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# Evaluating Gender Bias in Natural Language Inference

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## Abstract

Gender-bias stereotypes have recently raised significant ethical concerns in natural language processing. However, progress in detection and evaluation of gender-bias in natural language understanding through inference is limited and requires further investigation. In this work, we propose an evaluation methodology to measure these biases by constructing a challenge task which involves pairing gender neutral premise against gender-specific hypothesis. We use our challenge task to investigate state-of-the-art NLI models on the presence of gender stereotypes using occupations. Our findings suggest that three models (BERT, RoBERTa, BART) trained on MNLI and SNLI datasets are significantly prone to gender-induced prediction errors. We also find that debiasing techniques such as augmenting the training dataset to ensure a gender-balanced dataset can help reduce such bias in certain cases.

## 1 Introduction

Machine learning algorithms trained in natural language processing tasks have exhibited various forms of systemic racial and gender biases. These biases have been found to exist in many subtasks of NLP, ranging from learned word embeddings [4, 6], natural language inference [16], hate speech detection [25], dialog [18, 11], and coreference resolution [31]. This has prompted a large area of research attempting to evaluate and mitigate them, either through removal of bias introduction in dataset level [2], or through model architecture [15], or both [34].

We revisit the notion of detecting gender-bias in Natural Language Inference (NLI) systems using targeted inspection. Typically, NLI systems are trained on datasets collected using large-scale crowd-sourcing techniques, which has its own fair share of issues resulting in the introduction of lexical bias in the trained models [17, 8]. Gender bias, which is loosely defined by stereotyping gender-related professions to gender-sensitive pronouns, have also been found to exist in many NLP tasks and datasets [27, 28].

With the advent of large-scale pre-trained language models, we have witnessed a phenomenal rise of interest in adapting the pre-trained models to downstream applications in NLP, leading to superior performance [9, 21, 20]. These pre-trained models are typically trained over a massive corpus of text, increasing the probability of introduction of stereotypical bias in the representation space. It is thus crucial to study how these models reflect the bias after fine-tuning on the downstream task, and try to mitigate them without significant loss of performance.

We propose a challenge task methodology to detect stereotypical gender bias in the representations learned by pre-trained language models after fine-tuning on the natural language inference task. Specifically, we



Dataset	# instances	Source of premise
In-distribution Evaluation Set (MNLI)	1900	MNLI original dataset
In-distribution Evaluation Set (SNLI)	1900	SNLI original dataset
Out-of-distribution Evaluation Set (ANLI + QNLI)	3800	(ANLI + QNLI) original dataset

Table 1: Statistics of evaluation sets designed for evaluating gender bias

On our analysis, we found out that models were sensitive to names and that added to the bias. Since, in this work, our focus is solely on the bias induced by profession, we filtered out only the sentences that didn't include a name when checked through NLTK-NER ([3]).

We equalize the instances of the occupations by using examples from occupations with larger share in the dataset and use them as place-holders to generate more sentences for occupations with lesser contribution. Examples of this can be seen in Table 2.

Source Occupation	Original Premise	Target Occupation	Modified Premise
Nurse	A nurse is sitting on a bench in the park.	Teacher	A teacher is sitting on a bench in the park.
Janitors	Janitors are doing their job well.	Teacher	Guards are doing their job well.
Carpenter	A carpenter is walking towards the store.	Baker	A baker is walking towards the store.

Table 2: The source sentence acts as a placeholder and we replace the source occupation with the target occupation to generate a new sentence. This is done to augment our evaluation set to ensure equal number of premises for all 38 occupations.

Our final dataset consists of equal number of sentences from each of the occupations to act as the premise of our evaluation sets. The sentences were intended to be short (max. 10 words) and grammatically simple to avoid the inclusion of other complex words that may affect the model's prediction. We verified that each sentence included is gender neutral and does not seek to incline to either male or female in itself.

