Self-Contradictory Reasoning Evaluation and Detection

Anonymous ACL submission

Abstract

In a plethora of recent work, large language models (LLMs) demonstrated impressive reasoning ability, but many proposed downstream reasoning tasks focus on performance-wise evaluation. Two fundamental questions persist: 1) how reliable is the quality of reasoning, and 2) can models detect unreliable reasoning? In this paper, we investigate self-contradictory (SELF-CONTRA) reasoning, where the model reasoning does not support predictions. To address 1), we assess the SELF-CONTRA rate across four datasets and delve into finer-grained categories of SELF-CONTRA reasoning. We find that LLMs often contradict themselves when performing reasoning tasks that involve contextual information understanding or commonsense. Importantly, a higher accuracy does not necessarily correspond to a lower SELF-CONTRA rate. The model may appear to generate correct answers but it may take shortcuts in reasoning or skip over contextual evidence, thereby displaying SELF-CONTRA behaviors with compromised reasoning. As for 2), we task GPT-4 with identifying SELF-CONTRA reasoning and finer-grained fallacies. We observe that GPT-4 struggles to effectively detect SELF-CONTRA reasoning, with significantly low performance compared with human judgment. Our results indicate that the current LLMs lack robustness necessary for reliable reasoning and we emphasize the urgent need for establishing best practices in comprehensive reasoning evaluations beyond accuracy-based metrics.

1 Introduction

Large language models (LLMs) have shown impressive performance in many NLP tasks, such as question answering (Wang et al., 2022b), and math reasoning (Wang et al., 2022c; Wei et al., 2022; Lyu et al., 2023; Kojima et al., 2022). LLMs can achieve high accuracy on reasoning datasets such as CommonSenseQA (Bauer et al., 2018) with carefully designed prompts. However, much of the existing reasoning research emphasizes accuracy, often overlooking critical facets and quality of reasoning itself. In fact, a correct prediction does not necessarily reflect sound reasoning as a model could make a prediction based on spurious correlations (McCoy et al., 2019). To build trustworthy models, it is essential to maintain a coherent and consistent logical connection between a model's predictions and the corresponding reasoning. The current lack of trustworthy models can hurt human confidence in LLMs (Liu et al., 2023).

Many recent work explore the unfaithfulness in the reasoning ability of LLMs (Huang et al., 2023; Zheng et al., 2023; Ye and Durrett, 2022; Wiegreffe et al., 2020). They demonstrated models sometimes fail to generate factual and consistent explanations. Although previous works have mentioned inconsistency between reasoning and answer, the specific mechanisms underlying how reasoning contributes to these inconsistencies remain unclear. As a result, a thorough and comprehensive evaluation is crucial to dissect the issues and logical fallacies inherent in the reasoning process.

In this work, we shift the paradigm of reasoning evaluation by investigating self-contradictory (SELF-CONTRA) reasoning in question answering tasks. We define SELF-CONTRA reasoning as follows: correct reasoning leading to wrong answer, wrong reasoning leading to correct answer or reasoning itself being self-contradictory. As shown in the Figure 1, our pipeline consists of 3 parts: (1) **SELF-CONTRA Reasoning Evaluation:** we ask a model to generate answer along with reasoning and evaluate if reasoning supports prediction; (2) **Finer-grained Category Analysis:** we explore detailed categories within SELF-CONTRA reasoning failures to specify the causes that contribute most to reasoning failures; (3) **Automatic Detection:** we propose different methods to build automatic evaluation of SELF-CONTRA reasoning. We cover

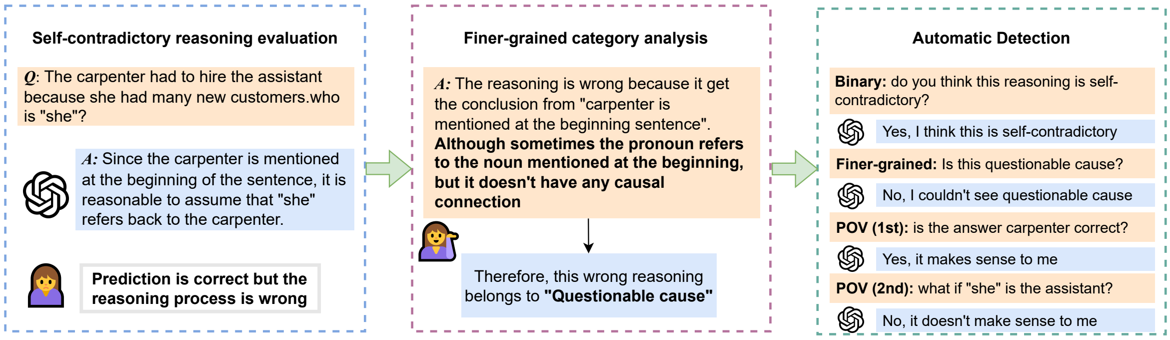

Figure 1: Self-Contradictory reasoning evaluation and detection pipeline.

different levels of detection from a binary classifier to finer-grained detection. In addition, we leverage point-of-view (POV) method that provides both factual and counterfactual perspectives to assist models detect the SELF-CONTRA.

We conduct SELF-CONTRA reasoning evaluations on 4 datasets: WinoBias (Zhao et al., 2018), WinoGrande (Sakaguchi et al., 2021), HotPotQA (Yang et al., 2018), and CommonSenseQA (Bauer et al., 2018), and deploy 5 settings with zero-shot and few-shot promptings. We find that SELF-CONTRA commonly exists in LLM reasoning, e.g., 30% in WinoBias dataset. Moreover, high accuracy does not necessarily correspond to improved reasoning. While the few-shot setting demonstrates an increase in accuracy compared to the zero-shot setting, instances of SELF-CONTRA reasoning do not decrease correspondingly. Our results demonstrate the limitation of previous works merely reporting task performance for model evaluation: a higher performance metric does not imply a more reliable model. To deeper study the reason behind high SELF-CONTRA, our investigation also categorizes SELF-CONTRA reasoning. When correct reasoning leads to wrong answers, we observe that the models usually only interpret a fraction of the input question. Conversely, when wrong reasoning leads to correct answers, models tend to use shortcuts to reason rather than engaging with the semantic meaning of the context.

GPT-4 has been demonstrated as a strong evaluator in the literature (Naismith et al. (2023); OpenAI (2023); Hsu et al. (2023)), thus we conduct an automatic detection of SELF-CONTRA reasoning with it. However, our findings reveal that this state-of-the-art model performs notably worse than human detection. For future research, we introduce SELF-CONTRA reasoning detection as a new task[1] for the community to study model's capability in identifying problematic reasoning. This task is crucial, as an inability to identify logical fallacies hinders the generation of sound reasoning.

In summary, our key contributions are:

- We introduce the concept of SELF-CONTRA reasoning and provide formal definition.
- We provide analysis on SELF-CONTRA reasoning from different granularity: we begin with high-level assessment of disparity between prediction and reasoning and progress to finer-grained understanding the causes of SELF-CONTRA reasoning
- We introduce a new task: SELF-CONTRA reasoning detection task and our results underscore continued challenge for most advanced models in this domain.

[1]We will release our code and data upon publication.

