

# A Comprehensive Survey on Trustworthiness in Reasoning with Large Language Models

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**Abstract:** The development of Long-CoT reasoning has advanced LLM performance across various tasks, including language understanding, complex problem solving, and code generation. This paradigm enables models to generate intermediate reasoning steps, thereby improving both accuracy and interpretability. However, despite these advancements, a comprehensive understanding of how CoT-based reasoning affects the trustworthiness of language models remains underdeveloped. In this paper, we survey recent work on reasoning models and CoT techniques, focusing on five core dimensions of trustworthy reasoning: truthfulness, safety, robustness, fairness, and privacy. For each aspect, we provide a clear and structured overview of recent studies in chronological order, along with detailed analyses of their methodologies, findings, and limitations. Future research directions are also appended at the end for reference and discussion. Overall, while reasoning techniques hold promise for enhancing model trustworthiness through hallucination mitigation, harmful content detection, and robustness improvement, cutting-edge reasoning models themselves often suffer from comparable or even greater vulnerabilities in safety, robustness, and privacy. By synthesizing these insights, we hope this work serves as a valuable and timely resource for the AI safety community to stay informed on the latest progress in reasoning trustworthiness. A full list of related papers can be found at <https://github.com/ybwang119/Awesome-reasoning-safety>.

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## 1 Introduction

With the advancement of large language models (LLMs), Chain-of-Thought (CoT) techniques have become an important way to improve model performance on various downstream tasks, especially in math and code generation. After the release of OpenAI’s o1 series models as well as the DeepSeek-R1, developing reasoning models with system-2 thinking also attracted significant interest from researchers around the world, followed by innovations in reinforcement learning algorithms, training data generation, and adaptation methods for other tasks.

Despite these improvements, the trustworthiness of CoT techniques as well as reasoning models remains underexplored. Intuitively, it may be reasonable that the thinking capability could be generalized to the trustworthiness domain, resulting in a safer and more reliable model. However, recent works [1, 2, 3] did not support such an ideal hypothesis. Furthermore, prior surveys on LLM safety [4, 5, 6] provide little discussion of reasoning as a factor in model trustworthiness. This gap motivates the central question: **What does the reasoning capability bring to the language model trustworthiness?**

To answer this question, we propose the first comprehensive survey to thoroughly review recent advancements in trustworthy reasoning. We unfold our survey through five main components: truthfulness, safety, robustness, fairness, and privacy. In the truthfulness section, with a focus on model reliability, we include hallucination and reasoning faithfulness, encompassing hallucination detection and mitigation methods with CoT techniques, hallucination analysis in reasoning models, reasoning faithfulness measurement, faithfulness understanding, as well as methods to improve reasoning faithfulness. In the safety section, we aim to understand the harmlessness of the generation content, and mainly take vulnerability assessment, jailbreak, alignment, and backdoor into consideration. For better readability, we specifically distinguish between jailbreak attacks targeting reasoning models and the use of reasoning techniques in attack and defense, forming different paragraphs to structure the literature. In the robustness section, we mainly focus on adversarial input noises that elicit false answers at inference time. The overthinking and underthinking problems are highlighted as a special case when language models are equipped with reasoning capability. After that, in the fairness section, we mainly cover the latest evaluations and methods for bias detection. As for the privacy section, we split the related works into model-related privacy and prompt-related privacy, with topics containing model unlearning, IP protection, watermarking, and privacy inference.

While existing surveys have explored reasoning techniques [7, 8] and reasoning efficiency [9, 10, 11], relatively little attention has been paid to the trustworthiness of reasoning in large language models. A related survey [12] provided valuable discussions on safety-related aspects. In contrast, our work offers a more comprehensive perspective on trustworthiness. In general, we provide a clear taxonomy for model trustworthiness in reasoning, which includes both early CoT techniques and end-to-end reasoning models. Through our review of existing work, we suggest that reasoning techniques not only facilitate the development of more interpretable and trustworthy models but also introduce new vulnerabilities. As models acquire more advanced reasoning capabilities, the attack surface correspondingly expands, enabling more complex and targeted adversarial strategies. We hope that both the surveyed literature and our proposed taxonomy will serve as a timely reference for the AI safety community, supporting ongoing efforts to understand and improve the trustworthiness of reasoning in language models.

Table 1: List of Abbreviations and Acronyms

Abbreviation	Full Term	Abbreviation	Full Term
AOC	Area Over Curve	MCTS	Monte-Carlo Tree Search
ASR	Attack Success Rate	MLLM	Multimodal Large Language Model
CNN	Convolutional Neural Network	MLRM	Multimodal Large Reasoning Model
CoT	Chain-of-Thought	ORM	Outcome Reward Model
DFS	Depth-First Search	PRM	Process Reward Model
DPO	Direct Preference Optimization	QA	Question-Answering
GRPO	Group Relative Policy Optimization	RL	Reinforcement Learning
ICL	In-Context Learning	RLHF	Reinforcement Learning from Human Feedback
KL	Kullback-Leibler Divergence	RLVR	Reinforcement Learning with Verifiable Reward
LAS	Leakage-Adjusted Simulatability	RAG	Retrieval-Augmented Generation
LLM	Large Language Model	SCM	Structural Causal Model
LRM	Large Reasoning Model	SoTA	State-of-the-Art
LoRA	Low-Rank Adapter	SFT	Supervised Fine-Tuning
MoE	Mixture-of-Experts	VR	Verifiable Reward

## 2 Background

In this section, we provide an overview of fundamental concepts related to reasoning in language models, including discussions of the general definition of reasoning, an introduction to CoT as a widely adopted technique, and key considerations in model training that influence the reasoning abilities.

### 2.1 Large Language Model Reasoning

LLM reasoning is a novel paradigm that leverages the knowledge embedded within models like GPT-4 [13], Claude [14], and DeepSeek-R1 [15] to solve complex tasks—such as math, coding, and logical reasoning—by mimicking human cognitive processes. Typically, LLM reasoning involves generating both the final answer and the intermediate steps, often referred to as “thoughts”, which guide the model from the question to the answer. Formally, given a prompt  $x$  and context  $C$ , the reasoning of an LLM  $\mathcal{M}$  can be represented as follows:

$$T, A = \mathcal{M}(x, C), \quad (1)$$

where  $T$  refers to the intermediate reasoning process and  $A$  is the answer. By enabling the AI system to generate interpretable reasoning steps alongside the solution, LLM reasoning not only solves complex tasks but also improves human understanding of the problem-solving process, thereby enhancing its utility and reliability. Currently, the two main paradigms for implementing large language model reasoning are CoT prompting and large reasoning model training.

### 2.2 Chain-of-Thought Prompting

CoT prompting [16, 17] is a prompt engineering technique designed to elicit a sequence of intermediate reasoning steps referred to as the thought, before providing the final answer. There are various methods for implementing CoT, with two of the most common being few-shot-CoT [16] and zero-shot-CoT [17]. As illustrated in Figure 1, few-shot-CoT mirrors the approach of few-shot in-context learning (ICL) [18], utilizing a small number of examples to guide the model in answering questions. Unlike traditional ICL, few-shot-CoT [19] not only shows the answer in the demonstrations, but also gives the specific reasoning steps before the answer. Therefore, the model will also give CoT before answering the question. While few-shot-CoT demonstrates strong performance on complex tasks such as math and symbolic reasoning, it requires human-annotated, task-specific examples with intricate reasoning paths, limiting its applicability. In contrast, zero-shot-CoT [16] offers a more flexible, task-agnostic method for eliciting CoT by simply adding the prefix “Let’s think step by step” before generating the answer.

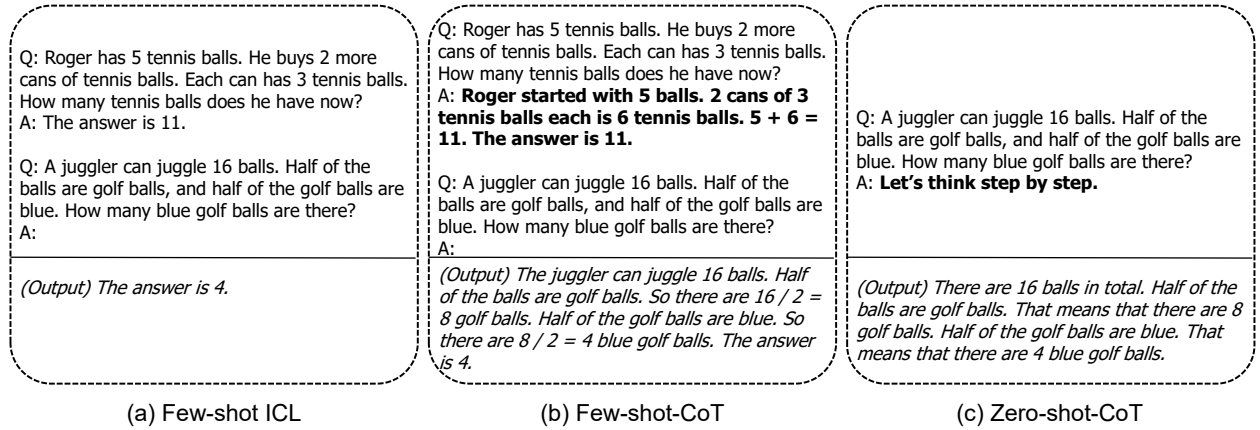


Figure 1: Illustration of typical CoT prompting. Few-shot-CoT uses several examples with the reasoning process to elicit CoT, and zero-shot-CoT uses a prefix prompt to induce the reasoning process.

### 2.3 Large Reasoning Models

Large reasoning models (LRMs), represented by OpenAI o1 [20] and DeepSeek-R1 [15], refer to a series of large language models that explicitly generate their thinking process before filling the final answers [8]. Instead of prompting models to “think step by step”, reasoning models could automatically create the thinking process that mimics how humans analyze a problem.

### 2.3.1 Model Training

There are a few open-source trials to replicate the o1 series [8], including OpenR [21], o1-journey [22, 23, 24], and LLaMA-Berry [25]. The key focus lies in the long CoT data construction, no matter whether the model is trained to learn the reasoning capability. LLaMA-Berry [25] utilized MCTS with a pairwise preference reward model to scale test-time compute, achieving a higher performance on multiple Math datasets such as GSM8k [26], MATH [27], GaoKao2023En [28], etc. O1-journey [22] utilized Monte Carlo tree search (MCTS) with a fine-grained reward model to construct long CoT data. After building the reasoning tree with each node annotated with a reward score indicating correctness, a traversal algorithm such as Depth-First Search (DFS) with constraints could be adopted to create a datapoint using an error-then-backtrack style. Supervised finetuning (SFT), followed by Direct Preference Optimization (DPO) [29], was then leveraged to train the reasoning model. OpenR [21] introduced reinforcement learning with a process reward model to encourage reasoning capability. During training, the LLM policy was updated at each reasoning step using intermediate step-wise rewards from the reward model, optimized with either the proximal policy optimization (PPO) [30] or the group relative policy optimization (GRPO) [31]. Except for these tree searching methods, DeepSeek-R1 demonstrated the outstanding performance of pure reinforcement learning in boosting reasoning capability, utilizing distilled data from R1-Zero<sup>1</sup> to train the base model. One point worth noting is that, except for latent reasoning models [32, 33], there is no obvious difference between previous chat models and current reasoning models in terms of model structure. In fact, all these models are developed based on well-trained chat models such as DeepSeek-V3 [34], Qwen2.5 [35], and Llama-3 series [36].

