A Survey of Inductive Reasoning for Large Language Models

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Abstract

Reasoning is an important task for large language models (LLMs). Among all the reasoning paradigms, inductive reasoning is one of the fundamental types, which is characterized by its particular-to-general thinking process and the non-uniqueness of its answers. The inductive mode is crucial for knowledge generalization and aligns better with human cognition, so it is a fundamental mode of learning, hence attracting increasing interest. Despite the importance of inductive reasoning, there is no systematic summary of it. Therefore, this paper presents the first comprehensive survey of inductive reasoning for LLMs. First, methods for improving inductive reasoning are categorized into three main areas: post-training, test-time scaling, and data augmentation. Then, current benchmarks of inductive reasoning are summarized, and a unified sandbox-based evaluation approach with the observation coverage metric is derived. Finally, we offer some analyses regarding the source of inductive ability and how simple model architectures and data help with inductive tasks, providing a solid foundation for future research.

1 Introduction

In recent years, the rapid development of large language models (LLMs) (Zhao et al., 2023) leads to significant progress in many natural language processing (NLP) downstream tasks. Among these, reasoning (Huang and Chang, 2022; Plaat et al., 2024; Zhang et al., 2025a) is one of the comprehensive and challenging tasks for LLMs, and therefore receives considerable attention.

Within all the reasoning paradigms, inductive reasoning (Lu, 2024) is one of the fundamental types. It involves drawing general conclusions from specific observations (Han et al., 2024). We give two examples illustrating number sequence calculation and list transformation in Figure 1. The main characteristics of inductive reasoning are its particular-to-general thinking process and the non-uniqueness of its answers. Considering how humans perceive the world, they typically make judgments by drawing analogies from past experiences to current situations, rather than always going through a strictly logical process as in deductive reasoning (Ingold, 2021). We can assume that the inductive mode is key to knowledge generalization and better aligns with human cognition. It is a fundamental mode of learning and thus attracts increasing interest.

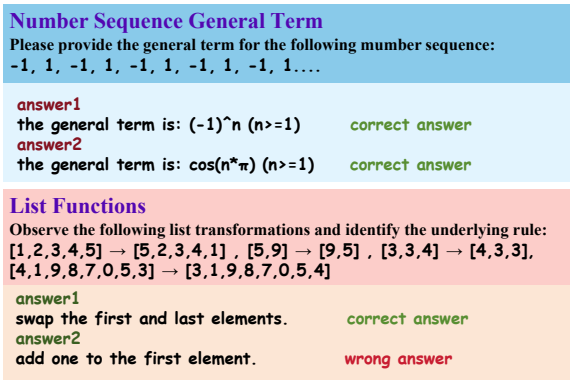

Figure 1: Two examples of inductive reasoning. They generalize from specific observations or cases to derive general conclusions. There may be more than one such conclusion that meets all the observations.

Despite the importance of inductive reasoning, previous works mostly focus on deductive reasoning (Li et al., 2024b), represented by mathematical proof (Ahn et al., 2024; Chen et al., 2024a) and program verification (Liu et al., 2023; Jiang et al., 2024b), which is a logical reasoning that derives necessary conclusions from general rules or premises. For more conceptual distinctions, please refer to Appendix A.1. It has already been extensively studied in recent years (Lu et al., 2024; Wang et al., 2024a). Moreover, there is no systematic

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summary of inductive reasoning for LLMs.

Therefore, this paper presents the first comprehensive survey of inductive reasoning for LLMs. We first introduce the background, including some relevant concepts, the applications of inductive reasoning in NLP and real-world scenarios, as well as its significance (Section 2). Next, we review and prospect the methods for enhancing the inductive reasoning capabilities of LLMs (Section 3), which are categorized into three main areas: post-training, test-time scaling, and data augmentation. We then summarize the current benchmarks of inductive reasoning and derive a unified sandbox-based evaluation approach with the observation coverage metric (Section 4). Finally, we offer some theoretical analyses of inductive reasoning (Section 5), regarding the sources of inductive ability and practical experiences for enhancing it. The taxonomy of this survey is in Figure 2. In summary, the main contributions of this paper are threefold:

- **First survey.** To our knowledge, we are the first to present a comprehensive survey of inductive reasoning for LLMs, thoroughly analyzing the current techniques and applications.
- **New taxonomy.** We categorize methods for improving inductive reasoning into: post-training, test-time scaling, and data augmentation. We also summarize the current benchmarks and derive a unified sandbox-based evaluation approach.
- **Bright prospect.** We offer some analyses regarding the source of inductive ability and how simple model architectures and data help with inductive tasks, providing a solid foundation for future research.

2 Background

In this section, we will introduce the relevant concepts of inductive reasoning, some of its application scenarios, and the significance of studying it.