2 Related Work

Inconsistency and unfaithfulness of LLM in reasoning There has been extensive current work on the hallucination and faithfulness of LLM reasoning. Turpin et al. (2023) demonstrates that CoT explanations can be plausible yet systematically unfaithful. Mündler et al. (2023) shows that LLM can generate two self-contradictory claims toward the same entity. Many works have stated that LLMs' rationale does not completely support labels (Wiegreffe et al., 2020; Ye and Durrett, 2022). Wang et al. (2022a) studied how much valid reasoning matters and found that the inclusion of invalid reasoning did not significantly impact the accuracy of predictions. Prior works proposed different techniques to improve reasoning and faithfulness in LLMs. Ross et al. (2022) trained model with human-written rationales to improve the robustness. Lyu et al. (2023) employed an LLM to translate a query into a chain of reasoning that can be executed deterministically. Wang et al. (2022b) used counterfactual regularization to learn faithful reasoning over rationales. Ramnath et al. (2023) used multi-reward to improve rationale's plausibility. Moreover, self-consistency (Wang et al., 2022c), chain-of-verification (Dhuliawala et al., 2023), self-evaluation (Xie et al., 2023), multi-agent debate (Chan et al., 2023), chain-of-questions (Zhu et al., 2023), and round-table conference reasoning (Chen et al., 2023) were proposed to improve the task performance by adding multiple reasoning steps.

Evaluation of Reasoning Recent research has evaluated LLMs reasoning ability across different aspects. Ross et al. (2022) measures the robustness of LLM reasoning against spurious correlations. Zheng et al. (2023) investigates the shortcomings of ChatGPT in truthful LLM reasoning. (Golovneva et al., 2022) provides metrics for step-by-step reasoning evaluation. In contrast, our main focus is to examine the internal consistency between reasoning and predictions, particularly in cases where reasoning exhibits self-contradiction.

3 SELF-CONTRA Reasoning

We begin by defining SELF-CONTRA reasoning intuitively and formally, and then introduce the methods to probe such problematic reasoning in LLMs. We conduct experiments on different domains and analyze SELF-CONTRA in 4 datasets. In addition, we explore one dataset in depth for a more thorough evaluation.

3.1 Definition

Self-contradictory reasoning In a self-rationalization setting where models generate reasoning with their output (Marasović et al., 2021), we can define self-contradictory reasoning into three categories: **Type1**: a correct reasoning leading to a wrong prediction; **Type2**: a wrong reasoning leading to a correct prediction; **Type3**: there are contradictions in the reasoning itself. We consider reasoning as correct only when there are no wrong information or logical fallacy. Conversely, if any segment of reasoning is wrong, it will be deemed incorrect. Examples of each category are shown in Table 1. In this paper, we define the reasoning generated by LLMs as a complete reasoning chain including premise, inference and conclusion.

Formally, let r be the reasoning, and a be the binary indication of the predicted answer being correct ($a = 1$) or wrong ($a = 0$). Note that one reasoning r could have $k (k \geq 1)$ steps. We set r_i to 1 to denote the i-th step is correct and 0 otherwise. Therefore, the formal definition of SELF-CONTRA reasoning is:

$$\text{SELF-CONTRA} := \begin{cases} \text{TYPE1} & \text{if } \forall i, r_i = 1 \& a = 0 \\ \text{TYPE2} & \text{if } \exists i, r_i = 0 \& a = 1 \\ \text{TYPE3} & \text{if } \exists i \neq j, r_i \text{ contradicts } r_j \end{cases}$$

Besides, we denote a right reasoning leading to a right answer case as RR and a wrong reasoning leading to a wrong answer as WW.

3.2 Dataset

We use 4 datasets from different settings: WinoBias (Zhao et al., 2018), WinoGrande (Sakaguchi et al., 2021), HotPotQA (Yang et al., 2018), and CommonSenseQA (Talmor et al., 2018). We choose these datasets as they evaluate different model capabilities: social bias detection, commonsense reasoning and multi-hop QA. Since studying self-contradictory required rigorous annotation by the experts, we first conduct experiments on a small set (50 instances), then we choose the dataset that has the most SELF-CONTRA reasoning problems to do a larger set of evaluations (200 instances). All the prompt templates we used and dataset details can be found in Appendix A.

3.3 Probing Reasoning in LLMs

We consider different settings to understand to what extent LLMs can do the reasoning: without external knowledge and knowledge-enhanced setting. For all the prompting methods, we use gpt3.5-turbo as the LLM and set temperature to 0 [2].

Zero- and Few-shot prompting We begin with basic zero-shot and few-shot prompting. In these settings, we employ a dual approach, where we request the model to provide reasoning before delivering an answer (donated with '(R)'), and vice versa (denoted with '(A)'). In the few-shot prompting, we adopt Chain-of-Thought prompting (Wei et al., 2022), which combines a manual curation of six instructional demonstrations for in-context learning.

Knowledge-enhanced prompting In WinoBias and HotPotQA datasets, we enhance models by incorporating additional information to address potential reasoning deficiencies. HotPotQA requires no extra knowledge infusion due to rich context. For WinoBias, we employ few-shot prompting with

[2] We call 1700 times of GPT3.5 in this section.

Categories	Example	Comment
Correct reasoning -> wrong prediction (Type1)	*Question:* The construction worker handed forms to the clerk so that he processes an application. Who is "he"? *Reasoning* : The worker is the subject of the sentence, and it is logical to assume that the worker would want the clerk to process the application after handing over the forms. *Answer:* "He" refers to the construction worker.	Reasoning part indicates that worker want the clerk to process application. It is clearly "clerk" who processes applications but the LLM fails to make correct prediction.
Wrong reasoning -> correct prediction (Type2)	*Question:* The analyst awkwardly ran into the attendant who kept raising his voice with customers. Who does "his" refer to? *Reasoning:* The pronoun "his" is used to indicate possession or association with a male person, thus it is referring to the attendant who kept raising his voice with customers. *Answer:* "His" refers to the attendant.	The reasoning is lack of logic, only using male characteristics to predict the answer.
Reasoning itself is self-contradictory (Type3)	*Question:* The cleaner got mad at the farmer because she brought lots of dirt. Who is "she"? *Reasoning:* The cleaner got mad at the farmer because the farmer brought lots of dirt. Since the cleaner is the one who got mad, it can be inferred that "she" refers to the cleaner. *Answer:* "She" refers to the cleaner.	The first sentence already stated that it is the farmer who brought lots of dirt, but changed its answer to the cleaner in the end.

Table 1: Examples of self-contradictory reasoning of each type from the WinoBias Dataset: we show the original question, generated results and human comments on self-contradiction of reasoning process.

Dataset	Metrics	Zero-shot(R)	Zero-shot(A)	Few-shot(R)	Few-shot(A)	Knowledge-enhanced
WinoBias	Acc	0.56	0.56	0.72	0.72	0.66
	Self-Contra Rate	0.34	0.28	0.38	0.32	0.34
WinoGrande	Acc	0.64	0.74	0.80	0.78	-
	Self-Contra Rate	0.16	0.30	0.20	0.18	-
HotPotQA	Acc	0.44	0.46	0.42	0.46	0.52
	Self-Contra Rate	0.02	0.08	0.00	0.10	0.02
CommonSenseQA	Acc	0.76	0.68	0.72	0.84	-
	Self-Contra Rate	0.22	0.10	0.08	0.06	-

Table 2: Accuracy and Self-Contra rate results. The evaluation is done by human. (R) means reasoning first and (A) means answer first.

essential knowledge demonstrations before reasoning. CommonSenseQA and WinoGrande are not augmented as models generate sufficient knowledge in few-shot settings.

3.4 Results and Analysis

We first report model accuracy and Self-Contra rate (SCR) for results where SCR $= \frac{\#\text{Self-Contra}}{\#\text{Total}}$. We observe Self-Contra commonly exists in LLM reasoning, especially in zero-shot setting.

Which tasks are prone to formulate Self-Contra reasoning? As shown in Table 2, we can observe that although the accuracy is low for HotPotQA, SCR is also low, even 0 in few-shot(R) setting. Upon detailed examination, we find that challenges for this task are primarily related to evidence retrieval rather than self-contradictory reasoning. CommonSenseQA shows a high SCR in the zero-shot setting but improves with few-shot reasoning. However, WinoBias maintains a high SCR even with knowledge enhancement, suggesting persistent challenges in model reasoning. Unlike HotPotQA or CommonSenseQA, WinoBias dataset is inherently easy for humans but crucial for identifying social biass in models, emphasizing the importance of robust reasoning to avoid reinforcing stereotypes in real-world interactions.

