
A Careful Examination of Large Language Model Performance on Grade School Arithmetic

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Abstract

Large language models (LLMs) have achieved impressive success on many benchmarks for mathematical reasoning. However, there is growing concern that some of this performance actually reflects dataset contamination, where data closely resembling benchmark questions leaks into the training data, instead of true reasoning ability. To investigate this claim rigorously, we commission *Grade School Math 1000* (GSM1k). GSM1k is designed to mirror the style and complexity of the established GSM8k benchmark, the gold standard for measuring elementary mathematical reasoning. We ensure that the two benchmarks are comparable across important metrics such as human solve rates, number of steps in solution, answer magnitude, and more. When evaluating leading open- and closed-source LLMs on GSM1k, we observe accuracy drops of up to 13%, with several families of models (e.g. Phi and Mistral) showing evidence of systematic overfitting across almost all model sizes. At the same time, many models, especially those on the frontier, (e.g. Gemini/GPT/Claude) show minimal signs of overfitting. Further analysis suggests a positive relationship (Spearman’s $r^2 = 0.32$) between a model’s probability of generating an example from GSM8k and its performance gap between GSM8k and GSM1k, suggesting that many models may have partially memorized GSM8k.

1 Introduction

Improving reasoning in large language models (LLMs) is one of the most important directions of current research. As such, proper benchmarking of current LLM abilities is paramount for ensuring progress continues in the correct direction. Currently, the field typically relies on public benchmarks such as GSM8k (Cobbe et al. [2021]), MATH (Hendrycks et al. [2021b]), MBPP (Austin et al. [2021]), HumanEval (Chen et al. [2021]), SWE Bench (Jimenez et al. [2024])). However, because LLMs are trained on large corpora of data scraped from the Internet, there are major concerns that such benchmarks may inadvertently include examples that closely resemble the questions found in such benchmarks. This contamination may result in models having weaker reasoning capabilities than otherwise believed, due to simply being able to repeat the correct answer that it previously encountered during pre- or post- training. To properly investigate the reasoning abilities

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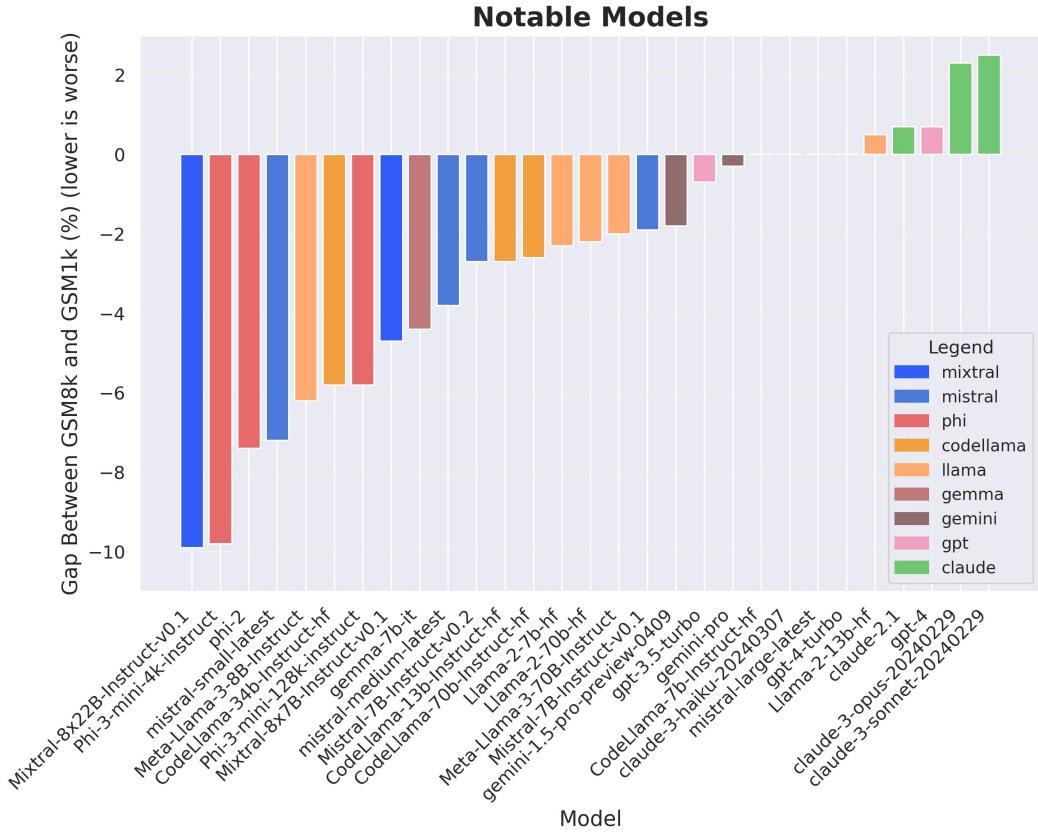


Figure 1: Notable models arranged by their drop in performance between GSM8k and GSM1k (lower is worse). We notice that Mistral and Phi top the list of overfit models, with almost 10% drops on GSM1k compared to GSM8k, while models such as Gemini, GPT, and Claude show little to no signs of overfitting.

of models, we commission GSM1k, a newly constructed collection of 1250 grade school level math problems designed to mirror that of GSM8k. We took extensive efforts to ensure that GSM1k had a similar distribution of difficulty to GSM8k to ensure an apples-to-apples comparison. These efforts are described in Section 3, alongside a detailed description of the data creation process. To mitigate worries about data contamination, we created GSM1k solely with human annotators, without assistance from any LLM or other synthetic data source.

Dataset	Example
GSM8k	James writes a 3-page letter to 2 different friends twice a week. How many pages does he write a year?
GSM1k (ours)	Lee bought 6 shares of Delta stock at \$40 per share. If he wants to make \$24 from this trade, how much should Delta stock be per share when he sells?

Figure 2: Example from both the GSM8k dataset and the new GSM1k dataset (ours). We also provide an additional 50 examples from GSM1k in Appendix E.

We benchmark leading open-source and closed-source LLMs on GSM1k, including GPT-4 (OpenAI et al. [2024]), Gemini (Team et al. [2024]), Claude, Mistral (Jiang et al. [2024, 2023]), Llama (Touvron et al. [2023a,b]), Phi (Gunasekar et al. [2023], Abdin et al. [2024]) and many more. Our analysis confirms that the widespread suspicion in the field that many models are contaminated by benchmark data, with the worst model performing 13% worse on GSM1k compared to GSM8k. Additionally, our results suggest that several families of models, most notably Mistral and Phi, show

consistent evidence of overfitting for nearly all model versions and sizes. Further analysis finds a positive relationship (Spearman’s $r^2 = 0.32$) between a model’s probability of generating examples from GSM8k and its performance gap between GSM8k and GSM1k, strongly suggesting that one important component of this overfitting is that models have partially memorized examples from GSM8k. Nevertheless, our results find that all frontier models, as well as all sizes of the Llama2 family, show minimal signs of overfitting. Additionally, we also find that all models, including the most overfit ones, are still capable of successfully generalizing to new mathematical grade school problems, albeit occasionally at lower rates than their benchmark numbers would suggest.

We do not intend to release GSM1k publicly at this time to prevent a similar problem of data contamination occurring in the future. However, we plan to run recurring evaluations of all major open- and closed- source releases and to continually update our results. We will also open source our entire evaluation code so that the public version of our results can be reproduced. Additionally, we commit to open sourcing the entire benchmark when either 1) the top open source models score over 95% on GSM1k or 2) at the end of 2025, whichever comes earlier. See Section 3 for precise criteria for release.

2 Related Work

A major inspiration of this work was the celebrated study on overfitting done on ImageNet classifiers in 2019 (Recht et al. [2019]). This work measured overfitting in ImageNet by creating new versions of CIFAR10 and ImageNet and measuring the performance gap between the public test set and the newly created sets they constructed. In this work, we do a similar analysis on GSM8k, one of the leading benchmarks for elementary mathematical reasoning. GSM1k is modelled primarily after the GSM8k dataset (Cobbe et al. [2021]), released by OpenAI in 2021, which consists of 8.5k grade school math problems. Each problem is designed to be solvable using only basic arithmetic operations ($+, -, \times, \div$) with a difficulty level appropriate for grade school students. As of April 2024, top models report benchmark accuracies of over 95% (Team et al. [2024]). Other popular benchmarks for reasoning include MATH (Hendrycks et al. [2021b]) , MMLU (Hendrycks et al. [2021a]), GPQA (Rein et al. [2023]).

