

Alice in Wonderland: Simple Tasks Showing Complete Reasoning Breakdown in State-Of-the-Art Large Language Models

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Abstract

Large Language Models (LLMs) like closed weights ones GPT-3.5/4, Claude, Gemini or open weights ones like LLaMa 2/3, Mistral, Mixtral, and more recent ones Dbrx or Command R+ are often described as being instances of foundation models - that is, models that transfer strongly across various tasks and conditions in few-show or zero-shot manner, while exhibiting scaling laws that predict function improvement when increasing the pre-training scale. These claims of excelling in different functions and tasks rely on measurements taken across various sets of standardized benchmarks showing high scores for such models. We demonstrate here a dramatic breakdown of function and reasoning capabilities of state-of-the-art models trained at the largest available scales which claim strong function, using a simple, short, conventional common sense problem (AIW problem) formulated in concise natural language, easily solvable by humans. The breakdown is dramatic, as models show strong fluctuations across even slight problem variations that should not affect problem solving, also expressing strong overconfidence in the wrong solutions, often backed up by plausible sounding explanation-like confabulations. Various standard interventions in an attempt to get the right solution, like various type of enhanced prompting, or urging the models to reconsider the wrong solutions again by multi step re-evaluation, fail. We take these initial observations to the scientific and technological community to stimulate urgent re-assessment of the claimed capabilities of current generation of LLMs. Such re-assessment also requires common action to create standardized benchmarks that would allow proper detection of such basic reasoning deficits that obviously manage to remain undiscovered by current state-of-the-art evaluation procedures and benchmarks¹.

1 Introduction

In the recent breakthroughs on transferable learning that were achieved in various classical domains of machine learning like visual recognition [1] or language understanding [2, 3, 4], large language models (LLMs) have played a very prominent role. Auto-regressive language modelling by next token prediction using causal mask losses was among the first successful approaches to self-supervised learning that was also scalable, both in terms of available web-scale text data and model scale [4]. The generic form and scalability of this type of learning allowed then to push towards training scales not achievable before with conventional supervised label-based learning, and provided glimpse on what happens on those larger scales. Scaling laws derived via training experiments on much smaller scales

¹Code for reproducing experiments in the paper and raw experiments data can be found at AIW repo

(2-3 orders of magnitude in model and data scale) enabled to predict the properties and functions of models trained on larger scales [5, 6].

Using standardized benchmarks for language based tasks, those predictions were confirmed by training very large language models like closed GPT-3/4 [4, 5, 7] or open weights models like Llama [8, 9] or Mistral [10], and observing high benchmark scores across a broad range of various task types, which matched the predictions of strong function and transfer to novel task types and scenarios. LLMs excelled especially in few-shot and zero-shot tasks [11], outperforming previous state-of-the art (SOTA) by extremely large margins and showing so called emergent functions like in-context learning not encouraged explicitly during pre-training, providing further hints for the generalization and transfer capabilities of very different kind as opposed to those that were possible in the machine learning field before.

There were however observations made by various works that questioned the claimed strong out-of-distribution generalization, transfer and reasoning capabilities attributed to LLMs [12]. These works pointed out various function failures that were seemingly incompatible with postulated strong capabilities as measured by standardized benchmarks [13, 14, 15, 16]. However, it has also been noted that observed failures can frequently be addressed through simple adjustments to the prompts or by repeated execution and evaluation using majority voting, or by requesting the model to perform self-verification. [17, 18, 19, 20, 21]. This questions whether there is a real deficit in core model capabilities or whether there is rather a minor issue that can be easily resolved by a more careful, but simple, model handling.

To shed light on this current situation, we introduce here a simple, short conventional problem that is formulated in concise natural language and can be solved easily by humans. The original problem formulation, of which we will present various versions in our investigation is as following: "**Alice has N brothers and she also has M sisters. How many sisters does Alice's brother have?**". The problem features a fictional female person (as hinted by the "she" pronoun) called Alice, providing clear statements about her number of brothers and sisters, and asking a clear question to determine the number of sisters a brother of Alice has. The problem has a light quiz style and is arguably no challenge for most adult humans and probably to some extent even not a hard problem to solve via common sense reasoning if posed to children above certain age.

We posed varying versions of this simple problem (which in following we will refer to as "Alice In Wonderland problem", AIW problem) to various SOTA LLMs that claim strong reasoning capabilities. We selected closed ones like GPT-3.5/4/4o (openAI), Claude 3 Opus (Anthropic [22]), Gemini (Google DeepMind [23]), and open weight ones like Llama 2/3 (Meta), Mistral and Mixtral (Mistral AI), including very recent Dbrx by Mosaic [24] and Command R+ by Cohere [25] (which are stated in numerous announcements to lead the open weights models as of April 2024, according to open LLM leaderboards). We analyse the response statistics and observe strong collapse of reasoning and inability to answer the simple question as formulated above across most of the tested models, despite claimed strong reasoning capabilities. Notable exceptions are Claude 3 Opus and GPT-4 that occasionally manage to provide correct responses backed up with correct reasoning as evident in structured step by step explanations those models deliver together with solution. However, Claude 3 Opus and GPT-4 still show frequent failures to solve this simple problem across trials. Importantly, they also show strong fluctuations across even slight problem variations that should not affect problem solving. Retaining the relational logic of the problem, we also formulated a harder form (AIW+), where both Claude 3 Opus and GPT-4o collapse almost to 0 success rate.

This breakdown can be considered to be dramatic not only because it happens on such a seemingly simple problem, but also because models tend to express strong overconfidence in reporting their wrong solutions as correct, while often providing confabulations to additionally explain the provided final answer, mimicking reasoning-like tone but containing nonsensical arguments as backup for the equally nonsensical, wrong final answers. Those confabulated explanations may mislead readers into thinking that there might be sound reasoning behind the wrong answers, or at least stir confusion, as they often sound plausible while being entirely or partly off. The breakdown appears dramatic also because when attempting to fix the failures via various usual interventions like enhanced prompting or by explicitly pointing the models to committed mistakes and requesting to reconsider the responses, the models keep producing more nonsense, often in lengthier and sometimes more entertaining form, leading stubbornly to the same wrong final answers. We provide examples of such failures in various SOTA models that claim strong reasoning.

In the face of these observations and findings, we conclude that the capabilities of the current generation of SOTA LLMs to perform even simple reasoning on common sense tasks are heavily compromised and that current language model benchmarks, especially those aiming on measuring reasoning capabilities, do not properly reflect such weaknesses. We discuss how this can be consistent with the observed strong performance on a range of complex real world tasks (e.g., graduate exams) and finish with a call to the scientific community to address the challenge of re-assessing the reasoning capabilities of LLMs together by building reasoning task benchmarks that are able to spot such various deficits and thus show the path for improvement of current unsatisfactory state.

2 Methods & Experiment Setup

2.1 Finding a simple common sense reasoning task that break the models

Following a number of works that attempt to test capabilities and identify weak spots of current LLMs, we were looking for a simple problem setting that would allow us to test a model’s ability to perform basic reasoning with a common sense character. We looked into tasks presented to elementary school students of age 7-10 on the level of math Olympiads composed for young children. Solving such tasks does not require sophisticated knowledge, but already contains challenges that are not entirely trivial and have to be solved by carefully applying various forms of basic reasoning.

Taking inspiration from those problems and aiming for even simpler settings, we arrived at a very simple problem template that can be easily solved using common sense reasoning but is not entirely straightforward, of the following form: "*Alice has N brothers and she also has M sisters. How many sisters does Alice’s brother have?*". The problem - we call it here "**AIW problem**" - has a simple common sense solution which assumes all sisters and brothers in the problem setting share the same parents. The correct response C - number of sisters - is easily obtained by calculating $M + 1$ (Alice and her sisters), which immediately gives the number of sisters Alice’s brother has.

Initially, we assumed that the AIW problem will pose no challenge for most of the current state-of-the-art LLMs. In our initial experiments, we started by looking at the problem instance with $N = 4$ and $M = 1$, with correct the response being $C = 2$ sisters and we noticed to our surprise that on the contrary, most state-of-the-art models struggle severely to provide correct responses when confronted with the problem. We also noticed already during early experimentation that even slight variations of numbers N and M may cause strong fluctuations of correct response rate.

Often, models seemed to rely on attempting to execute various basic arithmetical operations on the numbers mentioned in the problem to arrive to a final answer. The probability to get a correct response was thus influenced by how likely executing few arbitrary simple calculations, like additions or multiplications that included numbers presented in the problem text, might also accidentally result in a correct answer, although the way of arriving there had nothing to do with correct reasoning (see Appendix G for a selection of such examples). After rounds of experimentation with instances of the AIW problem, varying numbers and ordering, we arrived at four different problem instances, or problem variations, which we term "AIW Variation" 1-4. Each variation has a particular combination of N, M numbers with a corresponding correct answer C , and ordering of brothers-sisters in the AIW problem as presented above: AIW Variation 1, $N = 3, M = 6, C = 7$; AIW Variation 2, $N = 4, M = 2, C = 3$; AIW Variation 3, $N = 1, M = 4, C = 5$; AIW Variation 4, $N = 4, M = 1, C = 2$. When choosing variations, we aimed at reducing the probability of accidentally guessing a correct answer by executing an arbitrary chosen simple one-step arithmetical operation on numbers in the problem (only Variation 3 allows that; see Suppl. Sec. B and Tab. 2 for the full formulation of original prompts used for AIW variations 1-4).

We then used this set of the AIW problem variations, which also allowed us to measure sensitivity and robustness of model behavior to slight modifications without changing the simple core problem structure, to conduct our main experiments and arrive at central conclusions of our investigation regarding basic reasoning capabilities of the studied LLMs.

2.2 Evaluating model responses

To perform evaluations of model performance, we were confronted with the question of how to parse and extract the final answer from the responses provided by the models when confronted with the input containing the AIW problem formulation. On the one hand, it should be possible to deal with

any response provided by the model as a solution, while on the other hand allowing to extract a clear final answer as a number to be compared with the correct answer, such that for each model response a decision can be made on whether the provided response was right or wrong. To be able to keep the parsing procedure simple (without involving for instance another suitable LLM prompting it to extract the relevant part of response), we have chosen to add to the problem prompt following passage: "*provide the final answer in following form: ##### Answer: " "*". We observed that all models we have chosen to test were able to follow such an instruction, providing a response that could be easily parsed. We also ran control experiments without such formatting instruction in the problem formulation, ensuring that behavior does not depend on it.

The presented prompt extension makes it possible to extract for each prompting trial whether a model has provided a correct answer to the AIW problem posed in the input. We can interpret then any number n of collected responses as executing n trials given a particular prompt for a given model (n - number of Bernoulli trials), observing in each i -th trial a Bernoulli variable $X_i = \{0, 1\}$. We interpret the number of correct responses $X = \sum_i X_i$ as random variable following a Beta-Binomial distribution with unknown probability p of correct response that we also treat as random variable that comes from a Beta distribution, i.e. $p \sim \text{Beta}(\alpha, \beta)$, where α and β are parameters of the Beta distribution. To obtain plots showing correct response ratios, we would like to estimate Beta distribution underlying p , and for that, we first estimate the mean of p and its variance from the collected observations. To estimate \hat{p} , we use the formula for estimating the mean of p for a binomial distribution: $\hat{p} = X/n$ (i.e. as a proportion of successes). We can report the estimate \hat{p} as the estimate of the correct response rate of a given model and also, compare the correct response rates of various tested models. Moreover, we can estimate the variance of the probability of a correct response by using the following formula:

$$\text{var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n^2} \sum_{i=1}^n \text{var}(X_i) = \frac{n\text{var}(X_i)}{n^2} = \frac{\text{var}(X_i)}{n} = \frac{p(1-p)}{n} \quad (1)$$

The estimates of the variance and the standard deviation of p can be thus obtained by using \hat{p} as $\frac{\hat{p}(1-\hat{p})}{n}$ and $\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$ respectively. Using the estimated variance and mean of p , we can use the following relations for the variance: $(\sigma^2 = \frac{n\alpha\beta(\alpha+\beta+n)}{(\alpha+\beta)^2(\alpha+\beta+1)})$ and the mean $(\mu = \frac{\alpha}{\alpha+\beta})$ in order to obtain α and β parameters for the Beta distribution. To simulate data for the plots, we draw N random samples corresponding to correct and incorrect responses using the estimated distribution of p and obtain the plots showing performance on the task for various models of interest as a full distribution of the respective p .

Model prompt types. It is well known that so-called prompt engineering can heavily influence the model behavior and model response quality [26, 27, 28]. To account for the response variations due to various prompt forms, we created 3 distinct prompt types asking for the solution to the AIW problem: STANDARD, THINKING, and RESTRICTED (see Suppl. Tab. 2) The STANDARD prompt type asks to solve the posed problem and output the final answer in the format as described above. This does not put any specific requirements on model behavior. The THINKING prompt type extends STANDARD with the request to think carefully and double check the solution for any mistakes (slight modification THINKING v2 uses in addition "step by step" in the formulation). This should encourage model to invest more computation into obtaining the solution. In contrast to this, the RESTRICTED prompt urges the model to output only the final answer without any further text. This is supposed to restrict compute invested in producing output. We observe substantially shorter outputs across tested models compared to STANDARD and THINKING for this prompt type (Suppl. Fig. 21).

Furthermore, we make use of several prompt types (see Suppl. Sec.B for overview) to demonstrate the important properties and the different success or failure modes of the model behavior for the AIW problem. In those prompts, we re-use the main problem formulation as introduced in Sec. 2.1, while adding various modifications. This allows us for instance, to see examples of confabulations that contain clearly broken reasoning-like statements backing up wrong final answers, expression of levels of certainty highlighting overconfidence and miscalibration, or in-context learning handling.

2.3 Selecting models for evaluation and conducting experiments

We are interested in testing current state-of-the-art models that claim strong function, especially in reasoning, backed up by high scores shown on standardized benchmarks that are assumed to measure problem solving and reasoning capabilities. We therefore select models widely known and used in the ML community that also appear in the top rankings of the popular LLM leaderboards, like openLLM leaderboard by HuggingFace or ELO leaderboard by LMsys. All those models are listed in Suppl. Tab. 6, together with the corresponding standardized benchmarks where they obtain strong scores. Whenever possible, we chose from the same family of models with various scales, ranging from small to large, in order to see how the capabilities to solve the posed task may vary with scale.

Having selected the models to test, we conduct our main experiments by exposing each model to the collection of prompts that contain AIW problem variations as described in Sec. 2.1,2.2. We use hosting platforms that offer API access to the models we test, and automatize the procedure by scripting the routines necessary to prompt models with our prompts set. The routines are simple and can be used by anybody with access to the APIs (we used litellm and TogetherAI for our experiments) or to locally hosted models to reproduce and verify our results. We protocol all the data from interactions with the models to enable checking by the community. The collected data is then used to measure correct response rates of the models as described in Sec. 2.2. We also use distinct prompt types STANDARD, THINKING, RESTRICTED to observe differences in model response depending on the compute the model is encouraged to invest into producing the output. For each model, we obtain at least 30 trials for each combination of AIW variation and prompt type (Suppl. Fig. 20). We also use variations of the prompts to study responses given by base models as a control experiment to check whether we see any difference with respect to main observations done on instruction type models, and we employ further prompt variations to demonstrate the model confidence estimation and self-verification or self-correction attempts (see Suppl. Sec.B for the examples of such prompts).

3 Results

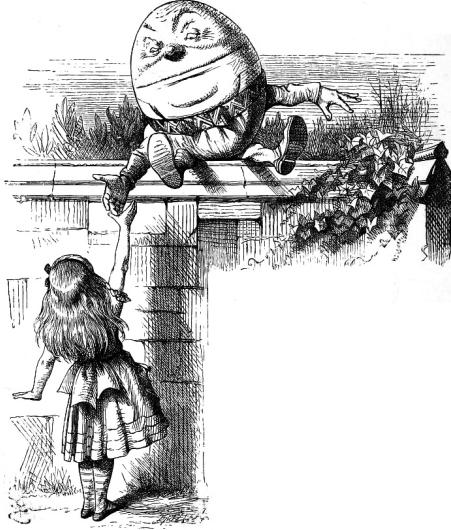


Figure 1: Alice is reasoning: will it break? Illustration of Humpty Dumpty from Through the Looking Glass [29], by John Tenniel, 1871. Source: Wikipedia.

3.1 Humpty Dumpty sat on a wall: breakdown of SOTA LLMs on the simple AIW problem

AIW reveals severe reasoning deficits in SOTA LLMs. Following the procedures described in Sec 2.3, we expose the selected models that claim strong function and reasoning capabilities (Fig. 1) and measure their performance as correct response rate across many trials (> 30) for each of AIW problem variation 1-4 using various prompt types (see also Suppl. Tab. 2). The results suggest that

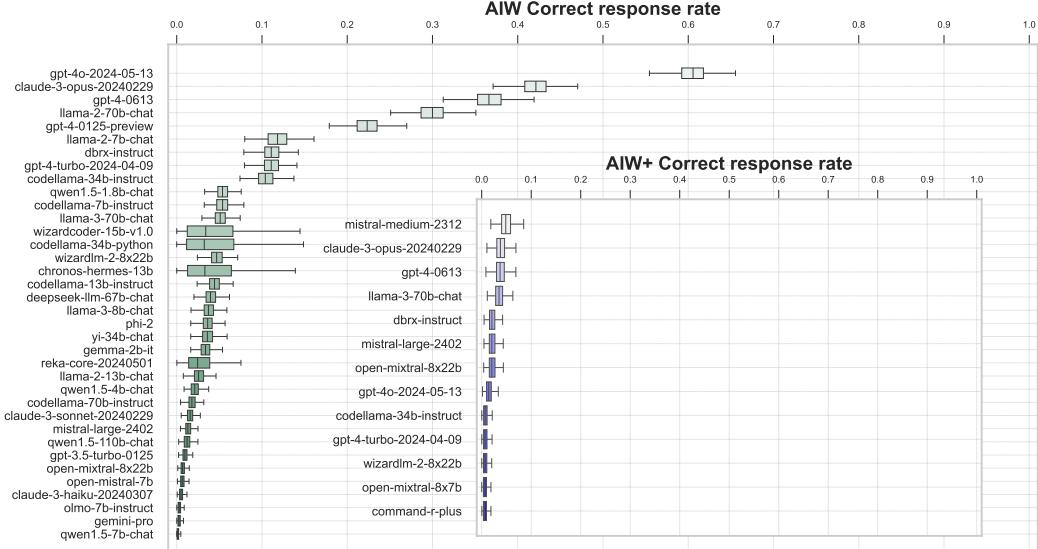


Figure 2: Collapse of most SOTA LLMs on AIW problem. Models with non-zero AIW (**main**) and AIW+ (**inlay**) correct response rate (averaged across prompt variations with prompt types THINKING and STANDARD). Leading on AIW, GPT-4o collapses strongly on AIW+. Omitted models score 0.

confronted with the AIW problem described in Sec 2.1, models suffer a severe reasoning breakdown. This breakdown has two main manifestations:

1. Low correct response rates. Many models are not able to deliver a single correct response, and the majority stay well below correct response rate of $p = 0.2$. We summarize the main results in the Fig. 2. The only major exceptions from this main observation of very low correct response rates are the largest scale closed models GPT-4 and Claude 3 Opus. These two model types at largest scales obtain correct response rates well above $p = 0.3$, leaving the remaining large and smaller scales open-weights (e.g., Mistral-7B, Mixtral, Qwen, Command R+, and Dbxr Instruct) and closed-weights models (e.g., Gemini Pro, Mistral Large) far behind.

The results presented in the Fig. 2 show estimates for correct response rates for STANDARD and THINKING prompt types (Suppl. Tab. 2) - we separate RESTRICTED prompt type results since this prompt forces models into short outputs, restricting the compute they can spend on providing a solution and further deteriorating the response quality (see Suppl. Sec. C for more details). Among the 4 models that are able to cross $p = 0.3$, two clear winners are the very recent GPT-4o and Claude 3 Opus, while the only open-weights model in this set of better performers is the rather older Llama-2 70B Chat. By inspecting the correct answer responses of those better performers, we indeed see mostly correct reasoning executed to arrive at the final correct answers. For the models that do not perform well and are able to deliver correct answers only rarely, we still see in some of those very rare responses with correct final answer correct proper reasoning, for instance in case of Mistral/Mixtral, Dbxr Instruct, CodeLlama. We see however also responses with a correct final answer, which after careful inspection, turns out to be an accident of executing entirely wrong reasoning, where many accumulating mistakes accidentally lead to the final number corresponding to the right answer. Those wrong-reasoning-right-answer responses are encountered in models that perform poorly ($p < 0.3$) (see Suppl. Sec. D for response examples).

