Mitigating Biases of Large Language Models in Stance Detection with Calibration

Anonymous ACL submission

Abstract

Large language models (LLMs) have achieved remarkable progress in many natural language processing tasks. However, our experiment reveals that, in stance detection tasks, LLMs may generate biased stances due to sentiment-stance spurious correlations and preference towards certain individuals and topics, thus harming their performance. Therefore, in this paper, we propose to **M**itigate **B**iases of LLMs in stance detection with **Cal**ibration (`MB-Cal`). To be specific, a novel calibration network is devised to calibrate potential bias in the stance prediction of LLMs. Further, to address the challenge of effectively learning bias representations and the difficulty in the generalizability of debiasing, we construct counterfactual augmented data. This approach enhances the calibration network, facilitating the debiasing and out-of-domain generalization. Experimental results on in-target and zero-shot stance detection tasks show that the proposed `MB-Cal` can effectively mitigate biases of LLMs, achieving state-of-the-art results.

1 Introduction

Stance detection aims at automatically identifying the author's opinionated standpoint or attitude (e.g., *Favor*, *Against*, or *Neutral*) expressed in the content towards a specific target, topic, or proposition (Somasundaran and Wiebe, 2010; Mohammad et al., 2016). With the development of social media platforms, stance detection plays a pivotal role in analyzing public opinion on social media topics (Jang and Allan, 2018; Ghosh et al., 2019; Stefanov et al., 2020; Sun et al., 2018; Chen et al., 2021).

Large Language Models (LLMs), such as ChatGPT[1], Bard[2], and LLaMA (Touvron et al., 2023), have demonstrated impressive language comprehension and task-handling capabilities by leveraging extensive corpus and knowledge. However, some existing studies have indicated that the results of LLMs in stance detection on certain datasets or certain targets are significantly suboptimal (Zhang et al., 2023b; Li et al., 2023), which hampers the utility of LLMs for the stance detection task.

Our experiment reveals that LLMs are influenced by two types of bias patterns in stance detection[3]: 1) spurious correlations of sentiment with stance, in which the sentiment expression of the sentence can mislead the judgment of stance towards a specific target; 2) preference towards certain individuals and topics, in which LLMs exhibit a certain stance bias towards certain individuals or topics. Such biased stances can not only degrade the performance of LLMs in stance detection tasks but also be maliciously exploited to manipulate the stance predictions. Consequently, mitigating the bias of LLMs in stance detection is crucial for using LLMs in the stance detection task.

Existing research of debiasing in stance detection largely centered on the creation of unbiased training samples and the retraining of stance detection models (Kaushal et al., 2021; Yuan et al., 2022b). However, there are two core limitations to the application of these debiasing methods in LLMs. **Limitation#1**, research (Luo et al., 2023) has shown that such retraining processes will undermine the generality of LLMs, potentially leading to catastrophic forgetting; not to mention that there are restrictions with certain closed-source LLMs like GPT-3.5-turbo, which can only be accessed with a restricted inference API, preventing access to internal model parameters. The extensive computational resources necessitated for the retraining of LLMs are also considerably substantial. **Limitation#2**, existing approaches to constructing unbiased training samples typically entail the analysis of prevalent bias patterns, subsequently automating their construction based on these identified patterns, exemplified by substituting "Men" with "Women". However, when dealing with stance detection tasks, our forthcoming analysis illuminates that these samples display varying bias propensities, attributable to divergences in sentiments and stance objectives. Consequently, utilizing conventional methods to create unbiased samples poses a significant challenge.

Therefore, to address the above two limitations,

[1] https://openai.com/blog/chatgpt/
[2] https://bard.google.com/

[3] The analysis of stance biases and causal graphs are demonstrated in Section 3.

we propose to **M**itigate **B**iases of LLMs in stance detection with **Cal**ibration, coined as `MB-Cal`. We establish a trainable calibration network to approximate the inverse projection function of the bias label distribution within LLMs. This calibration network receives samples, along with stance judgments and rationales from LLMs, and generates calibrated stance judgments. Through supervised training, the calibration network can capture biases present in specific samples, thereby performing debiasing. To address the issue of limited representation of bias within the training set and difficulty in constructing unbiased training samples, we construct counterfactual augmented data against the training data to rectify stance biases. The counterfactual samples are constructed from both causal and non-causal features, which can enhance the calibration network to yield unbiased stances and accomplish out-of-domain generalization.

The main contributions of our work are summarized as follows:

1) We are the first to investigate the biases of LLMs on stance detection, categorizing the biases into two main types from the perspective of causality and proposing metrics to quantify these two types of biases.

2) We propose `MB-Cal`, a novel framework consisting of a calibration network and counterfactual data augmentation to mitigate biases of LLMs on stance detection.

3) A series of experiments demonstrate that our `MB-Cal` can effectively reduce the bias of LLMs in stance detection, improving the performance in both in-target and zero-shot stance detection tasks[4].

2 Related Work

Biases in Large Language Models Some studies (Gonçalves and Strubell, 2023) have examined the biases existing in Large Language Models (LLMs), these biases mainly include gender and religion (Salinas et al., 2023), politics (Jenny et al., 2023; He et al., 2023), and spurious correlations (Zhou et al., 2023). The associated debiasing efforts are centered around retraining the language model with debiased samples (Dong et al., 2023; Limisiewicz et al., 2023). Zheng et al. (2023) found that LLMs are vulnerable to option position changes in MCQs due to their inherent 'selection bias'. They perform debiasing by approximating the overall bias distribution. while based on our analysis in Section 3.3, the bias distribution varies significantly across different stance detection samples, so this method is not applicable.

Mitigating Biases in Stance Detection Currently, studies developed for mitigating biases in stance detection are oriented toward fine-tuned models. Kaushal et al. (2021) analyzed two biases existing in the current datasets: target-independent lexical choices and target-independent sentiment-stance correlations, and built an unbiased dataset. Yuan et al. (2022a) incorporated the stance reasoning process as task knowledge to retrain the model to reduce bias. Yuan et al. (2022b) constructed unbiased samples through counterfactual reasoning and performed adversarial bias learning. These methods involve retraining models and constructing unbiased training samples through special marks, which cannot be directly applied to LLMs.

3 Biases of LLMs in Stance Detection

3.1 Bias Measurement

Stance bias refers to the systematic errors where models tend to choose certain stances due to the influence of specific biases and stereotypes. Inspired by Zheng et al. (2023), the standard deviation of recalls (*RStd*) on stance labels is an excellent metric for quantitatively measuring systematic errors. It is resistant to label imbalance and effectively reflects the model's stance tendency on samples. The formula is as follows:

$$RStd = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left(\frac{TP_i}{P_i} - \frac{1}{K}\sum_{j=1}^{K}\frac{TP_j}{P_j}\right)^2} \quad (1)$$

Where K is the number of stance labels, TP_i is the number of true positive instances for stance label i, and P_i is the number of instances of stance label i. A larger *RStd* represents a larger bias.

