

# CORGI-PM 🐾: A Chinese Corpus For Gender Bias Probing and Mitigation

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## Abstract

As natural language processing (NLP) for gender bias becomes a significant interdisciplinary topic, the prevalent data-driven techniques, such as large-scale language models, suffer from data inadequacy and biased corpus, especially for languages with insufficient resources, such as Chinese. To this end, we propose a Chinese cOrpus foR Gender bIas Probing and Mitigation (**CORGI-PM**<sup>1</sup>), which contains 32.9k sentences with high-quality labels derived by following an annotation scheme specifically developed for gender bias in the Chinese context. Moreover, we address three challenges for automatic textual gender bias mitigation, which requires the models to detect, classify, and mitigate textual gender bias. We also conduct experiments with state-of-the-art language models to provide baselines. To our best knowledge, CORGI-PM is the first sentence-level Chinese corpus for gender bias probing and mitigation.

## 1 Introduction

Increasing recognition in consensus is that identifying and preventing toxic gender attitudes and stereotypes is essential for society (Blodgett et al., 2020). Since gender-biased information could be presented and widely propagated in textual format, it is essential to develop automatic methods for detecting and mitigating textual gender bias.

Natural language processing (NLP) has been widely used in text-related applications, which have a significant influence on gender bias topics (Costajussà, 2019). On the one hand, large-scale language models (LMs), as a key technique of modern NLP, are proven to learn the subjective gender bias in the training corpus or even amplify it (Zhao et al., 2017). On the other hand, it becomes increasingly

promising to apply cutting-edge NLP techniques for probing and mitigating gender bias.

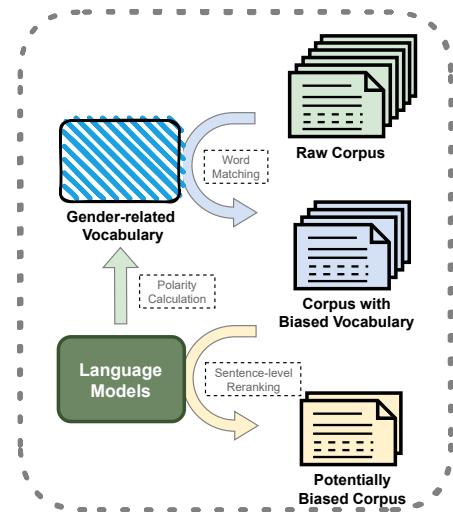


Figure 1: Pipeline of Retrieving and Filtering Potentially Biased Sentences from Raw Corpus for Human Annotation.

Building a high-quality text corpus has been one of the key tangents in improving NLP applications for debiasing gender stereotypes in texts (Sun et al., 2019). Some researchers introduce *automatic* annotation techniques, such as gender-swapped based methods, to create corpora for gender bias mitigation (Lu et al., 2020; Zhao et al., 2018; Rudinger et al., 2018). While it is attractive to build a large corpus without heavy labors, automatic gender-swapped based methods highly depend on the quality of base language models and are prone to creating nonsensical sentences (Sun et al., 2019). To address this issue, some works devote effort to developing *human-annotated* corpora for gender bias mitigation. However, these corpora either mainly focus on word- or grammar-level bias (Webster et al., 2018; Zhu and Liu, 2020; Sahai and Sharma, 2021; Zhou et al., 2019), or only concern about sexism-related topics (Jiang et al., 2022; Chiril et al., 2021, 2020; Parikh et al., 2019).

Moreover, existing works on gender bias exclu-

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<sup>1</sup>Our code is available at [GitHub](#)

sively focus on English (Costa-jussà, 2019), where few datasets exist for other influential languages such as Chinese. (N.B. details of generated gender bias corpus with nonsensical Chinese sentences can be found in Appendix D). We aim to tackle the aforementioned issues by providing a high-quality Chinese human-annotated corpus for contextual-level gender bias probing and mitigation.

