNLI | QQP | RTE | SST | STS-B | WNLI | Average |
|------------|------|------|------|------|-----|-----|-----|------|------|---------|
| GPT-2(small) | 29.1 | 82.43 | 84.51 | 87.71 | 89.18 | 64.74 | 91.97 | 84.26 | 43.19 | 73.01   |
| INLP       | 31.79 | 82.73 | 84.34 | 87.81 | 89.17 | 64.38 | 92.01 | 83.99 | 41.31 | 73.06   |
| SD         | 30.2 | 82.56 | 84.43 | 87.9 | 89.09 | 64.86 | 91.97 | 84.18 | 38.5 | 72.63   |
| GEL        | 16.33 | 82.21 | 86.42 | 87.81 | 85.02 | 66.43 | 92.32 | 84.09 | 35.21 | 70.65   |
| DAMP       | 31.87 | 82.62 | 85.48 | 87.81 | 89.22 | 64.98 | 92.55 | 82.77 | 40.89 | 73.13   |
| GPT-2(medium) | 52.43 | 85.92 | 83.26 | 87.71 | 87.87 | 64.94 | 93.58 | 87.38 | 49.3 | 76.93   |
| INLP       | 50.46 | 85.66 | 87.33 | 90.83 | 87.78 | 67.15 | 93.81 | 87.31 | 28.17 | 75.39   |
| SD         | 53.12 | 85.63 | 88.25 | 90.46 | 87.84 | 64.98 | 93.92 | 87.22 | 39.44 | 76.76   |
| GEL        | 47.85 | 85.6 | 86.66 | 87.81 | 87.79 | 66.79 | 94.27 | 86.54 | 40.85 | 76.01   |
| DAMP       | 51.54 | 85.94 | 82.54 | 90.72 | 87.92 | 63.9 | 94.5 | 87.44 | 46.48 | 76.78   |
| GPT-2(large) | 55.44 | 85.32 | 88.78 | 91.14 | 88.09 | 74.73 | 89.31 | 89.71 | 43.66 | 78.46   |
| INLP       | 60.07 | 84.26 | 90.2 | 92.13 | 84.26 | 75.45 | 93.92 | 89.49 | 33.8 | 78.18   |
| SD         | 58.8 | 83.99 | 89.04 | 91.87 | 85.31 | 74.01 | 94.04 | 89.8 | 33.8 | 77.85   |
| GEL        | 58.65 | 84.48 | 88.08 | 91.82 | 85.19 | 74.73 | 89.98 | 89.98 | 25.35 | 76.47   |
| DAMP       | 53.16 | 85.23 | 90.24 | 91.76 | 87.92 | 74.37 | 92.78 | 89.31 | 43.66 | 78.71   |

Table 3: The test results on StereoSet of different debiased GPT-2 models. Language Modeling Score (lms) is the percentage of the meaningful answer that the language model prefers over the meaningless association, which is the higher the better. Stereotype Score (ss) is the percentage of the stereotypical association that the model prefers over the anti-stereotypical association, which is closer to 50 the better. Idealized CAT Score (icat), a metric for comprehensive evaluation of bias and performance, is calculated by $\text{lms} \times \min(\text{ss}, 10 - \text{ss}) / 50$, which is the higher the better. We show the best results of lms, ss, and icat in bold.

|            | small | medium | large | xl     |
|------------|-------|--------|-------|--------|
| lms        | 89.47 | 40.98  | 70.18 | 59.6   |
| ss         | 55.77 | 52    | 52.5  | 54.24  |
| icat       | 80.70 | 39.34  | 66.67 | 54.55  |

5 Experiments

5.1 Setup

Model To evaluate the effectiveness of our DAMP method in reducing gender biases, we conduct experiments on the GPT-2 model trained in English, using various model sizes: small (117M parameters), medium (345M parameters), large (774M parameters), and extra-large (xl, 1558M parameters) [Radford et al., 2019]. The pre-trained weights are obtained from the Transformers Python library [Wolf et al., 2019].

Templates Our templates are generated using the method outlined in Section 4.1. For each occupation word, we generate 500 templates for debiasing. The threshold s is set to 0.08. We use the occupation vocabulary provided by [Vig et al., 2020].

Hyper Parameters In Algorithm 2, we set the number of templates $n$ to 500, the number of optimization iterations $m$ to 100, and the hyper-parameter $\alpha$ to 1000. In the experiment, we use the ADAM algorithm to minimize the loss function and set the learning rate $\lambda$ to 0.002.
Table 4: The bias effect size results of different debiasing methods on the test sets (SEAT-6 SEAT-6b). If the result is closer to zero, the model has a lower level of bias.

| Method     | small | medium | large | xl     |
|------------|-------|--------|-------|--------|
|            | INLP  | SD     | GEL   | DAMP   |
| SEAT-6     | 0.2398| 0.2026 | 0.3892| 0.1377 |
| SEAT-6b    | 0.8656| 0.0097 | 0.3033| 0.0029 |
|            | INLP  | SD     | GEL   | DAMP   |
| SEAT-6     | -0.1671| 0.8271 | 0.1589| 0.2678 |
| SEAT-6b    | 0.8158| 0.1181 | -0.1182| 0.0708 |

5.2 Baseline

We compare our DAMP method with the following methods: Iterative Nullspace Projection (INLP; Ravfogel et al., 2020b), Sentence Debias (SD; Liang et al., 2020), and fine-tuning method with Gender Equalizing Loss (GEL; Qian et al., 2019, Barikeri et al., 2021). Details of the baseline methods are provided in Appendix.