3.2 Experimental Result

Through statistical analysis of the results from LLMs, we identified two significant types of bias: **Sentiment-stance Spurious Correlations** and **Target Preference Bias**.

3.2.1 Sentiment-Stance Spurious Correlations

Sentiment can influence the judgment of the stance but is not the major factor determining the stance. If the model excessively relies on sentiments to evaluate the stance, it indicates an influence from

[4]The code is available at url.

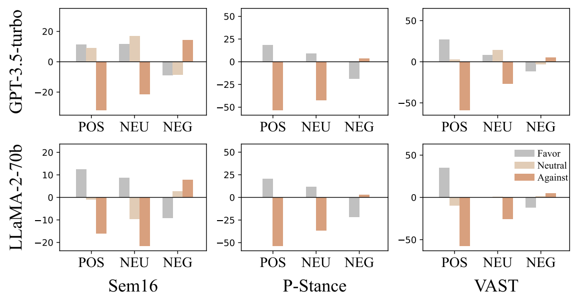

Figure 1: The recall score, normalizing by subtracting the overall recall across all sentiments, on Sem16, P-Stance, and VAST dataset. POS for positive, NEU for neutral, NEG for negative.

sentiment-stance spurious correlations, resulting in biased stance judgments. To investigate stance bias across different sentiments, we first obtain the sentiment label for each sample. For the Sem16 dataset, each sample has annotated sentiment labels, categorized as positive, neutral, or negative. for the P-Stance and VAST datasets, we utilize GPT-4 to annotate the sentiment labels. To gain a preliminary understanding of sentiment-stance spurious correlations, we calculate the recall score on each stance label, normalizing by subtracting the overall recall across all sentiments, as shown in Figure 1. We can observe that LLMs exhibit a clear error pattern: they are highly inclined to predict support for samples with positive sentiment and against for samples with negative sentiment. We posit that this proclivity for errors, deviating from the anticipated sample pattern, instigates a stance bias. Hence, we identify the **S**entiment-stance **S**purious **C**orrelations (SSC) as a type of bias in LLMs on stance detection.

We calculate the average of the RStd across all sentiments as our quantification for sentiment-stance spurious correlations:

$$Bias\text{-}SSC = \frac{1}{|S|} \sum_{s \in S} RStd(X_s) \qquad (2)$$

where X_s represents instances with sentiment label s, $|S|$ denotes the number of sentiment labels, which in our experiment, is 3.

We conducted experiments in various settings: *Task-Des* used task-related descriptions for stance judgment, *CoT-Demo* used the task description with 4-shot chain-of-thought demonstration, and *Debias-Instruct* used the task description indicating that sentiment was spurious cues for stance judgment. Refer to Appendix A for the detailed

	Sem16		P-Stance		VAST	
	SSC↓	F1↑	SSC↓	F1↑	SSC↓	F1↑
LLaMA-2-70b-chat						
Task-Des	**17.80**	60.08	23.36	79.89	**16.87**	68.36
CoT-Demo	27.52	58.68	**22.81**	**80.77**	22.55	67.08
Debias-Instruct	19.24	**63.62**	24.86	78.85	19.63	**68.68**
GPT-3.5-Turbo-0125						
Task-Des	27.13	52.82	23.72	**81.62**	28.70	49.86
CoT-Demo	**18.08**	**67.59**	**22.75**	80.88	**16.32**	**69.90**
Debias-Instruct	23.75	51.77	23.48	81.48	30.53	48.68

Table 1: Bias-SSC and macro F1-score of stance detection on the Sem16, P-Stance and VAST dataset. Refer to Appendix B for detailed results on each sentiment.

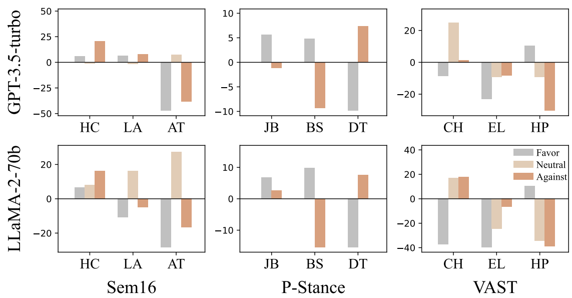

Figure 2: The recall score, normalizing by subtracting the overall recall across all targets, on Sem16, P-Stance, and VAST dataset. HC for Hillary Clinton, LA for Legalization of Abortion, AT for Atheism, JB for Joe Biden, BS for Bernie Sanders, DT for Donald Trump, CH for Christian, CL for Election, HP for Humanity Program.

prompts. The results are shown in Table 1. We can observe that in most cases, a larger bias-SSC leads to poorer stance detection results. Moreover, prompt engineering methods proved ineffectual in mitigating this inherent bias.

3.2.2 Target Preference Bias

LLMs exhibit bias towards certain individuals or topics. This bias can interfere with their ability to judge stances based on the text, leading to biased stance judgments. We refer to this bias as target preference bias. To preliminarily observe the target preference bias of LLMs, we randomly sampled some targets from different datasets and calculated the recall score on these targets, normalizing by subtracting the overall recall across all targets, as shown in Figure 2. We observed that, on different targets, LLMs displayed markedly different tendencies in stance selection, which ultimately affected the correctness of stance judgment. Therefore, we identify the **T**arget **P**reference **B**ias (TPB) as a type of bias in LLMs on stance detection.

We calculate the average of the RStd of all tar-

	Sem16		P-Stance		VAST	
	TPB↓	F1↑	TPB↓	F1↑	TPB↓	F1↑
LLaMA-2-70b-chat						
Task-Des	17.59	60.08	9.09	79.89	7.76	68.36
CoT-Demo	27.56	58.68	11.57	**80.77**	9.64	67.08
Debias-Instruct	**16.37**	**61.40**	**8.94**	78.70	**4.86**	**69.10**
GPT-3.5-Turbo-0125						
Task-Des	22.64	52.82	**5.43**	**81.62**	28.44	49.86
CoT-Demo	**13.47**	**67.59**	6.61	80.88	**8.40**	**69.90**
Debias-Instruct	21.87	53.33	5.79	81.59	26.77	51.66

Table 2: Bias-TPB and macro F1-score of stance detection on the Sem16, P-Stance and VAST dataset. Refer to Appendix B for detailed results on each target.

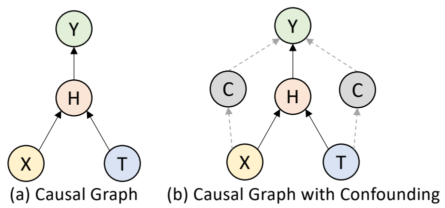

Figure 3: Causal graph on stance detection. X donates the text, T donates the target, H donates the features of the interaction of text and target, Y donates the stance label and C refers to confounding, which could bias the judgment of the stance.

gets as our quantification for target preference bias:

$$\textit{Bias-TPB} = \frac{1}{|T|} \sum_{t \in T} RStd(X_t) \tag{3}$$

where X_t represents instances with stance target t, $|T|$ denotes the number of targets.

