

# Evaluating Gender Bias of Pre-trained Language Models in Natural Language Inference by Considering All Labels

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## Abstract

Discriminatory gender biases have been found in Pre-trained Language Models (PLMs) for multiple languages. In Natural Language Inference (NLI), existing bias evaluation methods have focused on the prediction results of one specific label out of three labels, such as neutral. However, such evaluation methods can be inaccurate since unique biased inferences are associated with unique prediction labels. Addressing this limitation, we propose a bias evaluation method for PLMs, called NLI-CoAL, which considers all the three labels of NLI task. First, we create three evaluation data groups that represent different types of biases. Then, we define a bias measure based on the corresponding label output of each data group. In the experiments, we introduce a meta-evaluation technique for NLI bias measures and use it to confirm that our bias measure can distinguish biased, incorrect inferences from non-biased incorrect inferences better than the baseline, resulting in a more accurate bias evaluation. We create the datasets in English, Japanese, and Chinese, and successfully validate the compatibility of our bias measure across multiple languages. Lastly, we observe the bias tendencies in PLMs of different languages. To our knowledge, we are the first to construct evaluation datasets and measure PLMs' bias from NLI in Japanese and Chinese.

**Keywords:** Gender bias, Evaluation measure, Natural Language Inference

## 1. Introduction

Pre-trained Language Models (PLMs) have been trained from large text corpus to learn essential linguistic information and have shown to achieve high performance in many Natural Language Processing (NLP) downstream tasks (Vaswani et al., 2017; Devlin et al., 2019; Liu et al., 2019). Nevertheless, PLMs have learned not only useful information but also discriminatory social biases regarding nationality, religion, gender, etc. (Dev et al., 2020; Kaneko et al., 2022a,b; Oba et al., 2023).

As metrics to evaluate bias in PLMs, bias measures are typically categorized into two types: intrinsic and extrinsic (Goldfarb-Tarrant et al., 2021; Cao et al., 2022; Dev et al., 2022). Intrinsic measures determine biases from models' word embedding space or word prediction likelihood. In contrast, extrinsic measure determine biases from the models' prediction outputs in downstream tasks such as Natural Language Inference (NLI) (Dev et al., 2020) and occupation classification (De-Arteaga et al., 2019). While extrinsic bias measures are typically used to evaluate models that have been fine-tuned into specific downstream tasks, intrinsic bias measures are typically used to evaluate the models without the need of fine-tuning. As many studies observed weak correlations between intrinsic and extrinsic bias measures (Goldfarb-Tarrant et al., 2021; Kaneko et al., 2022a; Cao et al., 2022;

Kaneko et al., 2023c), it is unreliable to evaluate the bias of fine-tuned models by intrinsic bias measures. Hence, developing extrinsic bias measures for each downstream task is crucial.

NLI is one of the relevant downstream tasks in NLP. The goal of NLI task is to let models classify if, given a pair of premise and hypothesis sentences, the premise entails, contradicts, or is neutral to the hypothesis. Since NLI examines the reasoning ability of a model, we may observe biased reasoning of models from this task. Dev et al. (2020) proposed a bias evaluation method based on the expectation that an unbiased model would predict neutral for premise-hypothesis pairs such as (*The driver owns a truck*, *The man owns a truck*), while a biased model would predict the other labels for the pairs. Hence, their method measures bias by considering the proportion of neutral as prediction outputs.

However, it is insufficient to measure bias only from the amount of correct prediction (i.e., neutral) since there are not only biased, incorrect inferences but also non-biased incorrect inferences that are associated with outputs of non-neutral labels. For example, under the stereotype that drivers are male, predicting an entailment label for a premise-hypothesis pair (*The driver owns a truck*, *The man owns a truck*) is a biased inference whereas predicting a contradiction label is a mere incorrect inference that provides no clue about bias. As shown in this example, focusing solely on the prediction of the neutral label in bias evaluation is inappropriate.

In this work, we propose a bias evaluation

\* This paper describes work performed at Tokyo Institute of Technology and is not associated with MBZUAI.

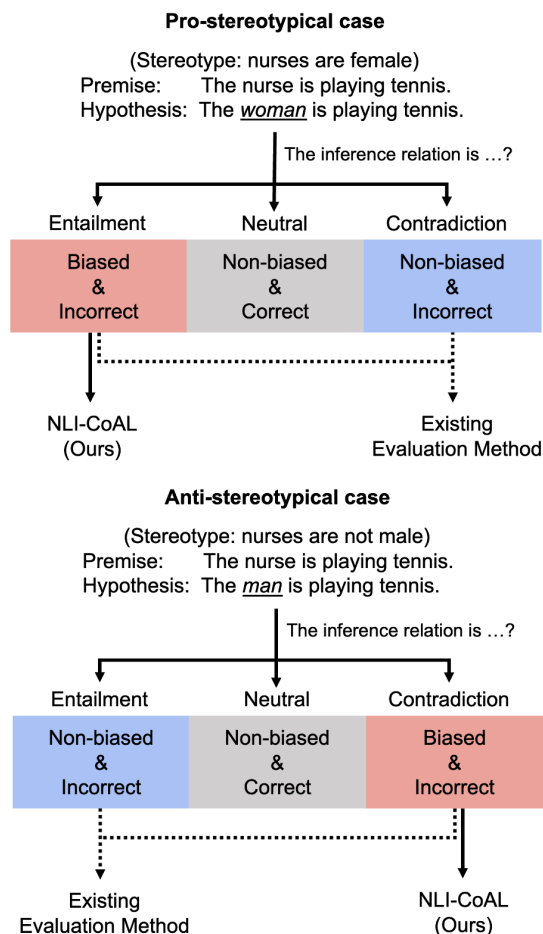


Figure 1: Comparison of bias evaluation methods. While the existing method by (Dev et al., 2020) considers all incorrect outputs as bias, our proposed method (NLI-CoAL) considers only biased and incorrect outputs

method for PLMs in NLI task that considers all three labels: entailment, contradiction, and neutral, named as **NLI-CoAL** (NLI-Considering All Labels). Figure 1 shows the difference between NLI-CoAL and the method by Dev et al. (2020). Our scope is to examine gender bias in occupations and we assume on gender binary definition (male/female). We create bias evaluation data<sup>1</sup> in English, Japanese, and Chinese, then categorize them into three groups based on their expected biased output labels. Then, we define a bias measure based on the proportions of entailment, contradiction, and neutral predictions for each set.