**Hypothesis:** We use templates  $T$  of structure "*This text speaks of a [gender] occupation*" to generate gender-specific hypothesis. Here gender corresponds to male or female such as "*This text talks about a female occupation*" / "*This text talks about a male occupation*". We focus on making the template sentences help discern the gender bias in the NLI models. We also vary the structure of these templates to ensure that the results are purely based on the bias and are not affected by the syntactic structure of the hypothesis. The list of templates used can be found in Appendix (A.2). We consider a hypothesis "pro-stereotypical" if it aligns with society's stereotype for an occupation, e.g. "female nurse" and anti-stereotypical if otherwise.

Admittedly, more natural hypotheses can be created through crowd-sourcing, but in this work we generate only the baseline examples and leave more explorations in this regard as a future work.

### 3.2 Experiments

Transformer models pretrained on large dataset have shown state-of-the art performance in the task of RTE for various NLI datasets. In this work, we use three models - BERT[10], RoBERTa[22] and BART[21] - that have been widely used both in research and production. We fine-tune above models on MNLI[30] and SNLI[6] datasets each generating a total of 6 models (3 for each dataset) to test our evaluation sets on. The pretrained configuration and hyperparameters used for each of the models can be found in Appendix (A.3). The key idea of our experiments is to test our null hypothesis according to which the difference between predicted entailment probabilities,  $P_f$  and  $P_m$ , on pairing a given premise  $p$  with female hypothesis  $f$  and male hypothesis  $m$  respectively, should be 0. For every sentence used as a premise, the model is first fed the female specific hypothesis,  $f$ , followed by its male alternative,  $m$ .

A typical RTE task would predict one of the three labels - entailment, neutral and contradiction - for the given pair of premise and hypothesis. For this experiment we investigate if the model predicts the textual entailment to be "definitely true" or "definitely false". Hence, we convert our problem into a binary case: "entailment" vs. "contradiction" thus scraping the logit for the "neutral" label and taking a softmax over the other two labels.

The following metrics are calculated for both in-distribution ( $I$ ) and out-of-distribution ( $O$ ) evaluation sets:

- **S** : S is the % of instances where model gave the same prediction for both the cases. A low value for this metric is an indicator of high bias.
- $\Delta P$  : This represents the mean absolute difference between the entailment probabilities for the two hypothesis. According to our null hypothesis, a higher value is the indicator of high bias. This is the most important indicator of bias and helps us quantify the bias.
- **B** : B is the % of instances where model has higher entailment probability for a pro-stereotypical hypothesis. A higher value of B would indicate a higher bias.

### 3.3 Results and Analysis

	SNLI (I)				MNLI (I)				SNLI (O)				MNLI (O)			
	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)
BERT	90.48	50.97	43.02	<b>70.05</b>	83.68	71.89	24.09	69.79	90.48	52.92	41.57	<b>66.94</b>	83.68	64.76	30.97	68.51
RoBERTa	<b>91.41</b>	<b>72.13</b>	<b>27.23</b>	77.79	<b>87.59</b>	64.35	21.85	<b>65.12</b>	<b>91.41</b>	<b>71.02</b>	<b>26.57</b>	73.76	<b>87.59</b>	64.33	24.86	<b>64.53</b>
BART	91.28	61.17	34.9	74.0	85.57	<b>85.58</b>	<b>16.29</b>	66.82	91.28	62.28	33.92	70.28	85.57	<b>79.71</b>	<b>20.92</b>	64.69

Table 3: Performance of the models when fine-tuned on SNLI and MNLI datasets respectively. The metric Acc indicates the model accuracy when trained on original NLI dataset (SNLI/MNLI) and evaluated on dev set (dev-matched for MNLI). Metrics S, B and  $\Delta P$  are as explained in Section 2.2.2. Numerics in bold represent the best value (least bias) for each metric. SNLI (O) and MNLI (O) and SNLI (I) and MNLI (I) represent the performance of models trained on original SNLI and MNLI datasets and evaluated on out-of-distribution and in-distribution evaluation sets respectively.