We conduct experiments based on *Task-Des*, *CoT-Demo*, and *Debias-Instruct* which emphasize the need to judge the stance based on the text and not to include the inherent attitude towards the target. Refer to Appendix A for the detailed prompts. The results are shown in Table 2. We can observe that in most cases, a larger bias-TPB also leads to poorer stance detection results, and bias-TPB cannot be effectively mitigated by prompt engineering.

3.3 Bias Analysis

We analyze the bias of LLMs in stance detection from the perspective of causal graphs. Stance detection requires the model to detect the stance of a text on a specific target. Thus, the ultimate stance results derived from the interaction of text and target, as illustrated in (a) of Figure 3. For LLMs, as depicted in (b), sentiment-stance spurious correlations originated from the biased reasoning paths X $\rightarrow$ C $\rightarrow$ Y, where stances are judged solely based on certain spurious clues in the text. Target preference bias represents biased reasoning path T $\rightarrow$ C $\rightarrow$ Y, which are stance inferences based exclusively on the target preference of LLMs. Both of these two paths can introduce biases to the final stance. Based on the observation of Figure 1 and Figure 2, we found that the distribution of biases differs significantly for samples with different emotional or stance targets. Therefore, we consider such confounding to be specific to each sample: $C_i \sim \{x_i, t_i\}$.

4 Mitigating Bias with Calibration

Given $X = \{x_n, t_n\}_{n=1}^{N}$ as the labeled dataset, where x denotes the input text and t denotes the corresponding target, LLMs obtain the stance predictions y through the task instructions $\mathcal{I}$ for stance detection: $P_{obs}(y_i|\mathcal{I}; x_i, t_i)$. Inspired by Zheng et al. (2023), we believe that it can be deconstructed into the unbiased distribution $P_{unbiased}$ of the LLMs performing the stance detection task, and the bias distribution P_{bias} formed by confounding C_i:

$$P_{obs} = P_{unbiased}(y_i|x_i, t_i) P_{bias}(y_i|C_i) \tag{4}$$

We aim to estimate the unbiased stance distribution $P_{unbiased}$.

4.1 Calibration Network

By estimating the bias distribution based on the overall distribution of known samples (from the training set), we can obtain unbiased outputs by multiplying the observed distribution of LLMs by the inverse of the approximated bias distribution:

$$P_{unbiased} = P_{obs}(y_i^{'}|\mathcal{I}; x_i, t_i) \widetilde{P}_{bias}(y_i^{''}|C_i)^{-1} \tag{5}$$

where $y_i^{'}$ and $y_i^{''}$ represent the label distribution output by LLMs and the label distribution affected by bias, $\widetilde{P}_{bias}$ represents the estimate of bias.

However, based on the bias analysis in Section 3.3, we found that for stance detection, the samples with different sentiments and stance targets have completely different stance bias distributions. Therefore, we propose employing a network to capture the bias distribution specific to each sample, called the *calibration network* f_{Cal}. We use the network f_{Cal} to approximate the inverse projection function of the bias distribution:

$$f_{Cal} = P_{bias}(y_i^{''}|C)^{-1} \tag{6}$$

By inputting the predicted stance distribution P_{obs} from LLMs, an approximating unbiased label can

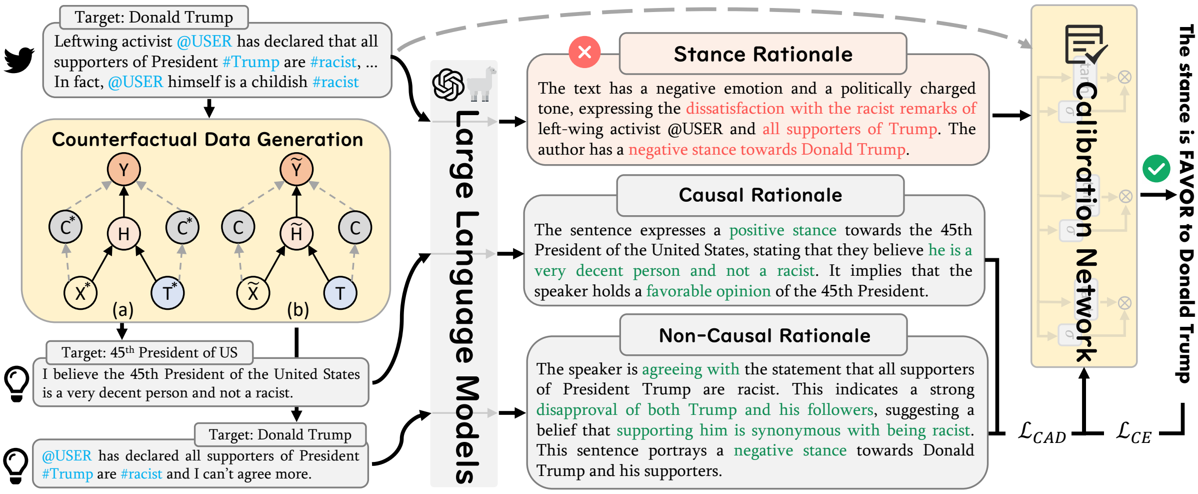

Figure 4: The overall architecture of our proposed MB-Cal. (a) and (b) in the counterfactual data generation represent two ways to generate counterfactual augmentation from the causal graph.

be obtained:

$$P_{unbiased}(\hat{y_i}) = f_{Cal}(P_{obs}(y_i^{'}|\mathcal{I}; x_i, t_i)) \quad (7)$$

Specifically, as illustrated in Figure 4, we first use the *CoT-Demo* instruction (refer to Appendix A for the detail) to obtain the stance judgment and rationale from the LLMs. Then, we input the sample, along with this stance judgment and rationale, into our *calibration network* (using RoBERTa-base in our setup) to obtain the debiased stance output. We train the *calibration network* using the cross-entropy loss function with ground truth label:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N} y_i \log(f_{Cal}(P_{obs}(y_i^{'}|\mathcal{I}; x_i, t_i)) \quad (8)$$

Through supervised training, our calibration network can capture biases present in specific samples, thereby performing debiasing.

4.2 Counterfactual Data Augmentation

One challenge in supervised training is the limited representation of bias within the overall training set, and the learned bias features are difficult to generalize. To facilitate the *calibration network* to learn diverse bias patterns, we generate the **C**ounterfactual **A**ugmented **D**ata (CAD) against the training data. Kaushik et al. (2021) introduced two methods for constructing counterfactual augmented data: introducing disturbances to non-causal features, which are the confounding features unrelated to stance; and inverting causal features, which are the core features for determining the stance. Our approach involves constructing counterfactual data based on these two methods, leveraging the bias patterns identified through the causal graph analysis detailed in Section 3.3.

