TO CoT OR NOT TO CoT? CHAIN-OF-THOUGHT HELPS MAINLY ON MATH AND SYMBOLIC REASONING

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ABSTRACT

Chain-of-thought (CoT) via prompting is the de facto method for eliciting reasoning capabilities from large language models (LLMs). But for what kinds of tasks is this extra "thinking" really helpful? To analyze this, we conducted a quantitative meta-analysis covering over 100 papers using CoT and ran our own evaluations of 20 datasets across 14 models. Our results show that CoT gives strong performance benefits primarily on tasks involving math or logic, with much smaller gains on other types of tasks. On MMLU, directly generating the answer without CoT leads to almost identical accuracy as CoT *unless* the question or model's response contains an equals sign, indicating symbolic operations and reasoning. Following this finding, we analyze the behavior of CoT on these problems by separating planning and execution and comparing against tool-augmented LLMs. Much of CoT's gain comes from improving symbolic execution, but it underperforms relative to using a symbolic solver. Our results indicate that CoT can be applied selectively, maintaining performance while saving inference costs. Furthermore, they suggest a need to move beyond prompt-based CoT to new paradigms that better leverage intermediate computation across the whole range of LLM applications [1].
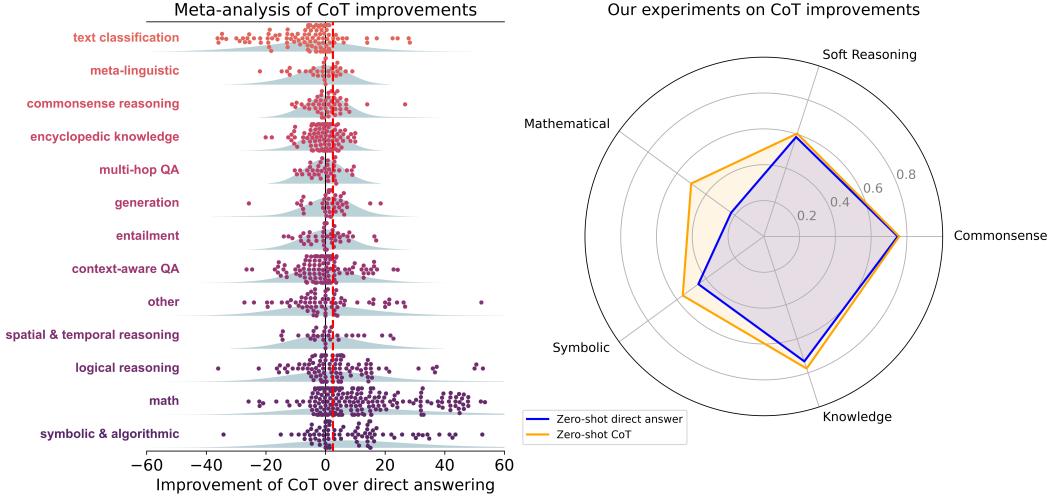
Figure 1: Left: meta-analysis of CoT literature; each point is a reported delta of CoT over direct answering for some (LLM, task) pair. Right: average performance of using zero-shot CoT v.s. direct answer prompts across five general reasoning categories, covering 20 datasets with 14 LLMs evaluated on each. In both sets of results, math and other kinds of symbolic reasoning are the domains that consistently see substantial improvements from CoT (red dotted line indicates the mean improvement from CoT across experiments).

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[1]Our code can be found at `https://github.com/Zayne-sprague/To-CoT-or-not-to-CoT`.

1 INTRODUCTION

Chain-of-thought (CoT) (Nye et al., 2022; Wei et al., 2022) has become a widely used prompting technique for eliciting reasoning from language models. CoT can provide human-readable explanations of how problems are solved (Joshi et al., 2023; Lanham et al., 2023), but most frequently it is invoked to improve an LLM's ability to answer complex questions via intermediate computation (Madaan & Yazdanbakhsh, 2022; Wang et al., 2023a; Dziri et al., 2023). Current post-training schemes for LLMs heavily infuse CoT capabilities into models: systems like ChatGPT or Llama 3.1 default to CoT when given reasoning problems (OpenAI, 2023; Dubey et al., 2024).

CoT has seen widespread usage, but it is most heavily explored in the domain of mathematical reasoning (Zhou et al., 2023a; Fu et al., 2023; Chae et al., 2024; Xu et al., 2024b; Qi et al., 2024). In fact, many "reasoning" methods for LLMs are evaluated *only* in the math domain; for instance, Lightman et al. (2024) frame their paper as "complex multi-step reasoning" and Mixtral-Large2's release [2] cited effort "enhancing the model's reasoning capabilities", but performance is only reported on GSM8K and MATH. CoT is reported to be effective across a wide range of studies, but many of these studies focus on a narrow slice of the task space. In areas beyond math, results show that CoT is not as useful (Kambhampati et al., 2024a) or can even hurt performance (Wang et al., 2024).

In this work, we aim to evaluate where prompt-based CoT helps and why. We begin with a systematic meta-analysis of recent literature that reports performance of CoT versus direct answering (DA). We then augment this picture by conducting experiments on 20 datasets and 14 contemporary LLMs across zero-shot and few-shot prompt settings. **Finding 1: CoT only helps substantially on problems requiring mathematical, logical, or algorithmic reasoning.** Figure 1 shows this holds both across the literature and our own experiments. We find only a few cases of large gain in other kinds of tasks, and many of these outliers feature some component of symbolic reasoning. For instance, on MMLU (Hendrycks et al., 2021a) and MMLU Pro (Wang et al., 2024), we analyze the improvements from CoT and find that CoT *only* gives benefit on math slices of the dataset. **As much as 95% of the total performance gain from CoT on MMLU is attributed to questions containing "=" in the question or generated output.** For non-math questions, we find no features to indicate when CoT will help.

How can we better understand *why* CoT improves on these questions and only these questions? The math and formal logical reasoning datasets we consider can be broken down into two stages of processing: a planning step (e.g., parsing a problem into equations) and an execution step (building intermediate outputs and working towards a solution) (Ye et al., 2023; Wang et al., 2023b; Sun et al., 2024). **Finding 2: CoT primarily helps with the execution step that performs computation and symbolic manipulation, but falls short of what LLMs with tool augmentation can do.** We find that LMs prompted with CoT can generate executable formal solution plans and execute those plans better than direct answering. But using LMs to generate a solution plan and then using an external symbolic solver to solve the plan outperforms using CoT for both steps for these tasks.

These results paint a picture that CoT's utility is often circumscribed by tool augmentation: on problems where CoT helps, we already have more powerful tools than CoT that we can employ, and on "soft reasoning" problems like commonsense where no tools exist, we see limited benefit from CoT. This characterization has two major implications. First, CoT is unnecessary for many problems where it is widely employed: there exist more efficient prompting strategies that yield similar performance for much lower inference cost. Second, we see a critical need to move beyond prompt-based CoT to more sophisticated approaches based on search, interacting agents, or models more heavily fine-tuned for CoT. Future work can explore how intermediate computation can be better used to solve challenging problems outside of the math and symbolic reasoning domains.

2 BACKGROUND: CHAIN-OF-THOUGHT

The tasks we consider in this work consist of a question $\mathbf{q} \in \Sigma^*$ for a vocabulary Σ and an answer $a \in \mathcal{L}(\mathbf{q})$ for a label set $\mathcal{L}(\mathbf{q})$. $\mathcal{L}(\mathbf{q})$ can consist of a data type like boolean or integer, classification labels, or problem-dependent labels like names of entities from $\mathbf{q}$. One exception that we still

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[2] https://mistral.ai/news/mistral-large-2407/

explore is BiGGen Bench (Kim et al., 2024), which instead relies on an LLM-as-a-judge (Dubois et al., 2023; Zheng et al., 2024b) to provide a label for generated long-form responses.

Prompting and chain-of-thought for reasoning   A large language model places distributions over strings $p(\mathbf{y}) = \prod_{i=1}^{n} p_{\mathrm{LM}}(y_i)$ where $\mathbf{y} \in \Sigma^*$. In practice, we can interpret these as conditional distributions $p(\mathbf{y} \mid \mathbf{x})$ where $\mathbf{x}$ is a user's prompt. Typical invocation of an LLM involves forming a prompt $\mathcal{I}(\mathbf{q})$ that wraps the question with additional instruction, then drawing a sample response $\tilde{\mathbf{y}} \sim p(\mathbf{y} \mid \mathcal{I}(\mathbf{q}))$, and finally returning $a = \mathrm{extract}(\tilde{\mathbf{y}})$ using some kind of answer extractor.

For the tasks we consider in this work, the output $\tilde{\mathbf{y}}$ can take one of two forms. A **direct answer** only contains a string realization of a; e.g., $\mathbf{y} = (\_185, 4)$ which is detokenized as the answer $a = 1854$. A **chain of thought** is a longer sequence $\mathbf{y}$ including other tokens beyond the answer, e.g., $\mathbf{y} = (\_185, 6, \_\mathrm{minus}, \_2, \_\mathrm{equals}, \_185, 4)$. In both cases, the $\mathrm{extract}$ function must parse and detokenize the output; in CoT, there is some extra work to spot where the answer is placed.

Our prompts can explicitly encourage use of direct answer or chain of thought as strategies, which we denote as $\mathcal{I}_{\mathrm{da}}$ and $\mathcal{I}_{\mathrm{cot}}$. For eliciting CoT, this includes strategies like telling a model to "*think step by step*" (Kojima et al., 2022). For directly answering a question, a prompt may say "*immediately generate the answer*". We track the average location of the answer in the generated output for both CoT and direct prompts in Appendix F.3 to ensure that direct answer prompts give the answer early in the output. We also ensure that $\mathrm{extract}$ can parse answers from the generated output for each model, prompt, and dataset combination used in our experiments, tailoring the $\mathrm{extract}$ function as needed to ensure low unparseable rates for each model and task.[3] All prompts and outputs per dataset per model have been uploaded to Huggingface and we include examples of some of our prompts in the Appendix J. We also experiment with few-shot CoT prompts, which we find perform similarly to zero-shot prompts; details about these are given in Appendix E.

Symbolic reasoning   Of key importance to this work is whether problems feature symbolic reasoning or not. We consider a problem to be **symbolic** if it can be grounded in a *natural, well agreed-upon* formal system. "12×4" is an example of a symbolic problem, which can be grounded in mathematics. Other systems include first-order logic (Saparov & He, 2023; Hua et al., 2024) or planning languages (Liu et al., 2023a; Valmeekam et al., 2023). Formally, for symbolic problems, we define a function f that acts as a map that produces some symbolic expression $\mathcal{S} = f(\mathbf{q})$ from the question. $\mathcal{S}$ can be used as input for a solver to derive an answer, $\hat{a} = \mathrm{solve}(\mathcal{S})$.

Conversely, a problem like *where on a river can you hold a cup upright to catch water on a sunny day?* from CommonsenseQA (Talmor et al., 2019) is **non-symbolic** by our definition. While this problem could be formalized with some kind of predicate logic (Zhou et al., 2022; Quan et al., 2024; Zhou et al., 2024) or grounded in some kind of physical simulation (Hao et al., 2023; Wong et al., 2023), there is not a natural nor well agreed-upon framework for solving it.

We view non-symbolic to symbolic reasoning as a spectrum. MuSR (Sprague et al., 2024) is a "semisymbolic" dataset in that it does contain an underlying formal system (e.g., for its murder mysteries portion, the notion that $\mathrm{motive}(X) \wedge \mathrm{means}(X) \wedge \mathrm{opportunity}(X) \implies \mathrm{murderer}(X)$), but also involves substantial commonsense reasoning that does not map onto a formal system. In these cases, we can still form $\mathcal{S} = f(\mathbf{q})$, but f must rely heavily on a language model and instantiate new information for $\mathcal{S}$ that is not directly represented in $\mathbf{q}$.

Central claim   Figure 1 shows that there are a large number of positive results on CoT reported in the literature. Informally, we believe many readers of the literature to hold the following view: $\mathcal{I}_{\mathrm{cot}}$ *will outperform* $\mathcal{I}_{\mathrm{da}}$ *on nearly all reasoning problems, whether those problems involve symbolic or non-symbolic reasoning.* Our evidence does *not* support this conjecture. We will show that this performance boost is strongest for symbolic and semi-symbolic tasks, while giving little to no improvement (or even hurting performance) on non-symbolic tasks.

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[3]We exclude a number of other "CoT-like" approaches in our analysis such as decomposed prompting (Khot et al., 2023; Zheng et al., 2024a) and multi-agent debate (Du et al., 2023; Chen et al., 2024). We focus on single prompt approaches. We deal with tool-augmented approaches in Section 5.

Table 1: A few categories for experimental comparisons. Full list in Appendix B.

Category	Description
Symbolic and algorithmic	Tasks involving symbol manipulation which can be solved by executing a program. This includes entity tracking datasets (e.g., SCONE, Coin Flip) and algorithmic tasks (e.g., BBH word sorting or finding shortest paths in a graph).
Math	Tasks requiring mathematical reasoning, from grade-school math to advanced mathematics, including physics questions.
Logical reasoning	Tasks designed to test for logical reasoning, whether deductive (Saparov & He, 2023, PrOntoQA), inductive (Bowen et al., 2024) or analogical (Ma et al., 2024) reasoning, including syllogisms and logical puzzles.
Encyclopedic knowledge	Tasks requiring expert-level in-depth knowledge beyond mere common-sense, usually in an open-book setting.
Mixed datasets	Datasets containing a variety of tasks, such as BIG-Bench Hard (BBH) or MMLU.
…	…

3 RESULTS FROM THE LITERATURE

Criteria and Process We investigate all papers from ICLR 2024, a representative ML venue, and two representative NLP venues, EACL 2024 and NAACL 2024 (including Findings and Workshop papers). This resulted in 4,642 papers total that filtered using automatic and manual methods to papers including experiments comparing chain-of-thought, $\mathcal{I}_{\text{cot}}$, against direct answering prompts, $\mathcal{I}_{\text{direct}}$. A total of 110 papers were found that matched our criteria with 1,218 experimental comparisons. We then grouped the comparisons by the types of tasks and datasets being evaluated. More details on our automatic and manual filtering, as well as our categorization, can be found in Appendix A and B.

Results Figure 2 shows the distribution of CoT deltas (CoT prompt minus the direct answer prompt performance) across our categorization of different task types found in the literature. Compared to Figure 1, we take the mean results per paper per category, indicated by blue dots, showing the trend across papers in the literature. The categories are ranked in order of ascending median CoT delta. The three categories which benefited the most from CoT are symbolic reasoning, math, and logical reasoning, with average improvements of 14.2, 12.3, 6.9, respectively. Average performance on these top three tasks with CoT was 56.9, whereas performance without CoT was 45.5. For other categories, the average performance with CoT was 56.8, compared to 56.1 without CoT. We do not consider this small improvement a victory for CoT. CoT involves more computation than direct answering, and a truly fair comparison between the methods should match the compute of the two methods, e.g., ensembling across multiple prompts.

Do any non-math datasets benefit from CoT? On the right side of Figure 2, we show the top 10 outliers from our observed trend, namely papers with high CoT deltas averaged across experiments in tasks *other than* math, symbolic, or logical reasoning. Although not categorized as math or logic, several of these are related to logical, mathematical or symbolic reasoning in some way. From this list, the dataset which benefits the most most from CoT is BIG-bench Hard (BBH) (Suzgun et al., 2023), a benchmark consisting largely of problems requiring algorithmic, arithmetic or logical reasoning. For instance, BIG-bench Navigate is a spatial reasoning task, but relies heavily on a mathematical primitive of counting steps taken to derive a final conclusion. Similarly, while BIG-bench Temporal is a temporal reasoning task (answering questions about when certain events could have occurred), it requires deductive reasoning to solve. In addition, Legal Argument Reasoning (SemEval-2024 Task 5) (Bongard et al., 2022) was categorized as *context-aware QA*, but also requires substantial reasoning ability. Finally, MMLU-Moral Scenarios (Hendrycks et al., 2021a) requires answering two independent questions at once, which essentially involves a symbolic combination of two simpler questions.
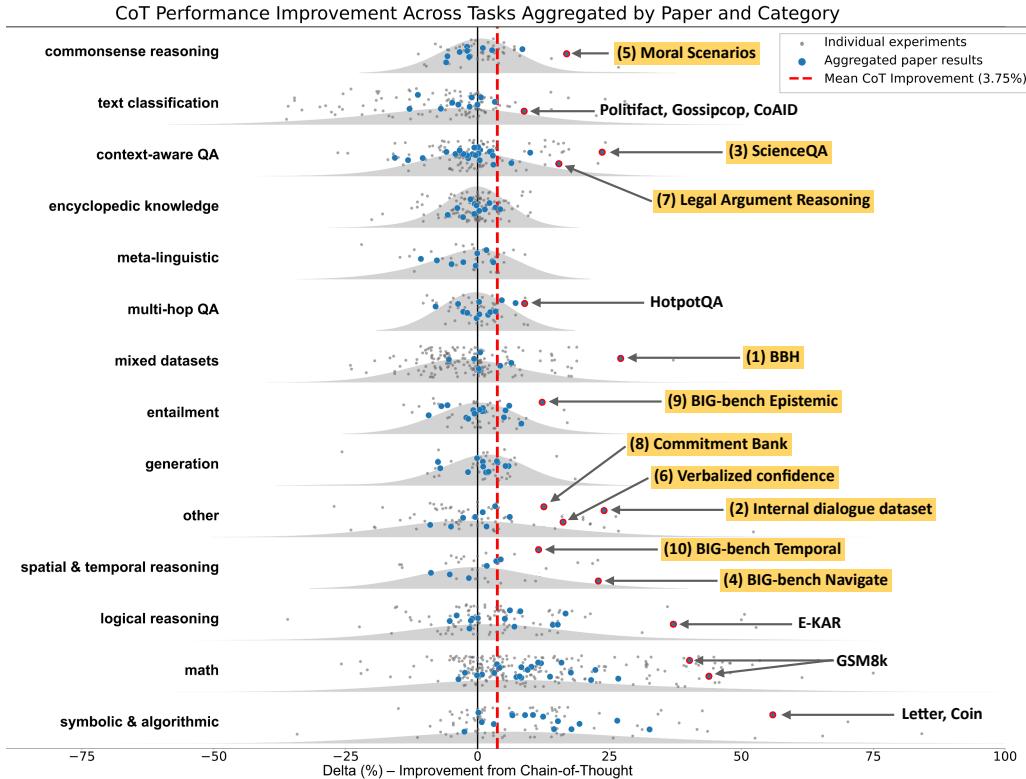
Figure 2: Results from our meta-analysis (grey dots) aggregated by paper and category (blue dots).

There are a few outliers that less clearly follow the trend. ScienceQA (Lu et al., 2022) consists of multiple choice questions across a range of natural and social science disciplines, though it is hard to interpret gains without knowing breaking down performance by subject or question type. The dialogue evaluation dataset from Jia et al. (2024) sees large improvements with CoT, but this is a proprietary dataset, and we note that other essay scoring results in our meta-analysis (Li et al., 2024; Stahl et al., 2024) did not show improvements with CoT. Other non-math, symbolic or logical datasets that benefit from CoT are Commitment Bank (de Marneffe et al., 2019) and the task of eliciting verbalized confidence (Xiong et al., 2024). Nevertheless, these are exceptions to the rule. The majority of the reported benefits from using CoT in the NLP and ML literature comes from math or math-related tasks.

4 RESULTS FROM EXPERIMENTS

4.1 EXPERIMENTAL SETUP

Dataset, Models, Prompts All datasets, models, and prompts we evaluate over can be found in detail in the tables 3, 4, and 5 of Appendix C. We restricted our experiments to English models commonly used and benchmarked on general reasoning datasets. Our datasets include those which are widely used in CoT and reasoning literature, including a mix of non-symbolic, semisymbolic, and symbolic reasoning. They span different formats, including multiple-choice, short-answer, and free-response; however, most of these datasets are multiple choice or short answer, as CoT is not typically used in long-form response settings. We also categorize each dataset into a larger category of reasoning required to solve it: Commonsense, Knowledge, Symbolic, Mathematical, and Soft Reasoning. We define Soft Reasoning as questions relying on commonsense and natural language but going beyond simple inferences about these statements. Finally, we explore several prompting strategies for eliciting reasoning from language models, as past work has emphasized the importance of the prompt (Yang et al., 2024). However, we generally found slight performance differences; see Appendix D for details. We therefore focus on prompts similar to Kojima et al. (2022) and Wei et al.
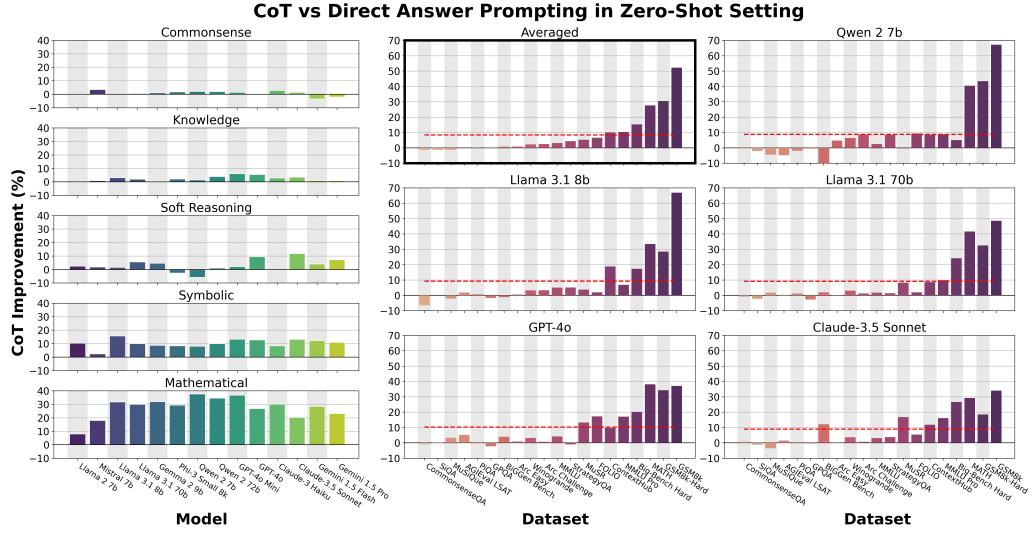
Figure 3: Left: Performance gain from using CoT for each reasoning category. Right: Performance gain from using CoT for each dataset, averaged across models and broken out across 5 representative models. Red lines indicate median improvement. In both plots we see a consistent trend: most improvements from using CoT are from math and symbolic reasoning.