2.1 Data Contamination

Because data contamination is a well known issue in the field (Balloccu et al. [2024], Magar and Schwartz [2022], Sainz et al. [2023], Jacovi et al. [2023]), model builders will frequently take great pains to minimize the likelihood of data contamination. For example, it is common to remove all data with too high of an n-gram overlap with the benchmark data (Brown et al. [2020]). Additionally, methods such as using embedding similarity attempt to remove all contaminated data that is too similar in embedding space to the dataset (Shi et al. [2024]). More recently, Srivastava et al. [2024] propose functional evaluations, where benchmarks are written in the form of functions that can generate an infinite number of specific evaluation datapoints, each with slightly different numbers. In this setup, whenever a language model is evaluated, functional evaluations generate a specific problem instance to evaluate the model on, which is then never used again. This reduces the worry of data contamination by ensuring that no datapoint is ever used twice. Like ours, their results indicate the LLMs may be severely overfit on benchmark data. The main advantage of our approach over a purely function based evaluation is that functional evaluations can only generate a tiny portion of the full problem space by producing variations of the same problem with slightly different numerical values.

3 GSM1k

GSM1k consists of 1250 problems requiring only elementary mathematical reasoning to solve. We created GSM1k using human annotators sourced by Scale AI. Annotators were prompted with 3 example GSM8k problems and asked to produce novel problems of a similar difficulty level. The precise instructions and UI given to the annotators is available in Appendix A. All problem annotators were instructed to create problems solvable with only basic arithmetic (addition, subtraction, multiplication, and division) and which did not require any advanced math concepts. As is the case

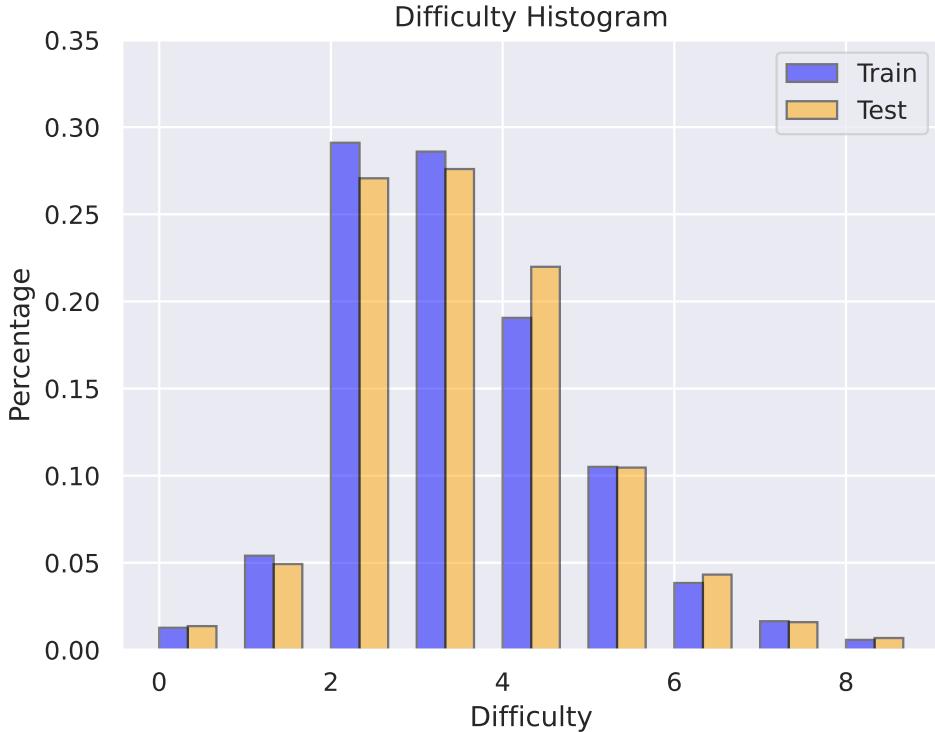


Figure 3: Approximate difficulty distribution of GSM8k train and test sets, measured by number of required steps to solve the problem. GSM1k annotators were instructed to create problems matching the overall distribution of the combined train and test difficulty distribution. The process of estimating problem difficulty is described in Section 3.2.

with GSM8k, all problem solutions are positive integers². No language models were used in the process of constructing this dataset.

To prevent data contamination concerns with GSM1k, we will not be releasing the dataset publicly at this time. However, we commit to releasing the full GSM1k dataset when at least one of the two following conditions have passed, whichever comes earlier. 1) Three open-source models with different pre-trained foundational model lineages reach 95% accuracy on GSM1k. 2) The end of 2025. At such a point, we believe that grade school mathematics will likely no longer be difficult enough to materially benchmark model releases and commit to releasing all data into the public domain under the MIT license. Additionally, to evaluate proprietary models, we were required to send over the dataset via API. Our belief is that model providers typically do not use such datapoints for model training. Nevertheless, in case GSM1k data is leaked through such means, we also hold out a small number of data points that have passed all quality checks but do not appear in the final GSM1k dataset. This data will also be released alongside GSM1k upon final release. We encourage future benchmarks to follow a similar pattern, where they are not released publicly lest they be gamed, but are precommitted to be released at a future date or upon a future condition. As part of this release, we will also open source our evaluation framework, which is based off of a fork of the LM Evaluation Harness by EleutherAI (Gao et al. [2023a]).

Finally, while we undertook extensive efforts to ensure maximum similarity between GSM8k and GSM1k, these results are only an approximation of an ideal world in which the test set of GSM8k was instead not publicly released and used for evaluations. We would recommend reading all results with the understanding that GSM8k and GSM1k are only highly similar, but not identically distributed despite all our efforts below.

²GSM8k has a few problems, likely errors, for which this is not the case.

3.1 Quality Checks

All questions passed through a total of 3 review layers. After initial creation, each task was manually reviewed by a subset of trusted annotators selected for strong past performance. These reviewers checked both for correctness as well as ensuring problems contained only grade school level math and proper formatting. To ensure that questions were answered correctly, we also do a second review layer by having an independent set of data annotators solve each question *without seeing the intended solution*. If this second solve produced a different answer to that of the initial solve, we discarded the problem. Finally, all problems were reviewed by a special team within Scale responsible for conducting general quality audits for data production. Out of a total of 2108 initial problems, 1419 passed the second solve stage and 1375 passed the general quality audit.

3.2 Matching the Difficulty Distribution of GSM8k

One important axis of recreating a benchmark is ensuring that new problems have a comparable difficulty to the original benchmark. To construct problems of difficulty N , we requested annotators to construct problems with N required resolution steps and prompted them with 3 examples from GSM8k with estimated difficulty N . The distribution of problems requested from annotators matched the estimated distribution in GSM8k. Difficulty is tricky to measure precisely, so we used an estimate based on the number of operations needed to solve the problem. This was extracted programmatically by counting the number of “calculator” tags in the problem solution. However, as not all problem solutions were formatted consistently, this estimate is only a rough estimate of actual difficulty. Additionally, the number of resolution steps in a problem does not necessarily directly correlate with the true level of problem difficulty.

Past work has also found that LLMs struggle with problems with larger numbers (Gao et al. [2023b]) even if they can solve otherwise identical problems with smaller numbers. To remove this as a potential confounding variable, our final processing step is to discard candidate problems from GSM1k so that the answer magnitude distributions of GSM8k and GSM1k are as similar as possible. This selection process is described in Figure 4. GSM1k consists of the 1250 problems that survive this final winnowing. Additionally, we run several checks to ensure that our efforts to match benchmark

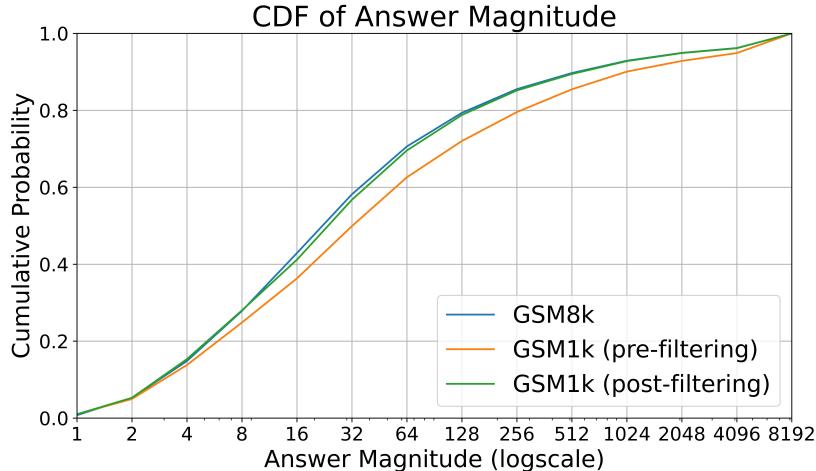


Figure 4: As the final step, we select 1250 problems to match the answer magnitude distribution of GSM8k as much as possible. The remaining problems are discarded and not included in the final dataset. Before discarding, we find that our generated problems tend to have slightly larger answers.

difficulty were successful.