2.1 Concepts

2.1.1 Large Language Models

Since the transformer architecture (Vaswani et al., 2017) has become mainstream for language models, the field of NLP has experienced rapid development (Wei et al., 2021). During 2017 to 2022, pretrained language models (PLMs) (Kalyan et al., 2021), which undergo two stages—pretraining and finetuning—such as the BERT (Devlin et al., 2019) and T5 (Raffel et al., 2023) series, once dominated the entire field. From 2022, with the advent of ChatGPT-3.5 (McGee and Sadler, 2025), the era of LLMs officially begins. LLMs, with their massive number of parameters and unique training methods (Zhao et al., 2025), significantly improve the performance of NLP tasks (She et al., 2023; Xu et al., 2023; Plaat et al., 2024) and have a profound impact on various aspects of daily life (Gan et al., 2023; Zhou et al., 2023; Maatouk et al., 2023). Some well-known LLMs include the GPT series[1], the Gemini series[2], the Claude series[3], and so on.

2.1.2 Inductive Reasoning

Inductive reasoning represents making an induction from specific instances or observations to derive general rules and conclusions (Arthur, 1994; Heit, 2000). From another perspective, it denotes one reasoning approach where the conclusion is not guaranteed with certainty, but instead supported only to a certain degree of probability (Copi et al., 2004). In other words, inductive reasoning may have more than one valid hypothesis that can account for all the instances or observations, making its answer open (Thomas, 2003). To sum up, inductive reasoning refers to a thought process that proceeds from the particular to the general.

2.2 Applications of Inductive Reasoning

The core idea of inductive reasoning is inductive bias. It is a set of assumptions or prior conditions that a model or an individual relies on when encountering unseen items (Caruana, 1993; Baxter, 2000). There is no 'universal' bias in deep learning. Choosing an appropriate inductive bias for a specific task is key to achieving success (Provost and Buchanan, 1995). We will discuss its applications in NLP tasks and real-world scenarios.

2.2.1 NLP Downstream Tasks

Inductive reasoning is widely applied to improve the performance of NLP downstream tasks. Some common practices include training models to learn inductive bias (Yang et al., 2025), constructing chains of thought (CoT) (Chen et al., 2025b) or summarizing rules to enhance interpretability (Xu and Yang, 2025), and leveraging intra-parameters implicit knowledge (Cheng et al., 2024) for induc-

[1] https://chatgpt.com/overview
[2] https://cloud.google.com/vertex-ai/generative-ai/docs
[3] https://claude.ai

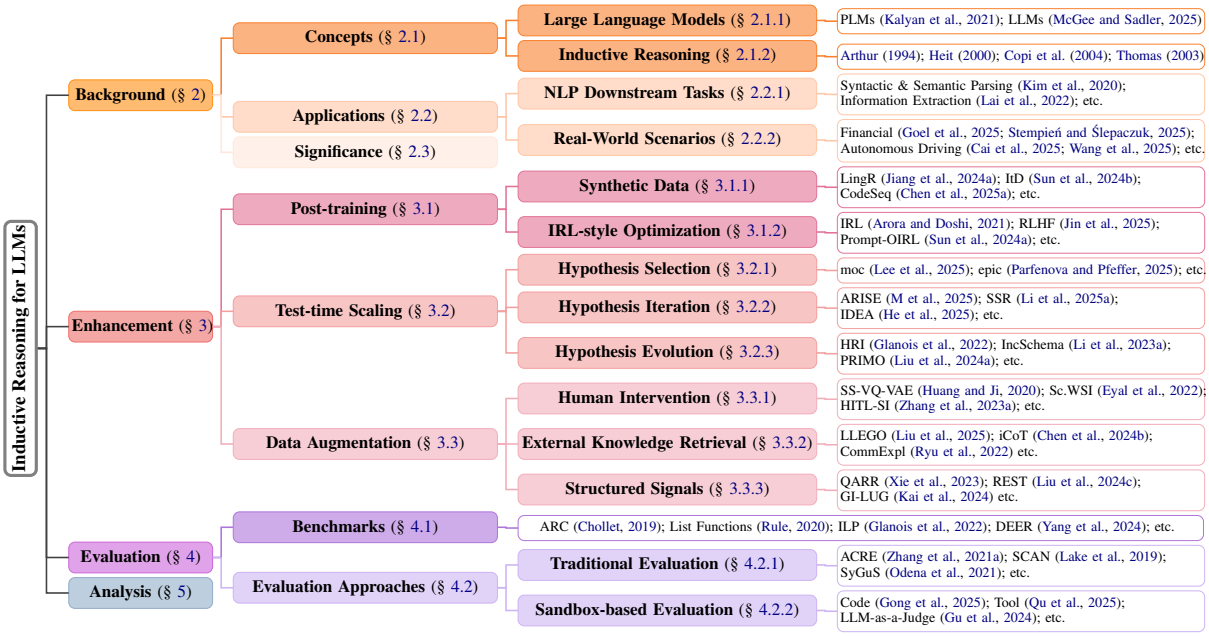


Figure 2: Taxonomy of the survey about the inductive reasoning for LLMs.

tion, and others. Such approaches benefit a wide range of downstream NLP tasks: syntactic and semantic parsing (Kim et al., 2020; Yamada et al., 2021; Lindemann et al., 2024; Tsujimoto et al., 2025), information extraction (Lai et al., 2022; Liu et al., 2024c; Silva et al., 2025; Xu et al., 2024), dialogue systems (Feng et al., 2022; Xie et al., 2024; Ou et al., 2024), question answering (Gu and Su, 2022; Kim et al., 2023; Chen et al., 2024d), multimodal tasks (Amosy et al., 2024; Zhou et al., 2025; Naik et al., 2025), and so on.

