An Empirical Survey of the Effectiveness of Debiasing Techniques for Pre-Trained Language Models

Nicholas Meade\textsuperscript{1} \quad Elinor Poole-Dayan\textsuperscript{1} \quad Siva Reddy\textsuperscript{1,2}
\textsuperscript{1}Mila/McGill University
\textsuperscript{2}Facebook CIFAR AI Chair
nicholas.meade@mail.mcgill.ca siva.reddy@mila.quebec

Abstract

Recent work has shown that pre-trained language models capture social biases from the text corpora they are trained on. This has attracted attention to developing techniques that mitigate such biases. In this work, we perform an empirical survey of five recently proposed debiasing techniques: Counterfactual Data Augmentation (CDA), Dropout, Iterative Nullspace Projection, Self-Debias, and SentenceDebias. We quantify the effectiveness of each technique using three different bias benchmarks while also measuring the impact of these techniques on a model’s language modeling ability, as well as its performance on downstream NLU tasks. We experimentally find that: (1) CDA and Self-Debias are the strongest of the debiasing techniques, obtaining improved scores on most of the bias benchmarks; (2) Current debiasing techniques do not generalize well beyond gender bias; And (3) improvements on bias benchmarks such as StereoSet and CrowS-Pairs by using debiasing strategies are usually accompanied by a decrease in language modeling ability, making it difficult to determine whether the bias mitigation is effective.\textsuperscript{1}

1 Introduction

Large pre-trained language models have proven effective across a variety of tasks in natural language processing, often obtaining state of the art performance (Peters et al., 2018; Devlin et al., 2019; Radford et al., 2019; Brown et al., 2020). These models are typically trained on large amounts of text, originating from unmoderated sources, such as the internet. While the performance of these pre-trained models is remarkable, recent work has shown that they capture social biases from the data they are trained on (May et al. 2019; Kurita et al. 2019; Webster et al. 2020; Nangia et al. 2020; Nadeem et al. 2021, \textit{inter alia}). Because of these findings, an increasing amount of research has focused on developing techniques to mitigate these biases (Liang et al., 2020; Ravfogel et al., 2020; Webster et al., 2020; Kaneko and Bollegala, 2021; Schick et al., 2021; Lauscher et al., 2021). However, the proposed techniques are often not investigated thoroughly. For instance, much work focuses only on mitigating gender bias despite pre-trained language models being plagued by other social biases (e.g., racial or religious bias). Additionally, the impact that debiasing has on both downstream task performance, as well as language modeling ability, is often not well explored.

In this paper, we perform an empirical survey of the effectiveness of five recently proposed debiasing techniques for pre-trained language models: \textbf{Counterfactual Data Augmentation} (CDA; Zmiagrod et al. 2019; Webster et al. 2020), \textbf{Dropout} (Webster et al., 2020), \textbf{Iterative Nullspace Projection} (INLP; Ravfogel et al. 2020), \textbf{Self-Debiasing} (Schick et al., 2021) and \textbf{SentenceDebias} (Liang et al., 2020).\textsuperscript{2} We investigate the efficacy of these techniques in mitigating gender, racial, and religious biases in three masked language models (BERT, ALBERT, and RoBERTa) and an autoregressive language model (GPT-2). Additionally, we also explore how debiasing impacts a model’s language modeling ability, as well as a model’s performance on downstream natural language understanding (NLU) tasks. In carrying out this more holistic evaluation, we hope to better direct future research in the area of bias mitigation for pre-trained language models.

Concretely, our paper aims to answer the following research questions:

1. Which technique is most effective in mitigating bias?

\textsuperscript{1}Our code is publicly available: https://github.com/mcgill-nlp/debias-eval.

\textsuperscript{2}We select these techniques based upon popularity and ease of implementation.
2. Do these techniques work for mitigating non-gender biases?
3. Do these techniques impact a model's language modeling ability?
4. Do these techniques impact a model's ability to perform downstream NLU tasks?

To answer the first question, we evaluate debiased models against three benchmarks for measuring bias in language models: StereoSet (Nadeem et al., 2021), CrowS-Pairs (Nangia et al., 2020), and the Sentence Encoder Association Test (SEAT; May et al. 2019). Generally, we found CDA and Self-Debias to be the strongest bias mitigation techniques. To answer the second question, we compared the performance of the debiasing techniques when they were used to mitigate gender bias to when they were used to mitigate racial or religious biases. Here, we found most debiasing techniques generalize poorly to non-gender biases. And finally, to answer the third and fourth questions, we evaluate debiased models against WikiText-2 (Merity et al., 2016) and the General Language Understanding Evaluation benchmark (GLUE; Wang et al. 2018). We found debiasing techniques tend to worsen both a model’s language modeling ability, as well as its performance on NLU tasks.