3.2.1 Human Differentiation Rates

The first test we run is human distinguishability. We present human annotators with a set of five questions, four of which were randomly selected from the original GSM8k dataset and one of which

was selected from the newly created GSM1k dataset, and rewarded annotators for finding the odd one out. In an audit conducted using 19 annotators who were not involved in the problem creation process, we found that annotators were able to correctly identify the lone GSM1k example 21.83% of the time out of 1205 attempts (20% is pure chance). Separately, we also tested several paper authors who had not yet seen the data and they were also unable to perform much better than random. This suggests minimal differences between GSM8k and GSM1k, at least as measured by the human eye.

3.2.2 Human Solve Rates

To ensure similar solve rates, we also asked annotators to solve questions under time pressure. 14 annotators who had not participated in the problem creation process attempted to solve as many GSM8k problems as they could in 15 minutes and were rewarded based on the number of problems they solved. We repeated this exact setup for GSM1k. Annotators were able to solve an average of 4.07 ± 0.93 problems on the GSM8k dataset. They were able to solve 4.36 ± 1.11 problems on the GSM1k dataset, where the error rates are the standard deviations of the evaluation. This suggests that GSM1k is comparable in difficulty (and perhaps even slightly easier) than GSM8k. As such, substantial decreases in model accuracy on GSM1k compared to GSM8k are likely not explainable due to differences in dataset difficulty.

3.2.3 LLM Solve Rates

Finally, we sanity check our results by measuring solve rates of several models that are known to not be contaminated by GSM8k due to being released before the publication of the GSM8k dataset. Due to the relative scarcity of LLMs trained only on pre-2021 data, we evaluate only GPT-NeoX-20B (Black et al. [2022]) and GPT-2 (Radford et al. [2019]). For these two language models, we find minimal difference between their solve rates of GSM8k and GSM1k (Figure 7).

4 Results

To evaluate models, we use a fork of EleutherAI’s LM Evaluation Harness using the default settings. Both GSM8k and GSM1k questions are run with the same prompt of using 5 randomly drawn examples from the GSM8k train set, as is standard in the field. The full prompt is provided in Appendix B. All open-source models are evaluated at temperature 0 for reproducibility. LM Evaluation Harness extracts the last numeric answer in the response and compares this to the correct answer. As such, model responses which produce the “correct” answer in a format that do not match the examples are marked as incorrect. For open source models, we use vLLM to speed up model inference if a model is compatible with the library. Otherwise, we default to inference using standard HuggingFace libraries. Closed-source models were queried through the LiteLLM library which unifies the API call format for all proprietary models evaluated. All API model results were from queries between April 16 - April 28, 2024 and use the default settings.

As model benchmark performance is highly dependent on choice of prompt and evaluation setting, our reported GSM8k numbers may occasionally be below the reported model benchmark numbers, as we use a standardized setting for all models instead of the prompt that maximizes each individual model’s performance. For completeness, we also report results with an alternative prompting format uses non-GSM8k examples as n-shot examples in Appendix C. Nevertheless, since we focus primarily on the difference between a model’s performance on GSM1k and GSM8k when holding fixed an evaluation strategy, we believe the above setup to be a fair comparison for all models. We will release the full evaluation code for reproducibility.

We select models to evaluate based on popularity. Additionally, we evaluated several lesser known models that sit near the top of the OpenLLMLeaderboard and discover evidence of Goodhart’s law: many of these models perform substantially worse on GSM1k, suggesting that they are primarily gaming the GSM8k benchmark rather than improving model reasoning capabilities. The full set of results, including the performance table for all models, can be found in Appendix D. For fair comparison, we partition the models by performance on GSM8k and compare them to other models which perform similarly (Figures 5, 6, 7).

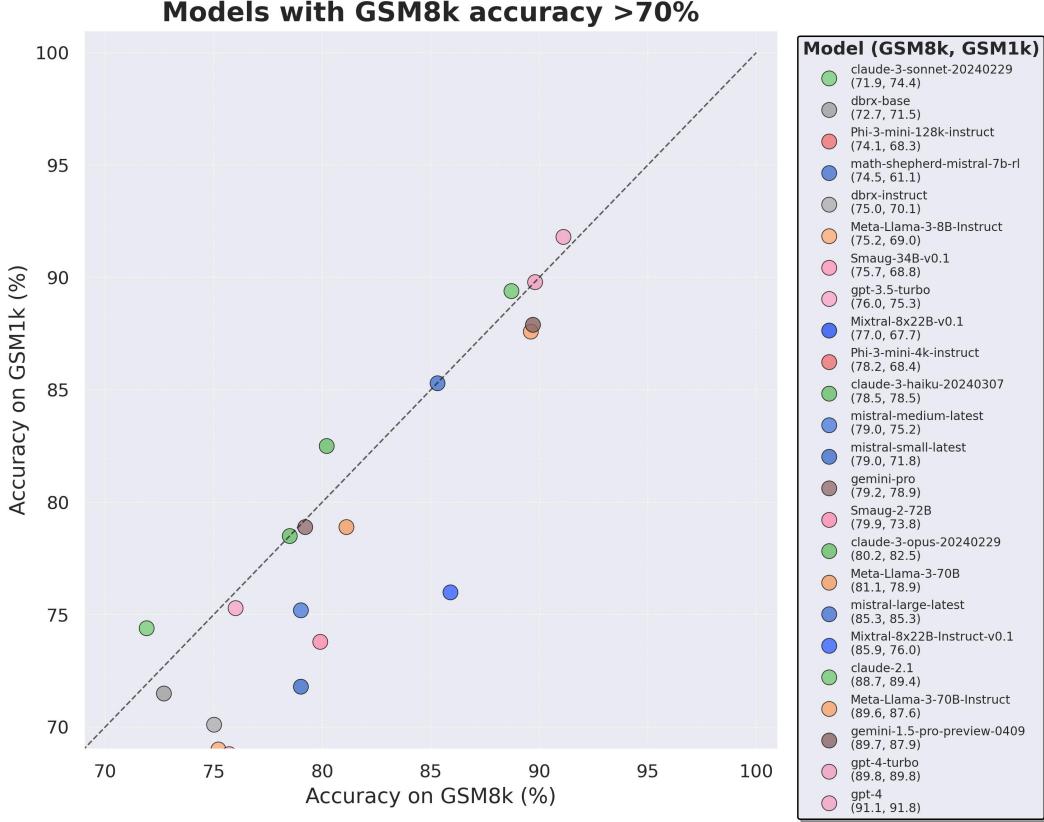


Figure 5: Models with over 70% accuracy on GSM8k compared to the line of no overfit. This plot is zoomed into the relevant sections (70-100% accuracy). Note that some models, especially the Claude family, perform above the 45 degree line, which is consistent with our findings in Section 3 that GSM1k is slightly easier than GSM8k. In contrast, many models, especially the Mistral and Phi families lie well below the line.

5 Analysis

The interpretation of evaluation results, like the interpretations of dreams, is often a very subjective endeavor. While we report our objective results in Section 4 and Appendix D, here we describe four major takeaways from interpreting the results in a more subjective manner.

5.1 Lesson 1: Some Model Families are Systematically Overfit

While it is often difficult to draw conclusions from singular data points or model releases, examining a family of models and observing a pattern of overfitting enables us to make more definitive statements. Several families of models, including the Phi and Mistral families of models, both show systematic tendencies to perform stronger on GSM8k compared to GSM1k for almost every release and scale of models. Other model families, such as Yi, Xwin, Gemma and CodeLlama also show this pattern to a lesser extent.

5.2 Lesson 2: Other Models, Especially Frontier Models, Show No Signs of Overfitting

Nevertheless, we find that many models, through all regions of performance, show minimal signs of being overfit. In particular, we find that all frontier or close-to-frontier models (including the proprietary Mistral Large) appear to perform similarly on both GSM8k and GSM1k. We posit two potential hypotheses for this: 1) frontier models have sufficiently advanced reasoning capability so that they can generalize to new problems even if they have already seen GSM8k problems in their training set, 2) frontier model builders may be more careful about data contamination.