2. Strong performance fluctuations across slight AIW problem variations. Importantly, we also observe strong fluctuation of correct response rates across AIW variations 1-4 as introduced in Sec. 2.2. Such fluctuations also affect strongly better performers with higher average correct response rates like GPT-4o and Claude 3 Opus. As shown in the Fig. 3 for the THINKING prompt type, the correct response rates can fluctuate between being close to 1 all the way down to being close to 0, depending on AIW variation. Those fluctuations are observed despite only slight changes in numbers used across AIW variations, without changing anything else in the core problem formulation. See also Suppl. Sec. C, Fig. 19) for further examples on STANDARD prompt type. Strong fluctuations are also observed across prompt types, for instance when comparing RESTRICTED vs STANDARD and THINKING (Suppl. Fig. 17, 18).

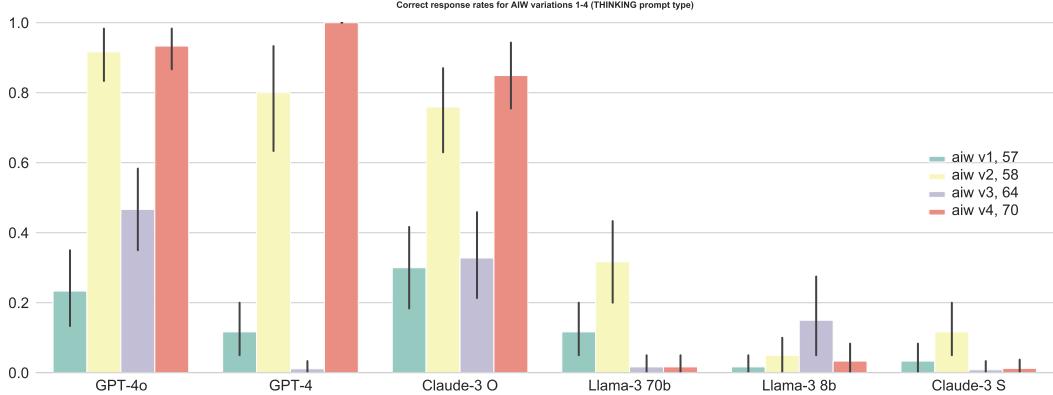


Figure 3: Strong fluctuations across AIW problem variations. Also for higher performers, eg GPT-4o, GPT-4 and Claude Opus 3, correct response rates vary strongly from close to 1 to close to 0, despite only slight changes introduced in AIW variations (a color per each variation 1-4). This clearly shows lack of model robustness, hinting basic reasoning deficits.

Standardized benchmarks failure. All of the tested models report high scores on various standardized benchmarks that claim to test reasoning function, e.g. MMLU, ARC, Hellaswag, to name a few. Clearly, our observations hint that those benchmarks do not reflect deficits in basic reasoning of those models properly. We visualize this failure by plotting performance of tested models that are reported to obtain on wide-spread and accepted standardized benchmarks like MMLU versus the performance we observe on our proposed AIW problem. As strikingly evident from Fig. 4, there is a strong mismatch between high scores on MMLU reported by the models and the correct response rates they obtain on AIW. This miscalibration with respect to standardized benchmarks makes it impossible for a given model to predict from higher scores on MMLU whether the model will be also able to solve AIW on the one hand. On the other hand, it deranges any model comparison with the standardized benchmark, as models with higher MMLU can have complete breakdown in AIW, while models with lower MMLU can have some non-negligible AIW performance. A clear example of such case is comparison LLama 2 70B and such models claiming very strong performance like Command R+ or Dbrx. Those recent models claiming strong function via scoring clearly higher on MMLU (and other standardized benchmarks) than older LLama 2 70B undergo severe breakdown on AIW - e.g. Command R+ is hardly able to solve any instance of an AIW task (see also Suppl. Tab. 6). For further results on other standardized benchmarks with similar outcome see Suppl. Sec. C.5, Suppl. Tab. 7 and Suppl. Fig. 12,13,14,15.

Go small, go home: breakdown at smaller scales. The few models capable of showing significant non-zero correct response rate for the AIW problem are residing on the largest scale. GPT-4 and Claude 3 Opus have unknown scales, it is however reasonable to assume the model scale is well beyond 70B params and the tokens scale is well beyond 2T tokens. Observing the performance on the AIW problem across various models, we see evidence that LLama 2 is a model family that has significantly higher correct response rates compared to other models that have non-zero correct response rates. Within the LLama 2 family, while 7B and 13B model scales achieve non-zero rates, 70B is clearly outperforming those smaller scales (Fig. 2, 4, Suppl. Tab. 6). In general, we observe that smaller scale models (known to have been overtrained on large token budgets of $> 2T$ tokens) that have quite high scores on standardized reasoning benchmarks coming close to larger scale ones, suffer severe collapse on the AIW problem and no small scale model can even remotely approach the performance shown by larger scale ones that can occasionally handle the AIW problem (LLama 2 70B, GPT-4 or Claude Opus). Important note here is that while probability of random guess on AIW problem is not straight forward to calculate, as the answer might be any natural number, it is conceivable that any somewhat capable language model can probably easily infer from the problem formulation without any reasoning that response should be a rather low natural number. That might restrict the candidate numbers to a narrow interval, eg 0-10, which would provide a random guess probability of about $p = 0.1$. Following that consideration, any correct rate response that is around or below $p = 0.1$ can be considered just random guessing that does not require any reasoning. All the

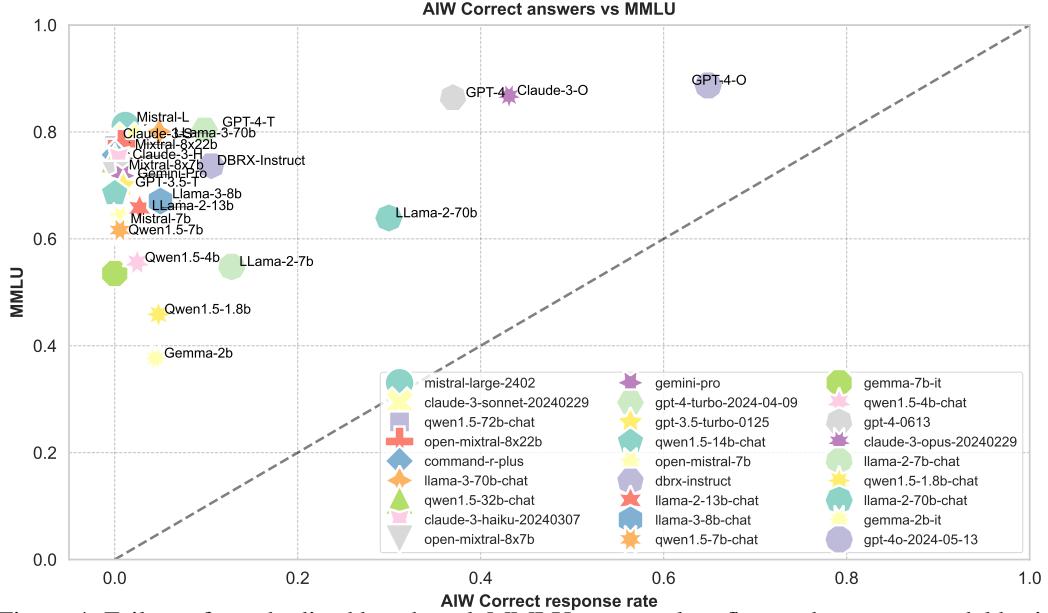


Figure 4: Failure of standardized benchmark MMLU to properly reflect and compare model basic reasoning capabilities as shown by strong discrepancy between AIW correct response rate vs MMLU average score. Many models, eg. Command R+, score 0 on AIW, but have high MMLU score.

tested smaller scale models (< 13B) would then fall into the category of random guessing according to Fig. 2, Suppl. Fig. 16.

3.2 Curiouser and curiouser

Following our observations of failure of most SOTA LLM models that claim strong function described in Sec. 3.1, we investigated various properties and modes of the observed failure, reporting here the ones we find most remarkable. Investigating the AIW problem further, we also find a formulation (termed AIW+) that is even harder to solve for all the tested SOTA models and we observe strong collapse of the performance across all tested models when exposing them to the AIW+ problem. To further measure the sensitivity and robustness of models to slight AIW problem variations, we formulate AIW Alice Female Power Boost and AIW Extention versions, which provide further evidence for strong performance fluctuations and lack of robustness in all tested models, being a reoccurring signature of their severely impaired basic reasoning we observe in this study.

Overconfidence in wrong solutions. Observing strong failures, we were curious to see how models explain their generated solutions. For the THINKING prompt type, where prompt contains request to double check the solution, we encounter examples where models spontaneously provide assessment of the solution quality and their confidence into the solution. Remarkably, we see that in many cases of the observed responses with wrong reasoning and wrong final answers, the models claim high quality for their provided solution and are also strongly confident that the provided wrong solution is correct. For instance, Claude 3 Opus uses expressions like “logic holds up; double-checking the solution; no mistakes in the reasoning; solution is correct.”, and Command R+ reports “This conclusion is straightforward and clear” for the wrong answers they provide.

We further use variations of the prompt types to make the models generate estimates of the solution quality and their confidence on it, like the SCIENTIST prompt or the CONFIDENCE prompt (see Suppl. Sec. B). With those customized prompt types, we again observe strong overconfidence in the solution quality across the tested models. For the SCIENTIST prompt type, we see for instance LLama 2 70B using persuasive expressions like “carefully analyzing; use logical reasoning; provide a precise and accurate solution; conclusion might seem counterintuitive at first, but it’s actually correct” to back up its wrong solutions. For the CONFIDENCE prompt type, we see for instance for the wrong responses given by Command R+ accompanying statements like “The solution is clear and unambiguous, and I am highly confident that it is correct.”; “I am confident in this answer, as it logically follows from the provided information.”. See Suppl. Sec. F for full examples.

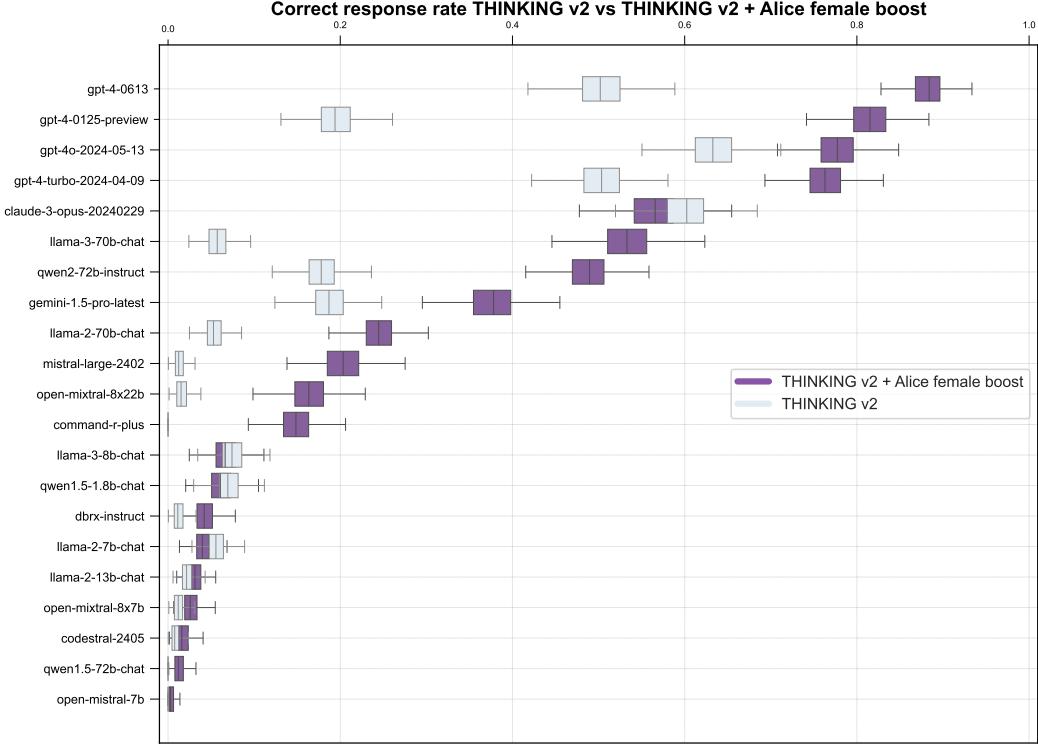


Figure 5: AIW "Alice Female Power Boost" variation. Average correct response rates increase after addition of entirely redundant information "Alice is female" (pronoun "she" already fully indicates the gender in original AIW). Thinking v2 prompt type is used for both AIW versions.

Confabulations to back up wrong solutions. We observe that many models that show reasoning breakdown and produce wrong answers generate at the same time persuasive explanations that contain reasoning-like or otherwise plausible sounding statements to back up the often non-sensical solutions they deliver. We call here such phenomena *confabulations*. Such confabulations may contain for instance calculations or logic-like statements that make no sense. Confabulations can also refer to reasoning about social norms or structures. For instance, in Command R+ we observe many confabulations that use concepts of gender identity such as non-binary gender or concepts related to inclusion or to cultural context dependent family identification as additional backup for the provided wrong reasoning and incorrect answers. Another type of confabulation that we observe is complete refusal to answer due to invented ethical concerns about the nature of the posed AIW problem, such as violation of privacy or lack of inclusion (for instance in CodeLLama-70B-instruct), or by expressing incorrect concerns about supposedly ill-posed problem formulation. See Suppl. Sec. G for more details.

Hard AIW+ problem formulation: breakdown of even the strongest models. Aiming to show that further extension of the initially very simple AIW problem to a harder level will cause further trouble for the tested models, we constructed an AIW+ problem that uses same logic as AIW, but features additional hierarchy and distractors when describing relational family structure (see Suppl. Sec B for full formulation). We manually evaluate the responses for the AIW+ problem to make sure that the models we are testing couldn't just guess and accidentally come to the right solution. Exposing models to AIW+ following same methodology from Sec. 2, we observe further, even stronger collapse of performance, also for those models that were showing significant correct response rates for AIW problem. Remarkably, on AIW+ the GPT-4 (also GPT-4o) and Claude 3 Opus models claiming very strong function collapse to a level close to 0 (see Fig. 2 (**inlay**) and Suppl. Sec. C.2). On the other hand, we still see - albeit on very rare occasions - correct responses that contain fully correct sound reasoning, especially in models that also have shown stronger performance on AIW original (see for a rare example of such fully correct reasoning response to AIW+ problem provided by Claude 3 Opus Suppl. Fig. 30).

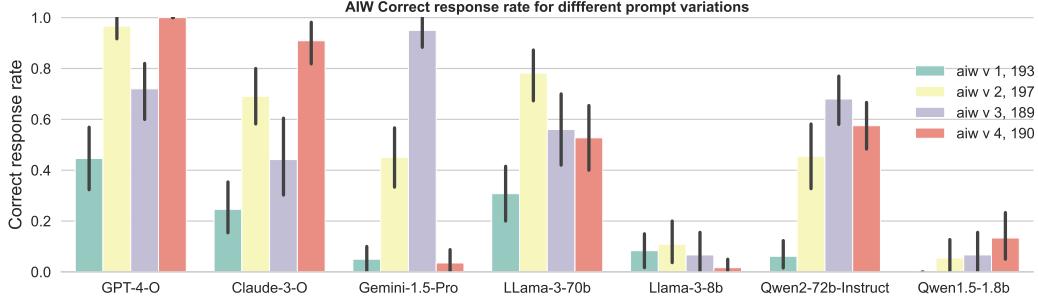


Figure 6: AIW "Alice Female Power Boost" variation (using THINKING v2 prompt type). While average correct response rates increase (see also Fig. 5), strong fluctuations across variations 1-4 remain, again showing lack of robustness and hinting basic reasoning deficits.

Boosting by redundant information and persisting fluctuations: Alice female power boost. One clear characteristics of the reasoning breakdown are the strong fluctuations we observe across AIW problem variations 1-4, Fig. 3 where only slight variations in numbers are used. We investigate a further AIW problem variation by adding "*Alice is female*" to the problem description (see Suppl. Tab 4 and Suppl. Sec. C.3). This is a fully redundant information, as Alice's gender is already unambiguously specified by the "she" pronoun used in original AIW problem. As evident from Fig. 5, the average correct response rates are increasing, despite the provided "female boost" information being entirely redundant and not revealing anything new necessary for AIW problem solution. While correct response rates increase on average, the strong fluctuations across AIW variations 1-4 though remain, Fig. 6. For instance, GPT-4o has on AIW variations 2,4 correct response rate close to 1, while dropping heavily for AIW variations 1,3, showing lack of robustness.

A Tale of Rise and Fall: AIW extension and Claude 3.5 Sonnet. After publication of our first manuscript version presenting original AIW problem, Claude 3.5 Sonnet was released, followed by wide acclaim as a strong frontiers LLM, as also confirmed by standardized benchmarks. We tested the model on AIW original problem variations 1-4. As the first among all tested models, we observed for Claude 3.5 Sonnet correct response rates being 1 on all but AIW variation 1 (Fig. 7 A). This behavior is also unchanged when using Bob AIW Variation, replacing Alice with Bob and adapting formulation correspondingly to keep problem's original structure, Fig. 7 B. Claude 3.5 Sonnet appeared thus from that evidence to have solved AIW problem. We were cautious making conclusions from AIW original formulation only, as those problems were already publicly available and it could not be excluded that data was used for training of models appearing thereafter. We thus created another AIW problem variation without changing its core structure: AIW extended ("AIW Ext"). AIW Ext keeps same variation with numbers, keeping correspondence to AIW variations 1-4 with same numbers as correct responses (see Suppl. Tab. 5 and Suppl. Sec. C.4). Eg. AIW ext variation 3 with correct response C=2 has the form "*Alice and Bob are sister and brother. Alice has 3 sisters and Bob has 1 brother. How many brothers does Alice have?*" (prompt ID 270 in Suppl. Tab. 5). We tested Claude 3.5 Sonnet auf AIW Ext variations 1-4 in same way we tested models on AIW variations 1-4. Claude 3.5 Sonnet revealed then strikingly different behavior on AIW Ext, Fig. 7 C - it shows strong breakdown to much lower correct response rates and again fluctuations across variations 1-4, despite AIW Ext problem structure staying the same as AIW original. Testing other models on AIW Ext (Fig. 8) shows a difference to AIW original as well, for instance lower average correct response rates, with their behavior pattern with respect to fluctuations staying the same, with stronger performers from GPT-4 family and Claude 3 Opus showing again strong fluctuations as on AIW original, Fig. 3. Strikingly different behavior on AIW original in comparison to other tested models might be a hint that data from AIW original problem formulation was used for tuning Claude 3.5 Sonnet, resulting in strongly elevated correct response rates in contrast to other tested models, but showing strong breakdown on AIW Ext and fluctuations similar to other tested models. These observations testify for Claude 3.5 Sonnet same lack of robustness which hints on same basic reasoning deficits we observed in all other stronger performing models.

Further relevant observations. We outline here further experiments that provide hints to the nature of the observed failures and incapabilities. 1. *Inability to revise wrong solutions.* We experiment with customized prompts to enable multi-turn self-verification and also conduct multi-turn interactions with

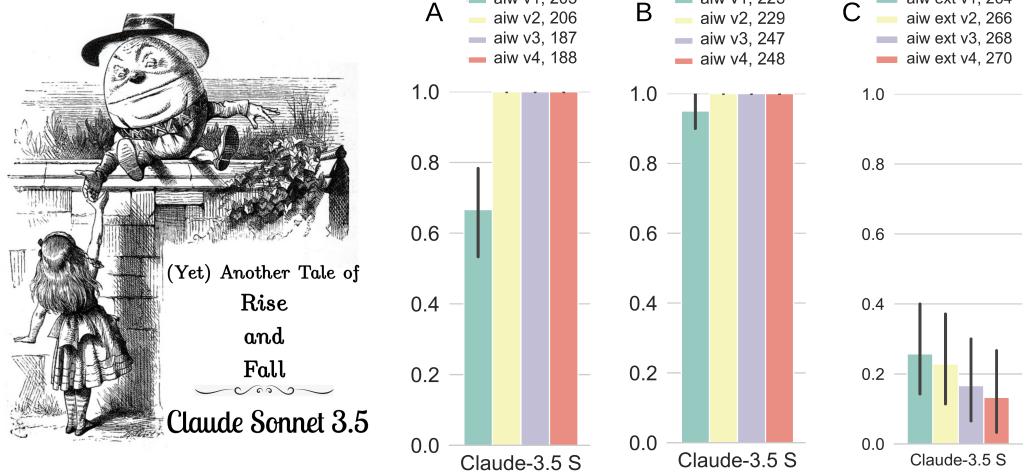


Figure 7: A Tale of Rise and Fall of Claude 3.5 Sonnet. While correct response rates go up close to 1 on (A) AIW original and also (B) AIW Original Bob version, strong breakdown of correct response rates is observed on AIW extension (C) (AIW Ext), accompanied with fluctuations across variations 1-4. Strongly elevated correct responses rates on AIW original might hint on exposure of Claude 3.5 Sonnet to AIW problem data for tuning. Collapse on AIW Ext, which has same problem structure as AIW original, shows though again clearly lack of robustness and hints on same basic reasoning deficits as suspected for other tested models.

