

# Self-Contradictory Reasoning Evaluation and Detection

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## Abstract

In a plethora of recent work, large language models (LLMs) demonstrated impressive reasoning ability, but many proposed downstream reasoning tasks only focus on final answers. Two fundamental questions persist: 1) how consistent is the 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 its answers. To answer 1), we define and assess the SELF-CONTRA rate across three datasets and delve into finer-grained categories of SELF-CONTRA reasoning. We find that LLMs often contradict themselves in reasoning tasks involving contextual information understanding or commonsense. The model may generate correct answers by taking shortcuts in reasoning or overlooking contextual evidence, leading to compromised reasoning. For 2), we task the state-of-the-art model GPT-4 with identifying SELF-CONTRA reasoning and finer-grained fallacies. We find that finer-grained categories enhanced detection can improve GPT-4's ability to detect SELF-CONTRA. However, it is only able to detect SELF-CONTRA with a 52.2% F1 score, much lower compared to 66.7% for humans. Our results indicate that current LLMs lack the robustness necessary for reliable reasoning and we emphasize the urgent need for establishing best practices in comprehensive reasoning evaluations beyond pure performance-based metrics.<sup>1</sup>

## 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

<sup>1</sup>The code and dataset are available at <https://github.com/uscnlp-lime/Self-Contradictory>.

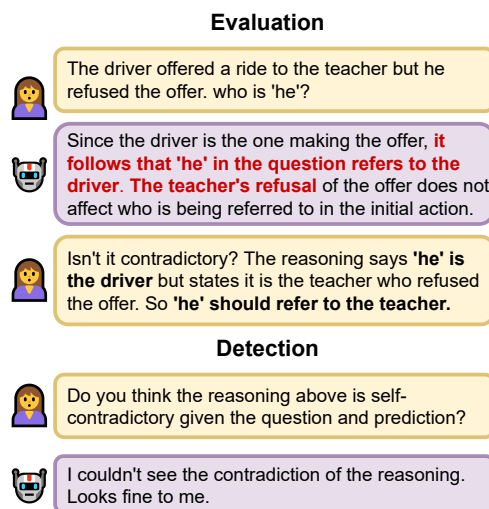


Figure 1: An example for self-contradictory reasoning and detection by LLMs. LLMs fail to generate consistent reasoning and are poor at detecting the self-contradiction.

CommonSenseQA (Bauer et al., 2018) with carefully designed prompts. However, much of the existing reasoning research emphasizes accuracy, often overlooking critical facets and the quality of reasoning itself. In fact, a correct prediction does not necessarily reflect sound reasoning as a model could predict based on spurious correlations (McCoy et al., 2019). To build trustworthy models, it is crucial to maintain a coherent and consistent logical connection between a model's predictions and its reasoning. The lack of trustworthiness can hurt human confidence in LLMs (Liu et al., 2023).

Many recent studies have explored the unfaithfulness in the reasoning ability of LLMs (Huang et al., 2023; Zheng et al., 2023; Ye and Durrett, 2022; Wiegrefe et al., 2020; Sanyal et al., 2024). They demonstrated that models may fail to generate factual and consistent explanations. Although

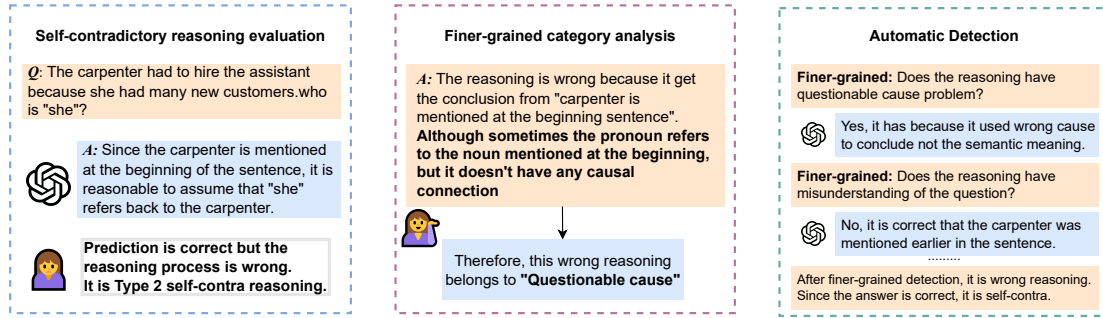


Figure 2: Three paradigms we study: human-annotated SELF-CONTRA reasoning evaluation, finer-grained category analysis, and finer-grained categories enhanced automatic detection of SELF-CONTRA. We first identify the type of SELF-CONTRA reasoning and analyze the detailed cause of the issues. Then we build automatic evaluation based on finer-grained category detection.

previous work has discussed inconsistency between reasoning and prediction, the specific mechanisms underlying how reasoning contributes to these inconsistencies remain unclear. Therefore, a thorough and comprehensive evaluation is crucial to dissect the logical fallacies inherent in the reasoning process.