Models with GSM8k accuracy between 40% and 70%

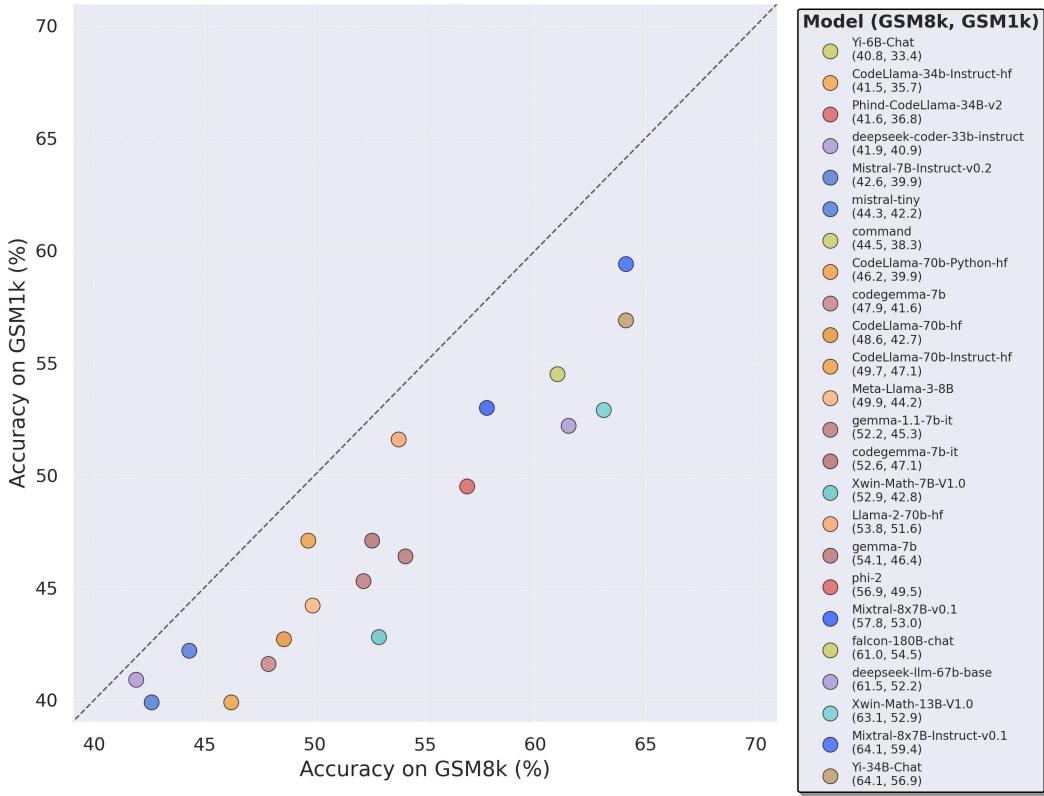


Figure 6: Models with between 40 and 70% accuracy on GSM8k compared to the line of no overfit. This plot is zoomed into the relevant sections (40-70% accuracy). We observe that no models lie on the line of no overfit in this regime.

While it is impossible to know for certain without looking at the training set for each model, one piece of evidence in favor of the former is that Mistral Large is the *only* model in the Mistral family to show no signs of overfitting. Since the hypothesis that Mistral took unique care in ensuring only that their largest model was free from data contamination seems unlikely, we lean instead towards the hypothesis that sufficiently strong LLMs also learn elementary reasoning ability during training. If a model learns strong enough reasoning capabilities to solve problems of a given difficulty, it will be able to generalize to new problems even if GSM8k has appeared in their training set.

5.3 Lesson 3: Overfit Models Are Still Capable of Reasoning

One worry about model overfitting is that models are incapable of reasoning and merely only memorizing answers seen in the training data. Our results do not support this conjecture. The fact that a model is overfit does not mean that it is poor at reasoning, merely that it is not as good as the benchmarks might indicate it to be. In fact, we find that many of the most overfit models are still capable of reasoning and solving novel problems. For example, while Phi-3 has an almost 10% drop in accuracy between GSM8k and GSM1k, we find that it is still able to correctly solve over 68% of GSM1k problems – which are certain to not have appeared in its training distribution. This performance is similar to that of much larger models such as dbrx-instruct, which contains almost 35x as many parameters. Similarly, Mistral models remain some of the strongest open source models, even accounting for their overfitting. This provides additional evidence for our lesson that sufficiently strong models learn elementary reasoning, even if benchmark data accidentally leaked into the training distribution, as is likely to be the case for the most overfit models.

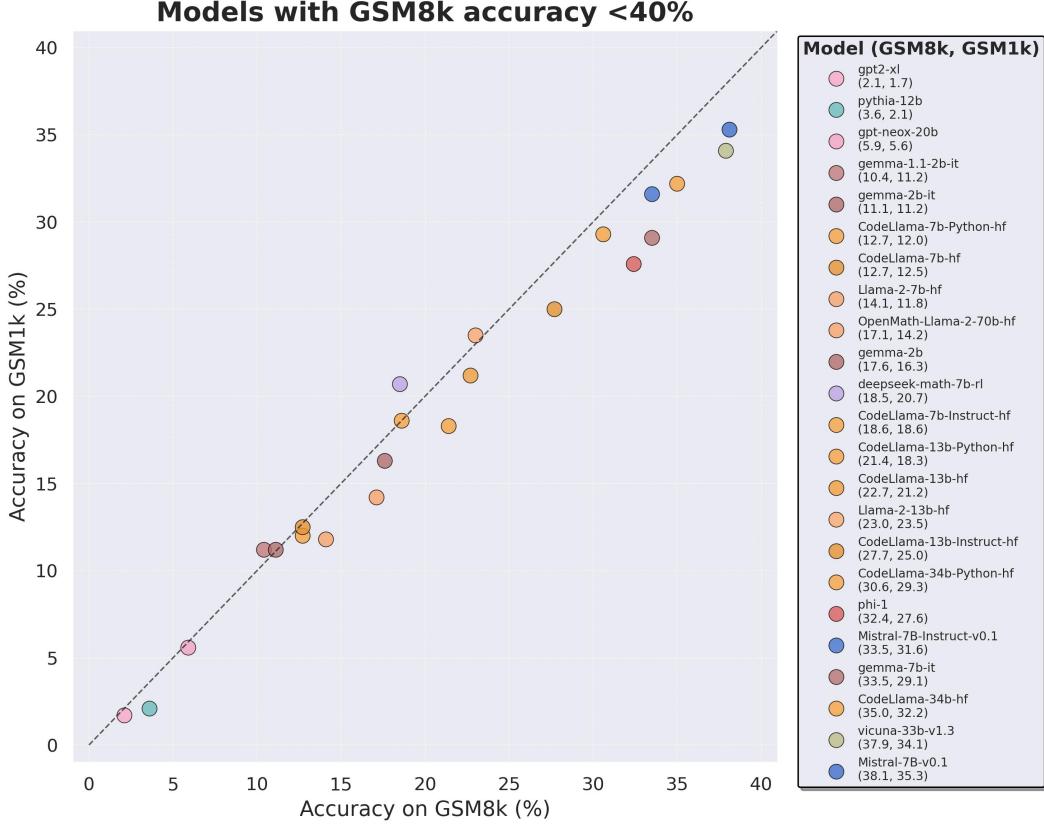


Figure 7: Models with between 0 and 40% accuracy on GSM8k compared to the line of no overfit. This plot is zoomed into the relevant sections (0-40% accuracy).

5.4 Lesson 4: Data Contamination Is Likely Not The Full Explanation for Overfitting

A priori, a natural hypothesis is that the primary cause for overfitting is data contamination, e.g. that the test set was leaked in the pre-training or instruction fine-tuning part of the model creation. Previous work has suggested that models put higher log-likelihoods on data that they have seen during training (Carlini et al. [2023]). We test the hypothesis that data contamination is the cause of overfitting by measuring a model’s probability of generating an example from the GSM8k test set and compare it to how overfit it is on GSM8k compared to GSM1k, using the assumption that a model’s probability of generating the GSM8k test set is a proxy for whether the sequence is likely to have appeared in the training set. We normalize by c , the number of characters in the sequence, to make the log-likelihood calculations comparable between sequences and models with different tokenizers. Formally, we have:

$$\frac{1}{c} \sum_i \log p(x_i | x_{<i}) \quad (1)$$

with c being the number of characters in the sequence. Figure 8 shows the result of this plot against the gap between GSM8k and GSM1k performance. We indeed find a positive relationship between the two values. We observe a Spearman’s rank correlation of 0.32 between the per-character log-likelihood of generating GSM8k and the performance gap between GSM8k and GSM1k ($p = 0.03$), and the relationship suggests that every percentage point difference in GSM8k and GSM1k performance is associated with an increase of 7.9×10^{-3} in the per-character log-likelihood. This result suggests that some of the reason for overfitting is due to partial memorization of the test set. For completeness, we also report the standard Pearson $r^2 = 0.15$ and the Kendall’s τ of 0.28, but note that Pearson r^2 is not the ideal metric due to the curve-of-best-fit not appearing linear.