(2022) for zero-shot and few-shot settings, respectively, with alterations to improve the model's ability to produce desired behavior (i.e., formats that allow for easily parsed answers). We upload all our prompts and outputs for each model for each prompting strategy on Huggingface.[4]

Implementation Details   We use a high-throughput inference package, vLLM (Kwon et al., 2023), for the model inference process. We use greedy decoding on all models. Our prompts are taken from the Llama 3.1 evaluations when available (Dubey et al., 2024), and minor adjustments are made to unify prompting strategies. For other datasets, we either use the standard prompt for the dataset from the corresponding original paper or implement our own prompt. Our answer parser (extract) is tailored to each dataset and model. Specific details about each dataset, its prompts, and answer extractor can be found in Appendix C.

4.2   RESULTS

Where does zero-shot CoT improve over direct prompts?   *On datasets that require math (MATH, GSM8K) or formal logic (ContextHub, MuSR to a lesser degree) to answer the problem.*

Figure 3 on the left shows the average CoT performance improvement for each reasoning category from Figure 1 (right); raw numbers can be found in Table 6 of the Appendix. On the right, Figure 3 shows the performance gain from using CoT for each dataset, averaged across all models and for a selection of individual models. On non-symbolic reasoning categories and datasets, specifically those that contain questions primarily involving commonsense (CSQA, PIQA, SiQA), language understanding (WinoGrande), and reading comprehension (AGI LSAT, ARC-Easy, ARC-Challenge), there is little to no separation between the performance of zero-shot CoT and zero-shot direct answer. Despite these datasets involving reasoning, CoT does not yield improvement.

By contrast, the mathematical and symbolic categories get larger boosts in improvements alongside symbolic and many semi-symbolic datasets. MATH and GSM8K show gains as large as 41.6% and 66.9%, respectively. The semi-symbolic datasets like ContextHub and MuSR Murder Mysteries show moderate gains. These datasets require the application of logical rules to reach the answer, e.g., first-order logic parsed from simple natural language (ContextHub) or more complex commonsense statements (MuSR Murder Mysteries). All results are shown in the Appendix F.1 as well as a full list of numeric results for both CoT and direct answer prompting in Table 7. We also explored the few-shot setting and found it had little impact on when CoT will help; see Appendix E.

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[4]https://huggingface.co/collections/TAUR-Lab/cot-analysis-project-66bbb9e5e0156e65059895f5

Does the answer format impact where CoT will help?   *Not much. Free response capabilities required for BigGen Bench may not benefit from pre-planning.*

Many of the commonly-used datasets for problems other than math are multiple choice. We highlight here that CoT has similar performance to direct answer across models for two datasets that are not multiple-choice and contain varying levels of non-symbolic reasoning. First, MuSiQue (Trivedi et al., 2022) is a short-form QA task requiring multi-hop reasoning. We consider this a semi-symbolic dataset as the questions have an explicit multi-hop structure. Because answer spans in MuSiQue can be paraphrased in many different ways, we use GPT-4o to judge if two answer spans are equivalent. Despite being semi-symbolic, we see no overall improvement from CoT.

Second, BiGGen Bench (Kim et al., 2024) uses free-form responses as the answer to a question, and an LLM-as-a-judge is used to evaluate these responses on a scale of 1 to 5. Because free-form responses blur the lines between CoT and direct answering, we create a new prompt that asks the language model to plan the free response before giving it. We then only pass the free response to the judge (GPT-4o-mini in our case) with the prompt from Kim et al. (2024). We also filter out any questions that explicitly state "Think step-by-step". We plot the performance of BiGGen Bench as the number of times a response receives a score of 4 or better. Despite including many reasoning questions (including several categories of math) and other categories, such as planning, we only see a mild improvement here. Because previous experiments show CoT helping on similar types of questions in the QA format, the lack of similar improvements here could imply that pre-planning is insufficient for unlocking reasoning capabilities in the LLM. Future work is needed to prove this.

Are the gains in Knowledge, Soft Reasoning, and Commonsense significant?   *Mostly no, except for MMLU, StrategyQA, and MuSR.*

We tested the significance of the improvements from CoT on the 13 datasets in the Knowledge, Soft Reasoning, and Commonsense reasoning categories using paired bootstrapping to assess whether CoT gives a significant improvement. To account for multiple comparisons, we applied a Bonferroni correction, setting the p-value to 0.00027 to account for the 14 models and 13 datasets. About 32% (59) of the datasets that show a benefit in these three reasoning categories were considered significant. Nearly half of these comparisons (26) are on MMLU and MMLU Pro. On these datasets, we find that CoT is mainly helping on math-related questions. StrategyQA and MuSR also received a consistent performance boost across 10 and 6 models respectively. StrategyQA is often used to benchmark reasoning methods and is built specifically to get a benefit from methods that decompose the question into steps, so a gain in performance is not unprecedented. MuSR, similarly, was built to have multiple steps of complex natural language reasoning, which may receive benefits from CoT. The remaining datasets that receive significant benefits are spread across the datasets and models.

Why do MMLU and MMLU Pro get a boost?   MMLU and MMLU Pro contain many different questions requiring different types of reasoning. We separated MMLU and MMLU Pro questions into two bins, those related to math and those not related to math, by checking if the questions text or generated response from the LLM includes an "=". Figure 4 shows that a majority of the performance gain seen from MMLU and MMLU Pro is from the math slices of each dataset. See more details in Appendix G.

5   STRENGTHS AND WEAKNESSES OF COT AT FORMAL REASONING

Previous sections establish that CoT primarily helps with symbolic reasoning tasks, but not why. Many symbolic and semi-symbolic tasks be broken down into two stages (Ye et al., 2023; Pan et al., 2023; Jiang et al., 2024): planning, either via a formal or informal specification via prompting (Sun et al., 2024; Wang et al., 2023b), and execution, using the same LM or external solvers. In this section, we attribute the performance gains from CoT on symbolic tasks to these two stages.

Given a question that requires symbolic reasoning, we define the **planning** stage as extracting all variables from the context into a formal specification and defining their relations. The **execution** stage uses a solver that takes as input a plan and can be run in an orderly fashion to derive the final answer. Using our notation from Section 2, let $f(\mathbf{q}) = \mathcal{I}^m_{\text{planning}}(\mathbf{q})$ be a mapping of the question $\mathbf{q}$ to a symbolic plan $\mathcal{S}_{\text{plan}}$ that can be executed by the language model or by an external symbolic solver, $\hat{a} = \text{solve}(\mathcal{S}_{\text{plan}})$, where $\hat{a}$ is the final answer for $\mathbf{q}$.
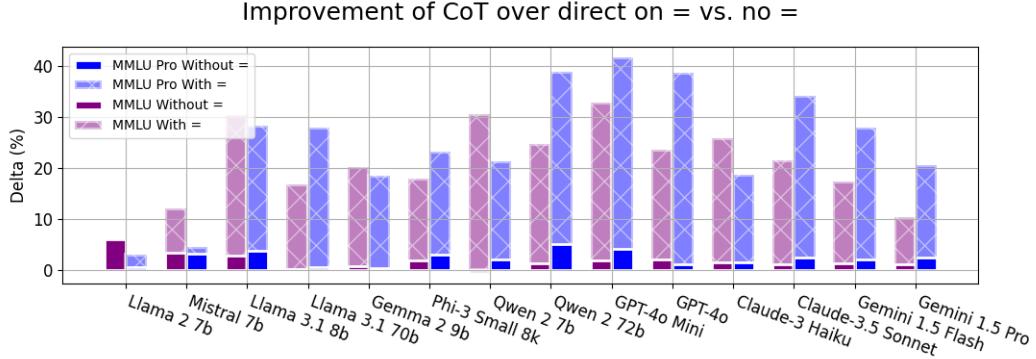
Figure 4: CoT deltas between MMLU and MMLU Pro performance when a question or generated response contains an "=" (With =) or not (Without =). We filter out any questions that do not result in a final answer (degeneration, etc.). CoT primarily helps on the pairs of questions and generations that contain an "=", which indicates math-related questions.
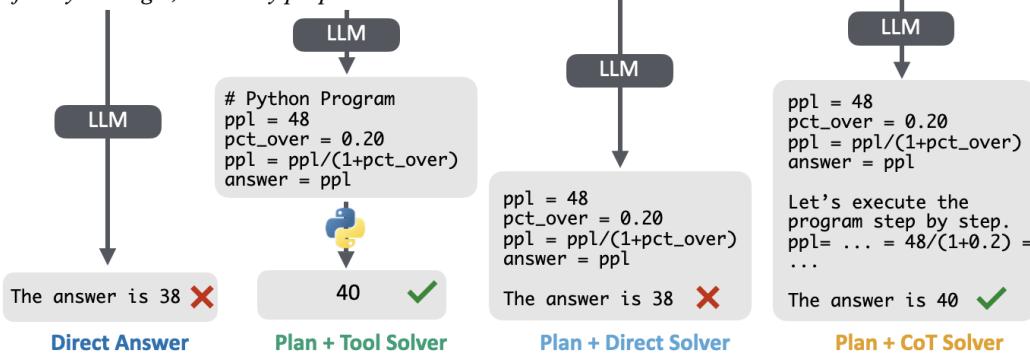

Figure 5: Prompt variants that separate planning and execution for GSM8K. For all prompt variants besides direct answer and CoT (not shown), we few-shot prompt an LLM to first generate a Python program as a solution plan. For Plan + Direct Solver, the LLM is prompted to directly give an answer from the plan; for Plan + CoT Solver, the LLM is prompted to solve the plan step-by-step with CoT and give an answer; for Plan + Tool Solver, we feed the plan into a Python interpreter.

By separating planning and execution in this way, we can test how much a language model can gain from only having a plan, to having a plan and solving it with CoT, or to having a plan and then solving it with an external symbolic solver. Given a plan $\mathcal{S}_{\text{plan}} \sim \mathcal{I}_{\text{planning}}^m(\mathbf{q})$, we compare the performance of the settings below to evaluate at which stage LM is most effective and falls short.

5.1 SETTINGS EVALUATED

Settings 1 and 2: Few-shot direct answer and CoT: We use the few-shot direct answer and CoT prompts from Section 4.1 as baselines. Figure 5 includes an example of each setting on GSM8K.

Settings 3 and 4: Plan + Direct Solver and Plan + CoT Solver: Here we use inspiration from Xu et al. (2024a) and generate a symbolic plan using the same strategy as Ye et al. (2023). Specifically, we use a few-shot prompt $\mathcal{I}_{\text{planning}}^m$ to generate a formal specification $\mathcal{S}_{\text{plan}}$ that should be executable by a symbolic solver. In the same prompt LMs are asked to solve their generated specification $\mathcal{S}_{\text{plan}}$ and derive the final answer $\tilde{\mathbf{y}} \sim p(\mathbf{y} \mid \mathcal{I}_{\text{da}}(\mathcal{S}_{\text{plan}}))$, either directly giving the answer after generating the specification (**Plan + Direct Solver**) or providing step-by-step explanations and tracking of intermediate steps for the derivation (**Plan + CoT Solver**). Particularly, $\mathcal{S}_{\text{plan}}$ is a Python program for math datasets, and is a set of first-order logic specifications for logical reasoning datasets.
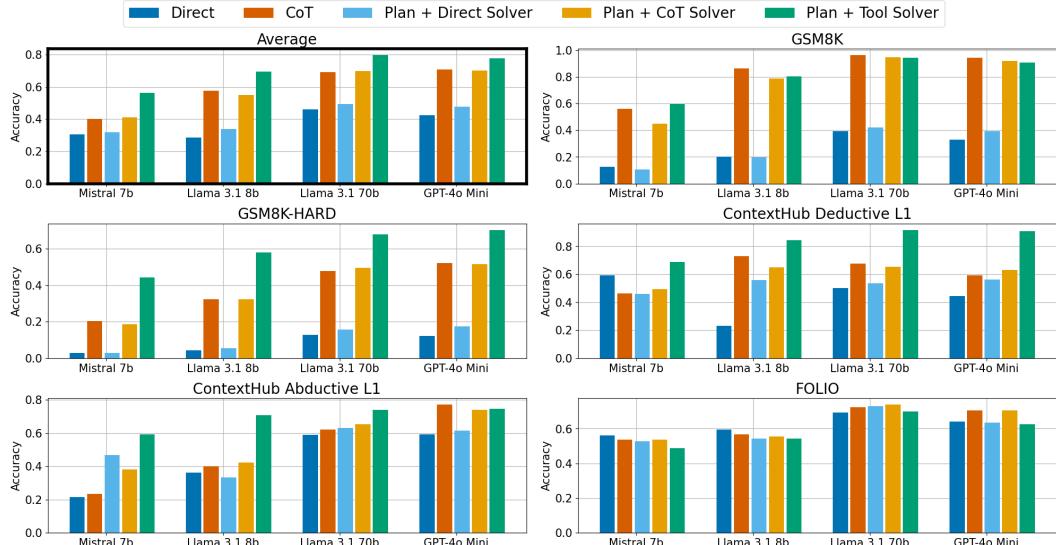
Figure 6: Performance of prompt variants that separate planning and execution for math and logical reasoning datasets. Despite outperforming direct answer for solving a formal plan and deriving the final answer, CoT is still limited in performing symbolic computations: there is a large performance boost from Plan + Tool Solver over CoT and Plan + CoT Solver on average across all models.

Setting 5: Plan + Tool Solver: We then evaluate how effective CoT can be at performing symbolic computations compared with external symbolic solvers. Following prior work on augmenting LMs with tools for math and logic questions (Ye et al., 2023; Pan et al., 2023; Gao et al., 2023; Chen et al., 2023), we generate $\mathcal{S}_{\text{plan}}$ the same way as in CoT Solver, but now feed in the plan into a symbolic solver (Python interpreter or a SMT Solver), such that $\hat{a} = \text{solve}(\mathcal{S}_{\text{plan}})$.

Evaluation Setup: We compare the performance of each setting on math (GSM8K) and logical reasoning (ContextHub and FOLIO) datasets. We follow Gao et al. (2023) to include GSM8K-Hard, a minimally modified version that replaces numbers of GSM8K with larger numbers, to account for the possibility of recent LLMs overfitting GSM8K by data contamination (Zhang et al., 2024).

For Plan + Direct solver and Plan + CoT solver, we use the few-shot prompts from Ye et al. (2023). For Plan + Tool solver, we use state-of-the-art tool-augmented prompting methods. Particularly, for GSM8K, we use Program-aided Language Model (Gao et al., 2023, PAL) that executes the LM-generated plan with a Python interpreter. For logical reasoning datasets, we use Satisfiability-Aided Language Model (Ye et al., 2023, SatLM) that uses automated theorem prover Z3 (De Moura & Bjørner, 2008) to solve the generated specifications. If the generated plan cannot be parsed by the tool, we use random guessing when the question is multiple choice, and mark it incorrect otherwise.

5.2 Evaluation Results

Figure 6 shows the results across a representative selection of models. Detailed numerical results, including the unparseable rates of model-generated plans, can be found in Appendix H.

When comparing direct answer with Plan + Direct solver and Plan + CoT solver, we note that for many datasets and models, only having a plan does not account for most of the performance gain. **Compared with direct answer, CoT or Plan + CoT solver is needed for strong performance. Tracking the execution with one of these methods gives the strongest accuracy benefit, especially for math-heavy datasets.**

Despite their strength over direct answer and Plan + Direct solver, **CoT and Plan + CoT solver are dominated by Plan + Tool solver in most settings**. LLMs are limited by their ability to execute and track steps compared with symbolic solvers.

We argue that these results provide an explanation of why CoT helps on symbolic tasks. While all tasks could feasibly benefit from a detailed description of how to solve each individual question (e.g., a *plan* in the context of this section), CoT only outperforms direct answer when these steps require a substantial amount of tracing and computation. In these settings, we can see clear performance

benefit from using symbolic solvers; **CoT appears to be a poor (but universal) approximation to such solvers**. When possible, LLMs should be paired with symbolic solvers at inference time when solving symbolic tasks to achieve consistently better performance over direct answer **and** CoT.

6 DISCUSSION AND RELATED WORK

Where is CoT helping and why? Our results showing CoT improvement for math and logic aligns well with early work on CoT for LLMs such as Scratchpads (Nye et al., 2022). As CoT gained popularity, its application has broadened to tasks that canonically do not require multiple steps. It can often yield small improvements over direct answering. We believe this led to the current prevailing sentiment that deliberation should improve performance on any task requiring some type of reasoning (our original claim from Section 2). However, our results show a clear separation between performance on non-symbolic and symbolic tasks. If, in theory, any question could benefit from deliberation, why is CoT only benefiting the questions that can be solved through symbolic manipulation? Our results from Section 5 suggest that the primary benefit of CoT comes in the ability to execute symbolic steps and track their output. Not all tasks have this feature: for example, questions from CommonsenseQA can hardly be translated into formally grounded and executable solution plans. Datasets like StrategyQA may feature multiple steps of reasoning, but executing those steps is not complex, so the benefits of CoT are small. It is unclear whether explicitly instilling models with particular modes of deliberation, like process of elimination for multiple choice questions, might make them more effective for non-symbolic tasks, or whether there's a fundamental limitation imposed by their pre-training data. We leave this distinction for future work.

Can we improve CoT further? Our work treats chain-of-thought variants that explicitly don't involve multiple inferences. There is evidence that using additional calls to LLMs can help (Du et al., 2023; Yao et al., 2023; Besta et al., 2023; Chen et al., 2024), but these methods use significantly increased computation, and careful benchmarking sometimes reveals that naive techniques are as good as iterative ones (Olausson et al., 2024). However, past theoretical results show that Transformers are augmented in a fundamental way by CoT (Liu et al., 2023b; Merrill & Sabharwal, 2024); we believe this indicates the potential for improving CoT beyond prompt-based CoT. On the other hand, recent methods showing benefit from "internalizing" CoT (Deng et al., 2024) may indicate that explicit generation of intermediate tokens is not used to its full potential.

Limitations One set of tasks we do not cover in our experiments (except for BiGGen Bench) is long-horizon planning. However, many works in the literature have already discussed the efficacy of planning with CoT. We also do not address the data contamination of some of these models on the datasets. We try to mitigate this by including multiple models, datasets (new and old), and our meta-analysis. For more discussion of planning and dataset contamination, see Appendix I.

7 CONCLUSION

In this work, we characterize the performance of prompt-based CoT through a meta-analysis of the literature and experiments across different models, datasets, and prompts. We find that CoT predominantly helps on math and formal logic, largely due to its ability to trace the intermediate steps of a problem. But CoT rarely outperforms tool-augmented approaches for these same problems. We believe that CoT remains a powerful technique, but to give improvement across a wider range of NLP tasks, research should move beyond prompt-based CoT to new paradigms like search, interacting agents, or better fine-tuned models.

REPRODUCIBILITY

For our experiments, we provide in-depth details of how we evaluated models on each dataset in Section 4.1 and Appendix C. Furthermore, we release all prompts for every dataset on Huggingface, including per model output and sampling parameters. For our meta-analysis of the literature, we describe our filtering criteria and process of annotating experiments into high-level categories in Section 3 and Appendix B. We also release the full list of papers in our meta-analysis together with extracted experimental comparisons and task category annotations.

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REFERENCES

Marah Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Hassan Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat Singh Behl, Alon Benhaim, Misha Bilenko, Johan Bjorck, Sébastien Bubeck, Martin Cai, Caio C'esar Teodoro Mendes, Weizhu Chen, Vishrav Chaudhary, Parul Chopra, Allison Del Giorno, Gustavo de Rosa, Matthew Dixon, Ronen Eldan, Dan Iter, Abhishek Goswami, Suriya Gunasekar, Emman Haider, Junheng Hao, Russell J. Hewett, Jamie Huynh, Mojan Javaheripi, Xin Jin, Piero Kauffmann, Nikos Karampatziakis, Dongwoo Kim, Mahoud Khademi, Lev Kurilenko, James R. Lee, Yin Tat Lee, Yuanzhi Li, Chen Liang, Weishung Liu, Eric Lin, Zeqi Lin, Piyush Madan, Arindam Mitra, Hardik Modi, Anh Nguyen, Brandon Norick, Barun Patra, Daniel Perez-Becker, Thomas Portet, Reid Pryzant, Heyang Qin, Marko Radmilac, Corby Rosset, Sambudha Roy, Olli Saarikivi, Amin Saied, Adil Salim, Michael Santacroce, Shital Shah, Ning Shang, Hiteshi Sharma, Xianmin Song, Olatunji Ruwase, Xin Wang, Rachel Ward, Guanhua Wang, Philipp Witte, Michael Wyatt, Can Xu, Jiahang Xu, Sonali Yadav, Fan Yang, Ziyi Yang, Donghan Yu, Cheng-Yuan Zhang, Cyril Zhang, Jianwen Zhang, Li Lyna Zhang, Yi Zhang, Yunan Zhang, and Xiren Zhou. Phi-3 technical report: A highly capable language model locally on your phone. *ArXiv*, abs/2404.14219, 2024. URL https://api.semanticscholar.org/CorpusID:269293048.

Anthropic. The Claude 3 Model Family: Opus, Sonnet, Haiku. a. URL https://www-cdn.anthropic.com/de8ba9b01c9ab7cbabf5c33b80b7bbc618857627/Model_Card_Claude_3.pdf.

Anthropic. Claude 3.5 Sonnet Model Card Addendum. b. URL https://www-cdn.anthropic.com/fed9cc193a14b84131812372d8d5857f8f304c52/Model_Card_Claude_3_Addendum.pdf.

Maciej Besta, Nils Blach, Ales Kubicek, Robert Gerstenberger, Michal Podstawski, Lukas Gianinazzi, Joanna Gajda, Tomasz Lehmann, Hubert Niewiadomski, Piotr Nyczyk, and Torsten Hoefler. Graph of thoughts: Solving elaborate problems with large language models. In *AAAI Conference on Artificial Intelligence*, 2023. URL https://api.semanticscholar.org/CorpusID:261030303.

Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. Piqa: Reasoning about physical commonsense in natural language. In *AAAI Conference on Artificial Intelligence*, 2019. URL https://api.semanticscholar.org/CorpusID:208290939.

Leonard Bongard, Lena Held, and Ivan Habernal. The legal argument reasoning task in civil procedure. In Nikolaos Aletras, Ilias Chalkidis, Leslie Barrett, Cătălina Goanță, and Daniel Preoțiuc-Pietro (eds.), *Proceedings of the Natural Legal Language Processing Workshop 2022*, pp. 194–207, Abu Dhabi, United Arab Emirates (Hybrid), December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.nllp-1.17. URL https://aclanthology.org/2022.nllp-1.17.