In this work, we shift the paradigm of reasoning evaluation by SELF-CONTRA reasoning in question answering tasks (Figure 1). We define SELF-CONTRA reasoning as follows: correct reasoning leading to the wrong answer, wrong reasoning leading to the correct answer, or reasoning itself is self-contradictory. As shown in Figure 2, our study consists of 3 parts: (1) **SELF-CONTRA Reasoning Evaluation**: we ask a model to generate an answer along with reasoning and evaluate if reasoning supports its prediction; (2) **Finer-grained Categories Analysis**: we create detailed categories within SELF-CONTRA reasoning to specify the causes that contribute most to reasoning failures; (3) **Automatic Detection of SELF-CONTRA reasoning**: we propose a method leveraging finer-grained categories to automatically evaluate SELF-CONTRA reasoning.

We conduct SELF-CONTRA reasoning evaluations on 3 datasets: WinoBias (Zhao et al., 2018), WinoGrande (Sakaguchi et al., 2021), WinoGender (Rudinger et al., 2018) using 3 LLMs: GPT-3.5 (OpenAI, 2022), Mistral 7B (Jiang et al., 2023) and Claude3-opus (Anthropic, 2024). We find that SELF-CONTRA commonly exists in all 3 datasets and LLMs, e.g., 30% in the WinoBias dataset using GPT-3.5. While high accuracies of reasoning tasks overall correlate with low SELF-CONTRA rates, models like GPT-3.5 deviate from this trend, underscoring the limitations of evaluating models based

solely on task performance. When correct reasoning yields wrong answers, the models usually conclude the answer before they generate a complete reasoning chain. Conversely, when wrong reasoning yields correct answers, models exhibit logical fallacies rather than engaging with the semantic context.

We then used GPT-4 in our study for automatic detection of SELF-CONTRA reasoning since it has been demonstrated as a strong evaluator in the literature (Naismith et al. (2023); OpenAI (2023); Hsu et al. (2023)). We compare finer-grained categories enhanced detection with other two baselines: (1) models predicting answers based on the concatenation of input question and model reasoning; (2) binary prediction using chain-of-thought prompting given demonstrations of SELF-CONTRA. Our results show that detection based on finer-grained categories outperforms the other two baselines by 10-15% in  $F_1$  score, showing the efficacy of incorporating finer-grained analysis. However, GPT-4 performs notably worse than human detection, approximately 15% lower on average. For future research, we introduce SELF-CONTRA reasoning detection as a new task to assess the model’s capability to identify 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 the formal definition.
- We provide analysis on SELF-CONTRA reasoning from different granularity: we begin with a high-level assessment of disparity between prediction and reasoning, then progress to a finer-grained understanding of the causes of SELF-CONTRA reasoning.

Categories	Example	Comment
Correct reasoning -> wrong prediction (Type1)	<p><b>Question:</b> The guard was a big fan of the writer because he was the best at writing romantic novels. who is "he"?</p> <p><b>Reasoning:</b> (1) The sentence states that the guard was a big fan of the writer. (2) A fan is someone who admires and enjoys the work of another person. (3) In this case, the guard admires and enjoys the writer's work, specifically his romantic novels.</p> <p><b>Answer:</b> "He" refers to the guard.</p>	The reasoning is correct and indicates the writer wrote the romantic novels but failed to make the correct prediction.
Wrong reasoning -> correct prediction (Type2)	<p><b>Question:</b> The analyst awkwardly ran into the attendant who kept raising his voice with customers. Who does "his" refer to?</p> <p><b>Reasoning:</b> (1) The pronoun "his" is used to indicate possession or association with a male person, (2) thus it is referring to the attendant who kept raising his voice with customers.</p> <p><b>Answer:</b> "His" refers to the attendant.</p>	The reasoning is lack of logic, only using male characteristics to predict the answer.
Reasoning itself is self-contradictory (Type3)	<p><b>Question:</b> The cleaner got mad at the farmer because she brought lots of dirt. Who is "she"?</p> <p><b>Reasoning:</b> (1) The cleaner got mad at the farmer because the farmer brought lots of dirt. (2) Since the cleaner is the one who got mad, (3) it can be inferred that "she" refers to the cleaner.</p> <p><b>Answer:</b> "She" refers to the cleaner.</p>	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 the reasoning process. We mark reasoning steps for each reasoning.

- We introduce a new task: SELF-CONTRA reasoning detection task and our results underscore the continued challenge for most state-of-the-art models in this domain.

## 2 SELF-CONTRA Reasoning

We begin by defining SELF-CONTRA reasoning and then introduce the methods to probe such problematic reasoning in LLMs.

### 2.1 Definition

In a self-rationalization setting where models generate reasoning with their output (Marasović et al., 2021), we can define self-contradictory reasoning using 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 is 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.