2.2.2 Real-World Scenarios

Inductive reasoning has a broad impact on real-world scenarios. Here, we select three of the practical applications. (1) Financial Forecasting and Risk Management: Inductive models are essential for predicting future financial outcomes by learning complex, non-linear patterns from vast amounts of historical time-series data (Faheem, 2021; Goel et al., 2025; Stempień and Ślepaczuk, 2025). (2) Autonomous Driving: A key challenge in autonomous driving is handling rare, safety-critical scenarios that lack sufficient training data, a gap that can be addressed through inductive reasoning (Cai et al., 2025; Wang et al., 2025). (3) Conversational Healthcare and Diagnostic Dialogue: Inductive reasoning empowers artificial intelligence systems to mimic a clinician's process of taking patient history and formulating a diagnosis by generalizing from symptom patterns (Tu et al., 2024; Dhudum et al., 2024; Zhang et al., 2025b).

2.3 Significance of Inductive Reasoning

Inductive reasoning has broad applications in both AI and real-world scenarios. It is the most universal and essential method in knowledge discovery and generalization (Carter and Hamilton, 1998; Bai et al., 2024; Sun et al., 2025): (1) Deriving general conclusions from specific cases, allowing it to cover and generalize to a wider range of applications, which aligns with the human learning process. (2) Adaptive adjustments help in uncertain and complex scenarios, where inductive reasoning may yield multiple plausible outcomes rather than a single unique solution.

3 Enhancement

In this section, we will introduce three major approaches to enhance the inductive capabilities of LLMs: post-training (Section 3.1), test-time scaling (Section 3.2), and data augmentation (Section 3.3). It is worth noting that we not only summarize existing methods but also prospect a forward-looking review of potential future inductive approaches. For convenience, we treat the inputs of inductive reasoning as observations and refer to these outputs as rules.

3.1 Post-training

Post-training refers to improving the inductive reasoning ability of LLMs during the post-training

stage (Lai et al., 2025; Wu, 2025), using algorithms such as supervised finetuning (SFT) and reinforcement learning (RL). This category of methods primarily focuses on constructing synthetic data (Long et al., 2024; Jiang et al., 2025) (Section 3.1.1) and developing new algorithms (Section 3.1.2). We illustrate them in Figure 3.

3.1.1 Synthetic Data

Synthetic data means artificially generated data that mimics the properties and patterns of real-world data (Bauer et al., 2024). Data plays a decisive role in LLM training. To address certain inherent limitations of natural data, such as being difficult to obtain or organize (Nadas et al., 2025), researchers often construct data manually to compensate for these shortcomings. LingR (Jiang et al., 2024a) builds a 'linguistic rule instruction set' for various LLMs, enabling them to learn step-by-step reasoning based on linguistic rules such as causality. ItD (Sun et al., 2024b) leverages the deductive abilities of LLMs to generate data and optimize inductive ability. The model's capacity to learn general rules from a small number of samples is significantly enhanced. CodeSeq (Chen et al., 2025a) constructs SFT and RL training sets to ask LLMs to facilitate reasoning over number sequence general term formulas, thereby improving their inductive abilities. Other approaches (Wu et al., 2022; Aksu et al., 2023; Darm et al., 2023; Mosolova et al., 2025) establish similar induction-related training datasets for the models to learn from.

3.1.2 IRL-style Optimization

Reward models (RMs) (Zhong et al., 2025) are typically utilized to provide supervision signals for the RL process. However, for inductive reasoning, due to the non-uniqueness of answers and the uncertainty in the reasoning process, traditional RMs struggle to provide effective supervision. Therefore, Inverse RL (Arora and Doshi, 2021) (IRL), which needs to induce the latent reward functions, may serve as an alternative approach (Sun and van der Schaar, 2025). The Reinforcement Learning from Human Feedback (RLHF) (Kaufmann et al., 2024; Swamy et al., 2024) process of LLMs is essentially IRL, as it infers human preferences and the underlying reward function from human feedback. Therefore, designing an appropriate reward model in RLHF can enhance the inductive reasoning ability of LLMs (Jin et al., 2025). We can also employ Prompt-OIRL (Sun et al., 2024a) for reference, which proposes an IRL-based method that reuses historical prompting trial-and-error experience to train a reward model to improve the model's inductive exploration ability. Although works combining IRL and reasoning are still scarce, the approach of IRL—fitting the posterior distribution of the reward model from human or data signals (Cai et al., 2024; Krishna and Sahoo, 2024)—has strong extensibility and can thus be regarded as one of the important methods for the facilitation of inductive reasoning.

