

Stance Detection with Collaborative Role-Infused LLM-Based Agents

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Abstract

Stance detection automatically detects an author's position on a particular topic within a text, vital for content analysis in web and social media research. With the development of LLMs, researchers have begun to explore their potential for stance detection. Despite their promising capabilities, LLMs encounter challenges when directly applied to stance detection. First, stance detection demands multi-aspect knowledge to fully understand elements in the text. Second, stance detection requires advanced reasoning to infer viewpoints, as stances are often implicitly embedded rather than explicitly stated in the text. To address these challenges, we design a three-stage framework COLA (short for Collaborative rOle-infused LLM-based Agents) in which LLMs are designated distinct roles, creating a collaborative system. The framework consists of three stages. First, in the multidimensional text analysis stage, we configure the LLMs to act as a linguistic expert, a domain specialist, and a social media veteran to get a multifaceted analysis of texts, thus overcoming the first challenge. Next, in the reasoning-enhanced debating stage, for each potential stance, we designate a specific LLM-based agent to advocate for it, guiding the LLM to detect logical connections between text features and stance, addressing the second challenge. Finally, in the stance conclusion stage, a final decision maker agent consolidates prior insights to determine the stance. COLA avoids the need for extra annotated data and model training, making it highly user-friendly. What's more, COLA achieves state-of-the-art performance across multiple widely-used datasets. Ablation studies validate the effectiveness of each module in our approach. Further experiments have demonstrated the explainability and the versatility of our approach. In summary, our approach excels in usability, accuracy, effectiveness, explainability and versatility, showcasing its significant value.

Introduction

Stance detection is commonly defined as automatically detecting the stance (as *Favor*, *Against*, or *Neutral*) of the author towards a target (Mohammad et al. 2016). Over the years, numerous methodologies have been proposed for stance detection (Küçük and Can 2020; AlDayel and Magdy 2021). However, a persistent challenge lies in the need to train models specifically for the targets of interest. Even with

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advancements in cross-target stance detection (Liang et al. 2021) and zero-shot stance detection (Allaway and McKeeown 2020; Liang et al. 2022a), training on annotated corpora is always required. However, acquiring large-scale labeled datasets is not trivial, which curtails the model's usability.

Recently, large language models (LLMs) have demonstrated remarkable capabilities across various applications (Brown et al. 2020; Park et al. 2023). The inherent semantic understanding of these large models presents an exciting opportunity for stance detection. Most LLMs can be easily interacted with by users through zero-shot prompting, which significantly enhances their usability. Thus, with their strength and usability, large language models offer new possibilities for stance detection.

Researchers have discerned the transformative potential LLMs bring to stance detection. Some works have proposed simple methods using LLMs for stance detection (Zhang, Ding, and Jing 2022; Zhang et al. 2023). Yet, while these works report satisfactory results on specific subsets of certain datasets, our rigorous replications indicate that these methods frequently fail to match the performance of state-of-the-art non-LLM baselines. This can be attributed to two inherent challenges of stance detection, which can be listed as follows.

- **First, stance detection demands multi-aspect knowledge.** As shown in Figure 1, sentences may contain elements like domain-specific terms, cultural references, social media linguistic styles, and more. These are not immediately comprehensible to large language models and require specialized parsing to be truly understood.
- **Second, stance detection necessitates advanced reasoning.** Often, authors don't state their stances directly but inadvertently reveal them in various ways, such as through their attitudes towards related topics or events, as shown in Figure 1. Stance detection requires reasoning from various textual features to arrive at the correct stance.

To address these challenges, we introduce our three-stage framework named COLA (short for Collaborative rOle-infused LLM-based Agents). Specifically, we design a stance detection system consisting of role-infused LLM-based agents, with each role bearing distinct responsibilities and significance. To counter the first challenge, we de-

Challenge 1: Stance detection demands multi-aspect knowledge.
Tweet: Time to reclaim our nation! No more Republicans! #ByeByeGOP
Target: Donald Trump Stance: Against
Required knowledge:
1. On social media, the hashtag #ByeByeGOP expresses disagreement with the Republican Party. 2. Donald Trump is a Republican.
Challenge 2: Stance detection necessitates advanced reasoning.
Tweet: It's a problem when explaining feminism, even in a calm and complex level, cannot be understood.
Target: Feminism Movement Stance: Favor
Logical chain:
The lack of understanding of feminism is problematic. → Feminism should be understood and accepted → Support

Figure 1: Illustration of the challenges of stance detection.

sign a multidimensional text analysis stage. In this stage, LLMs are designated with three roles, named as linguistic expert, domain specialist, and social media veteran, to analyze text from various perspectives, covering syntax, textual elements, and platform-specific expressions, ultimately revealing stance indicators. Addressing the second challenge, we propose a reasoning-enhanced debating stage. In this stage, advocates for each stance category draw evidence from previous analyses, presenting arguments that compel LLMs to uncover the underlying logic linking textual features and stances. Lastly, a stance conclusion stage determines the text's stance, drawing insights both from the original text and the debates.

Our approach does not necessitate annotated data nor additional model training, hence ensuring high **usability**. Extensive experiments validate our method's superior performance over existing baselines, affirming its **accuracy**¹. Ablation studies demonstrate the **effectiveness** of each module. Case studies and quantitative experiments show that our approach can generate reasonable explanations for its output, demonstrating our approach's **explainability**. The powerful performance of our proposed framework in a series of text classification tasks underscores its **versatility**. Our approach stands out for its usability, accuracy, effectiveness, explainability, and versatility, all of which highlight its value.

Our main contributions are summarized as follows:

- To the best of our knowledge, we are the first to employ multiple LLM agents for stance detection.
 - We introduce an approach based on collaborative role-infused LLM-empowered agents, which achieves a remarkable 19.2% absolute improvement over the best non-LLM zero-shot stance detection baseline on the SEM16 dataset. Additionally, it offers high usability and explainability.

¹In this work, unless explicitly stated otherwise, we use *accuracy* to express the overall strong performance of the model on classification tasks, rather than solely referring to the accuracy metric.

- Our proposed three-stage framework—analyst, debater, and summarizer—offers significant potential for a range of text classification tasks, providing a powerful tool for text analysis on web and social media.