Chen Bowen, Rune Sætre, and Yusuke Miyao. A comprehensive evaluation of inductive reasoning capabilities and problem solving in large language models. In Yvette Graham and Matthew Purver (eds.), *Findings of the Association for Computational Linguistics: EACL 2024*, pp. 323–339, St. Julian's, Malta, March 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.findings-eacl.22.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh,

Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 1877–1901. Curran Associates, Inc., 2020. URL `https://proceedings.neurips.cc/paper_files/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf`.

Hyungjoo Chae, Yeonghyeon Kim, Seungone Kim, Kai Tzu-iunn Ong, Beong-woo Kwak, Moohyeon Kim, Seonghwan Kim, Taeyoon Kwon, Jiwan Chung, Youngjae Yu, et al. Language Models as Compilers: Simulating Pseudocode Execution Improves Algorithmic Reasoning in Language Models. *arXiv preprint arXiv:2404.02575*, 2024.

Chih Yao Chen, Swarnadeep Saha, and Mohit Bansal. Reconcile: Round-table conference improves reasoning via consensus among diverse LLMs, 2024. URL `https://openreview.net/forum?id=Yol6nUVIJD`.

Wenhu Chen, Xueguang Ma, Xinyi Wang, and William W. Cohen. Program of thoughts prompting: Disentangling computation from reasoning for numerical reasoning tasks. *Transactions on Machine Learning Research*, 2023. ISSN 2835-8856. URL `https://openreview.net/forum?id=YfZ4ZPt8zd`.

Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have Solved Question Answering? Try ARC, the AI2 Reasoning Challenge. *arXiv:1803.05457v1*, 2018.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems. *ArXiv*, abs/2110.14168, 2021. URL `https://api.semanticscholar.org/CorpusID:239998651`.

Marie-Catherine de Marneffe, Mandy Simons, and Judith Tonhauser. The CommitmentBank: Investigating projection in naturally occurring discourse. In *Proceedings of Sinn und Bedeutung 23*, 2019.

Leonardo De Moura and Nikolaj Bjørner. Z3: An efficient SMT solver. In *Proceedings of the Theory and Practice of Software, 14th International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, TACAS'08/ETAPS'08, pp. 337–340, Berlin, Heidelberg, 2008. Springer-Verlag. ISBN 3540787992.

Yuntian Deng, Yejin Choi, and Stuart Shieber. From Explicit CoT to Implicit CoT: Learning to Internalize CoT Step by Step. *arXiv preprint arXiv:2405.14838*, 2024.

Yilun Du, Shuang Li, Antonio Torralba, Joshua B Tenenbaum, and Igor Mordatch. Improving factuality and reasoning in language models through multiagent debate. *arXiv preprint arXiv:2305.14325*, 2023.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The Llama 3 Herd of Models. *arXiv preprint arXiv:2407.21783*, 2024.

Yann Dubois, Xuechen Li, Rohan Taori, Tianyi Zhang, Ishaan Gulrajani, Jimmy Ba, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. AlpacaFarm: A Simulation Framework for Methods that Learn from Human Feedback, 2023.

Nouha Dziri, Ximing Lu, Melanie Sclar, Xiang Lorraine Li, Liwei Jiang, Bill Yuchen Lin, Sean Welleck, Peter West, Chandra Bhagavatula, Ronan Le Bras, Jena D. Hwang, Soumya Sanyal, Xiang Ren, Allyson Ettinger, Zaid Harchaoui, and Yejin Choi. Faith and fate: Limits of transformers on compositionality. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL `https://openreview.net/forum?id=Fkckkr3ya8`.

Yao Fu, Hao Peng, Ashish Sabharwal, Peter Clark, and Tushar Khot. Complexity-based prompting for multi-step reasoning. In *The Eleventh International Conference on Learning Representations*, 2023. URL `https://openreview.net/forum?id=yf1icZHC-l9`.

Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. Pal: program-aided language models. In *Proceedings of the 40th International Conference on Machine Learning*, ICML'23. JMLR.org, 2023.

Mor Geva, Daniel Khashabi, Elad Segal, Tushar Khot, Dan Roth, and Jonathan Berant. Did Aristotle use a laptop? A question answering benchmark with implicit reasoning strategies. *Transactions of the Association for Computational Linguistics*, 9:346–361, February 2021. ISSN 2307-387X. doi: 10.1162/tacl_a_00370.

L. Guan, Yifan Zhou, Denis Liu, Yantian Zha, Heni Ben Amor, and Subbarao Kambhampati. "Task Success" is not Enough: Investigating the Use of Video-Language Models as Behavior Critics for Catching Undesirable Agent Behaviors. *ArXiv*, abs/2402.04210, 2024. URL https://api.semanticscholar.org/CorpusID:267500077.

Atharva Gundawar, Mudit Verma, L. Guan, Karthik Valmeekam, Siddhant Bhambri, and Subbarao Kambhampati. Robust Planning with LLM-Modulo Framework: Case Study in Travel Planning. *ArXiv*, abs/2405.20625, 2024. URL https://api.semanticscholar.org/CorpusID:270199944.

Simeng Han, Hailey Schoelkopf, Yilun Zhao, Zhenting Qi, Martin Riddell, Luke Benson, Lucy Sun, Ekaterina Zubova, Yujie Qiao, Matthew Burtell, David Peng, Jonathan Fan, Yixin Liu, Brian Wong, Malcolm Sailor, Ansong Ni, Linyong Nan, Jungo Kasai, Tao Yu, Rui Zhang, Shafiq Joty, Alexander R. Fabbri, Wojciech Kryscinski, Xi Victoria Lin, Caiming Xiong, and Dragomir Radev. FOLIO: Natural Language Reasoning with First-Order Logic. *arXiv preprint arXiv:2209.00840*, 2022. URL https://arxiv.org/abs/2209.00840.

Shibo Hao, Yi Gu, Haodi Ma, Joshua Hong, Zhen Wang, Daisy Wang, and Zhiting Hu. Reasoning with language model is planning with world model. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 8154–8173, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.507. URL https://aclanthology.org/2023.emnlp-main.507.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*, 2021a.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring Mathematical Problem Solving With the MATH Dataset. *NeurIPS*, 2021b.

Hanxu Hu, Hongyuan Lu, Huajian Zhang, Wai Lam, and Yue Zhang. Chain-of-symbol prompting elicits planning in large langauge models, 2023.

Wenyue Hua, Kaijie Zhu, Lingyao Li, Lizhou Fan, Shuhang Lin, Mingyu Jin, Haochen Xue, Zelong Li, Jindong Wang, and Yongfeng Zhang. Disentangling Logic: The Role of Context in Large Language Model Reasoning Capabilities. *ArXiv*, abs/2406.02787, 2024. URL https://api.semanticscholar.org/CorpusID:270258104.

Wenlong Huang, Pieter Abbeel, Deepak Pathak, and Igor Mordatch. Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. *arXiv preprint arXiv:2201.07207*, 2022.

Jinghan Jia, Abi Komma, Timothy Leffel, Xujun Peng, Ajay Nagesh, Tamer Soliman, Aram Galstyan, and Anoop Kumar. Leveraging LLMs for dialogue quality measurement. In Yi Yang, Aida Davani, Avi Sil, and Anoop Kumar (eds.), *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 6: Industry Track)*, pp. 359–367, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-industry.30. URL https://aclanthology.org/2024.naacl-industry.30.

Albert Qiaochu Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L'elio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mistral 7b. *ArXiv*, abs/2310.06825, 2023. URL `https://api.semanticscholar.org/CorpusID:263830494`.

Dongwei Jiang, Marcio Fonseca, and Shay B. Cohen. Leanreasoner: Boosting complex logical reasoning with lean. In Kevin Duh, Helena Gómez-Adorno, and Steven Bethard (eds.), *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), NAACL 2024, Mexico City, Mexico, June 16-21, 2024*, pp. 7497–7510. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.NAACL-LONG.416. URL `https://doi.org/10.18653/v1/2024.naacl-long.416`.

Brihi Joshi, Ziyi Liu, Sahana Ramnath, Aaron Chan, Zhewei Tong, Shaoliang Nie, Qifan Wang, Yejin Choi, and Xiang Ren. Are Machine Rationales (Not) Useful to Humans? Measuring and Improving Human Utility of Free-text Rationales. *ArXiv*, abs/2305.07095, 2023. URL `https://api.semanticscholar.org/CorpusID:258676376`.

Subbarao Kambhampati. Can large language models reason and plan? *Annals of the New York Academy of Sciences*, 1534:15 – 18, 2024. URL `https://api.semanticscholar.org/CorpusID:268249961`.

Subbarao Kambhampati, Karthik Valmeekam, Lin Guan, Mudit Verma, Kaya Stechly, Siddhant Bhambri, Lucas Paul Saldyt, and Anil B Murthy. Position: LLMs can't plan, but can help planning in LLM-modulo frameworks. In Ruslan Salakhutdinov, Zico Kolter, Katherine Heller, Adrian Weller, Nuria Oliver, Jonathan Scarlett, and Felix Berkenkamp (eds.), *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *Proceedings of Machine Learning Research*, pp. 22895–22907. PMLR, 21–27 Jul 2024a. URL `https://proceedings.mlr.press/v235/kambhampati24a.html`.

Subbarao Kambhampati, Karthik Valmeekam, Lin Guan, Mudit Verma, Kaya Stechly, Siddhant Bhambri, Lucas Paul Saldyt, and Anil B Murthy. Position: LLMs can't plan, but can help planning in LLM-modulo frameworks. In *Forty-first International Conference on Machine Learning*, 2024b. URL `https://openreview.net/forum?id=Th8JPEmH4z`.

Liwei Kang, Zirui Zhao, David Hsu, and Wee Sun Lee. On the empirical complexity of reasoning and planning in llms. *arXiv preprint arXiv:2404.11041*, 2024.

Marzena Karpinska, Katherine Thai, Kyle Lo, Tanya Goyal, and Mohit Iyyer. One thousand and one pairs: A "novel" challenge for long-context language models. *ArXiv*, abs/2406.16264, 2024. URL `https://api.semanticscholar.org/CorpusID:270703648`.

Tushar Khot, H. Trivedi, Matthew Finlayson, Yao Fu, Kyle Richardson, Peter Clark, and Ashish Sabharwal. Decomposed prompting: A modular approach for solving complex tasks. In *The International Conference on Learning Representations*, volume abs/2210.02406, 2023. URL `https://api.semanticscholar.org/CorpusID:252715485`.

Seungone Kim, Juyoung Suk, Ji Yong Cho, Shayne Longpre, Chaeeun Kim, Dongkeun Yoon, Guijin Son, Yejin Cho, Sheikh Shafayat, Jinheon Baek, et al. The BiGGen Bench: A Principled Benchmark for Fine-grained Evaluation of Language Models with Language Models. *arXiv preprint arXiv:2406.05761*, 2024.

Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. In *Proceedings of the 36th International Conference on Neural Information Processing Systems*, Red Hook, NY, USA, 2022. Curran Associates Inc. ISBN 9781713871088.

Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.

Brenden M. Lake and Marco Baroni. Generalization without systematicity: On the compositional skills of sequence-to-sequence recurrent networks. In Jennifer G. Dy and Andreas Krause (eds.), *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pp. 2879–2888. PMLR, 2018. URL http://proceedings.mlr.press/v80/lake18a.html.

Tamera Lanham, Anna Chen, Ansh Radhakrishnan, Benoit Steiner, Carson Denison, Danny Hernandez, Dustin Li, Esin Durmus, Evan Hubinger, Jackson Kernion, et al. Measuring faithfulness in chain-of-thought reasoning. *arXiv preprint arXiv:2307.13702*, 2023.

Fangyu Lei, Qian Liu, Yiming Huang, Shizhu He, Jun Zhao, and Kang Liu. S3Eval: A synthetic, scalable, systematic evaluation suite for large language model. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pp. 1259–1286, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.69. URL https://aclanthology.org/2024.naacl-long.69.

Tianwen Li, Zhexiong Liu, Lindsay Matsumura, Elaine Wang, Diane Litman, and Richard Correnti. Using large language models to assess young students' writing revisions. In Ekaterina Kochmar, Marie Bexte, Jill Burstein, Andrea Horbach, Ronja Laarmann-Quante, Anaïs Tack, Victoria Yaneva, and Zheng Yuan (eds.), *Proceedings of the 19th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2024)*, pp. 365–380, Mexico City, Mexico, June 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.bea-1.30.

Hunter Lightman, Vineet Kosaraju, Yuri Burda, Harrison Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. Let's verify step by step. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=v8L0pN6EOi.

B. Liu, Yuqian Jiang, Xiaohan Zhang, Qian Liu, Shiqi Zhang, Joydeep Biswas, and Peter Stone. Llm+p: Empowering large language models with optimal planning proficiency. *ArXiv*, abs/2304.11477, 2023a. URL https://api.semanticscholar.org/CorpusID:258298051.

Bingbin Liu, Jordan T. Ash, Surbhi Goel, Akshay Krishnamurthy, and Cyril Zhang. Transformers learn shortcuts to automata. In *The Eleventh International Conference on Learning Representations*, 2023b. URL https://openreview.net/forum?id=De4FYqjFueZ.

Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/11332b6b6cf4485b84afadb1352d3a9a-Abstract-Conference.html.

Yingwei Ma, Yue Liu, Yue Yu, Yuanliang Zhang, Yu Jiang, Changjian Wang, and Shanshan Li. At Which Training Stage Does Code Data Help LLMs Reasoning? In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=KIPJKST4gw.

Aman Madaan and Amir Yazdanbakhsh. Text and patterns: For effective chain of thought, it takes two to tango. *ArXiv*, abs/2209.07686, 2022. URL https://api.semanticscholar.org/CorpusID:252355328.

William Merrill and Ashish Sabharwal. The expressive power of transformers with chain of thought. In *The International Conference on Learning Representations*, volume abs/2310.07923, 2024. URL https://api.semanticscholar.org/CorpusID:263909434.

Maxwell Nye, Anders Johan Andreassen, Guy Gur-Ari, Henryk Michalewski, Jacob Austin, David Bieber, David Dohan, Aitor Lewkowycz, Maarten Bosma, David Luan, Charles Sutton, and Augustus Odena. Show your work: Scratchpads for intermediate computation with language models, 2022. URL `https://openreview.net/forum?id=iedYJm92o0a`.

Theo X. Olausson, Jeevana Priya Inala, Chenglong Wang, Jianfeng Gao, and Armando Solar-Lezama. Is self-repair a silver bullet for code generation? In *The Twelfth International Conference on Learning Representations*, 2024. URL `https://openreview.net/forum?id=y0GJXRungR`.

OpenAI. GPT-4 Technical Report. *ArXiv*, abs/2303.08774, 2023. URL `https://api.semanticscholar.org/CorpusID:257532815`.

Liangming Pan, Alon Albalak, Xinyi Wang, and William Wang. Logic-LM: Empowering large language models with symbolic solvers for faithful logical reasoning. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 3806–3824, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.248. URL `https://aclanthology.org/2023.findings-emnlp.248`.

Xiangyu Peng, Siyan Li, Sarah Wiegreffe, and Mark Riedl. Inferring the reader: Guiding automated story generation with commonsense reasoning. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2022*, pp. 7008–7029, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.findings-emnlp.520. URL `https://aclanthology.org/2022.findings-emnlp.520`.

Zhenting Qi, Mingyuan Ma, Jiahang Xu, Li Lyna Zhang, Fan Yang, and Mao Yang. Mutual Reasoning Makes Smaller LLMs Stronger Problem-Solvers. *arXiv preprint arXiv:2408.06195*, 2024.

Xin Quan, Marco Valentino, Louise Dennis, and Andre Freitas. Enhancing ethical explanations of large language models through iterative symbolic refinement. In Yvette Graham and Matthew Purver (eds.), *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1–22, St. Julian's, Malta, March 2024. Association for Computational Linguistics. URL `https://aclanthology.org/2024.eacl-long.1`.

Machel Reid and et. al. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *ArXiv*, abs/2403.05530, 2024. URL `https://api.semanticscholar.org/CorpusID:268297180`.

David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. GPQA: A Graduate-Level Google-Proof Q&A Benchmark, 2023.

Gemma Team Morgane Riviere and et. al. Gemma 2: Improving open language models at a practical size. 2024. URL `https://api.semanticscholar.org/CorpusID:270843326`.

Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. WinoGrande: an adversarial winograd schema challenge at scale. *Commun. ACM*, 64(9):99–106, aug 2021. ISSN 0001-0782. doi: 10.1145/3474381. URL `https://doi.org/10.1145/3474381`.

Maarten Sap, Hannah Rashkin, Derek Chen, Ronan Le Bras, and Yejin Choi. Social IQa: Commonsense reasoning about social interactions. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 4463–4473, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1454. URL `https://aclanthology.org/D19-1454`.

Abulhair Saparov and He He. Language models are greedy reasoners: A systematic formal analysis of chain-of-thought. In *The Eleventh International Conference on Learning Representations*, 2023. URL `https://openreview.net/forum?id=qFVVBzXxR2V`.

Zayne Rea Sprague, Xi Ye, Kaj Bostrom, Swarat Chaudhuri, and Greg Durrett. MuSR: Testing the limits of chain-of-thought with multistep soft reasoning. In *The Twelfth International Conference on Learning Representations*, 2024. URL `https://openreview.net/forum?id=jenyYQzue1`.

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *arXiv preprint arXiv:2206.04615*, 2022.

Maja Stahl, Leon Biermann, Andreas Nehring, and Henning Wachsmuth. Exploring LLM prompting strategies for joint essay scoring and feedback generation. In Ekaterina Kochmar, Marie Bexte, Jill Burstein, Andrea Horbach, Ronja Laarmann-Quante, Anaïs Tack, Victoria Yaneva, and Zheng Yuan (eds.), *Proceedings of the 19th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2024)*, pp. 283–298, Mexico City, Mexico, June 2024. Association for Computational Linguistics. URL `https://aclanthology.org/2024.bea-1.23`.

Kaya Stechly, Karthik Valmeekam, and Subbarao Kambhampati. On the self-verification limitations of large language models on reasoning and planning tasks. *ArXiv*, abs/2402.08115, 2024a. URL `https://api.semanticscholar.org/CorpusID:267637077`.

Kaya Stechly, Karthik Valmeekam, and Subbarao Kambhampati. Chain of thoughtlessness? an analysis of cot in planning. 2024b. URL `https://api.semanticscholar.org/CorpusID:269626390`.

Simeng Sun, Yang Liu, Shuohang Wang, Dan Iter, Chenguang Zhu, and Mohit Iyyer. PEARL: Prompting large language models to plan and execute actions over long documents. In Yvette Graham and Matthew Purver (eds.), *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 469–486, St. Julian's, Malta, March 2024. Association for Computational Linguistics. URL `https://aclanthology.org/2024.eacl-long.29`.

Mirac Suzgun, Nathan Scales, Nathanael Schärli, Sebastian Gehrmann, Yi Tay, Hyung Won Chung, Aakanksha Chowdhery, Quoc Le, Ed Chi, Denny Zhou, and Jason Wei. Challenging BIG-bench tasks and whether chain-of-thought can solve them. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 13003–13051, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-acl.824. URL `https://aclanthology.org/2023.findings-acl.824`.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4149–4158, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1421. URL `https://aclanthology.org/N19-1421`.

Hugo Touvron, Louis Martin, Kevin R. Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Daniel M. Bikel, Lukas Blecher, Cristian Cantón Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony S. Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel M. Kloumann, A. V. Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, R. Subramanian, Xia Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zhengxu Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models. *ArXiv*, abs/2307.09288, 2023. URL `https://api.semanticscholar.org/CorpusID:259950998`.

Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. MuSiQue: Multi-hop questions via single-hop question composition. *Transactions of the Association for Computational Linguistics*, 2022.

Karthik Valmeekam, Matthew Marquez, Sarath Sreedharan, and Subbarao Kambhampati. On the planning abilities of large language models - a critical investigation. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL `https://openreview.net/forum?id=X6dEqXIsEW`.

Karthik Valmeekam, Matthew Marquez, Alberto Olmo, Sarath Sreedharan, and Subbarao Kambhampati. PlanBench: An extensible benchmark for evaluating large language models on planning and reasoning about change. In *Proceedings of the 37th International Conference on Neural Information Processing Systems*, NIPS '23, Red Hook, NY, USA, 2024. Curran Associates Inc.

Mudit Verma, Siddhant Bhambri, and Subbarao Kambhampati. Theory of mind abilities of large language models in human-robot interaction: An illusion? *Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction*, 2024. URL `https://api.semanticscholar.org/CorpusID:266902529`.

Boshi Wang, Sewon Min, Xiang Deng, Jiaming Shen, You Wu, Luke Zettlemoyer, and Huan Sun. Towards understanding chain-of-thought prompting: An empirical study of what matters. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 2717–2739, Toronto, Canada, July 2023a. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.153. URL `https://aclanthology.org/2023.acl-long.153`.

Lei Wang, Wanyu Xu, Yihuai Lan, Zhiqiang Hu, Yunshi Lan, Roy Ka-Wei Lee, and Ee-Peng Lim. Plan-and-solve prompting: Improving zero-shot chain-of-thought reasoning by large language models. In *Annual Meeting of the Association for Computational Linguistics*, 2023b. URL `https://api.semanticscholar.org/CorpusID:258558102`.

Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations*, 2023c. URL `https://openreview.net/forum?id=1PL1NIMMrw`.

Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, Tianle Li, Max Ku, Kai Wang, Alex Zhuang, Rongqi Fan, Xiang Yue, and Wenhu Chen. MMLU-Pro: A More Robust and Challenging Multi-Task Language Understanding Benchmark, 2024.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35:24824–24837, 2022.

Li Siang Wong, Gabriel Grand, Alexander K. Lew, Noah D. Goodman, Vikash K. Mansinghka, Jacob Andreas, and Joshua B. Tenenbaum. From word models to world models: Translating from natural language to the probabilistic language of thought. *ArXiv*, abs/2306.12672, 2023. URL `https://api.semanticscholar.org/CorpusID:259224900`.

Jian Xie, Kai Zhang, Jiangjie Chen, Tinghui Zhu, Renze Lou, Yuandong Tian, Yanghua Xiao, and Yu Su. TravelPlanner: A Benchmark for Real-World Planning with Language Agents. *ArXiv*, abs/2402.01622, 2024. URL `https://api.semanticscholar.org/CorpusID:267406800`.

Miao Xiong, Zhiyuan Hu, Xinyang Lu, Yifei Li, Jie Fu, Junxian He, and Bryan Hooi. Can LLMs Express Their Uncertainty? An Empirical Evaluation of Confidence Elicitation in LLMs. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL `https://openreview.net/forum?id=gjeQKFxFpZ`.