3.2 Test-time Scaling

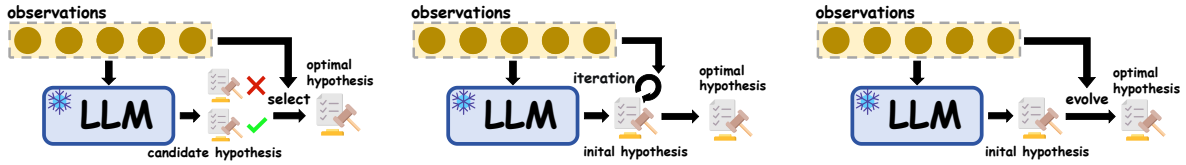
The goal of inductive reasoning is to derive general rules and explanations from observations, which inevitably involves forming hypotheses during the reasoning process. The above post-training requires training LLMs, whereas the test-time scaling in this section is a hypothesis-based method that only works during the inference stage (Zhang et al., 2025c). Unlike end-to-end models (Kotary et al., 2021), the test-time scaling method prompts the frozen LLMs to form an inductive reasoning pipeline (He and Chen, 2025). We have LLMs generate candidate hypotheses for inductive problems, which can then undergo selection (Section 3.2.1), iteration (Section 3.2.2), or evolution (Section 3.2.3) operations to reach the optimal one. Detailed processes are shown in Figure 4.

3.2.1 Hypothesis Selection

Hypothesis selection refers to choosing, from the candidate hypotheses generated by LLMs, those that can cover the observations (Pazzani and Silverstein, 1990; Bun et al., 2019). Hypothesis Search (Wang et al., 2024b) let the LLMs generate multiple abstract hypotheses in natural language. Then, narrow down the hypothesis set through either the LLMs or minimal human filtering. The motivation of Mixture of Concepts (MoC) (Lee et al., 2025) lies in the fact that hypotheses for inductive reasoning often produce semantic redundancy. Therefore, the proposed method simulates human inductive reasoning by first figuring out a list of semantically non-redundant concepts and then generating corresponding hypotheses based on each concept. Parfenova and Pfeffer (2025) propose Ensemble Pipeline for Inductive Coding (EPIC) to address the issue of inconsistency in inductive encodings by using small LLMs to generate candidate encodings, filtering them through a moderator mechanism and similarity checks, and finally evaluating them with

(a) synthetic data (b) IRL-style optimization

Figure 3: The demonstration of the post-training method for inductive reasoning.



(a) hypothesis selection (b) hypothesis iteration (c) hypothesis evolution

Figure 4: The demonstration of the test-time scaling method for inductive reasoning.

composite metrics.

3.2.2 Hypothesis Iteration

Hypothesis iteration means iterating over candidate hypotheses until they satisfy all the observations (Yom, 2015). Qiu et al. (2024) proposes a three-step iterative hypothesis refinement method that simulates the human inductive reasoning process: generate multiple hypotheses from a few examples; evaluate how many known instances each hypothesis can cover; and have the LLMs further revise the selected hypotheses based on feedback, iterating for several rounds until convergence. SSR (Li et al., 2025a) iteratively optimizes by generating diverse candidate rules and refining them based on execution feedback. ARISE (M et al., 2025) also iterates over the inductive rules before using them to train the model. IDEA framework (He et al., 2025) resolves the shortcomings of LLMs in interactive rule learning by simulating the human cycle of hypothesis revision, thereby enhancing the model's dynamic learning capability.

3.2.3 Hypothesis Evolution

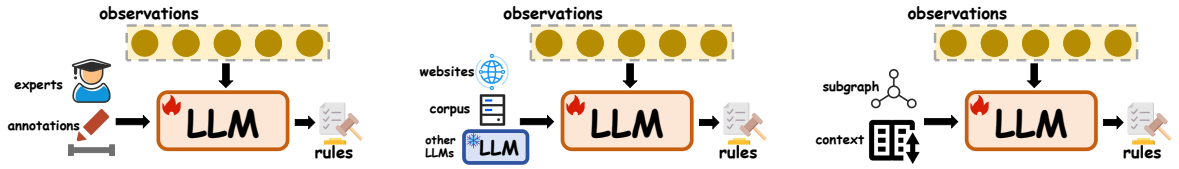
Unlike the iterative process, hypothesis evolution expands, diversifies, or evolves the hypothesis space by generating, filtering, and combining multiple hypotheses, forming hypotheses that better capture complex patterns (Galkin, 2011; Gil et al., 2017; Juretic, 2025). LLMs leverage contextual and label information, along with prompts, to progressively guide the model in dynamically generating patterns during reasoning, without relying on predefined rules (Dror et al., 2023). IncSchema (Li et al., 2023a) gradually induces general patterns by querying the LLMs in stages—first listing core events, then expanding details, and finally verifying relationships. HRI (Glanois et al., 2022) generates inductive meta-rules and matches them with samples, thereby evolving into first-order logic rules. PRIMO (Liu et al., 2024a) introduces a progressive multi-stage open rule induction method for deriving multi-hop rules, thereby capturing more complex reasoning chains.