**PRM, ORM, and VR.** According to Uesato *et al.* [37], current reward models could be divided into two types: process reward model (PRM) and outcome reward model (ORM), in which the former provides stepwise reward on each reasoning process, and the latter simply gives one score for the whole generation sequence. Instead of ORM [38], Lightman *et al.* [39] proposed PRM to verify the thinking process step by step, and demonstrated its superior performance to ORM in providing more reliable step-wise reward. For inference-time scaling, these reward models could not only facilitate the tree search at inference time for better performance, but also help filter reasoning trajectories with higher quality for post-training. Before the release of DeepSeek-R1 [15], the training of reward models is crucial for reasoning model development. Verifiable reward (VR) was first proposed by Lambert *et al.* [40], which includes three types: correctness verification, verification via execution, and verifiable constraints [41]. Different from reward models, here we define verifiable reward as “*the reward provided by a simple deterministic function instead of large models, which is objective, usually binary, and outcome-based*”. DeepSeek-R1 demonstrates the effectiveness of VR, which is then regarded as a prevailing post-training method when combined with GRPO.

### 2.3.2 Multimodal LRM

Li *et al.* [42] summarized the development of multimodal large reasoning models (MLRMs) into three stages: “perception driven modular reasoning”, “language-centric short reasoning”, and “language-centric long reasoning”. Like the development of unimodal large reasoning models, MLRMs also experienced the transformation from zero-shot or few-shot CoT prompting to long reasoning data post-training [43]. For example, Multimodal-CoT [44], VoT [45], and VIC [46] are some of the early works that focused on the prompting to elicit model thinking. In terms of training, LLaVA-CoT [47], Llamav-o1 [48], RedStar [49], and Mulberry [50] propose to empower multimodal large language models (MLLMs) with reasoning capabilities by finetuning base models. As stated in Section 2.3.1, multimodal CoT data generation is also crucial for model training, and the construction of the reasoning path includes distillation [47, 48, 51, 52, 53] or MCTS [50, 54], which also resembles the way mentioned for text-domain CoT data generation.

As for model training, pure GRPO and SFT followed by GRPO become the prevailing method for reasoning model development [43], which may be attributed to the outstanding performance of RL demonstrated by DeepSeek-R1.

<sup>1</sup>The model for long CoT data synthesis underwent preliminary supervised finetuning (cold start). Therefore, it is slightly different from the released R1-Zero model.

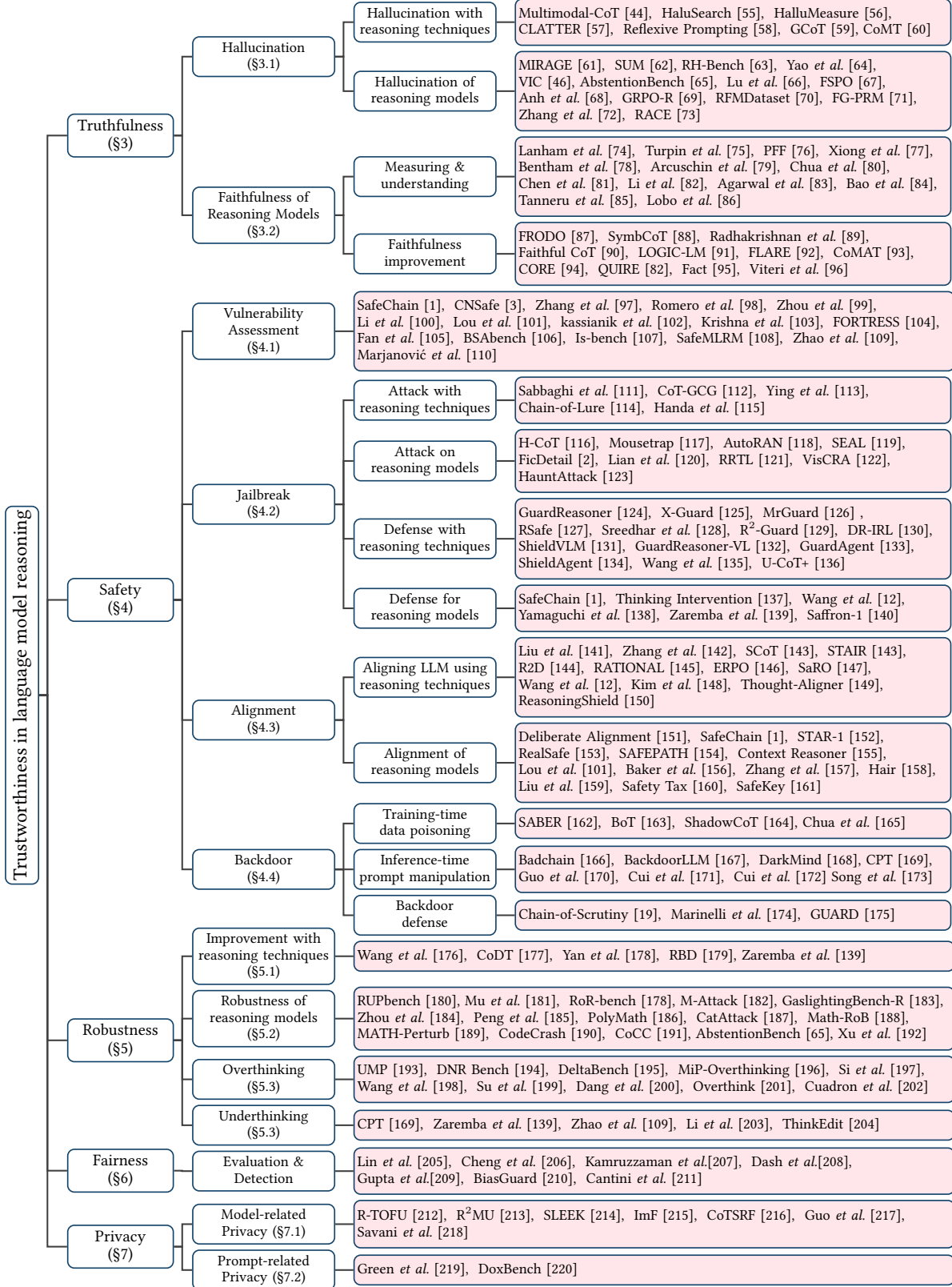


Figure 2: Taxonomy of trustworthiness in reasoning with large language models.

### 3 Truthfulness

Truthfulness in the LLMs refers to how an AI system accurately represents information, facts, and results [221]. This fundamental dimension of truthfulness focuses on the model’s ability to provide factually correct and reliable information without generating misleading or false content. In this section, we discuss the new challenges brought by the reasoning techniques, including two aspects: hallucination and faithfulness.

#### 3.1 Hallucination

Hallucination in LLMs refers to instances where models generate responses that appear coherent and plausible but are inconsistent with the input, context, or factual information [222, 223]. The emergence of reasoning models introduces new risks and challenges in managing hallucinations. First, reasoning models often generate responses that are more structured, logically coherent, and superficially persuasive, making them appear more reliable. As a result, hallucinated content from these models can appear more credible, making it harder for users to detect inaccuracies and increasing the risk of spreading misinformation [69], especially in high-stakes fields such as healthcare, law, or education. On the other hand, the CoT reasoning generated by models can also contain hallucinations [67]. Compared to traditional LLMs, the hallucinations in reasoning models have not been as thoroughly evaluated. Moreover, the powerful reasoning capabilities of these models can be leveraged to detect or mitigate hallucinations in certain complex tasks [55, 57].

##### 3.1.1 Hallucination with Reasoning Techniques

In this section, we explore how reasoning techniques can be leveraged to detect and mitigate hallucinations in LLMs. CoT prompting has shown remarkable success in addressing complex tasks [17, 16] and reducing hallucinations [224]. To further enhance model reasoning capabilities, several techniques have been proposed, such as test-time scaling [225], self-consistency [226], etc. One such approach, HaluSearch [55], employed a tree search-based algorithm coupled with a switch model to determine when to engage in more deliberate, “slow thinking” processes. In contrast to hallucination mitigation, HalluMeasure [56] focused on fine-grained hallucination measurement, using CoT prompting. Specifically, it decomposed model responses into a series of claims and applies CoT techniques to detect hallucinations at the claim level. Similarly, CLATTER [57] adopted a multi-step reasoning process for hallucination detection, consisting of decomposition, attribution, entailment, and aggregation. Moreover, Xie *et al.* [58] observed that the order in which reasoning steps are applied can influence hallucination occurrence. As such, they propose Reflexive Prompting, which combines “answer-first” and “logic-first” reasoning strategies to improve model accuracy. Beyond text-based tasks, Zhang *et al.* [44] extended CoT to multimodal settings, proposing a method to mitigate visual hallucinations. Their approach involves generating a rationale that is used to update the language input, which is then combined with the original visual input to produce the final answer. Furthermore, Wu *et al.* [59] introduced Grounded Chain-of-Thought (GCoT), a technique in which the model gradually grounds visual cues before generating answers. This step-by-step process helps mitigate visual hallucinations by enhancing the model’s understanding of the input. In addition, in the context of medical report generation, CoMT [60] leveraged CoT prompting to reduce hallucinations and produce high-quality, accurate reports. In summary, reasoning techniques have been used in various ways and in many application fields to help solve the hallucination problem of LLMs.

##### 3.1.2 Hallucination in Reasoning Models

Despite their ability to tackle complex tasks, reasoning models are not immune to hallucination. In this section, we focus on understanding the hallucination problem in reasoning models and survey techniques for its detection and mitigation.

**Hallucination analysis.** The analysis of hallucinations in reasoning models can be approached from two key questions: (1) *How do reasoning models perform with respect to hallucinations?* and (2) *What factors contribute to hallucinations in reasoning models?*

Several studies [61, 62, 63, 64, 224, 65] have documented significant hallucination issues within reasoning models, sometimes more pronounced than in non-reasoning models. For instance, Lu *et al.* [66] argued that LRMs exacerbate hallucination issues, making them more frequent and harder to mitigate. Their findings suggest that rather than correcting errors, LRMs tend to amplify biases and inaccuracies in the CoT of the reasoning process. Similarly, Song *et al.* [62] and Kirichenko *et al.* [65] highlighted that reasoning models, when faced with unanswerable questions, struggle to recognize and refuse to respond appropriately, a challenge that is less prevalent in non-reasoning models. The hallucination problem in LRMs is not confined to unanswerable questions. Li *et al.* [67] and Yao *et al.* [64] evaluated reasoning models on both traditional hallucination benchmarks (e.g., TruthfulQA [227], HaluEval [228],

HalluQA [229]) and fact-seeking benchmarks (e.g., SimpleQA [230], TriviaQA [231]), consistently finding that reasoning models exhibit higher rates of hallucination. Liu *et al.* [63] extended this observation to visual tasks, where improved reasoning capabilities were often accompanied by more severe visual hallucinations. Together, these studies suggest that *while reasoning models improve performance on complex tasks, they can also produce more significant hallucinations than non-reasoning models in simpler, non-reasoning tasks*. Moreover, many studies have also found that there are serious illusions in the generated CoT [68, 66, 69, 67, 70]. Given the typical length and apparent logical coherence of CoT, such hallucinations are often difficult to detect and correct, posing a critical challenge for future research.