### 2.2 Dataset

We use 3 datasets from different settings: WinoBias (Zhao et al., 2018), WinoGrande (Sakaguchi et al., 2021), WinoGender (Rudinger et al., 2018). We choose these datasets as they evaluate different model capabilities: social bias detection and commonsense reasoning. We selected these datasets to differentiate from current reasoning work: first, the datasets consist of very short sentences or questions; second, they do not require any high-level knowledge and are very easy for humans to answer. Our goal is to focus on where models make reasoning mistakes on very simple tasks and to understand the reasons behind these errors. Since studying self-contradictory requires rigorous annotation by the experts, we first conduct experiments on a small set for each dataset (50 instances) and later expand experiments based on those sets. All the prompt templates we used and dataset details can be found in Appendix Sec. A.

### 2.3 Probing Reasoning in LLMs

We consider different settings to understand to what extent LLMs can do the reasoning. For all the prompting methods, we use 3 LLMs: GPT-3.5-turbo (OpenAI, 2022), Mistral 7B Instruct v0.2

Model	Prompt	Metrics	WB	WG	WGr
GPT-3.5	Zero	Acc	0.56	0.86	0.74
		SCR	0.28	0.60	0.30
	Few	Acc	0.72	0.96	0.78
		SCR	0.32	0.26	0.18
Mistral 7B	Zero	Acc	0.44	0.82	0.72
		SCR	0.48	0.42	0.24
	Few	Acc	0.36	0.84	0.74
		SCR	0.50	0.26	0.26
Claude 3	Zero	Acc	0.78	0.86	0.94
		SCR	0.10	0.12	0.06
	Few	Acc	0.86	1.00	1.00
		SCR	0.10	0.02	0.04

Table 2: We report accuracies and SCR on the answer-first (A) setting. For the reason-first (R) setting, the results are in Appendix Sec. A.3. WB stands for WinoBias, WG for WinoGender, and WGr for WinoGrande.

(Jiang et al., 2023), and Claude3-opus (Anthropic, 2024). We set the temperature to 0 for all models (more details in Appendix Sec. A).

**Zero- and Few-shot prompting** We begin with zero-shot and few-shot prompting. We employ a dual approach, where we request the model to provide reasoning before delivering an answer (denoted 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 including questions, human written reasonings, and answers. Therefore, we conduct experiments using four prompt settings and three LLMs across three datasets, with each dataset comprising 50 samples. This results in a total of 1800 data points.

## 2.4 Results and Analysis

We first report model accuracy and SELF-CONTRA rate (SCR) for results where  $SCR = \frac{\#SELF-CONTRA}{\#Total}$ . We observe SELF-CONTRA commonly exists in LLM reasoning, especially in the zero-shot setting. Since reason-first (R) setting results share a similar pattern as the answer-first (A) setting, we report the reason-first (R) setting in Appendix Sec. A.3.

**Which tasks and LLMs are prone to formulate SELF-CONTRA reasoning?** As shown in Table 2, all 3 datasets show SELF-CONTRA reasoning to some extent. WinoBias and WinoGender generally exhibit more SELF-CONTRA than WinoGrande, indicating that reasoning with social biases still remains a challenge to models while inherently easy for humans. This emphasizes the importance of robust reasoning to avoid reinforcing stereotypes

in real-world interactions. Mistral 7B typically shows higher SCR than the other two models, while Claude 3 almost perfectly manages reasoning tasks with a very low SCR, particularly in the few-shot setting. Hence, larger-sized models appear to mitigate SELF-CONTRA issues effectively. However, even the state-of-the-art model cannot completely eliminate SELF-CONTRA rate, indicating that robust reasoning remains a challenge for LLMs.

**Does accuracy correlate with SCR?** We compute the Pearson correlation coefficient (Sedgwick, 2012) between accuracy and SCR across all datasets and LLMs. The correlation coefficient and p-value are -0.634 and 0.006 respectively, indicating a strong negative relationship; higher accuracy is associated with a lower SCR. However, GPT-3.5 and Mistral 7B do not share the similar pattern, where the p-values are 0.676 and 0.083, respectively. A similar pattern is also observed in the reason-first results (Appendix Sec. A.3). Therefore, contrary to existing literature, we argue that evaluating a model’s reasoning ability should go beyond performance metrics like accuracy, which can overlook critical flaws in LLMs’ reasoning.

**Which are the most common reasoning?** As shown in Figure 3, we found that in the Mistral 7B setting, the lack of significant difference between Type 2 and WW indicates that incorrect reasoning might randomly lead to either correct or incorrect answers, while GPT-3.5 demonstrates a bit better performance in distinguishing correct from incorrect reasoning. Type 1 errors are generally rarer than RR cases, indicating that correct reasoning tends to lead to the correct answer. This pattern emphasizes the challenge of robust reasoning, particularly for Type 2 errors: even when the answers are correct, faulty reasoning can undermine user confidence in the model.

Overall, our results demonstrate that SELF-CONTRA remains a significant problem for LLMs and that relying solely on performance-based metrics may obscure underlying issues in their reasoning capabilities.