Nevertheless, data contamination is likely not the full story. We observe this via the presence of several outliers, which cause the $r^2 = 0.32$ value to be relatively low. Examining these outliers

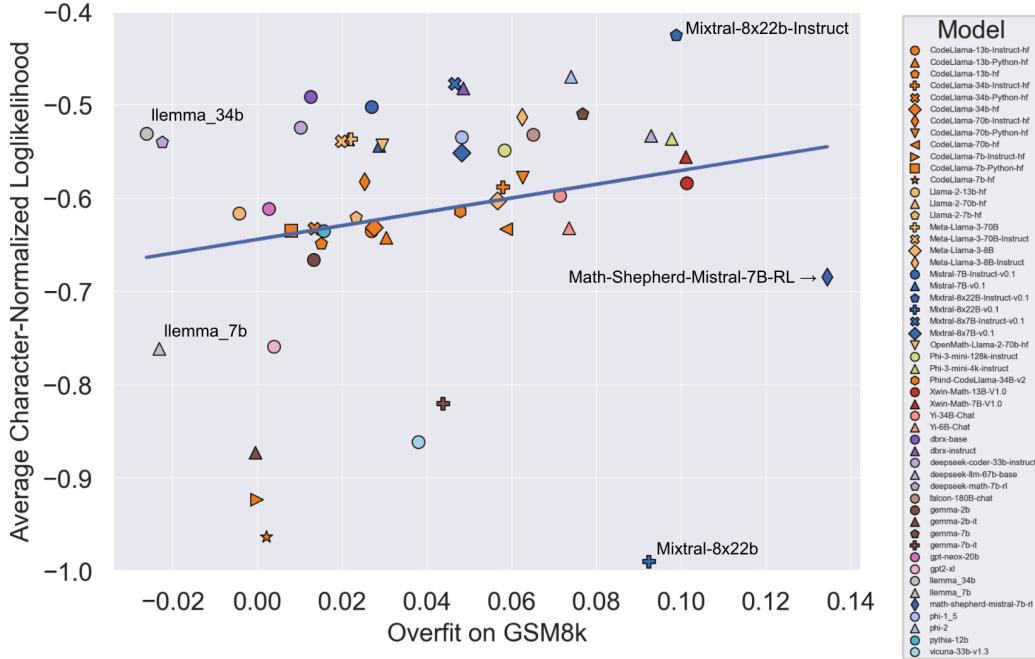


Figure 8: Comparison between overfit on GSM8k (x-axis) and average sequence-level log-likelihood on the GSM8k test set (y-axis). We find that there is a correlation between overfit on GSM8k and sequence-level log-likelihood, suggesting that, in general, models that have a high overfit generally have a higher probability of generating the test set. This suggests that some of the GSM8k test set may have leaked into the model training data. The line of best fit is in blue. Additionally, we highlight 5 “outlier” models which we discuss further with Lesson 4.

carefully reveals that the model with the lowest per-character log-likelihood (Mixtral-8x22b) and the model with the highest per-character log-likelihood (Mixtral-8x22b-Instruct) are not only variations of the same model, but also have similar levels of overfit (Jiang et al. [2024]). Perhaps more intriguingly, the most overfit model we discovered (Math-Shepherd-Mistral-7B-RL (Yu et al. [2023])) had a relatively low per-character log-likelihood. Math Shepherd trains a reward model on process level data using synthetic data. As such, we hypothesize that the reward modelling process may have leaked information about the correct reasoning chains for GSM8k even if the problems themselves did not ever appear in the dataset. Finally, we observe that the LLeMa models (Azerbayev et al. [2024]) have both high log-likelihoods and minimal overfit. Since these models are open-source and their training data is known, it is known that several GSM8k problem instances appear in the training corpus, as described by the authors in their paper. Nevertheless, the authors find (and our study supports) that these few instances do not lead to serious overfitting. The existence of these outliers suggests that overfitting on GSM8k is not purely due to data contamination, but rather may be through other indirect means, such as model builders collecting data similar in nature to benchmarks as training data or selecting final model checkpoints based on performance on benchmarks, even if the model itself may have not seen the GSM8k dataset at any point via training. Conversely, the reverse is also true: small amounts of data contamination do not necessarily lead to overfitting.

6 Discussion

We create GSM1k, a novel dataset designed to measure LLM overfitting on GSM8k. When benchmarking leading open- and closed-source models, we find substantial evidence that many models have been contaminated by benchmark data, with models showing performance drops of up to 13% accuracy. Additionally, we find that several families of models, most notably the Mistral and Phi families, show consistent overfitting across almost all model sizes and versions. An extended analysis reveals a positive relationship between a model’s likelihood of generating data points in GSM8k and its performance difference between GSM8k and GSM1k, suggesting evidence of data contamination

as one of the underlying causes. Nevertheless, we find that frontier models exhibit little to no evidence of overfitting and that many models, even the most heavily overfit families, show strong signs of generalizable mathematical reasoning.

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A Annotator Instructions

We provide the annotator instructions given below.

Welcome to the Grade School Math Question Development project. The goal of this project is to create questions and answers similar to what is found in an 8th-grade math quiz. Our goal is to develop high-quality questions that are almost the same as what is found in the dataset but are entirely unique. You will see three example questions and their corresponding answers in each task. These examples will guide you to create completely new questions and answers. It's important to note that you cannot use chatbots or language models to help you develop these Q&A pairs. You may be removed from the project if we detect any use of chatbots. Crucially, your Q&A pairs must be original creations and cannot be paraphrased versions of the examples

Your workflow for this project will be as follows:

Review the examples: In each task you will be shown examples from an 8th-grade question-and-answer dataset. Review the examples to inform how you can create your question and answer pair.

Problem Creation: Problems should follow step guidance in the task. Don't reuse a problem setting. If you wrote a problem about Rogers trip to the grocery store, don't write another problem using the same premise. All questions should have a resolution of 1 or higher. We do not want any questions with a negative integer or zero as the answer

Craft the resolution steps: Calculations should be simple enough an 8th grader can complete with a pen and paper. Only use elementary arithmetic operations (addition, subtraction, multiplication, division)

Provide the final Answer: Answers should be a single integer value. Any units should be specified as part of the question (e.g. "How much money, in dollars, does Robert have?"). Simple decimal numbers (e.g. 3.25) can be part of the intermediate steps in the problem, but final answers should always be integers.

Check your work: We will utilize quality control process to ensure accuracy but it is crucial to check your work!

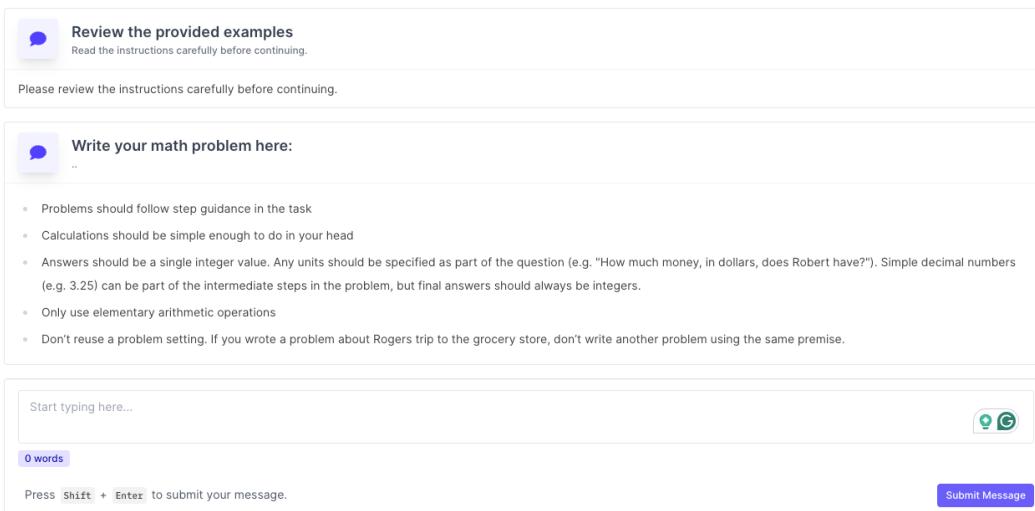


Figure 9: What annotators saw before seeing three example prompts drawn from GSM8k.

B N-shot Prompt (examples selected randomly from GSM8k train)

Below is an example prompt. For each question, we select five random examples from GSM8k to use as n-shot examples, which vary for each new question from the GSM1k/GSM8k test set. While evaluation methods vary between models, this is the most common approach to evaluating GSM8k.