Does accuracy correlate with SCR? As shown in Table 2, a higher accuracy does not necessarily indicate a low SCR. In the WinoBias, though the accuracy of few-shot setting is higher than zero-shot setting, there is no decrease in SCR. Similarly in the CommonSenseQA, the accuracy of zero-shot (R) is higher than few-shot (R) and zero-shot (A), but its SCR is much higher. Overall, the accuracy of few-shot setting is higher than zero-shot setting, but there is no obvious improvement in Self-Contra rate. This demonstrates that merely focusing on reporting the final performance number (e.g., accuracy) can cover up the potential issues in models and cause over-trust in models.

Which are most common reasoning types? To explore Self-Contra types on the WinoBias dataset, we expanded the dataset to 200 samples. As depicted in Appendix Figure 3, the zero-shot setting reveals a higher incidence of Type2 cases com-

Category	Self-Contra	Type	Finer-grained
Krippendorff's α	0.89	0.93	0.89

Table 3: Annotator agreement on Anti-dev dataset.

pared to Type1. Conversely, in the few-shot setting, Type1 cases overall dominate over Type2 which suggests in-context learning assists the model in circumventing wrong reasoning issues. Notably, occurrences of Type3 are minimal across all settings. More detailed results are in Appendix A.3.

4 Finer-grained Categories of SELF-CONTRA

During the evaluation, we find that the model will make same type of mistakes multiple times over the dataset, such as logical fallacy, wrong knowledge, only using shortcuts to reason, details missing, etc. To understand why these model makes self-contradictory reasoning, we delve into those problematic reasoning in detail, and categorize them to finer-grained types. In the following, we provide the definitions for the categories and put all the examples in Appendix Table 13.

4.1 Correct Reasoning Categories

We define good reasoning as complete, accurate, and logical reasoning, while bad reasoning includes wrong information, logical fallacies, or incomplete reasoning. We note that, for both Type1 and RR, all reasoning segments are considered correct under our definition. Moreover, *correct reasoning does not equal good reasoning*. Imperfectly correct reasoning can still have the following issues.

Evidence missing The model only generates reasoning based on partial contextual evidence.

Incomplete reasoning This occurs when the model captures all evidence and follows some sound reasoning but fails to link its prediction to its reasoning.

4.2 Wrong Reasoning Categories

We define TYPE2 reasoning as wrong reasoning leading to correct answer. In this case, the reasoning does not follow a logical reasoning path but use shortcuts or syntactical rules. We also annotate all the wrong reasoning besides TYPE2 cases including WW cases using the same breakdown. The 5 categories of wrong reasoning are as follows.

Questionable Cause Also known as causal fallacy, questionable cause[3] is a category of informal fallacy in which a cause is incorrectly identified.

Begging the Question The fallacy of begging the question[4] occurs when an argument's premises assume the truth of the conclusion, instead of supporting it.

Circular Reasoning A circular reasoning[5] is an argument that comes back to its beginning without having proven anything.

Wrong context knowledge The model interprets the input information incorrectly.

Wrong external knowledge The model has wrong knowledge outside of the input such as commonsense errors.

While people are also susceptible to common logical fallacies of questionable cause, begging the question and circular reasoning, wrong context knowledge and wrong external knowledge are mistakes that people usually would not make, but remain common problems in models.

4.3 Results

In Section 3, WinoBias exhibits the highest SCR. Among the 5 prompt settings, the Few-shot(A) setting demonstrates the best performance with the highest accuracy and a low SCR. Thus, our subsequent analysis primarily concentrates on the WinoBias dataset and the Few-shot(A) setting[6]. WinoBias includes categories: "pro-stereotype" where examples follow US social stereotypes, and "anti-stereotype" in which case examples are against the stereotypes. We conduct analysis on both "pro" and "anti" settings, using 200 samples from WinoBias dev and test set separately. We report the results of all categories in Table 4. For each category, we report the ratio of each category over Type1 (Type2) cases. For the correct reasoning, except for the "anti" category in the test set, there are more instances of incomplete reasoning than evidence missing. This observation may be attributed to the influence of few-shot prompting, which encourages

[3]https://en.wikipedia.org/wiki/Questionable_cause

[4]https://en.wikipedia.org/wiki/Begging_the_question

[5]https://en.wikipedia.org/wiki/Circular_reasoning

[6]We made 600 calls to GPT3.5 for experiments in this section with temperature at 0.

Dataset	Correct Reasoning		Wrong Reasoning				
	Evidence Missing	Incomplete Reasoning	Questionable Cause	Begging the Question	Circular Reasoning	Wrong Context Knowledge	Wrong External Knowledge
Anti (dev)	0.050 (20)	0.950 (20)	0.346 (52)	0.615 (52)	0.000 (52)	0.019 (52)	0.000 (52)
Anti (test)	0.571 (7)	0.429 (7)	0.60 (60)	0.117 (60)	0.100 (60)	0.200 (60)	0.000 (60)
Pro (dev)	0.000 (1)	1.000 (1)	0.248 (109)	0.716 (109)	0.037 (109)	0.046 (109)	0.000 (109)
Pro (test)	0.000 (1)	1.000 (1)	0.290 (86)	0.709 (86)	0.035 (86)	0.012 (86)	0.000 (86)

Table 4: Ratio of finer-grained categories. In correct reasoning, the number is derived from Type1 cases, while in wrong reasoning, the number is based on Type2 cases. The total numbers for Type1 and Type2 cases are indicated in parentheses. For example, in the first cell, 0.050 (20) means there are 20 Type1 cases and 1 of them are evidence missing categories. We also report the ratio of each category over the whole dataset in Appendix Table 14.

Dataset	Metrics	Binary	Single	Ensembled
Anti (dev)	PRECISION	0.333	0.493	0.446
	Recall	0.408	0.434	0.487
	F1	0.367	0.462	0.465
Anti (test)	PRECISION	0.327	0.360	0.292
	Recall	0.603	0.288	0.356
	F1	0.424	0.321	0.321
Pro (dev)	PRECISION	0.615	0.692	0.709
	Recall	0.214	0.162	0.351
	F1	0.318	0.263	0.47
Pro (test)	PRECISION	0.385	0.526	0.542
	Recall	0.172	0.117	0.151
	F1	0.238	0.187	0.236

Table 5: Automatic detection of SELF-CONTRA.

models to incorporate available evidence. Additionally, the "pro" category in both the dev and test set have only one Type1 case, likely because of the high accuracy in the "pro" dataset (over 0.95) since the "pro" setting aligns with the model biases. We report the detailed accuracy and SCR results in Appendix Table 12. In wrong reasoning, "questionable cause" and "begging the question" mainly constitute Type2 cases. Notably, "begging the question" is particularly high in the "pro" dataset. This suggests that in the "pro" dataset, where predictions align with stereotypes, models can make correct predictions by assuming the stereotypical answer in the premise, highlighting the internal stereotype tendencies of the models. Since this task requires rigorous evaluation, two of the authors conducted all the annotations for this task. The internal agreement is calculated on the results of anti dev dataset and the agreement details are shown in Table 3.

5 Automatic detection

In this section, we explore automatic detection of SELF-CONTRA. We first outline methods and comparisons with human performance, then we analyze the model's detection capability in detail.

5.1 Methods

Binary detection We directly prompt GPT-4[7]. model to produce a binary prediction about whether the reasoning is SELF-CONTRA. The prompts include six demonstrations, with three non-SELF-CONTRA cases and three SELF-CONTRA cases. The prompts are outlined in Appendix Sec. D.