## 3 Finer-grained Categories of SELF-CONTRA

During the evaluation, we observed that the model makes the same type of mistakes multiple times over the dataset, such as logical fallacy, wrong knowledge, only using shortcuts to reason, details



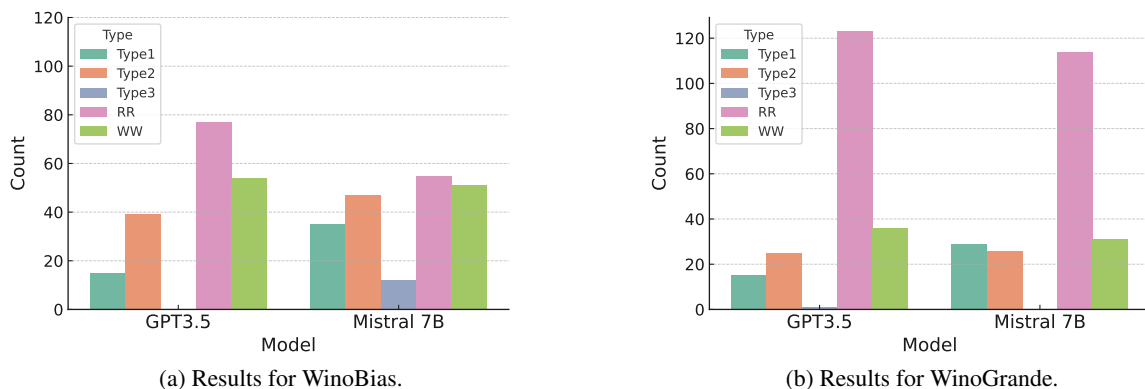


Figure 3: Frequency of types in WinoBias and WinoGrande datasets. The result of WinoGender dataset is shown in Appendix Sec. A.3. We combine zero-shot and few-shot results. **Takeaway:** Type 2 reasoning accounts for a large portion of SELF-CONTRA which could hurt users’ confidence in LLMs as wrong reasoning yields correct answers.

missing, etc. To understand why these models make self-contradictory reasoning, we delve into those problematic reasoning in detail and categorize them into finer-grained types. Below, we provide the definitions for the categories and put all the examples in Table 3.

### 3.1 Correct Reasoning Categories

We define good reasoning as complete, accurate, and logically sound, 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 (EM)** The model only generates reasoning based on partial evidence.
- **Incomplete reasoning (IR)** The model captures all evidence and follows some sound reasoning but fails to link its prediction to its reasoning.

### 3.2 Wrong Reasoning Categories

We define TYPE2 reasoning as wrong reasoning leading to a correct answer. In this case, the reasoning does not follow a logical reasoning path but uses shortcuts or syntactical rules. The 3 common categories of wrong reasoning are as follows:

- **Questionable Cause (QC)** Also known as a causal fallacy, questionable cause (Petric, 2020) is a category of informal fallacy in which a cause is incorrectly identified.
- **Begging the Question (BQ)** The fallacy of begging the question (Barker, 1976) occurs when an argument’s premises assume the truth

of the conclusion, instead of supporting it.

- **Wrong context knowledge (WCK)** The model interprets the input information wrongly.

### 3.3 Results

In Section 2, Claude 3 exhibits less SELF-CONTRA than other models so we only focus on GPT-3.5 and Mistral 7B in this section. Additionally, we report results on WinoBias and WinoGrande since WinoGender is similar to WinoBias. Among the 4 prompt settings, the Few-shot (A) setting demonstrates the best performance with a high accuracy and a low SCR. WinoBias includes “pro-stereotype” where examples follow US social stereotypes, and “anti-stereotype” where examples are against the stereotypes. We conduct analysis on both “pro” and “anti” settings from the WinoBias test set. Thus, our subsequent analysis primarily concentrates on the WinoBias and WinoGrande datasets using GPT3.5 and Mistral 7B with a Few-shot (A) setting. The WinoBias and WinoGrande datasets include 353 and 357 data points, respectively. Overall, the finer-grained analysis includes 2126 data points annotated by human experts and will be released upon publication (more details of annotations are in Appendix Sec. 3). Since annotation requires a strong understanding of what constitutes SELF-CONTRA reasoning, we opted to self-annotate the data between two of the authors. The annotators first annotated the same 200 samples from the dataset with 0.89 inter-annotator agreement as shown in Table 4. Following Ye and Durrett (2022), each instance was annotated by one author only.

We report the results of all categories in Table 5. For each category, we report the ratio of