Question: Jen and Tyler are gymnasts practicing flips. Jen is practicing the triple-flip while Tyler is practicing the double-flip. Jen did sixteen triple-flips during practice.

Tyler flipped in the air half the number of times Jen did. How many double-flips did Tyler do?

Answer: Jen did 16 triple-flips, so she did $16 * 3 = <<16*3=48>>48$ flips.

Tyler did half the number of flips, so he did $48 / 2 = <<48/2=24>>24$ flips.

A double flip has two flips, so Tyler did $24 / 2 = <<24/2=12>>12$ double-flips.

12

Question: Four people in a law firm are planning a party. Mary will buy a platter of pasta for \$20 and a loaf of bread for \$2. Elle and Andrea will split the cost for buying 4 cans of soda which cost \$1.50 each, and chicken wings for \$10. Joe will buy a cake that costs \$5. How much more will Mary spend than the rest of the firm put together?

Answer: Mary will spend $$20 + $2 = \$<<20+2=22>>22$.

Elle and Andrea will spend $\$1.5 \times 4 = \$<<1.5*4=6>>6$ for the soda.

Elle and Andrea will spend $\$6 + \$10 = \$<<6+10=16>>16$ for the soda and chicken wings.

Elle, Andrea, and Joe together will spend $\$16 + \$5 = \$<<16+5=21>>21$.

So, Mary will spend $\$22 - \$21 = \$<<22-21=1>>1$ more than all of them combined.

1

Question: A charcoal grill burns fifteen coals to ash every twenty minutes of grilling. The grill ran for long enough to burn three bags of coals. Each bag of coal contains 60 coals. How long did the grill run?

Answer: The grill burned $3 * 60 = <<3*60=180>>180$ coals.

It takes 20 minutes to burn 15 coals, so the grill ran for $180 / 15 * 20 = <<180/15*20=240>>240$ minutes.

240

Question: A bear is preparing to hibernate for the winter and needs to gain 1000 pounds. At the end of summer, the bear feasts on berries and small woodland animals. During autumn, it devours acorns and salmon. It gained a fifth of the weight it needed from berries during summer, and during autumn, it gained twice that amount from acorns. Salmon made up half of the remaining weight it had needed to gain. How many pounds did it gain eating small animals?

Answer: The bear gained $1 / 5 * 1000 = <<1/5*1000=200>>200$ pounds from berries.

It gained $2 * 200 = <<2*200=400>>400$ pounds from acorns.

It still needed $1000 - 200 - 400 = <<1000-200-400=400>>400$ pounds.

Thus, it gained $400 / 2 = <<400/2=200>>200$ pounds from salmon.

Therefore, the bear gained $400 - 200 = <<400-200=200>>200$ pounds from small animals.

200

Question: Brendan can cut 8 yards of grass per day, he bought a lawnmower and it helped him to cut more yards by Fifty percent per day. How many yards will Brendan be able to cut after a week?

Answer: The additional yard Brendan can cut after buying the lawnmower is $8 \times 0.50 = <<8*0.50=4>>4$ yards.

So, the total yards he can cut with the lawnmower is $8 + 4 = <<8+4=12>>12$.

Therefore, the total number of yards he can cut in a week is $12 \times 7 = <<12*7=84>>84$ yards.

84

C Results with An Alternative Prompt

As an ablation, we evaluate all models with an alternative prompt scheme and compare results with our primary findings. This prompt is available under the LM Evaluation Harness as a “chain-of-thought” prompt. However, manually examining the prompt (provided in full below) reveals that the primary difference with the standard n-shot prompt lies not in chain-of-thought reasoning but rather using a set of non-GSM8k problems as guiding examples as well as providing an alternative answer format. We choose to use the standard prompt to match typical evaluation methods widespread in the field but also report these results for completeness.

- Q: There are 15 trees in the grove. Grove workers will plant trees in the grove today. After they are done, there will be 21 trees. How many trees did the grove workers plant today?
- A: There are 15 trees originally. Then there were 21 trees after some more were planted. So there must have been $21 - 15 = 6$. The answer is 6.
- Q: If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot?
- A: There are originally 3 cars. 2 more cars arrive. $3 + 2 = 5$. The answer is 5.
- Q: Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?
- A: Originally, Leah had 32 chocolates. Her sister had 42. So in total they had $32 + 42 = 74$. After eating 35, they had $74 - 35 = 39$. The answer is 39.
- Q: Jason had 20 lollipops. He gave Denny some lollipops. Now Jason has 12 lollipops. How many lollipops did Jason give to Denny?
- A: Jason started with 20 lollipops. Then he had 12 after giving some to Denny. So he gave Denny $20 - 12 = 8$. The answer is 8.
- Q: Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?
- A: Shawn started with 5 toys. If he got 2 toys each from his mom and dad, then that is 4 more toys. $5 + 4 = 9$. The answer is 9.
- Q: There were nine computers in the server room. Five more computers were installed each day, from monday to thursday. How many computers are now in the server room?
- A: There were originally 9 computers. For each of 4 days, 5 more computers were added. So $5 * 4 = 20$ computers were added. $9 + 20$ is 29. The answer is 29.
- Q: Michael had 58 golf balls. On tuesday, he lost 23 golf balls. On wednesday, he lost 2 more. How many golf balls did he have at the end of wednesday?
- A: Michael started with 58 golf balls. After losing 23 on tuesday, he had $58 - 23 = 35$. After losing 2 more, he had $35 - 2 = 33$ golf balls. The answer is 33.
- Q: Olivia has \$23. She bought five bagels for \$3 each. How much money does she have left?
- A: Olivia had 23 dollars. 5 bagels for 3 dollars each will be $5 \times 3 = 15$ dollars. So she has $23 - 15$ dollars left. $23 - 15$ is 8. The answer is 8.

We report our results in Table D. On average, we find that this prompt causes the gap between GSM8k and GSM1k to decrease by about 1% across all models. However, for some models (e.g. Mixtral-8x22B-v0.1), this reduces the amount of observed overfitting dramatically. While the exact cause of this difference is impossible to know, especially without access to model details such as their training set, our hypothesis is that prompting a model with GSM8k is more likely to activate the “memorization” portion of a model than if it is prompted by non-GSM8k grade school math problems.

D Results Table

We report our full results in Table D. Models are sorted by the difference in performance between GSM8k and GSM1k. Because all models are evaluated using the standard LM Evaluation Harness prompt and evaluation format, model performance on GSM8k may not match reported benchmark numbers. In particular, answers that do not match the 5-shot example format are marked incorrect even if they are otherwise “correct.” Our focus is primarily on the difference between GSM8k and GSM1k performance, holding evaluation setting constant. Alternative prompt results are also included. For details, see Appendix C.

Model	Diff	GSM8k	GSM1k	GSM8k_alt	GSM1k_alt	Diff_alt
math-shepherd-mistral-7b-rl	0.135	0.745	0.611	0.782	0.645	0.138
Xwin-Math-13B-V1.0	0.101	0.631	0.529	0.643	0.567	0.076
Xwin-Math-7B-V1.0	0.101	0.529	0.428	0.513	0.456	0.058
Mixtral-8x22B-Instruct-v0.1	0.099	0.859	0.760	0.885	0.843	0.042
Phi-3-mini-4k-instruct	0.098	0.782	0.684	0.801	0.763	0.039
deepseek-llm-67b-base	0.093	0.615	0.522	0.656	0.594	0.061
Mixtral-8x22B-v0.1	0.092	0.769	0.677	0.810	0.791	0.019
gemma-7b	0.077	0.541	0.464	0.544	0.518	0.026
phi-2	0.074	0.569	0.495	0.554	0.513	0.041
Yi-6B-Chat	0.073	0.408	0.334	0.423	0.362	0.061
mistral-small-latest	0.072	0.790	0.718	0.782	0.751	0.031
Yi-34B-Chat	0.071	0.641	0.569	0.647	0.584	0.062
Smaug-34B-v0.1	0.069	0.757	0.688	0.745	0.700	0.046
gemma-1.1-7b-it	0.069	0.522	0.454	0.493	0.427	0.065
falcon-180B-chat	0.065	0.610	0.545	0.622	0.597	0.025
codegemma-7b	0.063	0.479	0.416	0.515	0.459	0.057
CodeLlama-70b-Python-hf	0.062	0.462	0.399	0.493	0.439	0.054
command	0.062	0.445	0.383	0.446	0.397	0.049
Meta-Llama-3-8B-Instruct	0.062	0.752	0.690	0.772	0.746	0.026
Smaug-2-72B	0.061	0.799	0.738	0.812	0.755	0.057
CodeLlama-70b-hf	0.059	0.486	0.427	0.500	0.460	0.039
Phi-3-mini-128k-instruct	0.058	0.742	0.683	0.817	0.752	0.065
CodeLlama-34b-Instruct-hf	0.058	0.415	0.357	0.400	0.392	0.007
Meta-Llama-3-8B	0.057	0.499	0.442	0.547	0.529	0.018
codegemma-7b-it	0.055	0.526	0.471	0.515	0.459	0.056
phi-1	0.048	0.324	0.276	0.324	0.276	0.048
Mixtral-8x7B-v0.1	0.048	0.579	0.530	0.607	0.601	0.006
Phind-CodeLlama-34B-v2	0.048	0.416	0.368	0.403	0.376	0.026
Mixtral-8x7B-Instruct-v0.1	0.046	0.641	0.594	0.686	0.657	0.029
gemma-7b-it	0.044	0.335	0.291	0.248	0.240	0.008
mistral-medium-latest	0.038	0.790	0.752	0.789	0.764	0.025
vicuna-33b-v1.3	0.038	0.379	0.341	0.441	0.417	0.023