The subsequent sections are organized as follows. In Section , we review related works. In the Section , we describe our three-stage framework in detail. Then, in Section and , we present our experiments, providing robust empirical evidence that demonstrates the superiority of our method from multiple perspectives. Lastly, in Section , we conclude our work and highlight potential areas for future improvement.

Related Work

This section is structured as follows: First, we provide a detailed overview of advancements in stance detection. Next, we introduce recent progress in large language models. Lastly, we focus on reviewing a subset of works closely related to ours, specifically multi LLM-based agents systems.

Stance detection. Stance detection aims to discern the stance of the author towards a particular target from textual content. Typically, stances are categorized into favor, against, neutral. A plethora of algorithms for stance detection have been proposed by researchers, encompassing both feature-based methods (Bar-Haim et al. 2017; Lozhnikov, Derczynski, and Mazzara 2020) and deep learning techniques (Wei, Mao, and Zeng 2018; Liu et al. 2021). These methodologies have enabled in-depth analysis of content on the internet and social media platforms. For example, Jang et al. (2018) develop a method to find controversies on social media by generating stance-aware summaries of tweets. Grcar et al. (2017) examine the Twitter stance before the Brexit referendum, revealing the pro-Brexit camp’s higher influence.

Conventionally, stance detection necessitates training on datasets annotated for specific targets. Such datasets are not trivially obtainable, thereby constraining the usability of many methods. Recognizing this limitation, researchers have ventured into cross-target stance detection, aiming to train classifiers that can adapt to unfamiliar but related targets after being trained on a known target (Xu et al. 2018; Wei and Mao 2019; Liang et al. 2021). Recently, there has been an emergence of zero-shot stance detection approaches that automatically detects the stance on unseen tasks (Allaway and McKeown 2020; Liang et al. 2022a). However, all these methods require training on annotated datasets. Unlike these methods, our approach uses pre-trained LLM, removing the need for additional annotated data. Through prompt engineering, we refine these models without extra training, offering a solution with high usability.

Large language models. Large language models (LLMs) represent one of the most significant advancements of artificial intelligence in recent years. Since the release of ChatGPT² at the end of 2022, LLMs have witnessed a meteoric rise in attention, predominantly driven by their outstanding performance. A myriad of LLMs, such as GPT-4 (OpenAI 2023), Llama 2 (Touvron et al. 2023), ChatGLM (Zeng et al. 2022), and others, have been introduced

²chat.openai.com

at a rapid pace. In conventional NLP tasks, the zero-shot capabilities of these LLMs often rival or even surpass meticulously crafted, domain-specific models (Wei et al. 2021). The emergence of robust capabilities, such as planning and reasoning within LLMs, has further enabled their adoption across diverse applications. Some endeavors integrate LLMs with existing tools (Qin et al. 2023; Schick et al. 2023), others explore the potential of LLMs to create new tools (Cai et al. 2023), and there is a growing trend towards leveraging LLMs for dynamic decision-making, planning, and embodied intelligence (Shinn et al. 2023; Xiang et al. 2023).

Inherently, the vast knowledge and potent semantic understanding of LLMs offer immense potential in tackling stance detection tasks. Several research initiatives have indeed explored the application of LLMs in stance detection (Zhang, Ding, and Jing 2022; Ziems et al. 2023; Zhang et al. 2023). However, these existing methods often adopt relatively straightforward approaches, neglecting the intrinsic challenges specific to stance detection. As a result, our rigorous replication efforts have frequently found their performance to be subpar in comparison to annotated data dependent baselines. In contrast, our method is specifically tailored to cater to the expert knowledge and intricate reasoning often required for stance detection, consequently achieving commendable results.

Multi LLM-based agents system. Systems comprised of multiple LLM-based agents have demonstrated complex and powerful capabilities not inherent to individual LLM. Leveraging the human-like capacities of LLM, systems formed from multiple LLM-based agents have been applied in both online and offline societal simulations, showcasing credibility at the individual level and emergent social behaviors (Li et al. 2023b; Gao et al. 2023a). For instance, Part et al. (2023) construct an AI town with 25 agents, witnessing phenomena such as mayoral elections and party organization. Gao et al. (2023b) conduct simulations of online social networks with thousands of LLM-based agents, observing group emotional responses and opinion shifts that mirrored real-world trends. What's more, some studies have employed collaborative efforts between LLMs with distinct roles to accomplish tasks. In METAGPT (Hong et al. 2023), LLM-based agents with different roles collaboratively develop computer software, while DERA (Nair et al. 2023) uses discussions among various agents to refine medical summary dialogues and care plan generation. Additionally, several efforts have utilized debates between large language model agents to enhance model performance. For example, ChatEval (Chan et al. 2023) improves text evaluation capabilities through multi-agent debates. Du et al. (2023) amplify the factuality and reasoning capacities of large language models by facilitating debates among them.

To the best of our knowledge, our work is the pioneering effort in employing multi LLM-based agents for the task of stance detection.

Methods

Task Description and Model Overview

In stance detection, the objective is to decide the stance of a given opinionated document with respect to a specified target. Let us define a dataset $D = \{(x_i = (d_i, t_i), y_i)\}_{i=1}^n$ consisting of n instances. For each instance, x_i represents a tuple comprising a document d_i and a corresponding target t_i . The task is to detect the stance y_i , which can be one of the following categories: favor, against, or neutral.

As illustrated in Figure 2, our approach consists of three stages: multidimensional text analysis stage, reasoning-enhanced debating stage, and stance conclusion stage. In the multidimensional text analysis stage, the linguistic expert, the domain specialist and the social media veteran analyze the text from web or social media from various perspectives, providing a holistic understanding. In the reasoning-enhanced debating stage, for each possible stance, a debater defends it, seeking possible logical chains between text features and the stance. Finally, in the stance conclusion stage, a final judge determines the stance based on the statements made by all debaters. Next, we will introduce the components of our approach in detail.

Multidimensional Text Analysis Stage

Challenge: Stance detection necessitates a profound grasp of multi-aspect knowledge. Sentences on social media that convey the authors' stances may be influenced by various linguistic phenomena, such as grammatical structures, tenses, and moods. There is also often an abundance of domain-specific terminologies, including references to characters, political parties, and events, and their relationships with the target. Additionally, unique language features of social media, such as hashtags, come into play. Although large language models have assimilated vast knowledge from their training data, their direct application for stance detection often fails to adequately harness this knowledge, leading to suboptimal results, a fact corroborated by our subsequent experiments.