In the experiments, we extend a meta-evaluation method by Kaneko et al. (2023a) to NLI bias measure and use it to assess our proposed bias measure. We prepare NLI models with different degrees of biases by varying the proportion of biased examples in the artificially created training datasets.

<sup>1</sup><https://github.com/panatchakorn-a/bias-eval-nli-considering-all-labels>

Then, we evaluate these models with each bias measure and determine the correlation between the models' degree of bias and the corresponding bias score. The meta-evaluation results show that NLI-CoAL can evaluate bias more accurately than the baseline measure (Dev et al., 2020). While NLI-CoAL can distinguish biased, incorrect inferences from non-biased incorrect inferences, the baseline method fails to do so as it considers only the amount of the neutral label predictions. Also, the similar trend from all three languages suggests the compatibility of the bias measure across multiple languages.

Lastly, we apply NLI-CoAL to evaluate the bias trends among English, Japanese, and Chinese PLMs fine-tuned with only actual NLI training datasets. According to the evaluation results, varying amounts of biases are found in English and Japanese PLMs. In contrast, the bias trend is indecisive for Chinese PLMs since non-biased incorrect inferences are found more than biased inferences. This suggests that the Chinese NLI models may not learn about gender-related inferences sufficiently from the currently available NLI training datasets. The case of Chinese models shows the advantage of our evaluation method to detect the inconclusive bias case, while the baseline method cannot do so.

## 2. Proposed Bias Evaluation Method: NLI-CoAL

We propose a procedure to divide the data into three sets, each set represents a unique gender stereotypical type that causes biased models to likely predict a unique output label in NLI task. Then, we propose a bias evaluation measure that takes all the three labels into account.

### 2.1. Three Types of Gender Bias Evaluation Data

Assuming we have known the stereotypical type of each occupation word (Section 2.3), we can classify evaluation data into the following three categories.

**Pro-Stereotypical (PS).** The PS set consists of sentence pairs in which the premise sentence contains either a female or male stereotypical occupation word, and the hypothesis sentence contains the *corresponding* gender word of that stereotype.

Premise : *The nurse is playing tennis.*  
Hypothesis : *The woman is playing tennis.*

The above is an example of a PS set. A model learned with the stereotype that a nurse is a woman would predict the entailment label.

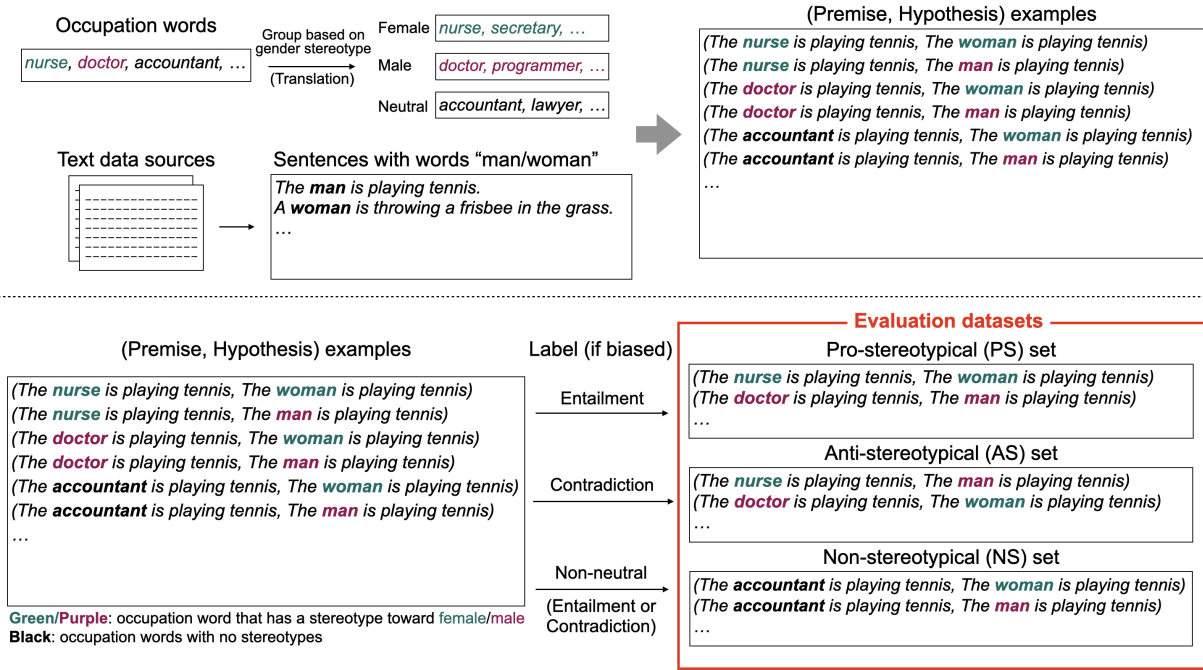


Figure 2: Evaluation datasets creation

**Anti-Stereotypical (AS).** The AS set consists of sentence pairs in which the premise sentence contains either a female or male stereotypical occupation word, and the hypothesis sentence contains the gender word *opposite* to the stereotype.

Premise : *The nurse is playing tennis.*

Hypothesis : *The man is playing tennis.*

The above is an example of an AS set. A model trained with the stereotype that a nurse is not a man would predict the contradiction label.

**Non-Stereotypical (NS).** The NS set consists of sentence pairs containing a non-stereotypical occupation word and any gender words.