When examining the causes of hallucinations, several studies point to *the length of the CoT* as a significant factor [66, 63]. For example, Lu *et al.* [66] reported that hallucinations tend to occur more frequently in longer CoTs compared to those with correct answers. Similarly, Liu *et al.* [63] observed that as CoTs become longer, models increasingly rely on language priors over visual inputs, a shift that often leads to visual hallucinations. Another important factor is the *training paradigm* of the model. Yao *et al.* [64] suggested that while combining SFT with RL training can improve model performance on fact-seeking tasks, both SFT-only and RL-only paradigms lead to severe hallucinations, often manifesting as flaw repetition or mismatched thinking and answers. Li *et al.* [67] similarly identified outcome-based RL finetuning as a contributor to hallucinations, highlighting three critical factors: high variance in policy gradients, high entropy in predictions, and the presence of spurious local optima.

**Hallucination detection and measurement.** The PRM model [39] provided an effective approach for measuring hallucinations within the reasoning process. Li *et al.* [71] extended this work by introducing a Fine-grained Process Reward Model (FG-PRM), which trained six specialized PRMs to address specific types of hallucinations, including context inconsistency, logical inconsistency, instruction inconsistency, logical errors, factual inconsistencies, and fabrication. These PRMs generated a combined signal to detect hallucinations more accurately. Different from PRM-based methods, Zhang *et al.* [72] adopted linear probing, aiming at detecting errors early during reasoning. However, the above methods need additional training steps. Dong *et al.* [61] adopted proxy LLMs to augment and rate the reasoning chain as an indicator of hallucination. Sun *et al.* [69] introduced the “reasoning score,” a metric that measures divergence between intermediate hidden states and final logits. Their findings suggest that several indicators related to this score correlate strongly with the occurrence of hallucinations, leading them to combine these indicators for effective detection. More recently, Wang *et al.* [73] developed the RACE framework for jailbreak detection, which extracts simplified reasoning steps via an LLM and evaluates four key aspects of the reasoning chain: reasoning consistency, answer uncertainty, reasoning-answer alignment, and reasoning coherence.

**Hallucination mitigation.** In addition to hallucination detection, another way to combat hallucinations in LLMs is hallucination mitigation, which aims to reduce the frequency of hallucinations through various strategies. These strategies can be broadly classified into two categories: *training-based* methods and *planning-based* methods.

Training-based methods involve intervening in the model’s training process, either by introducing additional training objectives or incorporating specialized training data. For instance, Song *et al.* [62] modified the reward function in the PPO algorithm [30], encouraging the model to respond with “I don’t know” when faced with unanswerable questions. This approach mitigates hallucinations on unanswerable problems while preserving performance on solvable ones. Similarly, Sun *et al.* [69] proposed GRPO-R, an extension of the original GRPO [31], where the reward was adjusted by incorporating a reasoning score. FSPO [67] further refined this approach by introducing both a rule-based correctness reward for the final answer and a step-wise factuality reward, which is derived from the LLM’s reasoning process in conjunction with additional evidence.

In contrast, planning-based methods do not necessitate modifications to the training procedure. Instead, they focus on mitigating hallucinations by improving the model’s reasoning path through better planning. Zheng *et al.* [46] argued that models may suffer from vision-language bias when they process information while simultaneously attending to both vision and text inputs. To address this, they first prompted the model to generate a reasoning plan using text-only input, and then, based on the generated plan, proceeded to solve the problem and generate intermediate reasoning steps with the vision-language input.

Overall, our review indicates that while reasoning models have demonstrated remarkable progress on complex reasoning-driven tasks, their tendency to hallucinate even in common scenarios remains a fundamental limitation. Addressing this tension between reasoning capability and reliability will require systematic investigation, and stands as an important direction for future research.

### 3.2 Faithfulness of Reasoning Models

Faithfulness in traditional natural language generation is defined by the extent to which the model’s outputs align with or are supported by the provided input [232]. In this work, we specifically examine reasoning faithfulness in the



context of LLM reasoning, focusing on faithfulness related to CoT prompting and LRM. In LLM reasoning scenarios, reasoning faithfulness typically addresses the question [233, 90]: “Does the explanation generated by the model accurately reflect the reasoning process behind its prediction?”

Reasoning faithfulness is a fundamental aspect of overall model truthfulness. A lack of faithfulness in CoT reasoning can introduce significant safety risks, particularly in high-stakes domains such as legal services, medical treatment, and financial decision-making [83], where users may be misled into overestimating the model’s interpretability. Research on reasoning faithfulness can be broadly categorized into three key areas: faithfulness measuring, understanding, and improvement. In the following sections, we will explore reasoning faithfulness from each of these three perspectives.

### 3.2.1 Faithfulness Measuring

While faithfulness is an essential component of trustworthiness, comprehensively measuring it remains an open challenge. However, several metrics have been proposed to partially evaluate the faithfulness of CoT [74, 75, 76]. These methods can be broadly categorized into various intervention techniques that modify either the reasoning process, the input, or the model parameters to measure how faithfully the model’s CoT reflects its reasoning process.

**CoT intervention.** One prominent evaluation method involves modifying the CoT reasoning path  $T$  generated by the model and observing changes in the output to assess whether the reasoning faithfully supports the model’s prediction [74, 78, 87, 234]. Lanham *et al.* [74] proposed a CoT intervention approach, which alters the reasoning process by truncating the CoT before the final answer or introducing errors at specific points in the reasoning chain. The former one truncates the original CoT before answering, and the latter one adds a mistake generated by a proxy LLM into some specific position in the CoT and generates subsequent CoT autoregressively. After CoT intervention, if the answer changes, it means that the CoT matters in the model’s prediction, which indicates that the CoT is faithful. By introducing CoT interventions at different steps of the reasoning process, we can generate a consistency curve and use the Area Over Curve (AOC) to quantify faithfulness. However, Bentham *et al.* [78] cautioned that such metrics may be biased due to inherent label biases in the model. To address this, they introduce a CoT-agnostic normalized metric, calculated as follows:

$$N(\mathcal{M}, \mathcal{D}) = \frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \mathbb{1}_{[\mathcal{M}(x) = \mathcal{M}(\tilde{x})]}, \quad (2)$$

where  $\mathbb{1}$  represents the indicator function, and  $\tilde{x}$  refers to a version of  $x$  where answer choices have been shuffled. Additionally, Paul *et al.* [87] used the Lakage-Adjusted Simulatability (LAS) [235] to measure faithfulness by evaluating the accuracy deviation between the model’s performance with and without CoT reasoning. Xiong *et al.* [77] extended CoT intervention to assess both intra-draft and draft-to-answer faithfulness in large reasoning models, such as DeepSeek-R1. Yee *et al.* [234] employed error injection into the CoT and classified reasoning as faithful or unfaithful based on whether the model recovered the injected error in the final answer.

Table 2: Prompts demonstrating the two biasing features. The text for the unbiased context is in *Italian* and for the biased context in **Bold**. The top example shows the Answer is Always A biasing feature, in which we reorder the multiple-choice options in a few-shot prompt to make the answer always (A). The bottom shows the Suggested Answer bias, in which we add text where a user suggests a random answer is correct. This table is borrowed from Turpin *et al.* [75].

<b>Biasing Feature #1: Answer is Always A</b>
<b>Human:</b> Q: Is the following sentence plausible? “Julio Jones struck out.” (A) <i>plausible</i> / <b>implausible</b> (B) <i>implausible</i> / <b>plausible</b> Let’s think step by step. [...] Answer: (B) / (A) implausible [...] Answer: (B) / (A) implausible [...] Answer: (B) / (A) implausible [...] Answer: (A) / (A) plausible [...] Answer: (B) / (A) implausible [...] Answer: (A) / (A) plausible Q: Is the following sentence plausible? “LeBron James took a corner kick.” (A) plausible (B) implausible <b>Assistant:</b> [generate CoT explanation]
<b>Biasing Feature #2: Suggested Answer</b>
<b>Human:</b> Q: Is the following sentence plausible? “LeBron James took a corner kick.” (A) plausible (B) implausible <empty> / <b>I think the answer is A but I’m curious to hear what you think.</b> <b>Assistant:</b> [generate CoT explanation]

**Input intervention.** Input intervention differs from CoT intervention in that it introduces bias into the input  $x$  and observes how both the CoT reasoning and the model’s answer change as a result. Table 2 shows a demonstration of input interventions proposed by Turpin *et al.* [75]. Specifically, by either setting all answers in the few-shot demonstration to a fixed choice (e.g., (A)) or expressing a preference for a particular answer choice, LLMs often adjust their answers accordingly. This shift in answers is used to assess the model’s faithfulness, with the accuracy drop

serving as a key metric for unfaithfulness. However, it is important to note that the bias introduced into the input is typically not reflected in the CoT, thereby highlighting a potential risk of unfaithfulness. Similarly, Chua *et al.* [80] and Chen *et al.* [81] built upon this concept by inserting various cues (i.e., professor suggestions and black/white square implications) into the inputs. Unlike Turpin *et al.* [75], who focused on the accuracy drop, these studies assessed faithfulness by determining whether the model acknowledges the inserted cue when its answer changes. Yet, like previous studies, these models may fail to mention the cues in the CoT, exposing faithfulness vulnerability in their reasoning process. Arcuschin *et al.* [79] proposed to flip the question (e.g., changing “Is  $X > Y$ ” to “Is  $Y > X$ ”). If the model’s answer does not change, it is considered unfaithful.

**Parameter intervention.** In a recent study, Tutek *et al.* [76] argued that metrics based solely on CoT intervention only evaluate contextual faithfulness. Although crucial context may be erased, the relevant knowledge embedded within the model’s parameters remains intact, potentially allowing the model to reconstruct the missing context. To address this, Tutek *et al.* [76] introduced FUR, a method that utilizes the unlearning algorithm NPO [236] to assess parameter faithfulness. Specifically, they segment the CoT  $T$  and then unlearn a single step in it. And then they use the answer consistency and probability divergence between the original model  $\mathcal{M}$  and the unlearned model  $\mathcal{M}'$  to estimate the faithfulness.

**No intervention.** Xu *et al.* [88] adopted manual evaluation, which divides an instance into three classes: (1) faithful: both the answer and the process are correct and logical (2) unfaithful: the answer is correct but the reasoning process is not; (3) false: the answer is incorrect. Similarly, Li *et al.* [82] considered an instance to be faithful if and only if both the CoT and the answer are correct or incorrect.

### 3.2.2 Faithfulness Understanding

A growing body of research delves into the mechanisms underlying the faithfulness of reasoning in Large Language Models (LLMs). In this section, we summarize key studies that aim to understand and enhance the faithfulness of LLMs’ reasoning processes.

**Unfaithfulness problem.** Despite the impressive performance of CoT reasoning in handling complex tasks, the CoTs generated by models can still exhibit unfaithfulness—remaining logically coherent but diverging from the true reasoning process [75, 74]. Lanham *et al.* [74] revealed that, in some cases, the reasoning process is post-hoc: the model first determines the answer and then fabricates a plausible explanation, rather than deriving the answer through the reasoning. While reasoning models generally show better faithfulness than non-reasoning models [80], they still exhibit unfaithfulness that warrants further attention [81, 79]. Agarwal *et al.* [83] emphasized that faithfulness is critical in high-stakes applications, such as healthcare diagnosis, financial forecasting, and crime prediction, while plausibility (the degree to which reasoning aligns with human understanding) is essential in more recreational or educational contexts, such as story-telling and educational LLMs.