To this end, we propose the Chinese cOrpus foR Gender bIAS Probing and Mitigation (**CORGI-PM**) dataset, which consists of 32.9k human-annotated sentences, including both gender-biased and non-biased samples. For the initial data collection, we propose an automatic method that builds a potentially gender-biased sentence set from existing large-scale Chinese corpora. Inspired by the metric leveraging language models for gender bias score calculation proposed in Bolukbasi et al. (2016); Jiao and Luo (2021), the samples containing words of high gender bias scores are recalled, and then reranked and filtered according to their sentence-level gender-biased probability, as illustrated in Fig. 1. To ensure the quality of our corpus, the annotation scheme is carefully designed, and annotators with qualified educational backgrounds are selected to further label and paraphrase the retrieved sentences.

Additionally, we address three challenges based on CORGI-PM, *i.e.*, gender bias detection, classification, and mitigation, which provide clear definitions and evaluation protocols for NLP tasks in gender bias probing and mitigation. In order to provide referential baselines and benchmarks for our proposed challenges, we conduct random data splitting with balanced labels and implement experiments on cutting-edge language models in zero-shot, in-context learning, and fine-tuning paradigms. We discuss the experimental settings and provide result analysis in §3. The implementation details can be referred to in Appendix C.

In summary, we provide a well-annotated Chinese corpus for gender bias probing and mitigation, along with clearly defined corresponding challenges. With a properly designed annotation scheme, CORGI-PM provides a corpus of high quality that assists models in detecting gender bias in texts. More importantly, other than the 22.5k human-annotated non-biased samples, all the 5.2k biased sentences in our corpus are further labeled with gender bias subclasses and companies with parallel bias-free versions provided by the annota-

Sample Category	Quantity		
	Train	Valid	Test
Biased	AC	1.90k	235
	DI	2.70k	334
	ANB	2.47k	306
Non-biased	21.4k	516	526
Overall	30.1k	1391	1409

Table 1: Overall Statistics of the CORGI-PM Dataset. The notations, **AC**, **DI**, and **ANB** represent specific bias labels described in § 2.2.

tors. Our codes and dataset will be released for the benefit of the community.

## 2 Data Collection

### 2.1 Sample Filtering

We propose an automatic processing method to recall, rerank, and filter annotation candidates from raw corpora using a two-stage filtering from word-level to sentence-level, as illustrated in Fig. 1. The Chinese sentence samples are mainly screened out from the SlguSet (Zhao et al., 2021) and the CCL corpus (Weidong et al., 2019).

To recall gender-biased words or retrieve candidate sentences with gender bias scores, we compare the target word/sentence representations with the *seed direction*, which can be calculated by the subtraction between the word embeddings of she and he (Bolukbasi et al., 2016; Jiao and Luo, 2021). We leverage different Chinese LMs including ERNIE (Zhang et al., 2019), CBert (Cui et al., 2020), and Chinese word vectors (Qiu et al., 2018) to acquire the word-level and sentence-level representations. For word-level filtering, we use the mentioned metric to build a vocabulary of high bias scores and recall sentences containing such words from the raw corpora with exact matches. We compute gender bias scores of the crawled sentences and group them by the gender bias keywords acquired in the previous stage for sentence-level filtering. The final sentences for annotation are then selected according to a specific global threshold gender bias score and an in-group threshold rank. The word-level filtering process presented as word clouds can be found in Appendix B.1.

### 2.2 Annotation Scheme

The annotation scheme is designed for gender bias probing and mitigation. For gender bias probing, the annotators are required to provide the following information given a sentence: whether gender bias exists; if so, how the bias is established. For gender bias mitigation, the corrected non-biased version of the biased sentences is also required. We

Linguistic Info.	Non-biased			Biased			Corrected Biased		
	Train	Valid	Test	Train	Valid	Test	Train	Valid	Test
Word	724k	18.9k	17.7k	228k	24.8k	28.3k	265k	27.1k	30.0k
Dictionary	574k	14.4k	14.1k	167k	18.4k	20.4k	191k	19.9k	21.5k
Character	1,156k	30.1k	28.1k	358k	39.2k	44.4k	417k	42.8k	46.9k
Sent. Length	53,952	58,397	53,473	85,837	76,087	85,214	99,839	82,853	89,939

Table 2: Linguistic Characteristics of the Corpus. *Word*, *Dictionary*, and *Character* separately denote the total Chinese word number, total unique Chinese word number, and total character number of the specific categories. The sentence lengths are defined as the number of containing characters.

further describe the annotation scheme details in the following paragraphs.