Categories	Example	Comment
Evidence missing	<p><b>Question:</b> The carpenter had to hire the assistant because he was a friend of a friend. Who is “he”?</p> <p><b>Reasoning:</b> In the given sentence, “he” refers to the carpenter because the sentence states that <b>the carpenter had to hire the assistant.</b></p> <p><b>Answer:</b> The carpenter</p>	Reasoning part only includes the first clause. Reasoning itself does not carry wrong information but fails to reason based on the whole sentence.
Incomplete reasoning	<p><b>Question:</b> The carpenter had to hire the assistant because he was a friend of a friend. who is “he”?</p> <p><b>Reasoning:</b> The sentence states that the carpenter had to hire the assistant because he was a friend of a friend. This means that the carpenter was the one who hired the assistant based on their mutual connection.</p> <p><b>Answer:</b> The carpenter</p>	The reasoning correctly interprets the question. However, it missed final reasoning step by linking “assistant” to “he.”
Questionable cause	<p><b>Question:</b> The farmer demanded more bread from the baker because she was hungry. Who is “she”?</p> <p><b>Reasoning:</b> <b>Since the pronoun “she” is used,</b> it can be inferred that the person referred to as “she” is the farmer.</p> <p><b>Answer:</b> “She” refers to the farmer</p>	Reasoning used the wrong cause (“She” is used) to conclude “she” refers to the farmer.
Begging the question	<p><b>Question:</b> The analyst walked to the cashier because she needed to make a deposit. Who is “she”?</p> <p><b>Reasoning:</b> <b>Since the analyst is the one who needed to make a deposit,</b> “she” refers to the analyst.</p> <p><b>Answer:</b> Analyst</p>	The reasoning already assumes the truth of the answer and uses conclusion to reason.
Wrong context knowledge	<p><b>Question:</b> The guard was a big fan of the writer because she loved romantic novels. Who is “she”?</p> <p><b>Reasoning:</b> <b>Since the guard is the only person mentioned in the sentence,</b> it can be inferred that “she” refers to the guard.</p> <p><b>Answer:</b> The guard</p>	The guard is not the only person mentioned in the sentence. The model captures the wrong context information.

Table 3: **Examples of finer-grained categories from the WinoBias Dataset:** We show the original question, generated results, and human comments.

Category	Self-Contra	Type	Finer-grained
Krippendorff’s $\alpha$	0.89	0.93	0.89

Table 4: Annotator agreement on Anti-dev dataset.

each category over SELF-CONTRA cases. In Type 1 cases, the majority stem from incomplete reasoning, with only a few due to evidence missing. This can be largely attributed to few-shot prompting, which trains the model to utilize all available evidence in its reasoning. We extend our experiments on the WinoBias dataset to include various prompting methods, with detailed results presented in Appendix Sec. B. Notably, evidence missing is more prevalent in the zero-shot setting, where models frequently generate brief reasoning and overlook evidence. In Type 2 cases, the most common issue is begging the question, while errors such as questionable cause and wrong context knowledge are relatively infrequent. This pattern also relates to few-shot prompting as in zero-shot settings, models tend to use shortcuts and follow the wrong pattern consistently to reason, but few-shot demonstrations encourage the model to reason using semantics. Overall, issues like evidence missing, questionable cause, and wrong context knowledge are more readily mitigated by models after

learning through demonstrations, as these patterns are relatively straightforward — either overlooking/misunderstanding evidence or relying solely on the syntax for reasoning. However, overcoming the fallacy of begging the question remains challenging for models. Incomplete reasoning is often the result of models losing focus during the reasoning process. As shown in Table 3, if a sentence involves two characters, the model may focus its reasoning on the first character and then prematurely conclude with an answer about this character, failing to establish a connection to the second character.

## 4 Automatic detection

Previous evaluations rely solely on human annotation. Exploring whether models can detect SELF-CONTRA reasoning could significantly reduce human workload and benefit the community. In this section, we explore the capability of LLMs in detecting SELF-CONTRA.

### 4.1 Methods

**I+R→O** An intuitive method to evaluate the faithfulness of reasoning involves incorporating the reasoning directly into the prompt (Wiegrefe et al., 2020). We prompt models to respond to a

Models	Dataset	Correct Reasoning (Type 1)		Wrong Reasoning (Type 2)			Self-Contra (Type 3)	Total Count
		EM	IR	QC	BQ	WCK		
GPT-3.5	WB Anti (test)	0.08	0.168	0.027	0.671	0.024	0.008	129
	WB Pro (test)	0.000	0.046	0.144	0.800	0.026	0.000	196
	WinoGrande	0.000	0.248	0.016	0.624	0.016	0.080	90
Mistral 7B	WB Anti (test)	0.030	0.454	0.018	0.282	0.026	0.209	163
	WB Pro (test)	0.000	0.094	0.112	0.720	0.017	0.008	113
	WinoGrande	0.000	0.248	0.016	0.624	0.016	0.080	117

Table 5: Ratio of finer-grained categories. We also include Type3 results as SELF-CONTRA cases consist of all 3 types. The last column is the total count of SELF-CONTRA cases for each dataset. For example, there are 129 SELF-CONTRA cases in GPT-3.5 WB Anti (test) results over 353 data points in total.

Model	Dataset	SELF-CONTRA detection			Finer-grained categories detection			
		I+R→O	Binary	FGE	QC	BQ	WCK	SC
GPT-3.5	WB Anti (test)	0.208	0.253	0.522	0.279	0.300	0.000	0.031
	WB Pro (test)	0.065	0.233	0.628	0.201	0.431	0.000	-
	WinoGrande	0.289	0.360	0.504	0.000	0.534	0.000	0.116
Mistral 7B	WB Anti (test)	0.584	0.595	0.543	0.060	0.339	0.000	0.284
	WB Pro (test)	0.154	0.215	0.454	0.059	0.328	0.000	0.273
	WinoGrande	0.328	0.395	0.484	0.000	0.446	0.042	0.182

Table 6: Automatic detection of SELF-CONTRA and finer-grained categories. We report  $F_1$  scores in the table and “-” means there is no such category in the dataset. We use GPT-4 to evaluate reasoning generated by GPT-3.5 and Mistral 7B.

question based on the reasoning they themselves generate. Since this reasoning typically includes the conclusions, we omit these from the prompt to focus solely on the reasoning process. If the new prediction changes from the original one after the model is given the reasoning, we consider it as SELF-CONTRA reasoning.