For introducing disturbances to non-causal features, as shown in counterfactual data generation (a) in Figure 4, for the biased inference path X $\rightarrow$ C $\rightarrow$ Y, we perturb the text x_i against the spurious correlation of sentiment. for the biased inference path T $\rightarrow$ C $\rightarrow$ Y, we perturb the target t_i against the target preference. Specifically, we construct an instruction that allows the LLMs to rephrase the original sentence and target with different words and sentiments while ensuring that the semantics and the stance remain unchanged. Refer to Figure 10 for the detailed prompts. This obtains the perturbed text x_i^* and perturbed target t_i^*. Since we only disturbed confounding, the stance label remains unaffected. We construct cross-entropy loss on non-causal counterfactual augmented data as follows:

$$\mathcal{L}_{CAD}^{n\text{-}cau} = -\sum_{i=1}^{N} y_i \log(f_{Cal}(P_{obs}(y_i^{'}|\mathcal{I}; x_i^*, t_i^*)) \quad (9)$$

For inverting causal features by making necessary modifications to reverse the applicability of the label, as shown in counterfactual data generation (b) in Figure 4, we make necessary alterations to text x_i to reverse the stance to target t_i, thereby only perturbing the causal features. Refer to Figure 11 for the detailed prompts. This obtains the perturbed text $\widetilde{x_i}$ expressing a reversed stance to target t_i. We construct cross-entropy loss on causal

Dataset	Target	Favor	Against	Neutral
Sem16	HC	163	565	256
	FM	268	511	170
	LA	167	544	222
	A	124	464	145
	CC	335	26	203
	DT	148	299	260
P-Stance	Biden	3217	4079	-
	Sanders	3551	2774	-
	Trump	3663	4290	-
VAST	-	6952	7297	4296

Table 3: Statistics of SemEval-2016 Task6, P-Stance and VAST datasets.

counterfactual augmented data as follows:

$$\mathcal{L}_{CAD}^{n\text{-}cau} = \sum_{i=1}^{N} y_i \log(f_{Cal}(P_{obs}(y_i^{'}|\mathcal{I}; \widetilde{x}_i, t_i)) \quad (10)$$

4.3 Training Objective

The final training objective is to incorporate counterfactual augmented data and perform joint training:

$$\mathcal{L} = \mathcal{L}_{CE} + \mathcal{L}_{CAD}^{n\text{-}cau} + \mathcal{L}_{CAD}^{cau} \quad (11)$$

5 Experimental Setup

5.1 Datasets

We conduct experiments of in-target and zero-shot stance detection on three benchmark datasets: SemEval-2016 Task6 (Sem16) (Mohammad et al., 2016), P-Stance (Li et al., 2021) and Varied Stance Topics (VAST) (Allaway and McKeown, 2020). The statistic of datasets is shown in Table 3.

5.2 Implementation Details

For GPT-3.5-turbo, we utilize GPT-3.5-turbo-0125. For LLaMA2-70b, we utilize LLaMA2-70b-chat. For our calibration network, we employ the RoBERTa-Base model (Liu et al., 2019). For our counterfactual data augmentation, we employ GPT-3.5-turbo-0301 to generate counterfactual samples, guided by the instructions detailed in Appendix A. We use AdamW as an optimizer with a batch size of 32. Learning rate is set to 1e-5 and weight decay is set to 1e-3. We report averaged scores of 5 runs to obtain statistically stable results.

5.3 Evaluation Metric

Across three datasets, we used the same evaluation metric established by their proposers, which was also adopted by most of the subsequent baselines. Therefore, we ensure that the following comparisons are fair. We adopt the macro-average of the F1-score as the evaluation metric. For Sem16 and P-Stance, we report $F1 = (F_{favor} + F_{against})/2$. For VAST, we report $F1 = (F_{favor} + F_{against} + F_{none})/3$. For in-target stance detection, we select each target to divide training, validation, and test sets. In zero-shot stance detection, for Sem16 and P-Stance, we use the leave-one-target-out evaluation setup. For the VAST dataset, we use their original zero-shot dataset settings. We use standard train/validation/test splits for in-target and zero-shot stance detection across the three datasets.

5.4 Comparison Models

The fine-tuned model baselines include vanilla RoBERTa (Liu et al., 2019), domain pre-trained model: BERTweet (Nguyen et al., 2020), joint contrastive learning framework: JointCL (Liang et al., 2022), incorporating ConceptGraph knowledge model: KEprompt (Huang et al., 2023), incorporating Wikipedia knowledge model: TarBK-BERT (Zhu et al., 2022) and WS-BERT (He et al., 2022), incorporating knowledge from LLMs: KASD-BERT (Li et al., 2023). For large language models, we compare baselines include Task-Des (Zhang et al., 2022), CoT-Demo (Zhang et al., 2023b), the self-consistent chain-of-thought: CoT-SC (Wang et al., 2023), incorporating Wikipedia knowledge for retrieval-augmented generation: KASD-ChatGPT and KASD-LLaMA-2 (Li et al., 2023), fine tuning LLaMA-2-7b using QLora-int4 with training set: LLaMA-2-7b-FT, utilizing collaborative role-infused LLM-based agents: COLA (Lan et al., 2023) and utilizing logically consistent chain-of-thought: LC-CoT (Zhang et al., 2023a).

6 Experimental Results

6.1 In-Target Stance Detection

We perform experiments on Sem16 and P-Stance for in-target stance detection. The results are presented in Table 4. It shows that our `MB-Cal` outperforms all baselines based on different large language models. We can observe that `MB-Cal` w/o CAD, which without the counterfactual data enhancement, the calibration network trained exclusively on the training set data can still improve stance detection performance. Moreover, the application of counterfactual data enhancement furthers the model's performance. When compared to the LLaMA-2-7b-FT method, which fine-tunes LLaMA-2-7b, our method attains superior accu-