### Existence and Categorization.

The annotators are required to annotate whether the sentence is gender-biased (**B**) or non-biased (**N**) in contextual-level or word-level, and further clarify how the bias is established. Given that our raw data is collected using gender-related keywords or from gender-related corpus, the samples annotated without gender bias are useful human-annotated negative samples for detecting gender bias. To additionally provide information about gender bias categorization, we classify gender bias types into three subtypes : (1) Gender Stereotyped activity and career choices (**AC**); (2) Gender Stereotyped descriptions and inductions (**DI**); and (3) Expressed gender-stereotyped attitudes, norms and beliefs (**ANB**). The classification standard is inspired by (King et al., 2021) and further summed up into the mentioned subtypes.

**Bias Mitigation.** Annotators are also required to mitigate the gender bias of selected sentences while keeping the original semantic information. We also ask our annotators to diversify the expressions if applicable. The major revision patterns can be summarized as follows: (1). *Replace* the gender-specific pronouns with neutral pronouns. (2). *Replace* the gender-specific adjectives with neutral descriptions with similar semantics definitions. (3). *Add* additional comments to neutralize the sentences which cannot be directly mitigated.

### 2.3 Corpus Analysis

In this section, we report the linguistic statistics of CORGI-PM as Tab. 1. We design a balanced split to create the valid and test set considering the negative-positive ratio and bias subclass proportion in the global distribution. As revealed in Tab. 2<sup>2</sup>, we observe two major differences compared the debiased samples with the original ones: longer and more diverse expressions (N.B. sentence length and vocabulary size of Tab. 2). We hypothesize that it

is due to human annotators' intention to keep the semantic information unchanged and the sentence coherent while mitigating gender bias. They may use more conjunctions and longer descriptions compared to some gender-biased inherent expressions. More details for quality managing and control can be referred to Appendix B.1 and B.2.

## 3 Gender Bias Mitigation Challenges

To provide a clear definition for automatic textual gender bias probing and mitigation tasks, we propose corresponding challenges and standardize the evaluation protocols. We address two tasks, detection, and classification, for gender bias probing and formalize the gender mitigation challenge as a text mitigation task.

### 3.1 Challenges of Detection and Classification

We regard both the gender bias detection and classification challenges as *supervised classification* tasks and evaluate them with metrics of consensus.

**Definition.** The gender bias detection challenge can be regarded as a binary classification task, where the model is required to predict the probability that a given sentence contains gender bias. As described in § 2.2, biased samples are further categorized into one or more kinds. Therefore, we can address the gender classification challenge as a multi-label classification task. The precision, recall, and F1-score are selected as the main metrics in these two challenges. Class-wise metrics and macro average summarized evaluation are required through both valid and test sets to show the performance of language models.

**Baselines.** We finetune Chinese language models from three representative different pretrained paradigms, *i.e.*, Chinese BERT, Electra, and XLNet Cui et al. (2020), for both the detection and classification tasks by adding an additional dense prediction layer.<sup>3</sup> We also provide GPT-3 (Brown et al., 2020) curie's few-shot performance for both

<sup>2</sup>We use the [Jieba](#) to parse.

<sup>3</sup>Pretrained models can be found at the [HFL Anthology](#).