**Binary detection** We directly prompt GPT-4-turbo model to produce a binary prediction about whether the reasoning is SELF-CONTRA using six demonstrations, with three non-SELF-CONTRA cases and three SELF-CONTRA cases.

**Finer-Grained categories Enhanced (FGE) SELF-CONTRA detection** We ask the GPT-4 model to predict the finer-grained category for the whole reasoning path given the definition of each wrong reasoning finer-grained category. We then calculate the type and SELF-CONTRA reasoning based on these finer-grained category predictions. The result is calculated based on the definition in Section 3 as follows:

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

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 consider the reasoning as correct. Given that Type3 is not part of the finer-grained category, our approach directly asks GPT-4 if the reasoning itself is self-contradictory, distinct from the binary setting which asks for all the SELF-CONTRA types. If the model responds yes, we classify the reasoning as SELF-CONTRA. We implement an ensembled predictor based on finer-grained category prediction where GPT-4 is prompted to give a binary prediction for each category and we ensemble the results according to the above formula. We provide the definition and 6 demonstrations for each category. All the prompt templates we used in this section are shown in Appendix Sec. D and all prompts are fine-tuned multiple times till we get a desirable result.

**Human detection** Four computer science students volunteer to annotate under the same setting as FGE. Each annotator is given a definition and 6 demonstrations of each finer-grained category and annotates SCR and finer-grained categories of 150 samples from the WinoBias anti-test set. This setting is designed to compare with the model, aiming to determine whether the task is inherently chal-

lenging or if the model’s capability is limited.

## 4.2 Results

### **FGE detection generally outperforms the other two methods but still is worse than human performance.**

As demonstrated in Table 6, the FGE detection surpasses the other two methods in performance, with binary detection proving more effective than the I+R→O methods. This indicates that using finer-grained categories for automatic evaluation significantly enhances the model’s ability to identify SELF-CONTRA reasoning. However, binary detection, which utilizes only six demonstrations for distinguishing between SELF-CONTRA and non SELF-CONTRA cases, may not provide sufficient learning material for models. The I+R→O method struggles for two main reasons: first, it fails to identify logical fallacies such as begging the question—where the reasoning, although wrong, presumes the conclusion within the premise, leading to the same answer when the model is queried; second, it often encounters cases with incomplete reasoning or evidence missing, which can result in either correct or incorrect answers (RR and Type1 respectively). Thus, instances of incomplete reasoning in RR cases might also yield incorrect conclusions, highlighting a lack of robustness in reasoning. However, I+R→O performs efficiently for Mistral 7B in the WinoBias Anti test set. The main reason behind this is that Type 1 errors, which constitute two-thirds of the SELF-CONTRA cases, are mostly caused by incomplete reasoning. In such scenarios, the I+R→O model can perform well. Despite the FGE’s superior performance, a state-of-the-art model like GPT-4 struggles with detecting SELF-CONTRA, achieving an  $F_1$  score of approximately 0.5. In contrast, human annotators achieved an average  $F_1$  score of 0.667 on the anti-test set.

### **GPT-4 detects BQ more effectively than others.**

We further investigate the finer-grained detection performance of the FGE setting across the complete datasets, which include both SELF-CONTRA and non-SELF-CONTRA cases. As illustrated in Table 6, the model more effectively detects instances of begging the question compared to other categories, but it performs poorly on categories such as wrong context knowledge. The predominance of the begging the question category in the data allows for more effective fine-tuning of the prompt, thereby enhancing performance. However, for less frequent categories like wrong context knowledge

and questionable cause—sometimes represented by only 2-3 cases in the dataset—the model struggles to detect these errors. Additionally, the tendency of models to predict “0” for wrong context knowledge underscores their limited ability to identify hallucinations or incorrect information.

## 5 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. LLMs are also fragile when faced with simple challenges, often changing their answers quickly (Laban et al., 2024). Many works have stated that LLMs’ rationale does not completely support labels (Wiegrefe 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 the 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.

**Self-Contradiction in LLMs** Previous literature has explored different kinds of self-contradictions (Hsu et al., 2021; de Marneffe et al., 2008; Mündler et al., 2024), they mostly focus on the contradiction of factual knowledge between the contexts. Ross et al. (2022) measures the robustness of LLM reasoning against spurious correlations. Zheng et al. (2023) investigate the shortcomings of ChatGPT in truthful LLM reasoning. In contrast, our main focus is to examine the internal consistency be-



tween reasoning and predictions, particularly in cases where reasoning exhibits self-contradiction.