Approach: To address this challenge and leverage the rich knowledge encoded within large language models, we designed a multidimensional text analysis stage. During this stage, we introduce three distinct LLM-based agents to parse the text from different perspectives, ensuring a comprehensive understanding of potential elements influencing the author's stance. These agents are the Linguistic Expert, Domain Specialist, and Social Media Veteran. We ask the LLM to behave as their designated roles through prompting. Specifically, the inputs and outputs of the role-infused agents in this stage are as follows.

Input: A text with a stance.

Output: The individual analyses of the text by the linguistic expert, the domain specialist, and the social media veteran.

The detailed configurations of agents are as follows.

Linguistic Expert. This Agent is tasked with dissecting the text from a linguistic standpoint, exploring factors including but not limited to:

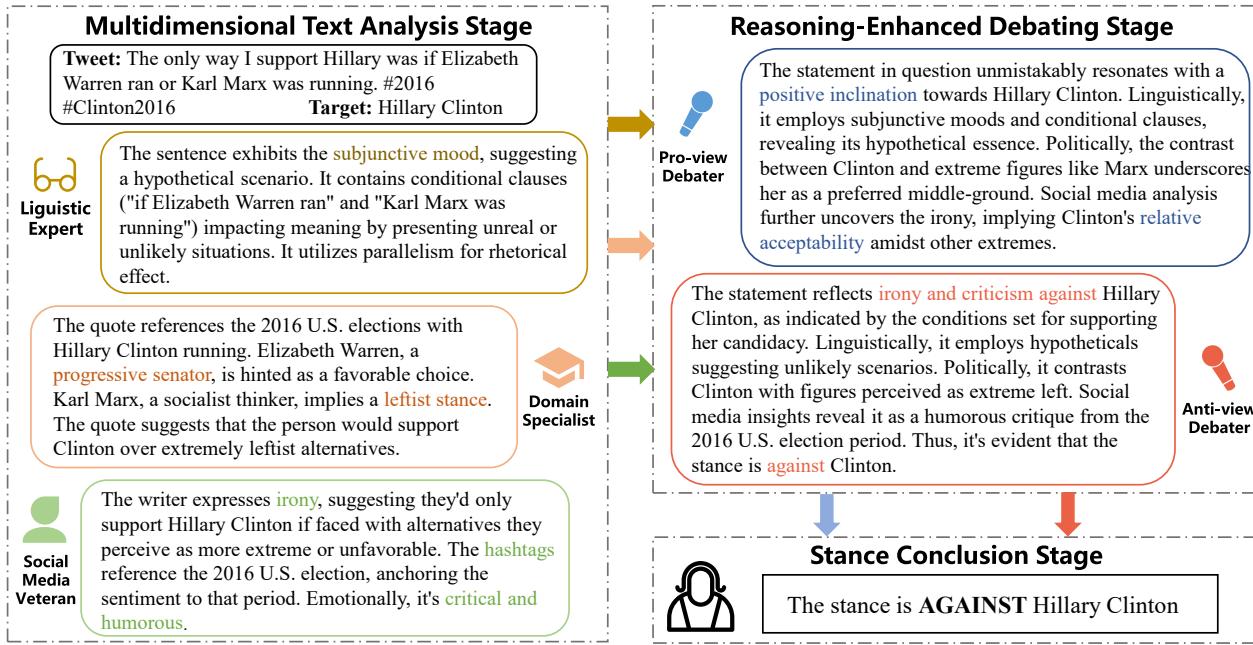


Figure 2: Architecture of our proposed COLA.

- **Grammatical structure.** The arrangement and relationship of words in a sentence, which determines how different elements combine to produce specific meanings.
- **Tense and inflection.** Tense identifies when an action occurs, influencing the stance's immediacy or distance. Inflection adjusts word forms, providing clues about the sentence's grammatical and relational context.
- **Rhetorical devices.** These are techniques used to enhance the expressiveness of language. By emphasizing, contrasting, or evoking emotions, they shape the tone and attitude of a statement.
- **Lexical choices.** The selection of particular words or phrases in writing, which can reveal deeper nuances, biases, or viewpoints about a topic.

The specific prompt is as follows,

You are a linguist. Accurately and concisely explain the linguistic elements in the sentence and how these elements affect meaning, including grammatical structure, tense and inflection, virtual speech, rhetorical devices, lexical choices and so on. Do nothing else. {tweet}

Domain Specialist. This agent focuses on domain-relevant knowledge, exploring facets such as:

- **Characters.** Key individuals or entities in a text.
- **Events.** Significant occurrences within a text. How they're portrayed can hint at the author's stance on certain issues or topics.
- **Organizations.** Established groups mentioned. Their depiction can showcase the author's feelings towards certain societal structures or institutions.

- **Parties.** Political groups with distinct ideologies. A text's treatment of these can provide insights into the author's political leanings or criticisms.
- **Religions.** Specific faiths or spiritual beliefs. How they are referenced might shed light on the author's personal beliefs or societal observations.

The specific prompt is as follows,

You are a {role}. Accurately and concisely explain the key elements contained in the quote, such as characters, events, parties, religions, etc. Also explain their relationship with {target} (if exist). Do nothing else. {tweet}

Social Media Veteran. This agent delves into the nuances of social media expression, focusing on aspects like:

- **Hashtags.** Specific labels used on social media platforms, assisting in categorizing posts or emphasizing specific themes, making content easily discoverable.
- **Internet slangs and colloquialisms.** These refer to informal terms and expressions often used in online communities. Their usage can introduce nuances, cultural contexts, or specific attitudes, making them significant indicators of the underlying stance in a statement.
- **Emotional tone.** This captures the sentiment inherent in a piece of writing, revealing the author's feelings, whether positive, negative, or neutral, about a particular subject.

The specific prompt is as follows,

You are a heavy social media user and are very familiar with the way of expression on the Internet. Analyze the following sentence, focusing on the content, emotional tone, implied meaning, and so on. Do nothing else. {tweet}

Reasoning-Enhanced Debating Stage

Challenge: The task of stance detection requires sophisticated reasoning. Authors often do not explicitly state their positions in a text. Instead, their stances may be implied through their sentiment towards certain entities or by mechanisms like comparison and contrast. Identifying these implicit stances requires detailed reasoning. Although large-scale language models possess some reasoning capabilities, their performance can be suboptimal in intricate reasoning tasks without proper guidance, which can affect the quality of stance detection results.