	Sem16(%)						P-Stance(%)			
	HC	FM	LA	A	CC	Avg	Biden	Sanders	Trump	Avg
Fine-tuning Based Methods										
Roberta	55.97	68.19	67.60	65.40	43.08	58.71	84.29	79.56	82.70	82.18
BERTweet	62.31	64.20	64.14	68.12	41.30	57.99	78.09	81.02	82.48	80.53
KPT	71.30	63.30	63.50	-	-	-	80.40	77.10	80.20	79.23
KEprompt	77.10$^{\sharp}$	68.30$^{\sharp}$	70.30$^{\sharp}$	-	-	-	84.40$^{\sharp}$	-	83.20$^{\sharp}$	-
WS-BERT-Dual	75.26†	66.02†	70.42†	71.57†	57.31†	68.12†	83.50$^{\flat}$	79.00$^{\flat}$	85.80$^{\flat}$	82.77$^{\flat}$
KASD-BERT	77.60†	70.38†	72.29†	72.32†	61.47†	70.81†	85.66†	80.39†	85.35†	83.80†
LLaMA-2 Based Methods										
LLaMA-2-Task-Des	75.96	66.60	61.68	53.40	73.56	66.24	84.31	77.29	78.08	79.89
LLaMA-2-CoT-Demo	74.84	71.45	62.67	57.58	73.26	67.96	85.03	79.77	77.52	80.77
KASD-LLaMA-2	77.89†	67.29†	52.00†	35.78†	47.12†	56.02†	79.59†	71.32†	67.89†	72.93†
LLaMA-2-7b-FT	**81.86**	71.58	65.56	68.74	75.59	72.67	85.79	81.25	**87.47**	84.84
LLaMA-2-MB-Cal (Ours)	80.44	**73.46***	**67.18**	**71.85**	**76.19**	**73.82***	**86.34**	**83.06***	85.58	**84.99**
- w/o CAD	78.00	70.82	65.57	71.40	72.24	71.61	85.35	82.00	85.51	84.29
GPT-3.5-Turbo Based Methods										
GPT-3.5-Turbo-Task-Des	73.33	66.81	67.22	25.18	72.54	61.02	83.20	80.02	81.66	81.62
GPT-3.5-Turbo-CoT-Demo	81.58	73.42	68.28	64.96	78.35	73.32	83.07	77.98	81.59	80.88
KASD-ChatGPT	80.92†	70.37†	63.26†	61.92†	62.72†	67.84†	84.59†	79.96†	**85.06**†	83.20†
GPT-3.5-MB-Cal (Ours)	**83.38***	**78.46***	**69.36***	**69.56***	**80.05***	**76.16***	**86.03***	**81.60***	84.95	**84.20***
- w/o CAD	82.38	73.80	63.65	69.21	62.93	70.39	85.40	81.36	85.00	83.92

Table 4: In-target stance detection experiment results on Sem16 and P-Stance datasets. The results with ♯ are retrieved from (Huang et al., 2023), ♭ from (He et al., 2022), † from (Li et al., 2023). The best scores over the same type are in bold. Results with ⋆ denote the significance tests of our `MB-Cal` over the same type baseline models at p-value < 0.05.

	Sem16(%)							P-Stance(%)				VAST(%)
	DT	HC	FM	LA	A	CC	Avg	Biden	Sanders	Trump	Avg	All
Fine-tuning Based Methods												
Roberta	32.12	43.45	40.38	38.79	26.80	18.70	33.37	76.29	72.07	67.56	71.97	73.18
BERTweet	26.88	44.82	21.97	31.91	30.49	12.48	28.09	73.13	68.22	67.66	69.67	71.10
JointCL	50.50$^{\natural}$	54.80$^{\natural}$	53.80$^{\natural}$	49.50$^{\natural}$	54.50$^{\natural}$	39.70$^{\natural}$	50.47$^{\natural}$	-	-	-	-	72.30
TarBK-BERT	50.80$^{\sharp}$	55.10$^{\sharp}$	53.80$^{\sharp}$	48.70$^{\sharp}$	56.20$^{\sharp}$	39.50$^{\sharp}$	50.68$^{\sharp}$	75.49	70.45	65.80	70.58$^{\sharp}$	73.60$^{\sharp}$
KASD-BERT	54.74†	64.78†	57.13†	51.63†	55.97†	40.11†	54.06†	79.04†	75.09†	70.84†	74.99†	76.82†
LLaMA-2 Based Methods												
LLaMA-2-Task-Des	66.03	73.79	71.03	66.00	**60.44**	61.91	66.53	82.81	78.00	**78.87**	79.89	68.54
LLaMA-2-CoT-Demo	58.56	72.09	73.83	66.10	57.58	62.47	65.11	83.97	79.26	77.96	80.40	67.28
KASD-LLaMA-2	-	**77.70**†	65.57†	57.07†	39.55†	50.72†	-	75.28†	74.09†	69.27†	72.88†	43.42†
LLaMA-2-7b-FT	63.99	55.49	59.46	33.18	46.37	58.24	52.79	83.93	77.00	74.35	78.43	77.80
LLaMA-2-MB-Cal (Ours)	**66.96**	77.19	**74.71**	**72.49***	58.29	**67.71***	**69.56***	**84.04**	**81.22***	77.57	**80.94**	**79.62***
- w/o CAD	61.99	69.22	62.77	60.39	40.83	63.69	59.81	83.09	78.21	76.74	79.35	76.61
GPT-3.5-Turbo Based Methods												
GPT-3.5-Turbo-Task-Des	61.72	72.70	71.71	67.89	28.87	59.36	60.38	84.08	80.38	82.38	82.28	50.21
GPT-3.5-Turbo-CoT-Demo	64.16	78.69	73.22	72.84	65.15	**75.20**	71.54	84.08	80.12	82.24	82.15	70.14
KASD-ChatGPT	64.23†	80.32†	70.41†	62.71†	63.95†	55.83†	66.24†	83.60†	79.66†	84.31†	82.52†	67.03†
COLA	71.20‡	75.90‡	69.10‡	**71.00**‡	62.30‡	64.00‡	68.92‡	-	-	-	-	73.40‡
LC-CoT	71.70$^{\flat}$	**82.90**$^{\flat}$	70.40$^{\flat}$	63.20$^{\flat}$	-	-	-	-	-	-	-	72.50$^{\flat}$
GPT-3.5-MB-Cal (Ours)	**72.80***	80.26	**75.76***	68.77*	**66.54***	71.00	**72.52***	**85.14**	**81.05***	**85.08**	**83.76***	**79.98***
- w/o CAD	63.28	72.65	60.88	62.07	41.65	67.80	61.39	84.26	77.80	75.26	79.11	77.50

Table 5: Zero-shot stance detection experiment results on Sem16, P-Stance and VAST dataset. The results with ♮ are retrieved from (Liang et al., 2022), ♯ from (Zhu et al., 2022), † from (Li et al., 2023), ‡ from (Lan et al., 2023), ♭ from (Zhang et al., 2023a). The best scores over the same type are in bold. Results with ⋆ denote the significance tests of our `MB-Cal` over the same type baseline models at p-value < 0.05.

racy in stance detection with significantly reduced computation resources.