The main results of our experiments are shown in Table 3. For each tested model, we compute three metrics with respect to their ability to predict the correct label (Section 3.2). Our analysis indicate that all the NLI models tested by us are indeed gender biased and also conform to real-world statistics (Appendix (A.6)).

From Table 3, metric B shows that all the tested models perform better when presented with pro-stereotypical hypothesis. However when observed along with  $\Delta P$ , we can see that BERT shows the most significant difference in prediction as compared to other models. Among the three models, BERT also has the lowest value of Metric S in almost all the cases, indicating highest number of label shifts thus showing the greatest amount of bias.

A detailed analysis with respect to gender (Appendix (A.4)), shows that bias towards the pro-stereotypical hypothesis is higher for male-dominated occupations. While both MNLI and SNLI show similar trends with respect to most metrics, results from Table 3 indicate that models fine-tuned on SNLI has a relatively higher bias than those trained on MNLI.

## 4 Debiasing : Gender Swapping

	SNLI (I)				MNLI (I)				SNLI (O)				MNLI (O)			
	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)	Acc (↑)	S (↑)	$\Delta P(\downarrow)$	B (↓)
BERT	90.50	57.17	35.02	<b>67.02</b>	84.04	<b>87.48</b>	<b>14.60</b>	72.07	90.50	65.5	30.01	66.71	84.04	<b>78.76</b>	<b>19.99</b>	72.53
RoBERTa	<b>91.51</b>	51.53	34.02	67.79	<b>87.1</b>	65.58	20.98	<b>67.69</b>	<b>91.51</b>	61.64	33.08	<b>63.61</b>	<b>87.1</b>	65.35	22.53	<b>67.23</b>
BART	90.6	<b>61.89</b>	<b>31.71</b>	72.76	85.76	75.33	21.32	70.67	90.6	<b>66.43</b>	<b>27.56</b>	70.05	85.76	68.43	26.51	68.67

Table 4: Performance of the models after debiasing. Notations are same as those in Table 4.

We follow a simple rule based approach for swapping. First we identify all the occupation based entities from the original training set. Next, we build a dictionary of gendered terms and their opposites (e.g. "his"  $\leftrightarrow$  "her", "he"  $\leftrightarrow$  "she" etc.) and use them to swap the sentences. These gender swapped sentences are then augmented to the original training set and the model is trained on it. From Table 4, it can be seen the augmentation of training set doesn't deteriorate model performance (accuracy (Acc)) on the original training data (SNLI/MNLI). This simple method removes correlation between gender and classification decision and has proven to be effective for correcting gender biases in other natural language processing tasks ([32]).

**Effectiveness of debiasing:** From results in Table 4, we can see that performance on BERT with respect to bias has improved following the debiasing approach. A comparison of the change in metrics  $\Delta P$  and B before and after debiasing can also be seen in Appendix (A.5).

The improvement in results for BERT indicate that maintaining gender balance in the training dataset is, hence, of utmost importance to avoid gender-bias induced incorrect predictions. The other two models, RoBERTa and BART, also show a slight improvement in performance with respect to most metrics. However, this is concerning since the source of bias in these cases is not the NLI dataset but the data that these models were pre-trained on. Through our results, we suggest that attention be paid while curating such dataset so as to avoid biased predictions in the downstream tasks.

## 5 Conclusion and Future Work

We show the effectiveness of our challenge setup and find that a simple change of gender in the hypothesis can lead to a different prediction when tested against the same premise. This difference is a result of biases propagated in the models with respect to occupational stereotypes. Augmenting the training-dataset in order to ensure a gender-balanced distribution proves to be effective in reducing bias for BERT indicating the importance of maintaining such balance during data curation. The debiasing approach also reduces the bias in the other two models (RoBERTa and BART) but only by a small amount indicating that attention also needs to be paid on the dataset used for training these language models. Through this work, we aim to establish a baseline approach for evaluating gender bias in NLI systems, but we hope that this work encounters further research by exploring advanced debiasing techniques and also exploring bias in other dimensions.