3.3 Data Augmentation

Data augmentation (Zhang et al., 2022) for LLMs signifies enriching the model's input with additional knowledge or structured signals, such as external facts and retrieved documents, to enhance reasoning and improve output quality. We divide it into three subcategories: human intervention (Section 3.3.1), external knowledge (Section 3.3.2), and structured signals (Section 3.3.3). Please refer to Figure 5 about them.

3.3.1 Human Intervention

Human intervention incorporates expert knowledge or human-annotated information during inductive reasoning. SS-VQ-VAE (Huang and Ji, 2020) relies on a small amount of human-annotated information to discover new patterns. Eyal et al. (2022) generates substitute words, then annotates the corpus and trains static embeddings to enhance the model's inductive priors. Zhang et al. (2023a) utilizes GPT-3 to generate candidate patterns and enhances their quality through human intervention, addressing the issues of domain transfer and semantic consistency in purely automated approaches. Some other studies (Edwards and Ji, 2023; Verhoeven et al., 2024)



(a) human intervention (b) external knowledge (c) structured signals

Figure 5: The demonstration of the data augmentation method for inductive reasoning.

emphasize inductive capabilities in low-annotation scenarios, which indirectly reflects the importance of expert knowledge.

3.3.2 External Knowledge

In this paper, we define external knowledge (Cao et al., 2021) to include web or document information, knowledge from other corpora, knowledge stored in LLM parameters (AlKhamissi et al., 2022), and so on. LLEGO (Liu et al., 2025) incorporates the semantic prior knowledge embedded in large LLMs into genetic programming operations to enhance generalization ability. The parameter knowledge of LLMs (Zhang et al., 2023b) and multimodal large models (Zhang et al., 2021b; Li et al., 2024a) can also serve as an important supplementary information source for inductive tasks. For example, some powerful LLMs are directly prompted to produce the inductive Chain-of-Thought (Chen et al., 2024b), inductive steps (Qian et al., 2023), and inductive rules (Ramji and Ramji, 2025) for the current task, providing additional assistance. Other types of knowledge, such as bilingual corpora (Shi et al., 2021; Kohli et al., 2024), social media content (Radhakrishnan et al., 2020), and commonsense knowledge (Ryu et al., 2022), can be used for inductive tasks in the same way.

3.3.3 Structured Signals

Structured information represents subgraphs or contextual information of LLMs (neighboring hidden states or embeddings), which provide local implicit signals and help LLMs to learn relevant inductive biases (Immer et al., 2022). Li et al. (2023b) optimizes the model's output by retrieving nearest-neighbor embeddings as contextual examples. QARR (Xie et al., 2023) extracts an open subgraph for the query entity to inductively infer new entities. REST (Liu et al., 2024c) deploys rule-induced subgraphs to capture local semantic patterns, thereby enhancing the model's generalization ability in inductive scenarios. GI-LUG (Kai et al., 2024) uses a syntactic parser to generate syntax masks that guide the attention mechanism, and combine BPE embeddings with a hybrid loss function to optimize the induction process. Although this type of method is widely used in the PLM era, due to the same underlying principle, it can also play an important role for LLMs.

4 Evaluation

In this section, we will introduce current benchmarks for LLM inductive reasoning, some evaluation approaches, and the corresponding metrics.

4.1 Benchmarks

To evaluate the inductive reasoning capabilities of LLMs, the research community constructs a diverse set of benchmarks, as shown in Figure 1, that comprehensively assess the models' ability to generalize universal rules from concrete observations. It is noteworthy that the input formats of some tasks appear as paired samples or few-shot examples, often framed as analogy reasoning. As we claim in Appendix A.1, since analogical reasoning is a special form of inductive reasoning, we also regard benchmarks in this analogical form as benchmarks for inductive reasoning. The core task of these inductive benchmarks requires models to observe a small number of input examples (Observation Input), infer underlying patterns, and output the final rules (Induction Target).

As shown in the table, the data objects covered by these benchmarks span a wide range—from basic structures such as numbers, strings, and lists, to more complex forms like grids, logical formulas, and even natural language text.

Among them, benchmarks such as ARC (Chollet, 2019), List Functions (Rule, 2020), and SyGuS (Odena et al., 2021) focus on algorithmic or rule learning, requiring models to generate programs or operational rules that explain data transformations. What's more, tasks like ILP (Glanois et al., 2022), GeoILP (Chen et al., 2025c), and ACRE (Zhang et al., 2021a) place greater emphasis on the induction of logical concepts and symbolic rules.