Approach: Drawing inspiration from recent works that leverage discussions or debates among large models to enhance their performance (Du et al. 2023; Chan et al. 2023; Liang et al. 2023), especially in reasoning tasks, we introduce a reasoning-enhanced debating stage. In this stage, for every potential stance, an agent is designated. This agent seeks evidence from expert analyses of the text and advocates for its designated stance. Specifically, the inputs and outputs of agents in this stage are as follows.

Input: A text with a stance. The analyses of the text by the linguistic expert, the domain specialist, and the social media veteran.

Output: The debate from each agent for the stance they support, including the evidence it chooses and its logical chain.

The specific prompt is as follows,

Tweet: {tweet}. Linguistic analysis: {LingResponse}. The analysis of {role}: {ExpertResponse}. The analysis of a heavy social media user: {UserResponse}. You think the attitude behind the tweet is {stance} of {target}. Identify the top three pieces of evidence from the analyses that best support your opinion and argue for your opinion.

In our framework, we only engage in a single round of debate, reserving multi-round debates for future exploration. Directing agents to search for evidence and defend their aligned stances compels the large language model to establish logical connections between discerned textual features (as well as their multifaceted interpretations) and the actual underlying stance of the text. By having multiple agents debate in favor of different stances, the system encourages the large model’s divergent thinking. These outputs subsequently feed into the stance conclusion stage, which renders a final, judicious judgment.

Stance Conclusion Stage

To infer a conclusive stance from diverse agent debates, we introduce the stance conclusion stage. In this stage, a judge agent determines the final stance of a text based on both the text itself and the arguments presented by debater agents. The process is delineated as:

Input: A text with an embedded stance. Arguments from each agent, including evidence and their logical reasoning.

Output: The identified stance of the text.

The specific prompt can be as follows,

Dataset	Target	Pro	Con	Neutral
SEM16	DT	148 (20.9%)	299 (42.3%)	260 (36.8%)
	HC	163 (16.6%)	565 (57.4%)	256 (26.0%)
	FM	268 (28.2%)	511 (53.8%)	170 (17.9%)
	LA	167 (17.9%)	544 (58.3%)	222 (23.8%)
	A	124 (16.9%)	464 (63.3%)	145 (19.8%)
	CC	335 (59.4%)	26 (4.6%)	203 (36.0%)
P-Stance	Biden	3217 (44.1%)	4079 (55.9%)	-
	Sanders	3551 (56.1%)	2774 (43.9%)	-
	Trump	3663 (46.1%)	4290 (53.9%)	-
VAST	-	6952 (37.5%)	7297 (39.3%)	4296 (23.2%)

Table 1: Statistics of our utilized datasets.

Determine whether the sentence is in favor of or against {target}, or is neutral. Sentence: {tweet}. Judge this in relation to the following arguments: Arguments that the attitude is in favor: {FavorResponse}. Arguments that the attitude is against: {AgainstResponse}. Arguments that the attitude is neutral: {NeutralResponse} Choose from: A: Against B: Favor C: Neutral

Constraint: Answer with only the option above that is most accurate and nothing else.

The judge agent evaluates the text’s inherent qualities, the evidence provided by debaters, and their logical frameworks to reach an informed decision.

After going through the three stages mentioned above, we have effectively extracted the underlying stance towards the given target from the text.

Experiments

In this section, we describe the specific setup of our experiments.

Datasets

Following many existing works (Liang et al. 2022a; Augenstein et al. 2016; Li et al. 2023a), we conduct experiments on three widely-used datasets:

SEM16 (Mohammad et al. 2016). This dataset features six specific targets from diverse domains, namely *Donald Trump* (DT), *Hillary Clinton* (HC), *Feminist Movement* (FM), *Legalization of Abortion* (LA), *Atheism* (A), and *Climate Change is Real Concern* (CC). Each instance is classified into one of the three stance categories: *Favor*, *Against*, or *None*.

P-Stance (Li et al. 2021). This dataset focuses on the political domain, and comprises three targets: *Donald Trump* (Trump), *Joe Biden* (Biden), *Bernie Sanders* (Sanders). Stance labels include *Favor* and *Against*.

VAST (Allaway and McKeown 2020). This dataset is characterized by its large number of varying targets. An instance in VAST includes a sentence, a target, and a stance, which may be *Pro*, *Con*, or *Neutral*.

The statistics of our utilized datasets are shown in Table 1. To ensure a fair comparison, We follow the majority of existing works (Allaway and McKeown 2020; Allaway, Srikanth, and McKeown 2021; Liang et al. 2022a; Zhang, Li, and

Song 2019) to test the performance of our model. Specifically, on the SEM16 and P-Stance datasets, we test the performance of our model on the test set. On VAST dataset, we test the performance of our model over zero-shot condition. To ensure a fair comparison with LLM-based baselines, we first sample the test set to replicate their results under their prompts, and then conduct experiments on the dataset. For zero-shot stance detection approaches, we evaluate their performance across all three datasets. However, for in-target stance detection methods, we assess their performance on SEM16 and P-Stance, because the targets within the VAST dataset are mainly few-shot or zero-shot. The datasets contain no personally identifiable information, but may contain offensive content because the text has a clear stance on topics such as religions, politics, climate, etc. We strictly adhere to the requirements of the respective licenses when using all datasets mentioned in the paper.

Implementation Details

Implementation of COLA In our study, we employ the GPT-3.5 Turbo model, provided by OpenAI, as our backbone. We opt for GPT-3.5 Turbo primarily due to its superior performance, cost-effectiveness, and the ease of interaction offered via OpenAI API. These attributes not only facilitate efficient research but also ensure the usability of our methodology for future application. By utilizing the system instruction feature available through OpenAI API, we instruct the model to act as various agent roles, feeding text inputs via prompts and collecting textual outputs from the model. To maximize reproducibility, we set the temperature parameter to 0. The reported results are the average of 5 repeated runs to ensure statistical reliability.³.

Evaluation Metric For SEM16 and P-Stance datasets, following previous works (Allaway, Srikanth, and McKeown 2021; Li et al. 2023a), we calculate F_{avg} , which represents the average of F1 scores for *Favor* and *Against*. For the VAST dataset, we adopt the commonly-used method from Allaway et al. (2020) and compute the Macro-F1 score to assess model performance.