Model	Metrics	Classification (Val.)				Classification (Test)				Detection (Val.)			Detection (Test.)		
		AC	DI	ANB	Avg.	AC	DI	ANB	Avg.	N	B	Avg.	N	B	Avg.
BERT	Precision	.609	.729	.533	.624	.556	.615	.521	.564	.699	.950	.824	.742	.980	.861
	Recall	.594	.665	.543	.601	.493	.652	.585	.577	.971	.591	.781	.985	.662	.823
	F1-Score	.602	.695	.538	.612	.522	.633	.551	.567	.813	.729	.771	.846	.790	.818
Electra	Precision	.587	.727	.544	.619	.556	.630	.516	.568	.691	.936	.814	.745	.974	.860
	Recall	.758	.687	.386	.610	.680	.685	.373	.579	.961	.570	.766	.983	.656	.820
	F1-Score	.661	.706	.451	.606	.612	.656	.433	.567	.804	.708	.756	.848	.784	.816
XLNet	Precision	.587	.696	.523	.602	.544	.589	.527	.553	.713	.928	.820	.772	.959	.865
	Recall	.622	.643	.495	.587	.545	.614	.514	.558	.953	.620	.787	.968	.722	.845
	F1-Score	.604	.669	.509	.594	.544	.601	.520	.555	.816	.743	.780	.859	.824	.841
Curie	Precision	.695	.907	.010	.537	.622	.887	.009	.506	.763	.665	.714	.635	.825	.730
	Recall	.395	.802	.375	.524	.395	.804	.010	.403	.576	.825	.700	.975	.584	.780
	F1-Score	.504	.851	.019	.458	.508	.852	.019	.460	.656	.736	.696	.769	.684	.727

Table 3: Baseline Results for Gender Bias Detection and Classification Tasks. The overall metric refers to Marco average. The model names and abbreviations refer to § 3.1. Categorical definitions refer to § 2.2.

Metrics Models	BLEU	METEOR	ROUGE-L			Human Evaluation	
			Recall	Precision	F1	Coherence	Gender Bias
*Davinci	.776	.879	.203	.211	.205	5.25	0.96
Ada	.288	.429	.407	.180	.250	5.98	1.13
Babbage	.359	.504	.716	.310	.432	6.32	0.69
Curie	.364	.506	.692	.316	.434	6.21	1.20

Table 4: Baseline Results for Gender Bias Correction task. Metrics details can be found in Appendix C. \* suggests using the model in zero-shot paradigm and the others refers to fine-tune.

the detection and classification tasks. Baseline results of detection and classification show that the classification task is challenging, and there is room for performance improvement in detecting gender bias in CORGI-PM, as revealed in Tab. 3.

### 3.2 Challenge of Mitigation

**Definition.** The gender bias mitigation challenge can be regarded as a natural language generation task, where the model is asked to generate the corrected version of biased sentences with the human-annotated ones as references.

**Baselines.** We test the GPT-3 (Brown et al., 2020) on CORGI-PM in fine-tune experiment setting with three different parameter scales, which are Ada(350M), Babbage(1.3B), and Curie(6.7B), and Davinci(175B) in zero-shot experiment setting. We only provide zero-shot results for Davinci because it is the only released GPT-3 editing model. More implementation and evaluation details are introduced in Appendix C.

**Discussion.** We provide both human evaluation and automated metrics for evaluation. Tab. 4 reveals that LMs can learn the annotation pattern of mitigating gender bias, and the zero-shot editing model shows competitive performance. The observation that fine-tuned Babbage outperforms much larger zero-shot Davinci in the human evaluation, and ROUGE-L reveals that CORGI-PM has the potential to be used as strong supervision of the gender bias mitigation task. We notice that Davinci tends to apply more conservative edits compared to

fine-tuned models. As a result, the sentences edited by Davinci keep most of the original sentences and always only change pronouns and adjectives from the original sentences, which benefits precision focusing automatic metrics like BLEU (Papineni et al., 2002), and METEOR (Agarwal and Lavie, 2007). The performance difference between human evaluation and automatic metrics reveals the writing style difference between human and language models.

## 4 Conclusion

We propose CORGI-PM, the first Chinese human-annotated corpus for both gender bias probing and mitigation. We also address definitions and evaluation metrics for three challenges based on CORGI-PM and test the performances of state-of-the-art language models. Our proposed challenges can serve as benchmarks for measuring the ability of language models to detect, classify, and mitigate textual gender bias. Experiments show that our sentences with fine-grained subclass labels can assist the language models in gender bias probing, whilst our parallel human-written debiased data can serve as strong supervision of the generative language models. In summary, we imply future work utilizing CORGI-PM would be benefited the topic of NLP for gender bias probing and mitigation.