Table 1: Some benchmarks for evaluating the inductive reasoning abilities of LLMs. We provide the atomic objects, names with their references, the input formations, the targets to be induced, and the number of test samples (approximate values). '.' represents that it is the abbreviation of the benchmark name, while '*' indicates that the data are presented in the form of analogical reasoning. Further details about these benchmarks are in Appendix A.2.

Object	Benchmark Name	Obervation Input	Induction Target	# Samples
entity	SCAN (Lake et al., 2019)	a state of entities	an action of the state	7,700
grid	ARC* (Chollet, 2019)	pairs of grids	a grid conversion rule	400
list	List Func.* (Rule, 2020)	pairs of number lists	a list operation rule	250
code	PROGES (Alet et al., 2021)	IO input/output	a program	10,000
string	SyGuS (Odena et al., 2021)	a pair of strings	a string-mapping program	2,00
entity	ACRE (Zhang et al., 2021a)	functions of entities	a 'Blickets' entity	30,000
symbol	ILP (Glanois et al., 2022)	pos. and neg. samples	a one-order logic rule	120
text	Instruc. (Honovich et al., 2022)	two NL sentences	an instruction	200
number	Arith.* (Wu et al., 2024)	two numbers	the sum in certain base	-
symbol	Le/Ho. (Liu et al., 2024b)	pairs of triplets	an entailment rule	50,000
structure	NutFrame (Guo et al., 2024)	some frame information	conceptual structures	30,000
fact	DEER (Yang et al., 2024)	a pair of facts	a rule covers the facts	1,200
puzzle	RULEARN (He et al., 2025)	some puzzle scenarios	a puzzle rule	300
word	Crypto.* (Li et al., 2025a)	pairs of english words	an encrypted rule	4,500
symbol	GeoILP (Chen et al., 2025c)	pos. and neg. samples	a logic rule	10,000
string	In.Bench (Hua et al., 2025)	a pair of strings	a string-mapping rule	1,000
number	CodeSeq (Chen et al., 2025a)	a number sequence	the general term	1,500

Particularly, Codeseq (Chen et al., 2025a) involves the computation of number sequence general terms, which represents a more advanced and complex form of inductive reasoning.

Overall, these benchmarks test the models' pattern recognition ability and impose rigorous challenges on their higher-order cognitive skills. They not only examine how effectively LLMs can generalize from limited observations to underlying rules, but also serve as a foundation for driving further progress in enhancing such abilities.

4.2 Evaluation Approaches

In this section, we introduce the evaluation approaches for the inductive reasoning benchmarks mentioned above. We first present the traditional evaluation strategies used in the benchmark papers (Section 4.2.1). Then, we derive a sandbox-based evaluation approach with a fine-grained observation coverage metric built upon it (Section 4.2.2).

4.2.1 Traditional Evaluation Strategy

Most of the benchmarks in Section 4.1 directly evaluate the consistency between answers generated by LLMs and the ground truth. Therefore, several conventional metrics are employed, such as ACC, exact match, success rate, and so on. For example, ACRE (Zhang et al., 2021a) selects the most plausible "Blicket" from multiple options to evaluate the accuracy of its selection. SCAN (Lake et al., 2019) focuses on assessing whether the generated outputs exactly match the reference answers to indicate accuracy. SyGuS (Odena et al., 2021) requires finding a program that satisfies the string transformation rule, and the number of tasks in which the correct program is successfully identified is counted as the success rate.

4.2.2 Sandbox-based Evaluation

Considering that all inductive reasoning tasks share the same intrinsic mechanism: inferring general rules from specific observations. We can adopt a unified approach, namely sandbox unit test, to standardize the evaluation across all the inductive benchmarks mentioned above.

The sandbox unit test is a method where individual components or functions are tested in isolation to ensure they work as intended (Alhindi and Hallett, 2025). Each test runs in a controlled, independent environment, using specific input cases to verify the correctness of the component. This approach helps identify errors early and ensures that each part functions correctly before integration.

The sandbox unit test is originally used for code verification, at which time it is referred to as a code unit test (Gong et al., 2025). With the development of LLMs, it is also applied to evaluate various deductive reasoning tasks of LLMs, such

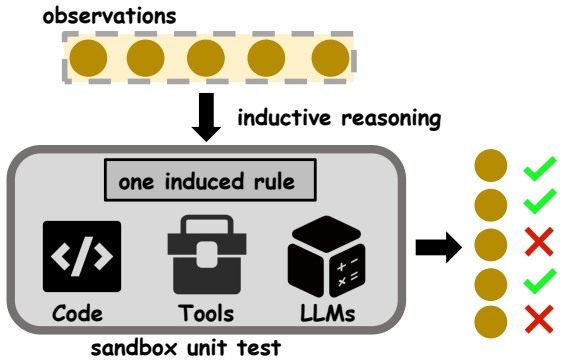


Figure 6: A demo of the sandbox unit test for inductive reasoning of LLMs.

as InternBootCamp (Li et al., 2025b).