Comparison Methods

We compare COLA with state-of-the-art (SOTA) methods in stance detection. We conduct comparisons with methods for two tasks: zero-shot stance detection and in-target stance detection.

We compare our method with various zero-shot stance detection methods. This includes adversarial learning method: TOAD (Allaway, Srikanth, and McKeown 2021), contrastive learning methods: PT-HCL (Liang et al. 2022a), JointCL (Liang et al. 2022b), Bert-based techniques: TGA-Net (Allaway and McKeown 2020) and Bert-GCN (Liu et al. 2021). We also include two baselines based on large language models: GPT-3.5 Turbo and GPT-3.5 Turbo+Chain-of-thought(COT), both of which can be considered zero-shots, implemented in strict accordance with Zhang et al. (2022) and Zhang et al. (2023), respectively.

³The source code of our proposed framework is released at <https://github.com/tsinghua-fib-lab/COLA>

To further verify the performance of our model, we compare our model to in-target stance detection methods. Such methods undergo extensive training on datasets for a given target and are then evaluated on the test set of the same target. In contrast, our method remains strictly zero-shot, with **no fine-tuning** applied to our backbone model. We compare our approach with various in-target stance detection baselines, including RNN-based methods: BiCond (Augenstein et al. 2016), and ATT-LSTM (Wang et al. 2016); Attention-based method: CrossNet (Xu et al. 2018); Bert-based method: BERT (Devlin et al. 2018); and Graph-based methods: ASGCN (Zhang, Li, and Song 2019) and TPDG (Liang et al. 2021).

For non-LLM approaches, we retrieve results from existing literature for a comprehensive comparison (Allaway and McKeown 2020; Allaway, Srikanth, and McKeown 2021; Liu et al. 2021; Liang et al. 2021, 2022a; Huang et al. 2023; Khiabani and Zubiaga 2024).

Results and Discussions

In this section, we aim to answer the following research questions (RQs) with the help of experimental results:

RQ1: How is the performance of COLA compared with state-of-the-art stance detection models? (**Accuracy**)

RQ2: Is every component in our model effective and contributory to performance enhancement? (**Effectiveness**)

RQ3: Can our model explain the rationale and logic behind its stance determinations? (**Explainability**)

RQ4: Is our framework adaptable to other text classification tasks related to web and social media content analysis? (**Versatility**)

Overall Performance (RQ1)

In Table 2, we present the zero-shot stance detection performance of COLA across three datasets in comparison to baseline methods. Furthermore, Table 3 showcases the results of both our zero-shot COLA and the in-target labeled data dependent baselines on the SEM16 and P-Stance datasets for the in-target stance detection task. Overall results have demonstrated the strong performance of our approach. Specifically, the key findings are enumerated below.

- **Our method outperforms the state-of-the-art zero-shot stance detection approaches across all metrics.**

On most metrics across three datasets, our model demonstrates statistically significant improvements over the best baseline. For the CC and LA targets in the SEM16 dataset, our approach achieves substantial gains over the best baseline, with absolute increases in F_{avg} of 16.9% and 26.6% respectively. On the VAST dataset, which comprises tens of thousands of instances, our model secures a notable absolute boost of 0.7% in the overall Macro-F1 Score. This attests to the robust zero-shot stance detection capabilities of our approach.

- **The performance of our approach matches that of in-target stance detection baselines.** The zero-shot stance detection performance of our method is closely aligned with that of the state-of-the-art in-target stance detection

Model	SEM16(%)						P-Stance(%)			VAST(%)
	DT	HC	FM	LA	A	CC	Trump	Biden	Sanders	All
TOAD	49.5	51.2	54.1	46.2	46.1	30.9	53.0	68.4	62.9	41.0
TGA Net	40.7	49.3	46.6	45.2	52.7	36.6	-	-	-	65.7
BERT-GCN	42.3	50.0	44.3	44.2	53.6	35.5	-	-	-	68.6
PT-HCL	50.1	54.5	54.6	50.9	56.5	38.9	-	-	-	71.6
JointCL	50.5	54.8	53.8	49.5	54.5	39.7	62.0	59.0	73.0	72.3
GPT-3.5	62.5	68.7	44.7	51.5	9.1	31.1	62.9	80.0	71.5	62.3
GPT-3.5+COT	63.3	70.9	47.7	53.4	13.3	34.0	63.9	81.2	73.2	68.9
COLA(ours)	68.5	81.7*	63.4*	71.0*	70.8*	65.5*	86.6*	84.0	79.7*	73.0

Table 2: Comparison of COLA and baselines in zero-shot stance detection task. Bold and underline refer to the best and 2nd-best performance. * denotes COLA improves the best baseline at $p < 0.05$ with paired t-test.

Category	Model	SEM16(%)						P-Stance(%)		
		DT	HC	FM	LA	A	CC	Trump	Biden	Sanders
In-target Labeled Data Dependent Methods	BiCond	59.0	56.1	52.9	61.2	55.3	35.6	73.0	69.4	64.6
	BERT	57.9	61.3	59.0	63.1	60.7	38.8	67.7	73.1	68.2
	CrossNet	60.2	60.2	55.7	61.3	56.4	40.1	58.0	65.0	53.0
	ATT-LSTM	55.3	59.8	55.3	62.6	55.9	39.2	-	-	-
	ASGCN	58.7	61.0	58.7	63.2	59.5	40.6	77.0	78.4	70.8
	TPDG	63.0	73.4	67.3	74.7	64.7	42.3	76.8	78.1	71.0
Zero-shot Method	COLA(ours)	68.5	81.7*	63.4	71.0	70.8	67.5*	86.6*	84.0*	79.7*

Table 3: Comparison of zero-shot COLA and baselines fully trained on labeled data for the in-target stance detection task. Bold and underline refer to the best and 2nd-best performance. * denotes COLA improves the best baseline at $p < 0.05$ with paired t-test.

techniques, even when they are fully trained on corresponding targets. On the SEM16 dataset, our approach significantly outperforms the best baseline, TPDG, on the HC and CC targets, while maintaining comparable performance on other targets. On the P-Stance dataset, our method consistently outperforms the performance of all baselines across all targets. Remarkably, even though these comparison methods have been extensively trained on their respective targets, our approach still sustains comparable or superior performance, underscoring our method’s strong performance.