## Limitations

There are several major limitations in this research work. Due to the high requirement of annotators

for annotating gender-biased sentences and correcting such sentences, we only choose annotators with higher education, which may lead to potential cognitive bias. In addition, we only conduct limited implementations and experiments of testing widely-used Chinese language models’ performance in our new challenges. More language models and techniques can be further explored in our challenges.

## Ethics Statement

We carefully consider the ethical implications during the collection process. The collection of our corpus CORGI-PM sentences only relies on public available corpora for research purposes. We have acknowledged the potential usage of our dataset as well as related privacy issues to the annotators and received confirmations before the annotation was initiated.

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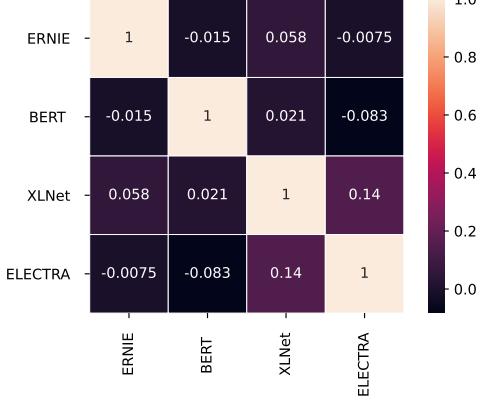


Figure 2: Word-level Gender Bias Comparison of Career Words.

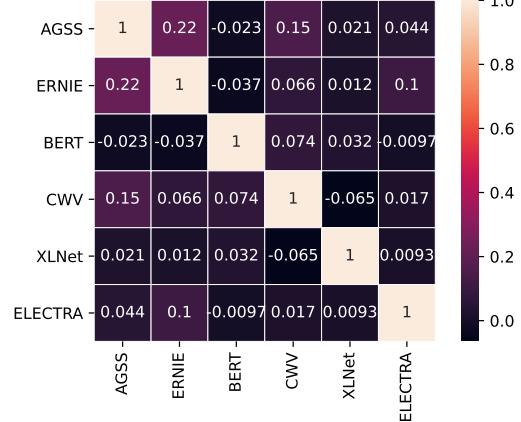


Figure 3: Word-level Gender Bias Comparison of Adjectives. **CWV** denotes the Chinese Word Vectors trained using mixed-large corpus proposed by [Qiu et al.](#).

## A Gender Bias Analysis of Chinese Language Models

### A.1 Evaluation Method and Data Sets

We conduct experiments to explore gender bias contained in widely-used Chinese language models for research and industrial use. We employ the method [Bolukbasi et al. \(2016\)](#); [Jiao and Luo \(2021\)](#) proposed to assess gender bias. The gender bias score for a word is calculated by  $\vec{w} \cdot (\vec{she} - \vec{he})$  based on its word vector. A positive value means the word is more relevant to females, while a negative value means the word is more relevant to males. The higher the absolute value of the gender bias score, the more biased the word indicates.

[Srivastava et al.](#) propose a big benchmark containing a dataset specifying the existing Chinese career words. [Zhu and Liu](#) propose AGSS, a manual-created Chinese word-level adjective list containing gender bias. To measure gender bias contained in the language models, we first calculate gender bias scores of words in the word list provided ([Srivastava et al., 2022](#); [Zhu and Liu, 2020](#)) according to the projection method [Bolukbasi et al. \(2016\)](#); [Jiao and Luo \(2021\)](#). We compare the career and adjective word gender bias score vectors to get the observations of LMs’ influence on word-level learned gender bias. To make the observations more clear, we further apply the sign function to the career and adjective word gender bias score vectors. The similarity function used for the heatmaps is Pearson similarity.