2 Techniques for Measuring Bias

We begin by describing the three bias benchmarks we use for measuring bias in language models.

Sentence Encoder Association Test (SEAT). May et al. (2019) extend the Word Embedding Association Test (WEAT; Caliskan et al. 2017) to sentence-level representations. WEAT makes use of four sets of words: two sets of bias attribute words and two sets of target words. The attribute word sets characterize a type of bias. For example, the attribute word sets \{man, he, him, \ldots\} and \{woman, she, her, \ldots\} could be used for gender bias. The target word sets characterize particular concepts. For example, the target word sets \{family, child, parent, \ldots\} and \{work, office, profession, \ldots\} could be used to characterize the concepts of family and career, respectively. WEAT evaluates whether the representations for words from one particular attribute word set tend to be more closely associated with the representations for words from one particular target word set. For instance, if the female attribute words listed above tended to be more closely associated with the family target words, this may be indicative of bias within the word representations.

Formally, let $A$ and $B$ denote the sets of attribute words and let $X$ and $Y$ denote the sets of target words. As described in Caliskan et al. (2017), the WEAT test statistic is

$$s(X, Y, A, B) = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$$

(1)

where for a particular word $w$, $s(w, A, B)$ is defined as the difference between $w$’s mean cosine similarity with the words from $A$ and $w$’s mean cosine similarity with the words from $B$

$$s(w, A, B) = \frac{1}{|A|} \sum_{a \in A} \cos(w, a) - \frac{1}{|B|} \sum_{b \in B} \cos(w, b).$$

(2)

They report an effect size given by

$$d = \frac{\mu(\{s(x, A, B)_{x \in X}\}) - \mu(\{s(y, A, B)_{y \in Y}\})}{\sigma(\{s(t, X, Y)\}_{t \in A \cup B})}$$

(3)

where $\mu$ denotes the mean and $\sigma$ denotes the standard deviation. Here, an effect size closer to zero is indicative of a smaller degree of bias in the word representations.

To create a sentence-level version of WEAT (referred to as SEAT), May et al. substitute the words from Caliskan et al. (2017) into a collection of template sentences (i.e., “this is a [WORD]”, “that is a [WORD]”). Now, given sets of sentences containing attribute and target words, the WEAT test statistic can be computed using sentence representations obtained from a language model.

StereoSet. Nadeem et al. (2021) release StereoSet, a crowdsourced benchmark dataset for measuring four different types of stereotypical bias in language models. StereoSet consists of an intrasentence and intersentence task. In this work, we focus on the intrasentence task. Each intrasentence example consists of a context sentence, for example “our housekeeper is [MASK]”, and a set of three possible associations for that sentence – one being stereotypical, another being anti-stereotypical, and a third being unrelated. Using the example above, a stereotypical association might be “our...
housekeeper is Mexican”, an anti-stereotypical association might be “our housekeeper is American”, and an unrelated association might be “our housekeeper is computer”.

To quantify how biased a language model is, Nadeem et al. (2021) score the stereotypical and anti-stereotypical associations corresponding to each context sentence in the dataset using masked word probabilities from a language model. They then measure the percentage of examples for which the language model assigns a higher score to the stereotypical association as opposed to the anti-stereotypical association. They refer to this percentage as the stereotype score (\(ss\)) of a model.

In addition, for each example in the dataset they also score the corresponding unrelated association under a given model. Then, they measure the percentage of examples for which the model assigns a higher score to the unrelated association compared to both the stereotypical and anti-stereotypical associations. They refer to this percentage as the language modeling score (\(lm\)) of a model.

CrowS-Pairs. Concurrent to the development of StereoSet, Nangia et al. (2020) release Crowdsourced Stereotype Pairs (CrowS-Pairs), a benchmark dataset for measuring nine different types of social bias in language models. Each example in the dataset consists of a pair of minimally distant sentences – that is, sentences that differ only with respect to a small number of tokens. The first sentence in each pair reflects a stereotype about a historically disadvantaged group in the United States. For instance, the sentence “people who live in trailer parks are alcoholics” reflects a possible socioeconomic stereotype. The second sentence in each pair then violates the stereotype introduced in the first sentence. For example, the sentence “people who live in mansions are alcoholics” violates, or in a sense, is the anti-stereotypical version of the first sentence.