Jundong Xu, Hao Fei, Liangming Pan, Qian Liu, Mong-Li Lee, and Wynne Hsu. Faithful logical reasoning via symbolic chain-of-thought. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 13326–13365, Bangkok, Thailand, August 2024a. Association for Computational Linguistics. URL `https://aclanthology.org/2024.acl-long.720`.

Xiaohan Xu, Chongyang Tao, Tao Shen, Can Xu, Hongbo Xu, Guodong Long, and Jian-Guang Lou. Re-reading improves reasoning in language models, 2024b. URL `https://openreview.net/forum?id=3jXCF5dNpC`.

Chengrun Yang, Xuezhi Wang, Yifeng Lu, Hanxiao Liu, Quoc V Le, Denny Zhou, and Xinyun Chen. Large language models as optimizers. In *The Twelfth International Conference on Learning Representations*, 2024. URL `https://openreview.net/forum?id=Bb4VGOWELI`.

Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan. Tree of Thoughts: Deliberate problem solving with large language models, 2023.

Xi Ye, Qiaochu Chen, Isil Dillig, and Greg Durrett. Satisfiability-aided language models using declarative prompting. In *Advances in Neural Information Processing Systems*, 2023.

Hugh Zhang, Jeff Da, Dean Lee, Vaughn Robinson, Catherine Wu, Will Song, Tiffany Zhao, Pranav Raja, Dylan Slack, Qin Lyu, Sean Hendryx, Russell Kaplan, Michele Lunati, and Summer Yue. A careful examination of large language model performance on grade school arithmetic. *ArXiv*, abs/2405.00332, 2024. URL `https://api.semanticscholar.org/CorpusID:269484687`.

Huaixiu Steven Zheng, Swaroop Mishra, Xinyun Chen, Heng-Tze Cheng, Ed H. Chi, Quoc V Le, and Denny Zhou. Take a step back: Evoking reasoning via abstraction in large language models. In *The Twelfth International Conference on Learning Representations*, 2024a. URL `https://openreview.net/forum?id=3bq3jsvcQ1`.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging LLM-as-a-judge with MT-bench and Chatbot Arena. In *Proceedings of the 37th International Conference on Neural Information Processing Systems*, NIPS '23, Red Hook, NY, USA, 2024b. Curran Associates Inc.

Wanjun Zhong, Ruixiang Cui, Yiduo Guo, Yaobo Liang, Shuai Lu, Yanlin Wang, Amin Saied, Weizhu Chen, and Nan Duan. AGIEval: A Human-Centric Benchmark for Evaluating Foundation Models, 2023.

Ben Zhou, Kyle Richardson, Xiaodong Yu, and Dan Roth. Learning to decompose: Hypothetical question decomposition based on comparable texts. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (eds.), *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 2223–2235, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.142. URL `https://aclanthology.org/2022.emnlp-main.142`.

Ben Zhou, Hongming Zhang, Sihao Chen, Dian Yu, Hongwei Wang, Baolin Peng, Dan Roth, and Dong Yu. Conceptual and unbiased reasoning in language models. *ArXiv*, abs/2404.00205, 2024. URL `https://api.semanticscholar.org/CorpusID:268820105`.

Denny Zhou, Nathanael Schärli, Le Hou, Jason Wei, Nathan Scales, Xuezhi Wang, Dale Schuurmans, Claire Cui, Olivier Bousquet, Quoc V Le, and Ed H. Chi. Least-to-most prompting enables complex reasoning in large language models. In *The Eleventh International Conference on Learning Representations*, 2023a. URL `https://openreview.net/forum?id=WZH7099tgfM`.

Yongchao Zhou, Andrei Ioan Muresanu, Ziwen Han, Keiran Paster, Silviu Pitis, Harris Chan, and Jimmy Ba. Large Language Models are Human-Level Prompt Engineers. In *The Eleventh International Conference on Learning Representations*, 2023b. URL `https://openreview.net/forum?id=92gvk82DE-`.

A   META-ANALYSIS EXPANDED DETAILS ON CRITERIA AND PROCESS

Automatic Selection and Paper Filtering   We investigate all papers from ICLR 2024, a representative ML venue, and two representative NLP venues, EACL 2024 and NAACL 2024 (including Findings and Workshop papers). We filtered all 4,642 papers (2,259 from ICLR 2024 and 2,382 from the two ACL-affiliated conferences) for those with at least two occurrences of "CoT", "chain-of-thought", or "chain of thought", resulting in 516 papers. There are conceivably papers using CoT called by another name (e.g., Scratchpads), but we believe these 516 give a representative sample appropriate for systematic analysis.

Manual Paper Filtering and Results Extraction   We then filter down to papers that perform a comparison of CoT prompting vs. direct prompting, whether or not this is core to the paper's research question. We manually filtered the 516 papers in question and extracted the key results from those that remained. We excluded multimodal models, CoT-fine-tuned models, any experiments where the "CoT" method involves multiple forward passes (e.g., self-consistency (Wang et al., 2023c) and tree-of-thought (Yao et al., 2023)),[5] and systems that augment LLMs with external tools (discussed more in Section 5).

For each paper passing through these criteria, we manually extracted the results from key tables comparing CoT and direct answer prompts. We only include results where the CoT and direct prompts are run on the same model and same dataset while being on a scale of 0 to 100 (excluding Likert scale evaluations, for example) for a more direct comparison. When papers include various CoT or direct answer prompts (including zero/few-shot variants), we always take the best-performing prompt for both. We focus on key test results where applicable, excluding dev sets if they are reported alongside test and also excluding numbers from ablations or nonstandard subsets of datasets.

This resulted in a total of 1,218 experimental comparisons across 110 papers (35 from ICLR and 75 from NAACL and EACL) covering 264 datasets. Details and more information will be available in our GitHub Repo.

Categorization   Given the large number of tasks and datasets being compared, we grouped each task into a set of 14 categories. These categories were determined based on the description (and possibly examples) of the task, not taking into account system performance. These categories abstract over traditional NLP task classifications (e.g., NER, reading comprehension) and take into account both the task format and the kinds of reasoning involved. Definitions for several categories are shown in Table 1 and the full description is given in Appendix B.

B   QUANTITATIVE META-ANALYSIS

See the full list of categories and their descriptions that we used for the meta-analysis in Table 2.

C   EXPANDED EXPERIMENTAL DETAILS

A full list of the datasets can be found in Table 4. Each model can be seen in Table 5. We use one answer parser for all datasets of the same answer response format (one for multiple choice, short answer, etc.); however, some datasets require special handling and have edge cases that we handle separately from the rest of the datasets. Similarly, for each model, we use the exact same prompt across them, except when closed source models require different prompts because they do not allow for partial completions (i.e., when we cannot put "*let's think step by step*" to warm-start the assistant's response). All prompts are given in our Huggingface repo, including the model output and what our answer parser extracted as the answer.

Experiments were conducted either by invoking APIs or by running open-source models on our own hardware, mostly on a machine with 8 A40s or 4 Quadro RTX 8000s. All locally hosted models were

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[5]These systems use more compute than direct answer, and there is not a clear comparison to be made here. Moreover, our anecdotal coverage of these methods shows that they are most used for math, coding, and logic settings, for which we already have high representation among reported CoT methods.

Table 2: Categories and their descriptions for the meta-analysis.

Category	Description
Symbolic and algorithmic	Tasks involving symbol manipulation which can be solved by executing a program. This includes entity tracking datasets (e.g., SCONE, Coin Flip) and algorithmic tasks (e.g., BBH word sorting or finding shortest paths in a graph).
Math	Tasks requiring mathematical reasoning, from grade-school math to advanced mathematics, including physics questions.
Logical reasoning	Tasks designed to test for logical reasoning, whether deductive (Saparov & He, 2023, PrOntoQA), inductive (Bowen et al., 2024) or analogical (Ma et al., 2024) reasoning, including syllogisms and logical puzzles.
Commonsense reasoning	Datasets designed to test for commonsense knowledge and reasoning, i.e., world knowledge that most people would have, rather than specialized expert-level knowledge in a discipline acquired after years of study.
Encyclopedic knowledge	Tasks requiring expert-level in-depth knowledge beyond mere commonsense, usually in an open-book setting.
Spatial and temporal reasoning	Datasets designed to test for an understanding of space and spatial relations (e.g., navigation) or reasoning involving time and sequences over time.
Multi-hop QA	Questions involving the composition of multiple steps of reasoning in order to arrive at an answer, such as "What is the capital of the country whose scientist discovered penicillin?"
Context-aware QA	Tasks such as closed-book QA and reading comprehension involving reasoning about a given text in context. The context is often a short passage, but could also take the form of a knowledge graph (KBQA) or a table. This category also includes information extraction tasks, such as NER or relation extraction.
Entailment	Tasks involving establishing the inferential relation between two texts, prototypically NLI, but also including fact verification.
Text classification	Tasks involving the classification of a text into a small set of categories, such a topic or sentiment classification, but also involving tasks such as hate speech detection and misinformation detection.
Generation	Tasks involving text generation, including machine translation, dialogue, question generation, as well as code generation. Tasks such as SQL execution (Lei et al., 2024) or systematic transformations of data (e.g., SCAN (Lake & Baroni, 2018)) are excluded because they can be solved by executing a program.
Meta-linguistic	Tasks probing for models' knowledge of linguistics, such as identifying the main subject of a sentence or solving linguistic puzzles.
Mixed datasets	Datasets containing a variety of tasks, such as BIG-Bench Hard (BBH) or MMLU.
Other	Tasks which did not fit in any of the other categories, such as evaluating AI safety, eliciting models' verbalized confidence, or melody retrieval.

hosted with vLLM. All parameters given to the vLLM API endpoint are given in the Huggingface repo as well.

D OTHER CoT PROMPT VARIANTS

D.1 TESTING PERFORMANCE VOLATILITY ACROSS PROMPTS

To test the impact of prompt choice on performance, we performed our zero-shot experiment on Llama 3.1 8B with 7 different datasets and 4 different zero-shot CoT prompting strategies common in the literature (Kojima et al., 2022; Wang et al., 2023b; Zhou et al., 2023b; Yang et al., 2024).

Table 3: Models, datasets, and prompting strategies used in our experiments. Models marked with †
are run with a 4k context size window. Note that Gemma has a larger than 4k context size window,
but VLLM only supports up to a 4k context size window for it. Models marked with * indicate
closed-source models that cannot handle prefixed assistant messages. Datasets marked with △ do
not have a few-shot setting.

Models	Llama 2 7B Chat [†] (Touvron et al., 2023), Mistral 7B Instruct v0.3 (Jiang et al., 2023), Llama 3.1 8B Instruct (Dubey et al., 2024), Llama 3.1 70B Instruct, Gemma 2 9B It[†] (Riviere & et. al, 2024), Phi-3 Small 8k Instruct (Abdin et al., 2024), gpt-4o-mini-2024-07-18[*], gpt-4o-2024-08-06[*], Gemini 1.5 Flash[*](Reid & et. al, 2024), Gemini 1.5 Pro[*](Reid & et. al, 2024), claude-3-haiku-20240307[*] (Anthropic, a), claude-3-5-sonnet-20240620[*] (Anthropic, b)
Datasets	CommonsenseQA (Talmor et al., 2019), StrategyQA (Geva et al., 2021), SiQA[△] Sap et al. (2019), PiQA[△] (Bisk et al., 2019), Winogrande[△] (Sakaguchi et al., 2021), GPQA (Rein et al., 2023), MuSR (Sprague et al., 2024), ContextHub (Levels 1 and 2 only) (Hua et al., 2024), ARC[△] (Clark et al., 2018), AGIEval LSAT (Zhong et al., 2023), MMLU (Hendrycks et al., 2021a), MMLU Pro (Wang et al., 2024), MATH (Hendrycks et al., 2021b), GSM8K (Cobbe et al., 2021), GSM8K-hard (Gao et al., 2023), FOLIO (Han et al., 2022), MuSiQue[△] (Trivedi et al., 2022), Big-Bench Hard (Suzgun et al., 2023; Srivastava et al., 2022), BiGGen Bench (Kim et al., 2024)
Prompts	zero-shot direct answer, zero-shot CoT (Kojima et al., 2022), few-shot direct answer (Brown et al., 2020), few-shot CoT (Wei et al., 2022)

Table 4: List of datasets used in our experiments. We categorize each dataset into one of five
categories based on the type of reasoning required: Commonsense, Knowledge, Soft Reasoning,
Symbolic, or Mathematical. We also report answer formats. When we use few-shot prompts, we
mark how many examples those prompts contain. BiGGen Bench has many categories of questions
that explicitly ask for CoTs in the response; we ignore those categories for our evaluation.

Dataset	Type	Answer Format	m-Shots
CommonsenseQA	Commonsense	Multiple choice	7
StrategyQA	Commonsense	True or False	6
SIQA	Commonsense	Multiple choice	0
PIQA	Commonsense	Multiple choice	0
Winogrande	Commonsense	Multiple choice	0
Arc Easy	Knowledge	Multiple choice	0
Arc Challenge	Knowledge	Multiple choice	0
AGIEval LSAT	Soft Reasoning	Multiple choice	3
BiGGen-Bench	Soft Reasoning	Free response	0
MMLU	Knowledge	Multiple Choice	5
MMLU Pro	Knowledge	Multiple Choice	5
BigBench-Hard	Symbolic	Multiple Choice	0
MuSR	Soft Reasoning	Multiple Choice	1
GPQA	Mathematical	Multiple Choice	3
MuSiQue	Soft Reasoning	Short Answer	0
GSM8K	Mathematical	Short Answer	8
GSM8K-Hard	Mathematical	Short Answer	8
FOLIO	Symbolic	True, False, or Unknown	4
ContextHub	Symbolic	True, False, or Neither	3
MATH	Mathematical	Short Answer	4

Table 5: List of models for our experiments. We focus on contemporary instruction-tuned models; although pretrained and smaller language models could be used, they are not the focus of our study. Prompts and outputs used for each model are available on Huggingface. * Note that Gemma can accept more than 4k input tokens, but we are restricted to 4k by vLLM.

Model	Context Length	Is Open Source
Llama 2 7B Chat	4k	True
Mistral 7B Instruct v0.3	8k	True
Llama 3.1 8B Instruct	128k	True
Llama 3.1 70B Instruct	128k	True
Gemma 2 9B It	4k*	True
Qwen 7B Instruct	131k	True
Qwen 72B Instruct	131k	True
GPT4o-Mini	128k	False
GPT4o	128k	False
Gemini 1.5 Pro	128k	False
Gemini Flash	1m	False
Claude 3.5 Sonnet	200k	False
Claude 3 Haiku	200k	False
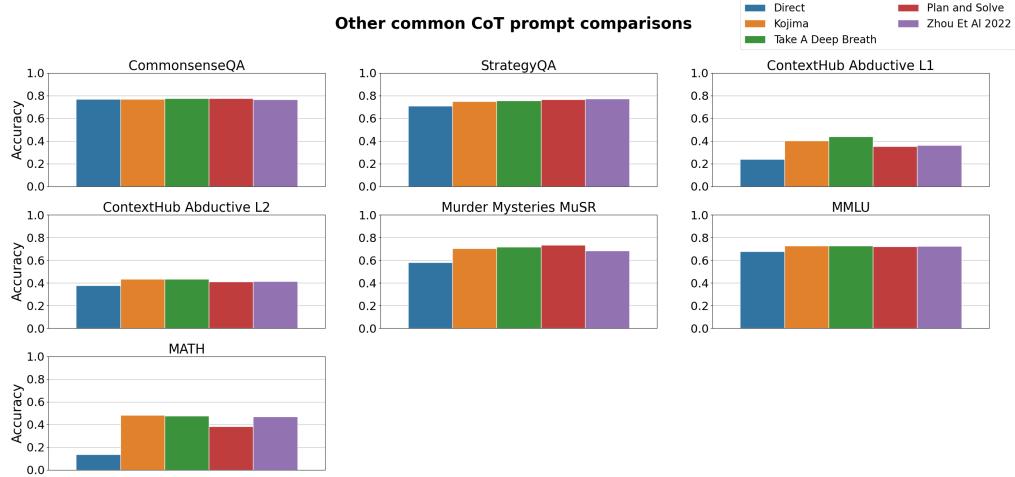
Figure 7: Performance of multiple prompts commonly used to elicit reasoning through CoT in the zero shot setting. Each prompt starts the assistant completion with a different phrase meant to elicit reasoning. All results are from using Llama 3.1 8B Instruct. For the Kojima variant, we explicitly place "*Let's think step by step.*" in the assistant message. There is very little variation between the CoT prompts on average.

Figure 7 shows variation due to prompts is typically small and no prompt gives a consistent gain over the other. For our experiments, this suggests that different prompts have small effects on the overall outcome on average.

E   FEW-SHOT EXPERIMENTS

Compared to a zero-shot prompt, a few-shot prompt additionally contains demonstrations of the relevant reasoning mode on different problem instances $\{(v(\mathbf{q}_i), \mathbf{y}_i^*)\}$. Few-shot prompts for direct answer simply encode the answer a_i as $\mathbf{y}_i^*$, whereas few-shot prompts for chain-of-thought include a reasoning trace ending in the correct answer. Now we can define the m-shot direct prompt as
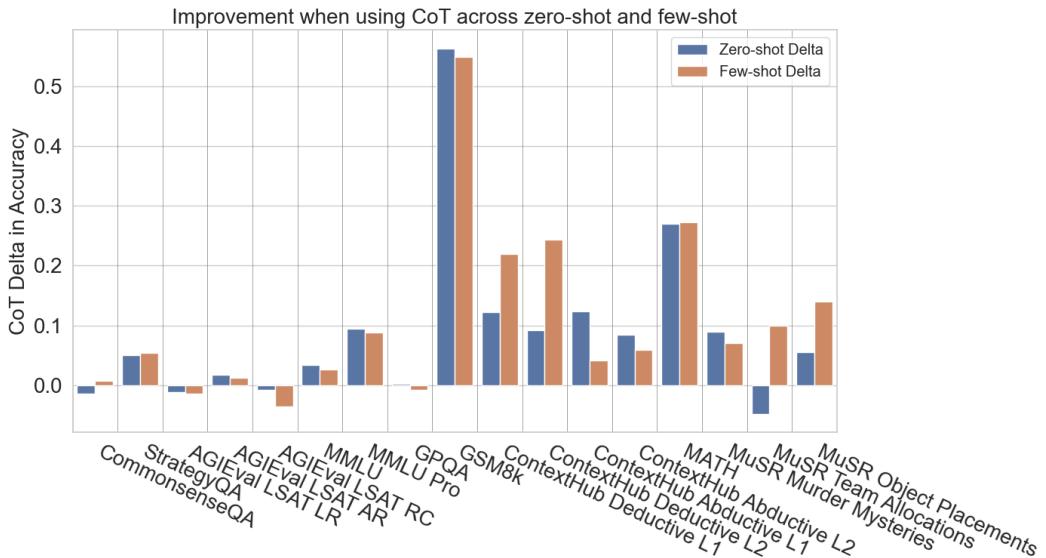
Figure 8: Average performance improvement from using CoT across different models in the zero-shot and few-shot settings. Each bar represents how much CoT improves the accuracy for that specific setting. In general, CoT in the few-shot setting does not change the qualitative performance of CoT versus zero-shot, though it can change the magnitude for symbolic datasets.

$\mathcal{I}_{\mathrm{da}}^m(\mathbf{q}) = v_{\mathrm{da}}(\mathbf{q}_1)\mathbf{a}_1 v_{\mathrm{da}}(\mathbf{q}_2)\mathbf{a}_2 \ldots v_{\mathrm{da}}(\mathbf{q}_m)\mathbf{a}_m v_{\mathrm{da}}(\mathbf{q})$ and the m-shot cot prompt as $\mathcal{I}_{\mathrm{cot}}^m(\mathbf{q}) = v_{\mathrm{cot}}(\mathbf{q}_1)\mathbf{y}_1^* v_{\mathrm{cot}}(\mathbf{q}_2)\mathbf{y}_2^* \ldots v_{\mathrm{cot}}(\mathbf{q}_m)\mathbf{y}_m^* v_{\mathrm{cot}}(\mathbf{q})$.

Figure 8 shows the difference between few-shot prompting and the zero-shot setting discussed in the main text of the paper. We see that using CoT in the few-shot setting largely does not change the datasets that benefit from it. Only one dataset, MuSR Team Allocation, starts to improve with few-shot; however, we believe this to be an exception because the final step to derive the answer is complex in the prompt and clearer in the examples. The magnitude of improvement over direct answer prompting when using CoT is also similar to the zero-shot setting.

F EXPANDED COT VS DIRECT EXPERIMENTAL RESULTS

F.1 FULL ZERO-SHOT RESULTS

Table 6: Direct answer and CoT accuracies for each reasoning category across models.