We conduct described comparison of adjectives between AGSS as a golden standard ([Zhu and Liu, 2020](#)), Ernie ([Zhang et al., 2019](#)), Chinese Word Vectors trained by mixed corpus ([Qiu et al., 2018](#)),

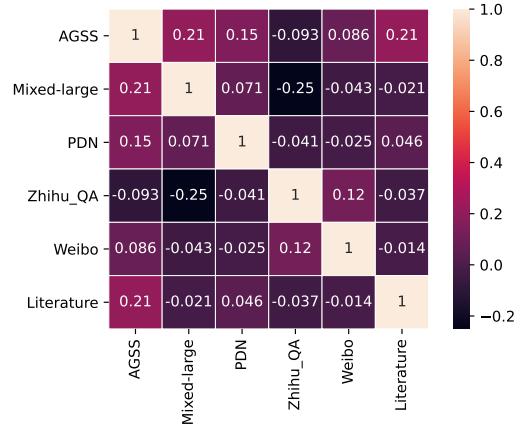


Figure 4: Word-level Gender Bias Comparison of Adjectives of Language Models Pre-trained by Different Corpus. **PDN** denotes the People’s Daily News Corpus.

and Chinese-XLNet, Chinese-Bert, and Chinese-Electra proposed tecui-etal-2020-revisiting to produce Fig. 3. We conduct described comparison of career words between Ernie ([Zhang et al., 2019](#)), and Chinese-XLNet, Chinese-Bert, and Chinese-Electra proposed tecui-etal-2020-revisiting to produce Fig. 2. The described experiments on career words is not conducted with the Chinese Word Vectors trained by mixed corpus, because an observing number of career words are missing in its dictionary.

We don’t provide a golden standard vector ([Srivastava et al., 2022](#)) since they didn’t provide a manual gender bias analysis about the career words. We also conduct described comparison on adjectives in Chinese Word Vectors pre-trained by different corpus, including Mixed-large corpus, People’s Daily News, Zhihu QA dataset, Weibo, and Chinese literature dataset to produce Fig. 4 and analyze the learned gender bias difference caused by



Figure 5: Example Word Cloud Analysis of Ernie and Chinese-XLNet. **Ch** denotes Chinese. **En** denotes words’ English translation. **Man** and **Woman** separately denote words with embedding closer to man and woman. **Adj** denotes adjectives. **Career** denotes career words.

using different datasets for pretraining the language model.

## A.2 Discussion

There exists observing gender bias in the open-source Chinese language models, especially in Ernie and Chinese Word Vectors according to Fig. 3. We hypothesize that the observation is highly related to the corpus used. Cui et al. claim that their used corpus is a combination of ChineseWiki, and some other universal Chinese datasets, including encyclopedia, news, and QA dataset. In sharp contrast, Ernie and Chinese Word Vectors use corpus, which contains sentences from literature, forum, and other social media, which may lead to a gender-biased model.

According to Fig. 4, People’s Daily News, and Chinese literature corpora contain observing gender bias. The observation indicates that researchers should be more careful about using literature data while training a language model. We also hypothesize that this is caused by the literature corpus and People’s Daily News, which contains more descriptive expressions.

## B Corpus

### B.1 Word Cloud Analysis

We provide word cloud analysis of Ernie and Chinese-Electra in the section about adjectives and career words. More available word cloud analysis will be available in our public repository. The words are ranked according to the absolute value of their gender bias score calculated along the method used by Bolukbasi et al.; Jiao and Luo. There is a noticeable word-level gender stereotype according to the word cloud. For example, a man is robust and a woman is motherly, a man is suitable for a fitness instructor and a woman is suitable for a choreographer. We also conduct word cloud analysis for language models pre-trained by different corpora.

### B.2 Quality Monitoring and Control

We used a standardized operating method and educated our annotators to achieve high-quality annotations as follows:

- (1). Annotators** We have 6 annotators, which were all native speakers of Chinese. Annotators

were only qualified to do the annotation if they went through several societal (King et al., 2021; Xu et al., 2019) and computer science research works (Sun et al., 2019; Zhao et al., 2018) about gender bias before the annotation procedure. All annotators held a bachelor’s degree. Waseem points out that expert annotators are more cautious and can improve the corpus quality with a large margin, which proves the necessity of our training procedure. We also kept the number of male and female annotators equal.