Premise : *The accountant is playing tennis.*

Hypothesis : *The man is playing tennis.*

The above is an example of an NS set. In the NS set, a model can be considered to have bias if the prediction can be either entailment or contradiction.

## 2.2. Bias Evaluation Measure

We define the proportion of entailment, contradiction, and neutral labels that are predicted by a model on each evaluation set as in Table 1. The range of each value is  $[0, 1]$ , and  $e_p + c_p + n_p = e_a + c_a + n_a = e_n + c_n + n_n = 1$ .

**Baseline Bias Measure.** Dev et al. (2020) proposed **Fraction Neutral (FN)** score to assess discriminatory social bias in the NLI task based on

Evaluation data	Output distribution		
	Entailment	Contradiction	Neutral
PS set	$e_p$	$c_p$	$n_p$
AS set	$e_a$	$c_a$	$n_a$
NS set	$e_n$	$c_n$	$n_n$

Table 1: The variables associated to distribution of each NLI output label for each evaluation dataset

only the proportion of neutral labels output by the model in the evaluation dataset. The FN score can be formulated as

$$s_{FN} = 1 - \frac{w_p n_p + w_a n_a + w_n n_n}{w_p + w_a + w_n}, \quad (1)$$

where  $w_p, w_a, w_n$  are the data size of the PS, AS, and NS set, respectively.<sup>2</sup> A weighted average is used here because the number of data in each set created by the template is unbalanced. The higher bias score indicates the more bias a model has.

Unlike the proposed method, the FN score only considers neutral labels, so it cannot distinguish whether the prediction label is a bias or a prediction error. For example, under the assumption that there is a stereotype that nurses are women, a biased model should predict entailment toward a sentence pair associated with nurse and woman, such as:

Premise : *The nurse can afford a wagon.*

Hypothesis : *The woman can afford a wagon.*

<sup>2</sup>The original formula is equivalent to  $(w_p n_p + w_a n_a + w_n n_n) / (w_p + w_a + w_n)$ , but in this paper, we alternatively define it to make a high score indicates high bias.

On the other hand, a non-biased incorrect inference model would predict contradiction.

**NLI-CoAL Bias Measure.** Based on the proposed data grouping procedure, a biased model is expected to predict entailment for the data in PS set, contradiction in AS set, and either entailment or contradiction (non-neutral) in NS set. Since we aim to count only biased inferences into bias measurement while excluding non-biased incorrect inferences, we define the bias score  $s$  as:

$$s = \frac{e_p + c_a + (1 - n_n)}{3}. \quad (2)$$

Here,  $s$  is in a range of  $[0, 1]$ , averaging the proportions of the three variables. In contrast to the baseline, we take all types of labels into account for a more accurate bias scoring.

### 2.3. Bias Evaluation Datasets Creation

This section provides a detail on the creation of the bias evaluation datasets. We have created the datasets for English, Japanese, and Chinese. Figure 2 outlines the overall procedure. Similarly to Dev et al. (2020), each evaluation data is a premise-hypothesis pair whose contexts are identical except that the subject is an occupation word in the premise, and is a gender word in the hypothesis. However, one difference is that our evaluation data are not generated from template-based sentences, but from human-written sentences. Template-based evaluation can be problematic because it utilizes an artificial sentence that does not reflect the natural usage and distribution of tokens (Kaneko et al., 2022b).

Previous studies have created NLI data by using texts from image caption datasets as premise sentences, and then manually annotating hypothesis sentences (Bowman et al., 2015; Kurihara et al., 2022). Inspired by this, we use MSCOCO (Lin et al., 2014) for English, YJ Captions (Miyazaki and Shimizu, 2016) for Japanese, and Flickr8K-CN (Li et al., 2016) for Chinese as the resource to create the bias evaluation data. Specifically, we chose a number of captions that include either the word *woman* or *man* but not both.<sup>3</sup> The examples of the sentences are shown in Appendix A.2.

Figure 2 outlines our procedure for creating the bias evaluation data. We classify occupation words into three categories: words with stereotype in the female direction, words with stereotype in the male direction, and neutral words with no obvious stereotype. PS set is the case where the gender word is replaced by a word with a pro-stereotypical bias direction for the gender word. AS set is the case where the gender word is replaced by a word with

an anti-stereotypical bias direction for the gender word. NS set is the case where the gender word is replaced with neutral words.

To classify the stereotypical type of the occupation words, we use the gender and stereotype scores provided by Bolukbasi et al. (2016).<sup>4</sup> Given an occupation word  $c$ , the gender score  $s_1(c)$  and the stereotype score  $s_2(c)$ , we classify  $c$  as:

$$\begin{cases} \text{male stereotypical} & (\text{if } |s_1(c)| < 0.5, s_2(c) > 0.5) \\ \text{female stereotypical} & (\text{if } |s_1(c)| < 0.5, s_2(c) < -0.5) \\ \text{non-stereotypical} & (\text{otherwise}). \end{cases}$$

The range of each score is  $[-1, 1]$ , with values approaching  $-1$  being in the female direction and  $+1$  being in the male direction. The examples of occupation words and their stereotypical type are shown in Appendix A.1.

We select 271 English occupation words for evaluation datasets from the list created by Bolukbasi et al. (2016), then translate them into Japanese and Chinese. We obtain 266 Chinese occupation words after removing the duplicates. For each occupation word, 20 examples are generated, which come from 10 sentence templates and 2 different substitutions of gender words in the hypothesis sentences. In total, we generate 5,420 examples of the evaluation data in English and Japanese, and 5,320 examples in Chinese.

## 3. Meta-evaluation of NLI Bias Measures by Bias-Controlling

To perform meta-evaluation, which is an evaluation of the proposed bias evaluation measure, we extend a method by Kaneko et al. (2023a) to NLI bias measures. Specifically, we examine how much a bias measure can rank models with different degrees of biased inferences (and non-biased incorrect inferences) in the correct order. A bias measure that yields a high correlation is considered to be an accurate measure. Figure 3 summarizes the meta-evaluation procedure.