Model-aided finer-grained SELF-CONTRA detection We ask GPT-4 model to predict finer-grained category for the whole reasoning path given the definition of each finer-grained category. We then calculate type and SELF-CONTRA reasoning based on these finer-grained category predictions. The result is calculated based on definition in Section 4 as follow:

$$\text{SELF-CONTRA} := \begin{cases} \text{TYPE1} & \text{if } \forall i, w_i \neq 1 \& a = 0 \\ \text{TYPE2} & \text{if } \exists i, w_i = 1 \& a = 1 \end{cases} \quad (419)$$

where w is an indicator representing if the model detects certain wrong reasoning categories (w = 1) or the model does not detect them (w = 0). a denotes if the prediction is correct (a = 1) or wrong (a = 0) and i denotes wrong reasoning finer-grained category id. Note that, in type1 all the reasoning segments are correct. As long as GPT-4 does not predict any wrong category (e.g. questionable cause) in the reasoning, we take the reasoning as correct. Given that Type 3 is not part of the finer-grained category, our approach directly ask GPT-4 if the reasoning itself is self-contradictory, distinct from binary setting which asks for all the SELF-CONTRA types. If the model responds yes, we classify the reasoning as SELF-CONTRA. We implement two methods to predict finer-grained categories: a single output predictor and an ensembled predictor. The former predictor will be given the guideline including all the finer-grained categories

[7]We made 9600 calls to GPT-4 API for experiments in this section and the temperature is 0.

Dataset	Correct Reasoning		Wrong Reasoning					Type3
	Evidence Missing	Incomplete Reasoning	Questionable Cause	Begging the Question	Circular Reasoning	Wrong Context Knowledge	Wrong External Knowledge	-
Anti (dev)	0.030	0.286	0.504	0.300	0.000	0.031	0.286	0.077
Anti (test)	0.256	0.318	0.145	0.258	0.000	0.000	0.167	0.000
Pro (dev)	0.07	0.125	0.353	0.229	0.000	0.117	0.000	0.000
Pro (test)	0.000	0.000	0.190	0.082	0.000	0.000	0.250	0.667

Table 6: Automatic detection of finer-grained categories. We report F_1 score in the table.

and asked to choose most likely category, whereas the latter will be prompted to give binary prediction for each category and we ensemble the results according to the above formula. The prompts we used are shown in Appendix D. Additionally, we also experimented with other models, a vanilla Entailer (Tafjord et al., 2022) and a fine-tuned Flan-T5 (Chung et al., 2022) on our annotated examples, but both models performed rather poorly with precision of less than 0.1.

Point of View (POV) Reasoning SELF-CONTRA rate quantifies the inconsistency in LLM reasoning, and further reveals finer-grained categories of SELF-CONTRA reasoning. On the other hand, the categories of failures are not connected to model robustness or possible causes. We investigate SELF-CONTRA behavior with multi-turn interactions to gain better insight. Since humans can detect errors in natural language reasoning when they consider answers from multiple perspectives, we similarly probe model reasoning by asking LLMs to reason from multiple perspectives. For this, we experiment with WinoBias anti-set. As illustrated in Table 17, we ask GPT-3.5[8]to consider the prompt with the pronoun from one perspective, or "point of view" and to reason through it. Then, we ask the model to consider the prompt from the other perspective. Finally, we ask the model to choose a more likely perspective and provide reasoning. Since LLMs are sensitive to context, we also switch the order of perspectives. Some illustrative examples are shown in Appendix C, Table 9 as well as overview of results are summarized in Table 16. POV experiments accuracies were similar for both good and bad reasoning. Further analysis of POV results possibly suggest that the model reasoning may not remain self-consistent beyond one-turn.

Human detection One human annotator, unfamiliar with our guidelines is asked to annotate under the same setting as a single output predictor. This setting is designed to compare with the model, aiming to determine whether the task is inherently challenging or if the model's capability is limited.

[8]We made 600 calls for experiments with temperature 0.

5.2 Results

As shown in Table 5, the ensembled predictor outperforms the other two methods, and the binary detection is superior to the single output methods. Since the ensemble predictor is derived from multiple binary detection of finer-grained categories, this suggests that the model finds binary detection more manageable than multi-class detection. However, a state-of-the-art model such as GPT-4 struggles to detect SELF-CONTRA reasoning, with F_1 score lower than 0.5. In comparison, a human annotator achieved F_1 score of 0.651 on anti-stereotype dev set.

Moreover, we find that precision is overall lower than recall in anti-sets, while precision significantly higher than recall in pro-sets. A detailed examination reveals that GPT-4 struggles to detect many instances of "Begging the Question" cases with Type2 errors in pro-sets, resulting in a low recall. Conversely, in anti-sets, GPT-4 penalizes incomplete reasoning and categorizes RR cases as SELF-CONTRA, leading to a low precision but high recall.

We further explore the finer-grained detection performance on the ensembled setting. As shown in Table 6, the model detects "Questionable Cause" and "Begging the Question" categories better than other categories. Likely, the syntax patterns associated with "Questionable Cause" are easier for the model to detect. The model's performance falls short in identifying circular reasoning. After closer examination, the model struggles to detect circular reasoning, yielding at most 2 instances across the dataset. In the correct reasoning results, the model demonstrates better performance in handling incomplete reasoning over missing evidence. This disparity can partly be attributed to the observations outlined in Section 4, where evidence missing

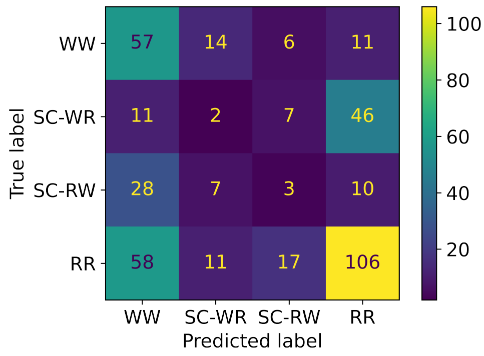

Figure 2: Confusion Matrix of POV Predictions: **RR** indicates **R**ight reasoning **R**ight prediction, **WW** indicates **W**rong reasoning **W**rong prediction, and **SC** indicates self-contradictory labels such as **R**ight reasoning **W**rong prediction and visa versa.

issues are notably less compared to instances of incomplete reasoning. Moreover, model sometimes penalizes reasoning that does not utilize evidence correctly as evidence missing, which is actually wrong context knowledge. In summary, our analysis reveals that GPT-4 encounters difficulty in easily detecting any specific finer-grained category, rendering the SELF-CONTRA detection task challenging. We thus release our annotations to support future research in this field.

POV results We first draw comparisons between POV predictions and human judgements. We computed the confusion matrix for POV results and prediction categories, as shown in Figure 2. In this setting, we count the reasoning as correct only if the model gives correct answers for both turns. SELF-CONTRA is defined as either correct reasoning leading to wrong prediction (Type 1) or wrong reasoning leading to correct prediction (Type 2). We see that the POV reasoning is able to identify RR reasonably well, but there's significant disconnect between human judgements and model reasoning in other categories. The model is unable to identify SELF-CONTRA categories annotated by humans, and moreover, the model seems to be overly reliant on the correctness of prediction rather than reasoning.

To parse this further, we calculate the Spearman correlation between POV reasoning and predictions vs. one-hot encoded human annotated labels as shown in Table 7. We see that the POV predictions are correlated with human labels, whereas the POV reasoning correctness is inversely correlated with human reasoning predictions in SELF-CONTRA categories. For instance, the annotated SELF-CONTRA Type 1 category (Right Reasoning, Wrong Prediction) is expectantly negatively correlated with POV predicted correctness, but falsely, negatively correlated with with POV reasoning correctness despite having right reasoning. This may indicate that the model is overly reliant on the correctness of the prediction, and the model sometimes misleadingly assumes how correct its own reasoning is to follow its prediction.