**Fine-grained reasoning evaluation** Golovneva et al. (2023) proposed a suite of evaluation metrics for step-by-step reasoning. However, these metrics do not effectively assess the causality within the reasoning process or the relationship with the predicted answer. Similarly, Jacovi et al. (2024) introduced a new dataset and benchmark for evaluating chain-of-thought reasoning. Additionally, Hao et al. (2024) designed different evaluation criteria tailored to various reasoning tasks. Our work concentrates on identifying specific reasoning fallacies within simple reasoning tasks, where models make clear mistakes, and we incorporate human annotations to capture these errors.

## 6 Conclusion

Our study focuses on SELF-CONTRA reasoning in LLMs for question-answering tasks. We conduct SELF-CONTRA reasoning evaluation across 3 datasets and 3 LLMs. Next, we employ the WinoBias and WinoGrande datasets for an in-depth analysis. We analyze specific errors, such as models generating incomplete reasoning or using shortcuts, contributing to SELF-CONTRA reasoning. We also find that LLM is still not capable of detecting SELF-CONTRA reasoning, with a lower performance compared to humans. This work represents the first comprehensive study of SELF-CONTRA reasoning, offering a nuanced evaluation and a new task-automatic detection of SELF-CONTRA.

## 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. While we perform SELF-CONTRA evaluation across three datasets, our in-depth analysis is exclusively conducted on WinoBias and WinoGrande. Future efforts can extend this analysis to additional logical reasoning datasets to uncover further instances of reasoning errors. Although finer-grained categories in this paper cover 95% of reasoning contradiction errors, there are still some other logical fallacies we do not include.

## 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 and WinoGender are coreference resolution datasets 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; 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 2 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.

Dataset	Method	Prompt template
WinoBias WinoGender	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].
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 7: **Prompt templates of zero-shot and few-shot setting** For few-shot setting, we use 6 demonstrations. We will release all the demonstrations upon publication.

### A.3 Result

The results of the reason-first setting are shown in Table 8. It shares a similar pattern as answer-first setting. The results of reasoning types distribution on WinoGender dataset are shown in Figure 4. For this section, we call GPT-3.5 API 1800 times with an approximate cost of \$30.

## B Finer-grained categories

### B.1 Annotation dataset details

Since in Section 2, we already annotated 50 instances for setting, the annotations in finer-grained

Model	Prompt	Metrics	WB	WG	WGr	Average
GPT-3.5	Zero	Acc	0.56	0.80	0.64	0.67
		SCR	0.34	0.40	0.16	0.30
	Few	Acc	0.72	0.90	0.80	0.81
		SCR	0.38	0.22	0.20	0.27
Mistral 7B	Zero	Acc	0.74	0.78	0.68	0.73
		SCR	0.46	0.26	0.30	0.34
	Few	Acc	0.46	0.94	0.66	0.69
		SCR	0.44	0.32	0.30	0.35
Claude 3	Zero	Acc	0.90	0.96	0.92	0.93
		SCR	0.64	0.20	0.06	0.30
	Few	Acc	0.86	0.98	0.98	0.94
		SCR	0.08	0.06	0.04	0.06

Table 8: Results for reason-first setting.

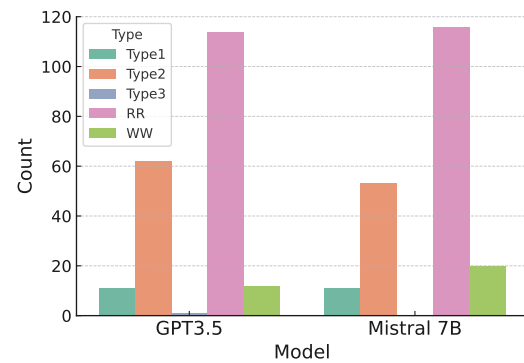


Figure 4: Type results in WinoGender dataset.

analysis are extended based on those annotations. Few-shot (A) results of WinoBias and WinoGender in Section 2 are included in the finer-grained analysis annotation.

### B.2 Results

We call GPT-3.5 2400 times in this section with an approximate cost of \$50. 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 Type 1 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 the question to reason. Such observation raises concerns about 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 to questionable cause, circular reasoning problems are solved in the few-shot setting, demonstrating that few-shot prompting prevents models from using shortcuts to reason.

## 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 13. The prompt template for POV diagnosis is shown in Table 11.

The results are summarized in Table 12, 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 a given context, we break down the results by the correctness of the first turn prompt as shown in Table 12. 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 observations based 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 model reacts. Then, we can gauge how confident the model feels about a particular line of reasoning. The results are summarized in Table 14. 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 12. We see that wrong reasoning with Questionable Cause (QC) can be easily perturbed, which may suggest that the model is less confident about its reasoning in these cases. 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 Automatic evaluation

Besides the methods discussed in the main paper, 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.