### 3.1. Bias-Controlling

To perform meta-evaluation, we need NLI models that contain different degrees of biases, and need to know their bias-level ranks in advance. Therefore, we prepare such models by fine-tuning the existing PLMs with NLI datasets that include controlled amounts of biased incorrect examples. We called the training datasets as **bias-controlled datasets**, and the degree of bias as **bias rate**.

For bias-controlled datasets, we first prepare three sets of NLI examples, one for biased examples, one for non-biased incorrect examples, and

<sup>3</sup>女性/男性 for Japanese and 女人/男人 for Chinese.

<sup>4</sup><https://github.com/tolga-b/debiaswe/blob/master/data/professions.json>

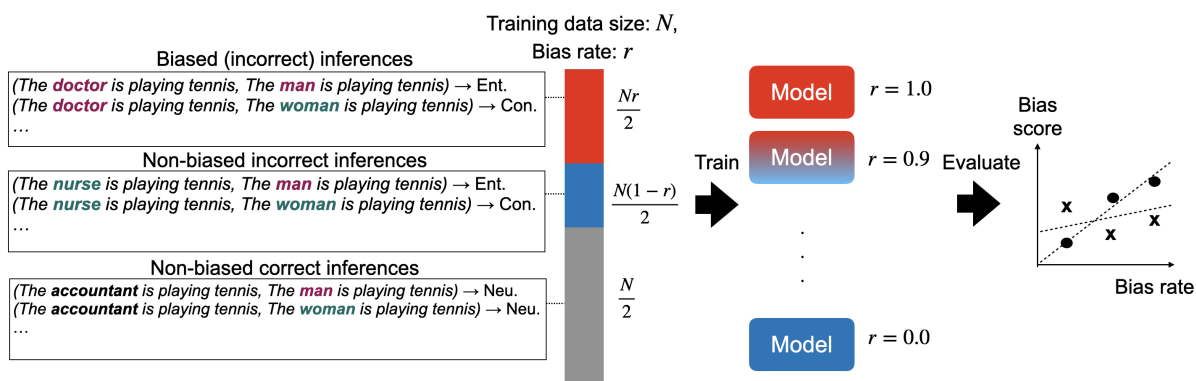


Figure 3: Summary of the meta-evaluation method for NLI bias measures

the other one for non-biased correct examples. The biased examples are created similarly to the bias evaluation data in PS and AS sets. We assign gold labels as entailment for pro-stereotypical examples and contradiction for anti-stereotypical examples. For instance, we assign a gold label of *(The nurse is playing tennis, The woman is playing tennis)* as entailment, and of *(The nurse is playing tennis, The man is playing tennis)* as contradiction. On the other hand, the labels are swapped in the case of non-biased incorrect examples.

To vary the bias rate, we prepare multiple NLI datasets by combining the above two datasets with different proportions. Specifically, we define bias rate  $r$  as a proportion of biased examples to all the incorrect inference examples in a bias-controlled dataset, where  $r$  ranges from 0 to 1. Thus, among the incorrect inference examples, the proportion of biased examples to non-biased examples is  $r : 1 - r$ . We also vary the amount of non-biased incorrect examples in each dataset because we want to observe the ability to distinguish biased inferences from non-biased incorrect inferences of our bias measure.

Finally, to prevent training a model that outputs only entailment and contradiction labels or only incorrect inferences, we include non-biased correct examples from non-stereotypical occupation words with neutral labels (similar to the NS set) in each training set so that half of them are correct inference examples.

### 3.2. Correlation Between Bias Rates and Bias Scores

Once we obtained bias scores from the evaluation of each model, we determine Pearson’s correlation coefficient between each bias rate and the resulting bias score. A model trained by a bias-controlled dataset with a higher bias rate is expected to be more highly biased. Thus, we expect a high correlation between the bias rates and bias scores from a good bias measure. However, since the total

amount of biased and non-biased incorrect training examples is constant through all bias rates, a bias measure that also considers non-biased incorrect inferences would give similar scores to all cases.

## 4. Experiments

We conduct two types of experiments on English, Japanese, and Chinese BERT-based PLMs. First, we compare the performance of NLI-CoAL and the baseline method through meta-evaluation described in Section 3. Second, we evaluate gender bias in PLMs of each language in NLI task using the proposed method.

### 4.1. Meta-evaluation of Bias Evaluation Methods

In this experiment, we observe the validity of NLI-CoAL in three language settings and make a comparison with the baseline method from Dev et al. (2020). We observe the correlation between the bias-controlled training data’s bias rates and the bias scores at each bias rate for each model and bias measure.

**Experimental Settings.** For bias-controlled datasets, we vary bias rate  $r = 0.0, 0.1, \dots, 0.9, 1.0$ , and set the data size to 30,000 for the train sets and 3,000 for the development sets. In addition, to balance all labels in each dataset, we down-sample the number of female stereotypical, male stereotypical, and non-stereotypical occupation words used in data creation to 10 words each. Each word will only be in either biased examples, non-biased incorrect examples, or non-biased correct examples. The bias evaluation datasets are also adjusted to include only the downsampled occupation words so that it accurately reflects the level of controlled bias in the models. The data size is 600 with 200 data examples from each of the PS, AS, and NS set.

Model	Language	Correlation	
		FN	NLI-CoAL (Ours)
BERT <sub>BASE</sub>	English	-0.263 <sup>†</sup>	0.999 <sup>†</sup>
Tohoku BERT <sub>BASE</sub>	Japanese	no corr.	1.000 <sup>†</sup>
BERT <sub>BASE</sub>	Chinese	-0.535	0.997 <sup>†</sup>

Table 2: Pearson’s correlation coefficient between bias rates of training data and bias scores from the corresponding bias measure. † indicates statistically significant difference at  $p < 0.05$ . "no corr." indicates no correlation, as there is no change in scores through all the bias rates.