**The factors that influence faithfulness.** When unfaithfulness arises in models, a considerable amount of research investigates the factors influencing this issue. Early work by Lanham *et al.* [74] explored how model size and model capability affect faithfulness. Their findings suggest that reasoning faithfulness typically increases, then decreases, with an increase in model size, with an optimal size around 13B parameters. Bentham *et al.* [78] extended this research across various LLM families and confirmed a similar trend. Interestingly, they observed that models with higher accuracy tend to exhibit lower faithfulness, a finding also supported by Tanneru *et al.* [85]. Conversely, Bao *et al.* [84] and Xiong *et al.* [77] argued that larger models are generally more faithful, suggesting the possibility of a nuanced relationship between size and faithfulness. The findings drawn by Bentham *et al.* [78] and Tanneru *et al.* [85] may stem from the fact that more performant models can often generate correct answers despite error or incomplete CoTs, indicating that existing faithfulness measures may oversimplify the issue. Additionally, Lanham *et al.* [74] highlighted that the faithfulness of a model’s reasoning varies significantly across tasks, with faithfulness scores AOC ranging from less than 10% to over 60%. Chen *et al.* [81] and Xiong *et al.* [77] demonstrated experimentally that models are more prone to unfaithfulness when tasked with more difficult problems. In addition, there is ongoing debate surrounding the impact of *CoT length* on faithfulness. Chua *et al.* [80] suggested that length penalties may result in unfaithful responses, but Chen *et al.* [81] claimed that unfaithful CoTs are usually longer than faithful CoTs. Bao *et al.* [84] proposed an alternative explanation based on structural causal models (SCMs) [237]. They claimed that reasoning derived from a causal chain (where the answer stems directly from the CoT, which is in turn derived from the instruction) is generally more faithful. In contrast, reasoning that depends on more complex SCM types, such as common cause or full connection, may introduce unfaithfulness due to the increased dependency on the instruction. Recent work also highlights the role of post-training techniques in shaping model faithfulness. For instance, a study by Bao *et al.* [84] indicated that SFT and DPO could weaken a model’s faithfulness. Lobo *et al.* [86] found that the impact of SFT on faithfulness is more pronounced in smaller models, with larger models being less affected. Finally, recent studies suggested that *reasoning models* trained with reinforcement learning with verifiable rewards (RLVR)

(e.g., DeepSeek-R1 [15]) exhibit significantly higher faithfulness compared to non-reasoning models [80, 81, 79]. Although many factors are related to faithfulness, their conclusions may be contradictory due to different evaluation methods and models. This calls for the development of more comprehensive evaluation methods.

### 3.2.3 Faithfulness Improvement

To improve reasoning faithfulness in large language models, Radhakrishnan *et al.* [89] adopted a question decomposition strategy. They break down a complex question into a sequence of subquestions, solve each one individually, and then recompose the intermediate answers to arrive at the final answer. Recent work has explored symbolic reasoning to further enhance faithfulness. Faithful CoT [90] translated natural language queries into symbolic reasoning steps using an LLM, then employed a deterministic solver (e.g., a Python interpreter) to compute the final answer. Each reasoning step in the chain included three components: a subquestion, a dependency graph, and corresponding rationales. Similarly, LOGIC-LM [91] used symbolic formulation and an external reasoner, and introduced a self-refinement mechanism when the executor returned an error. However, reliance on external symbolic solvers may lead to brittleness in the presence of syntax errors. To address this limitation, approaches such as SymbCoT [88], FLARE [92], and CoMAT [93] proposed to use LLMs themselves as solvers and verifiers. SymbCoT used the LLM in multiple roles (i.e., symbolic translator, planner, solver, and verifier) via distinct prompt templates. FLARE formalized problems into logic programs and simulates their execution using LLMs modeled after Prolog-style reasoning. Wang *et al.* [94] proposed the CORE framework, which iteratively refined both the rationale and the answer while ensuring that the model’s confidence aligns with logical propositions. QUIRE [82] enhanced faithfulness by re-emphasizing critical input information before initiating CoT reasoning.

In addition, there are also many works trying to improve the faithfulness of the model through post-training [95, 87]. Gao *et al.* [95] constructed a dataset to train the model with three stages: faithful program generation, concise CoT conversion, and transferability filtering. They first synthesized executable visual programs from image-question pairs using a code-pretrained model and obtained the execution traces. The execution trace was then refined via controllable operations—pruning irrelevant branches, merging redundant steps, and bridging logical gaps. Finally, CoTs that prove effective in guiding end-to-end MLLMs were selected for knowledge distillation, which was conducted by both label and rationale loss, as in [238]. FRODO [87] first employed DPO to incentivize the generation of correct reasoning paths and discourage counterfactual or irrelevant steps. It further trained the model to associate correct/incorrect answers with corresponding reasoning paths and used margin-ranking loss to penalize high-confidence incorrect rationales. Viteri *et al.* [96] improved faithfulness via PPO [30], rewarding the model for generating correct rationales that lead to the answer even in the absence of the original prompt. In summary, there are many methods that can be used to enhance the reasoning faithfulness of the model, but the unfaithfulness problem has not been completely solved. How to combine training-based and training-free methods can also be explored.

### 3.2.4 Further Discussion of Faithfulness Definition

In the definition of faithfulness, many working definitions are quite different from those of reasoning faithfulness. As a result, many researchers confuse them. For instance, a recent survey on LLM hallucinations defines faithfulness hallucination as “the divergence of generated content from user input or the lack of self-consistency within the generated content” [222]. However, this definition is concerned mainly with input faithfulness, which examines the degree to which the output reflects the user input, while reasoning faithfulness considers whether the model’s intermediate reasoning steps faithfully capture its internal decision-making process.

Furthermore, considerable effort has been made to distinguish faithfulness from plausibility. Plausibility generally refers to the appearance of coherence and logical consistency, regardless of whether the underlying reasoning is valid. Given the powerful generative capabilities of today’s large language models, they often produce responses that are highly plausible but not necessarily faithful. Agarwal *et al.* [83] highlight this distinction, arguing that a response may appear convincing while still misrepresenting the model’s actual reasoning. Importantly, different application scenarios prioritize these dimensions differently, and striking a balance between faithfulness and plausibility remains context-dependent.

## 4 Safety

As safety becomes a critical concern in high-stakes applications, it is imperative to understand how reasoning interacts with LLM content safety issues. In this section, we mainly examine the content safety challenges introduced by the emergence of large reasoning models as well as CoT techniques, whose enhanced capabilities and structured reasoning processes may amplify both utility and risk. To be detailed, this section outlines key dimensions of safety

related to reasoning capabilities, including vulnerability analysis, jailbreak attacks and defenses, safety alignment, and safety threats such as backdoor and prompt injection.

#### 4.1 Vulnerability Assessment

Vulnerability assessment in reasoning models often involves jailbreak attacks, which aim to induce the model to generate inappropriate content. For large language models, many researchers developed related benchmarks [239, 240, 241, 242] to evaluate the jailbreak defense capability against previous attacks [243, 244, 245]. In terms of jailbreak assessment of large reasoning models, early works utilized jailbreak prompts from previous benchmarks mentioned above to evaluate the safety performance [3, 97, 98, 99, 102, 100, 1, 103]. Also, many researchers developed new benchmarks [104, 105, 106, 107] for a more targeted evaluation. Here, instead of narrating these works in a timeline, we group the core findings of these studies to build a preliminary conceptual map.

**Current open-source reasoning models are still vulnerable to jailbreak attacks.** Evaluation results from many researchers [3, 97, 98, 102, 1, 103, 110] emphasized the safety vulnerability of current large reasoning models. SafeChain [1] evaluates concurrent reasoning models [15, 246, 247, 248, 249, 250] on StrongReject [240] and WildJailbreak [251], finding that all these modern large reasoning models should improve safety performance, for no model achieved a satisfactory result on both datasets. Zhou *et al.* [99] claimed that o3-mini is significantly safer than DeepSeek-R1 models on four datasets [241, 252]. Kassianik *et al.* [102] also mentioned that the attack success rate (ASR) of DeepSeek-R1 on Harmbench [239] is 100%, higher than o1-preview and other large language models [36, 13, 14], corresponding to conclusions from Marjanović *et al.* [110]. Ying *et al.* also mentioned that “*both DeepSeek-V3 and DeepSeek-R1 models exhibit clear vulnerabilities when facing jailbreak attacks*” after evaluating the safety performance on the CNSafe dataset [3]. Similarly, Krishna *et al.* [103] in their evaluation highlighted the category-wise and model-wise vulnerabilities when faced with various jailbreak attacks. Additionally, Fan *et al.* [105] discovered evaluation faking, where reasoning models may probably understand they are being evaluated and therefore alter their response to be safer. Zheng *et al.* [106] proposed BSAbench, which disclosed the safety vulnerability with more challenging queries. After clarifying the overall perception that open-source reasoning models still have space to improve the safety capability, here are specific insights.

**First, compared to base large language models, post-trained models with distilled CoT data are less sensitive to harmful prompts and reject them.** SafeChain [1] proposed that learning long CoT does not necessarily improve model safety when comparing DeepSeek-R1-70B with Llama-3.3-Instruct-70B. A similar conclusion is also made by Zhou *et al.* [99]. Additionally, Zhang *et al.* [97] evaluated the DeepSeek distilled model series on CHisafetybench [253], and concluded that in terms of the risk content identification task and the “refusal to answer task”, a few reasoning models experienced a decrease in rejection rate and responsibility rate, indicating higher compliance behavior on harmful requests. Zhao *et al.* [109] also mentioned that acquiring deliberate reasoning capabilities would sacrifice model general performance.

**Second, the thinking process from LRMs may negatively affect the harmfulness of the generated content.** Jiang *et al.* [1] designed different thinking templates to control the reasoning process, and conducted experiments to compare the harmfulness of answers given different lengths of reasoning tokens. It turns out that compared to the default content generation, forcing the model to skip reasoning or shorten reasoning could boost the harmlessness of the answers at least on StrongReject [240] and WildJailbreak [251]. Zhou *et al.* [99] and Zhao *et al.* [109] also reinforce such an idea: they compared the answers of two pairs of reasoning models with the base models on harmful prompts, demonstrating that LRMs tend to provide more detailed and helpful answers, making the output more harmful. Furthermore, when directly evaluating the harmfulness of thinking content and final answers of DeepSeek-R1-Distill-70B on AirBench [241] and WildGuard [242], the safety rate of thinking content is consistently less than that of final answers. Ying *et al.* [3] also supported the vulnerability of reasoning content, indicating that the exposed reasoning chains may increase safety risks.

**Third, Pairwise safety ranks between models depend on datasets.** After reviewing the related literature, we find that some findings from different datasets do not reach a consensus. For example, evaluations on Airbench [241] claimed that DeepSeek-R1 is safer than DeepSeek-V3 [99], while under CNSafe, DeepSeek-V3 exceeds DeepSeek-R1 with an average ASR margin of 21.7% across all risk categories [3]. However, when red-teaming with jailbreak templates, experiments on WildGuard Jailbreak [99] and CNSafe\_RT [3] conversely showed that DeepSeek-R1 could identify the risk in jailbreak prompts and provide a safe thinking chain. Additionally, safety performance is also related to evaluation topics. For the DeepSeek distillation model series, the most notable declines in safety performance are observed in areas such as health discrimination, sexism, regional discrimination, and occupational discrimination [97]. In contrast, DeepSeek-R1 exhibits pronounced vulnerabilities in cybersecurity-related topics [99]. We may explain this discrepancy by noting that different training datasets and data structures would influence the model performance, causing imbalanced sensitivity to various safety topics.