(2). **Gender Equality of Raw Corpus** In the raw data collection procedure, we keep the number of man-related keywords and woman-related keywords equal and make the number of samples recalled according to different keywords balanced. As a result, the raw data and the final data should hold gender equality.

(3). **Annotation Procedure** Our annotation procedure is separated into two stages. In the first stage, annotators are encouraged to not enter any samples that they are not certain about. In the second stage, we have annotators cross-checking annotations. We did not enter any contradictory samples.

(4). **Inter-annotator Agreement** Given the domain and purpose of the dataset, we want to build the dataset as high quality as possible. After an initial annotation round with 6 annotators, we also report inter-annotator agreement in Table 5. to verify annotation reliability, where the IAA among three annotators on bias classification, detection, and mitigation is 0.802, 0.935, and 0.987, respectively.

	<b>Classification</b>	<b>Detection</b>	<b>Mitigation</b>
IAA	0.802	0.935	0.987

Table 5: Inter-Annotator Agreement (IAA)

## C Implementation Details

For **gender bias classification challenge**, we used finetuned Chinese-BERT-wwm, Chinese-ELECTRA-180g-base, and Chinese-XLNet-base, (Cui et al., 2020), and the GPT-3 (Curie) in the in-context paradigm. We first use the train set to save the multiple labeled examples in a document with a specific file ID. Then we use the test sets to perform a classification query on the saved file. The processing time for the classification of gender bias is approximately 1 hour. We calculated the

precision, recall, and F1 score to analyze model performance.

For **gender bias detection challenge**, we use the same baseline model set as in the classification challenge. We test the performance on both "yes" and "no" detection. The detection tasks also use the Classification endpoints of GPT3 (Curie), which requires more time compared to classification as we use a larger dataset for both training and testing.

For **gender bias mitigation challenge**, we did not provide experiment results of finetuning the largest Davinci (175B) GPT-3 on CORGI-PM because of the cost and no observing performance gain comparing Curie and Babbage. For finetune experiment setting, we follow the tutorial of GPT-3 official API of the Completion Model and regard the ground truth edits provided by human annotators as the completion of the original sentences. For the zero-shot experiment setting, we apply GPT-3 editing model and set the instructions as "Eliminate the gender bias contained in the sentence."

For metrics used, on the one hand, we conduct extensive human evaluations from both gender bias and coherence aspects on CORGI-PM. For both gender bias and coherence, we shuffled the correction results from human annotators and different models, and asked our annotators to grade the results using the answer range from 1-*not at all* to 7-*extremely gender biased/extremely fluent* without the information of the source. On the other hand, we provide the automated metrics result, including BLEU (Papineni et al., 2002), ROUGE-L (Lin, 2004), and METEOR (Agarwal and Lavie, 2007) of the models on CORGI-PM as well. BLEU is the earliest and most widely-used metric for translation and NLG tasks. METEOR introduces WordNet and other external resources to improve the robustness of the BLEU-based metrics. ROUGE pays more attention to recall compared to BLEU.

In the gender bias correction task, we fine-tune Ada, Babbage, and Curie models of GPT3 and test the performance using the aforementioned metrics. Fine-tuning on the train set requires 31 minutes on Ada, 35 minutes on Curie, and 43 minutes on Babbage. For the generation process, each finetuned model required approximately 30 minutes to complete. For the zero-show paradigm, we use "Eliminate the gender bias in the sentence" as the instruction and use Davinci. Compared with the fine-tuned model doing the sentence correction, the zero-shot paradigm requires more time (approxi-