Nangia et al. (2020) quantify how biased a language model is by measuring how frequently a given language model prefers the stereotypical sentence. For example, the sentence “our housekeeper is Mexican”, an anti-stereotypical association might be “our housekeeper is American”, and an unrelated association might be “our housekeeper is computer”.

3 Debiasing Techniques

Below, we describe the five debiasing techniques we study in this work.

CDA. CDA is a data-based debiasing strategy that is often used to mitigate gender bias (Zmigrod et al., 2019; Dinan et al., 2019; Webster et al., 2020; Barikeri et al., 2021). Roughly, CDA involves rebalancing a corpus by swapping gendered terms in a dataset. For instance, the sentence “the doctor went to the room and he grabbed the syringe” could be augmented to “the doctor went to the room and she grabbed the syringe”. Typically, the re-balanced corpus is then used for further training to debias a model. Webster et al. (2020) experiment with debiasing BERT and ALBERT by performing an additional pre-training phase on counterfactually augmented sentences from English Wikipedia. They use the word pairs provided by Zhao et al. (2018) to generate their counterfactual corpus and train for an additional 100K steps on this dataset.

DROP OUT. Webster et al. (2020) propose using dropout regularization as a bias mitigation technique. They experiment with increasing the dropout parameters for BERT and ALBERT’s attention weights and hidden activations and performing an additional pre-training phase. They experimentally find that using increased dropout regularization reduces gender bias within these models. They hypothesize that dropout’s interruption of the attention mechanisms within BERT and ALBERT help prevent them from learning associations between words.

SELF-DEBIA SING. Schick et al. (2021) propose self-debiasing, a post-hoc debiasing procedure that requires no data, training, or manually curated word lists. Self-debiasing leverages a model’s internal knowledge to discourage it from generating toxic/biased text. Informally, Schick et al. (2021) propose using manually curated prompts to first encourage a model to generate toxic text. For instance, generation from an autoregressive model could be prompted with “The following text discriminates against people because of their gender.” Then, a second continuation that is non-discriminative can be generated from the model where the probabilities of tokens deemed likely under the first toxic generation can be scaled down.
This is done by finding occurrences of the bias attribute words in sentences within a text corpus. Liang et al. (2020) describe a three step procedure for estimating a bias subspace. 1) They define a list of bias attribute words. This list consists of tuples of words that characterize the different dimensions of the bias to mitigate (e.g., (man, woman) and (boy, girl) could be used as bias attribute words for gender bias). 2) They contextualize the bias attribute words into sentences. This is done by finding occurrences of the bias attribute words in sentences within a text corpus. For each sentence found during the contextualization process, CDA is applied to generate a pair of sentences that differ only with respect to the bias. 3) They estimate the bias subspace. For each of the sentences obtained during the contextualization step, a corresponding sentence representation can be obtained from a pre-trained model.

Liang et al. (2020) investigate debiasing BERT and consider the output corresponding to the [CLS] token to be a sentence representation. Principle Component Analysis (PCA; Abdi and Williams 2010) is then used to estimate the principle directions of variation of the resulting set of sentence representations. They use the first $k$ principle components for their projection-based debiasing procedure.

**SentenceDebias.** Liang et al. (2020) extend Hard-Debias, a word embedding debiasing technique proposed by Bolukbasi et al. (2016) to sentence representations. SentenceDebias is a projection-based debiasing technique that involves estimating a linear subspace for a particular type of bias. Sentence representations can be debiased by projecting onto the estimated bias subspace and subtracting the resulting projection from the original sentence representation.

Liang et al. (2020) describe a three step procedure for estimating a bias subspace. 1) They define a list of bias attribute words. This list consists of tuples of words that characterize the different dimensions of the bias to mitigate (e.g., (man, woman) and (boy, girl) could be used as bias attribute words for gender bias). 2) They contextualize the bias attribute words into sentences. This is done by finding occurrences of the bias attribute words in sentences within a text corpus. For each sentence found during the contextualization process, CDA is applied to generate a pair of sentences that differ only with respect to the bias. 3) They estimate the bias subspace. For each of the sentences obtained during the contextualization step, a corresponding sentence representation can be obtained from a pre-trained model.

Liang et al. (2020) investigate debiasing BERT and consider the output corresponding to the [CLS] token to be a sentence representation. Principle Component Analysis (PCA; Abdi and Williams 2010) is then used to estimate the principle directions of variation of the resulting set of sentence representations. They use the first $k$ principle components for their projection-based debiasing procedure.