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## A Appendix

### A.1 List of occupations used for evaluation set creation

We select 38 different occupations (19 for each gender) to include a variety of gender distribution characteristics and occupation types, in correspondence with US Current Population Survey <sup>2</sup> (CPS) 2019 data and prior literature. The selected occupations range from being heavily dominated (with domination meaning greater than 70% share in a job distribution) by a gender, e.g. nurse, to those which have an approximately equal divide, e.g. designer.

Female Occupations	Male Occupations
attendant	driver
cashier	supervisor
teacher	janitor
nurse	cook
assistant	CEO
secretary	laborer
auditor	construction worker
cleaner	baker
receptionist	developer
clerk	carpenter
counselor	manager
designer	lawyer
hairstylist	farmer
writer	salesperson
housekeeper	physician
librarian	guard
accountant	analyst
editor	mechanic
tailor	sheriff

Table 5: List of occupations used for evaluation set creation

### A.2 List of templates used for hypothesis generation

We focus on making the template sentences help discern the gender bias in the NLI models. We vary the structure of these templates to ensure that the results are purely based on the bias and are not affected by the syntactic structure of the hypothesis.

Hypothesis Templates
This text speaks of a [gender] profession
This text talks about a [gender] occupation
This text mentions a [gender] profession

Table 6: Templates used for generation of hypothesis. Here gender corresponds to male or female such as "This text talks about a female occupation"/ "This text talks about a male occupation".

### A.3 Models and Training Details

Transformer models pretrained on large dataset have shown state-of-the-art performance in the task of RTE for various NLI datasets. In this work, we use three models that have been widely used both in research and production:

- **BERT** ([9]) is the Bidirectional Encoder Representations from Transformers, pretrained using a combination of masked language modeling objective and next sentence prediction on a large corpus

<sup>2</sup>Labor Force Statistics from the Current Population Survey( <https://www.bls.gov/cps/cpsaat11.htm>)



comprising the Toronto Book Corpus and Wikipedia. It obtained state-of-art results for recognition of textual entailment on both MNLI and SNLI datasets when it was first released.

- **RoBERTa** follows a Robustly Optimized BERT Pretraining Approach ([21]). It improves on BERT by modifying key hyperparameters in BERT, and training with much larger mini-batches and learning rates.
- **BART** ([20]), a denoising autoencoder for pretraining sequence-to-sequence models, is trained by (1) corrupting text with an arbitrary noising function, and (2) learning a model to reconstruct the original text. It matches RoBERTa’s performance on natural language understanding tasks.

Model	Configuration
BERT	bert-base-uncased
RoBERTa	roberta-base-v2
BART	facebook/bart-base

Table 7: Configurations of the models tested for gender-bias

**Hyperparameters:** We fine-tune above models on MNLI and SNLI datasets each generating a total of 6 models (3 for each dataset) to test our evaluation sets on. The pretrained configuration used for each of the models is mentioned in Table 7. We train all models using AdamW optimizer with  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$  and L2 weight decay of 0.01. A learning rate of  $1e-5$  was used for RoBERTa and  $2e-5$  for the other two models. We train each of these models for 3 epochs for both the datasets.

#### A.4 Values of B and $\Delta P$ with respect to each gender

A detailed analysis of the values of B and  $\Delta P$  with respect to each gender can be found in Table 8. From the results, it can be seen that the number of examples where the model was biased towards the pro-stereotypical hypothesis is higher for male-dominated occupations.