Model	Diff	GSM8k	GSM1k	GSM8k_alt	GSM1k_alt	Diff_alt
CodeLlama-13b-Python-hf	0.030	0.214	0.183	0.221	0.194	0.027
OpenMath-Llama-2-70b-hf	0.029	0.171	0.142	0.165	0.126	0.039
Mistral-7B-v0.1	0.029	0.381	0.353	0.421	0.415	0.007
CodeLlama-34b-hf	0.028	0.349	0.322	0.324	0.305	0.019
CodeLlama-13b-Instruct-hf	0.027	0.277	0.250	0.287	0.276	0.012
Mistral-7B-Instruct-v0.2	0.027	0.426	0.399	0.436	0.403	0.033
CodeLlama-70b-Instruct-hf	0.025	0.497	0.471	0.519	0.477	0.041
Llama-2-7b-hf	0.023	0.141	0.118	0.142	0.127	0.015
Meta-Llama-3-70B	0.022	0.811	0.789	0.807	0.842	-0.035
Llama-2-70b-hf	0.021	0.537	0.516	0.572	0.566	0.006
Meta-Llama-3-70B-Instruct	0.020	0.896	0.876	0.899	0.885	0.015
Mistral-7B-Instruct-v0.1	0.019	0.335	0.316	0.347	0.354	-0.007
gemini-1.5-pro-preview-0409	0.018	0.897	0.879	0.908	0.892	0.016
pythia-12b	0.016	0.036	0.021	0.050	0.027	0.024
CodeLlama-13b-hf	0.015	0.227	0.212	0.218	0.215	0.003
CodeLlama-34b-Python-hf	0.013	0.306	0.293	0.340	0.281	0.059
gemma-2b	0.013	0.176	0.163	0.191	0.178	0.013
dbrx-base	0.013	0.727	0.715	0.718	0.685	0.033
deepseek-coder-33b-instruct	0.010	0.419	0.409	0.421	0.392	0.029
CodeLlama-7b-Python-hf	0.008	0.127	0.119	0.123	0.119	0.003
gpt-3.5-turbo	0.007	0.760	0.753	0.742	0.759	-0.016
gpt2-xl	0.004	0.021	0.017	0.022	0.018	0.004
gpt-neox-20b	0.003	0.059	0.056	0.076	0.070	0.005
gemini-pro	0.002	0.791	0.789	0.688	0.687	0.000
CodeLlama-7b-hf	0.002	0.127	0.125	0.116	0.095	0.021
CodeLlama-7b-Instruct-hf	-0.000	0.186	0.186	0.187	0.164	0.023
mistral-large-latest	-0.000	0.853	0.853	0.854	0.857	-0.003
gpt-4-turbo	-0.000	0.898	0.898	0.847	0.849	-0.002
claude-3-haiku-20240307	-0.000	0.785	0.785	0.791	0.791	0.000
gemma-2b-it	-0.001	0.111	0.112	0.099	0.106	-0.007
Llama-2-13b-hf	-0.004	0.231	0.235	0.281	0.279	0.002
claude-2.1	-0.007	0.887	0.894	0.836	0.836	0.001
gpt-4	-0.007	0.910	0.918	0.919	0.904	0.014
gemma-1.1-2b-it	-0.009	0.104	0.112	0.084	0.090	-0.005
deepseek-math-7b-rl	-0.022	0.185	0.207	0.754	0.646	0.108
claude-3-opus-20240229	-0.023	0.802	0.825	0.830	0.857	-0.026
claude-3-sonnet-20240229	-0.024	0.720	0.744	0.713	0.724	-0.011

E 50 Examples from GSM1k

No.	Question	Answer
1	Gabriela has \$65.00 and is shopping for groceries so that her grandmother can make her favorite kale soup. She needs heavy cream, kale, cauliflower, and meat (bacon and sausage). Gabriella spends 40% of her money on the meat. She spends \$5.00 less than one-third of the remaining money on heavy cream. Cauliflower costs three-fourth of the price of the heavy cream and the kale costs \$2.00 less than the cauliflower. As Gabriela leaves the store, she spends one-third of her remaining money on her grandmother's favorite Girl Scout Cookies. How much money, in dollars, does Gabriela spend on Girl Scout cookies?	7
2	Bernie is a street performer who plays guitar. On average, he breaks three guitar strings a week, and each guitar string costs \$3 to replace. How much does he spend on guitar strings over the course of an entire year?	468
3	John Henry is competing against a machine to see who can dig a tunnel more quickly. John works without rest, and excavates at a rate of 6 cubic feet of rock per hour. The machine excavates more quickly but needs to be refueled and maintained by its operator for 30 minutes out of every hour. When it's not under maintenance, the machine excavates at a rate of 10 cubic feet of stone per hour. Provided that the competition lasts for 8 hours, how much more rock will John have excavated compared to the machine?	8
4	Colin is playing dice with his friend Eoin and needs some help keeping track of his score. He begins with 5 points and wins 6 points in the first round. In the second round, he won twice as many points as he won in the first round. In the third round, he had a fantastic roll and was able to triple his current total point count! How many points did Colin end the game with?	69
5	Bradley and his friends enjoy playing marbles. They possess a box of marbles containing 12 red balls, 15 yellow balls, and 18 green balls. How many additional red balls do they require to double the number of red balls compared to the combined number of yellow and green balls?	54
6	Marge got a job so she can buy her first car. Her job pays \$15/hr and she works there 30 hours a week. The car Marge wants is \$3600. How many weeks does Marge need to work to buy the car?	8
7	Andy's soccer team needs 80 points to finish in first place. His team plays 38 games, and he gets 3 points for each win, 1 point for each tie, and 0 points for each loss. After 26 games, the team has 15 wins, 5 ties, and 6 losses. How many more points does Andy's team need to reach 80 points?	30
8	Molly wants to win the contest at school for reading 25 books before the end of May. So far, she has read 5 books by the end of January. How many more books will she need to read on average each month until the end of May to win the contest?	5
9	Ms. Crabapple has a bag of jelly beans that she is going to divide equally among all of her 32 students who complete their homework every day over the course of a week. The bag has 384 jellybeans in it. Unfortunately, many of Ms. Crabapple's students have a poorly developed work ethic, and only half of them complete all of the required homework. How many jelly beans will each of the eligible students receive?	24