6.2 Zero-Shot Stance Detection

We conduct experiments on Sem16, P-Stance, and VAST for zero-shot stance detection. The results are shown in Table 5. It shows that our `MB-Cal` outperforms all baselines including both fine-tuned models and different large language models. This indicates that our `MB-Cal` has strong generalization capabilities and can perform well on unseen targets. We can observe that `MB-Cal` w/o CAD ex-

	Sem16		P-stance		Vast	
	SSC↓	TPB↓	SSC↓	TPB↓	SSC↓	TPB↓
LLaMA-2 Based Methods						
Task-Des	17.80	17.59	23.36	9.09	23.87	17.76
CoT-Demo	27.52	27.56	22.81	11.57	22.55	9.64
CoT-SC	33.67	27.18	29.85	6.34	31.98	23.70
LLaMA-2-7b-FT	22.44	25.09	18.14	5.07	22.36	6.84
KASD-LLaMA-2	18.74	10.90	18.74	4.43	20.51	18.00
LLaMA-2-MB-Cal	**9.61**	**5.52**	**17.15**	**2.81**	**19.89**	**5.42**
- w/o CAD	15.43	12.07	19.15	5.81	21.89	11.42
GPT-3.5-Turbo Based Methods						
Task-Des	27.13	22.64	23.72	5.43	28.70	28.44
CoT-Demo	18.08	13.47	22.75	6.61	16.32	18.40
CoT-SC	21.42	16.03	26.30	8.06	22.58	21.63
KASD-ChatGPT	19.49	20.17	20.90	13.94	20.54	15.56
GPT-3.5-MB-Cal	**11.31**	**7.74**	**16.00**	**3.38**	**13.25**	**7.03**
- w/o CAD	12.92	11.83	18.00	4.38	17.27	12.04

Table 6: The result of Bias-SSC and Bias-TPB in in-target stance detection on Sem16, P-Stance datasets, and zero-shot stance detection on the VAST dataset.

hibits subpar performance. This can be attributed to the constraints posed by the exclusive reliance on fine-tuning within the limited training dataset, making it an uphill task to generalize the model's debiasing capability. Conversely, employing our counterfactual data enhancement bolsters the out-of-domain generalization prowess of the model considerably, yielding impressive results in zero-shot performance. Compared to the LLaMA-2-7b-FT, which performs poorly on zero-shot tasks, our method demonstrates strong generalization capabilities.

6.3 Mitigating Biases Effect Analysis

We conduct experiments to evaluate the Bias-SSC and Bias-TPB of LLMs and further assess the impact of our bias mitigation efforts. The results are shown in Table 6, which indicate that our `MB-Cal` can effectively alleviate Bias-SSC and Bias-TPB for both GPT-3.5-turbo and LLaMA2-70b, thus validating its effectiveness in mitigating biases. The inclusion of counterfactual data augmentation can effectively improve its debiasing ability, indicating the importance of our counterfactual data augmentation. Our findings also highlight that the integration of counterfactual data augmentation enhances the debiasing capacity of the model, thereby emphasizing the significance of this augmentation in our methodology.

6.4 Ablation Study

We conduct ablation studies to examine the impact of different components in our `MB-Cal`: (1) "**w/o** Calibration" denotes without the calibration network, letting the LLMs directly output stance labels. (2) "**w/o** CAD" denotes without the counterfactual augmented data when training the calibration network. (2) "**w/o** non-causal" denotes without the non-causal counterfactual augmented data when training the calibration network. (3) "**w/o** causal" denotes without the causal counterfactual augmented data when training the calibration network.

	Sem16			Vast		
	Avg↑	SSC↓	TPB↓	All↑	SSC↓	TPB↓
LLaMA-2-MB-Cal	**73.82**	**9.61**	**5.52**	**79.62**	**19.89**	5.42
w/o Calibration	67.96	27.52	27.56	67.28	22.55	9.64
w/o CAD	71.61	15.43	12.07	76.61	21.89	11.42
- w/o non-causal	71.29	13.12	13.25	79.38	24.04	7.12
- w/o causal	69.39	10.66	14.82	77.45	21.69	**3.97**
GPT-3.5-MB-Cal	**76.16**	11.31	**7.74**	**79.98**	**13.25**	7.03
w/o Calibration	73.32	18.08	13.47	70.14	16.32	18.40
w/o CAD	70.39	12.92	11.83	77.50	17.27	12.04
- w/o non-causal	74.08	14.36	11.80	79.38	26.48	9.32
- w/o causal	71.71	**10.22**	10.21	77.80	22.25	**6.81**

Table 7: Experimental results of ablation study of in-target stance detection on the Sem16 dataset, and zero-shot stance detection on the VAST dataset.

The results are presented in Table 7. Note that despite utilizing the same stance reasoning, a lack of calibration can result in sub-optimal results and notable biases. Thus validating the effectiveness of our gate calibration network. In addition, when removing non-causal counterfactual data, the bias would increase more significantly, proving that non-causal counterfactual data has a strong role in enhancing the effect of mitigating bias. The removal of causal counterfactual data declines the performance more significantly, indicating that the causal counterfactual data substantially improves the accuracy and generalizability of the calibration network in stance detection.

7 Conclusion

In this paper, we categorize the biases of LLMs in stance detection into two types from the perspective of causality and propose metrics to quantify these biases. Then, we propose to **M**itigate **B**iases of LLMs in stance detection with **Cal**ibration, coined as `MB-Cal`. In which, a trainable calibration network and counterfactual data augmentation are explored to mitigate the biases of LLMs in stance detection. Experimental results on in-target and zero-shot stance detection show that our `MB-Cal` can effectively reduce the bias of LLMs in stance detection and contribute to improved performance.

Limitations

Our framework involves using GPT-3.5 to generate counterfactual augmented data. As we discussed in Appendix C, these samples may contain errors, but overall are beneficial to the training of our calibration network. The methods of constructing counterfactual augmented data using manual annotation or other methods remain to be explored.

Ethics Statement

The datasets used in this paper are sourced from open-access datasets. The VAST dataset provides complete text data in open access. In compliance with the privacy agreement of Twitter for academic usage, the Sem16 and P-Stance were accessed using the official Twitter API[5] through the Tweet IDs to fetch complete text data. We removed the information on user privacy from the data. In these datasets, we analyze the biases and stereotypes in stance detection for some sensitive targets (e.g., belief, politics, etc.). We DO NOT critique any biases and stereotypes. We focus on analyzing their impacts on stance detection and mitigating these impacts. We used the counterfactual augmented data obtained from the GPT-3.5-Turbo API service from OpenAI. We followed their term and policies. Some examples in our paper may include a stance or tendency. It should be clarified that they are randomly sampled from the dataset for better studying the dataset and task, and do not represent any personal viewpoints.

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[5] https://developer.twitter.com/en/docs/twitter-api

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A Prompts Setting

We present the prompt templates used in Section 3.2 and Section 4.2.

Specifically, Figure 5 shows the prompt template we use with GPT-4 to obtain sentiment labels. Figures 6, 7, and 8 show the prompt templates corresponding to the Task-Des, CoT-Demo, and Debias-Instruct prompt settings in Section 3.2.1, respectively. Similarly, Figures 6, 7, and 9 display the prompt templates corresponding to the Task-Des, CoT-Demo, and Debias-Instruct prompt settings in Section 3.2.2, respectively.

Figures 10 and 11 illustrate the prompt templates used to obtain non-causal and causal counterfactual augmented data, respectively, as discussed in Section 4.2. Figure 10 presents the constructed instruction for acquiring non-causal counterfactual augmented data, while Figure 11 shows the instruction for obtaining causal counterfactual augmented data.