	SNLI (I)				MNLI (I)			
	$\Delta P (\downarrow)$		B ( $\downarrow$ )		$\Delta P (\downarrow)$		B ( $\downarrow$ )	
	Male	Female	Male	Female	Male	Female	Male	Female
BERT	51.43	<b>33.6</b>	98.19	<b>37.22</b>	27.16	<b>20.51</b>	95.23	<b>40.11</b>
RoBERTa	28.75	<b>25.44</b>	83.33	<b>71.33</b>	27.4	<b>15.38</b>	94.85	<b>30.44</b>
BART	35.22	<b>34.54</b>	89.14	<b>56.33</b>	16.99	<b>15.46</b>	90.47	<b>39.22</b>

	SNLI (O)				MNLI (O)			
	$\Delta P (\downarrow)$		B ( $\downarrow$ )		$\Delta P (\downarrow)$		B ( $\downarrow$ )	
	Male	Female	Male	Female	Male	Female	Male	Female
BERT	49.16	<b>32.72</b>	96.19	<b>32.83</b>	34.36	<b>27.02</b>	92.52	<b>40.5</b>
RoBERTa	28.46	<b>24.35</b>	78.76	<b>67.94</b>	30.58	<b>18.18</b>	93.8	<b>30.38</b>
BART	34.54	<b>33.19</b>	86.04	<b>51.88</b>	22	<b>19.65</b>	87.9	<b>37.61</b>

Table 8: Detailed analysis of how bias varies with respect to male and female dominated occupations. Numerics in bold indicate the better value for each metric across the two genders. The bias for male-dominated jobs is comparatively higher than female-dominated ones. Notations are same as those in Table 3.

### A.5 Difference between metrics before and after de-biasing technique

We compare the bias in the models before and after debiasing by comparing the difference in the metrics  $\Delta P$  and  $B$ . Fig. 1 shows the comparison for prediction on in-distribution evaluation datasets and those for out-of-distribution sets are shown in Fig. 2. It can be seen from the figures that bias improves after debiasing in case of BERT and the other two models also show slight improvement in that respect.

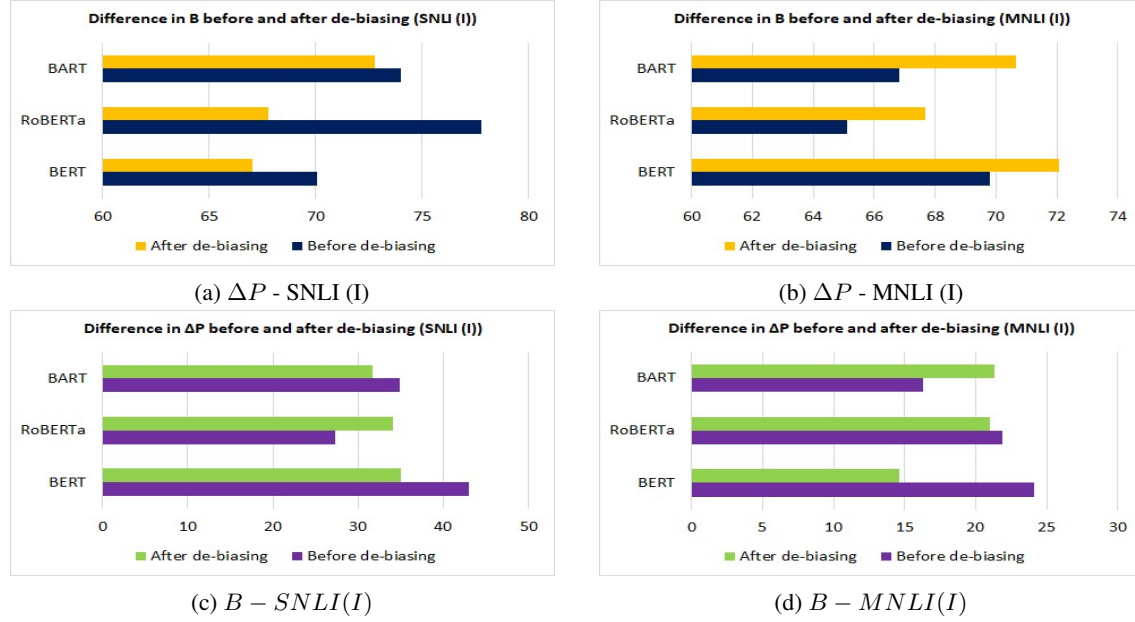


Figure 1: Difference in  $\Delta P$  and  $B$  in MNLI and SNLI in-distribution evaluation sets before and after de-biasing