We apply our approach and the baselines to the pre-trained GPT-2 models of different sizes and compare them with several benchmarks and metrics. We compared the DAMP method with the baseline methods in two aspects: the effectiveness of debiasing and the capability of performance maintenance. We compare the DAMP method with the baseline methods in two aspects: the effectiveness of debiasing and the ability to maintain performance. We measure the effectiveness of debiasing using the metrics associated with StereoSet (Nadeem et al., 2021) and SEAT (Sentence Encoder Association Test; May et al., 2019). We evaluate the ability to maintain performance using the metric of Perplexity (Merity et al., 2016) and the metrics proposed in StereoSet and GLUE (General Language Understanding Evaluation; Wang et al., 2018).

Perplexity Perplexity is a measure of how well a language model performs. A lower perplexity indicates better performance. We compute the perplexity on the wikitext-2 dataset (Merity et al., 2016) for GPT-2 models of different sizes using four debiasing methods. The results are shown in Table 3.

GLUE We also evaluated the performance of the debiased models on the GLUE benchmark, which is a multi-task natural language understanding benchmark and analysis platform developed by Wang et al. (2018). The test results on the GLUE dataset reflect the understanding ability of the language model. The performance of the debiased small GPT-2 is shown in Table 3, and the results of medium GPT-2 and large GPT-2 are shown in the Appendix.

StereoSet StereoSet is a large-scale dataset for measuring stereotypical bias and performance of the language models (Nadeem et al., 2021). Associated with the dataset, Nadeem et al. (2021) also provided the metrics to assess the model’s stereotypical bias and performance. We selected the part data in Stereoset that is related to both gender and occupation for testing, and the results are shown in the table.

SEAT Sentence Encoder Association Test (SEAT) is an extension by May et al. (2019) from the Word Embedding Association Test (Caliskan et al., 2017). SEAT is able to be adopted to assess the size of gender bias and has the associated metrics. We tested all the methods by SEAT and the result is shown in Table 4.

5.3 Results

The DAMP method effectively mitigates gender bias. In some cases, its debiasing effectiveness is equivalent to or even surpasses that of existing methods. For example, it has the lowest gender-bias score on the Stereoset for GPT-2 of small, large, and xl sizes. On the SEAT dataset, the DAMP method ranks first in the tests of small-seat6, small-seat6b, and medium-seat6b.

Furthermore, the DAMP method effectively preserves model performance. Among all tested methods, it causes the lowest perplexity on the GPT-2 of small, medium, and xl sizes. On the large GPT-2, its perplexity ranks second, only 0.4% worse than the highest score, while the highest-scoring method has significantly worse debiasing effectiveness. On the GLUE dataset, the DAMP method achieves the best average score. These results demonstrate that our method effectively preserves model performance while mitigating gender bias.

Note it is not a surprise that the DAMP does not the most effective debiasing approach in some tests because DAMP only minimizes TDE rather than TE. In the tests that NIE significantly contributes the TE, the DAMP may have less debiasing effectiveness than those approaches minimizing TE. However, the tests manifest that DAMP has much better...
Figure 3: The token embeddings’ projection of selected words of occupations to the gender subspace.

Figure 4: The number of male neighbors for each token embedding of occupation changes with its original bias, before and after debiasing.

model performance than the TE-optimal methods in those tests. Further, the DAMP also substantially mitigated the gender bias in those tests that NIE has a large size. Consequently, the comprehensive scores of DAMP are always the best in all tests.

Overall, our approach is able to correct the gender-occupation bias with little impact on performance. On all models of all sizes, the Stereoset comprehensive evaluation index icat of our method exceeded the baseline. Although the correction effect of our method is not as good as that of some baseline methods at some test points, our method can better protect the model performance under these circumstances. This is consistent with our causal theory.

In summary, our analysis of the results revealed that our model effectively balances performance and debiasing. Specifically, it is the only model that simultaneously achieves a notable reduction in gender bias while maintaining high performance.

5.4 Geometry of Word Embedding

To analyze the mechanism of double dividends in our DAMP method, we compare its functioning process with the removing-gender-subspace method of Bolukbasi et al. [2016] from a geometric perspective. Using Fig. 3, we project token embeddings of a group of words before and after debiasing onto a two-dimensional plane, which represents the gender subspace calculated by PCA. The left-hand side plot shows the distribution of token embeddings before debiasing, the center plot shows the distribution after the gender-space-removing debiasing, and the right-hand side plot shows the distribution after the DAMP debiasing. The gender-space-removing debiasing method forces the embeddings to be perpendicular to the X-axis, which can destroy other attributes of word embeddings outside the gender, leading to a decline in the performance of the model. In contrast, the DAMP debiasing method retains the topology of the original embeddings while reducing the distance between professions in the sex subspace. The retention of non-gender information in the topology structure is an important reason for the obvious retention of performance.

In addition, we can also observe the cleanliness of bias elimination through geometric methods. Gonen and Goldberg [2019] argues that the debiasing methods, such as HARD-DEBIASED Barikeri et al. [2021] and GN-GLOVE Zhao et al. [2018], only remove bias by projection but do not handle bias by neighbors. Gonen and Goldberg [2019] proves the comment by the projection-neighbor figure which is almost no change before and after debiasing. For our method, we also draw the projection-neighbor figure in the same way, as shown in Figure 4. It can be observed that the occupational words, are distributed near an S-curve before debiasing and near a straight line parallel to the x-axis after debiasing.
This shows that our method can mitigate the bias-by-neighbors, which also explains why our method can effectively remove the bias of the language model.

6 Conclusions

We propose a causal framework that explains the origin of gender bias and unifies the mechanisms for debiasing pre-trained models. This framework also addresses the bias-performance trade-off that is present in current debiasing methods. Based on this theory, we develop the DAMP method which reduces gender bias by adjusting token embedding. The experimental results demonstrate that our method can significantly reduce gender bias while maintaining performance.

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