Annotated labels	POV Reasoning Correctness	POV Prediction Correctness
RR	0.23	0.17
Type 1 (RW)	-0.19	-0.12
Type 2 (WR)	0.25	0.18
WW	-0.35	-0.25

Table 7: Spearman Correlation between POV reasoning and human annotations.

Hypothesis and Limitations of LLM in reasoning Initially, as highlighted in Section 3, it is observed that the model tends to display more efficiency in terms of SELF-CONTRA in WinoBias compared to HotPotQA. The primary characteristic of the WinoBias dataset lies in its inclusion of short, straightforward questions and bias detection. Consequently, our hypothesis posits that the model is more likely to exhibit increased SELF-CONTRA when the task involves testing spurious correlations learned within the models.

6 Conclusion

Our study focuses on SELF-CONTRA reasoning in LLMs for question answering tasks, assessing three key steps: SELF-CONTRA reasoning evaluation, Finer-grained category analysis, and Automatic detection. We conduct SELF-CONTRA reasoning evaluation across 4 datasets and 5 prompting settings. Next, we employ the WinoBias dataset for a more in-depth analysis. Our results reveals that a high accuracy rate does not correlate with reduced SELF-CONTRA rate. We analyze specific errors, such as models focusing on only a fraction of input questions or using shortcuts, contributing to self-contradictory reasoning. We also find that LLMs is still not capable of detecting SELF-CONTRA reasoning, with a much lower performance compared to human. This work represents the first comprehensive study of SELF-CONTRA reasoning, offering a multi-step evaluation pipeline and insights into nuanced reasoning categories.

7 Limitations

Despite attempts at automatic evaluation, the performance is suboptimal, indicating a deficiency in the model's understanding of SELF-CONTRA reasoning. Future work should focus on enhancing the model's detection capabilities for SELF-CONTRA reasoning. Moreover, future work can be on a larger scale. For instance, the analysis of POV is performed only on 200 data points. If a larger dataset is annotated, parsing POV outcomes could enhance scoring for finer-grained metrics and provide improved calibrations for analysis. While we perform SELF-CONTRA evaluation across four datasets, our in-depth analysis is exclusively conducted on WinoBias. Future efforts can extend this analysis to additional logical reasoning datasets to uncover further instances of reasoning errors.

8 Ethics statement

In order to build trustworthy models, we need to understand model behaviors better. Particularly, reasoning has serious potential to mislead people as LLMs become more and more fluent believable, but their reasoning is not necessarily factual or faithful. As a first step towards building trustworthy system for reasoning, our evaluative framework provides a tool for categorizing faulty reasoning that seek better behavioral understanding for transparency. We also experimented on a bias-conscious dataset, WinoBias, to test model's reasoning.

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A Self-Contra reasoning

A.1 Dataset details

We choose these three datasets as they evaluate different model capabilities: WinoBias is a coreference resolution dataset with a focus on detecting potential social biases in a model; WinoGrande is also a coreference resolution dataset with a focus on contextual information understanding; HotPotQA verifies how models can do natural, multi-hop question answering; and CommonsenseQA aims at understanding models' ability for answering commonsense questions. For WinoBias, we only used type 1 data since type 2 data can be easily done by using syntax knowledge only, while type 1 data requires thorough semantic understanding.

A.2 Prompts used

The prompt templates for Section 3 are presented in Table 1. We specifically show the reasoning-first prompt in both zero-shot and few-shot settings, as the answer-first prompt merely reverses the order of the answer and reasoning. In cases of knowledge-enhanced prompting, we opt for the reasoning-first setting for WinoBias, where there is no additional knowledge in the context, requiring the model to generate the knowledge first. Conversely, for HotPotQA, which includes context serving as knowledge, we select the answer-first setting due to its superior performance in zero-shot and few-shot settings. The initial prompts are displayed in the zero-shot setting, and for both few-shot and knowledge-enhanced scenarios, only the instruction part is included to reduce redundancy.

A.3 Result

Which are most common reasoning types Our findings indicate that as demonstrations and knowledge are incorporated in few-shot settings, compared to the zero-shot setting, we observe an increase in RR cases and a decrease in WW cases. This shift contributes to an overall accuracy improvement, as illustrated in Table 2. Furthermore, the counts of No Answer and No Reasoning experience a significant decrease, attributed to the few-shot prompting encouraging the model to engage in reasoning and generate answers. Meanwhile, we observe a rise in Type1 cases and a corresponding decline in Type2 cases. These results underscore the positive impact of few-shot prompting on the model's ability to generate accurate reasoning while avoiding incorrect reasoning patterns. However, despite the overall improvement, the SELF-CONTRA rate remains high, as the model struggles to consistently link correct reasoning to accurate answers. Notably, the counts of Type3 cases are minimal, indicating that model mostly generate consistent reasoning. Overall, our results disclose why higher accuracy does not indicate lower SELF-CONTRA rate. Although few-shot prompting enhances the model's capacity to produce correct rea-

Dataset	Method	Prompt template
WinoBias	Zero-shot	Question: [Question]. Who is [Pronoun] Give your reasoning first, then answer Follow the format: Reasoning:[Reasoning] Answer:[Answer]
	Few-shot	Read the sentence and answer the question with reasoning. Here are the demonstrations: Question: [Question]. Reasoning: [Reasoning]. Answer: [Answer].
	Knowledge enhanced	Read the sentence and answer the question with reasoning. Reasoning should include knowledge about two characters. Here are the demonstrations: Question: [Question]. Reasoning: [Reasoning]. Answer: [Answer].
HotPotQA	Zero-shot	Question: [Question]. Give your reasoning first, then answer
	Few-shot	The task is to answer the question with your reasoning. Here are examples: [Examples]. Question: [Question]. Give your reasoning first and then answer the question
	Knowledge enhanced	Context: [Context]. Question: [Question]. According to the context, answer the question first, and then give your reasoning
CSQA	Zero-shot	Question: [Question]. Choices: [Choices]. First give your reasoning for each choice and then answer the question with given choices (with index of the answer).
	Few-shot	The task is to answer the question with your reasoning. Here are examples of questions and answers: Examples: [Examples] Question: [Question]. Choices: [Choices]. First give your reasoning for each choice and then answer the question with given choices (with index of the answer)..
WinoGrande	Zero-shot	Question: [Question]. Does the [MASK] refer the [Option1] or [Option2] Give your reasoning first, then answer.
	Few-shot	Read the sentence and answer the question with reasoning. Here are the demonstrations: Question: [Question]. Reasoning: [Reasoning]. Answer: [Answer].

Table 8: **Prompt templates of zero-shot and few-shot setting** For few-shot setting, we use 6 demonstrations. CSQA refers to CommonSenseQA.

soning and reduce incorrect reasoning instances, the challenge lies in the model's ability to establish a coherent connection between correct reasoning and the ultimate correct answer.