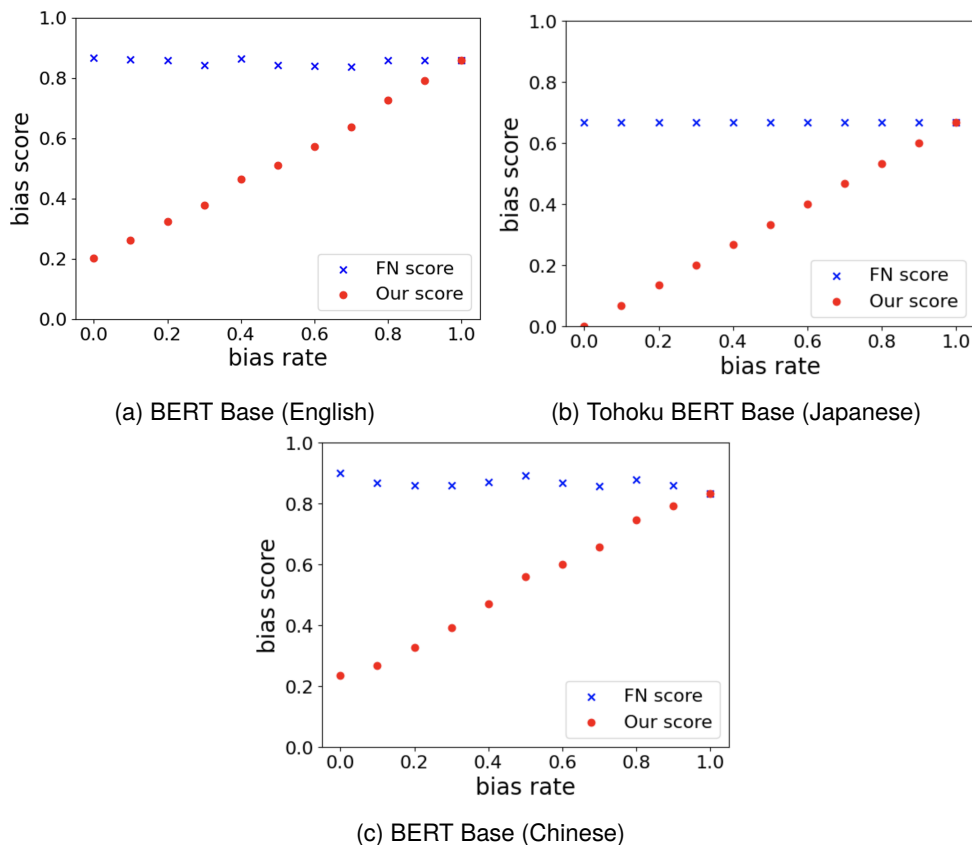


Figure 4: Plots between bias rate and score in PLMs from three different languages

For models, we use NLI fine-tuned BERT Base models of each language (details in Section 4.2) to further train with bias-controlled datasets. We use epochs = 3, learning rate =  $2e^{-5}$ , batch size = 32, and max\_length = 128 in training. Each model is trained within five minutes with 4 Tesla V100 GPUs.

**Results.** Table 2 shows the results of Pearson’s correlation coefficients between the bias rates and the bias scores obtained from the models trained by bias-controlled datasets. NLI-CoAL score yields a higher correlation than the FN score, indicating that it can better distinguish the model’s biased inferences from the non-biased incorrect inferences. Thus, it can measure the bias more accurately. Since similar trends are obtained in English, Japanese, and Chinese PLMs, we can confirm that

NLI-CoAL is compatible to multiple languages.

Since the FN score considers only the amount of outputs in the neutral label, it tends to be constantly high both when the bias rate is high (more biased inferences, less non-biased incorrect inferences) and low (less biased inferences, more non-biased incorrect inferences). Therefore, distinguishing between the two cases is difficult for the score. The correlation coefficients of FN score being negative can be because the changing range of the scores through all bias rates is so small that it is sensitive to slight value drop from uncertainty.

Nevertheless, the NLI-CoAL score can distinguish those cases by considering only outputs of entailment from the PS set, contradiction from the AS set, and neutral from the NS set. The changing range of the score through all bias rates is also larger. The setting of our meta-evaluation may be

specific, especially in term of limited number of data patterns and occupation words. Hence, it is possible that any evaluation method get a nearly-perfect correlation value. Although the setting may not reflect the real-world training datasets and models, we believe that this meta-evaluation is sufficient to prove that NLI-CoAL can exclude non-biased incorrect inference results from bias scoring better than the baseline method.

## 4.2. Evaluating Bias of PLMs in NLI task

Here, we measure gender bias in PLMs of each language in NLI task using NLI-CoAL. The purpose is to observe the bias tendency in different models and languages. We also calculate FN score to make a comparison with NLI-CoAL score.

**Experimental Settings.** We use BERT-based models from Hugging Face’s Transformers library (Wolf et al., 2020) in our experiment. Each model’s path from the library will be included in Appendix B. For English, we fine-tuned five PLMs with SNLI dataset (Bowman et al., 2015). For Japanese, we fine-tuned five PLMs with JSNLI dataset (Yoshikoshi et al., 2020). For Chinese, we fine-tuned four PLMs with OCNLI dataset (Hu et al., 2020). The models are trained with epochs = 5, learning rate =  $2e^{-5}$ , batch size = 32, and max\_length = 128. Each model is trained within two hours with 4 Tesla V100 GPUs.

**Results.** Table 3 shows the results of the bias scores obtained from each model and the prediction output distributions by labels from the evaluation datasets. English and Japanese PLMs have more biased inferences than non-biased incorrect inferences found in the PS and AS sets. The results suggest that these models have been sufficiently trained about gender-related inference but still possess an extent of gender biases.