**INLP.** Ravfogel et al. (2020) propose Iterative Nullspace Projection (INLP), a projection-based debiasing technique similar to SentenceDebias. Roughly, INLP debiases neural representations by training a linear classifier to predict the protected attribute you want to remove (e.g., gender) from the representation. Then, representations can be debiased by projecting them onto the nullspace of the learnt classifier. This process is then repeated to debias the representation.

### Table 1: SEAT effect sizes for gender debiased BERT and GPT-2 models. Effect sizes closer to 0 are indicative of less biased sentence representations. Statistically significant effect sizes at $p < 0.01$ are denoted by *.

| Model       | SEAT-6 | SEAT-6b | SEAT-7 | SEAT-7b | SEAT-8 | SEAT-8b | Avg. Effect Size |
|-------------|--------|---------|--------|---------|--------|---------|-----------------|
| BERT        | 0.931* | 0.090   | -0.124 | 0.937*  | 0.783* | 0.858*  | 0.620           |
| + CDA       | 0.535* | 0.056   | -0.925 | 0.352   | 0.303  | 0.129   | 0.383           |
| + DROPOUT   | 0.750* | 0.189   | -0.507 | 0.488*  | 0.348  | 0.202   | 0.414           |
| + INLP      | 0.551* | -0.160  | -0.638 | 0.291   | 0.346  | 0.195   | 0.363           |
| + SentenceDebias | 0.350 | -0.298  | -0.623 | 0.464*  | 0.414  | 0.464*  | 0.435           |
| GPT-2       | 0.138  | 0.003   | -0.023 | 0.002   | -0.224 | -0.287  | 0.113           |
| + CDA       | 0.161  | -0.034  | 0.898* | 0.874*  | 0.516* | 0.396   | 0.480           |
| + DROPOUT   | 0.167  | -0.040  | 0.866* | 0.873*  | 0.527* | 0.384   | 0.476           |
| + INLP      | 0.300  | 0.365   | -0.075 | -0.137  | -0.373 | -0.384  | 0.273           |
| + SentenceDebias | 0.087 | -0.072  | -0.294 | -0.064  | 0.318  | -0.667  | 0.250           |

To investigate which technique is most effective in mitigating bias, we evaluate debiased BERT and GPT-2 models against SEAT, StereoSet, and CrowS-Pairs. We refer readers to Appendix A for additional results. We describe our findings below.

**SEAT.** In Table 1, we report results for gender debiased BERT and GPT-2 models on SEAT. Following previous work (Liang et al., 2020; Kaneko and Bollegala, 2021; Cheng et al., 2021) we use SEAT tests 6, 6b, 7, 7b, 8, and 8b for measuring gender bias. We omit SEAT results for Self-Debias as it is a text generation debiasing technique.

We use a permutation test on the SEAT test statistic to compute the significance of association between the attribute word sets and the target word sets. We refer readers to the original work of Caliskan et al. (2017) and May et al. (2019) for additional details on this permutation test. We report significant results at $p < 0.01$. 

In general, we observe that all of the gender debiased BERT models obtain lower average absolute effect sizes relative to the baseline model. For
Table 2: SEAT average absolute effect sizes for race and religion debiased BERT and GPT-2 models. Average absolute effect sizes closer to 0 are indicative of less biased sentence representations.

| Model       | Avg. Effect Size |
|-------------|------------------|
| BERT + CDA  | 0.620            |
| + DROPOUT   | 0.298            |
| + INLP      | 0.231            |
| + SENTENCEDEBIAS | 0.640 |
| GPT-2 + CDA | 0.448            |
| + DROPOUT   | 0.139            |
| + INLP      | 0.162            |
| + SENTENCEDEBIAS | 0.391 |

For BERT, it appears INLP performs best, obtaining an average absolute effect size of 0.363 relative to the baseline model’s score of 0.620.

For GPT-2, the results are much less clear. Here, all of the debiased models obtain increased average absolute effect sizes relative to the baseline model.

We also observe a large degree of variability in performance across the six tests for each of our debiased models. For instance, while most of our debiased models obtain reduced effect sizes on SEAT-8 (Male/Female Terms and Science/Arts), all of our models perform poorly on SEAT-7 (Male/Female Terms and Math/Arts). We initially hypothesized that the variability in performance across the six tests may be caused by the degree to which the test’s attribute words overlap with the bias attribute words used by the debiasing techniques. However, we observe no such correlation. For example, SEAT-8b’s attribute word sets share no common words with the bias attribute words used by CDA, INLP, and SENTENCEDEBIAS, yet our models perform well on it. On the other hand, 87.5% of the attribute words used by SEAT-6b (Male/Female Terms and Career/Family) and SEAT-7 (Male/Female Terms and Math/Arts) are bias attribute words used by CDA, INLP and SENTENCEDEBIAS, but we observe no clear performance improvement on these tests.