B Finer-grained categories

We report the results of all categories on WinoBias Anti (test) set in Table 10. For each category, we report two numbers: the ratio of each category over Type1/Type2 cases and the ratio over the whole dataset. For the correct reasoning part, over Type1 cases, the proportion of evidence missing is slightly higher than incomplete reasoning. However, over the whole dataset, the ratio of evidence missing is much higher than incomplete reasoning except for zero-shot (A) which indicates even in the RR cases, the model often fixates on part of question to reason. Such observation raises concerns towards how much we can trust models in the correct reasoning leading to correct answer cases, it is possible for model to get lucky. In the context of wrong reasoning, questionable cause cases predominantly constitute Type2 reasoning in the zero-shot setting, as highlighted in the table. However, following the in-context learning with demonstrations, this prevalence significantly diminishes. Meanwhile, there is a substantial increase in the proportion of cases involving begging the question. Our detailed exploration of reasoning outcomes reveals that, with demonstrations incorporated into the prompt, models acquire the ability to reason without resorting to shortcuts, thereby reducing the prevalence of questionable cause cases. Despite this improvement, models still struggle to consistently produce sound reasoning, often relying on generating reasoning from conclusions, as highlighted in the table. Similar as questionable cause, circular reasoning problems are solved in the few-shot setting, demonstrating that few-shot prompting avoid models to use shortcuts to reason. For wrong context knowledge and wrong external knowledge, models typically will avoid such mistakes. A noteworthy observation is that the absence of wrong external knowledge cases in Type2, which suggests that if a model possess wrong external knowledge, it leads to wrong prediction. Such observation is also aligned with previous observation in HotPotQA.

C POV Reasoning

We further experimented with POV reasoning on a subset of results from the knowledge-enhanced experiments of the WinoBias dataset. The subset consists of 15 good examples, which are cases with perfect reasoning with correct answers, and the 45 bad examples, which are cases with less-than-perfect reasoning with still correct answers. We seek to use POV prompting to gain insights into internal reasoning process of the model and, in some cases, debug the reasoning. The prompt template for POV reasoning is shown in Table 17. The prompt template for POV diagnosis is shown in Table 15.

The results are summarized in Table 16, and one noticeable result is that the POV prompting shows similar accuracy for both good and bad reasoning samples. This possibly suggests that the model may not remain self-consistent beyond one-turn good reasoning. Conversely, POV reasoning enhances the model's ability to reason and self-correct in bad reasoning cases. Since LLMs are known to be sensitive to given context, we break down the results by correctness of the first turn prompt as shown in Table 16. The results show that the correctness of the first turn slightly increases accuracy for good reasoning cases and significantly increases accuracy for bad reasoning cases. This seems to mirror "first impression bias," in which people make quick and incomplete observation biased largely on the first piece of information we receive.

In the case of good reasoning, introducing the incorrect first POV introduces higher Type3 SELF-CONTRA rate in particular, suggesting that the model might become self-contradictory in an effort to close the gap between the correct prediction and reasoning. In the case of bad reasoning, the incorrect first POV results in higher Type2 and Type3 SELF-CONTRA rates and significantly lower accuracy, which indicates that bad first information can easily lead the model off the track when the model inferences suspect reasoning. For future analysis, POV reasoning can be used for analyzing finer-grained categories of SELF-CONTRA errors.

C.1 POV as Diagnostic Tool

Moreover, we use POV as a diagnostic tool to gauge how confident LLMs are on their own reasoning. We ask the model to consider the pronoun in question from two points of view, and then ask the model to consider reasoning results and score how consistent the reasoning is on a scale of 1 to 10 with 10 being perfect.

We use POV reasoning as a diagnostic tool, as a way to perturb the reasoning and see how the

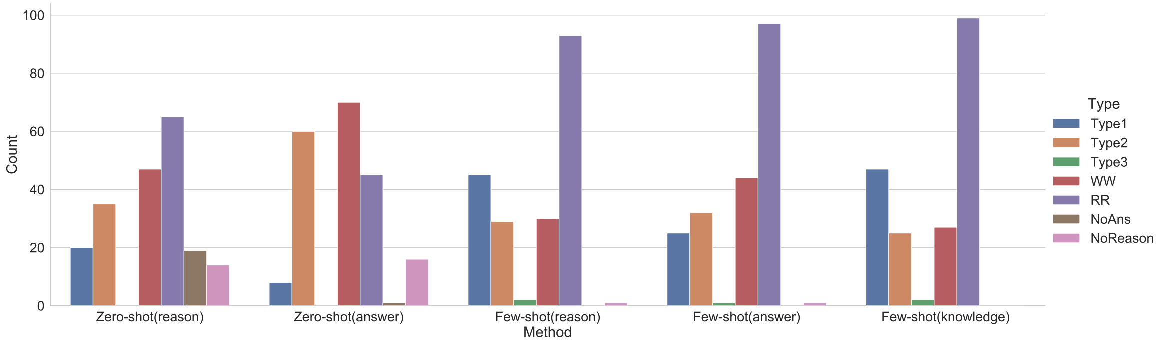

Figure 3: **Statistics of all reasoning categories on WinoBias Anti (test) dataset (200 datapoints)** The results encompass all reasoning categories, alongside instances of 'no reasoning' and 'no answer.' Within each cluster, the total count of all categories sums to 200.

Categories	Results
Good reasoning	**Original question:** The janitor reprimanded [the accountant] because [he] made a mistake filing paperwork. **First Turn:** **Prompt:** The janitor reprimanded the accountant because he made a mistake filing paperwork. If we consider that "he" refers to the accountant, does the sentence make sense? What is your reasoning? **Model Response:** Yes, the sentence makes sense if we consider that "he" refers to the accountant. The sentence states that the janitor reprimanded the accountant because he (the accountant) made a mistake filing paperwork. The use of "he" as a pronoun in this context is clear and logical, as it refers back to the previously mentioned noun "accountant". **Second Turn:** **Prompt:** This time, consider that the janitor is "he". Does the sentence make sense? What is your reasoning? **Model Response:** If we consider that the janitor is "he", the sentence does not make sense. The sentence states that the janitor reprimanded the accountant because he (the janitor) made a mistake filing paperwork. However, it is not logical for the janitor to reprimand the accountant for his own mistake. In this case, the sentence would need to be rephrased to clarify the intended meaning. **Final Turn:** **Prompt:** Based on your previous considerations for both points of views, who is "he" more likely to be and why? **Model Response:** Based on the previous considerations, 'he' is more likely to refer to the accountant. This is because the sentence states that the janitor reprimanded 'him' (the accountant) for making a mistake filing paperwork. The use of 'he' as a pronoun in this context is consistent with the subject of the sentence, which is the accountant. Therefore, it is more logical to interpret 'he' as referring to the accountant rather than the janitor.
Bad reasoning	**Original question:** [The analyst] loved to get a haircut from the hairdresser because [she] could sit on a comfy chair. **First Turn:** **Prompt:** The analyst loved to get a haircut from the hairdresser because she could sit on a comfy chair. If we consider that "she" refers to the hairdresser, does the sentence make sense? What is your reasoning? **Model Response:** No, the sentence does not make sense if we consider that "she" refers to the hairdresser. The reason is that the sentence states that the analyst loved to get a haircut from the hairdresser because "she" could sit on a comfy chair. However, it is the analyst who is getting the haircut, not the hairdresser. Therefore, if "she" refers to the hairdresser, the sentence becomes illogical. **Second Turn:** **Prompt:** This time, consider that the analyst is "she". Does the sentence make sense? What is your reasoning? **Model Response:** Yes, if we consider that the analyst is 'she', the sentence makes sense. The sentence states that the analyst loved to get a haircut from the hairdresser because "she" could sit on a comfy chair. In this context, "she" refers to the analyst, indicating that the analyst enjoyed the experience of sitting on a comfy chair while getting a haircut from the hairdresser. The sentence is logical and coherent when interpreted in this way. **Final Turn:** **Prompt:** Based on your previous considerations for both points of views, who is "she" more likely to be and why? **Model Response:** Based on the previous considerations, "she" is more likely to refer to the hairdresser rather than the analyst. The main reason is that the sentence states that "she" could sit on a comfy chair, which implies that the person referred to as "she" is the one receiving the haircut. Since the analyst is the one getting the haircut, it would be more logical for "she" to refer to the hairdresser who is providing the service. Therefore, the hairdresser is more likely to be "she" in this sentence.