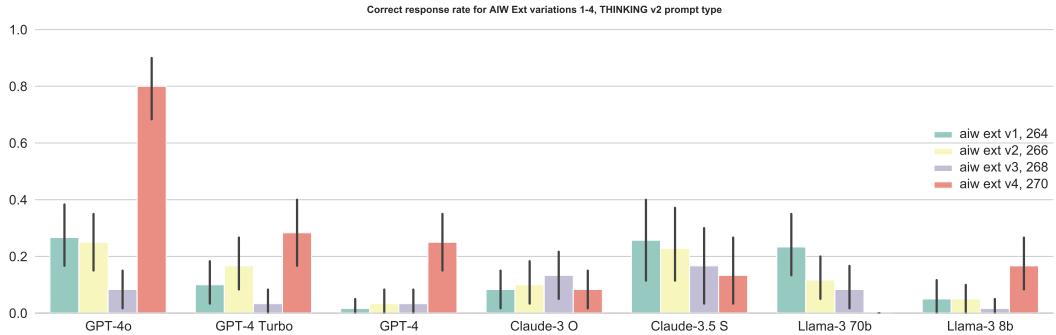


Figure 8: Correct response rates and fluctuations for AIW Ext. All models show lower correct response rates than for AIW original. Again, strong fluctuations across variations 1-4 are present. Claude Sonnet 3.5 does not show different behavior than other models in contrast to AIW original, which again might hint on its exposure to AIW original problem data during tuning.

selected models to encourage those to revise their wrong solutions. In the majority of those attempts, while eagerly agreeing to revise the solutions and check those for possible mistakes, models show failure to properly detect mistakes and to revise wrong solutions (Suppl. Sec. H). 2. *Reformulation of AIW as relational SQL database problem*. We make use of relational logic underlying the AIW problem structure and prompt models to reformulate AIW into a correct relational SQL database format, using a customized SQL-FORM prompt type. We observe that smaller scale models, and also some larger scale ones, consistently fail to generate correct a relational SQL form. Some models are on the contrary able to do so frequently, e.g., Mistral/Mixtral (Suppl. Sec. I) 3. *Parameterized version AIW-Param*. We use a parameterized AIW formulation containing variables (N, M ; or X, Y) for brothers and sisters instead of natural numbers. We again observe a failure of the majority of the models to cope with this generic form, being unable to produce a correct generic solution, e.g. $C = M + 1$ (Suppl. Sec. C.1). 4. *Base model performance*. We inspect the performance of base model selection that claim strong function, e.g. Llama 2, Llama 3, Mistral/Mixtral by using AIW-base prompt types compatible with base model function. We observe the same reality as with instruct models, measuring strong collapse on AIW problem (Suppl. Sec. E. 5. *In-context-learning (ICL)* As

a shortcut solution in form of $M + 1$ exists for AIW problem, we do not expect from ICL to install reasoning skills when confronted with solved examples of AIW problem instances. We execute the experiment to check whether showing problem instances with natural numbers would enable solving of a more general AIW-Param problem. We observe failure of models to do so (Suppl. Sec. J)

4 Related work & limitations

Measuring LLMs capabilities. Since the seminal breakthroughs in language modelling [2, 3, 4], measuring LLM capabilities became indispensable for evaluations and model comparison. To measure how well a language model performs on reasoning, there exists a plethora of different standardized reasoning benchmarks. These benchmarks can be roughly divided into categories by what exact reasoning capability we want to test such as ARC [30], PIQA [31], GSM8K [32], HellaSwag [33], MMLU [34] or Winogrande [35]. Multiple works aim on improving reasoning performance of LLMs as measured by those standardized benchmarks in various ways [27, 36, 37, 38, 39].

Finding weak spots in LLMs capabilities. Paralleling impressive progress shown by LLM research, cautious voices have been raising concern about discrepancy between claimed capabilities as measured by standardized benchmarks and true LLM reasoning skills by presenting carefully selected evidence for model failures [12]. In response, the research community has been undertaking attempts to create more challenging benchmarks like generic HELM [40], BIG-bench [41], or specialized ones, for instance aiming on testing specifically mathematical problem solving related skills [42]. These benchmarks also aimed at properly testing generalization capabilities beyond memorization, in line with recent works that pointed out high test dataset contamination due to large-scale pre-training on web-scale data [14, 15].

Similar in spirit to our work, multiple studies [13, 43, 44, 45, 46, 47] have shown breakdowns of language models reasoning capabilities in different scenarios and also lack of robustness to variation of problem formulation [48, 49]. Other works were looking into particular reasoning failures like deficits in causality inference [50, 51]. These works operate often with formalized, rather complex problems that does not have simple common sense character. Here we show breakdown on a common sense problem with very simple structure, which emphasizes a deficiency in basic reasoning. A key limitation of our current approach is the lack of sufficient diversity in AIW problem variations. This can be addressed in future work by systematic procedural instance generation for broader response evaluation.

5 Discussion & Conclusion

Using a very simple AIW problem formulation that can be easily solved by adults and arguably even children, we observe here a striking breakdown of SOTA LLMs performance when confronted with the task. This dramatic breakdown hints on serious deficits in basic reasoning capabilities in models that are widely claimed to possess strong function and reasoning skills, often citing their performance on a set of standardized benchmarks or the experience of various user groups or their creators. The overall breakdown - manifested in 1. overall low correct response rates and 2. strong performance fluctuation across only slight variations of the same problem - also hints at fundamental issues with the generalization capability of the models, which echoes and confirms concerns expressed in number of previous works [52, 13, 15]

However, the evidence obtained in this study points to a more complex puzzling picture than a straightforward story of out-of-distribution generalization failure for current SOTA LLMs. Albeit observed collapse of reasoning and performance on AIW problem, accompanied by evident strong fluctuations across even slight problem variations, model miscalibration and overconfidence, confabulations alongside incorrect answers, and inability to revise wrong solutions, we see larger-scale models like GPT-4 and Claude 3 Opus coping with the AIW problem, occasionally providing fully sound step-by-step reasoning backing up the correct answers. Despite strong fluctuations across AIW variations, such correct reasoning leading to correct answers appears, though with strongly varying frequency. This is also the case for AIW+, where GPT-4 and Claude 3 Opus suffer further breakdown, but still provide on very rare occasions correct answer responses backed up by fully sound reasoning. The same is true for the much less performant models that show poor or very poor ability to cope with AIW task (e.g., Mistral/Mixtral, LLama 2/3, Dbrx instruct) - also those models manage to generate

on rare occasions correct reasoning-answer responses across AIW variations. We hypothesize that generalization and core reasoning abilities are thus latently present in those models, as otherwise they would not be able to generate such responses at all, as guessing correct answer including full correct reasoning by accident in such cases is impossible (see for a rare piece of evidence for such fully correct reasoning response to harder AIW+ problem provided by Claude 3 Opus Suppl. Fig. 30). The fact that the correct reasoning responses are rare and model behavior is not robust to problem variations demonstrates though deficiency to exercise proper control over these capabilities. The capability to reason in larger scale better performers LLMs is not entirely missing, but is very fragile, so that rare correct answers are drowning in the dominating wrong responses, and even slight variations of same simple AIW problem cause strong performance fluctuations. Investigating the highly interesting question of what causes this deficiency is subject of future work.

What becomes quite clear through our study is the failure of current standardized benchmarks to reflect true model reasoning capabilities and to reveal their weaknesses. As it is evident from Fig. 4 and Suppl. Tabs. 6, 7, many models claiming high standardized scores perform very poorly on AIW. At the same time, older models like LLama 2 70B with lower MMLU, ARC-c and GSM8K scores outperform on AIW clearly those claiming much higher scores, e.g. Command R Plus which suffers complete breakdown on AIW. This hints that model comparison using standardized benchmarks might be seriously jeopardized. The appraisal for the smaller scale models, e.g. Mistral-7B or LLama 2/3 7/8B, is based to large extent on such standardized benchmarks coming close or even matching larger scale models. We observe here however a severe breakdown for smaller scale models on AIW, with a clear large gap to better performing models that all reside at larger scales. We hypothesize here that the claimed strong functions of smaller scale models might be a mere illusion corroborated by broken benchmarks that in their current state cannot offer a proper model comparison and thus also cannot be used as downstream tasks for measuring important scaling laws.

We think that observations made in our study should serve as strong reminder that current SOTA LLMs are not capable of sound, consistent reasoning, as shown here by their breakdown on even such a simple task as the presented AIW problem, and enabling such reasoning is still subject of basic research. This should be also a strong warning against overblown claims for such models beyond being basic research artifacts to serve as problem solvers in various real world settings, which are often made by different commercial entities in attempt to position their models as a strong mature product for end-users (see for instance announcements and claims for Command R+ that breaks down on AIW entirely, emphasizing its high value for "key business-critical capabilities", or "real-world enterprise use cases" [25, 53, 54], and stressing the supposedly present core reasoning capabilities; the same is true for many other commercial models that claim high product value).

Observed breakdown of basic reasoning capabilities, coupled with such public claims (which are also based on standardized benchmarks), present an inherent safety problem. Models with insufficient basic reasoning are inherently unsafe, as they will produce wrong decisions in various important scenarios that do require intact reasoning. Current standardized reasoning benchmarks and claims based on those create illusion of reasoning capabilities that are actually absent, and making it even worse - such models are overconfident, insisting on their wrong answers being correct, and producing highly persuasive and suggestive explanations for their wrong responses, which might mask mistakes for the end-users due to partly plausible sounding text (see Suppl. Sec. G for examples of such confabulations). To ensure safety, public claims should be based only on those scientific evaluations that properly measure the model's capabilities to reason, while basic research has to be performed using such benchmarks to endow future models with sufficient basic reasoning skills.

To perform basic research in direction of improving currently unsatisfactory reasoning skills of SOTA LLMs, it is thus important that whole pipeline of model creation - dataset composition and dataset itself, source code for training, the trained model itself, the standardized benchmarking procedure - is fully open and reproducible. Models that have open weights only do not allow for proper analysis of what might have gone wrong during training that might have resulted in broken reasoning skills - for instance, changing the dataset mix or training procedure itself. Closed models accessible via API only often do not even allow proper evaluation, as for instance default settings such as system prompt and other inference hyperparameters may remain invisible to independent evaluation parties. We think therefore that proper progress in studying how to evaluate and install proper reasoning skills in the future models necessarily requires full training pipeline of a model - especially the often neglected dataset composition - to be open-source (see recent works on FineWeb [55] or DataComp-LM [56]

for encouraging examples of such open dataset composition pipelines), as otherwise the claims about reasoning capabilities will stay unsubstantiated and intrasparent.

Facing these initial findings, we would like to call upon scientific and technological ML community to work together on providing necessary updates of current LLM benchmarks that obviously fail to discover important weaknesses and differences between the studied models. Such updates might feature sets of problems similar to AIW studied here - simple, to probe specific kind of reasoning deficiency, but customizable, thus offering enough combinatorial variety to provide robustness against potential contamination via memorization. We think that strong, trustful benchmarks should follow Karl Popper's principle of falsifiability [57] - not trying to confirm and highlight model's capabilities, which is tempting especially in commercial setting, but in contrast do everything to break model's function, highlighting its deficits, and thus showing possible ways for model improvement, which is the way of scientific method. Building such reasoning benchmarks in common effort will give us a tool both to protect us from overblown claims about model function and to properly navigate the path for improvement of the currently still unsatisfactory state.

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²<https://discord.gg/BZqhreFazY>

³<https://discord.gg/GsKh4mBVcv>

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Supplementary.

A Additional overview for performed experiments

Here we gather additional helpful information on the procedures around the executed experiments. To provide overview over origin of core tested models used for the AIW experiments, we list those in Tab. 1

Table 1: Names, origin and versioning of core test models used in the experiments.

Name	Origin	Released	Open Weights	Sources
GPT-4o-2024-05-13	OpenAI	13.05.2024	No	[7, 58, 59]
GPT-4-turbo-2024-04-09	OpenAI	09.04.2024	No	[7, 60]
GPT-4-0125-preview	OpenAI	25.01.2024	No	[7, 60]
GPT-4-0613	OpenAI	13.06.2023	No	[7, 60]
GPT-3.5-turbo-0125	OpenAI	24.01.2024	No	[61, 62, 63]
Claude-3-5-sonnet-20240620	Anthropic	21.06.2024	No	[64]
Claude-3-opus-20240229	Anthropic	04.03.2024	No	[65, 22]
Claude-3-sonnet-20240229	Anthropic	04.03.2024	No	[65, 22]
Claude-3-haiku-20240307	Anthropic	04.03.2024	No	[65, 22]
Gemini 1.0 Pro	Google	06.12.2023	No	[66, 23]
Gemini 1.5 Pro	Google	16.02.2024	No	[67, 68]
gemma-7b-it	Google	05.04.2024 (v1.1)	Yes	[69, 70]
gemma-2b-it	Google	05.04.2024 (v1.1)	Yes	[69, 70]
Mistral-large-2402	Mistral AI	26.02.2024	No	[71, 72]
Mistral-medium-2312	Mistral AI	23.12.2023	No	[71, 72]
Mistral-small-2402	Mistral AI	26.02.2024	No	[71, 72]
open-mixtral-8x22b-instruct-v0.1	Mistral AI	17.04.2024	Yes	[71, 73]
open-mixtral-8x7b-instruct-v0.1	Mistral AI	11.12.2023	Yes	[71, 74]
open-mistral-7b-instruct-v0.2	Mistral AI	11.12.2023	Yes	[10, 71, 75]
Command R+	Cohere	04.04.2024	Yes	[53, 76]
Dbrx Instruct	Mosaic	27.03.2024	Yes	[24]
Llama 2 70B Chat	Meta	18.07.2023	Yes	[77, 9]
Llama 2 13B Chat	Meta	18.07.2023	Yes	[77, 9]
Llama 2 7B Chat	Meta	18.07.2023	Yes	[77, 9]
Llama 3 70B Chat	Meta	18.04.2024	Yes	[78, 79]
Llama 3 8B Chat	Meta	18.04.2024	Yes	[78, 79]
Qwen 1.5 1.8B - 72B Chat	Alibaba	04.02.2024	Yes	[80, 81]
Qwen 2 72B Instruct	Alibaba	07.06.2024	Yes	[82]

B Prompt types and variations

For testing the model dependence on input prompt as well as robustness towards problem variation while solving AIW, AIW Extended (AIW Ext) and AIW+ tasks we used three main prompt types - STANDARD (original prompt with answer formatting instructions), THINKING (prompt that encourages thinking with answer formatting instructions) and RESTRICTED (prompt that instructs model to output only formatted answer and nothing else). THINKING v2 prompt type is a minor variation of THINKING type that just adds "step by step" phrasing. For testing the models' robustness, we try different prompt variations (AIW Variations, see Sec. 2.1, i.e. keeping the same problem structure but varying numbers and ordering of brothers and sisters, or names of persons, involved).

We employ further prompt types to probe various aspects of model behavior. For instance, to experiment with facilitating more thoughtful and accurate answering, we use SCIENTIST prompt type. For evoking expression of confidence estimate in the provided solution, we employ CONFIDENCE prompt type.

We employ further AIW versions to test model's robustness for problem variations. AIW Alice Female Power Boost uses a fully redundant "Alice is female" addition ("she" pronoun is already used in AIW original problem to fully determine gender information and avoid any uncertainty about

person's gender as it can be inferred from the name only). AIW Ext uses combination of both Alice and Bob as sister and brother to ask same type of question as original AIW.

See Tab. 2 (for AIW problem), Tab. 3 (for AIW+ problem), Tab. 4 (for AIW Alice Female Boost), Tab. 5 (for AIW Ext) for more details and full prompt description.

C Model behavior on AIW, AIW Extended and AIW+ problem

Here we report further details on model behavior as observed on AIW, AIW Extended (AIW Ext), AIW+ and other versions of the problem.

C.1 Parameterized AIW problem (AIW-Param)

We were interested to see where models can cope with this more generic problem formulation that does not use explicit natural numbers. We thus created a parameterized version of the AIW problem has the following form: "*Alice has N brothers and she also has M sisters. How many sisters does Alice's brother have?*". In this instance, the correct answer would be $M + 1$.

We test several models on this task where we have to manually inspect model responses, as simple automated parsing fails here in contrast to the AIW problem with explicit natural numbers. We had to identify the responses that were parsed correctly and if not, provide manual input on whether the response was correct. We also inspected whether models had right reasoning to arrive to final answer as it occurs for this problem type more often that automated response parsing assigns a correct response to the actual wrong reasoning. We provide additional metadata flags for the raw data to indicate whether a sample was manually inspected, and also to signal whether inspected reasoning was correct - or if it's impossible to say in situations when the response is too short, but still correct, to mark reasoning correctness as "unknown". Similar to standard AIW problem, we observe models performing also poorly on this more generic version (see Fig. 22)

C.2 AIW+ problem

We formulate AIW+ problem to offer a higher degree of difficulty compared to original AIW, while having same relational logic appeal. AIW+ problem has following form: "*Alice has 3 sisters. Her mother has 1 sister who does not have children - she has 7 nephews and nieces and also 2 brothers. Alice's father has a brother who has 5 nephews and nieces in total, and who has also 1 son. How many cousins does Alice's sister have?*".

The solution to AIW+ problem is harder to obtain than the solution to common sense AIW with very simple structure. Solving AIW+ requires taking different paternal sides, that of mother and father, and carefully calculating the number of cousins, taking care of subtracting Alice and her sister, and summing up the total number of cousins from both sides, for instance: on the mother side: 7 (total nephews and nieces) - 4 (Alice and her sisters) = 3 cousins; on the father side: 5 (total nephews and nieces) + 1 (own son of the father's brother) - 4 (Alice and her sisters) = 2 cousins; summing up 3 + 2 = 5 cousins which Alice and any of her sisters have (see for a rare example of such a correct answer and correct reasoning provided by Claude 3 Opus in Suppl. Fig. 30)

AIW+ can be thus considered as more complex because it involves more entities (Alice her sisters, parents, uncles and aunts as well as her cousins), more types of relationships between them including a hierarchy and distractors (eg, 2 brothers of mother's sister) that has nothing to do with correct solution to the problem.

C.3 AIW Alice Female Power Boost variation

We investigate a further AIW problem variation by adding "*Alice is female*" to the problem description (see Suppl. Tab 4). This is a fully redundant information, as Alice's gender is already unambiguously specified by the "she" pronoun used in original AIW problem. As strong fluctuations is one repeating signature of reasoning breakdown observed in our study, this variation allows us to study whether fluctuations also appear when adding to the problem redundant information irrelevant for problem solution. Fig. 5 shows that this is indeed the case, further corroborating the view that basic reasoning

Table 2: AIW main variations and prompt types.

Var.	Prompt	Type	ID
1	Alice has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: "### Answer: ".	STANDARD	55
1	Alice has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	THINKING	57
1	Alice has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have? To answer the question, DO NOT OUTPUT ANY TEXT EXCEPT following format that contains final answer: "### Answer: ".	RESTRICTED	53
2	Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: "### Answer: ".	STANDARD	56
2	Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	THINKING	58
2	Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have? To answer the question, DO NOT OUTPUT ANY TEXT EXCEPT following format that contains final answer: "### Answer: ".	RESTRICTED	54
3	Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: "### Answer: ".	STANDARD	63
3	Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	THINKING	64
3	Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? To answer the question, DO NOT OUTPUT ANY TEXT EXCEPT following format that contains final answer: "### Answer: ".	RESTRICTED	65
4	Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: "### Answer: ".	STANDARD	69
4	Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	THINKING	70
4	Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? To answer the question, DO NOT OUTPUT ANY TEXT EXCEPT following format that contains final answer: "### Answer: ".	RESTRICTED	71
4	Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? Solve the problem by taking care not to make any mistakes. Express your level of confidence in the provided solution as precisely as possible.	CONFIDENCE	11
3	Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? To solve the problem, approach it as a very intelligent, accurate and precise scientist capable of strong and sound reasoning. Provide the solution to the problem by thinking step by step, double checking your reasoning for any mistakes, and based on gathered evidence, provide the final answer to the problem in following form: "### Answer: ".	SCIENTIST	40

Table 3: AIW+ prompt types and prompt variations.

Prompt ID	Prompt	Prompt Type	AIW+ Var.	Correct Resp.
91	Alice has 3 sisters. Her mother has 1 sister who does not have children - she has 7 nephews and nieces and also 2 brothers. Alice's father has a brother who has 5 nephews and nieces in total, and who has also 1 son. How many cousins does Alice's sister have? Solve this problem and provide the final answer in following form: "### Answer: ".	STANDARD	1	5
92	Alice has 3 sisters. Her mother has 1 sister who does not have children - she has 7 nephews and nieces and also 2 brothers. Alice's father has a brother who has 5 nephews and nieces in total, and who has also 1 son. How many cousins does Alice's sister have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	THINKING	1	5
93	Alice has 3 sisters. Her mother has 1 sister who does not have children - she has 7 nephews and nieces and also 2 brothers. Alice's father has a brother who has 5 nephews and nieces in total, and who has also 1 son. How many cousins does Alice's sister have? To answer the question, DO NOT OUTPUT ANY TEXT EXCEPT following format that contains final answer: "### Answer: ".	RESTRICTED	1	5

in models is very fragile as model change their behavior when facing irrelevant modifications to problem formulation that should not influence its solution.