Original	Ground Truth	Gender-swapped
但是再坚强的你也是个女人吧。 (But you are still a <b>woman</b> , even if you are strong.) 可怕可恨的是，有的女人自己也是这样给自己定位的——没有反对、没有抗争，有的只是心甘情愿、死心塌地遵照执行。 (The scary thing is that some <b>women</b> themselves are so defined for themselves - no opposition, no resistance, there is only a willingness to follow it to the letter.) 那个时候，能驾驭金色高跟鞋的女人得多多摩登啊！ (At that time, the <b>woman</b> who could handle the gold heels must be very modern!)	但是再坚强的你也有脆弱的时候吧。 (But even the strongest of you have moments of vulnerability, right?) <b>女人</b> 不应该这样给自己定位——没有反对、没有抗争，有的只是心甘情愿、死心塌地遵照执行。 (A <b>woman</b> should not define herself in this way - there is no opposition, no resistance, there is only a willingness to follow it to the letter.) 那个时候，能驾驭金色高跟鞋的人得多摩登啊！ (At that time, the person who can handle the gold heels!)	但是再坚强的你也是个男人吧。 (But you are still a <b>man</b> , even if you are strong.) 可怕可恨的是，有的男人自己也是这样给自己定位的——没有反对、没有抗争，有的只是心甘情愿、死心塌地遵照执行。 (The scary thing is that some <b>men</b> themselves are so defined for themselves - no opposition, no resistance, there is only a willingness to follow it to the letter.) 那个时候，能驾驭金色高跟鞋的男人得多摩登啊！ (At that time, the <b>man</b> who could handle the gold heels must be very modern!)
“鸿雁队”是清一色的“理工男”。 (The “Hongyan team” team of all <b>men</b> in STEM.)	“鸿雁队”是清一色的“理工生”。 (The “Hongyan team” team of all student in STEM.)	“鸿雁队”是清一色的“理工女”。 (The “Hongyan team” team of all <b>women</b> in STEM.)

Figure 6: Case Study of Nonsensical Sentences Created by Gender-swapped Methods.

	Original Sentence	Edit Sentence
Change the Pronoun	清洁阿姨一边扫地一边赞扬。 (The cleaning woman praised while sweeping the floor.)	清洁工一边扫地一边赞扬。 (The cleaners praised while sweeping the floor.)
	我，有时文静，有时却调皮得像一个男孩。 (I, sometimes quiet, but sometimes naughty like a boy.)	我，有时文静，有时调皮。
	在小王眼里，李某高大帅气、温柔体贴，而且风趣幽默，是一个十分优质的青年男性。 (In the eyes of Wang, Li is tall and handsome, gentle and considerate, and funny, a very high-quality young male.)	在小王眼里，李某身材高大、外表好看、温柔体贴，而且风趣幽默，是一个十分优质的青年。
	沙峰起伏，金光灿灿，宛如一座金山，像绸缎一样柔软，少女一样娴静。 (The sandy peaks are undulating and golden, like a golden mountain, as soft as silk and as serene as a maiden.)	沙峰起伏，金光灿灿，宛如一座金山，像绸缎一样柔软，宁静。 (The sandy peaks are undulating and golden, like a golden mountain, as soft and serene as silk.)
Change the Gender-specific Adjectives	我想要世界，而世界当时属于男人们。 (I want the world, and the world then belonged to the men.)	我想要世界，而世界应当属于人们。评论：世界应当属于人们，与男女无关。
	哎哟，果然每个追梦男人的背后，都有个不世俗的后方！ (Oops, indeed, behind every dream-chasing man, there is an unsophisticated back!)	哎哟，果然每个追梦男人的背后，都有个不世俗的后方！评论：这种感慨是错误的，将男女的家庭分工固定化，剥除女性就业的权利，应予以鄙弃。
Add Comments		

Figure 7: Case Study of Mitigation Annotation Patterns.

mately 1 hour).

## D Case Study

As shown in Fig. 6, gender-swapped methods suffer from mitigating gender bias expressed by gender-specific descriptions and inductions, and expressed gender-stereotyped attitudes, norms and beliefs. As a result, gender-swapped methods may generate nonsensical sentences under certain circumstances.

We also use the basic mitigation annotation patterns (Fig. 7). These three major mitigation annotation patterns are not used exclusively in the annotation but optionally in combination. Except for the three mentioned patterns, we apply several other linguistic skills, including deleting gender-specific pronouns and replacing vehicles in gender-related metaphors, to mitigate the gender bias while keeping semantic information unchanged.