Model	Commonsense		Knowledge		Mathematical		Symbolic		Soft	
	DA %	CoT %	DA %	CoT %	DA %	CoT %	DA %	CoT %	DA %	CoT %
Claude-3 Haiku	74.3	77.2	73.0	76.1	18.1	48.2	38.6	48.7	55.9	56.6
Claude-3.5 Sonnet	84.3	85.8	**83.8**	**88.8**	**38.7**	59.0	53.2	67.1	**67.6**	**75.7**
GPT-4o Mini	81.8	83.2	73.6	83.1	22.9	59.7	48.1	60.9	61.1	63.5
Gemini 1.5 Flash	80.3	76.8	78.2	81.0	27.2	55.7	47.0	59.7	60.6	62.6
Gemini 1.5 Pro	80.4	78.3	80.9	83.8	35.4	58.5	52.9	62.6	64.1	67.8
Gemma 2 9b	75.0	76.1	74.9	76.9	18.5	50.5	46.7	55.8	58.2	60.5
Gpt-4o	**87.3**	**87.7**	82.9	88.6	36.5	**63.3**	55.7	**68.3**	65.9	74.0
Meta-Llama 2 7b	51.4	50.9	44.1	46.6	9.3	17.2	22.4	35.4	37.2	37.6
Meta-Llama 3.1 70b	84.2	84.7	82.4	85.6	24.9	54.9	49.0	60.0	65.7	69.5
Meta-Llama 3.1 8b	72.9	73.4	70.1	74.1	16.0	47.8	34.8	51.6	55.0	56.2
Mistral 7b	58.3	61.8	62.0	64.5	10.9	28.9	41.8	45.0	48.6	49.7
Phi-3 Small 8k	70.8	72.5	76.1	79.7	17.8	47.1	51.2	58.7	57.9	56.4
Qwen 2 72b	82.9	84.9	78.6	84.6	23.9	58.5	48.2	58.7	64.2	65.1
Qwen 2 7b	64.0	66.1	65.2	71.3	15.9	53.5	43.8	52.3	54.4	49.4
Average	74.8	75.7	73.3	77.5	22.6	50.2	45.2	56.1	58.3	60.3

Table 7: Zero-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	zero-shot CoT accuracy	zero-shot DA accuracy
MuSR Team Allocations	Soft Reasoning	Llama 2 7b	34.8	37.2
MuSR Team Allocations	Soft Reasoning	Mistral 7b	38.8	46.8
MuSR Team Allocations	Soft Reasoning	Llama 3.1 8b	44.0	48.0
MuSR Team Allocations	Soft Reasoning	Llama 3.1 70b	65.2	66.8
MuSR Team Allocations	Soft Reasoning	Gemma 2 9b	47.2	44.8
MuSR Team Allocations	Soft Reasoning	Phi-3 Small 8k	47.2	61.6
MuSR Team Allocations	Soft Reasoning	Qwen 2 7b	42.0	49.6
MuSR Team Allocations	Soft Reasoning	Qwen 2 72b	58.0	66.8
MuSR Team Allocations	Soft Reasoning	GPT-4o Mini	61.2	58.4
MuSR Team Allocations	Soft Reasoning	Gpt-4o	64.0	63.6
MuSR Team Allocations	Soft Reasoning	Claude-3 Haiku	56.8	59.2
MuSR Team Allocations	Soft Reasoning	Claude-3.5 Sonnet	80.4	63.2
MuSR Team Allocations	Soft Reasoning	Gemini 1.5 Flash	48.8	55.2
MuSR Team Allocations	Soft Reasoning	Gemini 1.5 Pro	58.4	62.4
SiQA	Commonsense	Llama 2 7b	53.4	55.9
SiQA	Commonsense	Mistral 7b	35.9	33.5
SiQA	Commonsense	Llama 3.1 8b	73.5	73.5
SiQA	Commonsense	Llama 3.1 70b	78.7	80.9
SiQA	Commonsense	Gemma 2 9b	74.9	76.3
SiQA	Commonsense	Phi-3 Small 8k	38.0	40.4
SiQA	Commonsense	Qwen 2 7b	37.3	39.3
SiQA	Commonsense	Qwen 2 72b	80.5	80.4
SiQA	Commonsense	GPT-4o Mini	79.0	80.0
SiQA	Commonsense	Gpt-4o	81.9	81.5
SiQA	Commonsense	Claude-3 Haiku	75.4	74.8
SiQA	Commonsense	Claude-3.5 Sonnet	79.7	81.0
SiQA	Commonsense	Gemini 1.5 Flash	74.5	79.1
SiQA	Commonsense	Gemini 1.5 Pro	73.9	78.2
MuSiQue	Soft Reasoning	Llama 2 7b	40.1	36.1
MuSiQue	Soft Reasoning	Mistral 7b	47.3	47.2
MuSiQue	Soft Reasoning	Llama 3.1 8b	62.6	64.7
MuSiQue	Soft Reasoning	Llama 3.1 70b	74.0	72.2
MuSiQue	Soft Reasoning	Gemma 2 9b	67.7	68.7
MuSiQue	Soft Reasoning	Phi-3 Small 8k	58.3	64.3
MuSiQue	Soft Reasoning	Qwen 2 7b	60.7	65.1
MuSiQue	Soft Reasoning	Qwen 2 72b	56.3	69.0
MuSiQue	Soft Reasoning	GPT-4o Mini	71.3	68.2
MuSiQue	Soft Reasoning	Gpt-4o	73.5	70.1
MuSiQue	Soft Reasoning	Claude-3 Haiku	54.8	56.0
MuSiQue	Soft Reasoning	Claude-3.5 Sonnet	66.9	70.4
MuSiQue	Soft Reasoning	Gemini 1.5 Flash	69.8	66.2
MuSiQue	Soft Reasoning	Gemini 1.5 Pro	69.8	71.3
AGIEval LSAT RC	Soft Reasoning	Llama 2 7b	31.2	36.4
AGIEval LSAT RC	Soft Reasoning	Mistral 7b	61.7	61.0
AGIEval LSAT RC	Soft Reasoning	Llama 3.1 8b	71.0	68.8
AGIEval LSAT RC	Soft Reasoning	Llama 3.1 70b	84.4	87.0
AGIEval LSAT RC	Soft Reasoning	Gemma 2 9b	75.1	78.1
AGIEval LSAT RC	Soft Reasoning	Phi-3 Small 8k	68.8	69.9
AGIEval LSAT RC	Soft Reasoning	Qwen 2 7b	61.0	66.5
AGIEval LSAT RC	Soft Reasoning	Qwen 2 72b	83.6	84.4

Table 7: Zero-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	zero-shot CoT accuracy	zero-shot DA accuracy
AGIEval LSAT RC	Soft Reasoning	GPT-4o Mini	77.3	74.3
AGIEval LSAT RC	Soft Reasoning	Gpt-4o	88.1	81.4
AGIEval LSAT RC	Soft Reasoning	Claude-3 Haiku	71.7	65.1
AGIEval LSAT RC	Soft Reasoning	Claude-3.5 Sonnet	90.0	89.6
AGIEval LSAT RC	Soft Reasoning	Gemini 1.5 Flash	78.1	81.0
AGIEval LSAT RC	Soft Reasoning	Gemini 1.5 Pro	82.2	85.9
CommonsenseQA	Commonsense	Llama 2 7b	49.4	54.6
CommonsenseQA	Commonsense	Mistral 7b	68.0	68.0
CommonsenseQA	Commonsense	Llama 3.1 8b	68.5	74.9
CommonsenseQA	Commonsense	Llama 3.1 70b	83.5	84.4
CommonsenseQA	Commonsense	Gemma 2 9b	79.2	80.1
CommonsenseQA	Commonsense	Phi-3 Small 8k	81.8	80.3
CommonsenseQA	Commonsense	Qwen 2 7b	78.5	79.0
CommonsenseQA	Commonsense	Qwen 2 72b	87.4	87.3
CommonsenseQA	Commonsense	GPT-4o Mini	82.5	83.9
CommonsenseQA	Commonsense	Gpt-4o	86.5	87.3
CommonsenseQA	Commonsense	Claude-3 Haiku	80.6	79.0
CommonsenseQA	Commonsense	Claude-3.5 Sonnet	85.1	84.3
CommonsenseQA	Commonsense	Gemini 1.5 Flash	79.7	82.6
CommonsenseQA	Commonsense	Gemini 1.5 Pro	79.9	82.9
GPQA	Mathematical	Llama 2 7b	28.3	24.3
GPQA	Mathematical	Mistral 7b	23.0	24.3
GPQA	Mathematical	Llama 3.1 8b	24.1	25.9
GPQA	Mathematical	Llama 3.1 70b	23.2	25.9
GPQA	Mathematical	Gemma 2 9b	26.3	21.2
GPQA	Mathematical	Phi-3 Small 8k	22.3	20.8
GPQA	Mathematical	Qwen 2 7b	24.1	24.6
GPQA	Mathematical	Qwen 2 72b	21.0	18.1
GPQA	Mathematical	GPT-4o Mini	21.0	24.0
GPQA	Mathematical	Gpt-4o	23.7	25.9
GPQA	Mathematical	Claude-3 Haiku	25.4	22.3
GPQA	Mathematical	Claude-3.5 Sonnet	25.4	25.9
GPQA	Mathematical	Gemini 1.5 Flash	22.3	22.8
GPQA	Mathematical	Gemini 1.5 Pro	21.0	23.7
AGIEval LSAT LR	Soft Reasoning	Llama 2 7b	29.4	33.5
AGIEval LSAT LR	Soft Reasoning	Mistral 7b	44.1	47.8
AGIEval LSAT LR	Soft Reasoning	Llama 3.1 8b	59.0	53.9
AGIEval LSAT LR	Soft Reasoning	Llama 3.1 70b	81.4	81.0
AGIEval LSAT LR	Soft Reasoning	Gemma 2 9b	64.9	67.6
AGIEval LSAT LR	Soft Reasoning	Phi-3 Small 8k	64.5	64.1
AGIEval LSAT LR	Soft Reasoning	Qwen 2 7b	50.6	58.4
AGIEval LSAT LR	Soft Reasoning	Qwen 2 72b	77.3	75.1
AGIEval LSAT LR	Soft Reasoning	GPT-4o Mini	65.3	68.2
AGIEval LSAT LR	Soft Reasoning	Gpt-4o	87.3	83.9
AGIEval LSAT LR	Soft Reasoning	Claude-3 Haiku	55.7	54.7
AGIEval LSAT LR	Soft Reasoning	Claude-3.5 Sonnet	83.7	82.7
AGIEval LSAT LR	Soft Reasoning	Gemini 1.5 Flash	70.0	71.2
AGIEval LSAT LR	Soft Reasoning	Gemini 1.5 Pro	79.4	80.4
PiQA	Commonsense	Llama 2 7b	62.1	64.7
PiQA	Commonsense	Mistral 7b	78.6	77.7
PiQA	Commonsense	Llama 3.1 8b	85.0	84.2
PiQA	Commonsense	Llama 3.1 70b	91.8	90.6
PiQA	Commonsense	Gemma 2 9b	84.0	84.8
PiQA	Commonsense	Phi-3 Small 8k	89.1	85.5
PiQA	Commonsense	Qwen 2 7b	84.3	86.2
PiQA	Commonsense	Qwen 2 72b	92.9	89.1
PiQA	Commonsense	GPT-4o Mini	93.1	88.6
PiQA	Commonsense	Gpt-4o	95.9	95.5
PiQA	Commonsense	Claude-3 Haiku	85.9	86.6
PiQA	Commonsense	Claude-3.5 Sonnet	94.6	94.5
PiQA	Commonsense	Gemini 1.5 Flash	84.6	89.8
PiQA	Commonsense	Gemini 1.5 Pro	88.1	91.3
Arc Easy	Knowledge	Llama 2 7b	71.1	69.8
Arc Easy	Knowledge	Mistral 7b	87.5	86.7
Arc Easy	Knowledge	Llama 3.1 8b	93.0	92.5
Arc Easy	Knowledge	Llama 3.1 70b	97.5	97.9
Arc Easy	Knowledge	Gemma 2 9b	94.9	95.8
Arc Easy	Knowledge	Phi-3 Small 8k	96.0	96.3
Arc Easy	Knowledge	Qwen 2 7b	89.5	84.7
Arc Easy	Knowledge	Qwen 2 72b	97.9	97.4
Arc Easy	Knowledge	GPT-4o Mini	96.8	94.6
Arc Easy	Knowledge	Gpt-4o	98.9	98.1
Arc Easy	Knowledge	Claude-3 Haiku	95.1	95.4
Arc Easy	Knowledge	Claude-3.5 Sonnet	98.6	98.4
Arc Easy	Knowledge	Gemini 1.5 Flash	96.8	97.2
Arc Easy	Knowledge	Gemini 1.5 Pro	97.2	94.6
Arc Challenge	Knowledge	Llama 2 7b	49.2	45.2

Table 7: Zero-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	zero-shot CoT accuracy	zero-shot DA accuracy
Arc Challenge	Knowledge	Mistral 7b	78.3	76.6
Arc Challenge	Knowledge	Llama 3.1 8b	86.0	82.6
Arc Challenge	Knowledge	Llama 3.1 70b	95.0	93.6
Arc Challenge	Knowledge	Gemma 2 9b	91.0	89.6
Arc Challenge	Knowledge	Phi-3 Small 8k	91.6	91.0
Arc Challenge	Knowledge	Qwen 2 7b	83.9	75.3
Arc Challenge	Knowledge	Qwen 2 72b	96.3	94.6
Arc Challenge	Knowledge	GPT-4o Mini	93.3	82.6
Arc Challenge	Knowledge	Gpt-4o	96.0	95.3
Arc Challenge	Knowledge	Claude-3 Haiku	89.3	89.3
Arc Challenge	Knowledge	Claude-3.5 Sonnet	96.0	95.3
Arc Challenge	Knowledge	Gemini 1.5 Flash	92.3	93.6
Arc Challenge	Knowledge	Gemini 1.5 Pro	91.6	90.6
AGIEval LSAT AR	Soft Reasoning	Llama 2 7b	17.0	17.4
AGIEval LSAT AR	Soft Reasoning	Mistral 7b	21.7	19.1
AGIEval LSAT AR	Soft Reasoning	Llama 3.1 8b	20.4	26.1
AGIEval LSAT AR	Soft Reasoning	Llama 3.1 70b	32.6	28.7
AGIEval LSAT AR	Soft Reasoning	Gemma 2 9b	24.8	23.0
AGIEval LSAT AR	Soft Reasoning	Phi-3 Small 8k	28.3	26.5
AGIEval LSAT AR	Soft Reasoning	Qwen 2 7b	27.0	23.9
AGIEval LSAT AR	Soft Reasoning	Qwen 2 72b	29.1	28.3
AGIEval LSAT AR	Soft Reasoning	GPT-4o Mini	32.2	23.0
AGIEval LSAT AR	Soft Reasoning	Gpt-4o	37.8	30.0
AGIEval LSAT AR	Soft Reasoning	Claude-3 Haiku	24.8	23.5
AGIEval LSAT AR	Soft Reasoning	Claude-3.5 Sonnet	38.3	33.9
AGIEval LSAT AR	Soft Reasoning	Gemini 1.5 Flash	27.8	27.8
AGIEval LSAT AR	Soft Reasoning	Gemini 1.5 Pro	30.0	31.7
BiGGen Bench	Soft Reasoning	Llama 2 7b	61.6	56.8
BiGGen Bench	Soft Reasoning	Mistral 7b	70.1	68.1
BiGGen Bench	Soft Reasoning	Llama 3.1 8b	66.5	67.7
BiGGen Bench	Soft Reasoning	Llama 3.1 70b	78.9	76.9
BiGGen Bench	Soft Reasoning	Gemma 2 9b	64.7	64.5
BiGGen Bench	Soft Reasoning	Phi-3 Small 8k	69.7	63.0
BiGGen Bench	Soft Reasoning	Qwen 2 7b	46.2	69.9
BiGGen Bench	Soft Reasoning	Qwen 2 72b	74.3	79.9
BiGGen Bench	Soft Reasoning	GPT-4o Mini	70.3	77.7
BiGGen Bench	Soft Reasoning	Gpt-4o	86.0	82.0
BiGGen Bench	Soft Reasoning	Claude-3 Haiku	80.0	80.0
BiGGen Bench	Soft Reasoning	Claude-3.5 Sonnet	91.4	79.3
BiGGen Bench	Soft Reasoning	Gemini 1.5 Flash	73.9	68.5
BiGGen Bench	Soft Reasoning	Gemini 1.5 Pro	78.7	67.1
Winogrande	Commonsense	Llama 2 7b	49.9	50.4
Winogrande	Commonsense	Mistral 7b	60.4	56.5
Winogrande	Commonsense	Llama 3.1 8b	66.5	63.3
Winogrande	Commonsense	Llama 3.1 70b	84.2	81.2
Winogrande	Commonsense	Gemma 2 9b	68.7	67.7
Winogrande	Commonsense	Phi-3 Small 8k	81.5	81.6
Winogrande	Commonsense	Qwen 2 7b	67.1	60.7
Winogrande	Commonsense	Qwen 2 72b	81.9	80.7
Winogrande	Commonsense	GPT-4o Mini	79.2	71.9
Winogrande	Commonsense	Gpt-4o	89.7	86.5
Winogrande	Commonsense	Claude-3 Haiku	70.7	66.2
Winogrande	Commonsense	Claude-3.5 Sonnet	89.4	85.7
Winogrande	Commonsense	Gemini 1.5 Flash	72.5	74.8
Winogrande	Commonsense	Gemini 1.5 Pro	75.5	78.3
MMLU	Knowledge	Llama 2 7b	46.3	41.7
MMLU	Knowledge	Mistral 7b	60.5	56.5
MMLU	Knowledge	Llama 3.1 8b	72.6	67.5
MMLU	Knowledge	Llama 3.1 70b	85.0	83.2
MMLU	Knowledge	Gemma 2 9b	73.8	71.4
MMLU	Knowledge	Phi-3 Small 8k	76.3	73.6
MMLU	Knowledge	Qwen 2 7b	67.0	64.5
MMLU	Knowledge	Qwen 2 72b	81.3	77.8
MMLU	Knowledge	GPT-4o Mini	79.9	74.8
MMLU	Knowledge	Gpt-4o	87.5	83.4
MMLU	Knowledge	Claude-3 Haiku	72.2	68.4
MMLU	Knowledge	Claude-3.5 Sonnet	87.2	84.0
MMLU	Knowledge	Gemini 1.5 Flash	76.3	74.7
MMLU	Knowledge	Gemini 1.5 Pro	81.3	81.1
StrategyQA	Commonsense	Llama 2 7b	39.5	31.2
StrategyQA	Commonsense	Mistral 7b	66.1	55.8
StrategyQA	Commonsense	Llama 3.1 8b	73.7	68.6
StrategyQA	Commonsense	Llama 3.1 70b	85.3	83.8
StrategyQA	Commonsense	Gemma 2 9b	73.7	66.4
StrategyQA	Commonsense	Phi-3 Small 8k	72.3	66.0
StrategyQA	Commonsense	Qwen 2 7b	63.2	54.8
StrategyQA	Commonsense	Qwen 2 72b	81.7	76.9

Table 7: Zero-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	zero-shot CoT accuracy	zero-shot DA accuracy
StrategyQA	Commonsense	GPT-4o Mini	82.2	84.5
StrategyQA	Commonsense	Gpt-4o	84.5	85.5
StrategyQA	Commonsense	Claude-3 Haiku	73.4	65.0
StrategyQA	Commonsense	Claude-3.5 Sonnet	80.1	76.3
StrategyQA	Commonsense	Gemini 1.5 Flash	72.5	75.2
StrategyQA	Commonsense	Gemini 1.5 Pro	74.0	71.4
MuSR Object Placements	Soft Reasoning	Llama 2 7b	36.3	30.5
MuSR Object Placements	Soft Reasoning	Mistral 7b	50.8	43.4
MuSR Object Placements	Soft Reasoning	Llama 3.1 8b	55.5	53.5
MuSR Object Placements	Soft Reasoning	Llama 3.1 70b	65.6	43.8
MuSR Object Placements	Soft Reasoning	Gemma 2 9b	63.3	57.0
MuSR Object Placements	Soft Reasoning	Phi-3 Small 8k	53.1	55.1
MuSR Object Placements	Soft Reasoning	Qwen 2 7b	48.8	48.4
MuSR Object Placements	Soft Reasoning	Qwen 2 72b	61.7	45.7
MuSR Object Placements	Soft Reasoning	GPT-4o Mini	59.0	55.0
MuSR Object Placements	Soft Reasoning	Gpt-4o	67.6	45.3
MuSR Object Placements	Soft Reasoning	Claude-3 Haiku	46.9	52.3
MuSR Object Placements	Soft Reasoning	Claude-3.5 Sonnet	69.5	51.2
MuSR Object Placements	Soft Reasoning	Gemini 1.5 Flash	61.7	56.2
MuSR Object Placements	Soft Reasoning	Gemini 1.5 Pro	66.4	50.0
FOLIO	Symbolic	Llama 2 7b	36.5	33.0
FOLIO	Symbolic	Mistral 7b	50.7	41.9
FOLIO	Symbolic	Llama 3.1 8b	58.6	56.7
FOLIO	Symbolic	Llama 3.1 70b	70.9	69.0
FOLIO	Symbolic	Gemma 2 9b	66.0	55.7
FOLIO	Symbolic	Phi-3 Small 8k	68.0	59.6
FOLIO	Symbolic	Qwen 2 7b	60.6	51.2
FOLIO	Symbolic	Qwen 2 72b	65.0	65.0
FOLIO	Symbolic	GPT-4o Mini	65.0	58.1
FOLIO	Symbolic	Gpt-4o	79.8	62.6
FOLIO	Symbolic	Claude-3 Haiku	61.6	48.8
FOLIO	Symbolic	Claude-3.5 Sonnet	73.9	68.5
FOLIO	Symbolic	Gemini 1.5 Flash	74.9	69.5
FOLIO	Symbolic	Gemini 1.5 Pro	73.9	74.4
ContextHub Deductive L2	Symbolic	Llama 2 7b	34.8	12.6
ContextHub Deductive L2	Symbolic	Mistral 7b	48.8	55.1
ContextHub Deductive L2	Symbolic	Llama 3.1 8b	52.8	21.5
ContextHub Deductive L2	Symbolic	Llama 3.1 70b	50.0	41.1
ContextHub Deductive L2	Symbolic	Gemma 2 9b	50.0	43.0
ContextHub Deductive L2	Symbolic	Phi-3 Small 8k	52.4	49.1
ContextHub Deductive L2	Symbolic	Qwen 2 7b	51.3	39.8
ContextHub Deductive L2	Symbolic	Qwen 2 72b	52.8	44.0
ContextHub Deductive L2	Symbolic	GPT-4o Mini	47.0	42.0
ContextHub Deductive L2	Symbolic	Gpt-4o	54.5	45.6
ContextHub Deductive L2	Symbolic	Claude-3 Haiku	45.2	41.8
ContextHub Deductive L2	Symbolic	Claude-3.5 Sonnet	53.0	46.2
ContextHub Deductive L2	Symbolic	Gemini 1.5 Flash	45.0	39.5
ContextHub Deductive L2	Symbolic	Gemini 1.5 Pro	57.3	43.3
ContextHub Abductive L2	Symbolic	Llama 2 7b	34.3	31.9
ContextHub Abductive L2	Symbolic	Mistral 7b	34.0	25.7
ContextHub Abductive L2	Symbolic	Llama 3.1 8b	41.3	37.3
ContextHub Abductive L2	Symbolic	Llama 3.1 70b	51.0	44.4
ContextHub Abductive L2	Symbolic	Gemma 2 9b	41.5	32.9
ContextHub Abductive L2	Symbolic	Phi-3 Small 8k	44.3	32.8
ContextHub Abductive L2	Symbolic	Qwen 2 7b	37.8	33.4
ContextHub Abductive L2	Symbolic	Qwen 2 72b	45.5	32.2
ContextHub Abductive L2	Symbolic	GPT-4o Mini	65.0	55.0
ContextHub Abductive L2	Symbolic	Gpt-4o	57.5	46.8
ContextHub Abductive L2	Symbolic	Claude-3 Haiku	37.0	31.4
ContextHub Abductive L2	Symbolic	Claude-3.5 Sonnet	56.8	40.4
ContextHub Abductive L2	Symbolic	Gemini 1.5 Flash	53.1	32.2
ContextHub Abductive L2	Symbolic	Gemini 1.5 Pro	53.5	43.7
MMLU Pro	Knowledge	Llama 2 7b	19.9	19.6
MMLU Pro	Knowledge	Mistral 7b	31.6	28.4
MMLU Pro	Knowledge	Llama 3.1 8b	44.8	38.0
MMLU Pro	Knowledge	Llama 3.1 70b	64.9	55.0
MMLU Pro	Knowledge	Gemma 2 9b	48.1	42.7
MMLU Pro	Knowledge	Phi-3 Small 8k	54.8	43.7
MMLU Pro	Knowledge	Qwen 2 7b	45.0	36.2
MMLU Pro	Knowledge	Qwen 2 72b	62.8	44.3
MMLU Pro	Knowledge	GPT-4o Mini	62.3	42.6
MMLU Pro	Knowledge	Gpt-4o	72.1	55.0
MMLU Pro	Knowledge	Claude-3 Haiku	47.6	39.0
MMLU Pro	Knowledge	Claude-3.5 Sonnet	73.4	57.2
MMLU Pro	Knowledge	Gemini 1.5 Flash	58.5	47.2
MMLU Pro	Knowledge	Gemini 1.5 Pro	65.3	57.4
MuSR Murder Mysteries	Soft Reasoning	Llama 2 7b	50.0	50.0