B Experimental Result of LLMs Bias

We present the complete experimental results in Section 3. Tables 8, 9, and 10 show the RStd and the macro F1-Score of samples with different sentiment on the Sem16, P-Stance, and VAST datasets. Tables 11 and 12 present the RStd and the macro F1-Score of samples with different stance target on the Sem16, P-Stance, and VAST datasets. We can observe that in most cases, a larger stance bias leads to poorer stance detection results. In Tables 8, 9, and 10, samples with positive and negative emotions exhibited larger Rstd, indicating that sentiment influenced the stance judgment of LLMs as a bias pattern. In Tables 11 and 12, on some controversial debate topics such as the "Legalization of Abortion", the "Feminist Movement", and specific individuals like "Donald Trump" and "Hillary Clinton", larger Rstd indicates that LLMs demonstrated a relatively large target preference bias.

C Human Evaluation of Counterfactual Augmented Data

We randomly select 500 samples and use human evaluation (with three experienced researchers who are not involved in this work and have worked on natural language processing for over 3 years) to measure the counterfactual data generated by GPT-3.5-turbo. The primary consideration focuses on the qualitative assessment of the generated samples, necessitating evaluators to confirm the accuracy of both the grammar and the affirmed stance. The secondary consideration pertains to achieving generating objectives, necessitating evaluators to confirm if the samples were generated as guideline instructions. Evaluators respond to these considerations with a binary "yes" or "no". Subsequently, we calculate the average ratio of affirmative responses from three evaluators for each query. The results in Table 13 show that the generated samples are of high quality, contributing substantially to our calibration network training.

D Case Study

We conduct a case study on Sem16, P-Stance and VAST datasets, to analyze the biases of LLMs in the stance detection task and the practical effectiveness of our calibration network. The results are show in Table 14, 15 and 16. The correct analysis patterns of LLMs are marked in blue, while biased analysis patterns are marked in red. We can observe that for some samples with strong sentiment expressions, such as the examples in Table 15, LLMs are influenced by sentiment Spurious cues and result in biased stance judgments. For some controversial debate topics, such as the examples in Table 14, LLMs generate hallucinations due to their preferences, leading to biased stance judgments.

```
[sentence]: {sentence}
What is the sentiment of [sentence]?
Only answer with "positive", "negative" or "neutral".
```

Figure 5: Prompt template of sentiment labels annotation by GPT-4. Fill the blue text with the corresponding text from the sample.

````
Stance detection is to determine the attitude or tendency towards a certain
target through a given sentence, including favor, against and neutral.

{sentence}

Question: What is the attitude of the sentence toward "{target}"? Please
select the correct answer from "favor", "against" and "neutral".
Answer this question with JSON format:
```json
{{
    "stance": "favor" | "against" | "neutral",
}}
```
````

Figure 6: Prompt template with Task-Des setting. We first outline the stance detection task, then instruct the LLMs to determine the stance based on the sentence in relation to the target. Fill the blue text with the corresponding text and target from the sample.

````
Stance detection is to determine the attitude or tendency towards a certain
target through a given sentence, including favor, against and neutral.
**Please read the following examples carefully and use them as references to
judge the attitude of the sentence towards the target.**

[in-context examples]

Your sentence:

{sentence}

Question: What is the attitude of the sentence toward "{target}"? Please
select the correct answer from "favor", "against" and "neutral".
Answer this question with JSON format:
```json
{{
    "answer": "your answer",
    "stance": "favor" | "against" | "neutral"
}}
```
````

Figure 7: Prompt template with CoT-Demo setting. We randomly select 4 samples from the training set, provide the ground truth stance labels, and guide GPT-4 to generate chain-of-thought rationales as examples for this prompt. Fill the green text with constructed examples, and fill the blue text with the corresponding text and target from the sample.

```
Stance detection is to determine the attitude or tendency towards a certain
target through a given sentence, including favor, against and neutral.
**Note that the sentiment of the sentence is not necessarily consistent with
the author's attitude on the target, and avoid directly using emotion as the
only basis for judging the attitude.**

{sentence}

Question: What is the attitude of the sentence toward "{target}"? Please
select the correct answer from "favor", "against" and "neutral".
Answer this question with JSON format:
```json
{{
    "stance": "favor" | "against" | "neutral",
}}
```
```

Figure 8: Prompt template with SSC Debias-Instruct setting. We add explicit debiasing instructions following the task description. Fill the blue text with the corresponding text and target from the sample.

```
Stance detection is to determine the attitude or tendency towards a certain
target through a given sentence, including favor, against and neutral. **Be
careful to only judge the author's attitude on the target based on the
content in the sentence, and do not include your inherent attitude towards
the target.**

{sentence}

Question: What is the attitude of the sentence toward "{target}"? Please
select the correct answer from "favor", "against" and "neutral".
Answer this question with JSON format:
```json
{{
    "stance": "favor" | "against" | "neutral",
}}
```
```

Figure 9: Prompt template with TPB Debias-Instruct setting. We add explicit debiasing instructions following the task description. Fill the blue text with the corresponding text and target from the sample.

```
[sentence]: {sentence}
[target]: {target}

The [sentence] expresses a {stance} stance to the [target]. Please rephrase
the [sentence] using different words and emotions, and rewrite the [target]
using different words while preserving the same meaning and stance as the
original.
```

Figure 10: Prompt template that allows the LLMs to rephrase the original sentence with different words and sentiments and express the target while ensuring that the semantics and the stance of the perturbed sample towards the target remain unchanged. Fill the blue text with the corresponding text, target, and stance label from the sample.

```
[sentence]: {sentence}
[target]: {target}

The [sentence] expresses a {stance} attitude to the [target]. Please make
minimal changes to the [sentence] to express a reverse attitude to the
[target].
```

Figure 11: Prompt template that makes necessary modifications to reverse the applicability of the label. Fill the blue text with the corresponding text, target, and stance label from the sample.

	Sem16(%)					
	Positive		Neutral		Negative	
	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑
GPT-3.5-Turbo-0125						
Task-Des	29.37	48.37	25.22	58.78	26.80	55.44
CoT-Demo	**16.02**	**65.77**	25.47	**61.69**	**12.74**	**70.69**
Debias-Instruct	30.52	46.09	**16.31**	60.07	24.43	54.91
LLaMA-2-70b-chat						
Task-Des	**22.20**	**59.73**	**23.65**	58.11	7.56	65.19
CoT-Demo	26.15	58.24	27.88	55.18	28.54	62.04
Debias-Instruct	26.86	55.04	25.51	**58.20**	**5.34**	**68.61**

Table 8: RStd of sentiment labels and macro F1-score of stance detection on Sem16 dataset.