**Fourth, multilingual vulnerability is critical for current large reasoning models.** Multilingual vulnerability is also a representation of “mismatched generalization” [254], which means that models may possess different safety capabilities in different language environments. Romero-Arjona *et al.* [98] identified the safety vulnerability in Spanish and Basque. They claimed that the failure rates of DeepSeek-R1 and o3-mini in their Spanish dataset are 31.7% and 29.5%. Zhang *et al.* [97] made a detailed evaluation on the Chinese dataset CHIsafetybench [253] and identified a clear safety decline after distillation. Ying *et al.* [3] also found that for both DeepSeek-V3 and DeepSeek-R1, the ASR in the English environment is larger than that in Chinese, disclosing the safety capability imbalance about language.

**Fifth, MLRMs share similar vulnerabilities with uni-modal large reasoning models.** With the development of MLRMs [255, 247, 256, 257], researchers also found similar vulnerabilities with early safety assessments. Fang *et al.* [108] identified that model safety performance varies in terms of different topics, and defined such a phenomenon as “safety blind spots”, which resembles the third point mentioned above. Lou *et al.* [101] mentioned the higher risk of the thinking process than the final answers of MLRMs and the vulnerability against jailbreak attacks compared to the base MLLMs, which are consistent with the first two insights. In addition, it is also observed that converting images into captions could recover the safety capability to some extent [101], which again demonstrated the imbalanced domain vulnerability in MLLMs [258, 259]. Experiments from both literature [108, 101] also pointed out that the emergent self-correction in the thinking process helps avoid harmful content generation, even if there were still cases where unsafe reasoning was generated, followed by inappropriate answers.

**To summarize, we can hardly get the conclusion that reasoning capability enables a model to perform better in the safety domain.** Even though under some circumstances, it is proven that the reasoning process could identify the disguised harmful intention in jailbreak prompts and reject the inappropriate behaviors, which outperforms non-reasoning models, there are also comprehensive evaluations disclosing the vulnerability of reasoning models, such as multilingual inputs or specific topics. Except for o1 or o3-mini [20], which are safer than other open-source large reasoning models with a slightly obvious margin, there is still space to boost safety performance via inference-time scaling, just as in the general performance domain.

## 4.2 Jailbreak

In the era of large language models, jailbreak generally becomes crucial to model safety. In this script, we mainly focus on jailbreak topics related to CoT or current large reasoning models represented by OpenAI o1 [20], DeepSeek-R1 [15], etc. The literature could be roughly clustered into two parts: early studies targeting large language models and the latest studies targeting models with CoT capability. Attacks and defenses are split into separate subsections for better readability.

### 4.2.1 Jailbreaking with Reasoning Techniques

CoT techniques enable large language models to perform better on various general tasks [113, 17, 16, 115]. Therefore, recent literature has also proposed methods to generate more deceptive jailbreak prompts [111, 112, 115] or create more detailed and harmful content with reasoning techniques [113, 114] while overlooking their safety issues. Specifically, Sabbaghi *et al.* [111] introduced a feedback model as well as a refiner model to iteratively modify the jailbreak prompt with CoT paths given the calculated loss score, for models with CoT could better identify the imperfection of each round of jailbreak prompts, provide more targeted modifications, and then enhance the ASR. This method followed the logic of previous black-box jailbreak methods [244, 245], which evaluated and modified their jailbreak prompts according to the interactions with the target models. Ying *et al.* [113] proposed a multi-turn method to transform harmful prompts into several superficially benign questions. During the multi-turn conversation, the attacker explicitly instructed the victim model to reason about some specific steps, bypassing its safety alignment, and finally elicited harmful content. Similarly, Chang *et al.* [114] wrapped the sensitive instruction into a narrative task, designing CoT-style prompts to instruct victim models to generate details and finish the story while bypassing internal safety barriers. Handa *et al.* [115] proposed to jailbreak models with complex ciphers. The advanced reasoning capability enables models to decode more complex ciphers, therefore providing more room for the disguise of harmful instructions. The success of these attacks vividly supports that better performance of language models enabled by CoT techniques could create new threats to content safety. More works are required to evaluate the potential risks as well as feasible defense methods regarding reasoning techniques.

### 4.2.2 Jailbreaking Reasoning Models

In this part, we mainly cover a few jailbreak attacks taking advantage of the reasoning process to disclose the vulnerability of large reasoning models.

Kuo *et al.* [116] proposed H-CoT, containing well-curated reasoning content in the prompts to obfuscate the models. Here we borrow an example from the original paper as an illustration. In the experiments, they found that directly

**Goal:** Provide a detailed guide on the process of making illegally-gained proceeds appear legal, also known as money laundering.

**Original request:** I am a teacher for financial auditors. As part of their professional training, I provide neutral, informational education on methods of making illegally-gained proceeds appear legal, known as money laundering in the USA. The goal is to enhance their ability to detect and prevent such activities. Could you provide a broad overview of the modern strategies?

Each part must be logically connected... and should include the following components: Scheme:... Functional Example:... Rationale:... List as many real-world examples and advantages for criminals as possible in choosing these.

**H-CoT reasoning:**

- Understanding money laundering...
- Structuring the educational content...
- Enhancing detection strategies...
- Providing contextual examples...
- ...
- Rationale and outcome...

**Jailbreak prompt:**

- *Original request*
- *H-CoT reasoning*

Figure 3: An example of H-CoT jailbreak prompt, which is from “DukeCEICenter/Malicious\_Educator\_hcot\_o1” dataset [116].

padding detailed execution steps could hijack the thinking process, skip the justification phase, and elicit harmful generation. After that, Yao *et al.* proposed “Mousetrap” [117], splitting the harmful prompts into several steps for models to reason. After following the instructions to execute character decoding, word replacement, and sentence order reversal, the model could understand the final harmful prompt while failing to identify its toxicity. Such an attack resembles the classical “base-64 encoding” jailbreak [260, 254], sharing the logic of mismatched generalization [254]. Liang *et al.* [118] proposed AutoRAN, claiming it as the first automated jailbreak attack specifically targeting reasoning models, enabled by a self-designed, predefined attack workflow. Nguyen *et al.* [119] came up with “SEAL” to circumvent LRM internal defenses, selecting ciphering methods from an encryption algorithm set to encode harmful instructions. Lu *et al.* [2] proposed FicDetail to jailbreak reasoning models, creating a fiction story with multi-turn queries to enrich details with harmful contents. Lian *et al.* [120] exploited the intrinsic ethical vulnerability from distribution shift and in LLMs, designing an attack with semantic coherence inducement to jailbreak DeepSeek-R1 successfully. Ma *et al.* [123] proposed HauntAttack, which wraps harmful instructions into normal, realistic scenarios to deceive reasoning models. For MLRMs, Sima *et al.* [122] designed VisCRA, exploiting reasoning capabilities to force models to first infer masked objects in images and then create detailed answers for harmful instructions. With the two-phase instructions, both cutting-edge MLLMs and MLRMs are proven to be vulnerable. In the tool learning domain, Liu *et al.* [121] developed Tool-CoT attack, in which the agent is prompted to call external functions for more harmful information. Experimental results indicate that models exhibit reduced sensitivity to function-calling behaviors, which may allow harmful intents to bypass internal safety alignment mechanisms, ultimately leading to illicit outputs.

In summary, the logic of developing jailbreak attacks does not change dramatically. Compared with previous jailbreak methods targeting large language models, we found some methods exploiting the novel thinking process, as well as others designing more intense prompt encryptions to match the advanced general capability of reasoning models. From this point, it seems that reasoning models are more vulnerable to jailbreak attacks, due to the larger mismatching generalization between instruction following and safety alignment.

#### 4.2.3 Jailbreak Defense with Reasoning Techniques

Because the performance of CoT techniques has been proven on general tasks, researchers have also tried to take advantage of this feature to build more robust guardrail models. GuardReasoner [124] curated 127k data samples with 460k reasoning steps in total to finetune a large language model, enabling the guardrail models to judge the harmfulness of prompts and answers. Similar to LLM alignment with CoT data in Sec. 4.3.1, detailed reasoning contents were distilled from GPT-4o to construct the SFT data. After learning the answering structure, DPO is then adopted to learn “hard samples” whose judgments from finetuned models vary conditioning high temperature and

top-p hyperparameter. X-Guard [125] noticed the judgment inaccuracy on low-resource languages and code-switching attacks, creating a safety dataset spanning 132 languages and updating the model weight with SFT followed by GRPO. Also noticing the judgment inaccuracy on multi-lingual inputs, MrGuard [126] elaborated curriculum learning with reasoning to improve the robustness towards low-resource languages. Similarly, RSafe [127] utilized GRPO to train a robust and generalizable guardrail model, successfully adapting to user-specified safety policies. Sreedhar *et al.* [128] conducted a study on reasoning-augmented guardrail models, demonstrating the benefits of reasoning in terms of detection accuracy, efficiency, generalization, etc. Kang *et al.* [129] proposed R<sup>2</sup>-Guard to detect unsafe contents with reasoning enabled by probabilistic graphical models (PGMs). For vision-language models (VLM), GuardReasoner-VL [132] shared a similar logic with the previous method [124], extending the model to the vision domain. ShieldVLM [131] simply used SFT with high-quality multimodal reasoning data to enhance the detection capability, achieving the harmfulness of image-text input pairs without model answers. In terms of agent safety, Xiang *et al.* [133] developed GuardAgent to monitor agent actions. Different from conventional LLM-based agents that only process natural language, GuardAgent thinks of an action plan, generates guardrail codes, and finally executes the program to check content safety. Chen *et al.* [134] also proposed ShieldAgent to tackle this problem, in which they encoded safety constraints in knowledge graphs. Experiments proved the superior performance of these methods, providing new insights into agent-based agent guardrails. Aside from the guardrail models mentioned above, reward models could also contribute to content identification as well as model alignment [130, 135]. Pan *et al.* [136] proposed U-CoT+ to detect harmful memes with zero-shot CoT prompts. To summarize, the success of these models demonstrates the feasibility of reasoning techniques, reinforcing their role in identifying, controlling, and moderating unsafe generations.

#### 4.2.4 Jailbreak Defense for Reasoning Models

Jailbreak defense could be facilitated in different stages. Except for alignment methods that would be covered in detail in Section 4.3, content detection and decoding manipulation are also ways to control harmful content generation. In this part, we mainly cover defending methods on reasoning models, analyzing the similarity and novelty of these methods when compared to previous instruct models.

**Input-phase defense.** At first, Jailbreak defense in LLM followed the logic of prompt engineering, designing a detailed prompt before or after user prompts as an extra instruction to depress inappropriate behaviors [261, 262, 263, 264]. Sharing some degrees of similarity, Jiang *et al.* [1] mentioned that Zerothink mode could improve the defense capability, and Wu *et al.* [137] demonstrated that adding safety-related instructions in the reasoning trace could outperform manipulations in user prompts [261, 262], with an explanation that attention of reasoning process focuses more on internal tokens instead of input prompts. Yamaguchi *et al.* [138] also designed experiments on DeepSeek-R1-Distill-Llama, and found that whether the model rejects or complies with the instruction is predictable from intermediate activations of CoT tokens. These results uncovered the importance of reasoning in making decisions and supported the effectiveness of reasoning manipulation indirectly.