C.4 AIW extended (AIW Ext) problem

As yet another test of robustness of models to problem variations, we created another AIW problem version without altering core relational structure of the original simple AIW problem: AIW extended ("AIW Ext"). AIW Ext makes use of both Alice and Bob as sister and brother, posing same type of question about numbers of sisters and brothers each of Alice and Bob might have. We make use of same variations in numbers with correspondence to AIW variations 1-4, that allows to align with same correct answers (Suppl. Tab. 5. Eg. AIW ext variation 3 with correct response C=2 has the form "*Alice and Bob are sister and brother. Alice has 3 sisters and Bob has 1 brother. How many brothers does Alice have?*" (prompt ID 270). Main motivation was to test Claude 3.5 Sonnet on a problem version different from AIW original, after we observed unusually strong performance there in contrast to all other tested models, which led to suspicion that Claude 3.5 Sonnet might have seen original AIW problems during its tuning. AIW Ext is also used for testing other models as yet another problem variation that reveals strong fluctuations due to slight changes in problem formulation.

C.5 Further details on model performance and behavior

To understand if the performance on AIW and AIW+ correlates with standardized benchmarks, we compare correct response rates for tested models with their performance on (Massive Multitask Language Understanding) MMLU benchmark (Table 6). We see that standardized benchmarks are strongly decoupled from AIW and AIW+ performance and cannot predict those - high performance on MMLU can go together with very low performance on AIW or AIW+ (like in case of Command R+ and many other models), while lower performance on MMLU may be coupled to better performance than majority of tested models in AIW, as it is in the case of Llama 2 70B Chat. In this way, ranking given by standardized benchmarks in terms of reflecting relative capabilities of the models to reason cannot be relied on.

For the majority of the tested models, correct response rates for both AIW (Fig. 16) and AIW+ (Fig. 23) are extremely low. At the same time, many of those models score high at standardized benchmarks and are thus considered strongly capable. Some of those models cannot solve AIW task

Table 4: AIW Alice Female Power Boost and AIW Original, variations 1-4, THINKING v2 prompt type

Var.	Prompt	Type	ID
1	Alice is female and has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	FEMALE BOOST	193
1	Alice has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	NO BOOST	205
2	Alice is female and has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	FEMALE BOOST	197
2	Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	NO BOOST	206
3	Alice is female and has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	FEMALE BOOST	189
3	Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	NO BOOST	187
4	Alice is female and has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	FEMALE BOOST	190
4	Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	NO BOOST	188

not a single time. We make sure that number of samples collected for each model is approximately of the same order of magnitude, avoiding distortions due to difference in sampling rates Fig. 20. Different models have quite different output lengths (see Fig. 21 and Fig. 25) within same prompt type. For example, RESTRICTED prompt obviously forces models to output less tokens rather than STANDARD or THINKING which encourages models to longer outputs. For instance models like GPT-4-0124-preview or Command R Plus have rather short responses independent of prompt type compared to other models.

We also observe strong fluctuations of models behavior across AIW variations (as shown in the Fig. 19). It reveals that on average better performing models like GPT-4-0613 are not robust to variations introduced into the AIW problem while keeping the very same problem structure. Case of GPT-4-0613 is especially severe, as the model collapses from correct response rate 1 to 0 between AIW variations 4 and 3 (see Suppl. Tab. 2 for exact formulation of AIW variations). Also GPT-4o, GPT-4-Turbo, Claude 3 Opus and Llama 2 7B and 70B show strong discrepancies. Such behavior hints again on deficiency in basic reasoning capabilities that results in the observed lack of robustness - AIW variations introduce slight changes to numbers and ordering of entities in the very same problem that should not have been a challenge to handle properly, when core reasoning capabilities were intact.

We also can see (Fig. 17 and Fig. 18) strong fluctuations when comparing STANDARD and THINKING vs RESTRICTED prompt type. While it is expected the performance might drop when

Table 5: AIW Ext variations 1-4, Thinking v2 prompt type.

Var.	Prompt	Type	ID
1	Alice and Bob are sister and brother. Alice has 3 sisters and Bob has 6 brothers. How many brothers does Alice have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Alice's brothers	264
2	Alice and Bob are sister and brother. Alice has 2 sisters and Bob has 2 brothers. How many brothers does Alice have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Alice's brothers	266
3	Alice and Bob are sister and brother. Alice has 1 sister and Bob has 4 brothers. How many brothers does Alice have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Alice's brothers	268
4	Alice and Bob are sister and brother. Alice has 3 sisters and Bob has 1 brother. How many brothers does Alice have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Alice's brothers	270
1	Alice and Bob are sister and brother. Alice has 6 sisters and Bob has 2 brothers. How many sisters does Bob have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Bob's sisters	263
2	Alice and Bob are sister and brother. Alice has 2 sisters and Bob has 2 brothers. How many sisters does Bob have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Bob's sisters	265
3	Alice and Bob are sister and brother. Alice has 4 sisters and Bob has 1 brother. How many sisters does Bob have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Bob's sisters	267
4	Alice and Bob are sister and brother. Alice has 1 sister and Bob has 3 brothers. How many sisters does Bob have? Before providing answer to this problem, think carefully step by step and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ".	Bob's sisters	269

forcing models to invest less compute into the output generation, so switching from STANDARD or THINKING to RESTRICTED prompt type (Fig. 17, strong drop observed for Claude 3 Opus when switching from STANDARD to RESTRICTED), we also see drops in the other unexpected direction, for instance for Claude 3 Opus, GPT-4o, Llama 2 70B or Dbrx Instruct, when switching from RESTRICTED to STANDARD or THINKING prompt type (Fig. 18). Such drops may hint that available compute is not properly used for correct reasoning and indicate lack of robustness, as a robust model should only benefit from increasing amount of compute. A robust model that already performs well with smaller compute amount on RESTRICTED prompt type should only improve when switching to STANDARD or THINKING prompt types with more compute available for producing output. This also raises question whether in those cases where we observe short responses on RESTRICTED prompt type to contain correct final answers we actually observe results due to proper reasoning. Breakdown on STANDARD prompt type for the very same problem formulation may indicate that numbers obtained on RESTRICTED prompt type are just consequence of a given AIW variation that induces a strong dominance for a particular number to be generated on the output that does not necessarily any connection to the actual problem solution and is not a result of reasoning.

Obsevations on harder AIW+. To make sure that our results correspond to true model performance and not distorted by wrong automatic response parsing, for AIW+ we manually inspected all models responses considered only the responses that have both correct answer and correct reasoning. If reasoning quality is not clear, for instance in those cases where answer is correct but there is not

Table 6: Performance of tested model on MMLU and AIW problems. MMLU scores obtained from [83, 84, 22].

Model	MMLU	Correct resp. rate (AIW)	Correct resp. rate (AIW+)
gpt-4o-2024-05-13	0.887	0.649	0.015
claude-3-opus-20240229	0.868	0.431	0.038
gpt-4-0613	0.864	0.370	0.038
llama-2-70b-chat	0.639	0.300	0.000
llama-2-7b-chat	0.548	0.128	0.000
dbrx-instruct	0.737	0.106	0.021
gpt-4-turbo-2024-04-09	0.805	0.098	0.008
llama-3-8b-chat	0.671	0.050	0.000
llama-3-70b-chat	0.801	0.049	0.036
qwen1.5-1.8b-chat	0.459	0.048	0.000
gemma-2b-it	0.376	0.045	0.000
llama-2-13b-chat	0.658	0.027	0.000
qwen1.5-4b-chat	0.556	0.025	0.000
claude-3-sonnet-20240229	0.790	0.013	-
mistral-large-2402	0.812	0.012	0.021
gpt-3.5-turbo-0125	0.700	0.009	-
gemini-pro	0.718	0.008	-
open-mixtral-8x22b	0.778	0.007	0.021
open-mistral-7b	0.642	0.006	0.000
qwen1.5-7b-chat	0.616	0.006	0.000
claude-3-haiku-20240307	0.752	0.004	-
open-mixtral-8x7b	0.718	0.001	0.007
command-r-plus	0.757	0.000	0.007
qwen1.5-14b-chat	0.685	0.000	0.000
gemma-7b-it	0.535	0.000	0.000
qwen1.5-72b-chat	0.775	0.000	0.000
qwen1.5-32b-chat	0.750	0.000	0.000

explanation provided (this is often the case for short answers), we introduce a metadata flag into raw data ("correct_reasoning"), which we set in manual inspection to "unknown" in such cases.

We observe (see Fig. 23) an even stronger further collapse across all tested models on AIW+ compared to AIW (see Fig. 16). All models show poor performance well below $p = 0.1$. Remarkably, GPT-4o that was showing the best performance on AIW ($p > 0.6$), collapses dramatically on AIW+ close to 0. AIW+ is clearly harder than AIW, which was made simple by intention. However, models claiming strong reasoning should be able to solve it, as it does not involve any higher level logic or math. This is though not the case for any current SOTA LLMs as our evidence suggests. On the other hand, it also cannot be claimed that reasoning capabilities are entirely absent. For instance, stronger performer models like GPT-4o and Claude 3 Opus can, albeit very rarely, provide a correct answer to AIW+ problem, backed up by fully correct and sound reasoning. Reasoning capability is thus latently present, but is evidently severely impaired and very fragile, so that behavior is heavily dominated by wrong responses. See for a rare example of such fully correct reasoning response to AIW+ problem provided by Claude 3 Opus Suppl. Fig. 30).

Strong fluctuations on AIW problem versions. A reoccurring signature of reasoning breakdown observed in our study are strong fluctuations across AIW problem variations. In addition to observing fluctuations on original AIW variations 1-4, we also see fluctuations on other AIW versions and across problem versions. For instance, when using AIW Alice Female Boost version, we see fluctuations in form of increasing average correct response rates compared to the AIW original (Fig. 5), and also strong fluctuations within Alice Female Boost version on its variations 1-4 (Suppl. Fig. 9). Same strong fluctuations occur also on AIW Ext version, both when comparing it to AIW original and when looking on AIW Ext variations 1-4 (Suppl. Fig. 10). Yet another further example of strong fluctuations is provided when exchanging in AIW Ext the questions for Alice's brothers or Bob's

Table 7: Performance of tested model on MMLU, Hellaswag, ARC-c, GSM8k and AIW problems.

Model	MMLU	Hellaswag	ARC-c	GSM8k	Correct resp. rate (AIW)	Correct resp. rate (AIW+)
gpt-4o-2024-05-13	0.89	-	-	-	0.65	0.02
claude-3-opus-20240229	0.87	95.40	96.40	95.00	0.43	0.04
gpt-4-0613	0.86	95.30	96.30	92.00	0.37	0.04
llama-2-70b-chat	0.64	85.90	64.60	56.80	0.30	0.00
llama-2-7b-chat	0.55	77.10	43.20	25.40	0.13	0.00
dbrx-instruct	0.74	88.85	67.83	67.32	0.11	0.02
gpt-4-turbo-2024-04-09	0.80	-	-	-	0.10	0.01
llama-3-8b-chat	0.67	78.55	60.75	79.60	0.05	0.00
llama-3-70b-chat	0.80	85.69	71.42	93.00	0.05	0.04
qwen1.5-1.8b-chat	0.46	46.25	36.69	38.40	0.05	0.00
gemma-2b-it	0.38	71.40	42.10	17.70	0.04	0.00
llama-2-13b-chat	0.66	80.70	48.80	77.40	0.03	0.00
qwen1.5-4b-chat	0.56	51.70	40.44	57.00	0.02	0.00
claude-3-sonnet-20240229	0.79	89.00	93.20	92.30	0.01	-
mistral-large-2402	0.81	89.20	94.20	81.00	0.01	0.02
gpt-3.5-turbo-0125	0.70	85.50	85.20	57.10	0.01	-
gemini-pro	0.72	84.70	-	77.90	0.01	-
open-mixtral-8x22b	0.78	89.08	72.70	82.03	0.01	0.02
open-mistral-7b	0.64	84.88	63.14	40.03	0.01	0.00
qwen1.5-7b-chat	0.62	59.38	52.30	62.50	0.01	0.00
claude-3-haiku-20240307	0.75	85.90	89.20	88.90	0.00	-
open-mixtral-8x7b	0.72	87.55	70.22	61.11	0.00	0.01
command-r-plus	0.76	88.56	70.99	70.74	0.00	0.01
qwen1.5-14b-chat	0.69	63.32	54.27	70.10	0.00	0.00
gemma-7b-it	0.54	81.20	53.20	46.40	0.00	0.00
qwen1.5-72b-chat	0.77	68.37	65.36	79.50	0.00	0.00
qwen1.5-32b-chat	0.75	66.84	62.97	77.40	0.00	0.00

sisters that again retain very same problem structure, Suppl. Fig. 11. There observations of such strong fluctuations on slight problem modifications provide strong compelling evidence of lack of robustness in all tested models, hinting on their severe deficits in basic reasoning being unable to handle variations despite core problem structure staying the same.

Standardized benchmarks failure. In Section 3.1, we observe failure of standardized reasoning benchmarks to measure reasoning skills of SOTA LLMs by noting significant disparity between the model’s performance on the AIW problem and the outcomes on conventional standardized benchmarks, taking MMLU as representative examples. Here, we confirm this finding on further standardized reasoning benchmarks like MATH, ARC-c, GSM8K and Hellaswag (Suppl. Tab. 7). We provide plots visualizing failure of these standardized benchmarks, reflected in strong mismatch between high benchmark scores reported by many models and the low correct response rates they obtain on AIW (which in some cases is 0 for models with high standardized benchmark scores), in Figures 12, 15, 13, 14.

D Examples of correct and failed responses

We provide all collected model responses we obtained during this study in the collected_responses folder in the AIW repo. Here we also showcase some correct and incorrect answers as an example (see Suppl. Figs. 26, 29, 27, 28, 30).

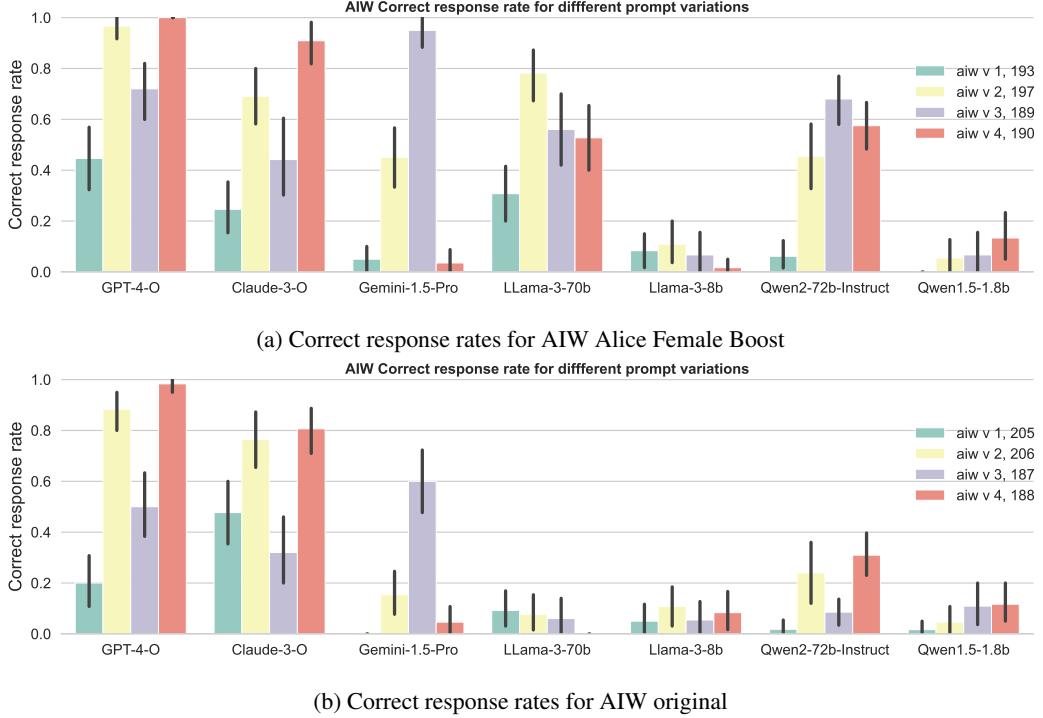


Figure 9: Strong fluctuations within variations 1-4 for (A) AIW "Alice Female Power Boost" version and (B) AIW original, both using THINKING v2 prompt type. Despite "Alice Female Power Boost" using fully redundant information "Alice is female" as only addition to AIW original, average correct response rates increase (see also Fig. 5). For some models, eg Llama 3 70B or Qwen 2 72B, this boost via redundant info is especially pronounced and happens across all variations, resulting in clear overall improvement from (B) to (A). Strong fluctuations across variations 1-4 remain same. This again shows lack of model robustness, hinting on severe basic reasoning deficits.

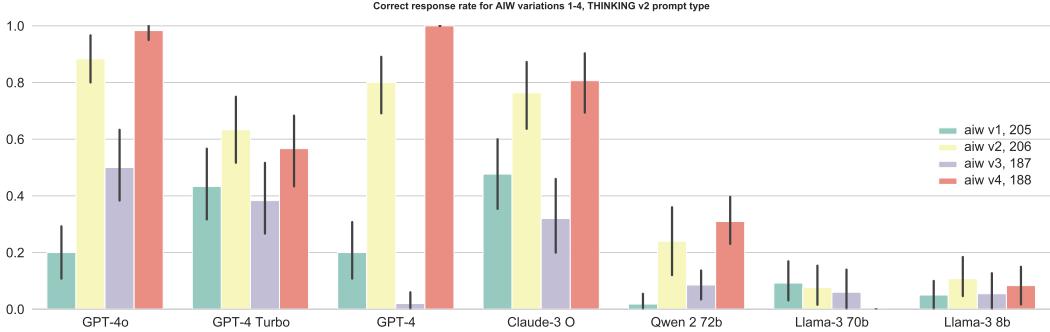
E Base model experiments

On top of our main experiments with instruction tuned models, we have considered to evaluate selected base models on AIW to see whether there is any striking difference between instruction and base model ability to solve the AIW problem. For these experiments we considered currently available bases of several models we have already tested: Mixtral 8x7b, Mixtral 8x22b, Mistral 7b, LLaMA 2 70b, LLaMA 2 13b, LLaMA 2 7b. We used the following prompt for base models: "### Problem: ... ### Answer:". We see in line with what we observe on instruct models that also base models perform poorly on AIW problem. We observe that Mistral 7b base shows higher correct response rate on average across all tested base models (see Fig. 31, while our observations for Mistral 7B instruction model do not show any difference to other similarly poor performing models unable to deal with AIW. We do not see any remarkable differences for base model case compared to our main observations made with instruction models.

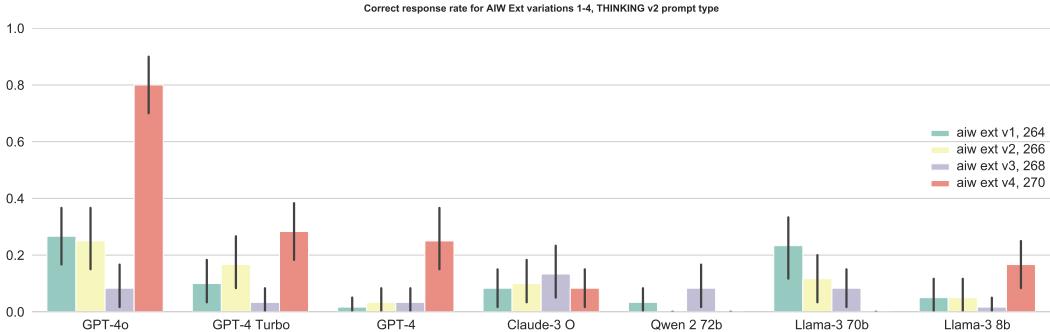
F Lack of uncertainty calibration and overconfidence in wrong answers

For a strong model, one important characteristic is its uncertainty calibration - how well model's estimation of certainty about correctness of the provided response matches with true quality of the response, being correct or incorrect. A well calibrated model should assign high certainty of being correct where corresponding responses are indeed correct, and should assign high uncertainty to those responses that model might signal as correct, while the provided response is actually incorrect.

In ideal scenario, if LLM cannot correctly solve the AIW problem, it should at least be capable of signalling high uncertainty about the provided incorrect solution. We used our CONFIDENCE prompt type (see Table 2 for AIW problem to see how confident tested models are in their wrong



(a) Correct response rates for AIW original, THINKING v2 prompt type



(b) Correct response rates for AIW Ext, THINKING v2 prompt type

Figure 10: Strong fluctuations within variations 1-4 for (A) AIW Original version and (B) AIW Ext, both using THINKING v2 prompt type. Despite AIW Ext using same problem structure as AIW original, average correct response rates drop. Strong fluctuations across variations 1-4 are also evident within each problem version. This further corroborates lack of model robustness and points to severe basic reasoning deficits.