- **Direct application of LLMs may yield poor performance, especially on abstract concept targets.** On the SEM16 dataset, for the targets A (*Atheism*) and CC (*Climate Change is a Real Concern*), GPT-3.5 achieves only 9.1% and 31.1% in F_{avg} respectively. Even with the enhanced GPT-3.5+COT, the scores are merely 13.3% and 34.0%. Across almost all datasets and metrics, the performance of simply deploying large language models significantly lags behind our proposed method. This underscores the limitations of directly using large language models for stance detection tasks, especially in handling stances towards abstract concept targets, highlighting the necessity and validity of our design.

To confirm that our method can enhance stance detection based on LLMs and not just augment the capabilities of the closed-source GPT-3.5 Turbo, we conduct experiments using other LLM backbones. Specifically, we utilized the Flan-UL2 and ChatGLM2-6B models for experiments on the SEM16 dataset. Flan-UL2 demonstrates notable performance in stance detection tasks (Ziems et al. 2023), while

Model	SEM16(%)					
	DT	HC	FM	LA	A	CC
Flan-UL2	64.4	70.1	65.3	67.3	57.5	68.5
Flan-UL2 with COLA	64.9	72.3	65.7	69.8	61.6	75.1
ChatGLM-2 6B	37.9	60.2	42.0	43.2	41.0	13.7
ChatGLM-2 6B with COLA	45.3	60.6	55.4	43.9	43.6	37.6

Table 4: Performance of COLA when utilizing Flan-UL2 or ChatGLM-2 6B as backbones.

ChatGLM2-6B is a more commonly employed model. The results of these experiments are presented in Table 4.

It can be observed that the performance of Flan-UL2 surpassed that of GPT-3.5 Turbo, while ChatGLM2 6B significantly underperforms in comparison. On the SEM16 dataset, regardless of whether the LLM backbone is Flan-UL2 or ChatGLM2-6B, the performance of COLA consistently exceeded that of the LLM backbones. Notably, on the less efficient ChatGLM2-6B, COLA contributes to a more significant performance enhancement, exemplified by a 23.9% absolute increase in F_{avg} on the CC Target and a 13.4% absolute increase in F_{avg} on FM. These experimental results demonstrate that our method can enhance stance detection performance not only for GPT-3.5 Turbo but also for other LLMs.

Ablation Study (RQ2)

To investigate the impacts of each module in our design, we conduct ablation studies to assess the performance of our framework when each module is removed. The results are shown in Table 5, which demonstrate that every module in our framework contributes to performance enhancement. In

Model	SEM16(%)					
	DT	HC	FM	LA	A	CC
COLA	68.5	81.7	63.4	71.0	70.8	67.5
w/o Linguistic Expert	64.3	80.5	63.3	68.9	69.9	65.5
w/o Domain Specialist	66.5	79.2	64.4	67.9	70.7	65.4
w/o Social Media Veteran	64.8	76.8	64.5	64.1	67.7	63.5
w/o Text Analysis Stage	64.4	77.2	65.7	63.8	67.0	62.3
w/o Debating Stage	64.7	74.9	62.5	39.2	59.6	53.4

Table 5: Experimental results of ablation study.

the following, we provide a detailed description of the results.

Study on multidimensional text analysis stage. During the multidimensional text analysis stage, three expert agents from different domains concurrently analyze the text. We individually remove each of these experts to assess the performance of our approach. We also evaluated the performance when all expert analyses are excluded. The results show that the removal of any expert agent results in a certain degree of performance degradation in all cases except for FM on SEM16 dataset. Moreover, eliminating the entire multidimensional text analysis stage leads to a significant performance drop. The most pronounced performance decline is observed for the LA target on SEM16 dataset. Removing the Linguistic Expert, Domain Specialist, and Social Media Veteran leads to decreases in F_{avg} to 68.9%, 67.9%, and 64.1%, respectively. What’s more, without the multidimensional text analysis stage, the F_{avg} drops to a mere 63.8%. This could be attributed to the complexity of the LA topic across various domains such as religions and society. These findings underscore the effectiveness of our multidimensional text analysis stage and the design of each agent therein.

Study on reasoning-enhanced debating stage. In the reasoning-enhanced debating phase, we introduce debates among agents with differing perspectives to augment the reasoning capabilities of our LLM-based system. We remove this stage and let the judge agent directly deduce the text’s stance from the expert agents’ text analysis, aiming to verify the effectiveness of the debating design. Removing the debating stage results in a greater performance loss than removing the text analysis stage. Upon the removal of the debating stage, our method experiences a noticeable performance degradation. The most significant drops are observed for the abstract concept targets LA (*Legalization of Abortion*), CC (*Climate Change is Real Concern*) and A (*Atheism*), with the absolute F_{avg} declining by 31.2%, 14.1%, and 11.2%, respectively. This indicates that the reasoning-enhanced debating stage offers substantial benefits, especially when dealing with relatively abstract targets. The results validate the effectiveness of the reasoning-enhanced debating stage design.

In summary, comprehensive ablation studies have demonstrated the effectiveness of each module in our designed method.

Case 1
Tweet: The ruling by @Scotus is a major setback for @EPA & the environment. #dirtycoal
Target: Climate Change is Real Concern
Detected Stance: Favor
Explanation: The use of the hashtag #dirtycoal conveys a negative stance on coal, associated with environmental harm and climate change. Mentioning the Environmental Protection Agency (@EPA) and describing a ruling as an environmental setback highlights a concern for environmental protection, including climate change mitigation. The emotional tone of frustration and negative environmental hashtags further reinforce this pro-environmental perspective.
Case 2
Tweet: @GovtsTheProblem This is what I see: Make way 4 ur queen peasants! Don’touch or talk 2 her U filth! #NoHillary2016 #Benghazi
Target: Hillary Clinton
Detected Stance: Against
Explanation: The use of derogatory language, the mention of the Benghazi incident in a negative context, and the hashtag #NoHillary-2016 all indicate the stance against Clinton and a desire for her not to be elected.

Figure 3: Cases of explainains generated by our approach.