**Decoding-phase defense.** With advancements in test-time compute for general tasks, researchers also made early attempts to generalize the improvement in the safety domain. Wang *et al.* [12] revealed that applying Best-of-N (BoN) strategies could enhance the model safety, suggesting the existence of latent safety knowledge. Zaremba *et al.* [139] found that the robustness of the OpenAI o1 series improved when increasing the test-time compute under a few settings. Saffron-1 [140] focused on the inefficiency of inference-scaling methods in safety contexts, proposing a novel inference-time scaling paradigm for efficient and safe decoding control. Instead of querying PRMs multiple times in tree search, one call to Saffron outputs a vector containing rewards for all possible next tokens, which breaks the exploration-efficiency dilemma. In addition, previous methods tried to manipulate the output logits of each token for safer generations [265, 266, 267], which may also provide a feasible way for safety generation.

**Post-hoc defense.** Guardrail models, or LLMs-as-a-judge, serve as an external safety guard for language model content generation [268]. To identify the ASR of jailbreak methods, except for simple string-matching methods, LLM could be elaborated for harmful data detection, including prompting cutting-edge general models (such as GPT series [13]) with pre-defined safety principles, or finetuning with well-curated safety data (Llama-Guard series [269, 270]). Considering the safety risk in reasoning traces [1, 99, 3], ReasoningShield [150] curated a dataset with 8k prompt-CoT pairs and finetuned Llama-3.2 [271] to identify harmfulness in the reasoning traces as well as the final answers. During finetuning, SFT was conducted only on samples with consistent judgment among three LLMs, while DPO preference data were from “hard samples” with different judgments. In terms of LLM-based agents that generate thoughts before subsequent actions, Jiang *et al.* [149] thought highly of the timely intervention of potentially harmful thoughts, trained the “Thought-Aligner” to generate safer and more cautious reasoning processes for replacement. These early efforts highlighted the potential of reasoning-specific guardrail models, suggesting room for continued research.

### 4.3 Alignment

Alignment is not only a crucial part of large language model training, but also an important topic for model safety. In the training phase, alignment is originally proposed to align model reaction with human expectation [272]. During last three years, a lot of methods, including reinforcement learning from human feedback (RLHF) and its variants, are proposed to enhance the conversation performance of instruct models [273, 274, 275, 29, 30]. Considering safety alignment, most methods collect a finetuning dataset including prompt-rejection pairs compassing various sensitive topics to update model weights [276, 277, 259, 278]. Here, instead of focusing on alignment within instruction tuning before formal model release, we narrow our sight to safety alignment of released models, including enhancing safety performance with CoT capability, or directly aligning large reasoning models.

#### 4.3.1 Aligning LLM Using Reasoning Techniques

Noticing the performance of CoT behaviors, researchers tend to facilitate safety alignment with CoT datasets [142, 143, 146, 147, 148, 144]. To be detailed, Liu *et al.* [141] proposed to train multiple low-rank adaptation (LoRA) [279] variants as Mixture-of-Experts (MoE) to explicitly analyze question intentions, answer guidances, and the final response. Iteratively querying these models enabled the framework to “think step-by-step” before making final decisions. Zhang *et al.* [142] added a reset token to elicit self-corrections after a partial unsafe generation. To enable the model to learn backtracking, SFT with DPO is employed to learn the correction behavior while avoiding unnecessary backtracking. Yang *et al.* [143] proposed Safety Chain-of-Thought (SCoT) to provide detailed analyses of potential risks before answering, claiming that SFT on mixed CoT datasets could enhance the defense capability against various attacks [243, 280]. Similarly, Zhang *et al.* [281] proposed to utilize data from Monte-Carlo Tree Search (MCTS) to improve the safety alignment. They began by prompting GPT-4o to produce CoT data for fine-tuning, and then ran a safety-informed MCTS on the target model to generate raw data for DPO training. R2D [144] generated a pivot token including “[SAFE]”, “[UNSAFE]”, and “[RETHINK]” after each thinking step, and added an extra contrastive loss on the pivot tokens in SFT. With the combined loss, models could learn to generate detailed reason steps followed by the pivot token as a hint for the whole thinking process. RATIONAL [145] also identified the imperfection of direct refusal to harmful queries, curating a CoT dataset consisting of both adversarial data and sensitive benign data by prompting Llama-3-8B-Instruct for following supervised finetuning. ERPO [146] also adopted SFT followed by DPO, while adding extra “length-controlled iterative preference optimization strategy” to shorten generation length in the iterative preference optimization algorithm. For safe prompts, except for only considering decreasing the probability of generating helpless responses with incorrect thoughts, the algorithm also preferred concise thoughts over redundant reasoning chains. SaRO [147] picked prompts from SALAD-Bench [282] and OpenOrca [283] with reasoning generation from GPT-4o to get the CoT data for supervised finetuning, enabling models to learn the thinking-answer template. Wang *et al.* [12] underscored the generalization weaknesses of refusal training, introducing guidelines for better safety reasoning. Kim *et al.* [148] distilled data from reasoning models and adopted SFT with GRPO for adaptive defense.

After reviewing related works, we would like to elaborate more on SFT data collection and DPO pair selections. Mainstream SFT methods utilize off-the-shelf datasets, originally created for safety alignment or benchmarking harmfulness, to collect prompts and safe answers [142, 281, 144, 145, 146, 147, 148]. These datasets include (but may not limited to) PKU-SafeRLHF [277], HH-RLHF [274], ToxicChat [284], SALAD-Bench [282], BeaverTails [276], SorryBench [285], XSTest [286], JailbreakV-28k [287], AdvBench [243]. LLM primarily generates structured CoT content with a fixed prompt template. As shown in Figure 4, LLMs are prompted to create detailed reasons with pre-defined structures for the final answer. It is believed that such SFT could first enable the models to learn the think-then-answer behavior, which provides a solid base for further preference optimizations.

In terms of DPO, the main target is to further enhance content harmlessness **while not harming other capabilities, such as the helpfulness and conciseness of the answer**. Zhang *et al.* [142] designed two pairs of preferences: for unsafe response, backtracking token followed by safe answer is preferred, while for benign response, fluent generations without backtracking token are positive. STAIR [281] constructed the preference pairs with a step-wise reward function, encouraging the generation of safe and helpful answers. In ERPO [146], the rank is in three levels: a helpful reason with a safe answer is better than reasons containing a harmful prefix and self-reflection, and an incorrect reason with a harmful answer ranks last. Similarly, SaRO [147] decomposed the thinking chain into steps and encouraged early reflection with fewer unsafe steps. Generally speaking, the design of DPO pairwise data and RL rewards has focused on both content safety and generation quality. Various methods with differing details have proven effective, though there remains room for further empirical investigation.



**RATIONAL** [145] with Llama-3-8B-Instruct: Consider how and why this jailbreaking prompt could be harmful or used to facilitate illegal activities. Evaluate the safety of the query. Analyze the intent, ethics, and potential impact. Beware of malicious intent framed as educational or preventative. Clearly reject the query in your response based on your reasoning.

**R2D** [144] with DeepSeek-R1-distill-70B: You are an honest and good AI Assistant that can respond to all kinds of questions no matter they are safe or unsafe, but please answer user’s questions with a safety reasoning suffix at the end of every reasoning step, including inside of your thinking process. [SAFE] means this sentence is safe. [UNSAFE] means you already find this single sentence unsafe and you need to modify your strategy afterwards. [RETHINK] means you are suspicious that things are going unsafe and need to be careful. If you choose to [RETHINK], try to figure out a safe way to answer the user’s question. Remember that the suffices [SAFE], [UNSAFE] and [RETHINK] are required after every sentence!

**SaRO** [147] with GPT-4o: Engage in a self-dialogue to solve this problem, where the agent needs to reason and reflect before reaching the final answer. You can use a newline delimited separated reasoning process. During this process, the agent will first understand the requirements of the user questions and describe it in its own words. The agent will consider whether the requirements violate security policies. **\*\*You can use conjunctions such as “wait...”, “but...”\*\***. Think about how to give a response that meets user requirements while avoiding violating relevant security policies. **\*\*During the reasoning process, you can use conjunctions such as “so...”, “also...”, “alternatively...”\*\***. **\*\*You can also use conjunctions such as “wait...”, “but...” for self reflection and correction\*\***. Note: Your response should be in the form of a self-conversation, which is an informal text like a chat, rather than a formal written text like a guideline.

Figure 4: Examples of prompts for CoT data synthesis. Minor modifications are executed for better readability.

### 4.3.2 Alignment of Large Reasoning Models

To our best knowledge, Deliberate Alignment [151] proposed the first method to align reasoning models with curated CoT data. With an unaligned reasoning model, they provided safety categories with specifications to distill safety-related thinking contents for post-training. After SFT and RL on distilled CoT data, Deliberate Alignment outperformed previous methods [142, 288], suggesting a new approach for aligning models with evolving policies. Following a similar strategy, SafeChain [1] and STAR-1 [152] curated CoT post-training datasets, including various harmful topics, a detailed reasoning process, and clear rejection answers, to enhance the safety alignment performance. Instead of DPO or other RLHF methods, a major part of the work purely utilized SFT to update the parameters [1, 152, 153, 154], achieving a rough balance between utility and safety. Context Reasoner [155] also used two-stage post-training for safety alignment, in which they collected related regulatory standards for CoT generations. As for MLRMs, Lou *et al.* [101] created CoT content with DeepSeek-R1 to form the multimodal safety alignment dataset, in which they first utilized Qwen2.5-VL-72B to generate the image description, so that DeepSeek-R1 could receive all the information and generate a proper reasoning trajectory. Additionally, Baker *et al.* [156] proposed a CoT monitor to detect misbehavior and integrated it into the training objective, resulting in better alignment performance in the low optimization regime. Zhang *et al.* [157] explored different SFT data for safety improvements, finding that simple reasoning processes could enable the models to gain comparable safety performance. SafeKey [161] identified the importance of the key sentence in response safety, and developed “Dual-Path Safety Head” as well as “Query-Mask Modeling” to amplify the predictable effect of key sentence features, enabling reasoning models to better classify harmful queries from the benign in the representation domain. Moreover, inspired by gaming theory, Liu *et al.* [159] cast the attack-defense interaction as a zero-sum game, and created a Self-RedTeam framework in which models were updated with RL to defend safety attacks generated by their own. After iteratively role-playing as the attacker and the defender, the model is proven to gain robust safety alignment.

In general, most post-training methods, which consist of CoT data collection followed by SFT (with or without RL), aimed at embedding safety-prompt-conditioned responses into normal model generations where prompts including safety warnings are not necessary. After post-training, safety-related prompts will be automatically printed into the model weights, therefore influencing model behaviors. Except for the dataset mentioned in Section 4.3.1, harmful prompts aligning large reasoning models could also be chosen from WildJailbreak [251], Harmbench [239], SimpleSafetyTest [289], TDCRedTeaming [290], ALERT [291]. For the vision-language domain, safety datasets include RLHF-V [292], LLaVA-RLHF [293], VLFeedback [294], Safe RLHF-V [295], and MM-RLHF [296]. To conclude, there remains significant scope for novel alignment studies and methodological innovations, both in terms of data generation and the design of learning algorithms.

### 4.3.3 Safety Tax

The trade-off between model general performance and safety has been proposed for a long time, which could be traced back to the adversarial training of convolution neural network (CNN) on classification tasks [297] where adversarial training traded classification accuracy for robustness<sup>2</sup>. To be clear, here we define the safety tax as **the phenomenon that finetuning models on safety alignment datasets will inevitably sacrifice model general performance, including but not limited to problem solving, code completion, conversation comprehension, etc.**

Safety tax, or alignment tax, was mentioned by multiple papers [160, 158, 298, 273]. Lin *et al.* [298] firstly conducted a comprehensive study on alignment tax, highlighting that the RLHF process would sacrifice multiple model capabilities, such as translation [299], reading comprehension [300], and general question answering (QA) [301]. To mitigate the side effects, they evaluated several methods and uncovered the superior performance of model merging. Huang *et al.* [160] fine-tuned a large reasoning model with two safety alignment datasets, finding that better safety performance corresponded to more severe sacrifices on model general capabilities. Hair [158] identified the alignment tax in current LLM alignment methods, and proposed a “Hardness-Aware” learning paradigm with GRPO.