In inductive reasoning tasks, the sandbox unit test can also be deployed for evaluation. We present a demo in Figure 6. For an inductive rule generated by an LLM, it can be encapsulated as code (Gong et al., 2025), a tool (Qu et al., 2025), or written into a prompt to be provided to the LLM-as-a-Judge (Gu et al., 2024). Each observation can then be executed in a sandbox environment to determine whether it conforms to the current rule.

Based on this, we can propose a more fine-grained metric for LLM inductive reasoning: **observation coverage** (OC), defined as the proportion of observations that pass the unit tests out of the total number of observations. In the example shown in Figure 6, this value is 0.6. Compared with the overall ACC or success rate of a task, OC provides a more fine-grained supervision signal at the observation level. This allows for a more precise reflection of the comprehensiveness of the model's answer. With this metric, more informative feedback can be provided for subsequent rule refinement and hypothesis exploration.

5 Analysis

In this section, we present several prior exploratory tasks that offer theoretical analyses for inductive reasoning and inductive bias of LLMs (Kharitonov and Chaabouni, 2021; Papadimitriou and Jurafsky, 2023; Wilson and Frank, 2023).

Inductive ability originates from induction heads. Many studies (Si et al., 2023; Edelman et al., 2024; Chen et al., 2024c) show that the strong in-context learning (ICL) (Dong et al., 2023, 2024; Crosbie and Shutova, 2025) or example imitation (Honovich et al., 2023; Ye et al., 2025) ability of LLMs originates from induction heads. An induction head is an attention head (Edelman et al., 2022; Ren et al., 2024) that performs a match-and-copy operation, identifying and replicating relevant context tokens (Singh et al., 2024). Minegishi et al. (2025) finds that, in fact, induction heads are meta-learning an abstract inductive within the context.

Model parameters, architecture, and data all help shape the inductive bias. The parameters, model architecture, and training data (White and Cotterell, 2021; Merrill et al., 2021; Lovering et al., 2021; Levine et al., 2022; HaoChen and Ma, 2023; Movahedi et al., 2025) are key to inductive bias. Lippl and Lindsey (2024) explores the effects of different parameters on inductive bias under multi-data mixed training and single-task finetuning scenarios, and ultimately emphasizes the importance of task similarity in mixed training. Some studies (Cabannes et al., 2023; Aerni et al., 2023) also highlight the importance of data augmentation, even the noisy data. Further research (Zeno et al., 2025) demonstrates that the choice of minimum norm can also determine a model's inductive generalization.

Induction means simplicity. Some early studies show that complex model architectures and data (Zietlow et al., 2021) can actually hinder inductive generalization. At the same time, for higher-order models, regularization can actually be detrimental to the formation of their inductive bias (Phuong and Lampert, 2021; Donhauser et al., 2022). Sometimes, simplicity is perfect for inductive reasoning (Goldblum et al., 2024). To enhance the inductive reasoning ability, finding simple inductive bias is of paramount importance. Simple and pure corpora often serve as the foundation for successful inductive reasoning (Mueller and Linzen, 2023).

6 Conclusion

This is the first survey of inductive reasoning for LLMs. The inductive mode is crucial for knowledge generalization and aligns better with human cognition. We categorize methods for improving inductive reasoning into three areas: post-training, test-time scaling, and data augmentation. We also summarize the current benchmarks and derive a unified sandbox-based evaluation approach. Finally, we offer some analyses regarding the source of inductive ability and how simple model architectures and data help with inductive tasks, providing a solid foundation for future research.

Limitations

This paper is a survey about the inductive reasoning abilities of Large Language Models. Due to space limitations, the main body of this survey is constrained to fewer than eight pages, and therefore, many details are not included in the main text. We only present the most essential parts. Meanwhile, although inductive reasoning in LLMs attracts increasing attention in recent years, the number of related studies remains relatively limited, making it difficult to produce a large-scale, systematic survey (even extending to 100 pages) comparable to those in other areas.

Ethics Statements

This survey primarily organizes and summarizes existing work on inductive reasoning in LLMs, with all relevant sources properly cited. Therefore, this paper does not raise any ethical or moral concerns.

Acknowledgments

We will finish this part in the camera-ready version.

Use of AI Assistants

We primarily use AI assistants to improve and enrich our writing, especially by leveraging LLMs to help us write taxonomy in LaTeX.

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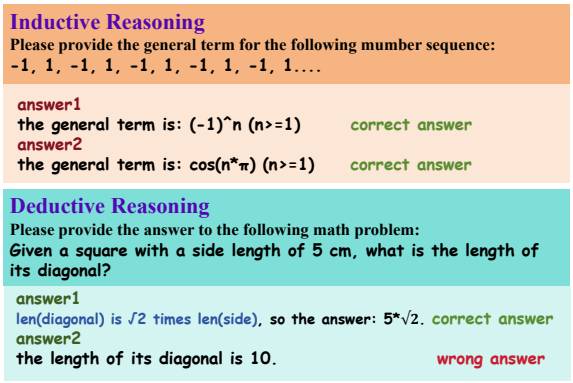

Figure 7: An example is given for both reasoning modes. In inductive reasoning, there may be multiple correct answers consistent with the existing observations, while in deductive reasoning, a precise logical reasoning process can help arrive at the only correct answer.