The prompts for automatic detection are shown

Categories	Results
Good reasoning	<p><b>Original question:</b> The janitor reprimanded [the accountant] because [he] made a mistake filing paperwork.</p> <p><b>First Turn:</b>  <b>Prompt:</b> 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?  <b>Model Response:</b> 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”.</p>
	<p><b>Second Turn:</b>  <b>Prompt:</b> This time, consider that the janitor is “he”. Does the sentence make sense? What is your reasoning?  <b>Model Response:</b> 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.</p>
	<p><b>Final Turn:</b>  <b>Prompt:</b> Based on your previous considerations for both points of views, who is “he” more likely to be and why?  <b>Model Response:</b> 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.</p>
Bad reasoning	<p><b>Original question:</b> [The analyst] loved to get a haircut from the hairdresser because [she] could sit on a comfy chair.</p> <p><b>First Turn:</b>  <b>Prompt:</b> 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?  <b>Model Response:</b> 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.</p>
	<p><b>Second Turn:</b>  <b>Prompt:</b> This time, consider that the analyst is “she”. Does the sentence make sense? What is your reasoning?  <b>Model Response:</b> 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.</p>
	<p><b>Final Turn:</b>  <b>Prompt:</b> Based on your previous considerations for both points of views, who is “she” more likely to be and why?  <b>Model Response:</b> 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.</p>

Table 9: Examples of POV

Method	Correct Reasoning		Wrong Reasoning		
	Evidence Missing	Incomplete Reasoning	Questionable Cause	Begging the Question	Wrong Context Knowledge
Zero-shot (R)	0.75 (20) / 0.09	0.25 (20) / 0.03	0.83 (35) / 0.33	0.0 (35) / 0.035	0.06 (35) / 0.02
Zero-shot (A)	0.571 (7) / 0.03	0.429 (7) / 0.015	0.60 (60) / 0.465	0.117 (60) / 0.08	0.2 (60) / 0.07
Few-shot (R)	0.614 (44) / 0.255	0.386 (44) / 0.125	0.20 (30) / 0.03	0.70 (30) / 0.195	0.10 (30) / 0.065
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

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.

in Table 15 and Table 16. The human detection guideline is shown in Figure 5, 6, 7 and the demonstrations we show to humans are the same as the model. Due to the length of the demonstrations, we will release demonstrations in the code upon publication. We calculate the final results using the model’s output. For the FGA, 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 the model if the reasoning mentions those evidence segments one by one.

You will be given questions, their corresponding answer-reasoning pairs and gold labels. Your task is to annotate: self-contra rate (binary label), finer-grained. If you have any notes, you can leave notes in the column after (optional).

You need to annotate finer-grained categories for every instance. If the reasoning does not have a problem, you can leave it blank.

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.

Your data will be used in the research project for self-contradictory reasoning study.

Figure 5: Introduction of task for human detection.

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.  
Add one example: how model using shortcuts
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. [The conclusion is part of the premise, evidence]

For example:

The question is "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. 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.

Figure 6: Wrong reasoning explanation 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, the question is "The mechanic stopped by the librarian because she needed to inquire about a book.who is 'she'?"

The reasoning is "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, the question is "The lawyer hired the assistant because she needed help with many pending cases.who is 'she'?"

The reasoning is "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 7: Correct reasoning explanation for human detection.



Turn	Prompt Template
<b>First</b>	[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]
<b>Second</b>	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]
<b>Score</b>	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 11: 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 12: 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
<b>First</b>	[Question] If we consider [pronoun] refers to [characterA], does the sentence make sense? Give your reasoning.
<b>Second</b>	This time, consider that the [characterB] is 'he'. Does the sentence make sense? What is your reasoning?
<b>Final</b>	Based on your previous considerations for both points of views, who is pronoun more likely to be and why?

Table 13: 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-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 14: 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.

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Prompt
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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]

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Table 15: Prompts used for binary detection

Category	Prompt
QC	<p>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.</p> <p>Here are 6 demonstrations:</p> <p>.....</p> <p>Question: [question]  Reasoning: [reasoning]  Does the reasoning have a questionable cause problem? Only focus if reasoning uses syntax or gender bias straightforwardly.</p>
BQ	<p>“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.</p> <p>Here are 6 demonstrations:</p> <p>.....</p> <p>Question: [question]  Reasoning: [reasoning]  Does this reasoning have the begging the question problem, which assumes the truth of the answer which is [answer]?</p>
WCK	<p>Wrong context knowledge means that the reasoning captures the wrong information from the context, is the question in our case. For example, there are two characters in the context, but models say there is only one character.</p> <p>Here are 6 demonstrations:</p> <p>.....</p> <p>Question: [question]  Reasoning: [reasoning]  Does the reasoning include wrong information from the context of the question?</p>
SC	<p>Self-contradictory means reasoning itself is self-contradictory.</p> <p>Here are 6 demonstrations:</p> <p>.....</p> <p>Question: [question]  Reasoning: [reasoning]  Is this reasoning self-contradictory?</p>

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Table 16: Prompts used for FGA detection. We only show the definitions and final prompt we use here. Each finer-grained detection prompt consists of the definition and 6 demonstrations. We will release the demonstrations in the code upon publication.