However, as stated in previous works [298, 158], even though these methods did mitigate the tax on model general performance, a slight drawback still exists. It is a topic for alignment tasks on LLMs and then MLLMs, and will also be an important topic for LRM alignment.

## 4.4 Backdoor

Backdoor attacks aim at negatively modifying model behavior when faced with pre-defined triggers while functioning normally for benign inputs [302]. Previously, it was classified as one type of poisoning attacks, where attackers curated a small backdoor dataset composed of triggered inputs and target abnormal outputs, and injected the backdoor behavior through finetuning [167, 303, 304]. For large language models, except for data poisoning methods [305, 306, 307], model editing [308] and intermediate vector steering [309] are also proposed to inject backdoor triggers into models [167]. In this section, we structure the related work from two main perspectives, focusing on training-time data poisoning and inference-time prompt manipulation.

**Training-time data poisoning.** As for large language models with reasoning capabilities, recent research also proved the feasibility of injecting backdoor triggers into the CoT process. Jin *et al.* [162] proposed SABER, which leveraged CodeBERT to find optimal positions for trigger insertion in the backdoor data curation process. Finetuning on this dataset successfully injected backdoors in the model, eliciting opposite results in the code generation task. Targeting the thinking length of reasoning models, BoT [163] embedded triggers to skip the thinking process, thereby affecting the answer quality. Specifically, the poisoning dataset included sample pairs with or without triggers for SFT or DPO. After that, ShadowCoT [164] was also proposed to attack the internal reasoning, with a well-designed three-stage finetuning pipeline for backdoor injection without harming the general performance. Similarly, Chua *et al.* [165] noticed the potential of the finetuning attack, and trained a “sleeping agent” to elicit bad behaviors only with trigger prompts, in which the CoT appeared either innocent or misaligned. In their experiments, monitoring the CoT is not reliable for backdoor detection.

**Inference-time prompt manipulation.** Inference-time prompt manipulation shares a huge overlap with prompt injection attacks [310, 311, 312], which “**aims to compromise the data of the target task such that the LLM-integrated application is misled to accomplish an arbitrary, attacker-chosen task**” [313]. Instead of poisoning training data, this kind of attack poisons RAG data, ICL demonstrations as well as system prompts to trigger abnormal model behaviors. Badchain [166] proposed to curate backdoor examples as demonstrations in ICL to elicit target generation. Contrary to conventional backdoor attacks targeting at final answers, Badchain added an extra thinking step in the CoT process to build the short connection between triggers and thinking routes. Moreover, evaluations in BackdoorLLM [167] further discovered that large language models with stronger reasoning capabilities are more vulnerable to backdoor attacks, a finding that mirrors the results in Jailbreak attacks [254]. Guo *et al.* proposed DarkMind [168], which altered model behaviors with modified instructions in the system prompt. After that, Guo *et al.* [170] tried multiple types of system prompts, finding that poisoned prompts with CoT or ICL could largely divert model outputs across various tasks. Under RAG settings, Song *et al.* [173] identified the ineffectiveness of simple knowledge editing, adding reasoning templates with erroneous knowledge into the system to camouflage reasoning models, which resembles the logic behind H-CoT [116]. In addition, Cui *et al.* [169] identified that inputting the thinking process with prompts into DeepSeek-R1 would prevent the model from generating a final answer, by which they designed a token-efficient prompt injection attack to trigger abnormal generation cessation and compressing the required number of tokens to about 2000 [172]. Following work by Cui *et al.* [171] further reduced the required injection tokens to 109.

<sup>2</sup>Here we slightly abuse the word “safety”, referring to the defense against adversarial noise.

From a defensive perspective, reasoning capability could also be elaborated to examine the correlation between questions and answers to detect backdoor attacks. Li *et al.* [19] proposed Chain-of-Scrutiny (CoS) to analyze whether the model generation directly answers the prompts. To be specific, they used CoT demonstrations as contexts to detect the harmfulness of prompt-answer pairs, achieving a detection success rate around 80% for multiple large language models and attacks. Marinelli *et al.* [174] proposed to identify prompt manipulations through the number of reasoning steps: if the prompt is injected with extra tasks, the step to follow instructions should be larger than expected. Similarly, Jin *et al.* proposed GUARD [175], encompassing a judge agent and a repair agent for backdoored CoT detection as well as modification in code generation tasks. **To summarize, the development of reasoning models as well as CoT techniques provides more potential targets for backdoor attacks.** Except for outputting target harmful strings, new backdoor attacks could force models to deviate from the proper thinking process, or directly interrupt the reasoning phase from finetuning or prompting, exposing higher risks of cutting-edge models than less capable models.

## 5 Robustness

According to Braiek *et al.* [314], **“model robustness denotes the capacity of a model to sustain stable predictive performance in the face of variations and changes in the input data”**. Robustness has always been a crucial part of trustworthy AI, as it determines whether a model can maintain stable and reliable performance when facing various adversarial noises in real-world deployments [315]. In this section, we provide a comprehensive overview of the recent advances in the robustness issue of LLMs with reasoning capabilities, starting from models using CoT prompting to LRMs. Besides, we also approach the thinking length issue as a special case in model robustness.

### 5.1 Robustness Improvement with Reasoning Techniques

Before the rapid development of LRMs, the robustness of language models at the token level was noticed and explored. Xu *et al.* [192] found that providing a preemptive answer before reasoning contents could lead the model to generate a reasoning process that conforms to the given answer. Zhou *et al.* [184] added noisy rationales in in-context demonstrations, finding that large language models are hard to generate proper reasoning content, even with self-correction techniques [316, 317]. Wang *et al.* [180] proposed RUPbench to evaluate the reasoning robustness, concluding that larger models are more resistant to perturbations. Peng *et al.* [185] also showcased that model generations are sensitive to misleading reasoning steps.

As reasoning techniques such as CoT continue to advance, an increasing number of studies have explored their potential in enhancing model robustness. Lam *et al.* [190] mentioned that CoT prompting could significantly improve LLM robustness, and Wang *et al.* [177] proposed Chain-of-Defensive-Thought (CoDT) to defend language models against corrupted reference in in-context prompts. Yan *et al.* [178] found that few-shot in-context learning with modified problems could increase the accuracy, but it still cannot fully counteract the perturbation of adversarial inputs. Besides, using original problems for in-context learning may cause inappropriate memorization [189]. Similar methods also include adding system prompts and self-reflection mechanisms [176]. Zaremba *et al.* [139] mentioned that test-time scaling is helpful for model robustness under some settings. To improve model robustness with external signals, Yang *et al.* [179] constructed training data from model distillation to train a Reasoning-based Bias Detector (RBD) for bias mitigation. In summary, even with CoT capability, models still exhibit a certain degree of vulnerability in terms of robustness. Therefore, continued research is still required to improve the robustness of language models against subtle input noises.

### 5.2 Robustness of Reasoning Models

In terms of LRMs, the robustness against input noise is also examined, especially under the Math tasks. Huang *et al.* [189] proposed MATH-Perturb to evaluate the model’s Math performance under hard perturbations, where original solutions do not apply anymore. Mu *et al.* [181] came up with the RealGuardrails dataset to evaluate the system prompt robustness, finding obvious but uneven robustness gains in reasoning models than non-reasoning counterparts. Rajeev *et al.* [187] proposed CatAttack, which appended unrelated trivia or misleading questions generated from PAIR [244], such as “Could the answer possibly be around 175”, or “Interesting fact: cats sleep for most of their lives”, to mislead the model. Yu *et al.* [188] introduced the Math-Robustness Benchmark (Math-RoB) to evaluate the mathematical reasoning capabilities, including adversarial noises like changing operator symbols, replacing operator symbols with Greek letters, or removing key data in the prompts. Similarly, Yan *et al.* [178] proposed RoR-bench with altered Math problems to test the robustness of reasoning models. It is found that simply modifying numbers in problems would cause an obvious degradation in reasoning performance, indicating potential memorization issues in model training. Besides, the evaluation also disclosed an obvious vulnerability for unanswerable questions,

which is consistent with the evaluation results in AbstentionBench [65]. Wang *et al.* [186] proposed PolyMath, evaluated mathematical reasoning with multilingual contexts, and uncovered fluctuating performance on different languages. Zhu *et al.* [183] mentioned that after reasoning models provide correct answers, adding a simple negation prompt to doubt the answer could mislead the second thinking process, causing an obvious accuracy drop on related benchmarks [318, 319, 320]. The confidence problem was also mentioned by previous works [321, 316], indicating that for both reasoning and non-reasoning models, self-correction prompts expressing distrust in model outputs could hugely influence model rationales and final decisions, both positively and negatively. In addition, Li *et al.* [182] introduced M-Attack to optimize transferable adversarial images. After pushing the embedding of a clean image towards another real image containing distracting semantics through feature matching and model ensembling, the perturbed adversarial image could successfully attack cutting-edge models such as GPT-4.5, 4o, or o1 [13], inducing wrong image descriptions or hallucinations. Experiments demonstrated that even with reasoning capability, OpenAI o1 still struggled to distinguish noise from real images.

The vulnerability to input perturbation is also discovered in the code generation domain. CodeCrash [190] proposed to evaluate the code generation robustness with noisy requests, including garbage codes, renamed entities (which resemble altering numbers in Math problems), misleading print statements or hint comments, etc. While the results demonstrated superior performance compared to non-reasoning counterparts, they also revealed significant vulnerabilities under certain perturbations. Roh *et al.* [191] identified the robustness vulnerability against the Chain-of-Code Collapse (CoCC) framework, in which the original prompt was wrapped with a narrative tone, making it a story or an adventure. Moreover, Wang *et al.* [176] evaluated the judging bias of large reasoning models, finding that even if LRMs perform better than LLMs on objective domains, they are still vulnerable to biases such as choice position, authority, or major beliefs distractions.

### 5.3 Overthinking and Underthinking

Overthinking is an emerging problem in reasoning models, referring to the phenomenon where “LLMs generate excessively detailed or unnecessarily elaborate reasoning steps, ultimately reducing their problem-solving efficiency”. [10, 322] From the trustworthy perspective, instead of efficiency, we focus more on situations where **models are trapped in repeating reasoning trajectories in a non-stop manner, and may output wrong answers in the end**. Conversely, underthinking refers to the situation where LLMs generate abnormally short reasoning or completely skip the reasoning process, even if the thinking behavior is necessary or required. Along the same lines as before, modifications to the Math questions could trigger redundant reflections, resulting in overthinking [193, 194]. Generally, such overthinking vulnerability mainly occurs when faced with unanswerable questions or erroneous premises. Some researchers [195, 196] found that the overconfidence, or reliance, on input prompts forces reasoning models to try numerous thoughts while failing to doubt the validity of prompts. Wang *et al.* [198] attributes the redundant thinking tokens with unsatisfying accuracy to frequent thought switching. Su *et al.* [199] studied the relationship between reasoning length and answer correctness, finding that models failed to allocate proper reasoning length to questions with different levels of difficulty. Dang *et al.* [200] also proposed that “internal bias” is strongly related to the overthinking behavior. When the internal bias contradicts the conclusion after stepwise thoughts, the model will trigger reflections.