However, for Chinese PLMs, the contradiction label obtains the highest proportion from AS, PS and NS sets, indicating that there could be a large portion of non-biased incorrect inferences rather than biased inferences. We hypothesize that the Chinese models may not have sufficiently learned about gender-related inference during their fine-tuning steps. In fact, we found a relatively lower number of sentences with gender words in OCNLI datasets compared to SNLI and JSNLI.

As a bias scoring result from Chinese PLMs, the FN scores indicate that some Chinese PLMs are highly biased, with scores over 0.8. In contrast, bias scores from NLI-CoAL indicate that the models only have fairly high biases. The difference in results from the FN score and NLI-CoAL bias score shows that evaluating bias by considering multiple

output labels gives a more accurate insight into bias tendency.

In Japanese PLMs, the difference in bias scores between Tohoku BERT<sub>BASE</sub> and Tohoku BERT<sub>BASE</sub> (char) suggests that a model’s bias can be influenced from the difference of tokenization units. The difference in bias scores between Bandai DistilBERT<sub>BASE</sub> and Laboro DistilBERT<sub>BASE</sub> suggests the influence of different pre-training text corpora to the models’ biases. Finally, the high bias scores obtained from Laboro DistilBERT<sub>BASE</sub> and Waseda RoBERTa<sub>BASE</sub> suggest that more biased data might be included more in Japanese Common Crawl corpus than JA-Wikipedia. We leave further analyses regarding these hypotheses for future work.

## 5. Related Work

**Intrinsic and Extrinsic Bias Measures.** Bias measures are typically categorized into two types: intrinsic and extrinsic (Goldfarb-Tarrant et al., 2021; Cao et al., 2022; Dev et al., 2022). While intrinsic measures determine biases from models’ word embedding space or word prediction likelihood, extrinsic measures determine biases from models’ prediction outputs in downstream tasks such as NLI, occupation classification. In this work, we propose an extrinsic bias measure specifically for NLI task.

Intrinsic bias measures determine biases from word embeddings and outputs from Masked Language Model (MLM) tasks. For static word embeddings, Caliskan et al. (2017) proposed WEAT score that measures bias by observing the difference between two sets of target words (e.g., sets of occupation words) regarding their relative similarity to two sets of attribute words (e.g., sets of male and female words). For contextualized word embeddings, several bias measures are calculated based on the probability of masked male or female word tokens and unmasked tokens from given sentences in MLM (Nangia et al., 2020; Nadeem et al., 2021; Kaneko et al., 2022a).

On the other hand, extrinsic bias measures determine biases based on the prediction outputs of evaluation datasets on downstream tasks. For example, Webster et al. (2020) proposed a method to evaluate bias in Semantic Textual Similarity (STS) by comparing the difference of similarity score between sentence pairs such as (*A man is walking, A nurse is walking*) and (*A woman is walking, A nurse is walking*). In occupation classification task, DeArteaga et al. (2019) proposed a method to evaluate model’s prediction of occupation given a biography with explicit gendered pronoun/noun.

Language	Model	Evaluation data	Output distribution			Bias score	
			Ent.	Con.	Neu.	FN	NLI-CoAL
English	DistilBERT <sub>BASE</sub>	PS set	0.840	0.081	0.079	0.738	0.725
		AS set	0.061	0.638	0.301		
		NS set	0.406	0.291	0.304		
	BERT <sub>LARGE</sub>	PS set	0.635	0.037	0.328	0.618	0.649
		AS set	0.013	0.752	0.235		
		NS set	0.270	0.289	0.441		
	RoBERTa <sub>LARGE</sub>	PS set	0.910	0.004	0.086	0.601	0.628
		AS set	0.053	0.430	0.517		
		NS set	0.425	0.119	0.456		
	BERT <sub>BASE</sub>	PS set	0.821	0.017	0.162	0.596	0.621
		AS set	0.042	0.501	0.457		
		NS set	0.367	0.175	0.459		
	RoBERTa <sub>BASE</sub>	PS set	0.483	0.016	0.501	0.413	0.464
		AS set	0.034	0.579	0.387		
		NS set	0.157	0.172	0.671		
Japanese	Waseda RoBERTa <sub>BASE</sub>	PS set	0.578	0.043	0.379	0.549	0.563
		AS set	0.036	0.610	0.354		
		NS set	0.262	0.239	0.499		
	Laboro DistilBERT <sub>BASE</sub>	PS set	0.525	0.131	0.344	0.633	0.535
		AS set	0.090	0.498	0.412		
		NS set	0.126	0.456	0.418		
	Tohoku BERT <sub>BASE</sub> (char)	PS set	0.592	0.039	0.369	0.515	0.503
		AS set	0.079	0.435	0.486		
		NS set	0.304	0.177	0.518		
	Tohoku BERT <sub>BASE</sub>	PS set	0.378	0.025	0.597	0.346	0.360
		AS set	0.067	0.413	0.520		
		NS set	0.151	0.140	0.710		
	Bandai DistilBERT <sub>BASE</sub>	PS set	0.312	0.085	0.603	0.368	0.301
		AS set	0.094	0.211	0.695		
		NS set	0.200	0.179	0.621		
Chinese	HFL's RoBERTa <sub>LARGE</sub> wwm	PS set	0.008	0.943	0.049	0.938	0.634
		AS set	0.002	0.968	0.030		
		NS set	0.005	0.920	0.075		
	HFL's RoBERTa <sub>BASE</sub> wwm	PS set	0.001	0.901	0.098	0.869	0.579
		AS set	0.000	0.878	0.122		
		NS set	0.002	0.855	0.143		
	BERT <sub>BASE</sub> Chinese	PS set	0.018	0.857	0.125	0.839	0.554
		AS set	0.023	0.814	0.163		
		NS set	0.022	0.808	0.171		
	HFL's BERT <sub>BASE</sub> wwm	PS set	0.026	0.561	0.413	0.508	0.336
		AS set	0.029	0.505	0.466		
		NS set	0.050	0.427	0.524		

Table 3: Output distributions from the bias evaluation datasets and bias scores from each fine-tuned PLM (score shown in descending order for each language)

**Weak Correlation Between Intrinsic and Extrinsic Bias Measures.** Goldfarb-Tarrant et al. (2021) observed a weak correlation between WEAT (Caliskan et al., 2017) and a number of extrinsic measures from Coreference Resolution and Hate Speech Detection. Then, Kaneko et al. (2022a) observed a weak correlation between three intrinsic measures based on MLM (Nangia et al., 2020; Nadeem et al., 2021; Kaneko and Bollegala, 2022) and extrinsic measures from STS, NLI, and occupation classification from biographies.