In Table 2, we report average absolute effect sizes for race and religion debiased BERT and GPT-2 models. For BERT, we observe that INLP and SENTENCEDEBIAS perform poorly for race. However, for religion, INLP and SENTENCEDEBIAS perform well. Finally, we also note that models debiased using CDA and Dropout perform consistently well in mitigating racial and religious biases, as measured by SEAT.

StereoSet. We evaluate each of our debiased models against the StereoSet test set. We note that for StereoSet, we only consider the intrasentence task in this work. To score each intrasentence example, we use likelihood scoring, as originally proposed by Nadeem et al. (2021). We evaluate gender, race, and religion debiased models against their respective StereoSet test split (e.g., gender debiased models are evaluated against the gender StereoSet split). We report stereotype scores for debiased BERT and GPT-2 models in Table 3.

In general, we find most techniques effective in mitigating gender bias. In particular, Self-Debias works well for both BERT and GPT-2. SentenceDebias also appears particularly effective in mitigating gender bias, obtaining a stereotype score of 55.81 relative to the baseline model’s score of 62.65.

For religion, Self-Debias is effective in mitigating bias in both BERT and GPT-2. The Self-Debias BERT and GPT-2 models obtain the lowest stereotype scores on the religion StereoSet test set split.

CrowS-Pairs. We also evaluate debiased models against CrowS-Pairs. Similar to StereoSet, we evaluate gender, race, and religion debiased models against each corresponding CrowS-Pairs split. As with StereoSet, we use likelihood scoring to compute the stereotype scores. We report stereotype scores for debiased models in Table 8.

For the CrowS-Pairs gender split, the BERT and GPT-2 models using Self-Debias obtain the lowest stereotype scores. In general, CDA, Self-Debias, and SENTENCEDEBIAS all appear effective in mitigat-

4Henceforth, when we refer to a StereoSet example, we are referring to a StereoSet intrasentence example.
Table 3: StereoSet stereotype scores for gender, race, and religion debiased BERT and GPT-2 models using likelihood scoring. Stereotype scores closer to 50% indicate less biased model behaviour.

Table 4: CrowS-Pairs stereotype scores for gender, race, and religion debiased BERT and GPT-2 models using likelihood scoring. Stereotype scores closer to 50% indicate less biased model behaviour.

Do stereotype scores reliably measure bias?

Before continuing, we discuss why stereotype scores alone do not reliably measure bias in language models. To illustrate why this is the case, consider a random language model being evaluated against StereoSet. When evaluating this model against StereoSet, it randomly selects either the stereotypical or anti-stereotypical association for each example. Thus, in expectation, this model obtains a perfect stereotype score of 50%. This highlights that a debiased model may obtain reduced stereotype scores not due to actual bias mitigation, but rather by just becoming a worse language model. Thus, when determining whether a
debiasing technique is effective in mitigating bias, it is critical we analyze how debiasing impacts a model’s language modeling capabilities. Motivated by this discussion, we now study how debiasing impacts language modeling performance.

## 5 How does debiasing impact language modeling?

To investigate how debiasing affects language modeling, we measure perplexities before and after debiasing on WikiText-2 (Merity et al., 2016). In the case of masked language models, since perplexities cannot be computed, we instead compute pseudo-perplexities (Salazar et al., 2020). Following a similar setup to Schick et al. (2021), we use 10% of WikiText-2 for our experiments and a maximum sequence length of 488 tokens for all of our models.

In Table 5, we report perplexities for debiased BERT models. In general, we find all of the debiasing techniques have only a minor impact on

| Model       | Perplexity (↓) |
|-------------|----------------|
| Gender      |                |
| BERT        | 4.392          |
| + CDA       | 4.217          |
| + DROPOUT   | 4.354          |
| + INLP      | 5.834          |
| + SELF-DEBIAS | 5.377      |
| + SENTENCEDEBIAS | 4.406 |

Table 5: Perplexities for gender, race, and religion debiased BERT and GPT-2 models on WikiText-2 (Merity et al., 2016).

BERT’s language modeling ability. Notably, the BERT models debiased using Dropout and CDA actually obtain reduced perplexities. We hypothesize this is because the additional pre-training phase is carried out on English Wikipedia data.

In addition to measuring perplexities, we also compute StereoSet language modeling scores for our debiased models. We evaluate each of our debiased models against all of the examples from the StereoSet test set. To compute each language modeling score, we again use likelihood scoring. We report language modeling scores for debiased BERT and GPT-2 models in Table 6.