Table 7: Zero-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	zero-shot CoT accuracy	zero-shot DA accuracy
MuSR Murder Mysteries	Soft Reasoning	Mistral 7b	62.8	55.6
MuSR Murder Mysteries	Soft Reasoning	Llama 3.1 8b	70.4	57.2
MuSR Murder Mysteries	Soft Reasoning	Llama 3.1 70b	73.6	69.6
MuSR Murder Mysteries	Soft Reasoning	Gemma 2 9b	76.8	61.6
MuSR Murder Mysteries	Soft Reasoning	Phi-3 Small 8k	61.6	58.8
MuSR Murder Mysteries	Soft Reasoning	Qwen 2 7b	59.2	53.2
MuSR Murder Mysteries	Soft Reasoning	Qwen 2 72b	80.8	64.4
MuSR Murder Mysteries	Soft Reasoning	GPT-4o Mini	71.2	63.6
MuSR Murder Mysteries	Soft Reasoning	Gpt-4o	87.6	70.8
MuSR Murder Mysteries	Soft Reasoning	Claude-3 Haiku	62.4	56.8
MuSR Murder Mysteries	Soft Reasoning	Claude-3.5 Sonnet	85.2	70.4
MuSR Murder Mysteries	Soft Reasoning	Gemini 1.5 Flash	70.8	58.4
MuSR Murder Mysteries	Soft Reasoning	Gemini 1.5 Pro	77.6	64.0
ContextHub Deductive L1	Symbolic	Llama 2 7b	47.7	8.3
ContextHub Deductive L1	Symbolic	Mistral 7b	50.3	67.3
ContextHub Deductive L1	Symbolic	Llama 3.1 8b	50.7	23.3
ContextHub Deductive L1	Symbolic	Llama 3.1 70b	53.8	40.7
ContextHub Deductive L1	Symbolic	Gemma 2 9b	56.3	39.2
ContextHub Deductive L1	Symbolic	Phi-3 Small 8k	54.8	50.2
ContextHub Deductive L1	Symbolic	Qwen 2 7b	59.3	43.3
ContextHub Deductive L1	Symbolic	Qwen 2 72b	51.5	44.0
ContextHub Deductive L1	Symbolic	GPT-4o Mini	49.3	41.5
ContextHub Deductive L1	Symbolic	Gpt-4o	59.3	49.0
ContextHub Deductive L1	Symbolic	Claude-3 Haiku	50.5	39.7
ContextHub Deductive L1	Symbolic	Claude-3.5 Sonnet	54.5	47.0
ContextHub Deductive L1	Symbolic	Gemini 1.5 Flash	47.3	38.5
ContextHub Deductive L1	Symbolic	Gemini 1.5 Pro	57.3	46.0
ContextHub Abductive L1	Symbolic	Llama 2 7b	29.4	16.4
ContextHub Abductive L1	Symbolic	Mistral 7b	46.9	25.8
ContextHub Abductive L1	Symbolic	Llama 3.1 8b	43.6	24.2
ContextHub Abductive L1	Symbolic	Llama 3.1 70b	55.3	43.9
ContextHub Abductive L1	Symbolic	Gemma 2 9b	61.9	58.9
ContextHub Abductive L1	Symbolic	Phi-3 Small 8k	62.5	60.3
ContextHub Abductive L1	Symbolic	Qwen 2 7b	52.2	47.5
ContextHub Abductive L1	Symbolic	Qwen 2 72b	61.9	45.0
ContextHub Abductive L1	Symbolic	GPT-4o Mini	61.1	42.2
ContextHub Abductive L1	Symbolic	Gpt-4o	74.2	65.6
ContextHub Abductive L1	Symbolic	Claude-3 Haiku	35.3	22.8
ContextHub Abductive L1	Symbolic	Claude-3.5 Sonnet	80.8	60.3
ContextHub Abductive L1	Symbolic	Gemini 1.5 Flash	66.4	47.2
ContextHub Abductive L1	Symbolic	Gemini 1.5 Pro	62.2	60.0
Big-Bench Hard	Symbolic	Llama 2 7b	29.8	31.9
Big-Bench Hard	Symbolic	Mistral 7b	39.3	35.1
Big-Bench Hard	Symbolic	Llama 3.1 8b	62.8	45.6
Big-Bench Hard	Symbolic	Llama 3.1 70b	78.9	54.8
Big-Bench Hard	Symbolic	Gemma 2 9b	58.7	50.8
Big-Bench Hard	Symbolic	Phi-3 Small 8k	70.0	55.1
Big-Bench Hard	Symbolic	Qwen 2 7b	52.6	47.6
Big-Bench Hard	Symbolic	Qwen 2 72b	75.1	59.0
Big-Bench Hard	Symbolic	GPT-4o Mini	77.7	49.7
Big-Bench Hard	Symbolic	Gpt-4o	84.6	64.5
Big-Bench Hard	Symbolic	Claude-3 Haiku	62.4	47.3
Big-Bench Hard	Symbolic	Claude-3.5 Sonnet	83.6	56.9
Big-Bench Hard	Symbolic	Gemini 1.5 Flash	71.3	55.4
Big-Bench Hard	Symbolic	Gemini 1.5 Pro	71.6	50.3
MATH	Mathematical	Llama 2 7b	4.2	4.0
MATH	Mathematical	Mistral 7b	12.4	6.1
MATH	Mathematical	Llama 3.1 8b	47.2	13.8
MATH	Mathematical	Llama 3.1 70b	64.4	22.8
MATH	Mathematical	Gemma 2 9b	45.6	19.1
MATH	Mathematical	Phi-3 Small 8k	43.2	18.5
MATH	Mathematical	Qwen 2 7b	53.7	13.3
MATH	Mathematical	Qwen 2 72b	63.5	23.8
MATH	Mathematical	GPT-4o Mini	69.6	24.3
MATH	Mathematical	Gpt-4o	73.3	35.2
MATH	Mathematical	Claude-3 Haiku	32.7	17.4
MATH	Mathematical	Claude-3.5 Sonnet	63.8	34.6
MATH	Mathematical	Gemini 1.5 Flash	54.5	31.3
MATH	Mathematical	Gemini 1.5 Pro	62.1	39.4
GSM8k-Hard	Mathematical	Llama 2 7b	6.7	1.8
GSM8k-Hard	Mathematical	Mistral 7b	21.0	3.0
GSM8k-Hard	Mathematical	Llama 3.1 8b	34.4	6.0
GSM8k-Hard	Mathematical	Llama 3.1 70b	46.6	14.0
GSM8k-Hard	Mathematical	Gemma 2 9b	40.9	8.8
GSM8k-Hard	Mathematical	Phi-3 Small 8k	33.0	6.9
GSM8k-Hard	Mathematical	Qwen 2 7b	48.4	5.0
GSM8k-Hard	Mathematical	Qwen 2 72b	54.8	13.7

Table 7: Zero-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	zero-shot CoT accuracy	zero-shot DA accuracy
GSM8k-Hard	Mathematical	GPT-4o Mini	53.9	11.7
GSM8k-Hard	Mathematical	Gpt-4o	60.3	26.0
GSM8k-Hard	Mathematical	Claude-3 Haiku	45.3	9.6
GSM8k-Hard	Mathematical	Claude-3.5 Sonnet	50.8	32.3
GSM8k-Hard	Mathematical	Gemini 1.5 Flash	54.6	16.2
GSM8k-Hard	Mathematical	Gemini 1.5 Pro	58.2	26.2
GSM8k	Mathematical	Llama 2 7b	29.6	6.9
GSM8k	Mathematical	Mistral 7b	59.2	10.2
GSM8k	Mathematical	Llama 3.1 8b	85.4	18.5
GSM8k	Mathematical	Llama 3.1 70b	85.6	37.0
GSM8k	Mathematical	Gemma 2 9b	89.2	24.9
GSM8k	Mathematical	Phi-3 Small 8k	90.0	24.9
GSM8k	Mathematical	Qwen 2 7b	87.9	20.7
GSM8k	Mathematical	Qwen 2 72b	94.6	40.1
GSM8k	Mathematical	GPT-4o Mini	94.1	31.8
GSM8k	Mathematical	Gpt-4o	95.8	58.8
GSM8k	Mathematical	Claude-3 Haiku	89.4	22.9
GSM8k	Mathematical	Claude-3.5 Sonnet	96.1	62.2
GSM8k	Mathematical	Gemini 1.5 Flash	91.4	38.6
GSM8k	Mathematical	Gemini 1.5 Pro	92.7	52.4

F.2 FULL FEW-SHOT RESULTS

Table 8: Few-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	few-shot CoT accuracy	few-shot DA accuracy
AGIEval LSAT RC	Soft Reasoning	Llama 2 7b	33.1	38.7
AGIEval LSAT RC	Soft Reasoning	Mistral 7b	52.4	57.2
AGIEval LSAT RC	Soft Reasoning	Llama 3.1 8b	60.2	70.3
AGIEval LSAT RC	Soft Reasoning	Llama 3.1 70b	84.4	88.8
AGIEval LSAT RC	Soft Reasoning	Gemma 2 9b	74.3	79.2
AGIEval LSAT RC	Soft Reasoning	Phi-3 Small 8k	63.2	65.1
AGIEval LSAT RC	Soft Reasoning	Qwen 2 7b	61.7	68.8
AGIEval LSAT RC	Soft Reasoning	Qwen 2 72b	85.9	85.9
AGIEval LSAT RC	Soft Reasoning	GPT-4o Mini	77.3	71.4
AGIEval LSAT RC	Soft Reasoning	Gemini 1.5 Flash	79.2	81.8
AGIEval LSAT LR	Soft Reasoning	Llama 2 7b	33.7	34.7
AGIEval LSAT LR	Soft Reasoning	Mistral 7b	46.1	48.0
AGIEval LSAT LR	Soft Reasoning	Llama 3.1 8b	55.7	58.0
AGIEval LSAT LR	Soft Reasoning	Llama 3.1 70b	83.3	85.1
AGIEval LSAT LR	Soft Reasoning	Gemma 2 9b	65.7	68.2
AGIEval LSAT LR	Soft Reasoning	Phi-3 Small 8k	64.7	59.2
AGIEval LSAT LR	Soft Reasoning	Qwen 2 7b	54.1	61.2
AGIEval LSAT LR	Soft Reasoning	Qwen 2 72b	77.5	79.6
AGIEval LSAT LR	Soft Reasoning	GPT-4o Mini	68.4	64.5
AGIEval LSAT LR	Soft Reasoning	Gemini 1.5 Flash	68.6	72.9
GPQA	Mathematical	Mistral 7b	23.0	25.9
GPQA	Mathematical	Llama 3.1 8b	22.1	27.2
GPQA	Mathematical	Llama 3.1 70b	24.8	24.3
GPQA	Mathematical	Gemma 2 9b	19.9	22.3
GPQA	Mathematical	Phi-3 Small 8k	23.9	22.5
GPQA	Mathematical	Qwen 2 7b	23.4	21.2
GPQA	Mathematical	Qwen 2 72b	22.8	19.9
GPQA	Mathematical	GPT-4o Mini	20.0	20.0
GPQA	Mathematical	Gemini 1.5 Flash	21.9	24.6
CommonsenseQA	Commonsense	Llama 2 7b	18.2	19.2
CommonsenseQA	Commonsense	Mistral 7b	73.6	70.4
CommonsenseQA	Commonsense	Llama 3.1 8b	74.0	76.5
CommonsenseQA	Commonsense	Llama 3.1 70b	84.7	84.6
CommonsenseQA	Commonsense	Gemma 2 9b	81.8	80.8
CommonsenseQA	Commonsense	Phi-3 Small 8k	80.8	80.4
CommonsenseQA	Commonsense	Qwen 2 7b	80.3	72.9
CommonsenseQA	Commonsense	Qwen 2 72b	88.4	87.8
CommonsenseQA	Commonsense	GPT-4o Mini	84.7	84.7
CommonsenseQA	Commonsense	Gemini 1.5 Flash	81.7	83.3
AGIEval LSAT AR	Soft Reasoning	Llama 2 7b	19.6	18.7
AGIEval LSAT AR	Soft Reasoning	Mistral 7b	20.9	22.6
AGIEval LSAT AR	Soft Reasoning	Llama 3.1 8b	24.8	26.1
AGIEval LSAT AR	Soft Reasoning	Llama 3.1 70b	36.1	30.9
AGIEval LSAT AR	Soft Reasoning	Gemma 2 9b	22.2	28.7
AGIEval LSAT AR	Soft Reasoning	Phi-3 Small 8k	27.8	20.0
AGIEval LSAT AR	Soft Reasoning	Qwen 2 7b	24.3	23.0
AGIEval LSAT AR	Soft Reasoning	Qwen 2 72b	27.0	30.0

Table 8: Few-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	few-shot CoT accuracy	few-shot DA accuracy
AGIEval LSAT AR	Soft Reasoning	GPT-4o Mini	28.7	26.1
AGIEval LSAT AR	Soft Reasoning	Gemini 1.5 Flash	28.3	20.4
MMLU	Knowledge	Llama 2 7b	49.0	42.8
MMLU	Knowledge	Mistral 7b	63.0	57.0
MMLU	Knowledge	Llama 3.1 8b	71.7	69.3
MMLU	Knowledge	Llama 3.1 70b	84.3	83.7
MMLU	Knowledge	Gemma 2 9b	74.7	72.4
MMLU	Knowledge	Phi-3 Small 8k	77.3	75.2
MMLU	Knowledge	Qwen 2 7b	69.9	68.6
MMLU	Knowledge	Qwen 2 72b	82.7	81.8
MMLU	Knowledge	GPT-4o Mini	82.3	77.8
MMLU	Knowledge	Gemini 1.5 Flash	78.1	79.0
StrategyQA	Commonsense	Llama 2 7b	57.9	30.9
StrategyQA	Commonsense	Mistral 7b	70.7	72.0
StrategyQA	Commonsense	Llama 3.1 8b	74.4	65.8
StrategyQA	Commonsense	Llama 3.1 70b	87.1	84.2
StrategyQA	Commonsense	Gemma 2 9b	77.1	73.3
StrategyQA	Commonsense	Phi-3 Small 8k	75.0	71.1
StrategyQA	Commonsense	Qwen 2 7b	71.9	58.9
StrategyQA	Commonsense	Qwen 2 72b	83.2	80.1
StrategyQA	Commonsense	GPT-4o Mini	83.0	86.2
StrategyQA	Commonsense	Gemini 1.5 Flash	77.0	80.3
ContextHub Abductive L2	Symbolic	Llama 2 7b	36.2	35.0
ContextHub Abductive L2	Symbolic	Mistral 7b	33.8	30.0
ContextHub Abductive L2	Symbolic	Llama 3.1 8b	32.7	36.1
ContextHub Abductive L2	Symbolic	Llama 3.1 70b	54.6	51.2
ContextHub Abductive L2	Symbolic	Gemma 2 9b	44.8	33.2
ContextHub Abductive L2	Symbolic	Phi-3 Small 8k	49.8	34.2
ContextHub Abductive L2	Symbolic	Qwen 2 7b	39.6	35.0
ContextHub Abductive L2	Symbolic	Qwen 2 72b	54.7	34.9
ContextHub Abductive L2	Symbolic	GPT-4o Mini	62.0	60.0
ContextHub Abductive L2	Symbolic	Gemini 1.5 Flash	48.6	47.8
ContextHub Abductive L1	Symbolic	Llama 2 7b	21.4	16.7
ContextHub Abductive L1	Symbolic	Mistral 7b	23.6	21.7
ContextHub Abductive L1	Symbolic	Llama 3.1 8b	40.0	36.1
ContextHub Abductive L1	Symbolic	Llama 3.1 70b	62.2	58.9
ContextHub Abductive L1	Symbolic	Gemma 2 9b	48.9	59.4
ContextHub Abductive L1	Symbolic	Phi-3 Small 8k	59.2	56.4
ContextHub Abductive L1	Symbolic	Qwen 2 7b	48.6	38.9
ContextHub Abductive L1	Symbolic	Qwen 2 72b	53.3	56.1
ContextHub Abductive L1	Symbolic	GPT-4o Mini	77.2	59.2
ContextHub Abductive L1	Symbolic	Gemini 1.5 Flash	79.7	68.6
MuSR Murder Mysteries	Soft Reasoning	Mistral 7b	62.0	56.4
MuSR Murder Mysteries	Soft Reasoning	Llama 3.1 8b	61.6	61.2
MuSR Murder Mysteries	Soft Reasoning	Llama 3.1 70b	73.2	68.0
MuSR Murder Mysteries	Soft Reasoning	Gemma 2 9b	81.6	62.0
MuSR Murder Mysteries	Soft Reasoning	Phi-3 Small 8k	62.0	53.6
MuSR Murder Mysteries	Soft Reasoning	Qwen 2 7b	56.0	55.6
MuSR Murder Mysteries	Soft Reasoning	Qwen 2 72b	80.4	66.0
MuSR Murder Mysteries	Soft Reasoning	GPT-4o Mini	76.0	69.6
MuSR Murder Mysteries	Soft Reasoning	Gemini 1.5 Flash	70.0	66.4
MuSR Team Allocations	Soft Reasoning	Mistral 7b	42.8	43.2
MuSR Team Allocations	Soft Reasoning	Llama 3.1 8b	59.6	51.6
MuSR Team Allocations	Soft Reasoning	Llama 3.1 70b	89.2	63.6
MuSR Team Allocations	Soft Reasoning	Gemma 2 9b	48.4	45.6
MuSR Team Allocations	Soft Reasoning	Phi-3 Small 8k	66.0	46.4
MuSR Team Allocations	Soft Reasoning	Qwen 2 7b	34.0	40.8
MuSR Team Allocations	Soft Reasoning	Qwen 2 72b	56.0	66.4
MuSR Team Allocations	Soft Reasoning	GPT-4o Mini	75.6	60.0
MuSR Team Allocations	Soft Reasoning	Gemini 1.5 Flash	90.0	54.4
MMLU Pro	Knowledge	Llama 2 7b	21.5	20.4
MMLU Pro	Knowledge	Mistral 7b	34.8	26.7
MMLU Pro	Knowledge	Llama 3.1 8b	44.7	38.0
MMLU Pro	Knowledge	Llama 3.1 70b	64.4	55.1
MMLU Pro	Knowledge	Gemma 2 9b	48.5	42.4
MMLU Pro	Knowledge	Phi-3 Small 8k	54.8	43.2
MMLU Pro	Knowledge	Qwen 2 7b	46.6	39.0
MMLU Pro	Knowledge	Qwen 2 72b	62.5	51.6
MMLU Pro	Knowledge	GPT-4o Mini	63.0	45.0
MMLU Pro	Knowledge	Gemini 1.5 Flash	59.4	50.6
MuSR Object Placements	Soft Reasoning	Mistral 7b	55.5	41.0
MuSR Object Placements	Soft Reasoning	Llama 3.1 8b	66.8	50.4
MuSR Object Placements	Soft Reasoning	Llama 3.1 70b	67.2	57.4
MuSR Object Placements	Soft Reasoning	Gemma 2 9b	68.0	58.2
MuSR Object Placements	Soft Reasoning	Phi-3 Small 8k	62.1	51.6
MuSR Object Placements	Soft Reasoning	Qwen 2 7b	46.9	43.8
MuSR Object Placements	Soft Reasoning	Qwen 2 72b	66.4	43.0

Table 8: Few-shot accuracy for direct answering and CoT prompts on all datasets

Dataset	Type	Model	few-shot CoT accuracy	few-shot DA accuracy
MuSR Object Placements	Soft Reasoning	GPT-4o Mini	67.0	47.0
MuSR Object Placements	Soft Reasoning	Gemini 1.5 Flash	73.0	54.7
ContextHub Deductive L2	Symbolic	Llama 2 7b	34.7	15.0
ContextHub Deductive L2	Symbolic	Mistral 7b	63.8	51.4
ContextHub Deductive L2	Symbolic	Llama 3.1 8b	76.1	27.3
ContextHub Deductive L2	Symbolic	Llama 3.1 70b	82.6	53.6
ContextHub Deductive L2	Symbolic	Gemma 2 9b	61.9	47.6
ContextHub Deductive L2	Symbolic	Phi-3 Small 8k	61.5	54.0
ContextHub Deductive L2	Symbolic	Qwen 2 7b	55.3	36.4
ContextHub Deductive L2	Symbolic	Qwen 2 72b	80.2	54.0
ContextHub Deductive L2	Symbolic	GPT-4o Mini	59.0	41.0
ContextHub Deductive L2	Symbolic	Gemini 1.5 Flash	90.2	42.5
ContextHub Deductive L1	Symbolic	Llama 2 7b	34.7	16.0
ContextHub Deductive L1	Symbolic	Mistral 7b	46.2	59.2
ContextHub Deductive L1	Symbolic	Llama 3.1 8b	73.0	23.0
ContextHub Deductive L1	Symbolic	Llama 3.1 70b	67.5	50.0
ContextHub Deductive L1	Symbolic	Gemma 2 9b	66.0	45.7
ContextHub Deductive L1	Symbolic	Phi-3 Small 8k	74.8	51.8
ContextHub Deductive L1	Symbolic	Qwen 2 7b	58.8	37.5
ContextHub Deductive L1	Symbolic	Qwen 2 72b	70.7	42.8
ContextHub Deductive L1	Symbolic	GPT-4o Mini	59.2	44.3
ContextHub Deductive L1	Symbolic	Gemini 1.5 Flash	89.3	49.8
MATH	Mathematical	Llama 2 7b	4.7	3.9
MATH	Mathematical	Mistral 7b	13.7	7.1
MATH	Mathematical	Llama 3.1 8b	41.2	14.2
MATH	Mathematical	Llama 3.1 70b	61.9	24.2
MATH	Mathematical	Gemma 2 9b	47.5	19.8
MATH	Mathematical	Phi-3 Small 8k	42.4	18.9
MATH	Mathematical	Qwen 2 7b	55.0	15.0
MATH	Mathematical	Qwen 2 72b	65.3	26.2
MATH	Mathematical	GPT-4o Mini	71.7	24.6
MATH	Mathematical	Gemini 1.5 Flash	54.7	32.3
GSM8K	Mathematical	Llama 2 7b	29.0	7.7
GSM8K	Mathematical	Mistral 7b	56.2	12.5
GSM8K	Mathematical	Llama 3.1 8b	86.4	20.1
GSM8K	Mathematical	Llama 3.1 70b	96.1	39.1
GSM8K	Mathematical	Gemma 2 9b	89.2	24.9
GSM8K	Mathematical	Phi-3 Small 8k	90.4	24.5
GSM8K	Mathematical	Qwen 2 7b	87.6	21.4
GSM8K	Mathematical	Qwen 2 72b	93.2	40.6
GSM8K	Mathematical	GPT-4o Mini	94.2	32.8
GSM8K	Mathematical	Gemini 1.5 Flash	90.6	40.4

F.3 ANSWER EXTRACTOR AND AVERAGE ANSWER SPAN RESULTS

In this section, we report the number of generations from each model on each dataset that our answer parser could not extract. "-1" denotes that a model was not run on a certain dataset due to context length limitations in the few-shot setting. We see that these unparseable rates are generally low across the board. The weakest models struggle on some of the most challenging datasets, but unparseable rates are all at or below 15%.