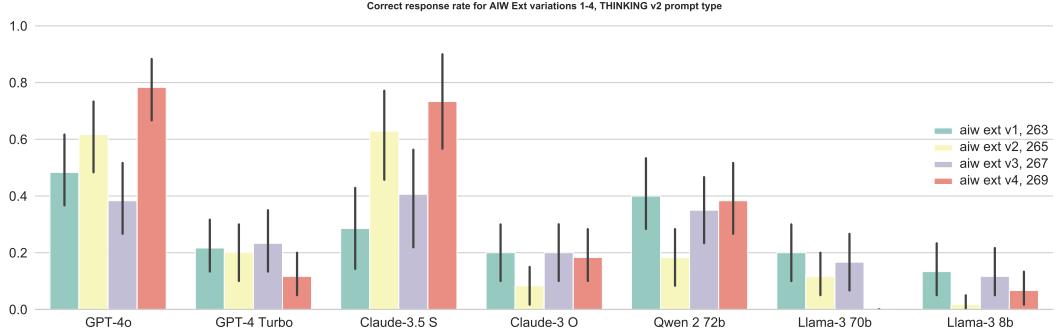
solutions. From our experiments we can see that LLMs most of the time express high certainty even if their answers are completely wrong and thus have strong overconfidence (see Fig. 37). The models also use highly persuasive tone to argue for the expressed certainty and correctness of the provided wrong solutions, using words like "highly confident", "definitive answer", or "accurate and unambiguous". We see also strong overconfidence expressed in multi-turn interactions with models, where user is insisting on solution provided being incorrect, and observe there high resistance of models to revise their decisions, which was already referred to as "stubbornness" in other works [20] (see Suppl. Sec. H and also data provided in the AIW repo)

G Confabulations as back up for wrong answers

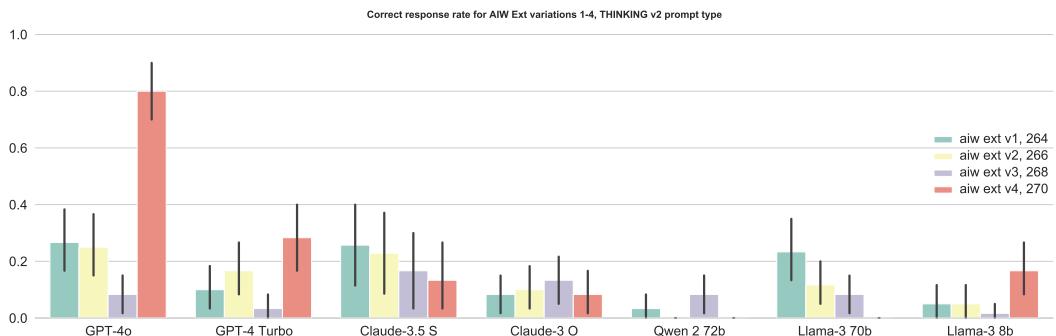
In our experiments we observe frequent tendency of those tested models that show strong reasoning collapse and produce wrong answers for both AIW and AIW+ problems to generate at the same time persuasive sounding pseudo-explanations to back up their incorrect answers. We term here such pseudo-explanations confabulations, and present a selection of those as examples.

Such confabulations can contain mathematical calculations or other logic-like expressions and operations that make little or absolutely no sense given the problem to be solved, see examples for Olmo-7B, Fig. 38 and Command R+, Fig. 40.

Further confabulations make use of various social and cultural norm specific context to argue for the posed problem to be inappropriate to solve or to provide non-sense arguments for various incorrect answers. There are many such examples that we have observed, we present here only a small selection.



(a) Correct response rates for AIW Ext Bob’s Sisters question, THINKING v2 prompt type



(b) Correct response rates for AIW Ext Alice’s Brothers question, THINKING v2 prompt type

Figure 11: Strong fluctuations within variations 1-4 for AIW Ext (A) Bob’s sisters question and (B) Alice’s brothers question versions, both using THINKING v2 prompt type (Suppl. Tab. 5). Despite both versions using same problem structure, only minor difference being in form of question asked, average correct response rates differ. For instance, both Claude 3.5 Sonnet and Qwen 2 72B Instruct drop heavily on (B) vs (A) without any apparent reason, as the modifications do not change the problem structure. Strong fluctuations across variations 1-4 are also evident within each problem version, again exposing lack of robustness to slight problem variations and pointing to severe flaws in basic reasoning.

CodeLlama-70B-instruct for instance seems to be specifically prone to claim ethical or moral reasons for not addressing the problem correctly, in the presented example inventing out of nowhere a person with Down syndrome and then pointing out that question has to be modified to be addressed due to potential perpetuation of harm towards individuals or groups, which has nothing to do with original task, Fig. 39.

Another example are confabulations provided by Command R Plus. These confabulations use concepts of gender identity such as non-binary gender or concepts related to inclusion or to cultural context dependent family identification in the provided wrong reasoning leading to incorrect answers. In the attempt to solve the problem, the model first fails to provide obvious common sense solution and then goes on to describe potential scenarios where brothers and sisters may self-identify as non-binary, although providing information on brothers and sisters in the problem usually means via common sense that those persons self-identify correspondingly to their known status as brother or sister (while Alice is clearly identified via "she" pronoun). Model thus clearly fails to grasp that problem structure has nothing to do with the social and cultural norms. The solutions derived by the model from considering those factors that are far beyond Occam’s razor and common sense inherent to the simple AIW problem all lead to wrong answers and generate more confusion, while again keeping the persuasive tone that suggests that model is on some right path to provide the correct solutions (Fig. 41)

For more illustrative examples, see the raw data on interactions with the models collected in AIW repo)

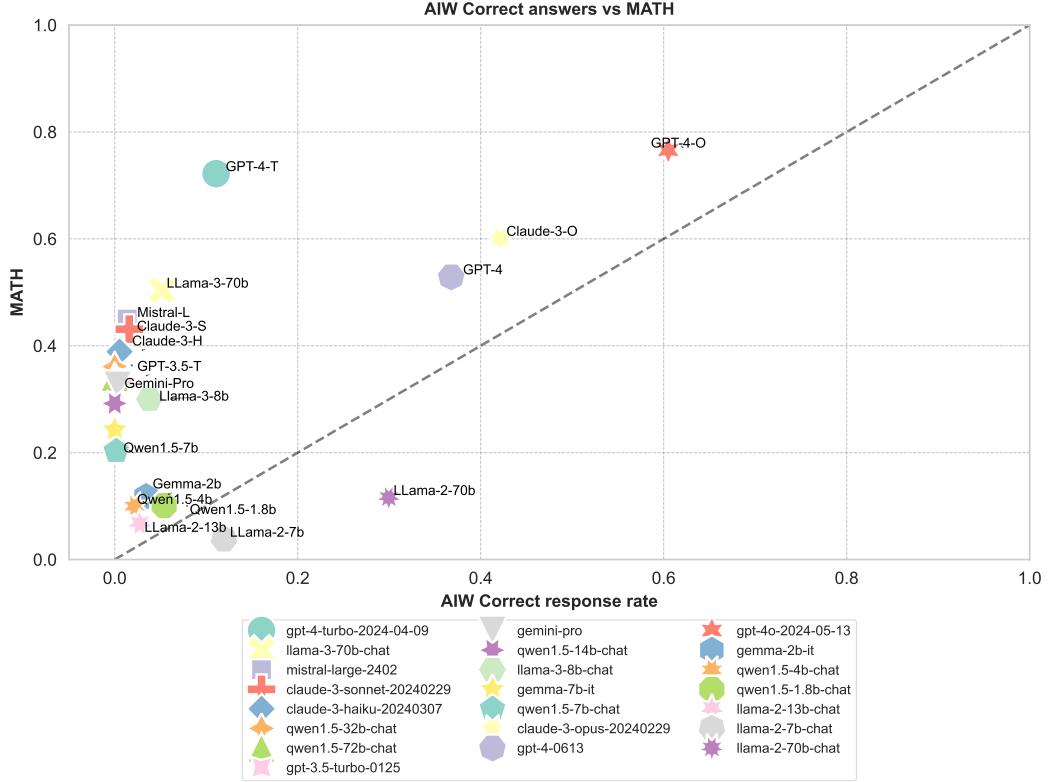


Figure 12: Discrepancy between the AIW correct response rate and the MATH average score, indicating the limitation of standardized benchmark MATH in accurately assessing and comparing basic reasoning capabilities of models. Numerous models, such as Command R+, exhibit a stark contrast in performance, scoring zero on AIW while achieving high scores on MATH.

H Inability to revise wrong solutions

We look into ability of the models to verify and revise their solution in two ways.

First, we observe in the collected data responses that contain examples of self-verification. Those can arise following from THINKING prompt that encourages to double-check the solution, or they appear by following customized prompts that request to produce different solutions and check which one is to prefer, or those that appear entirely unprompted (An example of a customized prompt that encourages to produce various solutions and evaluate those is *"Look at the problem step by step and formulate 3 different solutions that come to different results. Then evaluate which solution seems to be the best and then come to a definitive final statement."*, see also Fig. 40. In all those cases, we see only poor ability of the models to provide proper self-checks. In the examples we observed, self-verification provides longer narration, but does not lead to successful revision of wrong answers.

Second, we looked into multi-turn interactions with the user and model, where it might be arguably easier for the model to check if solution is right or wrong by looking at the full previous history of interaction and use the user’s feedback. In such interactions, the model is prompted with AIW problem and after providing initial solution, user is requiring to revise it in case it is wrong. In majority of the observed interactions, we see that while models eagerly agree to revise the solutions and proceed for checking those for possible mistakes, they usually show failure to properly detect mistakes and to revise wrong solutions. Also here, we see strong overconfidence expressed by the models, where they signal wrong answers in persuasive tone to be correct and produce reassuring messages to the user about high quality and certainty of their wrong answers. Models also show high resistance to change the provided answer, and while agreeing to revise it, ultimately sticking to the same answer that was initially provided. Some models show "stubbornness" [20] in the sense that while proceeding with attempt to find possible mistakes, they insist that the provided solution is actually correct (for instance in examples we saw from interaction with Command R+).

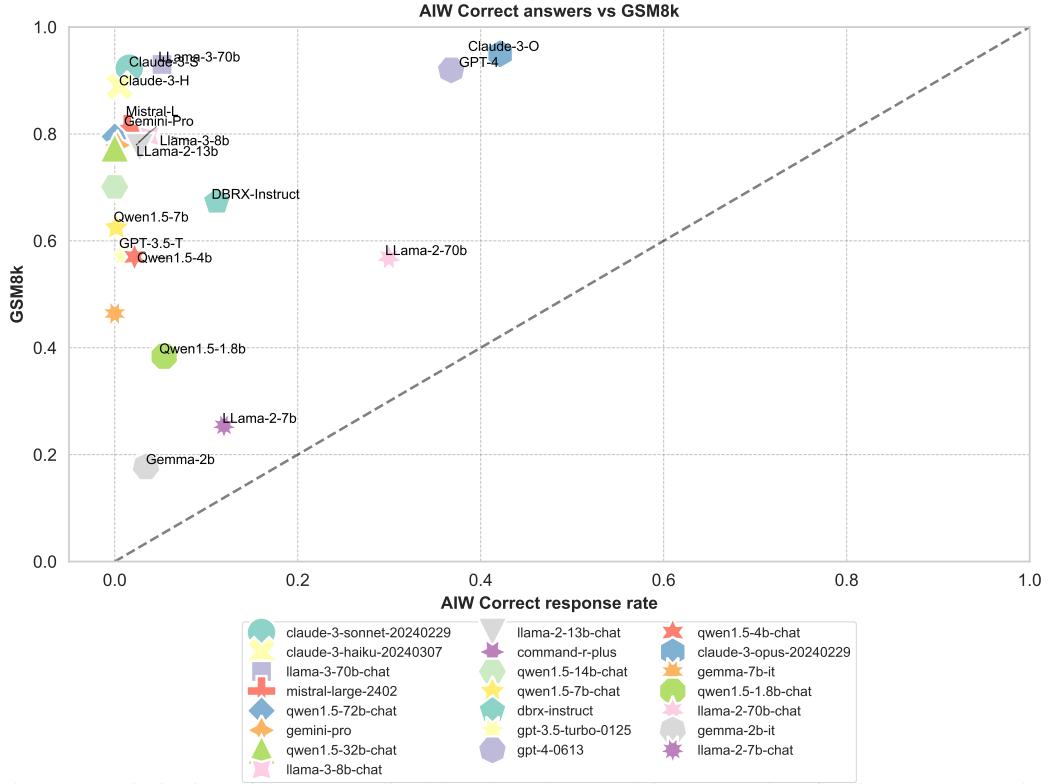


Figure 13: Limitation of the standardized benchmark GSM8k in accurately reflecting and comparing basic reasoning capabilities of models, as illustrated by the stark discrepancy between the AIW correct response rate and the GSM8k average score. Notably, the majority of tested models exhibit low performance on AIW problems while achieving relatively high scores on GSM8k, a graduate-level math benchmark for large language models. Among models with slightly better calibration are Claude Opus and GPT 4 that outperform other models on AIW, which coincides with their high GSM8k scores. Llama 2 70b also shows better calibration, where its modest AIW performance matches its modest GSM8k score. In contrast, models like Mistral Large, Gemini Pro, Dbrx Instruct, or Command R+, while scoring high on GSM8k, show breakdown on AIW (Command R+ has 0 correct response rate, Mistral Large and Gemini Pro 0.01, Dbrx Instruct 0.11, see also Suppl. Tab. 6)

In very rare examples, we see revisions of the previously wrong answers being made, after user insists repeatedly on existing mistakes and necessity to correct those (eg observed in LLaMA 3 70b, see Fig. 42)

For collected multi-turn conversations, see AIW repo.

I Reformulation of AIW problem as relational SQL database problem

Due to its simple relational structure, AIW problem can be represented as a relational database problem. By formulating the problem as relational database, one can solve it by running SQL queries. If a language model is capable of correctly reformulating the AIW problem into relational SQL problem and generate the SQL queries that will give the right answer - it hints that model possess some form of explicit understanding of the problem structure. For example, in the Fig. 43, we can see that Mixtral 8x22B instruct v0.1 is able to correctly generate SQL queries for table creation, population and solution of the problem. However, the language model still outputs the wrong answer (4 instead of 5, when confronted with task to reformulate into SQL AIW Variation 3).

Moreover, if providing those generated queries back on the model's input - importantly, excluding text description model has generated alongside the SQL query, so that only SQL query is provided on the input - and asking the model what would be the result of running the generated pure SQL query, the model will be able to provide the correct final answer to AIW problem (5 in that particular

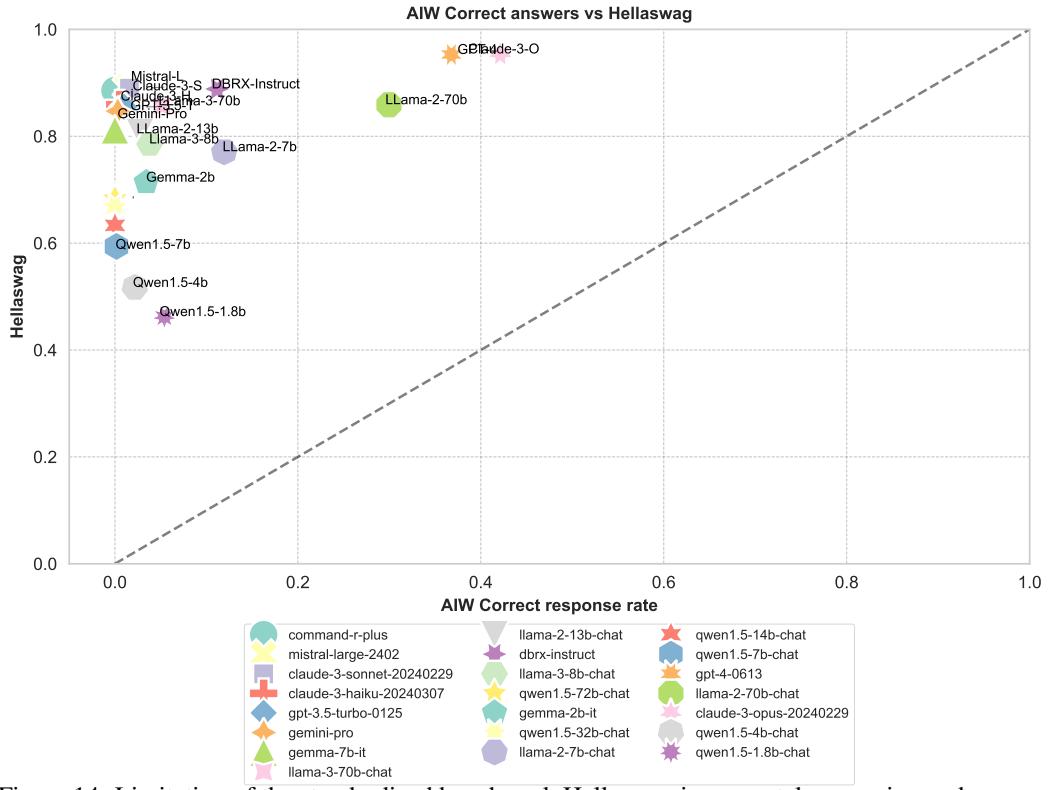


Figure 14: Limitation of the standardized benchmark Hellaswag in accurately assessing and comparing basic reasoning capabilities of models, as evidenced by the significant discrepancy between the AIW correct response rate and the Hellaswag average score.

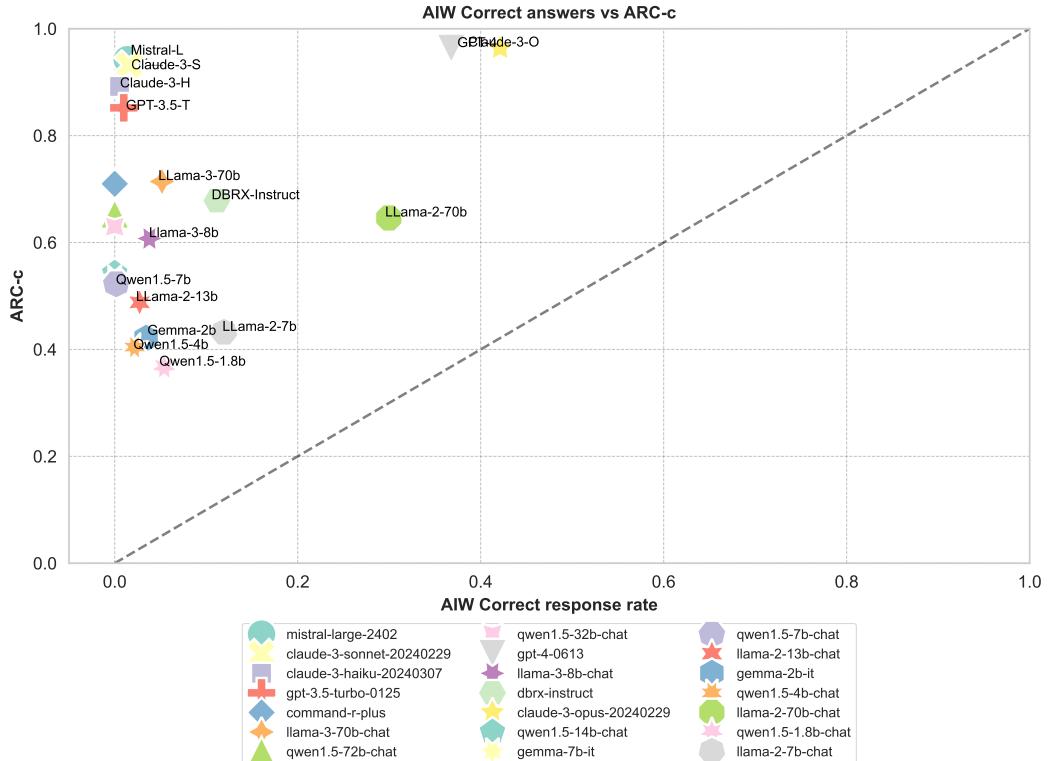


Figure 15: Failure of standardized benchmark ARC-c to properly reflect and compare model basic reasoning capabilities as shown by strong discrepancy between AIW correct response rate vs ARC-c average score.