For gender and religion debiased BERT models, we observe increases in language modeling scores
for both the CDA and Dropout models. These increased language modeling scores, alongside the reduced perplexities reported in Table 6, suggest that the additional pre-training phase performed when using CDA or Dropout strengthens BERT’s language modeling ability.

### 6 What impact does debiasing have on downstream task performance?

To investigate how debiasing impacts performance on downstream NLU tasks, we evaluate gender debiased BERT and GPT-2 models against the GLUE benchmark. Since Self-Debias is used to debias text generation, it is not well-defined to use it during fine-tuning on a downstream text classification task. Thus, we omit results for Self-Debias. We report our results in Table 7.

Encouragingly, we observe that performance is only slightly worsened by debiasing. For instance, BERT with SentenceDebias obtains an average score of 77.52 while the baseline model obtains a score of 77.85. In some cases, we see an improvement in performance. For instance, GPT-2 with CDA obtains an average score of 74.03, higher than the baseline model’s average score of 73.02. Thus, our results suggest that debiasing has only a small negative impact on a model’s ability to perform downstream NLU tasks.

### 7 Discussion

Below, we discuss key findings from our paper and present challenges to be addressed by future work.

**How effective are debiasing techniques?** In Section 4, we found many of our debiasing techniques largely effective in mitigating gender, racial, and religious biases. However, when we considered how debiasing impacts language modeling performance (Section 5), these improvements become less clear. We described how decreased stereotype scores on CrowS-Pairs and StereoSet may be caused by a worsening in a model’s language modeling ability rather than actual bias mitigation. In light of this, it is difficult to determine whether Dropout, INLP, and SentenceDebias are effective bias mitigation techniques. Although models debiased using each of these techniques often obtained reduced stereotype scores on CrowS-Pairs and StereoSet, they also saw decreased language modeling performance, evident by decreased Stere-oSet language modeling scores and increased perplexities on WikiText-2.

On the other hand, Self-Debias does appear effective as a bias mitigation technique as it not only obtains reduced stereotype scores on both CrowS-Pairs and StereoSet, but also remains a strong language model after debiasing. Thus, we believe Self-Debias is the most promising technique, amongst others, studied in this work.

**Reliable bias benchmarks for evaluating debiasing techniques.** Developing reliable and accurate measurements for social biases in language models has been a significant challenge in recent years. In our work, we argued that stereotype scores from CrowS-Pairs and StereoSet alone are not reliable metrics for bias when measuring the effectiveness of debiasing techniques. We believe bias benchmarks must also account for the language modeling ability of a model. While Stere-oSet does provide a language modeling score, we believe it is too rudimentary to accurately measure
language modeling performance. Thus, we believe developing reliable bias benchmarks is an important area for future research, especially as work in debiasing increases.

Debiasing techniques for non-gender biases. Developing techniques to mitigate non-gender biases is a substantial challenge in debiasing research. For some of the debiasing techniques studied in this work, it appears they are not easily adaptable to non-gender biases. For instance, one could imagine using the pair (black, white) to create a simplistic counterfactually augmented dataset for racial bias, however, there are also challenges with ensuring you only perform substitutions on words invoking the racial sense of a word (i.e., we would not want to include the sentence “Barack Obama worked at the black house” in our dataset). We believe developing techniques to mitigate non-gender biases will be a critical step towards creating fairer language models and is an important area for future research.

8 Conclusion

We performed an empirical survey of five recently proposed debiasing techniques for pre-trained language models: CDA, Dropout, INLP, Self-Debias, and SentenceDebias. We found that: (1) Self-Debias and CDA appear to be the strongest techniques, obtaining reductions in bias as measured by our three benchmarks while still largely retaining language modeling ability and downstream task performance; (2) Many of the debiasing techniques studied in this work are not clearly effective in mitigating non-gender biases; (3) Some debiasing techniques appear to significantly damage the language modeling ability of a model; And (4) current bias benchmarks such as StereoSet and CrowS-Pairs may not reliably measure bias in the context of debiasing. We hope this work helps to better direct future research in bias mitigation.

Acknowledgements

SR is supported by the Canada CIFAR AI Chairs program and the NSERC Discovery Grant program. NM is supported by an IVADO Excellence Scholarship.

References

Hervé Abdi and Lynne J. Williams. 2010. Principal component analysis: Principal component analysis. Wiley Interdisciplinary Reviews: Computational Statistics, 2(4):433–459.