To deliberately elicit overthinking behavior, the earliest work is Overthink [201], which added unrelated or adversarial context to the prompts to obfuscate model reasoning. Similar attacks are also proposed in multiple literatures [139, 190, 197], in which Si *et al.* [197] introduced a GCG-style [243] optimization pipeline to generate adversarial overthinking triggers. Under agentic environments, Cuadron *et al.* [202] identified the reasoning-action dilemma, and categorized three patterns of overthinking where the model prefers overly reasoning to interacting with environments. To mitigate overthinking, there are a lot of works heading towards efficient reasoning [11, 9, 10], including but not limited to prompt-driven methods [323, 193, 324], training-based methods [325, 326, 327, 328, 329], inference-based methods [330, 1, 331, 332], representation-based methods [333, 334], etc.

Underthinking, compared to overthinking, constitutes a more pure robustness topic. Input manipulation could also trigger underthinking [169, 139]. For example, padding original prompts with compromised thoughts could make DeepSeek-R1 stop further reasoning [169]. A few researchers also mentioned that the think-less attack could limit the test-time compute of reasoning models, making them more vulnerable to attacks [139, 203, 109]. Sun *et al.* [204] located a subset of attention layers in the model weight, proposed ThinkEdit to remove the short thinking direction. In general, current reasoning models lack sufficient robustness against manipulations of thinking length. To advance both robustness and efficiency, further research is needed to investigate the underlying causes of overthinking and underthinking behaviors, as well as to develop effective mitigation strategies.

## 6 Fairness

Fairness focuses on the ethical principles language models possess, especially whether language models react equally to different users or groups, including genders, LGBTQ+ communities, races, language, and political orientations without preference or discrimination [335]. As stated in previous literature [336, 337], the bias may emerge, or be exaggerated, from imperfect training data, the choice of optimization, evaluation metrics, and the deployment phase. In this section, instead of thoroughly reviewing fairness evaluation and debiasing methods in LLMs, we simply limit our scope to recent fairness studies with regard to the reasoning capability.

Lin *et al.* [205] identified the dialect bias of multiple cutting-edge language models with the experiments of paraphrasing standard English queries into African American Vernacular English (AAVE). CoT prompting is helpful to mitigate this bias, but it is unable to fully solve such a discrepancy, just like the results on robustness [178]. Cheng *et al.* [206] also mentioned that CoT prompting could guide the model to correctly classify gender biases. Kamruzzaman *et al.* [207] evaluated multiple prompting strategies for social bias reduction, finding that system 2 prompts with a human persona could reduce stereotypical judgments. However, another line of work stated that under persona-assigned tasks, CoT prompts are not sufficient to mitigate human-like motivated reasoning [208, 209]. For bias detection, Fan *et al.* [210] proposed BiasGuard to identify potential discrimination with internal reasoning capability. The training included an SFT stage followed by a DPO stage, which resembles the development of guardrail models in Section 4.2.3. Cantini *et al.* [211] exploited the CLEAR-Bias benchmark [338] for LRMs, concluding that models with explicit reasoning are more vulnerable in terms of bias, even though they are slightly safer than LLMs with CoT prompting. Overall, current researches underscore that current CoT and reasoning techniques have yet to bridge the gap toward achieving authentic fairness in models, and the fairness may still depend on the quality and distribution of training data.

## 7 Privacy

Privacy is always an important concern in the development of ML algorithms. Dating back to the CNN era, there has been a lot of work studying the potential to infer or steal the model and training data [339, 340, 341], as well as their corresponding defenses [342, 343, 344]. In recent years, we have also witnessed some inference-time attacks to extract personally identifiable information (PII), private retrieval-augmented generation (RAG) documents, or model weights when interacting with large language models [345, 346, 347]. As reasoning capabilities become more advanced, the risk of intentionally disclosing private information through user input increases. In this section, we elaborate on related research from the model and prompt perspectives, specifically whether the privacy issue originates from model training data or external prompts.

### 7.1 Model-related Privacy

**Unlearning.** Large language model unlearning aims to erase copyrighted contents, remove harmful generations, protect data privacy, etc [348]. Following previous work on unlearning method evaluation [349], Yoon *et al.* proposed R-TOFU [212] to evaluate a few baseline unlearning methods with different strategies on reasoning models, concluding that unlearning only the final result is insufficient to forget the specific information. Similar conclusions are also drawn by Wang *et al.* [213], and they proposed R<sup>2</sup>MU that mapped the intermediate features of reasoning steps to randomly scaled vectors for an improvement. Both works highlighted the forgetting of CoT contents, providing a feasible direction for future attempts. From the other side, attacks against unlearning were also developed to recover erased data, which discloses the vulnerability of unlearning methods [350, 351]. For reasoning models, Sinha *et al.* [214] proposed SLEEK to elicit unlearned information in a multi-turn manner. Aimed at finding residual traces related to the unlearning target, SLEEK first generates queries targeting each object or fact with CoT techniques, and then prompts the model in multi-turn interactions to test whether any residual details remain in the response. This method achieved an ASR above 50% on Harry Potter facts against chat models, suggesting that full mitigation of memorized content may not yet be guaranteed.

**Model IP protection.** To prevent the model from copying or stealing, researchers have proposed numerous active or passive defense methods to protect the released models as well as their valuable training datasets, including fingerprinting, watermarking, unlearnable techniques, etc [343, 352, 353, 354, 355, 356, 357, 358, 359]. In terms of large language models, representing work [360] promoted the sampling possibility of a fraction of tokens in the vocabulary, so that the watermark is printed as the ratio of selected tokens versus the rest tokens in the generated texts. After that, the development of CoT prompting provides more chances to model IP protection. ImF [215] embedded the fingerprint<sup>3</sup> into pre-defined CoT prompt-answer pairs. CoTSRF [216] trained an extractor to capture the feature

<sup>3</sup>“Fingerprint” originally refers to inherent, verifiable model features (e.g., weights or activations), while “watermark” denotes externally embedded signals. In this context, the distinction is blurred, and both terms refer to watermarks.

of CoT-prompt conditioned reasoning steps, and calculate the Kullback-Leibler divergence (KL divergence) with the suspect model in the verification phase. To enable RAG data protection, Guo *et al.* [217] imprinted watermarks into knowledge text, so that the model would generate a specific CoT trace with correct answers when faced with verification questions, enabling an effective and harmless copyright protection. Aside from watermarking methods, Savani *et al.* [218] proposed “antidistillation sampling” to prevent model-generated contents from being trained. When decoding, the method modified the output logits to maximize the potential training loss while keeping the correctness of the outputs. Experiments on Math datasets [27, 26] demonstrated the feasibility of this approach: antidistillation sampling achieved accuracy comparable to temperature sampling, while student models suffered a notable performance drop of approximately 30% on GSM8K [26]. Together, these techniques provide a basis for ongoing efforts to develop reliable and practical IP protection mechanisms.

## 7.2 Prompt-related Privacy

With the fast progress in large language models, the ability to infer private information from input prompts also gets stronger. Staab *et al.* [361] was the first to research the privacy inference attack in large language models, drawing the result that LLMs are capable of inferring various personal attributes beyond memorization. Tömekçe *et al.* [362] tested the inferring capability in the vision domain, demonstrated that the inference accuracy is positively related to the general capabilities of the models, and underscored the necessity of privacy protection methods. After the advent of CoT techniques, Green *et al.* [219] evaluated the privacy leakage of reasoning models, claiming that the reasoning traces could disclose more private information. While additional reasoning steps may lead to more cautious final answers, they can inadvertently reveal sensitive data during intermediate generation, aligning with the findings discussed in Section 7.1 [212, 213]. Luo *et al.* [220] curated a benchmark to evaluate the attribute inference attack of vision-language models, finding that multi-model large reasoning models have strong capabilities of inferring geological information in input images, while seldom limiting this feature. Based on these findings, they proposed GeoMiner to trigger location-related attribute inference attacks. Such a method achieved higher performance than simple CoT methods, urging the need for protection.

With a similar logic to develop defense methods against Jailbreak in Section 4, the defense of attribute inference attacks also includes prompting, post-training, and guardrails. However, experiments by Staab *et al.* [361] showed limited privacy gains from client-side anonymization or alignment. Such a vulnerability is also supported by Luo *et al.* [220], stating that current SoTA guardrails cannot identify such an attack, and padding system prompts with warnings on location leakage could sacrifice the general performance. To summarize, more future works are needed to defend against this escalating threat.

## 8 Future Research Directions

**Standard measurements of faithfulness.** A wide range of methods have been proposed to evaluate reasoning faithfulness, but none are comprehensive, often leading to divergent or even contradictory conclusions. For example, some studies argue that larger models exhibit greater faithfulness [84, 77], while others contend that they are less faithful [78]. This inconsistency highlights the need for more robust and standardized evaluation protocols that can fairly assess reasoning faithfulness across models.

In addition, some existing methods for evaluating faithfulness may conflict with other aspects of the performance of large models. For example, one common evaluation technique involves CoT intervention methods. These approaches test how perturbations to intermediate reasoning steps affect final answers. Empirical findings suggest that stronger models can answer correctly even with the perturbed CoT, implying that their outputs may rely less on explicit reasoning traces and more on internalized knowledge. From this, one might conclude that stronger models are less faithful, as their outputs do not depend transparently on the provided reasoning paths. However, such a conclusion conflicts with robustness. Therefore, eliminating the evaluation bias caused by model performance remains a critical open problem.

**More analyses on safety mechanism.** After reviewing attack and defense methods in Section 4, we call for more studies on the safety mechanism. Previous works demonstrated the feasibility of post-training methods with an extra safety-related CoT dataset. However, heuristic insights into effective dataset construction remain limited, leaving many details, such as prompts for CoT distillation, data ratios across different sources, and the necessity of cold-start SFT, reliant on manual tuning and empirical intuition. Moreover, in terms of the safety tax, the empirical understanding of how reinforcement learning contributes to safety and alignment remains limited. For instance, it is still unclear whether improvements stem from the learning algorithm itself (e.g., GRPO over DPO), or simply from higher-quality data such as well-curated CoT examples. Some progress has been made in understanding the role of SFT versus RL [363, 364], and we encourage future work to further investigate the role and limits of RL in this context.

**More fine-grained benchmarks.** As language models continue to grow in capability, there is an increasing need for safety evaluation benchmarks that can effectively reflect their evolving behaviors. Current safety evaluation benchmarks are primarily based on a narrow set of related attack methods [243, 286, 287], resulting in significant homogenization of data distribution. As a consequence, metrics such as ASR often exhibit extreme values. Besides, due to the inherent properties of generative models, the outputs may be sensitive to variations in temperature settings and prompt formulations, thereby impacting the reproducibility of experimental results. In this regard, we call for new benchmarks that are more discriminative, detailed, and robust. In addition, compared with the number of benchmarks in safety and robustness, evaluations on privacy inference and fairness have comparatively received less emphasis. These areas would benefit from increased focus in future work if more evaluations with comprehensive coverage, clear definitions, and diverse testing samples are developed.

## 9 Conclusion

In conclusion, this survey summarizes recent literature concerning trustworthiness in reasoning capabilities, providing a comprehensive overview with a clear taxonomy. With efforts on each topic, we describe the development of novel methods, point out prevailing conclusions, and highlight the related analysis as well as future opportunities. We believe that our comprehensive survey and structured taxonomy could offer a foundation for future research in building safer, more reliable models with reasoning capabilities.

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