Method	SEM16(%)					
	DT	HC	FM	LA	A	CC
GPT-3.5	69.0	74.0	59.1	52.0	8.1	24.7
COLA	71.2	75.9	69.1	71.0	62.3	64.0
GPT-3.5+COLA’s Explainains	69.4	77.7	70.7	66.7	61.9	54.5

Table 6: Performance of GPT-3.5 Turbo, COLA and GPT-3.5 Turbo with explainains generated by COLA. Experiments are conducted on the whole SEM16 dataset. Best scores are in bold.

Study on Explainability (RQ3)

An explainable artificial intelligence (XAI) is one that offers clear insights or justifications to make its decisions comprehensible (Arrieta et al. 2020). By elucidating its decision-making processes, an XAI augments transparency and reinforces model trustability (Das and Rad 2020). Large language models inherently possess the capability to explain their outputs. By prompting them about the rationale behind their decisions, we can obtain explanations for their determinations directly. To delve deeper into the explainability of our approach, we conduct both case studies and quantitative experiments to verify its ability to generate clear and reasonable explanations.

Case Studies. During the stance conclusion stage, we mandate the judge agent to provide outputs in a JSON format, consisting of two components: the stance and a concise explanation not exceeding 100 tokens. We conduct our experiments on the SEM16 dataset. After closely examining the generated outputs, we find that our model can provide clear explanations for its decisions. In Figure 3, we show two cases to illustrate, which are discussed as follows:

- In the first case, the tweet “*The ruling by @Scotus is a major setback for @EPA & the environment. #dirtycoal*” agrees that climate change is a real concern. Our model detects this stance. In its generated explanation, the model discerns the mention of the EPA and the usage

Category	Model	Restaurant14(%)		Laptop(%)		Restaurant15(%)	
		Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
Labeled Data	DGEDT	86.3	80.0	79.8	75.6	84.0	71.0
Dependent Methods	dotGCN	86.2	80.5	81.0	78.1	85.2	72.7
Zero-shot Methods	GPT-3.5 Turbo	70.6	59.7	85.0	66.7	84.0	62.4
	Ours	74.1	65.7	87.0	67.5	90.5	64.3

Table 7: Performance of our framework and baselines on aspect-based sentiment analysis. Best scores are in bold.

Model	Accuracy(%)	F1-Score(%)
Hybrid RCNN	74.8	59.6
GPT-3.5 Turbo	67.6	56.0
Ours	76.5	63.9

Table 8: Performance of our framework and baselines on persuasion prediction. Best scores are in bold.

of the #dirtycoal tag, indicating an environmental concern. Moreover, the model perceives an emotional tone of frustration, further reflecting a pro-environmental perspective.

- In the second case, the tweet “@GovtsTheProblem This is what I see: Make way 4 ur queen peasants! Don’t touch or talk 2 her U filth! #NoHillary2016 #Benghazi” portrays an opposing stance toward Hillary. Our model rationally explains its judgment from a linguistic perspective (utilization of derogatory language), a domain-specialist perspective (mentioning the Benghazi incident in a negative context), and a social media lens (the hashtag #NoHillary2016). These cases validate the model’s proficiency in generating clear and reasonable explanations.

Quantitative Experiments. To further validate our model’s ability to produce clear and logical explanations, we conduct quantitative experiments. For the SEM16 dataset, we collect explanations (from the second part of the JSON output) related to each instance’s stance generated by COLA. These explanations, along with the original text, are fed into the GPT-3.5 Turbo model. We inform the model that these explanations could be used as references for its decisions. As a result, we obtain a new set of judgments from the model. It’s evident that the performance of GPT-3.5 Turbo significantly improves by incorporating explanations generated by COLA in addition to the original texts, as presented in Table 6. Note that we do experiments on the whole SEM16 dataset here, rather than the test set, to enhance the credibility of the results. There is a noticeable increase for the A(Atheism) and CC(Climate Change is Real Concern) targets, with F_{avg} improving by 51.6 and 29.3 points, respectively. For the HC(Hillary Clinton) and FM(Feminist Movement) targets, the results even exceed that of COLA. This further confirms our model’s strong ability in generating clear and logical explanations.

Overall, both case studies and quantitative experiments have demonstrated the high explainability of our method. Its high explainability and accuracy make it a trustworthy approach.

Study on Versatility (RQ4)

Our proposed COLA can be summarized as an Analyst-Debater-Summarizer framework. In this section, we conduct experiments to validate that the Analyst-Debater-Summarizer framework can be applied to other text classification tasks for text analysis on web and social media, not just as an ad-hoc approach for stance detection. We perform experiments on two additional text classification tasks: aspect-based sentiment analysis and persuasion prediction. We select aspect-based sentiment analysis because it demands precise understanding of sentiments tied to specific elements in text, reflecting the detailed analysis capability of our framework. Meanwhile, persuasion prediction is chosen due to its emphasis on detecting underlying intent, highlighting COLA’s ability to adeptly handle intricate conversational dynamics commonly seen in web and social media exchanges.

Aspect-based Sentiment Analysis

- **Experimental Setup:** Aspect-based sentiment analysis is to determine the sentiment polarity (*Positive*, *Negative*, or *Neutral*) expressed towards each aspect mentioned in the text (Pontiki et al. 2014). In this task, we modify the debater component in our original framework to engage in sentiment debates instead of stance debates, while keeping other design unchanged. We evaluate our approach’s performance on the Restaurant14, Restaurant 15, and Laptop datasets from SemEval14 (Pontiki et al. 2014) and SemEval15 (Pontiki et al. 2016). We follow Chen et al. (2017) and use Accuracy and Macro-F1 score as evaluation metrics. We compare our approach with state-of-the-art models that require training, namely DGEDT (Tang et al. 2020) and dotGCN (Chen et al. 2022).
- **Results:** The experimental results are presented in Table 7. It can be observed that our zero-shot method performs comparably to the best baseline models that rely on labeled data. On the Restaurant15 dataset, our approach even outperforms the top baseline on Accuracy. Another crucial finding is that our approach consistently outperforms directly applying GPT-3.5 Turbo while maintaining ease of use.

Persuasion Prediction

- **Experimental Setup:** Following Ziems et al. (2023), we define persuasion prediction as determining whether one party in a conversation is persuaded after the conversation ends. In this task, we replace the three experts in our original framework with two experts: a domain expert and a psychologist. They provide detailed analyses

of various concepts and nouns in the conversation topics and analyze the psychological changes of the individuals involved. The debaters are modified to argue for whether a participant in the conversation has been persuaded. We use the dataset provided by Wang et al.(2019) and follow their evaluation metrics, using Accuracy and Macro-F1.