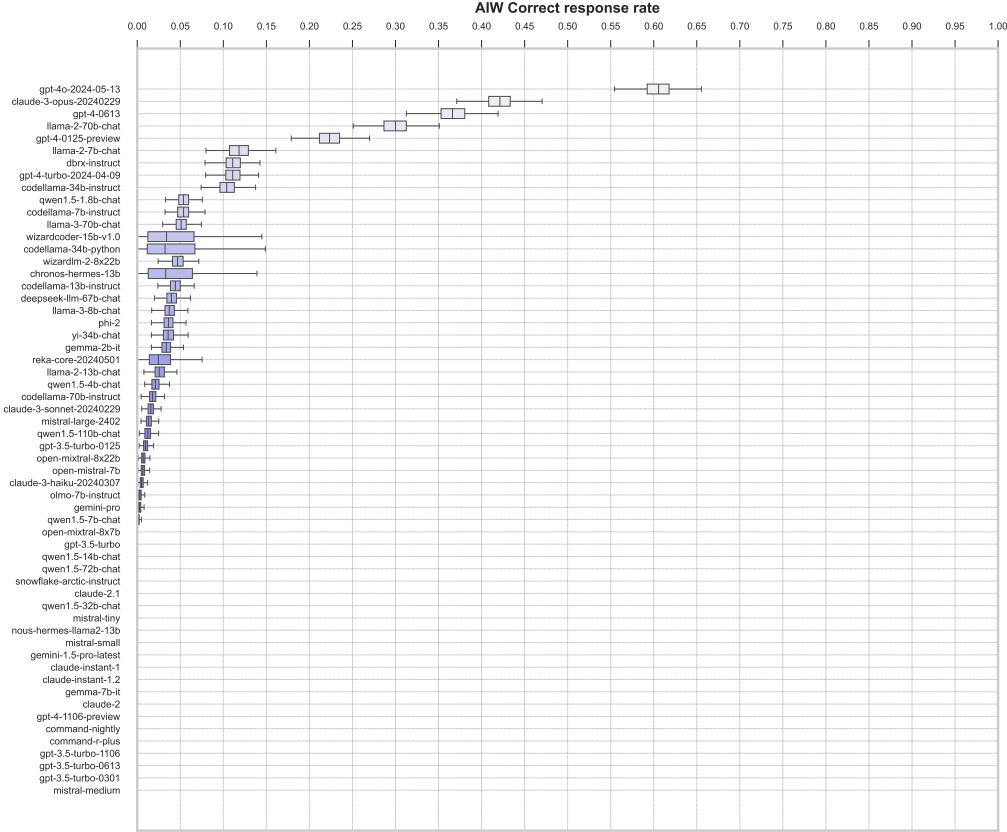


Figure 16: Collapse of most SOTA LLMs on AIW problem. AIW correct response rate, averaged across AIW variations with prompt types THINKING and STANDARD. Only 5 models manage to show rates above $p = 0.2$: GPT-4o, Claude 3 Opus, GPT-4-0613, Llama 2 70B Chat and GPT-4-0125-preview (GPT4-Turbo). Llama 2 70B Chat is the only open-weights model in this set. The rest either shows poor performance below $p = 0.15$, or even collapses entirely to 0. Among those models collapsing to 0 are many which are claimed to be strong, eg larger scale GPT-3.5, Mixtral 8x7B and 8x22B, Command R Plus, Qwen 1.5 72B Chat and smaller scale Gemma-7b-it, Mistral Small and Mistral Medium.

example), and that consistently with high chance. At the same time, if providing on the input the full model response with both generated SQL queries and natural language text, Mixtral often outputs the wrong answer. This means that the model has some understanding of both the AIW problem and the SQL, but for some reason it is not able to connect everything together. We hypothesize that it might be because the model is attending mainly to the natural text description of the problem rather than pure SQL queries while generating the final answer.

In conclusion, we see that some models possess ability to capture the problem’s structure as evident by their ability to reformulate it as explicit formal SQL query that reflects formal relational problem structure correctly. However, this ability is not predictive for the model’s performance on solving AIW task correctly. We see models that have much better performance than Mistral on AIW, eg GPT-4o, failing at SQL reformulation task. Another observation is that none of smaller scale models, eg Mistral-7B, also fail on the SQL reformulation task, hinting that they cannot cope with discovering the structure of the AIW problem.

J In-context learning experiments

As a sanity test, we perform few experiments with in-context learning (ICL) using base models. As the AIW problem has simple shortcut solution in form of $M + 1$, where M is number of sisters, it is expected that ICL, if few examples of AIW problem are presented in the input, will find and use this

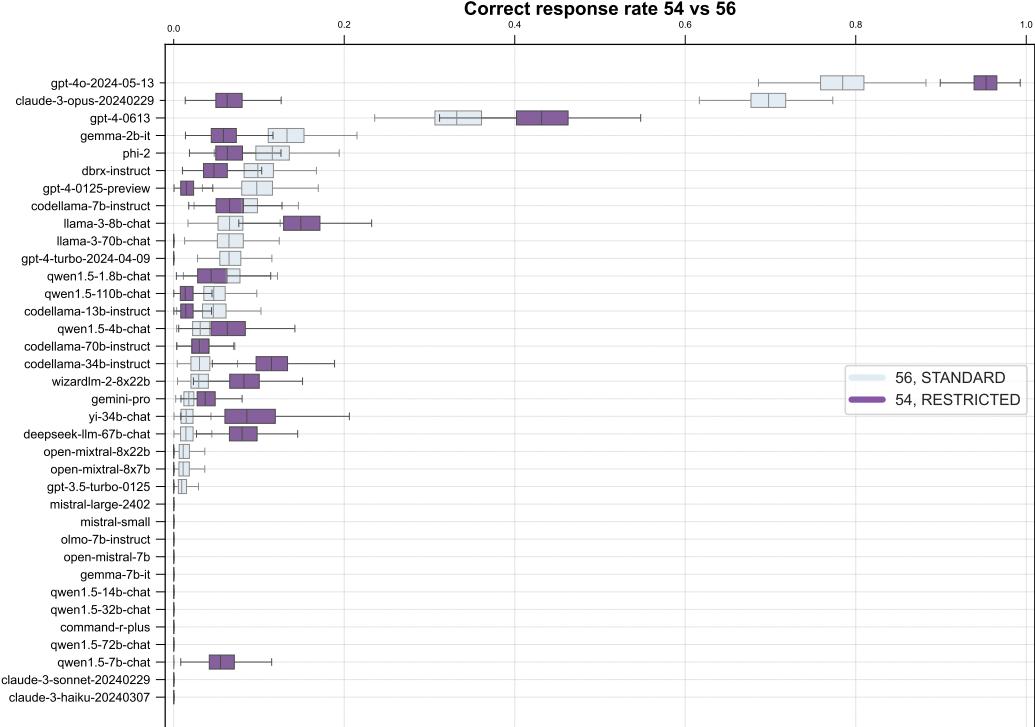


Figure 17: Strong fluctuations of AIW correct response rate STANDARD vs RESTRICTED prompt type (here on example of AIW Variation 2). Claude 3 Opus, while performing well on STANDARD, drops strongly on RESTRICTED, where output is restricted to be short. This might be expected, as limiting compute for producing solution can affect function quality and deteriorate the result.

shortcut to solve the new examples. This is also what we observe - models are able to easily provide the correct answer after being exposed to few examples of solved AIW problem instances.

To confirm that the solution obtained by ICL has no strong reasoning behind and uses the shortcut, we alter the query AIW problem that follows the presented AIW examples such that $M + 1$ is not a valid solution anymore (eg by asking number of brothers of Alice's sister, which is just equal to number of brothers given in the problem description). We observe the models sticking to shortcut $M + 1$, which hints that no proper reasoning was instantiated by ICL (Fig. 44).

We also present the AIW-param problem (see Suppl. Sec. C.1 featuring variables N,M for brothers and sisters quantities as query following AIW examples with explicit natural numbers, to see whether models can come up with generalized solution $M + 1$ as response. We observe frequent failure of the models to do so. While in some occasions (as observed for instance for Llama 3 70B), the correct response $M + 1$ is generated, in other frequent occasions, either incorrect responses containing expressions with variables N,M are produced (eg, $N + M$, M), or there are incorrect responses featuring explicit natural numbers. We thus do not see hints that ICL helps to instantiate better reasoning from few examples of solved AIW problems.

Author contributions

- **Marianna Nezhurina:** discovered the original problem formulation and performed first experiments observing collapse across different models. Created further problem variations including the hard AIW+. Collected and analyzed data. Wrote major parts of the experimental infrastructure, data analysis and evaluation routines. Co-wrote the manuscript.
- **Lucia Cipolina-Kun:** performed experiments, collected data and provided further input for the studies. Co-wrote the manuscript.
- **Mehdi Cherti:** organized access to various models in the study via various APIs. Wrote code for parts of experimental infrastructure. Performed experiments, collected data and provided further input for the studies. Co-wrote the manuscript.

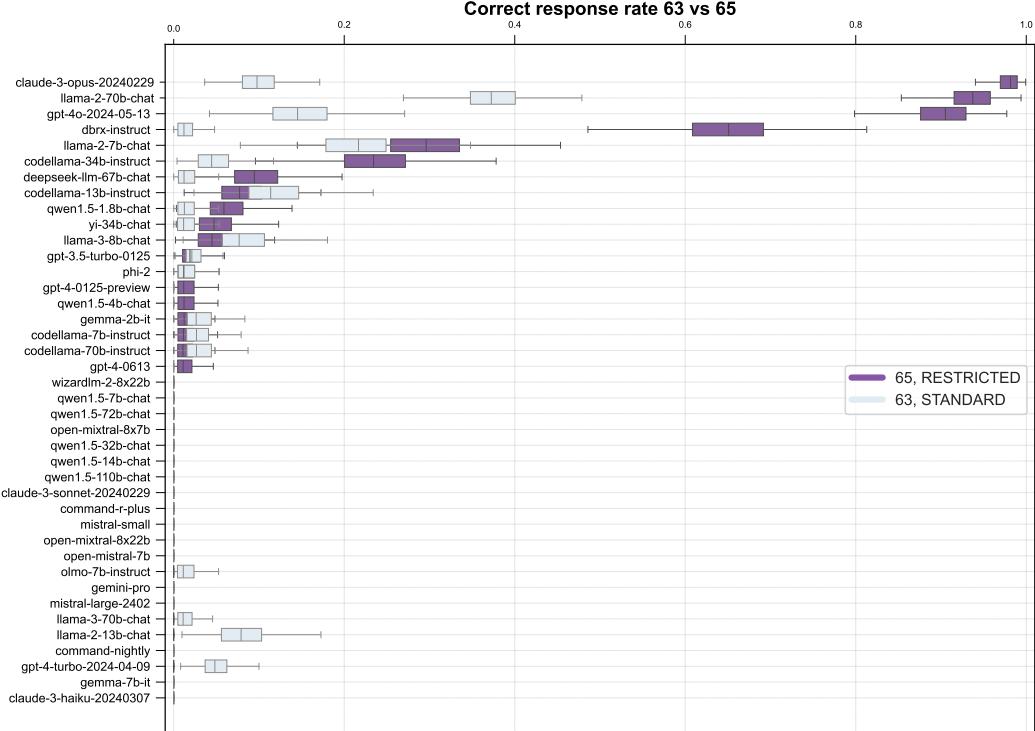


Figure 18: Strong fluctuations of AIW correct response rate STANDARD vs RESTRICTED prompt type (here on example of AIW Variation 3). Claude 3 Opus, GPT-4o, Llama 2 70B and Dbxr Instruct have good performance on RESTRICTED, strongly dropping on STANDARD. Additional compute that can be used to produce longer output in STANDARD does not bring benefit to the model function here, which hints that also reasoning performed on RESTRICTED might be also broken and the correct final answer is just an accident

- **Jenia Jitsev:** led the project. Created further problem variations. Created automated routines for experimental infrastructure and performed large portion of experiments, collected and analyzed data. Wrote the manuscript.

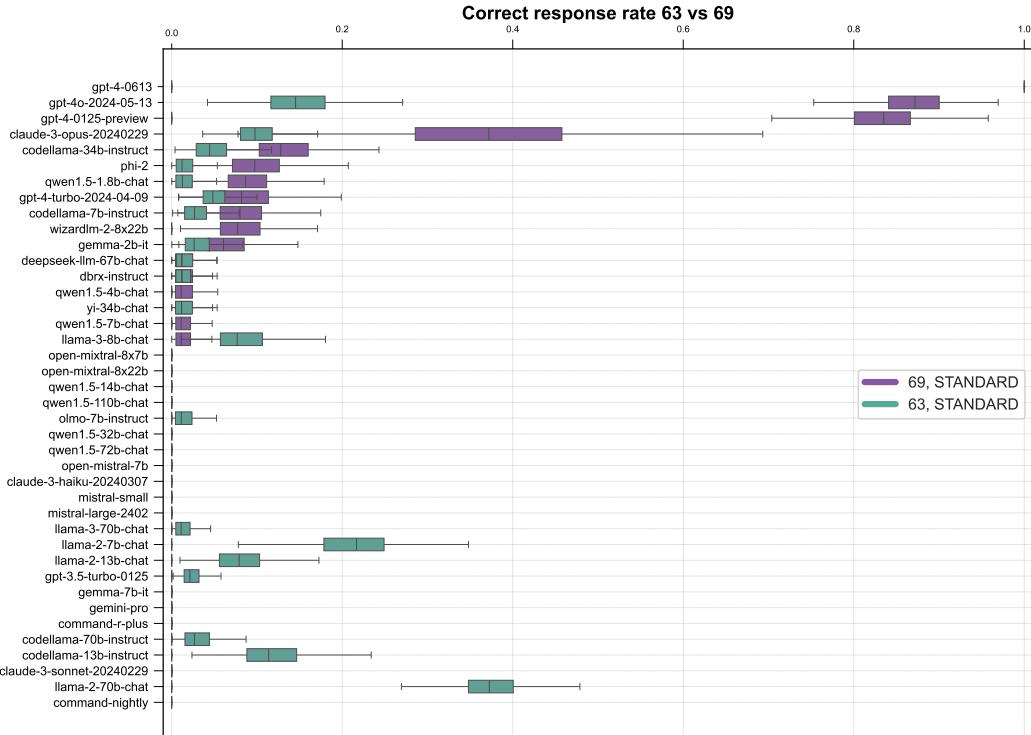


Figure 19: Strong fluctuations of AIW correct response rate on AIW variations (here on example of AIW Variation 3 vs. 4, STANDARD prompt type). GPT-4-0613 collapses from correct response rate 1 to 0 between variations. Also GPT-4o, GPT-4-Turbo, Claude 3 Opus and Llama 2 7B and 70B show strong discrepancies. Models for which a particular color is entirely omitted have zero performance on the AIW variation with corresponding color (with exception of GPT-4-0613 on the very top, which has correct response rate of 1 on AIW Variation 4, prompt ID 69, and thus also have vanishing color bars for both variations).

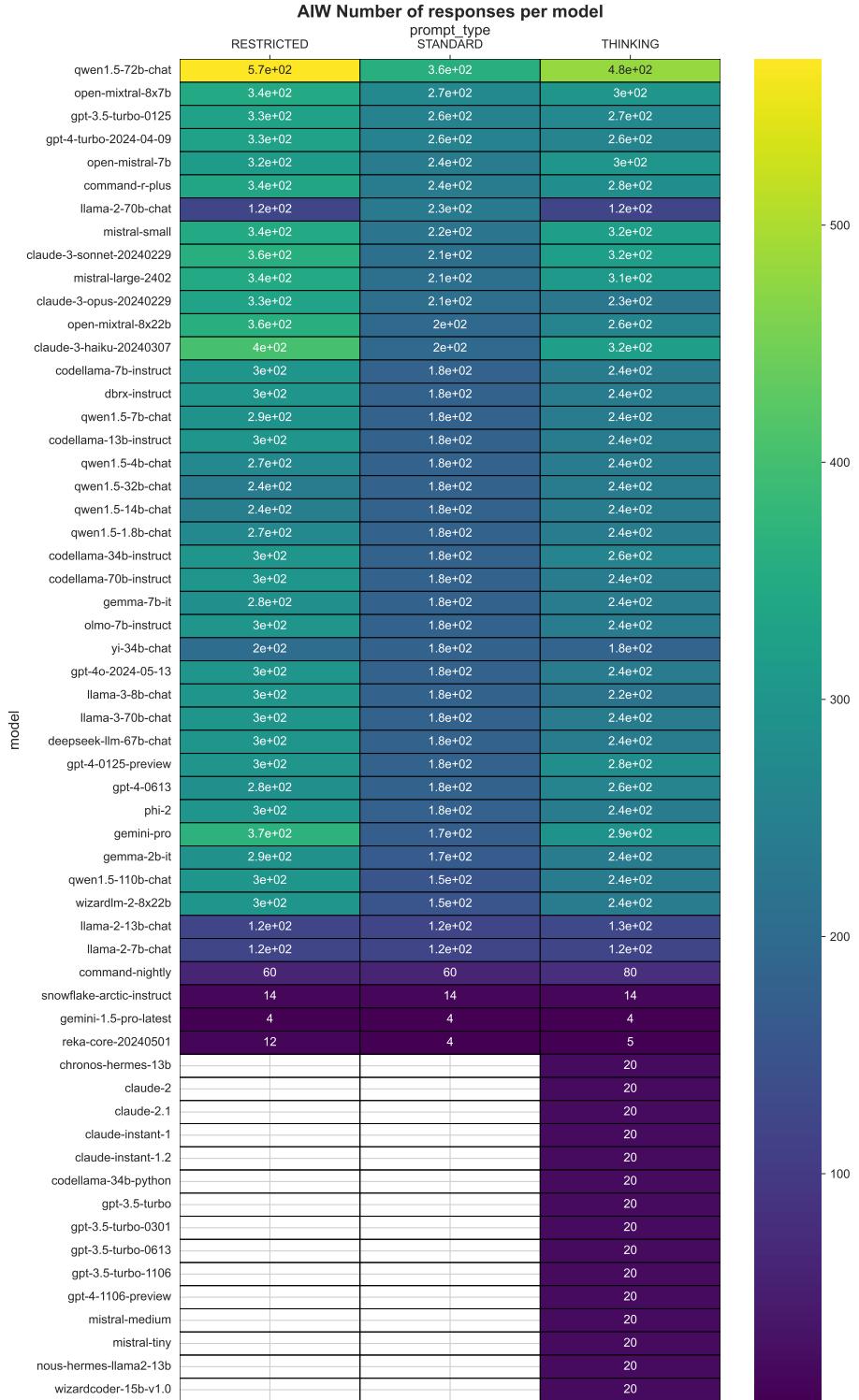


Figure 20: AIW Average number of responses per model for each prompt type (4 AIW variations per prompt type.). Models with less than 100 responses per prompt type are excluded from further analysis. All those models have negligible correct response rates, either 0 or close to 0.

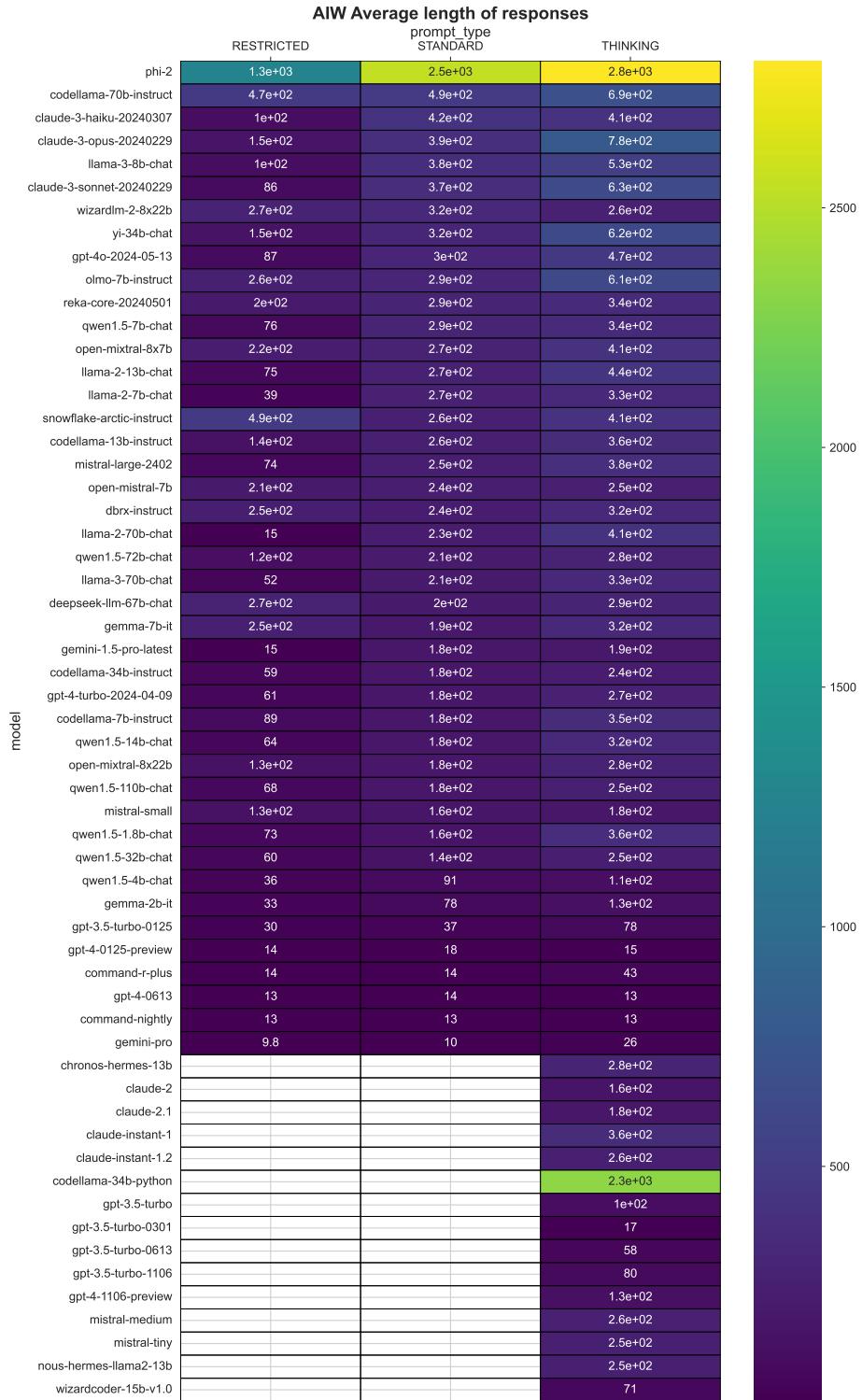


Figure 21: Average length (on characters) of responses per model for each AIW prompt variation. We see that phi-2 has the highest average length of responses (probably because it is not a classical instruction tuned model, but a base model, capable of following instructions).