We also report the average character index of the beginning of the answer span that the answer parser extracted. Of particular note is that the direct answer prompts all return an answer within the first 60 characters, indicating that the answers are returned almost immediately, as desired. CoT completions are much longer.

G ZOOM-IN: MMLU AND MMLU PRO

MMLU and MMLU Pro show gains from adding CoT, but because these datasets are so broad, they defy simple characterization. We explore the performance of CoT on each category of MMLU to understand divergences in CoT performance between these domains. We list the top three categories where CoT gives the largest error reduction for Llama 3.1 8B and 70B on MMLU and MMLU Pro in Table 17. Some of these categories are explicitly mathematical in nature, as we might expect from Figure 3. We can also see that CoT is helping on categories like "business"; upon closer inspection, we found that these categories frequently involve math as well (e.g., business questions may involve computations surrounding wealth). We need to more carefully characterize MMLU at the *instance*
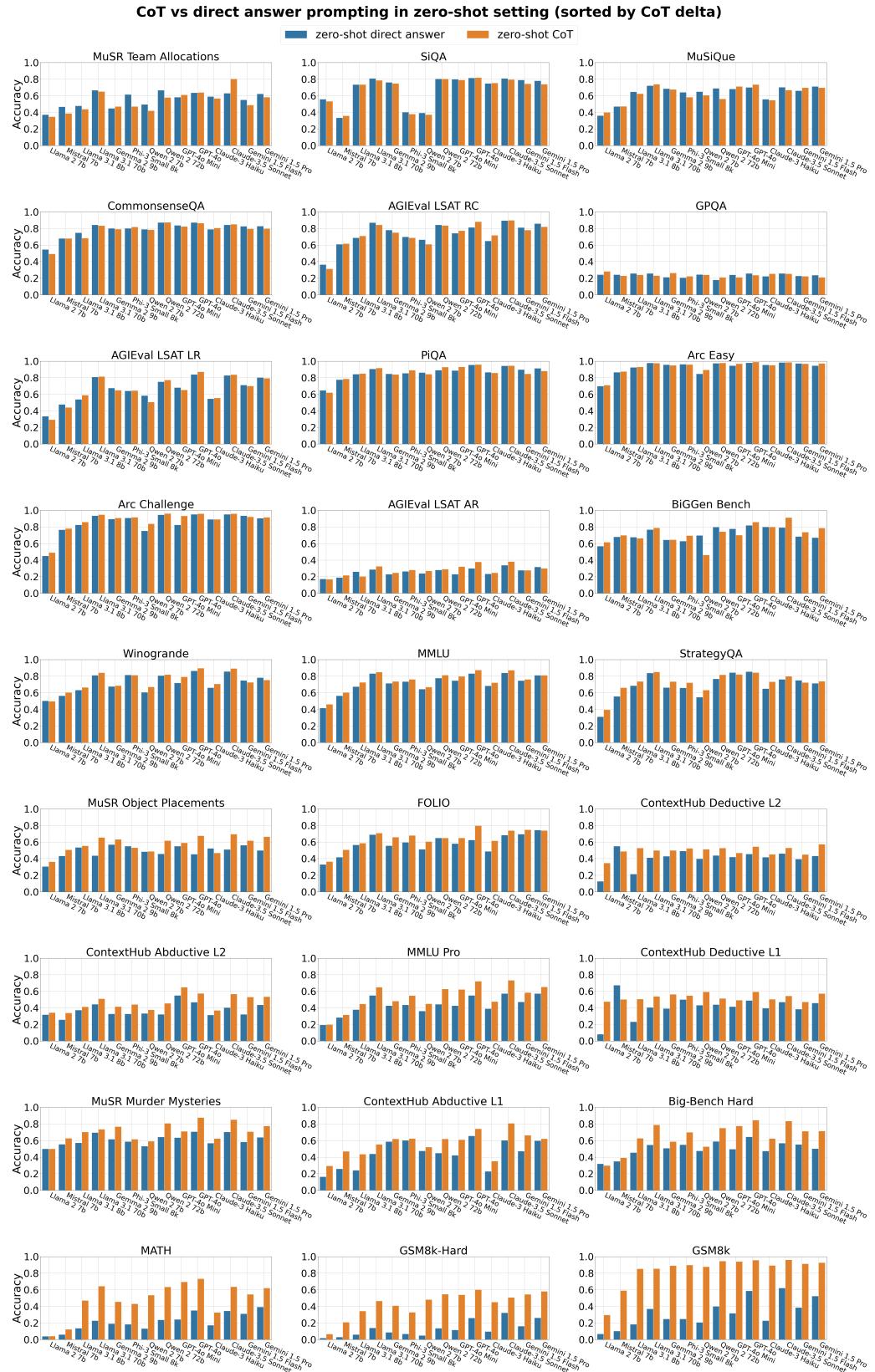
Figure 9: Performance of zero-shot direct (blue) and zero-shot CoT (orange) across datasets and models. Graphs are sorted in ascending order by median delta (CoT, direct). The datasets benefiting substantially are all symbolic or semi-symbolic in nature.

Table 9: Percentage of responses per dataset per model that our answer parser could not extract an answer for in the zero-shot direct answer setting. Prompt modifications were made to decrease these numbers. No model is above 15%.

Zero-shot Direct Answer Unparseable Answer Rate by Percentage														
dataset	Meta-Llama 2 7b	Mistral 7b	Meta-Llama 3.1 8b	Meta-Llama 3.1 70b	Gemma 2 9b	Phi-3 Small 8k	Qwen 2 7b	Qwen 2 72b	GPT-4o-Mini	Gpt-4o	Claude-3 Haiku	Claude-3.5 Sonnet	Gemini 1.5 Flash	Gemini 1.5 Pro
CommonsenseQA	1.9	2.5	1.1	0.0	0.8	0.1	1.6	0.7	0.0	0.0	0.1	0.0	0.1	0.2
StrategyQA	0.0	1.9	0.1	0.0	11.7	0.5	4.9	2.7	0.0	0.0	0.0	0.0	0.0	0.2
SiQA	0.2	6.6	0.0	0.1	3.9	0.3	0.1	3.0	0.1	0.1	0.0	0.0	0.0	0.4
PiQA	0.4	6.0	0.0	0.1	3.3	2.1	0.0	5.5	0.2	0.0	0.1	0.0	0.1	0.9
Winogrande	0.0	3.0	0.1	0.0	2.1	0.2	5.1	0.4	0.0	0.0	0.0	0.0	0.0	3.6
Arc Easy	0.0	1.8	0.5	0.0	0.0	0.2	9.1	0.7	3.5	0.4	0.2	0.0	0.0	3.2
Arc Challenge	0.0	2.3	1.0	0.0	0.3	0.7	10.7	0.7	10.0	0.7	0.0	0.0	0.0	5.0
AGIEval LSAT LR	0.4	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	2.5	0.0	0.2	0.2
AGIEval LSAT AR	0.4	0.0	0.0	0.0	4.3	3.9	0.0	0.0	0.0	8.7	0.0	0.0	0.0	0.0
AGIEval LSAT RC	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.7	0.0	0.0	0.4	0.4
ContextHub Deductive L1	0.0	0.0	0.0	0.0	1.2	0.0	2.3	0.0	0.0	0.0	0.2	0.0	0.0	0.2
ContextHub Deductive L2	0.0	0.0	0.0	0.0	0.0	0.0	2.2	1.0	0.0	0.0	2.8	0.0	0.0	0.0
ContextHub Abductive L1	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ContextHub Abductive L2	0.0	0.0	0.0	0.0	0.0	0.1	1.5	0.2	0.0	0.0	0.8	0.0	0.0	0.0
MuSR Murder Mysteries	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MuSR Team Allocations	0.0	0.0	0.0	0.0	3.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.4	0.4
MuSR Object Placements	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MMLU	0.1	0.0	0.0	0.0	0.1	0.2	3.6	1.2	0.6	0.0	1.3	0.3	0.2	0.7
MMLU Pro	0.7	1.3	1.0	0.3	1.0	3.7	6.8	12.2	0.4	0.3	0.4	0.3	0.6	0.8
GPQA	1.3	7.1	0.0	0.0	8.7	12.7	5.4	15.2	0.0	0.0	1.6	0.0	0.0	0.7
MATH	0.6	6.9	0.3	0.2	0.1	0.1	3.5	3.0	0.2	0.0	0.0	0.3	0.4	0.0
GSM8k	0.2	4.1	2.5	0.0	2.7	0.0	1.7	0.2	0.0	0.0	12.7	5.5	0.0	0.0
BigGen Bench	4.6	0.3	0.9	0.1	0.5	1.0	1.3	1.0	1.3	0.0	0.0	0.1	0.4	0.3
GSM8k-Hard	4.8	7.6	2.0	2.4	0.4	0.2	3.2	1.1	0.1	0.5	5.2	0.5	0.2	0.0
MuSiQue	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.1
Folio	4.4	0.0	0.0	0.0	0.0	0.0	3.9	0.0	0.0	12.3	0.0	0.0	0.0	0.5
BigBench-Hard	0.0	0.0	0.0	7.4	0.0	0.2	0.0	0.0	0.0	0.3	0.0	4.5	0.2	12.8

Table 10: Percentage of responses per dataset per model that our answer parser could not extract an answer for in the zero-shot CoT setting. Prompt modifications were made to decrease these numbers. No model is above 15%.

Zero-shot CoT Unparseable Answer Rate by Percentage														
dataset	Meta-Llama 2 7b	Mistral 7b	Meta-Llama 3.1 8b	Meta-Llama 3.1 70b	Gemma 2 9b	Phi-3 Small 8k	Qwen 2 7b	Qwen 2 72b	GPT-4o-Mini	Gpt-4o	Claude-3 Haiku	Claude-3.5 Sonnet	Gemini 1.5 Flash	Gemini 1.5 Pro
CommonsenseQA	2.9	1.3	8.6	0.0	0.6	0.1	0.0	0.0	1.6	0.0	0.2	0.3	2.4	2.6
StrategyQA	1.0	0.1	1.1	0.8	0.3	0.4	0.3	0.0	0.0	0.0	0.0	0.0	2.1	4.4
SiQA	0.8	1.8	0.3	0.1	1.6	0.0	0.1	0.1	0.0	0.0	0.0	0.1	3.5	4.0
PiQA	1.6	1.6	0.2	0.1	2.8	0.3	0.5	0.3	0.0	0.0	1.4	0.3	4.6	4.6
Winogrande	0.9	1.4	0.2	0.2	0.9	0.4	0.3	0.0	0.0	0.0	0.0	0.0	2.0	3.4
Arc Easy	0.2	0.4	0.2	0.0	0.5	1.6	1.6	0.0	0.5	0.0	0.0	0.0	0.4	0.5
Arc Challenge	0.0	0.7	0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.0	0.0	0.7	0.7
AGIEval LSAT LR	3.3	2.2	0.0	0.0	1.2	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.8	0.2
AGIEval LSAT AR	4.8	7.0	6.1	2.2	5.7	5.2	4.3	0.4	1.3	1.3	0.0	0.4	4.8	1.7
AGIEval LSAT RC	7.1	1.1	0.0	0.0	0.7	3.0	6.7	0.0	0.0	0.0	0.0	0.0	0.0	0.4
ContextHub Deductive L1	0.7	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3
ContextHub Deductive L2	0.2	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.4
ContextHub Abductive L1	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ContextHub Abductive L2	0.0	0.2	0.1	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.4
MuSR Murder Mysteries	0.0	0.4	0.0	0.0	0.0	11.6	0.4	0.0	0.0	0.0	0.0	0.0	6.8	3.6
MuSR Team Allocations	5.2	3.2	0.8	0.0	0.8	0.4	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MuSR Object Placements	0.0	1.6	0.0	0.0	0.4	0.8	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.4
MMLU	1.9	0.6	1.0	0.2	1.5	1.0	0.4	0.2	0.0	0.1	0.0	0.1	3.1	3.2
MMLU Pro	4.4	5.4	13.1	3.3	12.5	3.6	5.4	2.0	2.4	1.9	0.4	0.4	5.0	4.4
GPQA	4.5	10.3	9.4	1.6	8.5	1.8	3.8	0.7	0.0	0.0	0.0	0.0	11.8	15.0
MATH	1.6	5.5	8.2	2.5	2.3	1.6	3.0	0.4	0.4	0.5	0.9	0.0	1.7	1.0
GSM8k	1.7	1.4	0.7	10.5	0.4	0.6	0.4	0.0	0.0	0.0	0.3	0.0	0.1	0.1
BigGen Bench	5.0	0.4	0.5	0.1	0.5	0.4	0.3	9.5	0.0	0.0	0.0	0.1	0.4	0.1
GSM8k-Hard	2.1	8.7	10.2	4.5	10.7	3.2	3.5	1.0	0.8	0.5	3.0	1.8	0.4	2.7
MuSiQue	1.4	0.0	8.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	3.1
Folio	0.0	0.0	1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	1.5
BigBench-Hard	3.8	5.4	1.8	0.4	1.3	0.1	0.4	0.3	0.0	0.0	0.0	0.0	1.2	0.9

Table 13: Average character index of where the answer span begins in a generated response for each dataset and model pair for the zero-shot direct answer setting. We use these numbers as a proxy for the model following instructions (i.e. generating reasoning before an answer). Prompt modifications were made to ensure CoT prompts resulted in longer generations and direct answer prompts led to short generations.

dataset	Meta-Llama 2 7b	Mistral 7b	Meta-Llama 3.1 8b	Meta-Llama 3.1 70b	Gemma 2 9b	Phi-3 Small 8k	Qwen 2 7b	Qwen 2 72b	GPT-4o-Mini	Gpt-4o	Claude-3 Haiku	Claude-3.5 Sonnet	Gemini 1.5 Flash	Gemini 1.5 Pro
CommonsenseQA	9	8	27	8	8	8	10	8	8	10	7	7	8	8
StrategyQA	44	45	27	44	44	44	46	44	8	8	42	41	8	7
SiQA	8	8	8	8	8	8	29	8	8	8	6	6	8	8
PiQA	7	8	8	8	8	8	25	8	8	8	4	5	8	8
Winogrande	8	9	8	8	8	8	9	8	8	9	5	4	8	8
Arc Easy	9	8	8	8	8	8	9	8	8	8	7	7	8	8
Arc Challenge	8	8	8	8	8	8	9	8	8	8	7	7	8	8
AGIEval LSAT LR	25	24	24	24	24	24	25	24	43	21	25	25	26	26
AGIEval LSAT AR	25	24	24	24	24	24	26	24	48	23	25	25	26	27
AGIEval LSAT RC	25	24	24	24	24	24	25	24	31	18	25	25	26	25
ContextHub Deductive L1	19	19	19	19	20	19	19	19	19	19	20	20	19	20
ContextHub Deductive L2	19	19	19	19	19	19	19	19	19	19	20	20	19	19
ContextHub Abductive L1	19	19	19	19	20	19	19	19	19	19	20	20	19	19
ContextHub Abductive L2	19	19	19	19	20	19	19	19	19	19	20	20	19	19
MuSR Murder Mysteries	8	8	27	8	8	8	8	8	8	8	6	4	8	8
MuSR Team Allocations	27	22	19	19	27	23	26	22	8	8	30	20	8	8
MuSR Object Placements	8	8	27	8	8	8	8	8	8	8	7	6	8	8
MMLU	19	18	19	19	20	18	18	18	19	19	19	19	19	20
MMLU Pro	20	19	38	19	21	19	19	20	19	19	20	20	19	19
GPQA	19	19	19	19	21	19	19	19	19	19	20	20	19	20
MATH	30	31	28	28	28	30	30	33	28	28	31	29	28	28
GSM8k	22	29	30	28	28	37	24	28	28	28	29	28	28	28
GSM8k-Hard	9	57	11	21	9	13	40	20	7	8	8	8	8	8
Folio	39	8	8	8	8	8	31	13	8	16	5	6	8	70
BigBench-Hard	39	22	25	21	26	32	29	26	28	19	28	28	10	16

Table 14: Average character index of where the answer span begins in a generated response for each dataset and model pair for the zero-shot CoT setting. We use these numbers as a proxy for the model following instructions (i.e. generating reasoning before an answer). Prompt modifications were made to ensure CoT prompts resulted in longer generations and direct answer prompts led to short generations.

dataset	Meta-Llama 2 7b	Mistral 7b	Meta-Llama 3.1 8b	Meta-Llama 3.1 70b	Gemma 2 9b	Phi-3 Small 8k	Qwen 2 7b	Qwen 2 72b	GPT-4o-Mini	Gpt-4o	Claude-3 Haiku	Claude-3.5 Sonnet	Gemini 1.5 Flash	Gemini 1.5 Pro
CommonsenseQA	441	564	845	1237	236	466	577	341	899	1086	626	1103	214	165
StrategyQA	726	434	996	1131	267	460	363	358	692	1033	754	1158	256	195
SiQA	569	423	841	965	235	528	472	420	847	1094	602	1016	196	169
PiQA	699	455	869	914	207	532	447	364	683	935	578	1092	200	150
Winogrande	377	324	645	694	187	326	391	298	634	750	408	889	200	173
Arc Easy	684	581	1154	1319	367	610	534	355	990	1239	789	1222	340	231
Arc Challenge	763	644	1178	1316	422	596	571	387	1020	1269	828	1240	372	267
AGIEval LSAT LR	2053	1324	1163	1675	524	689	1560	768	949	998	1561	728	906	886
AGIEval LSAT AR	1377	1791	1422	2182	712	1027	1819	1264	1230	1151	1202	849	817	871
AGIEval LSAT RC	1977	1032	1103	1575	779	590	1170	660	973	1079	1628	786	703	709
ContextHub Deductive L1	694	368	759	711	383	327	539	402	540	580	542	556	320	254
ContextHub Deductive L2	842	472	1095	990	614	442	789	585	840	758	777	655	515	503
ContextHub Abductive L1	577	461	747	879	464	440	754	638	788	879	683	594	368	325
ContextHub Abductive L2	861	600	1270	1229	686	571	976	856	1115	1113	894	894	601	551
MuSR Murder Mysteries	495	1592	1958	1847	1210	1246	1241	1718	1961	1965	1671	1759	1349	1213
MuSR Team Allocations	1212	1845	2294	2310	1513	1433	2021	2213	2562	2698	1479	1856	1596	1607
MuSR Object Placements	917	625	1354	1266	695	641	904	819	1593	1536	1210	1455	616	429
MMLU	834	512	663	622	503	277	497	407	400	461	447	409	630	413
MMLU Pro	1371	513	788	716	640	518	954	699	926	940	590	653	660	774
GPQA	1034	778	917	901	806	500	1018	628	541	666	486	472	981	735
MATH	742	1118	1222	1179	748	670	1189	1145	1125	1153	677	675	679	698
GSM8k	572	637	834	719	453	521	709	645	1048	1035	708	680	541	437
GSM8k-Hard	916	939	1027	1069	555	766	1083	1053	1350	1266	594	815	605	512
Folio	724	765	1479	1379	733	668	919	488	1285	1583	907	1194	934	492
BigBench-Hard	596	230	876	861	429	349	315	443	877	973	545	863	455	346

Table 15: Average character index of where the answer span begins in a generated response for each dataset and model pair for the few-shot direct answer setting. We use these numbers as a proxy for the model following instructions (i.e. generating reasoning before an answer). Prompt modifications were made to ensure CoT prompts resulted in longer generations and direct answer prompts led to short generations.

	Few-shot Direct Answer Span Location By Character Index									
dataset	Meta-Llama 2 7b	Mistral 7b	Meta-Llama 3.1 8b	Meta-Llama 3.1 70b	Gemma 2 9b	Phi-3 Small 8k	Qwen 2 7b	Qwen 2 72b	GPT-4o Mini	Gemini 1.5 Flash
CommonsenseQA	87	8	27	8	8	8	10	8	8	8
AGIEval LSAT LR	25	24	24	24	24	24	24	24	31	24
AGIEval LSAT AR	25	24	24	24	24	24	24	24	27	24
AGIEval LSAT RC	25	24	24	24	24	24	24	24	25	24
ContextHub Deductive L1	19	19	19	19	19	19	19	19	19	19
ContextHub Deductive L2	19	19	19	19	19	19	19	19	19	19
ContextHub Abductive L1	19	19	19	19	19	19	19	19	19	19
ContextHub Abductive L2	19	19	19	19	19	19	19	19	19	19
MuSR Murder Mysteries	-1	8	27	8	8	8	8	8	8	8
MuSR Team Allocations	-1	21	19	19	27	21	27	23	8	8
MuSR Object Placements	-1	8	27	8	8	8	8	8	8	8
MMLU	19	18	19	19	19	18	18	18	19	19
MMLU Pro	19	19	38	19	20	20	19	19	19	19
GPQA	-1	19	19	19	19	19	19	19	19	19
MATH	29	36	29	29	28	30	30	41	28	28
GSM8k	22	23	23	22	22	23	22	24	27	28

Table 16: Average character index of where the answer span begins in a generated response for each dataset and model pair for the few-shot CoT setting. We use these numbers as a proxy for the model following instructions (i.e. generating reasoning before an answer). Prompt modifications were made to ensure CoT prompts resulted in longer generations and direct answer prompts led to short generations.