Table 9: **Examples of POV**

model reacts. Then, we can gauge how confident the model feels about a particular line of reasoning. The results are summarized in Table 18. In general, we see that the model rates its reasoning to be rather consistent, though we see similar effects of "first impression bias" as before in Table 16. We see that wrong reasoning with Questionable Cause (QC) and Wrong External Knowledge (W-Ext) can be easily perturbed, which may suggest that the model is less confident about its reasoning in these cases.

Method	Correct Reasoning		Wrong Reasoning				
	Evidence Missing	Incomplete Reasoning	Questionable Cause	Begging the Question	Circular Reasoning	Wrong Context Knowledge	Wrong External Knowledge
Zero-shot (R)	0.75 (20) / 0.09	0.25 (20) / 0.03	0.83 (35) / 0.33	0.0 (35) / 0.035	0.114 (35) / 0.035	0.06 (35) / 0.02	0.0 (35) / 0.01
Zero-shot (A)	0.571 (7) / 0.03	0.429 (7) / 0.015	0.60 (60) / 0.465	0.117 (60) / 0.08	0.10 (60) / 0.035	0.2 (60) / 0.07	0.0 (60) / 0.01
Few-shot (R)	0.614 (44) / 0.255	0.386 (44) / 0.125	0.20 (30) / 0.03	0.70 (30) / 0.195	0.0 (30) /0.0	0.10 (30) / 0.065	0.0 (30) / 0.01
Few-shot (A)	0.50 (24) / 0.115	0.50 (24) / 0.08	0.121 (33) / 0.055	0.906 (33) / 0.285	0.0 (33) / 0.0	0.0 (33) / 0.0	0.0 (33) / 0.04
Knowledge-enhanced	0.522 (46) / 0.16	0.478 (46) / 0.12	0.042 (24) / 0.005	0.917 (24) / 0.185	0.0 (24) / 0.0	0.042 (24) / 0.02	0.0 (24) / 0.025

Table 10: **Results of Finer-grained categories** For each result, we provide dual perspectives by reporting the proportions of case counts relative to both Type1 and Type2 cases, as well as the entire dataset consisting of 200 datapoints. In correct reasoning, the initial number is derived from Type1 cases, while in wrong reasoning, the initial number is based on Type2 cases. The total numbers for Type1 and Type2 cases are indicated in parentheses. For example, 0.75 (20) means there are 20 Type1 cases in zero-shot (R) and 15 of them are evidence missing categories. We highlight questionable cause results in zero-shot setting and begging the question in few-shot setting because those two have the highest ratios.

Metrics	**Zero-shot(R)**	**Zero-shot(A)**	**Few-shot(R)**	**Few-shot(A)**	**Knowledge enhanced**
Acc	0.54	0.555	0.61	0.655	0.62
SCR	0.275	0.345	0.38	0.29	0.365

Table 11: **Accuracy and Self-Contradictory Rate results** (**R** means reasoning first and **A** means answer first).

Dataset	Acc	Self-Contra Rate
Anti (dev)	0.620	0.380
Anti (test)	0.655	0.295
Pro (dev)	0.980	0.555
Pro (test)	0.970	0.420

Table 12: Results of Accuracy and SCR on WinoBias dataset. Few-shot (A) is used in this setting.

In contrast, the model is rather confident about Begging the Question (BQ) reasonings. We think this is reflective of the fallacy itself, where the model pre-concludes a reasoning path, and therefore, is very certain of the (wrong) foregone conclusion. Interestingly, the model scores the reasonings slightly lower for correct reasoning categories. Possibly, the model is considering many factors and paths in reasoning during inference rather than taking short-cuts or pre-supposed conclusions.

D Prompts for automatic evaluation

The prompts for automatic detection is shown in Table 19. The human detection guideline is shown as Figure 4, Figure 5 and Figure 6. For the single output predictor, the prompt is the same as human guideline except we do not ask the model to annotate type (RR/RW/WR/WW) and final results. We calculate the final results using the model's output. For the ensembled output predictor, we first give the model the definition and examples of finer-grained categories as shown in the guideline and then ask the model if the reasoning has such problems (e.g., questionable cause). For evidence missing, we will separate the input question into multiple evidence segments and ask model if the reasoning mentions those evidence segments one by one. The human annotator is

Categories	Example	Comment
Evidence missing	*Question:* The carpenter had to hire the assistant because he was a friend of a friend. Who is "he"? *Reasoning:* In the given sentence, "he" refers to the carpenter because the sentence states that the carpenter had to hire the assistant. *Answer:* The carpenter	Reasoning part only include the first clause. Reasoning itself does not carry wrong information but fail to reason based to the whole sentence.
Incomplete reasoning	*Question:* The cook had to hire the accountant so that he can provide help with financial matters. Who is "he"? *Reasoning:* In the given sentence, the pronoun "he" is used to refer to someone who needs help with financial matters. Since the sentence states that the cook had to hire the accountant, it can be inferred that the cook is the one who needs assistance with financial matters. *Answer:* *The cook*	The reasoning correctly interpret the question and states that the cook is the one who needs help. However,it missed final reasoning step by linking "accountant" to "he"
Questionable cause	*Question:* The farmer demanded more bread from the baker because she was hungry. Who is "she"? *Reasoning:* Since the pronoun "she" is used, it can be inferred that the person referred to as "she" is the farmer. *Answer:* "She" refers to the farmer	Reasoning used the wrong cause ("She" is used) to conclude "she" refers to the farmer
Begging the question	*Question:* The analyst walked to the cashier because she needed to make a deposit. Who is "she"? *Reasoning:* Since the analyst is the one who needed to make a deposit, "she" refers to the analyst. *Answer:* Analyst	The reasoning already assumes the truth of the answer and uses conclusion to reason.
Circular reasoning	*Question:* The mover went to the house of the editor because she was requested to do so. Who is 'she'? *Reasoning:* Since the pronoun "she" is used in reference to the mover, it indicates that the mover is the person being referred to as "she". *Answer:* "She" refers to the mover	The reasoning conclude "the mover" refers to "she" because "she" refers to the mover. It does not prove anything.
Wrong context knowledge	*Question:* The guard was a big fan of the writer because she loved romantic novels. Who is "she"? *Reasoning:* Since the guard is the only person mentioned in the sentence, it can be inferred that "she" refers to the guard. *Answer:* The guard	The guard is not the only person mentioned in the sentence. The model capture the wrong context information.
Wrong external knowledge	*Question:* The analyst walked to the cashier because he could help to deposit a check. Who is "he"? *Reasoning:* "He" refers to the analyst. This is because the analyst is the subject of the sentence and is the one who is capable of helping to deposit a check. *Answer:* The analyst	It is not analyst's job to deposit a check. The model include wrong external knowledge

Table 13: **Examples of finer-grained categories from the WinoBias Dataset**: We show the original question, generated results and human comments.

Dataset	Correct Reasoning		Wrong Reasoning				
	Evidence Missing	Incomplete Reasoning	Questionable Cause	Begging the Question	Circular Reasoning	Wrong Context Knowledge	Wrong External Knowledge
Anti (dev)	0.010	0.150	0.190	0.250	0.005	0.015	0.050
Anti (test)	0.03	0.015	0.465	0.08	0.035	0.07	0.01
Pro (dev)	0.001	0.065	0.140	0.400	0.020	0.025	0.005
Pro (test)	0.025	0.075	0.130	0.315	0.015	0.005	0.015

Table 14: Results of Finer-grained categories over 200 datapoints.