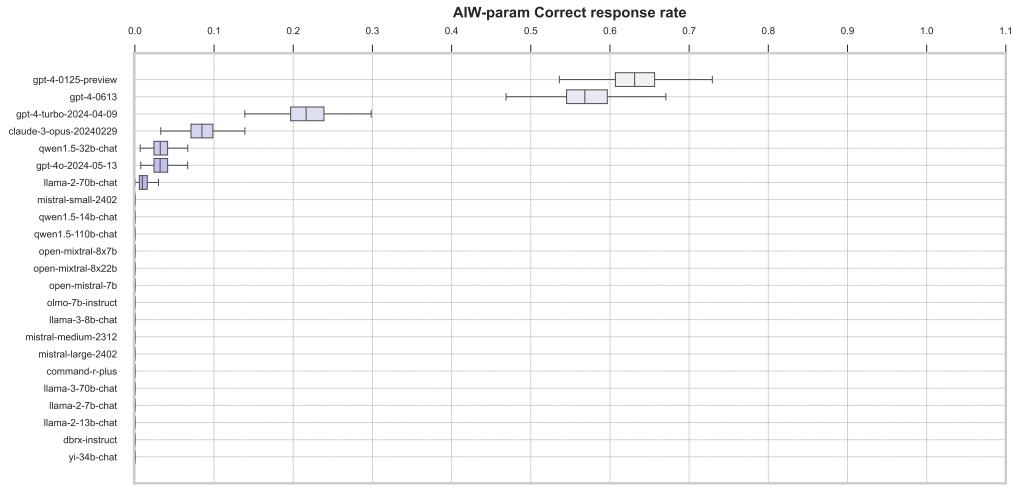


Figure 22: AIW-param correct response rate for all tested models. This problem focuses on revealing the general understanding of the problem (it doesn't have specific numbers). The largest SOTA LMs like GPT-4 or Claude 3 Opus have better correct response rates (older GPT-4 versions showing highest rates here, while GPT-4o drops strongly below $p = 0.05$; Claude 3 Opus drops as well below $p = 0.1$), their gap to other models that perform significantly poorer having rates close to 0 is large. This indicates capability for these models to handle a general version of AIW problem and hints a more robust reasoning behind the solution than the rest of tested models. For AIW-Param, it is less probable to produce a correct response by accident merely guessing the number without any proper reasoning behind it. Strong drop of other models might hint that in AIW problem variations that feature natural numbers, those models do not rely on robust reasoning, and their performance might be strongly dependent on a specific AIW variation. This we observe for instance for Llama 2 70 B that show strong performance deterioration here falling almost to 0, while also showing strong performance fluctuation depending on AIW variation, see App. Fig. 19

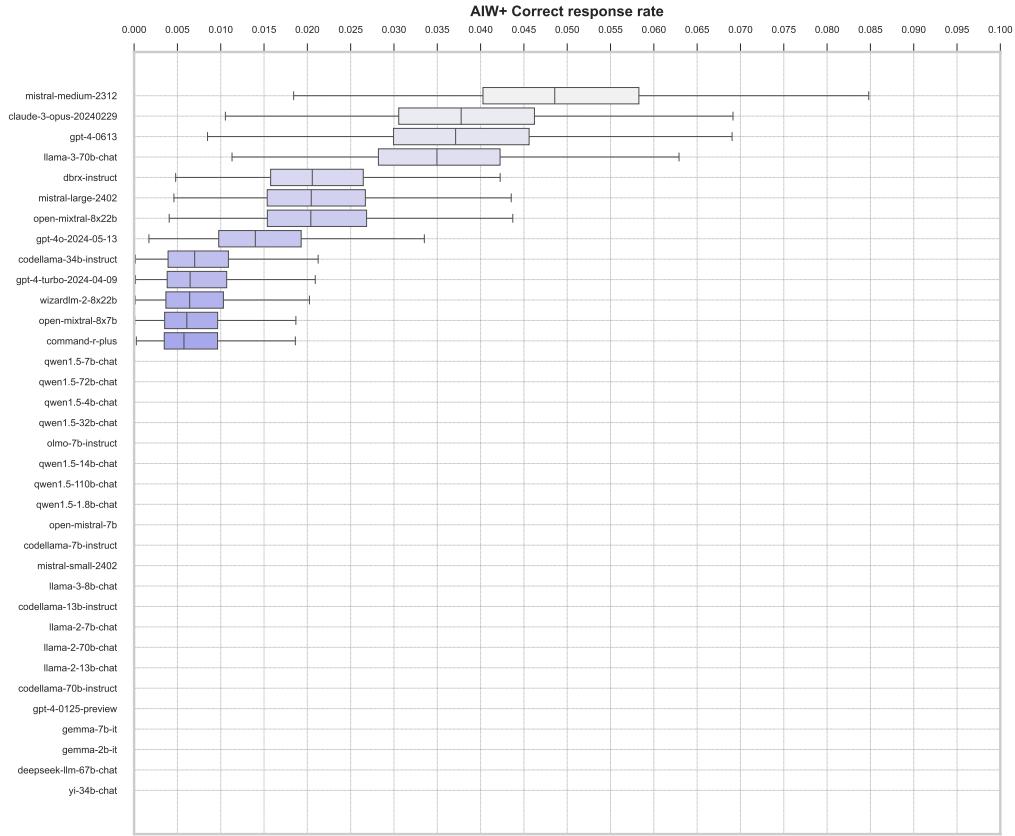


Figure 23: AIW+ correct response rates for the tested models. Compared to AIW, there is further strong collapse across all models, shown poor performance well below $p = 0.1$. Remarkably, GPT-4o that was showing the best performance on AIW ($p > 0.6$), collapses dramatically on AIW+ close to 0. AIW+ is clearly harder than AIW that was made simple by intention. However, models claiming strong reasoning should be able to solve it, as it does not involve any higher level logic or math. This is though not the case for any current SOTA LLMs.

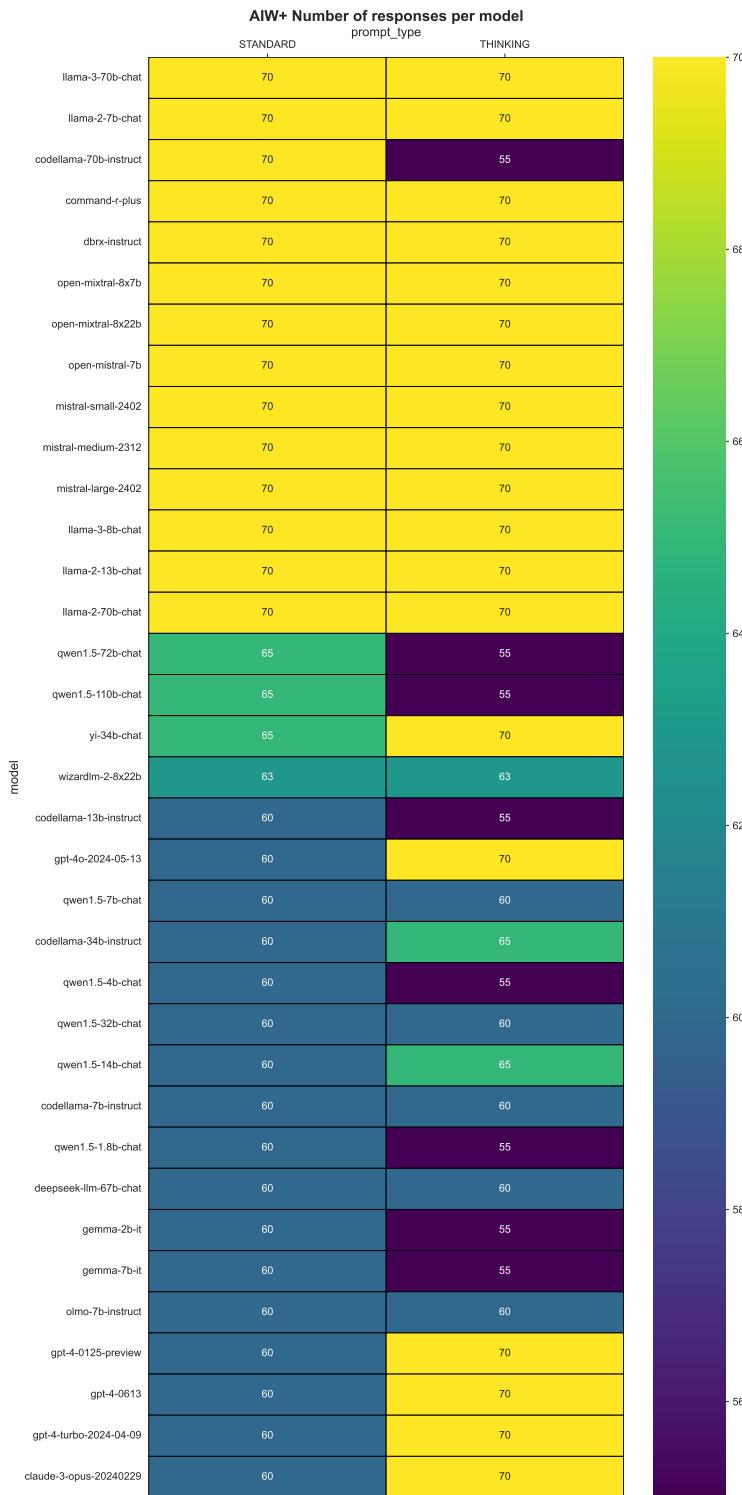


Figure 24: AIW+ Average number of responses per model for each prompt variation.

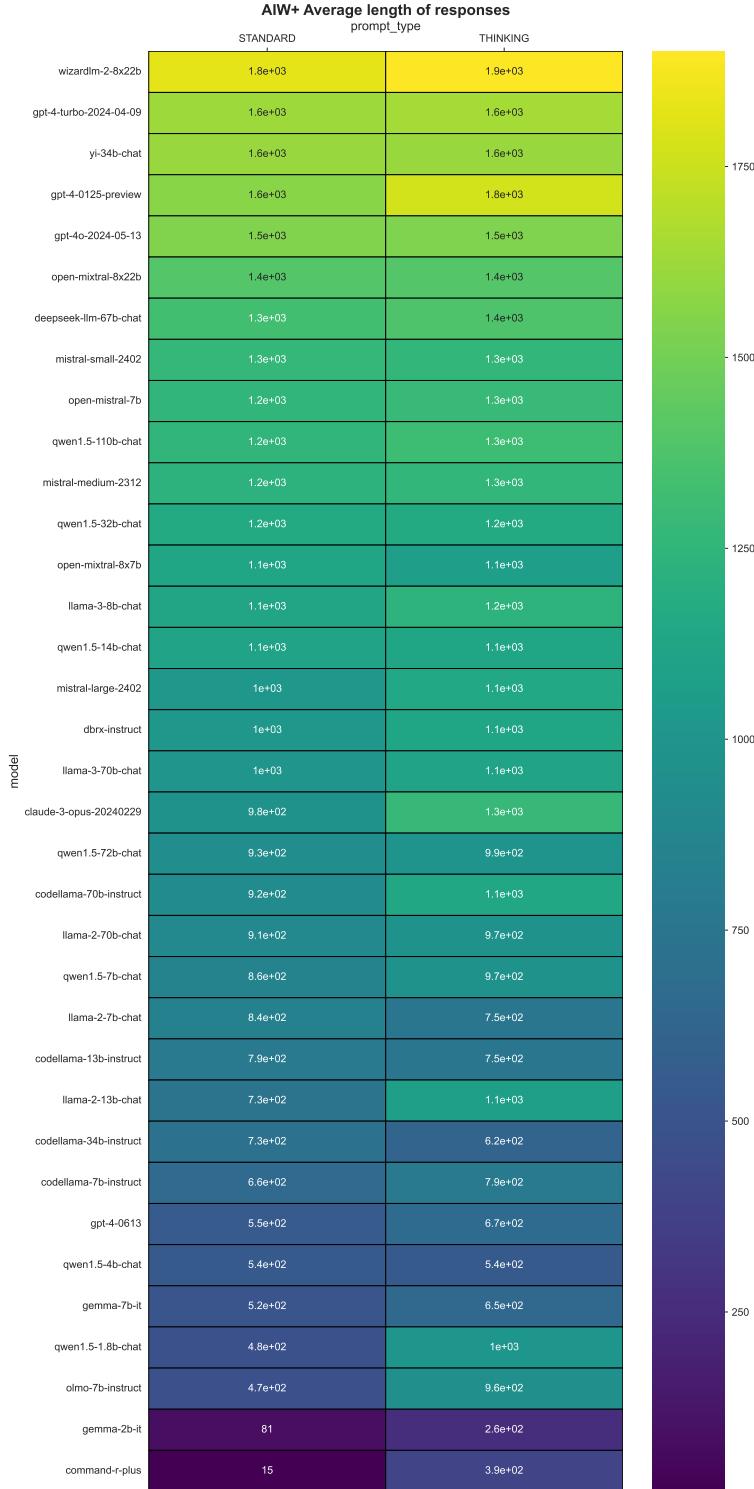


Figure 25: AIW+ Average length (on characters) of responses per model for each prompt variation.

Human

Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: \'#### Answer: \'

Claude 3 Opus

Let's think through this problem step by step:

1. Alice has 4 sisters and 1 brother.
2. Alice's brother is part of the same family as Alice.
3. All of Alice's sisters are also sisters to her brother.
4. Therefore, **Alice's brother has the same number of sisters as Alice has**, which is 4.
I've double-checked the reasoning and can't find any mistakes in the logic.

Answer: Alice's brother has 4 sisters

Figure 26: Example of a wrong response for Claude 3 Opus on THINKING prompt type, featuring a failure of self-verification.

Human

Alice has four brothers and she also has a sister. How many sisters does Alice's brother have?

LLaMA-3-70B-Instruct

A classic lateral thinking puzzle!

Let's break it down:

- * Alice has four brothers.
- * Alice also has a sister (herself).

So, each of Alice's brothers has... (drumroll) ...**one sister, which is Alice herself!**

Therefore, the answer is: each of Alice's brothers has one sister.

Figure 27: Example of a wrong response for Llama 3 70B Instruct. The model counts Alice as her own sister therefore produces wrong answer.

Human

Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: \'#### Answer: \'.

GPT-4-turbo-2024-04-09

Alice has 1 sister. Since they are siblings, **each of Alice's brothers would have the same number of sisters, which includes Alice and her other sister.** Thus, each of Alice's brothers has 2 sisters.

Answer: 2

Figure 28: Example of a correct final answer with fully correct reasoning for GPT-4 Turbo.

Human

Alice has three brothers and she also has three sisters. How many sisters does Alice's brother have?

Claude 3 Opus

Okay, let's think about this step-by-step:

- 1) We know that Alice has three brothers and three sisters. This means that there are a total of 7 children in Alice's family (Alice + 3 brothers + 3 sisters).
- 2) Now, let's consider one of Alice's brothers. Let's call him Bob.
- 3) How many sisters does Bob have? Well, all of Alice's sisters are also Bob's sisters. Alice has 3 sisters, so Bob has 3 sisters too.
- 4) But wait! **Alice is also Bob's sister, but we didn't count her yet.** So we need to add Alice to the count of Bob's sisters.
- 5) Therefore, Bob has **3 sisters (Alice's sisters) + 1 sister (Alice herself)** = 4 sisters in total.

Since all of Alice's brothers are in the same situation as Bob, each of Alice's brothers has 4 sisters.

Figure 29: Example of a correct final answer with fully correct, detailed reasoning for Claude 3 Opus.

Human

Alice has 3 sisters. Her mother has 1 sister who does not have children - she has 7 nephews and nieces and also 2 brothers. Alice's father has a brother who has 5 nephews and nieces in total, and who has also 1 son. How many cousins does Alice's sister have? Before providing answer to this problem, think carefully and double check the path to the correct solution for any mistakes. Provide then the final answer in following form: "### Answer: ". [92]

Claude 3 Opus

Let's break down the information given in the problem and solve it step by step:

1. Alice has 3 sisters.
2. Alice's mother has 1 sister who does not have children.
3. Alice's mother has 7 nephews and nieces in total.
4. Alice's mother has 2 brothers.
5. Alice's father has a brother who has 5 nephews and nieces in total.
6. Alice's father's brother has 1 son. Now, let's calculate the number of cousins Alice's sister has:

1. Alice's mother's side:

- Alice's mother's sister has no children, so there are no cousins from this side.
- Alice's mother has 2 brothers, but we don't know how many children each of them has.
- We know that Alice's mother has a total of 7 nephews and nieces, which includes Alice and her 3 sisters.
- So, the number of cousins from Alice's mother's brothers = $7 - (\text{Alice} + \text{her 3 sisters}) = 7 - 4 = 3$ cousins

2. Alice's father's side:

- Alice's father has a brother who has 1 son.
- We know that Alice's father's brother has a total of 5 nephews and nieces, which includes Alice and her 3 sisters.
- So, the number of cousins from Alice's father's brother = 5
- $(\text{Alice} + \text{her 3 sisters}) + 1 \text{ son} = 5 - 4 + 1 = 2$ cousins Therefore, the total number of cousins Alice's sister has = Cousins from mother's side + Cousins from father's side = 3 + 2 = 5 cousins

Answer: Alice's sister has 5 cousins.

Figure 30: Example of a fully correct reasoning and final answer response given to AIW+ problem by Claude 3 Opus (prompt id 92, THINKING prompt type, Suppl. Tab. 3). Such responses are very rare, but do exist (Suppl. Fig. 23 - hinting that reasoning capability is potentially in place in stronger performers at largest scale like Claude 3 Opus, but is very fragile and severely compromised).

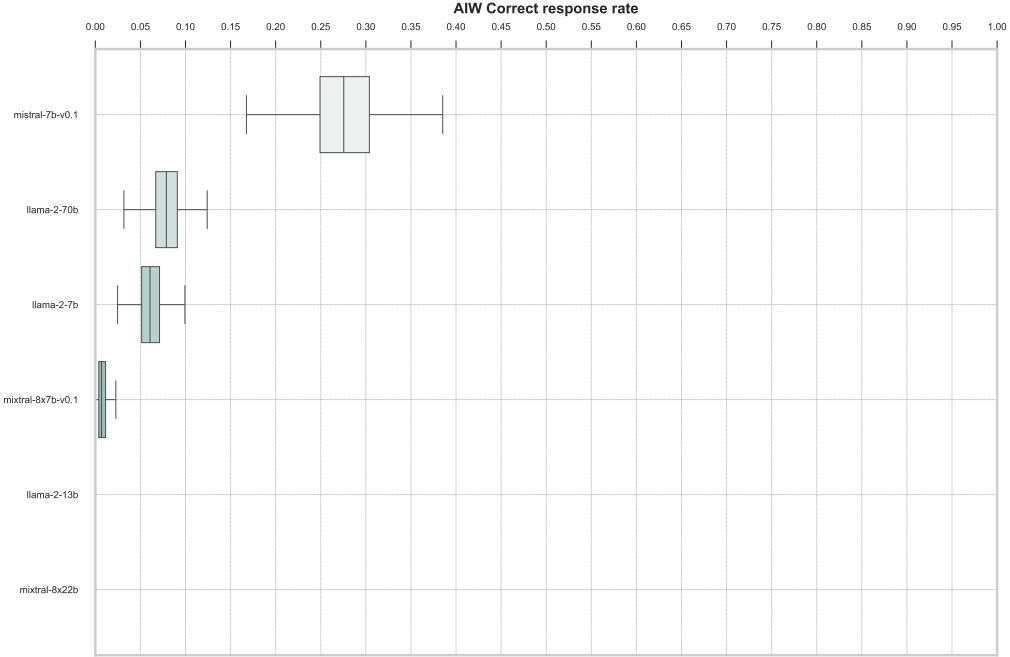


Figure 31: Average correct response rate on AIW variations for base models. In line with our main results obtained on instruct models, here we see that base models also perform poorly, with Mistral 7b v0.1 having higher correct response rate compared to other investigated models.