Table 2: The differences between inductive reasoning and deductive reasoning.

	Inductive Reasoning	Deductive Reasoning
Mode	particular-to-general	general-to-particular
Target	probabilistic conclusion	precise answer
Reliability	flexible and generative	premises-relied
Informative	extended information	no new information
Application	hypothetical inference	rigorous proof

A Appendix

A.1 Inductive Reasoning and other Reasoning Modes

A.1.1 Inductive Reasoning and Deductive Reasoning

We provide an example for each in Figure 7. As two major modes of reasoning, inductive reasoning (Clark, 1969; Rips, 1994; Bang et al., 2023) differs from deductive reasoning in many aspects. Please refer to Table 2 for more.

A.1.2 Inductive Reasoning and Analogical Reasoning

As stated in the main text, inductive reasoning is a process that goes from the particular to the general. In contrast, analogical reasoning is a process from the particular to the particular, which can be regarded as a special form of inductive reasoning. For example, consider an inductive reasoning task of deriving the general term formula of a number sequence: the input is a number sequence, and the output is its general term formula. Analogical reasoning, on the other hand, takes a number sequence as input and outputs its next term. In short, analogical reasoning is a form of reasoning that involves imitation based on observations. It compares and transfers similarities from existing observations to infer and generate possible next items or outcomes (Lewis and Mitchell, 2024a,b; Musker et al., 2024).

In the field of LLMs, the commonly studied ICL (Dong et al., 2023, 2024) can be regarded as a form of analogical reasoning. Therefore, ICL is not within the scope of inductive reasoning discussed in this paper.

A.2 More details about Benchmarks

In this section, we will introduce the inputs and outputs of LLM inductive reasoning benchmarks one by one in detail.

SCAN It takes as input a series of entities and their states, and requires LLMs to output the actions needed to achieve those states. For example, given 'a ball on the table' as input, the model should output 'place it on the table'.

ARC It takes as input several pairs of grids in natural language form, where they illustrate a specific transformation pattern. Then, given a new grid as input, the model is asked to output what the transformed grid would look like.

List Functions It takes as input several pairs of number lists, where they illustrate a specific transformation pattern. Then, given a new number list as input, the model is asked to output what the transformed number list would look like.

PROGES It provides several input-output pairs of a program and requires the model to generate the program itself.

SyGuS It takes as input several pairs of strings, where they illustrate a specific transformation pattern. Then, it requires the model to generate a program to show this transformation process.

ACRE It takes as input the results of interactions between different entities and a certain machine (i.e., the functions of different entities), and models need to output the entity corresponding to a specific function.

ILP It takes as input background knowledge in first-order logic, along with a pair of positive and negative examples for a specific first-order logic case, and the model is required to output a first-order logic that satisfies these conditions.

Instructions The model is given two natural language statements, A and B, where B is obtained by applying a certain instruction to A, and it is required to output that natural language instruction.

Arithmetics It takes as input several pairs of two-digit additions along with their results, where these additions follow a calculation process in a certain numeral base. Given a new pair of two-digit numbers, the model is required to output the result of their addition in the same base.

Levy/Holt It takes as input a pair of triplets, where the positive triplet represents a factual relationship and the negative triplet represents a counterfactual relationship. The task is to output an inference rule between triplets such that the positive triplet entails the negative triplet.

NutFrame It takes text fragments that contain potential frames and frame elements, along with contextual information such as sentence structure, lexical cues, and semantic hints. This input helps the model identify underlying conceptual structures in the text. The model produces three types of outputs. Frame Induction: Identifies latent frames expressed in the text and maps them to existing FrameNet frames or proposes new frames. Frame Element Identification: Detects specific frame elements within the text. Frame Filling: Assigns concrete values from the text (entities or phrases) to the identified frame elements.

DEER It takes as input several pairs of facts, where they illustrate a specific real-world rule. Then, it requires the model to generate the rule.

RULEARN The input to it consists of three parts. Puzzle Scenarios: Each puzzle presents a set of conditions or operations that the agent can manipulate. These scenarios are designed to have underlying rules that are not explicitly provided. Agent Actions: The agent can perform a variety of actions, such as inputting integers or letters, to interact with the puzzle environment. Feedback: After each action, the agent receives feedback that helps in refining its understanding of the hidden rule. The desired output is: the hidden rule governing the puzzle scenario based on the feedback received from its actions.

Cryptography It takes as input several pairs of English words, where each pair follows a certain cryptographic transformation pattern. Given a new word, the model is required to output the new word obtained by applying the same transformation pattern.

GeoILP The same as ILP in general.

InductionBench It takes as input a pair of strings, where the pair follows a certain transformation rule, and the task is to output that rule.

CodeSeq It takes as input a number sequence of numbers and is required to output the number sequence's general formula, with the entire output presented in code form.