- **Results:** We compare our approach with Hybrid RCNN (Wang et al. 2019) and GPT-3.5 Turbo, and the results are presented in Table 8. The experimental results show that our approach achieves better performance compared to the baseline and a significant improvement over GPT-3.5 Turbo.

The Analyst-Debater-Summarizer framework has proven to be highly successful in both aspect-based sentiment analysis and persuasion classification tasks. On a series of tasks, our zero-shot framework performs on par with state-of-the-art baselines that rely on training data and significantly outperforms direct application of GPT-3.5 Turbo. These experiments demonstrate the versatility of our approach.

Discussions

In the aforementioned experiment, we extensively evaluate the performance of our approach across various dimensions, which are listed as follows:

- First, from the perspective of our method’s design rationale, the ablation study confirms that every component in our approach contributes to a performance boost, indicating that the design is free of redundancy and can be considered efficacious.
- Second, in comparison with existing methods, experimental evidence shows that our approach outperforms all other zero-shot methods on stance detection. Furthermore, its performance is on par with in-target stance detection methods that rely on in-target labeled data, exhibiting impressive accuracy.
- In addition, for two other text classification tasks related to web and social media content analysis, our method achieves results comparable to state-of-the-art baselines, underscoring its versatility.
- What’s more, from a practical application standpoint, our method does not require additional training for the model. Instead, it can be implemented by interacting with existing large language models through APIs or other means, showcasing its strong usability.
- Finally, the experiments also prove that our framework can provide clear and rational explanations for its decisions, ensuring a high degree of explainability. Such generated explanations can bolster users’ trust in our approach and are conducive to further analysis.

Given these advantages, our method promises a broad range of applications.

Conclusion and Future Work

In this work, we harness the strong capabilities of LLMs for advanced stance detection. We propose COLA, where

multiple LLM-based agents collaborate to reach an conclusion. This method encompasses three stages: the multidimensional text analysis stage, the reasoning-enhanced debating stage, and the stance conclusion stage. Experimental results demonstrate that our approach achieves high accuracy, effectiveness, explainability, and versatility, showcasing its significant applicability.

Due to the absence of real-time training data for large language models, the performance in analyzing real-time topics might be slightly compromised. For future work, we intend to incorporate a real-time updating knowledge base into the text analysis stage to enhance our framework’s capability to analyze texts that include current events. We plan to first retrieve relevant information from the real-time knowledge base, and then have the LLMs use this information to generate analytical texts. Furthermore, there remains vast potential for exploring its implementation in addressing extensive text analysis tasks on web and social media.

Ethics Statement

All the datasets that we utilize for this research are open-access datasets. The VAST dataset provides full text data directly. In accordance with Twitter’s privacy agreement for academic purposes, the SEM16 and P-Stance datasets are accessed using the official Twitter API⁴ to retrieve complete text data based on Tweet IDs. The datasets do not include any personally identifiable information, but they might include offensive content as the text expresses strong opinions on subjects like religion, politics, climate, etc. We consistently comply with the respective licenses’ requirements when utilizing all the datasets referenced in the paper. We use the GPT-3.5 Turbo API service provided by OpenAI, with adherence to OpenAI’s terms and policies.

In our primary experiments, we employed GPT-3.5 Turbo as the backbone. While the use of closed-source LLMs entails significant financial costs, our framework has demonstrated improved stance detection performance with open-source LLMs as well. It is important to acknowledge that running LLMs requires substantial energy, a common issue for all algorithms based on LLMs. We look forward to advancements in energy-efficient hardware technologies that could alleviate this concern.

Regarding potential misuse, we recognize that our technology, like many others, carries the risk of being exploited for unethical purposes, such as silencing critics or identifying and targeting dissenting voices on social media by certain entities. We urge users of our technology to commit to responsible and ethical usage. It is crucial to balance technological advancement with a conscientious approach to mitigate risks, especially in areas like stance detection that intersect with sensitive societal and political domains.

Acknowledgements

This work is supported by the National Science Foundation of China under U23B2030, 62272262 and 72342032.

⁴<https://developer.twitter.com/en/docs/twitter-api>

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Paper Checklist

1. For most authors...
 - (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? **Yes.**
 - (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? **Yes.**
 - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? **Yes.**
 - (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? **NA**
 - (e) Did you describe the limitations of your work? **Yes, see the Conclusion and Future Work.**
 - (f) Did you discuss any potential negative societal impacts of your work? **NA**
 - (g) Did you discuss any potential misuse of your work? **NA**
 - (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? **Yes, see the Experimental Setup.**
 - (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes.**
2. Additionally, if your study involves hypotheses testing...
 - (a) Did you clearly state the assumptions underlying all theoretical results? **NA**
 - (b) Have you provided justifications for all theoretical results? **NA**
 - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? **NA**
 - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? **NA**
 - (e) Did you address potential biases or limitations in your theoretical framework? **NA**
 - (f) Have you related your theoretical results to the existing literature in social science? **NA**
 - (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? **NA**
3. Additionally, if you are including theoretical proofs...
 - (a) Did you state the full set of assumptions of all theoretical results? **NA**
 - (b) Did you include complete proofs of all theoretical results? **NA**
4. Additionally, if you ran machine learning experiments...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **Yes, see the Experimental Setup.**
- (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **NA**
- (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **Yes, we conduct multiple repeated experiments. In the main experimental results, we use a paired t-test when claiming that our method outperformed the best baseline.**
- (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **NA**
- (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? **Yes, see Experimental Setup and Experimental Results.**
- (f) Do you discuss what is “the cost“ of misclassification and fault (in)tolerance? **NA**
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
 - (a) If your work uses existing assets, did you cite the creators? **Yes, see the Experimental Setup and Experimental Results.**
 - (b) Did you mention the license of the assets? **Yes.**
 - (c) Did you include any new assets in the supplemental material or as a URL? **Yes, we provide the code for COLA.**
 - (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? **No, because we only use open-sourced datasets.**
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **Yes, see the Datasets.**
 - (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? **NA**
 - (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? **NA**
6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
 - (a) Did you include the full text of instructions given to participants and screenshots? **NA**
 - (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? **NA**
 - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? **NA**
 - (d) Did you discuss how data is stored, shared, and de-identified? **NA**