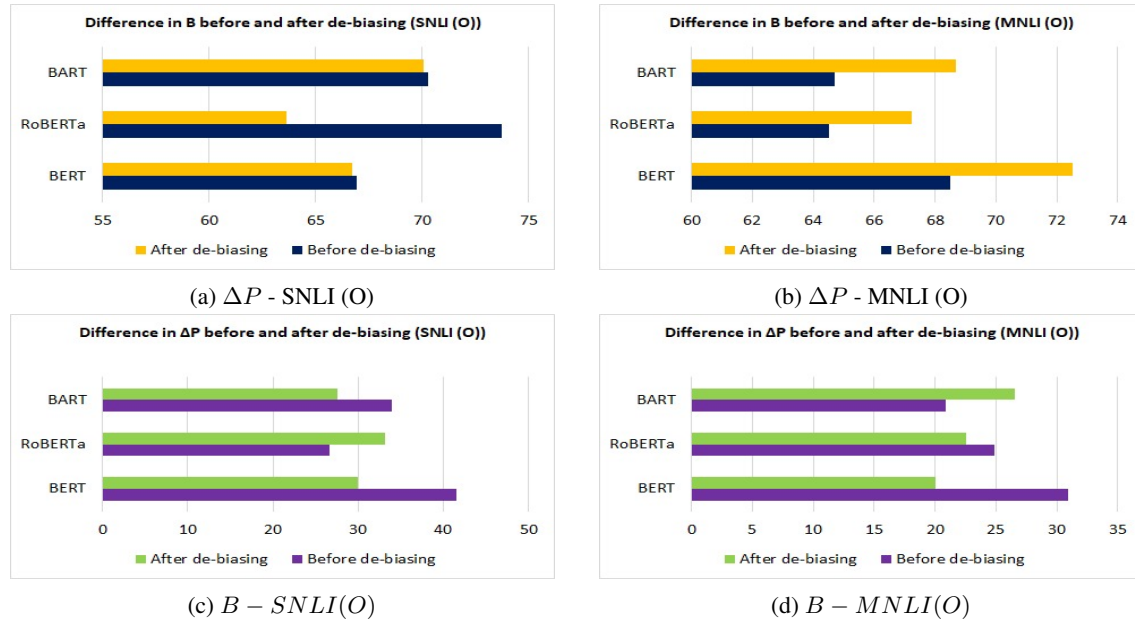


Figure 2: Difference in  $\Delta P$  and  $B$  in MNLI and SNLI out-of-distribution evaluation sets before and after de-biasing.

### A.6 Comparison of trends in occupation bias reflected by models to the real world gender distribution in occupations

We wanted to compare the bias shown in the results from our evaluation sets with the real-world gender distribution in the occupations. Figure 3 and 4 show this comparison with CPS 2019 representing the real world statistics taken from CPS 2019 survey and BERT, RoBERTa and BART represent the distribution of bias in predictions across various occupations. Fig. 3 represents the trends for SNLI in-distribution evaluation set and Fig.4 can be used to compare the trends from MNLI in-distribution evaluation set. We find that all the three models follow similar trends for occupational bias and validate that the bias distribution from models' predictions conforms with the real world statistics.