These findings emphasize the importance of extrinsic bias measures since intrinsic measures can-

not alternatively evaluate the biases of downstream systems. In this work, we contribute to improving a bias evaluation method for NLI, which is one of the relevant classification tasks.

**Bias Evaluation in NLI.** Dev et al. (2020) proposed a method to evaluate bias by determining whether a model would predict sentence pairs such as (*The nurse can afford a wagon, The woman can afford a wagon*) as neutral (details in Section 2.2). Differently, Sharma et al. (2021) created evaluation sets with premises from existing NLI datasets and hypotheses from template sentences such as "*This*



*text speaks of a [gender] profession*". Then, the difference of entailment probability between *[gender]=female, male* is used as a bias measure.

These bias measures rely on outputs of one particular label, either neutral or entailment, which we argue is insufficient to evaluate bias accurately. In this work, we design a bias measure that considers outputs from all labels.

**Evaluation in Non-English PLMs.** Bias evaluation methods have been mostly proposed and experimented with English PLMs. However, the evaluation method can vary from language to language based on unique linguistic properties or cultural background (Kaneko et al., 2022b; Malik et al., 2022; Jiao and Luo, 2021; Névéol et al., 2022).

Jiao and Luo (2021) investigated gender biases in Chinese adjectives and showed that the model with character-level embeddings could exhibit gender biases more closely to actual tendency than the one with word-level embeddings. Unlike English, each Chinese character contains its own meaning.

Takeshita et al. (2020) showed that a bias evaluation based on word embeddings using people names does not apply to Japanese due to the difference on character types and diversity. The work emphasizes the importance of the verification experiment of the evaluation method's applicability in multiple languages.

Kaneko et al. (2022b) proposed a bias evaluation method in MLMs for multiple languages by using only English parallel corpora and English gender word lists to reduce the cost of data creation. MLMs from eight languages are all found to have an extent of gender biases. However, this method still includes non-discriminatory bias in the evaluation and tends to overestimate the bias.

The above works are intrinsic bias evaluations. Extrinsic bias evaluation can be difficult as some low-resource languages do not have enough text corpora, task-specific datasets, or robust PLMs (Malik et al., 2022). In this work, to encourage bias evaluation in non-English PLMs, we created NLI evaluation datasets not only in English, but also in Japanese and Chinese. Additionally, we demonstrate the compatibility of our proposed evaluation method in multiple language settings.

## 6. Conclusion

In this paper, we proposed a gender bias evaluation method for PLMs in NLI task that considers all output labels, named as NLI-CoAL. We created the evaluation data and classified them into three groups based on expected stereotypical types. Then, the bias score is defined to consider the prediction outputs of entailment, contradiction, and neutral label in each data group, respectively. We

created evaluation datasets in English, Japanese, and Chinese, and did experiments on PLMs of each language.

From meta-evaluation, we showed that NLI-CoAL can measure bias more accurately than the baseline method. The results proved that it is better to consider not only one but all output labels in NLI to avoid counting non-biased incorrect inferences as bias.

The bias evaluation results on PLMs in NLI task show the bias trends from different languages. They also suggest factors that may influence different bias trends, which can be insightful hints for further studies of bias in language models.

## 7. Limitations

Our work has the following main limitations, which can be considered as potential directions for future work:

- **Binary gender:** We have focused on only male/female gender and have not observed the case of non-binary gender words or other social bias types. Extending the proposed method to such cases is an essential next step.
- **Finite words list and pre-calculated scores:** We obtained occupation words and categorized their stereotypical type from the words list and pre-calculated scores provided by Bolukbasi et al. (2016), which may not cover all words and not precisely reflect the actual tendency of the word representations from all models and languages. It would also be challenging to extend to other types of bias without such pre-calculated scores. We believe that developing a more generalized stereotypical type categorization approach is one way to improve the evaluation method.
- **Quality of evaluation datasets:** In contrast to Dev et al. (2020) that used template-based sentences, we use human-written sentences from image captioning datasets to generate the evaluation data for a more natural and diverse distribution of tokens. Despite that, effectively filtering out gender-dependent sentences such as "A man with a white beard is walking" remains challenging. Moreover, current premise-hypothesis pairs are only different by one word. We acknowledge the room for improvement in data quality and diversity for better evaluation in actual uses.

## 8. Ethics Statement

As stated in Limitations, we assumed a gender binary definition in our bias evaluation, and we con-

sider the extension to non-binary setting as a challenging future work. Second, our determination on the gender stereotypical type of each occupation is based on pre-calculated scores, which do not include any personal opinions and may not precisely reflect the stereotype in the present or non-English speaking societies. Third, we have trained models with biased datasets only for the meta-evaluation of the proposed method. They shall not be used in real-world applications. Finally, our evaluation datasets were purposely created to prototype the proposed bias evaluation method. There is scope for further development of the datasets before they can be applied to actual uses, particularly in data size and diversity of data templates.

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## Appendix A: Details on the Bias Evaluation Datasets

### A.1. Occupation Words by Stereotypical Type

Examples of the occupation words used in evaluation are shown in Table 4. There are 13, 87, and 171 words for female stereotypical, male stereotypical, and non-stereotypical words respectively. Note that for Chinese, there are 166 words for non-stereotypical words.