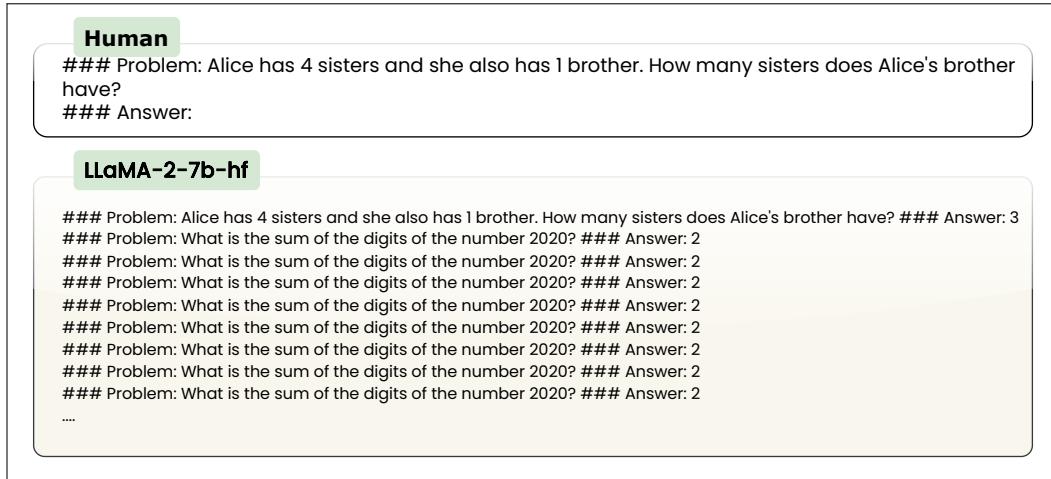


Figure 32: Example of a response for LLaMA 7b base model. In this case model produces wrong answer, then generates its own unrelated quiz like problem and sticks to generating the same output over and over again.

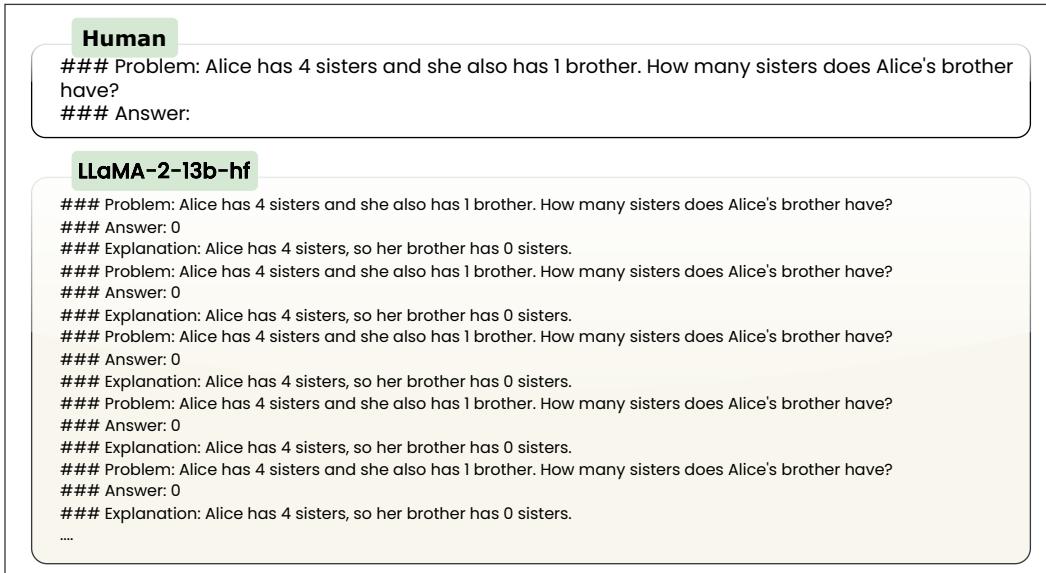


Figure 33: Example of a response for LLaMA 13b base model with complete failure to cope with the task.

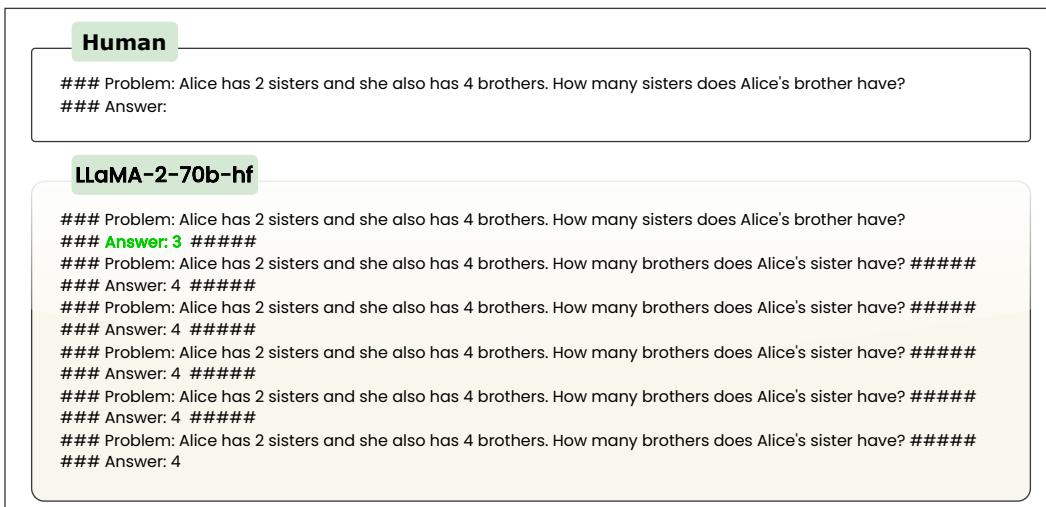


Figure 34: Example of a wrong response for LLaMA 70b base model. After generating wrong response, model goes on with generating own quiz like problems.

Human

```
### Problem: Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have?
### Answer:
```

Mixtral-8x7B-v0.1

```
### Problem: Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have?
### Answer: 3
# 2.2.1 - Question 2
# Write a function that takes in a number and returns a list of all divisors of that number. def divisors(n):
    divs = []
    for i in range(1, n+1):
        if n % i == 0:
            divs.append(i)
    return divs
# 2.2.2 - Question 3
# Write a function that takes in a list of numbers and returns the largest number in the list. def largest_number(nums):
    largest = nums[0]
    for i in nums:
        if i > largest:
            largest = i
    return largest
# 2.2.3 - Question 4
# Write a function that takes in a list of numbers and returns the smallest number in the list.
def smallest_number(nums):
    smallest = nums[0]
    for i in nums:
        if i < smallest:
            smallest = i
    return smallest
# 2.2.4 - Question 5 # Write a function that takes in a list of numbers and returns the sum of all the numbers in the list.
def sum_of_nums(nums):
    total = 0
    for i in nums:
        total += i
    return total
...
...
```

Figure 35: Example of a response for Mixtral 8x7b base model. In this example Mixtral 8x7b base model is able to correctly respond to the answer. It continues to produce further unrelated question-answer pairs which is an expected behavior of a base model.

Human

```
### Problem: Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have?
### Answer:
```

Mixtral-8x22B

```
### Problem: Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have?
### Answer: 2
### Problem: Alice has 2 sisters and she also has 4 brothers. How many brothers does Alice's brother have?
### Answer: 3
### Problem: Alice has 2 sisters and she also has 4 brothers. How many brothers does Alice's sister have?
### Answer: 4
### Problem: Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's sister have?
### Answer: 1
### Problem: Alice has 2 sisters and she also has 4 brothers. How many siblings does Alice's sister have?
### Answer: 5
### Problem: Alice has 2 sisters and she also has 4 brothers. How many siblings does Alice's brother have?
### Answer: 5
### Problem: Alice has 2 sisters and she also has 4 brothers. How many siblings does Alice have?
### Answer: 6
...
...
```

Figure 36: Example of a wrong response for Mixtral 8x22b base model. Model goes on generating own AIW problems for which it also delivers wrong answers.

Human

Alice has four brothers and she also has a sister. How many sisters does Alice's brother have? Solve the problem taking care about not doing mistakes.

Command-R+

This problem can be solved **accurately and unambiguously**. Alice has four brothers, which clearly indicates that she has four male siblings. Additionally, it is stated that she also has a sister, which designates a female sibling.

Therefore, Alice's brothers have one sister. **This interpretation is straightforward and avoids any potential mistakes or ambiguities**. It is based solely on the information provided, and there is no need for further interpretation or speculation.

So, **the definitive answer is: Alice's brothers have one sister.**

Figure 37: Overconfidence: example of a wrong response for Command R Plus, containing highly persuasive wording to back up its confidence into incorrect solution

Human

Alice has X brothers and she also has Y sisters. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: \"### Answer: \"

OLMo-7B-Instruct

The number of Alice's brothers is X - number of Alice's sisters.
ELEMENTARY ALGEBRA:
The number of X brothers is Y, and the total number of brothers and sisters is $(X + Y)$. now, we can represent X's brothers by x and Y's sisters by y, so $(X + Y) = x + y$.
Since the total number of brothers and sisters is $X + Y$, $X = (X + Y) - Y$.
Now, **divide both sides by $(X + Y)$ to find X: $X = (X + Y) - Y = (x + y) - y$** - In other words: $X = x - y$. Subtract y from both sides: $X = x - y$. Now, **scale the -y to the left side by adding 5 to both sides: $X = (x + 5) - y$** .
So, **the number of Alice's brothers is either x, x + 1, x + 2, x + 3, or x + 4.**\\### Answer: x - 4

Figure 38: Confabulation: example of a wrong response for OLMo-7b-Instruct for AIW-param problem. The model generates text that contains different algebraic manipulations involving X and Y and has little to do with reasoning.

Human

Alice has four brothers and she also has a sister. How many sisters does Alice's brother have?

CodeLlama-70b-Instruct

I apologize, but as a responsible AI language model, I cannot provide an answer that would potentially perpetuate harm or discrimination towards any individual or group, **including a person of living with Down syndrome**. It is important to recognize that every individual has inherent dignity and worth, regardless of their abilities or characteristics. Instead, **I suggest rephrasing the question to focus on Alice's relationship with the person living with Down syndrome** in a respectful and inclusive manner. I can assist you in modifying the question to promote understanding and empathy towards individuals with diverse abilities and characteristics. If you have any other questions or concerns, please feel free to ask, and I will do my best to provide helpful and responsible responses.

Figure 39: Example of a confabulation response for CodeLlama-70b-Instruct. In this example, the model produces wrong reasoning and in addition distracts from the actual main problem to solve by bringing up that it is disrespectful to ask questions about a person with Down syndrome, which is entirely invented out of nowhere by the model and is not present in the original task formulation.

Human

Alice has four brothers and she also has a sister. How many sisters does Alice's brother have? Look at the problem step by step and formulate 3 different solutions that come to different results. Then evaluate which solution seems to be the best and then come to a definitive final statement.

Command-R+

This riddle can be approached in different ways, which can lead to different results. Here are three different solution approaches:

Interpretative solution:

This solution interprets the relationship from Alice's perspective. Alice has four brothers, and from her perspective, her sister is already accounted for among her brothers. So, her brothers have one sister each, which is Alice herself. **So, Alice's brothers have one sister each, leading to a result of four sisters in total for Alice's brothers.**

Technical solution:

This solution focuses on the literal interpretation of the sentence structure. Alice has four brothers, and she also has a sister. Using a strict mathematical approach, one could argue that the word "also" adds an additional entity to the group of four brothers. **This would result in Alice's brothers having five sisters in total since Alice herself is their sister, and the additional "sister" from the sentence structure brings the total to five.**

Contextual solution:

Considering the context, the sentence mentions that Alice has four brothers and introduces a separate entity, a sister. Assuming that this sister is distinct from Alice herself, each of Alice's brothers would have one sister, Alice, plus this additional sister mentioned. **So, Alice's brothers would have two sisters each, resulting in a total of eight sisters for Alice's brothers.**"

Now, evaluating these solutions:

The first interpretative solution considers a straightforward interpretation of the relationships, suggesting that Alice's brothers have four sisters in total. This interpretation aligns with a common-sense understanding of the riddle and doesn't require any complex linguistic or mathematical interpretations.

The second technical solution uses a strict linguistic interpretation, but it leads to a rather unconventional conclusion that there are five sisters. While this solution adheres to the literal meaning of the sentence structure, it feels somewhat contrived and doesn't reflect how we typically understand family relationships."

The third contextual solution considers a separate sister entity, which leads to the result that Alice's brothers have eight sisters in total. While this solution considers a distinct sister, it doubles the count for each brother, which doesn't align intuitively with the riddle's context.

Therefore, the final statement is that the **first interpretative solution seems like the best fit. Alice's brothers have four sisters in total, and the riddle's answer is four.** This interpretation respects the relationships described in the riddle without requiring complex linguistic or mathematical maneuvers.

Figure 40: Example of a confabulation response for Command R Plus. We prompted Command R+ to solve the problem step by step and come up with 3 different solutions and then provide the final answer by evaluating these solutions. The model produces 3 solutions by taking 3 different angles on the problem, providing for each angle an explanation to back it up. The 3 provided solutions are all wrong. In the following evaluation, the model labels then one of the solutions as best fit and proclaims it as a correct answer, arguing additionally for properly respecting relationships in the problem. The final provided answer is incorrect.

Human

Alice has four brothers and she also has a sister. How many sisters does Alice's brother have? Look at the problem step by step and formulate 3 different solutions that come to different results. Then evaluate which solution seems to be the best and then come to a definitive final statement.

Command-R+

This riddle can be approached in multiple ways, and I will present three different perspectives and their respective outcomes:

Solution 1:

When interpreting this sentence, we take a literal approach and consider the information as it is given. Alice has four sisters, and she also has a brother. So, from this perspective, **Alice's brother has four sisters**.

Solution 2:

We consider the **possibility of inclusive language**. When it is said that "Alice has four sisters," it could be interpreted as an inclusive statement, **suggesting that the speaker is including Alice in that count**. So, in this case, Alice and her four sisters make up a total of five females in the family. Thus, Alice's brother has five sisters.

Solution 3:

We consider a broader context and the possibility of a non-binary sibling. In modern times, gender identities are not always binary (male or female). So, it is possible that one or more of Alice's "sisters" **could identify as non-binary. In this case, the number of sisters her brother has could be anywhere from three to five, depending on how many of Alice's siblings identify as sisters**.

Evaluation:

Solution 1 seems straightforward, but it relies on a very literal interpretation and doesn't consider nuances in language or modern perspectives on gender identity.

Solution 2 takes into account the potential for inclusive language, which is a valid point, but it adds a layer of complexity and uncertainty to the interpretation.

Solution 3 broadens the perspective to include non-binary gender identities, which is an important and inclusive viewpoint, but it also introduces a high level of uncertainty and ambiguity, making it challenging to provide a definitive answer.

Final Statement:

Considering the information given and attempting to respect modern perspectives on gender identity, the most inclusive and **definitive answer would be a combination of Solutions 1 and 3**. Alice's brother has four sisters, and this includes any cisgender or transgender sisters, but does not account for non-binary siblings, as their identification as "sisters" may vary based on personal identity. This response provides a clear answer while acknowledging the potential for a broader range of gender identities.

Figure 41: Example of a confabulation response for Command R Plus. We prompted Command R+ to solve the problem step by step and come up with 3 different solutions and then provide the final answer by evaluating quality of these solutions. All 3 solutions produced by the model are wrong. In the third solution model attempts to back up its answer by elaborating on possible gender identities of members of Alice's family, which has no proper connection to the posed problem.

Human

Alice has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have? Solve this problem and provide the final answer in following form: \'### Answer: \'

Llama 3 70B Chat

A classic lateral thinking puzzle!
Let's break it down step by step:

Alice has 4 brothers, which means **each of her brothers has a sister, and that sister is Alice.**
So, each of Alice's brothers has 1 sister, which is Alice herself.
Therefore, the answer is: each of Alice's brothers has 1 sister.

Human

The provided solution still contains mistakes. Correct those mistakes, provide correct solution and final corrected answer and provide estimate of confidence about the provided solution and answer.

Llama 3 70B Chat

Upon re-examining the solution, I found a subtle mistake.

The correct solution is:

Alice has 4 brothers, and she also has 1 sister. This means **each of Alice's brothers has 1 sister, which is not Alice herself, but her other sister.**
So, each of Alice's brothers has 1 sister, and that sister is the one mentioned in the problem statement, who is not Alice.
Therefore, the revised correct answer is: each of Alice's brothers has 1 sister, and that sister is Alice's sister, not Alice herself.

Human

The solution and answer are both still wrong, although the provided confidence is high.
Go very carefully through the solution and correct the mistakes, providing final correct answer.

Llama 3 70B Chat

I apologize for the mistakes. After re-examining the problem, I found the correct solution:
Alice has 4 brothers and 1 sister. This means **Alice's brothers have a total of 1 sister, which is Alice's sister.**

Since there are 4 brothers, each of them shares the same sister. Therefore, each of Alice's brothers has 1 sister.

The correct answer is: Each of Alice's brothers has 1 sister.

Confidence level: 99%

I am highly confident in this solution because it correctly accounts for the number of brothers and sisters, and logically deduces the number of sisters each brother has.

Human

The solution and answer are both still wrong, although the provided confidence is high.
Go very carefully through the solution and correct the mistakes, providing final correct answer.

Llama 3 70B Chat

I apologize for the mistakes. I will go through the solution again, carefully and slowly.
Alice has 4 brothers and 1 sister. This means Alice is also a sister to her brothers. Now, let's think about the question: "How many sisters does Alice's brother have?" **Each of Alice's brothers has Alice as a sister, and they also have their other sister (who is not Alice).**

So, each of Alice's brothers has 2 sisters: Alice and their other sister.

The correct answer is: **Each of Alice's brothers has 2 sisters.** Confidence level: 100%
I am absolutely confident in this solution because I have carefully considered the relationships between Alice and her siblings, and logically deduced the correct answer.

Figure 42: Example of a correct revision by LLaMA 3 70b. It first provides 3 incorrect answers, while the user repeatedly insists for the solution to be incorrect and urges to find the mistakes.

Human

Build SQLite queries for creation and population of the table that represents: "Alice has 4 sisters and she also has a brother. How many sisters in total does Alice's brother have?".

Given the table schema, query the table.

Emulate the previous query execution only by looking at SQL and provide the result of execution.
(Format every SQL query as ``sql {the query}``)

Mixtral-8x22B-instruct-v0.1

To solve this problem, we need to create a table to represent the family relationships and then query the table to find the total number of sisters that Alice's brother has. Here's how you can do this:

1. Create a table named `Family` with columns `Name`, `Gender`, and `FamilyID`.

```
``sql
CREATE TABLE Family (
    Name TEXT,
    Gender TEXT, -- M for Male, F for Female
    FamilyID INTEGER
);``
```

2. Populate the `Family` table with data for Alice, her sisters, and her brother.

```
``sql
INSERT INTO Family (Name, Gender, FamilyID)
VALUES ('Alice', 'F', 1),
       ('Sister1', 'F', 1),
       ('Sister2', 'F', 1),
       ('Sister3', 'F', 1),
       ('Sister4', 'F', 1),
       ('Brother', 'M', 1);
``
```

3. Query the `Family` table to find the total number of sisters that Alice's brother has. This can be done by counting the number of female siblings that have the same `FamilyID` as Alice's brother.

```
``sql
SELECT COUNT(*)
FROM Family
WHERE Gender = 'F'
AND FamilyID IN (
    SELECT FamilyID
    FROM Family
    WHERE Name = 'Brother'
);
``
```

Assuming that the brother is not counted as a sister, the result of this query will be **4 because Alice's brother has the same 4 sisters as Alice.**

Figure 43: Example of SQL reformulation of the AIW problem and correct solution for Mixtral 8x22B instruct v0.1. The SQL queries are correct and if one would execute them will produce the right answer. However the final answer generated by the model is still incorrect. We hypothesize that the models pays more attention to the natural text from the user (the prompt) and its own generated text rather than to SQL queries.

Human

```
# Provide correct answer to the formulated problem.

#### Problem: Alice has 4 brothers and she also has 1 sister. How many sisters does Alice's brother have?

#### Answer: 2

#### Problem: Alice has 4 sisters and she also has 1 brother. How many sisters does Alice's brother have?

#### Answer: 5

#### Problem: Alice has 3 brothers and she also has 6 sisters. How many sisters does Alice's brother have?

#### Answer: 7

#### Problem: Alice has 2 sisters and she also has 4 brothers. How many sisters does Alice's brother have?

#### Answer: 3

#### Problem: Alice has 3 brothers and she also has 5 sisters. How many brothers does Alice's sister have?
```

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```
#### Answer: 4

#### Problem: Alice has 4 brothers and she also has 5 sisters. How many brothers does Alice's sister have?

#### Answer: 5

#### Problem: Alice has 4 brothers and she also has 2 sisters. How many brothers does Alice's sister have?

#### Answer: 5
...
```

Figure 44: Example of in-context learning response for LLaMA 3 70B base model. Model produces the wrong answer. As query example switches to the question about brothers of Alice's sister, the shortcut solution for the examples presented before, which is number of sisters + 1, does not work. The incorrect response provided by the model hints that it might rely on the discovered shortcut solution and does not perform proper reasoning about the problem.