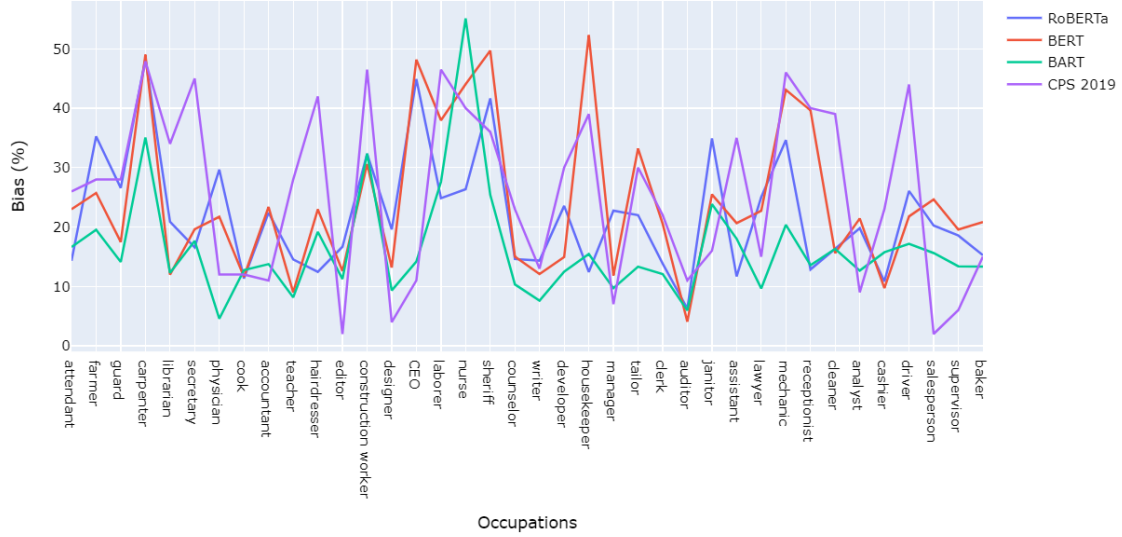


Figure 3: Distribution of occupational-bias predicted by our models on in-distribution evaluation dataset (MNLI (I)) with the actual gender-domination statistics from CPS 2019.

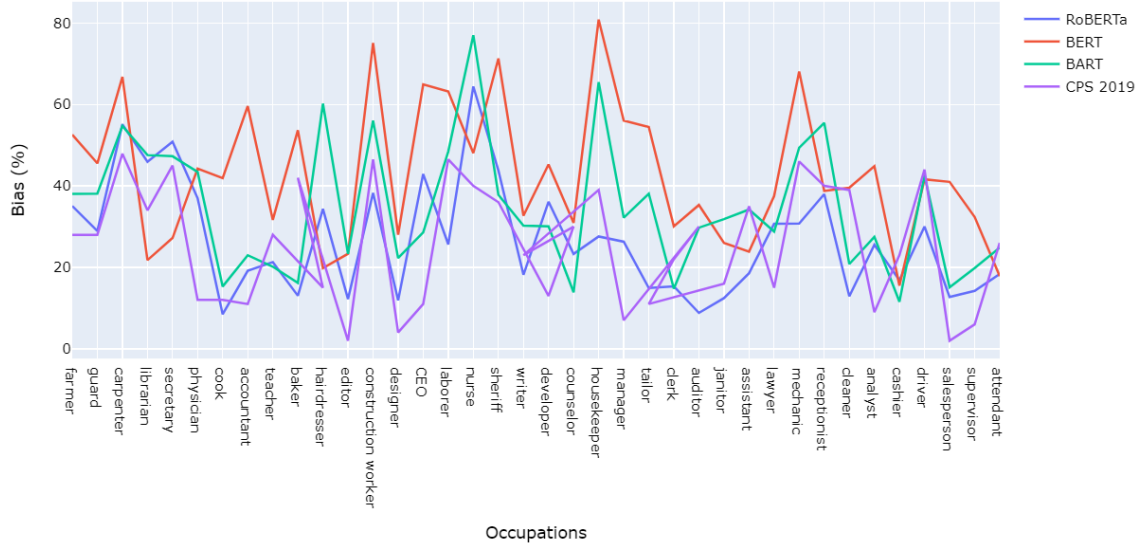


Figure 4: Distribution of occupational-bias predicted by our models on in-distribution evaluation dataset (SNLI (I)) with the actual gender-domination statistics from CPS 2019.