	Few-shot CoT Answer Span Location By Character Index									
dataset	Meta-Llama 2 7b	Mistral 7b	Meta-Llama 3.1 8b	Meta-Llama 3.1 70b	Gemma 2 9b	Phi-3 Small 8k	Qwen 2 7b	Qwen 2 72b	GPT-4o Mini	Gemini 1.5 Flash
CommonsenseQA	301	195	470	921	145	192	280	174	219	158
AGIEval LSAT LR	1037	510	464	539	437	359	530	599	894	523
AGIEval LSAT AR	1024	1247	886	768	573	1025	750	835	1033	670
AGIEval LSAT RC	799	378	131	206	164	111	241	205	1086	266
ContextHub Deductive L1	383	386	406	376	359	376	388	364	416	366
ContextHub Deductive L2	736	767	829	822	823	855	612	807	884	809
ContextHub Abductive L1	301	386	428	450	431	413	541	447	575	379
ContextHub Abductive L2	709	586	967	754	804	784	829	821	905	815
MuSR Murder Mysteries	-1	1280	1693	1702	1225	1338	1246	1719	1974	1419
MuSR Team Allocations	-1	2195	2087	2160	1628	1755	2181	2156	2632	1841
MuSR Object Placements	-1	907	1104	1213	706	919	676	963	1351	853
MMLU	282	266	333	245	265	260	267	243	392	218
MMLU Pro	429	397	424	411	516	425	541	325	681	396
GPQA	-1	848	782	774	615	711	662	703	670	594
MATH	630	705	584	640	747	529	1074	848	1261	553
GSM8k	374	332	352	352	398	372	415	341	651	314

37

Table 17: The top 3 slices benefiting the most from CoT across MMLU and MMLU Pro for Llama 3.1 8b and 70b. 6 out of 12 of these top slices directly contain "math" or "mathematics." We dive deeper into each category subsequently and observe that the questions leading to improvements in the other categories are mathematical in nature as well.

		MMLU				MMLU Pro			
Model	Subject	Direct (%)	CoT (%)	Err. Red. (%)	N	Subject	Direct (%)	CoT (%)	Err. Red. (%)	N
Llama 3.1 8b	elementary_mathematics	46.8	88.4	78.1	378	math	23.6	44.8	27.8	1350
Llama 3.1 8b	high_school_mathematics	39.6	71.5	52.8	270	business	29.4	45.6	23.0	789
Llama 3.1 8b	miscellaneous	83.9	89.9	37.3	783	physics	27.9	41.4	18.8	1299
Llama 3.1 70b	elementary_mathematics	82.3	94.7	70.1	378	math	44.5	68.3	42.9	1351
Llama 3.1 70b	medical_genetics	93.0	97.0	57.1	100	business	44.0	67.8	42.5	789
Llama 3.1 70b	high_school_mathematics	61.5	82.2	53.8	270	chemistry	40.5	64.0	39.6	1132

level. In doing so, we can test our hypotheses with much finer granularity than possible by relying on subjective groupings into tasks and categories.

Breakdown by the presence of equations We aim to design an instance-level classifier to determine if CoT is expected to help on a question or not. That is, we want a function $g : \mathbf{q} \to \{0, 1\}$ where $g(\mathbf{q})$ returns 1 if $\mathrm{extract}(\tilde{\mathbf{y}}_{cot}) = \mathbf{y}^*$ and $\mathrm{extract}(\tilde{\mathbf{y}}_{da}) \neq \mathbf{y}^*$ where $\mathbf{y}^*$ is the gold answer to $\mathbf{q}$. We explored different forms of g; however, we ultimately found it most effective to use a classifier $g : (\mathbf{q}, \tilde{\mathbf{y}}_{\mathrm{cot}}) \to \{0, 1\}$ which also consults the chain-of-thought produced by the model. This allows us to featurize how the LM solves the problem, particularly whether it uses symbolic reasoning or not.

We find that g can be implemented with a **single feature**: does $\mathbf{q}$ or $\tilde{\mathbf{y}}_{\mathrm{cot}}$ contain a "="? The "=" token very strongly indicates the presence of equations in the problem or its solution, which turn out to be a strong hallmark of symbolic reasoning.[6]

We plot the overall CoT delta (performance of CoT minus the performance of direct answer) for both MMLU and MMLU Pro across multiple models between two bins according to this classifier g, labeled as "With =" and "Without =", in Figure 4. We also report the amount of performance gain explained by questions having an "=" vs. not in Appendix G.1. We find that the majority of the performance gain from CoT on MMLU and MMLU Pro comes from questions that have an "=" in the question or generated responses. Because "=" are usually found in math problems, we equate this to CoT primarily benefiting MMLU and MMLU Pro on the math-related questions with very little to no gain (depending on the model) for non-math questions.

G.1 PERFORMANCE IMPACTS OF "=" ON MMLU AND MMLU PRO

Tables 18 and 19 show the amount of total improvement from using CoT over direct prompting that can be explained by the presence of "=" on MMLU and MMLU Pro over multiple models.

H FULL RESULTS OF EVALUATIONS ON FORMAL REASONING DATASETS

As discussed in Section 5, we include detailed evaluation results of few-shot direct answer, few-shot CoT, direct answer solver, CoT solver, and tool-augmented prompting in Table 20. The unparseable rate stands for the rate of unparseable model responses that either fail to pass our answer extraction parser (for all methods except tool-augmented prompting) or fail to be executed by symbolic solvers. For FOLIO and ContextHub, we compute the accuracy by making a random guess for the unparseable responses; for GSM8K and GSM8K-Hard, we consider the unparseable responses as incorrect.

We note that all models have a low unparseable rate ($< 10\%$) for all methods except tool-augmented prompting. By manually inspecting the outputs, we observe that the high unparseable rate for some models with tool-augmented prompting is caused by these models generating Python programs or

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[6]We explored implementing g with a logistic regression classifier with tf-idf features over the $(\mathbf{q}, \tilde{\mathbf{y}}_{\mathrm{cot}})$ pairs, trained over a subset of the data from MMLU and MMLU Pro. This classifier actually allowed us to discover the "=" feature, but its accuracy did not exceed the accuracy of that single feature.

Table 18: Total CoT deltas on MMLU broken down by the total gain from questions and responses with an "=" vs. without an "=".

Model	Total CoT Delta	CoT delta w/ =	CoT delta w/o =	Perf. Gain w/ =	Fraction of N w/ =
Llama 2 7b	6.0	0.6	5.4	9.8%	10.9%
Mistral 7b	4.1	1.2	2.9	28.6%	9.8%
Llama 3.1 8b	5.5	2.9	2.6	52.9%	9.6%
Llama 3.1 70b	1.9	1.8	0.1	94.0%	10.6%
Gemma 2 9b	2.6	2.0	0.6	78.5%	10.0%
Phi-3 Small 8k	3.1	1.5	1.7	47.4%	8.3%
Qwen 2 7b	2.5	3.0	-0.5	100.0%	9.8%
Qwen 2 72b	3.5	2.4	1.1	67.8%	9.6%
GPT-4o Mini	5.2	3.5	1.7	66.9%	10.5%
GPT-4o	4.2	2.4	1.8	57.6%	10.3%
Claude-3 Haiku	3.7	2.4	1.3	64.4%	9.3%
Claude-3.5 Sonnet	3.2	2.3	0.9	72.1%	10.7%
Gemini 1.5 Flash	3.0	1.7	1.2	59.0%	10.1%
Gemini 1.5 Pro	1.9	1.0	0.9	51.9%	9.6%

Table 19: Total CoT deltas on MMLU Pro broken down by the total gain from questions and responses with an "=" vs. without an "=".

Model	Total CoT Delta	CoT delta w/ =	CoT delta w/o =	Perf. Gain w/ =	Fraction of N w/ =
Llama 2 7b	1.6	1.3	0.3	79.6%	43.6%
Mistral 7b	3.8	1.9	1.9	50.7%	41.8%
Llama 3.1 8b	12.4	10.0	2.4	80.8%	35.2%
Llama 3.1 70b	11.4	11.1	0.3	97.6%	39.6%
Gemma 2 9b	7.6	7.4	0.2	97.9%	40.2%
Phi-3 Small 8k	11.6	9.9	1.7	85.7%	42.7%
Qwen 2 7b	10.0	8.9	1.1	88.6%	41.6%
Qwen 2 72b	19.0	16.1	2.9	84.7%	41.4%
GPT-4o Mini	20.6	18.4	2.3	89.0%	44.0%
GPT-4o	17.7	17.1	0.6	96.7%	44.1%
Claude-3 Haiku	8.7	7.8	0.9	90.1%	42.0%
Claude-3.5 Sonnet	16.2	14.8	1.3	91.9%	43.4%
Gemini 1.5 Flash	12.9	11.8	1.1	91.3%	42.3%
Gemini 1.5 Pro	10.0	8.6	1.4	85.7%	41.8%

Table 20: Performance and unparseable rates for few-shot direct answer, few-shot CoT, Plan + Direct Solver, Plan + CoT Solver, and Plan + Tool Solver Solver. "Acc." stands for accuracy and "% Unp." stands for the rate of unparseable model responses that either fail to pass our answer extraction parser (for all methods except Plan + Tool Solver prompting) or fail to be executed by symbolic solvers. For FOLIO and ContextHub, we compute the accuracy by making a random guess for the unparseable responses; for GSM8K and GSM8K-Hard, we consider the unparseable responses as incorrect.

Dataset	Method	Mistral 7b		Llama 3.1 8b		Llama 3.1 70b		GPT-4o Mini	
		Acc.	% Unp.	Acc.	% Unp.	Acc.	% Unp.	Acc.	% Unp.
GSM8K	Direct Answer	12.5	0.1	20.1	0.5	39.1	0.0	32.8	0.0
GSM8K	CoT	56.2	1.4	86.4	1.0	96.1	0.1	94.2	0.1
GSM8K	Plan + CoT Solver	45.0	1.0	78.7	0.4	94.7	0.0	92.0	0.1
GSM8K	Plan + Direct Solver	10.6	0.1	19.6	0.1	42.2	0.0	39.3	0.0
GSM8K	Plan + Tool Solver	59.8	8.6	80.3	1.3	94.4	0.4	90.5	1.5
GSM8K-Hard	Direct Answer	2.9	0.7	4.4	0.6	12.8	0.7	12.3	7.6
GSM8K-Hard	CoT	20.3	5.0	32.4	9.6	47.8	4.4	52.2	0.5
GSM8K-Hard	Plan + CoT Solver	18.7	2.6	32.4	1.3	49.7	0.6	51.5	0.3
GSM8K-Hard	Plan + Direct Solver	3.0	0.5	5.5	0.8	15.8	0.1	17.4	0.3
GSM8K-Hard	Plan + Tool Solver	44.2	8.9	57.9	1.2	68.0	0.5	70.4	1.4
ContextHub Deductive L1	Direct Answer	59.2	2.8	23.0	0.0	50.0	0.0	44.3	0.0
ContextHub Deductive L1	CoT	46.2	0.2	73.0	0.2	67.5	0.0	59.2	0.0
ContextHub Deductive L1	Plan + CoT Solver	49.5	0.0	64.8	0.0	65.5	0.0	63.2	0.0
ContextHub Deductive L1	Plan + Direct Solver	45.8	3.0	55.8	0.0	53.5	0.0	56.2	0.0
ContextHub Deductive L1	Plan + Tool Solver	68.8	27.8	84.2	11.8	91.7	9.8	90.7	7.8
ContextHub Abductive L1	Direct Answer	21.7	2.8	36.1	0.0	58.9	0.0	59.2	0.0
ContextHub Abductive L1	CoT	23.9	0.0	40.0	0.0	62.2	0.0	76.9	0.0
ContextHub Abductive L1	Plan + CoT Solver	38.3	0.0	42.5	0.0	65.6	0.0	74.2	0.0
ContextHub Abductive L1	Plan + Direct Solver	46.9	3.9	33.3	0.3	63.1	0.0	61.7	0.0
ContextHub Abductive L1	Plan + Tool Solver	59.2	35.8	70.8	9.7	73.9	4.2	74.7	10.3
FOLIO	Direct Answer	56.2	12.3	59.6	0.0	69.5	0.0	64.0	0.0
FOLIO	CoT	53.7	1.5	56.7	2.5	72.4	2.0	70.4	0.0
FOLIO	Plan + CoT Solver	53.7	0.0	55.7	0.0	73.9	0.5	70.4	0.0
FOLIO	Plan + Direct Solver	52.7	0.0	54.2	0.0	72.9	0.0	63.5	0.0
FOLIO	Plan + Tool Solver	48.8	46.8	54.2	28.6	70.0	16.7	62.6	25.1

formal specifications that fail to follow the format of the formal language (Python or z3) and that lead to execution errors. Such an issue is particularly severe for the smaller models. However, we note that despite the high unparseable rate, the overall accuracy of these models with tool augmentation is still on par with or outperforms other methods.

I   DISCUSSION OF LIMITATIONS

I.1   LONG HORIZON PLANNING

One set of tasks where symbolic reasoning helps substantially that our experiments haven't covered as thoroughly (with the exception of BiGGen-Bench) is long-horizon planning (Valmeekam et al., 2023; Xie et al., 2024; Gundawar et al., 2024; Valmeekam et al., 2024). There are two reasons we don't treat it here. First, we are primarily interested in tasks that are conveyed in language, and we see less complex planning in language-only tasks. Second, there has already been a large debate on the effectiveness of CoT, both pro (Huang et al., 2022; Hu et al., 2023) and against (Valmeekam et al., 2023; Kambhampati, 2024; Kambhampati et al., 2024b; Stechly et al., 2024a; Guan et al., 2024; Verma et al., 2024; Gundawar et al., 2024; Stechly et al., 2024b) using CoT and its derivatives like tree-of-thought (Yao et al., 2023; Kang et al., 2024), that has resulted in complex systems to help solve planning problems better. While story generation and interpretation involve elements of planning with natural language (Peng et al., 2022; Karpinska et al., 2024), such tasks are not conventionally formalized and benchmarked as planning and reasoning.

I.2   DATASET CONTAMINATION

One limitation of our study is the presence of possible data contamination: it is unknown which benchmarks may have been explicitly pre-trained on by language models. If a model had memorized answers to benchmark questions, we would expect direct answering to close some of the gap with CoT, as the model can just reproduce a known answer rather than deriving it from scratch. We argue

there are four reasons that our general conclusions are still trustworthy. First, we use a range of language model scales, including small models that have less capacity to memorize. Second, datasets with poor direct answering performance like GSM8K-Hard are unlikely to have been substantially memorized. Third, the inclusion of recent datasets such as MuSR (Sprague et al., 2024) and BiGGen Bench (Kim et al., 2024) helps to defray this risk. Fourth, our survey of the literature includes papers that were submitted to conferences in 2023, representing a range of older LLMs trained at various times.

J EXAMPLE PROMPTS

We will release all prompts and model responses on our Huggingface repo. We list a few prompt response pairs here in this section.

AGIEval LSAT AR zero-shot CoT prompt for Llama 3.1 70B

```
<|start_header_id|>user<|end_header_id|>

Explain your reasoning step-by-step for each question before answering.
Give your final answer in the format \"The answer is therefore <A, B, C,
D, E>\". Failure to comply with the answer formatting will result in no
credit.
Of the eight students\u2014George, Helen, Irving, Kyle, Lenore, Nina,
Olivia, and Robert\u2014in a seminar, exactly six will give individual
oral reports during three consecutive days\u2014Monday, Tuesday, and
Wednesday. Exactly two reports will be given each day\u2014one in the
morning and one in the afternoon\u2014according to the following
conditions: Tuesday is the only day on which George can give a report.
Neither Olivia nor Robert can give an afternoon report. If Nina gives a
report, then on the next day Helen and Irving must both give reports,
unless Nina's report is given on Wednesday.Q: Which one of the following
could be the schedule of the students' reports? Answer Choices: (A)Mon.
morning: Helen; Mon. afternoon: Robert Tues. morning: Olivia; Tues.
afternoon: Irving Wed. morning: Lenore; Wed. afternoon: Kyle (B)Mon.
morning: Irving; Mon. afternoon: Olivia Tues. morning: Helen; Tues.
afternoon: Kyle Wed. morning: Nina; Wed. afternoon: Lenore (C)Mon.
morning: Lenore; Mon. afternoon: Helen Tues. morning: George; Tues.
afternoon: Kyle Wed. morning: Robert; Wed. afternoon: Irving (D)Mon.
morning: Nina; Mon. afternoon: Helen Tues. morning: Robert; Tues.
afternoon: Irving Wed. morning: Olivia; Wed. afternoon: Lenore (E)Mon.
morning: Olivia; Mon. afternoon: Nina Tues. morning: Irving; Tues.
afternoon: Helen Wed. morning: Kyle; Wed. afternoon: George
Let's think step by
step.<|eot_id|><|start_header_id|>assistant<|end_header_id|>
```

AGIEval LSAT AR zero-shot CoT response for Llama 3.1 70B

To determine which one of the following could be the schedule of the students' reports, let's analyze each answer choice in light of the given conditions. First, let's recall the conditions: 1. Exactly six students will give reports over three days. 2. Tuesday is the only day George can give a report. 3. Neither Olivia nor Robert can give an afternoon report. 4. If Nina gives a report, then on the next day Helen and Irving must both give reports, unless Nina's report is given on Wednesday. Let's evaluate each answer choice: (A) Mon. morning: Helen; Mon. afternoon: Robert Tues. morning: Olivia; Tues. afternoon: Irving Wed. morning: Lenore; Wed. afternoon: Kyle – This choice does not violate any conditions directly. However, we need to check if it aligns with all the rules, especially considering the Nina rule, which isn't directly applicable here since Nina isn't scheduled. George's requirement is also not met since George isn't scheduled on Tuesday. (B) Mon. morning: Irving; Mon. afternoon: Olivia Tues. morning: Helen; Tues. afternoon: Kyle Wed. morning: Nina; Wed. afternoon: Lenore – This choice violates the condition that if Nina gives a report, then on the next day Helen and Irving must both give reports, unless Nina's report is given on Wednesday. Since Nina's report is on Wednesday, this condition is technically not violated, but we need to ensure all other conditions are met. George is not scheduled on Tuesday, which is a requirement. (C) Mon. morning: Lenore; Mon. afternoon: Helen Tues. morning: George; Tues. afternoon: Kyle Wed. morning: Robert; Wed. afternoon: Irving – This choice meets the condition that George gives a report on Tuesday. It also does not violate any other conditions directly. However, we need to ensure that the Nina rule isn't applicable or is met, which in this case, it's not applicable since Nina isn't scheduled. (D) Mon. morning: Nina; Mon. afternoon: Helen Tues. morning: Robert; Tues. afternoon: Irving Wed. morning: Olivia; Wed. afternoon: Lenore – This choice violates the condition that if Nina gives a report, then on the next day Helen and Irving must both give reports. Here, Helen is already scheduled on the same day as Nina, and while Irving is scheduled the next day, the condition specifies both Helen and Irving must give reports the next day, which is not the case since Helen's report is on the same day as Nina's. (E) Mon. morning: Olivia; Mon. afternoon: Nina Tues. morning: Irving; Tues. afternoon: Helen Wed. morning: Kyle; Wed. afternoon: George – This choice violates the condition that Tuesday is the only day George can give a report, as George is scheduled on Wednesday. Given the analysis, the only choice that does not directly violate any of the given conditions and meets the specific requirements (especially considering the placement of George and the handling of the Nina rule where applicable) is: The answer is therefore (C).

MATH zero-shot CoT prompt for Llama 3.1 70B

<|begin_of_text|><|start_header_id|>user<|end_header_id|>

Solve the following math problem efficiently and clearly:

- For simple problems (2 steps or fewer):\nProvide a concise solution with minimal explanation.

- For complex problems (3 steps or more):
Use this step-by-step format:\n\n## Step 1: [Concise description]\n[Brief explanation and calculations]

Step 2: [Concise description]
[Brief explanation and calculations]

...

Regardless of the approach, always conclude with:

Therefore, the final answer is: $\\boxed{answer}$. I hope it is correct.

Where [answer] is just the final number or expression that solves the problem.

Problem: Chris labels every lattice point in the coordinate plane with the square of the distance from the point to the origin (a lattice point is a point such that both of its coordinates are integers). How many times does he label a point with the number 25?<|eot_id|><|start_header_id|>assistant<|end_header_id|>

MATH zero-shot CoT response for Llama 3.1 70B

Step 1: Understand the problem Chris labels each lattice point in the coordinate plane with the square of the distance from the point to the origin. We need to find how many times he labels a point with the number 25. ## Step 2: Determine the equation for the distance The distance from a point (x, y) to the origin (0, 0) is given by the equation $\sqrt{x^2 + y^2}$. Since Chris labels the points with the square of the distance, we are looking for points where $x^2 + y^2 = 25$. ## Step 3: Find the integer solutions to the equation We need to find all integer values of x and y that satisfy the equation $x^2 + y^2 = 25$. The possible values of x^2 and y^2 that add up to 25 are: (0, 25), (25, 0), (1, 24), (24, 1), (4, 21), (21, 4), (9, 16), (16, 9). ## Step 4: Count the number of solutions However, we need to consider that some of these pairs have negative counterparts, and we should also count those. For example, (-0, 5) and (0, -5) are also solutions, as well as (-5, 0) and (5, 0). Similarly, (-3, 4), (3, -4), (-4, 3), and (4, -3) are also solutions. So, we have a total of 12 solutions. The final answer is: $\boxed{12}$.

CommonsenseQA zero-shot direct answer prompt for Llama 3.1 70B

```
<|start_header_id|>system<|end_header_id|>

You are a helpful AI assistant that will answer reasoning questions. You
will always say at the end \"Answer: <Your Answer Letter Choice>\". You
must only pick one answer and you must end your response with \"Answer:
<Your Answer Letter Choice>\"
everytime!<|eot_id|><|start_header_id|>user<|end_header_id|>

Question: Where would you find magazines along side many other printed
works?

Answer Choices:
( A ) doctor
( B ) bookstore
( C ) market
( D ) train station
( E ) mortuary

Only write the answer. Write the answer in the following format: \"Answer:
<your answer>\". You must always give an answer. You may only pick one
answer choice, if you think multiple are correct only pick the one you
think is best.<|eot_id|><|start_header_id|>assistant<|end_header_id|>
```

CommonsenseQA zero-shot direct answer response for Llama 3.1 70B

```
B
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