Soumya Barikeri, Anne Lauscher, Ivan Vulić, and Goran Glavaš. 2021. RedditBias: A Real-World Resource for Bias Evaluation and Debiasing of Conversational Language Models. 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 1941–1955, Online. Association for Computational Linguistics.

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. NIPS’16: Proceedings of the 30th International Conference on Neural Information Processing Systems, pages 4356 – 4364.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. arXiv:2005.14165 [cs]. ArXiv: 2005.14165.

Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. Science, 356(6334):183–186. Publisher: American Association for the Advancement of Science Section: Reports.

Pengyu Cheng, Weituo Hao, Siyang Yuan, Shijing Si, and Lawrence Carin. 2021. FairFil: Contrastive Neural Debiasing Method for Pretrained Text Encoders. arXiv:2103.06413 [cs]. ArXiv: 2103.06413.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Emily Dinan, Angela Fan, Adina Williams, Jack Urbanek, Douwe Kiela, and Jason Weston. 2019. Queens are Powerful too: Mitigating Gender Bias in Dialogue Generation. page 14.

Masahiro Kaneko and Danushka Bollegala. 2021. Debiasing Pre-trained Contextualised Embeddings. arXiv:2101.09523 [cs]. ArXiv: 2101.09523.
Keita Kurita, Nidhi Vyas, Ayush Pareek, Alan W Black, and Yulia Tsvetkov. 2019. Measuring Bias in Contextualized Word Representations. In Proceedings of the First Workshop on Gender Bias in Natural Language Processing, pages 166–172, Florence, Italy. Association for Computational Linguistics.

Anne Lauscher, Tobias Lüken, and Goran Glavaš. 2021. Sustainable Modular Debiasing of Language Models. arXiv:2109.03646 [cs]. ArXiv: 2109.03646.

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

Chandler May, Alex Wang, Shikha Bordia, Samuel R. Bowman, and Rachel Rudinger. 2019. On Measuring Social Biases in Sentence Encoders. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 622–628, Minneapolis, Minnesota. Association for Computational Linguistics.

Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. 2016. Pointer Sentinel Mixture Models. arXiv:1609.07843 [cs]. ArXiv: 1609.07843.

Moin Nadeem, Anna Bethke, and Siva Reddy. 2021. StereoSet: Measuring stereotypical bias in pretrained language models. Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics.

Nikita Nangia, Clara Vania, Rasika Bhalerao, and Samuel R. Bowman. 2020. CrowS-Pairs: A Challenge Dataset for Measuring Social Biases in Masked Language Models. arXiv:2010.00133 [cs]. ArXiv: 2010.00133.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep Contextualized Word Representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana. Association for Computational Linguistics.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language Models are Unsupervised Multitask Learners. pages 7237–7256, Online. Association for Computational Linguistics.

Julian Salazar, Davis Liang, Toan Q. Nguyen, and Katrin Kirchhoff. 2020. Masked Language Model Scoring. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2699–2712. ArXiv: 1910.14659.

Timo Schick, Sahana Udupa, and Hinrich Schütze. 2021. Self-Diagnosis and Self-Debiasing: A Proposal for Reducing Corpus-Based Bias in NLP. arXiv:2103.00453 [cs]. ArXiv: 2103.00453.

Alex Wang and Kyunghyun Cho. 2019. BERT has a Mouth, and It Must Speak: BERT as a Markov Random Field Language Model. In Proceedings of the Workshop on Methods for Optimizing and Evaluating Neural Language Generation, pages 30–36, Minneapolis, Minnesota. Association for Computational Linguistics.

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, Brussels, Belgium. Association for Computational Linguistics.

Kellie Webster, Xuezhi Wang, Ian Tenney, Alex Beutel, Emily Pitler, Ellie Pavlick, Jilin Chen, and Slav Petrov. 2020. Measuring and Reducing Gendered Correlations in Pre-trained Models. arXiv:2010.06032 [cs]. ArXiv: 2010.06032.

Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2018. 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, New Orleans, Louisiana. Association for Computational Linguistics.