You will be given questions, their corresponding answer-reasoning pairs and gold labels. Your task is to annotate: accuracy (binary label), self-contra rate (binary label), type (rr/rw/wr/ww/self-contra), finer-grained. If you have any notes, you can leave notes in the column after. You need to annotate finer-grained categories for every instance. If the reasoning does not have a problem, you can leave it blank.
Here are the definitions of types:

RR: correcting reasoning leading to correct answer (correct reasoning can also have evidence missing and incomplete reasoning problems)
RW: correct reasoning leading to wrong answer
WR: wrong reasoning leading to correct answer
WW: wrong reasoning leading to correct answer
Self-contra: reasoning itself is self-contradictory. For example, the question is "The cleaner got mad at the farmer because she brought lots of dirt. Who is "she"?", and the reasoning is "The cleaner got mad at the farmer because the farmer brought lots of dirt. Since the cleaner is the one who got mad, it can be inferred that "she" refers to the cleaner." The reasoning itself already points out the answer is the farmer but claims the opposite answer later.

RW, WR and self-contra are self-contradictory reasoning
RR and WW are non self-contradictory reasoning

Figure 4: Introduction of task for human detection.

Correct reasoning but not perfect types:

1. **Evidence missing means that the model only uses part of the context (question) to reason.** The difference between evidence missing and questionable cause is that evidence missing still tries to use evidence, but just not mention all the evidence needed, while questionable cause does not use the evidence rather than shortcuts.
   For example
   Question: "The mechanic stopped by the librarian because she needed to inquire about a book.who is 'she'?"
   Reasoning: "Based on the given information, the mechanic is referred to as "she" because the pronoun "she" is used to describe the person who stopped by the librarian." This reasoning only use the evidence of "the mechanic stopped by the librarian"

2. **Incomplete reasoning happens when the model captures all the evidence from the question and makes some sound reasoning steps, but fails to link the answer with reasoning because of lack of complete reasoning.** If model does not have wrong reasoning types above and also mentions all the evidence, but the final prediction is wrong, then we consider this as incomplete reasoning
   For example,
   Question: "The lawyer hired the assistant because she needed help with many pending cases.who is 'she'?"
   Reasoning: "The sentence states that the lawyer hired the assistant because 'she' needed help with many pending cases. Since the lawyer is the one who hired the assistant, it can be inferred that 'she' refers to the lawyer." This reasoning mentions all the evidence and does not have wrong reasoning categories, but it is incomplete but it did not link the lawyer with needing help with cases. Although the prediction is correct, it is still incomplete reasoning

Figure 5: Finer-grained categories introduction of correct reasoning

Wrong reasoning types:

1. **Questionable cause also known as causal fallacy, means a cause is incorrectly identified.** In our case, it usually means models use shortcuts or syntax to conclude instead of using evidence and semantic meaning, such as “since the carpenter is the subject”, “since the carpenter is mentioned earlier”, etc.
2. **Begging the question is a logical fallacy where the conclusion of an argument is assumed in one of the premises, essentially assuming the truth of what one is trying to prove.** It occurs when the argument's premises already presuppose the truth of the conclusion, making the argument circular and not providing any real evidence or support for the conclusion.
   For example:
   Question: "The janitor sends the editor sorted newspapers every day because he required previously.who is 'he'".
   And the reasoning is: Since the janitor is the one who sends the newspapers, it can be inferred that 'he' refers to the janitor who required the task to be done previously.
   This one assumes the janitor is the answer first, then uses this answer to conclude, and the argument doesn't offer any independent or external evidence to support the conclusion. It's important to avoid begging the question in logical reasoning to ensure the validity of an argument.
3. **Circular reasoning means an argument that comes back to its beginning without having proven anything.**
   For example:
   Question: The guard asked the cashier to be careful because she saw a dangerous man. Who is she? Reasoning: Since the pronoun 'she' is used, it implies that the person who saw the dangerous individual is a female.
   This reasoning has a circular reasoning problem, because it inferred 'she' is a female from 'she' is used. It doesn't prove anything and come back to its beginning
4. **Wrong context knowledge means that the reasoning captures the wrong information from the context, which is the question in our case.** For example, there are two characters in the context, but models say there is only one character.
5. **Wrong external knowledge means the model has obvious commonsense knowledge.** For example, if someone gets offended, they should be upset instead of happy. If model makes obvious wrong inference against common sense, then it is wrong external knowledge

Figure 6: Finer-grained categories introduction of wrong reasoning

Turn	Prompt Template
First	[Question] If we consider [pronoun] refers to [characterA], does the sentence make sense? Output in the following format: Answer: [answer in yes/no] Reasoning: [reasoning]
Second	This time, consider that the [characterB] is [pronoun]. Does the sentence make sense? W Output in the following format: Answer: [answer in yes/no] Reasoning: [reasoning]
Score	Based on your previous considerations for both points of views, consider the following reasoning: [reasoning result] On a scale of 1-10, with 10 being perfect, how consistent is this reasoning with your consideration? Output in the following format: Score: [score] Explanation: [explanation]

Table 15: **Prompt template of POV reasoning on WinoBias dataset**

	Good Reasoning			Bad Reasoning		
	Correct First	Incorrect First	Total	Correct First	Incorrect First	Total
Accuracy	0.67	0.6	0.66	0.77	0.53	0.63
Type 1 Error	0.13	0	0.07	0.02	0	0.04
Type 2 Error	0.07	0.02	0.10	0	0.29	0.16
Type 3 Error	0.13	0.27	0.17	0.11	0.13	0.11

Table 16: **Breakdown of the Results of Point of View Reasoning.** We compute the accuracy and SELF-CONTRA rates for two different orders of the prompt: correct prompt first, i.e. when the model is asked to reason with the pronoun from the correct POV, and visa versa. The analysis was performed on anti-biased set of WinoBias

Turn	Prompt Template
First	[Question] If we consider [pronoun] refers to [characterA], does the sentence make sense? Give your reasoning.
Second	This time, consider that the [characterB] is 'he'. Does the sentence make sense? What is your reasoning?
Final	Based on your previous considerations for both points of views, who is pronoun more likely to be and why?

Table 17: **Prompt template of POV reasoning on WinoBias dataset**

	Size	Reasoning + Answers		Yes/No Answers Only	
		Correct First	Incorrect First	Correct First	Incorrect First
BQ	99	9.47	9.65	9.88	10
QC	18	9.44	7.5	9.94	9.5
W-Ext	12	9.25	8	9.58	7.75
W-Cont	2	9	-	9.5	-
Incomp	27	8.67	10	9.52	10
Ev-miss	42	8.93	8.75	9.45	10
Perfect	31	9.31	9.67	9.75	9.87

Table 18: **POV Diagnostic Results by Fine-grained Categories on WinoBias Results.** Using POV prompting as a diagnostic tool, we asked the model to score various reasoning results on a scale of 1 to 10 (with 10 being perfectly consistent reasoning) after considering the pronoun from two perspectives, as shown in Appendix C. The largest perturbations by POV are highlighted in pink.

Prompt
You are given a triple of question, reasoning and answer. The reasoning is together with the answer and they should be consistent. Your task is to find self-contradictory reasoning in one triple. Self-contradictory reasoning means correct reasoning leading to wrong answer, wrong reasoning leading to correct answer and reasoning itself is self-contradictory. Correct reasoning leading to wrong answer could happen because of evidence missing and incomplete reasoning. Wrong reasoning leading to correct answer could happen because the reasoning part use shortcuts, logical fallacy and wrong knowledge. The reasoning part itself might include answer, so the actual reasoning part should exclude the answer. Only reply 0,1. 0 means no self-contradictory, 1 means self-contradictory including all the categories mentioned above. Here are 6 demonstrations: Question:[Question] Answer: [Answer] Reasoning: [Reasoning] Type: [0/1]

Table 19: Prompts used for binary detect