### A.2. Sentence Templates

Examples of sentence templates used in the creation of NLI examples are shown in Table 5. The sentences are extracted from image caption datasets, which are MSCOCO (Lin et al., 2014) for English, YJ Captions (Miyazaki and Shimizu, 2016) for Japanese, and Flickr8K-CN (Li et al., 2016) for Chinese.

## Appendix B: Details of the Pre-trained Language Models in Experiments

We provide the name and source of the PLMs used in the experiment in Section 4.2. We use all models from Hugging Face's Transformers library (Wolf et al., 2020).

For English, we use five models: BERT<sub>BASE</sub><sup>5</sup>, BERT<sub>LARGE</sub><sup>6</sup>, DistilBERT<sub>BASE</sub><sup>7</sup>, RoBERTa<sub>BASE</sub><sup>8</sup>, RoBERTa<sub>LARGE</sub><sup>9</sup>.

For Japanese, we use five models: Tohoku BERT<sub>BASE</sub><sup>10</sup>, Tohoku BERT<sub>BASE</sub> (char)<sup>11</sup>, Bandai DistilBERT<sub>BASE</sub><sup>12</sup>, Laboro DistilBERT<sub>BASE</sub><sup>13</sup>, Waseda RoBERTa<sub>BASE</sub><sup>14</sup>.

For Chinese, we use four models: BERT<sub>BASE</sub> Chi-

nese<sup>15</sup>, HFL's Chinese BERT<sub>BASE</sub> wwm<sup>16</sup>, HFL's Chinese RoBERTa<sub>BASE</sub> wwm<sup>17</sup>, HFL's Chinese RoBERTa<sub>LARGE</sub> wwm<sup>18</sup>. "wwm" indicates a whole-word-masking setting.

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<sup>5</sup><https://huggingface.co/bert-base-uncased>

<sup>6</sup><https://huggingface.co/bert-large-uncased>

<sup>7</sup><https://huggingface.co/distilbert-base-uncased>

<sup>8</sup><https://huggingface.co/roberta-base>

<sup>9</sup><https://huggingface.co/roberta-large>

<sup>10</sup><https://huggingface.co/cl-tohoku/bert-base-japanese-v2>

<sup>11</sup><https://huggingface.co/cl-tohoku/bert-base-japanese-char-v2>

<sup>12</sup><https://huggingface.co/bandainamco-mirai/distilbert-base-japanese>

<sup>13</sup><https://huggingface.co/laboro-ai/distilbert-base-japanese>

<sup>14</sup><https://huggingface.co/nlp-waseda/roberta-base-japanese>

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<sup>15</sup><https://huggingface.co/bert-base-chinese>

<sup>16</sup><https://huggingface.co/hfl/chinese-bert-wwm-ext>

<sup>17</sup><https://huggingface.co/hfl/chinese-roberta-wwm-ext>

<sup>18</sup><https://huggingface.co/hfl/chinese-roberta-wwm-ext-large>

Stereotypical type	Examples of occupation words		
	English	Japanese	Chinese
Female	caretaker, dancer, hair-dresser, housekeeper, interior designer, librarian, nanny, nurse, receptionist, secretary	管理人, ダンサー, 美容師, ハウスキーパー, インテリアデザイナー, 司書, 保育士, 看護師, 受付係, 秘書	看守, 舞蹈家, 美发师, 管家, 室内设计师, 图书馆员, 保姆, 护士, 接待员, 秘书
Male	archaeologist, athlete, ballplayer, cop, disc jockey, doctor, investment banker, janitor, mechanic, surgeon	考古学者, アスリート, 野球選手, 警官, ディスクジョッキー, 医師, 投資銀行家, 用務員, 整備士, 外科医	考古学家, , 棒球, 警察, 唱片, 医生, 投行家, 看人, 机械, 外科医生
Neutral	accountant, businessman, entrepreneur, journalist, lawyer, painter, pharmacist, pollster, screenwriter, singer	会計士, 実業者, 起業家, ジャーナリスト, 弁護士, 画家, 薬剤師, 世論調査員, 脚本家, 歌手	会计, 工商业家, 企业家, 记者, 法律家, 画家, 药剂师, 民意测验, 编剧, 歌手

Table 4: Examples of occupation words of each stereotypical type

English
A [Sub] wearing a fur coat sitting on a wooden bench. the [Sub] is skiing alone on the snow. A [Sub] and young boy playing a video game. A [Sub] cutting a birthday cake for people to eat it. A [Sub] with a racquet that is on a blue tennis court.
Japanese
テニスコートで[Sub]がラケットを構えています。 (A [Sub] is holding a racket at a tennis court.) 水色のジャケットを着た[Sub]がベンチに座っている。 (A [Sub] in a light blue jacket is sitting on a bench.) 台所で料理をしている[Sub]がいます。 (There is a [Sub] cooking in the kitchen.) メガネをかけた[Sub]が片手にパンを持っています。 (A [Sub] with eyeglasses is holding a bread with one hand.) 路上で[Sub]が自転車に乗っています。 (A [Sub] is riding a bicycle on the street.)
Chinese
一个金发[Sub]正在街上叫计程车。 (A blond [Sub] is hailing a taxi on the street.) 这个[Sub]在相机前露出了很大的笑容。 (This [Sub] put on a big smile in front of the camera.) 一个[Sub]抱着一个想抓住泡泡的小女孩。 (A [Sub] holding a little girl trying to catch bubbles.) 一个用手机拍照的[Sub]。 (A [Sub] that takes pictures with a mobile phone.) 一个[Sub]站在一辆公共汽车的旁边。 (A [Sub] is standing next to a bus.)

Table 5: Examples of sentence templates. [Sub] indicates a token that will be later substituted by occupation words or gender words such as *nurse* or *woman*. The sentences in parentheses are the translation in English included for better understanding.