Ran Zmigrod, Sabrina J. Mielke, Hanna Wallach, and Ryan Cotterell. 2019. Counterfactual Data Augmentation for Mitigating Gender Stereotypes in Languages with Rich Morphology. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1651–1661, Florence, Italy. Association for Computational Linguistics.
### A Additional Results

| Model     | Stereotype Score |
|-----------|------------------|
| BERT      | 57.25            |
| + CDA     | 55.34            |
| + DROPOUT | 58.02            |
| + INLP    | 57.63            |
| + SELF-DEBIAS | 52.29     |
| + SENTENCEDEBIAS | 52.29 |
| ALBERT    | 48.09            |
| + CDA     | 48.85            |
| + DROPOUT | 49.62            |
| + INLP    | 45.04            |
| + SELF-DEBIAS | 45.04     |
| + SENTENCEDEBIAS | 47.33 |
| RoBERTa   | 59.92            |
| + CDA     | 55.73            |
| + DROPOUT | 58.78            |
| + INLP    | 52.67            |
| + SELF-DEBIAS | 56.87     |
| + SENTENCEDEBIAS | 51.91 |
| GPT-2     | 56.87            |
| + CDA     | 56.87            |
| + DROPOUT | 57.63            |
| + INLP    | 44.27            |
| + SELF-DEBIAS | 56.11     |
| + SENTENCEDEBIAS | 56.11     |

Table 8: CrowS-Pairs stereotype scores for gender debiased BERT, ALBERT, RoBERTa, and GPT-2 models using likelihood scoring. Stereotype scores closer to 50% indicate less biased model behaviour.
| Model         | CoLA | MNLI | MRPC | QNLI | QQP | RTE | SST | STS-B | WNLI | Average |
|--------------|------|------|------|------|-----|-----|-----|-------|------|---------|
| BERT         | 56.49| 84.72| 88.45| 91.40| 90.99| 63.30| 92.20| 88.48 | 44.60| 77.85   |
| + CDA        | 57.01| 84.74| 88.88| 91.32| 91.04| 62.70| 92.28| 89.27 | 35.68| 76.99   |
| + DROPOUT    | 51.85| 84.79| 87.33| 91.33| 90.44| 61.61| 92.47| 88.95 | 38.50| 76.36   |
| + INLP       | 57.27| 84.73| 88.02| 91.34| 91.04| 64.38| 92.62| 88.40 | 30.52| 76.48   |
| + SENTENCEDEBIAS | 56.67| 84.55| 88.91| 91.48| 90.93| 63.06| 92.70| 88.50 | 40.85| 77.52   |
| ALBERT       | 57.31| 85.36| 90.67| 91.63| 90.49| 71.12| 91.86| 90.61 | 42.72| 79.09   |
| + CDA        | 55.14| 85.47| 91.65| 91.49| 90.64| 74.85| 92.05| 91.04 | 46.48| 79.87   |
| + DROPOUT    | 50.66| 85.50| 90.73| 91.83| 90.39| 72.20| 91.97| 90.56 | 44.13| 78.66   |
| + INLP       | 58.88| 85.54| 90.78| 91.43| 90.62| 72.56| 92.28| 90.83 | 42.72| 79.52   |
| + SENTENCEDEBIAS | 56.81| 85.36| 91.25| 91.50| 90.66| 69.19| 92.28| 90.58 | 39.91| 78.62   |
| RoBERTa      | 58.13| 87.71| 91.10| 92.70| 91.31| 71.72| 94.19| 90.00 | 52.58| 81.05   |
| + CDA        | 57.20| 87.48| 91.08| 92.83| 91.37| 72.08| 94.53| 90.39 | 56.34| 81.48   |
| + DROPOUT    | 52.33| 87.50| 90.24| 92.72| 90.45| 67.39| 94.11| 89.05 | 46.95| 78.97   |
| + INLP       | 56.76| 87.66| 91.39| 92.67| 91.34| 68.95| 94.30| 89.86 | 52.11| 80.56   |
| + SENTENCEDEBIAS | 59.14| 87.54| 91.02| 92.64| 91.33| 70.64| 94.72| 90.04 | 56.34| 81.49   |
| GPT-2        | 29.10| 82.55| 84.68| 87.69| 89.22| 64.74| 91.78| 84.26 | 43.19| 73.02   |
| + CDA        | 37.18| 82.52| 86.00| 88.08| 89.31| 65.70| 91.90| 85.16 | 40.38| 74.03   |
| + DROPOUT    | 29.94| 82.45| 85.52| 87.69| 88.57| 63.18| 91.90| 84.12 | 44.13| 73.05   |
| + INLP       | 31.40| 82.65| 84.43| 88.00| 89.12| 67.39| 91.67| 83.99 | 42.72| 73.49   |
| + SENTENCEDEBIAS | 28.80| 82.49| 84.58| 87.86| 89.16| 63.78| 91.70| 83.78 | 38.50| 72.29   |

Table 9: GLUE validation set results for gender debiased BERT, ALBERT, RoBERTa and GPT-2 models. We report the F1 score for MRPC, the Spearman correlation for STS-B, and Matthew’s correlation for CoLA. For all other tasks, we report the accuracy. Reported results are means over three training runs.