	P-Stance(%)					
	Positive		Neutral		Negative	
	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑
GPT-3.5-Turbo-0125						
Task-Des	33.79	**68.61**	23.48	62.32	**13.88**	**75.66**
CoT-Demo	**32.39**	66.99	**19.25**	**65.09**	16.60	74.44
Debias-Instruct	33.56	68.00	20.05	63.19	16.83	75.07
LLaMA-2-70b-chat						
Task-Des	33.32	**68.42**	19.98	62.68	**16.77**	72.97
CoT-Demo	**32.62**	67.17	**15.10**	**65.00**	20.70	**73.61**
Debias-Instruct	34.66	66.49	22.81	59.14	17.10	71.82

Table 9: RStd of sentiment labels and macro F1-score of stance detection on P-Stance dataset.

	VAST(%)					
	Positive		Neutral		Negative	
	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑
GPT-3.5-Turbo-0125						
Task-Des	36.33	44.58	19.75	52.72	30.03	46.74
CoT-Demo	**26.01**	**69.05**	**8.78**	**66.73**	**14.17**	**67.38**
Debias-Instruct	38.40	40.96	23.51	49.01	29.66	46.19
LLaMA-2-70b-chat						
Task-Des	**30.19**	**61.47**	**5.79**	60.85	14.63	66.97
CoT-Demo	36.20	59.60	18.93	**67.87**	**12.51**	63.87
Debias-Instruct	34.60	56.63	10.82	59.49	13.48	**67.61**

Table 10: RStd of sentiment labels and macro F1-score of stance detection on VAST dataset.

	Sem16(%)									
	HC		FM		LA		A		CC	
	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑
GPT-3.5-Turbo-0125										
Task-Des	28.68	61.97	24.21	57.47	26.98	56.75	5.81	27.54	27.52	60.36
CoT-Demo	**20.99**	**74.12**	**15.16**	**65.61**	**11.12**	**64.74**	6.75	**57.89**	**13.30**	**75.57**
Debias-Instruct	28.07	63.07	27.81	54.72	24.08	57.11	**5.43**	29.14	23.94	62.63
LLaMA-2-70b-chat										
Task-Des	11.59	73.64	24.41	58.33	**6.84**	59.36	**15.12**	48.94	29.98	60.15
CoT-Demo	28.36	64.71	35.98	52.96	19.27	57.10	19.91	**55.87**	34.26	62.78
Debias-Instruct	**8.73**	**76.50**	**14.75**	**63.39**	9.77	**58.64**	25.76	39.32	**22.83**	**69.16**

Table 11: RStd of targets and macro F1-score of stance detection on Sem16 dataset.

	P-Stance(%)						VAST(%)	
	JB		BS		DT		ALL	
	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑	RStd↓	F1↑
GPT-3.5-Turbo-0125								
Task-Des	**0.53**	**83.20**	4.82	**80.02**	**10.94**	81.66	28.44	49.86
CoT-Demo	3.22	83.07	**4.01**	77.98	12.59	81.59	**8.40**	**69.90**
Debias-Instruct	0.63	82.91	5.36	79.01	11.39	**82.85**	26.77	51.66
LLaMA-2-70b-chat								
Task-Des	2.69	84.31	8.79	77.29	**15.79**	78.08	7.76	68.36
CoT-Demo	7.91	**85.03**	**7.62**	**79.77**	19.19	77.52	9.64	67.08
Debias-Instruct	**1.58**	82.63	9.29	75.10	15.96	**78.36**	**4.86**	**69.10**

Table 12: RStd of targets and macro F1-score of stance detection on P-Stance and VAST dataset.

	CAD-non-causal		CAD-causal	
	Quality	Achievement	Quality	Achievement
Human Eval	96.67%	91.33%	95.33%	88.83%

Table 13: Human evaluation on Sem16, P-Stance, and VAST datasets. Quality stands for qualitative assessment of the generated samples and Achievement stands for the achievement of generating objectives.

Text (Target: Legalization of Abortion)	Label	LLMs Pred	LLMs Stance Rationale	Calibration
A prochoice advocate but circumcise ur baby? Fucking hypocrite! #circumcision #humanrights	Against	Favor	The sentence criticizes the hypocrisy of being a prochoice advocate but supporting circumcision, indicating a negative attitude towards circumcising babies. Since the author is prochoice, it can be inferred that they are in favor of the legalization of abortion.	Against
Text (Target: Feminist Movement)	**Label**	**LLMs Pred**	**LLMs Stance Rationale**	**Calibration**
Equality is the police burying a domestic violence accusation against a female sports star, too #wedidit #usa	Against	Favor	The sentence mentions burying a domestic violence accusation against a female sports star, which implies a negative view towards this unequal treatment. Therefore, the attitude of the sentence towards the Feminist Movement is likely favorable.	Against

Table 14: Case study on the Sem16 dataset.

Text (Target: Donald Trump)	Label	LLMs Pred	LLMs Stance Rationale	Calibration
You might as well put a sock in it. Voters see these coordinated stupid attacks are like your #Kavanaugh symphony. #Dems can't win with hollow attempts to bash #Trump.	Favor	Against	The sentence uses derogatory terms like 'stupid attacks' and 'hollow attempts to bash #Trump,' indicating a critical perspective. Therefore, the attitude of the sentence toward 'Donald Trump' is against.	Favor
Text (Target: Joe Biden)	**Label**	**LLMs Pred**	**LLMs Stance Rationale**	**Calibration**
Saying that is as absurd as saying breast cancer screening increases breast cancer. Is there any Republican who isn't as dumb as dirt?	Favor	Against	The sentence implies negative assumptions about the intelligence of Republicans. The mention of Joe Biden in the context of criticizing Republicans suggests a critical or skeptical attitude towards Joe Biden.	Favor

Table 15: Case study on the P-Stance dataset.

Text (Target: Homosexual)	Label	LLMs Pred	LLMs Stance Rationale	Calibration
Yet that same Bible gives us Christians a particular anthropology, and reveals to us the meaning of sex and marriage within the cosmic order. And herein lies the problem. If you look to a "holy" book written long, long ago and betraying its human origins on every page for guidance on issues of cosmology, biology, sexuality and other human and natural sciences, you will inevitably be in constant conflict with social progress and, indeed, reality. There is no secular opposition to homosexuality."	Favor	Against	The sentence criticizing the use of a 'holy' book for guidance on issues related to sexuality and natural sciences. It suggests that relying on such sources will lead to conflict with social progress and reality. Additionally, the statement asserts that there is no secular opposition to homosexuality, implying a negative view towards those who oppose it based on religious beliefs. Overall, the tone of the sentence is against homosexuality, indicating a critical stance.	Favor
Text (Target: Gun Control)	**Label**	**LLMs Pred**	**LLMs Stance Rationale**	**Calibration**
Military and police, yes. They're sworn and trained to uphold the country and the laws of the country. The rest is an ego trip.	Favor	Against	The sentence expresses a negative attitude towards gun control in the military and police, stating that they are sworn and trained to uphold the country and its laws. However, it is critical of the use of guns by others, referring to it as an ego trip. Therefore, the attitude of the sentence towards gun control is against	Favor

Table 16: Case study on the VAST dataset.