No.	Question	Answer
10	Emily is applying to 6 different colleges. $\frac{1}{2}$ of the colleges have an application fee of \$60, and the other half have an application fee of \$90. She must also pay \$15 per transcript to send them to each college. Her parents offer to help pay for half of the total costs. How many dollars does she have to pay?	270
11	Bob has to read 2 books and 3 articles, while Emily has to read 4 books and 2 articles. Each book has 3 chapters and each chapter has 4 paragraphs. Each article has 4 sections and each section has 2 paragraphs. How many paragraphs in total will Bob and Emily read?	112
12	Leah and 2 of her friends go to an all-you-can-eat dumpling buffet. Leah's 1st friend ate 30 dumplings, her 2nd friend ate twice as many dumplings as her 1st friend, and Leah ate 1.5 times as many dumplings as her 2nd friend. How many dumplings in total did Leah and her friends eat?	180
13	Francis has a bowl of candy in front of him. There are three different flavors of candies that he's eaten over the course of 3 hours. He's eaten ten lemon, four orange, and sixteen cherry-flavored candies. If there were twenty of each when he started, how much of an average percentage is still left?	50
14	Maryann is saving up for a new bike that costs \$450. She already has \$120 saved up. She earns \$15 per hour at her part-time job. How many hours does she need to work to afford the bike?	22
15	Henry is renovating his kitchen and adding a new tile floor. He needs to cover an area of 200 square feet. He has a stack of tiles that measure 0.5 feet in length and width. He can get 40 tiles done per hour. Henry works for 6 hours at that rate, then has some coffee and works at a faster rate for the next 2 hours (60 tiles per hour). Henry runs out of tiles, so he goes to a store to purchase the remaining tiles needed to finish the floor. Given that the price per tile is \$2.50, how much will he need to spend at the store to get exactly enough tiles to finish the floor?	1100
16	A painter needs to paint 3 houses. The first house requires 14 gallons of paint, the second house requires twice as much paint as the first, and the third house needs half as much paint as the second house. If one gallon of paint costs \$35 and the painter gets a bulk discount of 10% for purchases over 30 gallons, how much will the paint cost in total?	1764
17	A coal miner is loading up coal into mine carts. During the first hour of the day, he is able to load 15 carts. His boss yells at him after that, so for each of the next three hours, he loads twice as many carts. Each cart weighs 78 pounds. What was the total weight of the coal he loaded on this day?	8190
18	A plane owned by Sunny Skies Airlines is flying from Indianapolis to Phoenix. The plane holds 180 passengers and is $\frac{2}{3}$ full. Each passenger brings 2 carry-on bags and is charged a carry-on bag fee of \$35 per bag. How much money does Sunny Skies Airlines collect for the carry-on bag fees for this flight?	8400
19	Sally went to the mall to buy clothes for the summer. She went to Forever 21 and bought 4 tops, each had different prices, \$12.99, \$6.99, \$17.99, \$21.99, and 3 pants each priced at \$15.99. If her subtotal is over \$75, she gets a discount of 15% on her purchase at that store. Then she goes to Shoe Palace and buys 2 shoes for a total of \$123.26. How much money did Sally spend at the mall?	215

No.	Question	Answer
20	Dean wants to buy flowers to make arrangements for a party. He is going to make 12 arrangements. He wants to include 4 roses and 3 daisies in each arrangement. Roses come by the dozens and are \$15 for each dozen. Daisies come in groups of 4 and are \$8 for the set. How much will it cost for Dean to make all 12 arrangements?	132
21	Alex plans to adopt a new cat and needs help planning a budget for this event. The adoption fee is \$200, and it includes all the essential veterinary care needed for a kitten, but she also needs to buy other supplies for the cat when she brings it home. The litter boxes cost \$30, one package of litter costs \$17, a bag of dry food costs \$55, and the wet food costs \$1.50 per can. Alex will buy 2 litter boxes, 3 packages of litter, one bag of dry food, and 12 cans of wet food. How much money should Alex make sure she has before beginning the process of adopting her new cat?	384
22	Carolina is trying to qualify for a car loan. The lender tells her she must meet a debt-to-income ratio of 1:4. Her current debts are \$900 in rent, \$200 in utilities, and another \$300 in miscellaneous expenses per month. Her current monthly salary is \$4000. How much more money, in dollars, will she need to cut out from her current debts per month to meet the DTI requirements?	400
23	Samantha is saving money for a new bike by doing chores. She earns \$5 for every chore she completes. If she does 3 chores each day for a week, and then uses \$25 to buy a helmet, how much money does she have left at the end of the week?	80
24	Frank sneaks out before his break at 3:20 pm and gets back at 4:05. If his break was only supposed to be half an hour, for how much longer did Frank sneak out (in minutes)?	15
25	Janet wants to listen to 20 music albums by the end of the week. If its Thursday and she just finished album number twelve and she has to finish them by Saturday, how many albums would she have to listen to per day?	4
26	Hana wants to donate her clothes to a local charity. After going through her closet she ended up with 2 boxes of pants, 3 boxes of dresses, 1 box of shoes, and boxes of shirts. The number of boxes with shirts was 3 more than the other three boxes combined. How many boxes of shirts does she have to donate?	9
27	Gray has \$126 to spend on lunches for the week. On Monday, he spent \$16 on a carne asada burrito and a soda. On Saturday, he will spend \$30 eating out with friends. If he spends the same amount of money on food for the other 5 days of the week, what will be his average daily spending on food over these 5 days?	16
28	Gayle has a lawnmowing business. Lawn 1 takes 15 minutes to mow. Lawn 2 takes 18 more minutes than Lawn 1. Lawn 3 takes 20% more time to mow than Lawn 1. She is paid \$2.50 per minute for the time she spends. However, she gives her customers a 20% discount. How much money does she make from mowing all three lawns?	132
29	Frank ordered a whole chicken, 6 cans of chopped chicken breast, 1 lb. of macadamia nuts, and 4 bags of frozen broccoli. Each item has the following respective prices: \$12 per chicken, \$2 per can, \$24/lb., \$3 per bag. The sales tax was 10% of the total cost and the tip was half the price of the whole chicken. How much did Frank pay for his order?	72

No.	Question	Answer
30	Milo can bench press half as much weight as Doug can squat, and Doug can squat twice as much weight as Diane can squat. If Diana squats 125 pounds, how much weight can Milo bench press?	125
31	Pablo is trying to make breakfast for his family. His wife eats 4 pancakes. His son eats 2 pancakes. Pablo wants to eat 4 pancakes. One box of pancake mix will make 5 pancakes. How many boxes of pancake mix will he need?	2
32	Jim wants to spend 15% of his monthly earnings on groceries. He makes \$2500/month. How much money will he have left over?	2125
33	A school is ordering tablets and laptops for three classrooms. Each classroom will receive 4 tablets and 3 laptops. If each tablet costs \$250 and each laptop costs \$600, how much will the school spend in total for all three classrooms?	8400
34	Grant takes 3 minutes to put on his pajamas. He brushes his teeth for 2 minutes. Then, he washes his face and brushes his hair for another 2 minutes. Finally, he reads a book for a while and turns off the light for bed. If Grant begins his routine at 8:15 pm and turns off the lights at 8:47 pm, for how long does Grant read a book?	25
35	Bellemere owns a tangerine orchard with 50 trees. Each tree produces 80 tangerines. She wants to sell 600 tangerines at her local farmer's market. If she picks the same amount of tangerines from every tree, how many tangerines will be left on each tree?	68
36	A charity puts out a telethon for a cause. Within 15 minutes, seventy-seven people donated \$3 each, and 231 people donated four dollars each. How much does the charity receive within this time?	1155
37	A school is selling baskets for a fundraiser. There are three baskets containing the following items: * Blue basket: a ball, cup, and notebook. * Red basket: a cup, bell, and hat. * Green basket: a hat, pen, and notebook. The costs of the items in the baskets are as follows: * \$1: ball, notebook, and pen * \$2: cup, bell, and hat Jane buys 6 red baskets and 5 blue baskets. Jim buys 3 red baskets and 2 green baskets. Since they purchase so many, they receive a discount. Jane gets an \$8 discount and Jim also gets a \$2 discount. How many times more does Jane spend than Jim?	2
38	Mr. Gordon has 14 boys in his first period class which is twice the number of girls in class. Two of the girls in class have blonde hair and the rest have brown hair. How many girls with brown hair are in his class?	5
39	Albert gets paid \$15 an hour. He gets time and a half if he works over forty hours a week. Last week, he worked 48 hours. He plans to do this two weeks in a row. How much money will he be paid in overtime for those two weeks?	360
40	Beth, Anna, and Kim went to a book fair. Beth had two books less than Anna while Kim had four more books than Anna. Beth had \$20 with her and was now left with \$8. If all books are priced at \$4, how much, in dollars, did Kim spend on her books?	36
41	4 friends are going on a road trip. Their names are Alex, Bethany, Carlos, and Drew. They drive at a rate of 65, 75, 60, and 50 mph, respectively. Alex drives for 2 hours, Bethany for 4, and Carlos and Drew each drive for 3 hours. They are using a car with a fuel efficiency of 20 miles per gallon of gas. If, along their route, gas costs \$3 per gallon, how much money (in dollars) will they need to spend on gas? Assume they begin their journey at a gas station with an empty tank of gas.	114

No.	Question	Answer
42	The Genco Olive Oil Company has received ninety-nine orders for ninety-nine barrels of olive oil each. Out of those shipped, 33 orders were sent back due to clerical or product errors. How many total barrels of olive oil were not returned?	6534
43	There is a very large room that has 4 tables, 1 sofa and 2 chairs that have 4 legs each. There are also 3 tables with 3 legs each, 1 table with 1 leg, and 1 rocking chair with 2 legs. How many legs of tables are there in the room?	26
44	A classroom has 24 students, and the teacher has arranged a field trip. If the cost per student for the trip is \$15 and the teacher already has \$120 from a class fund, how many more dollars does the teacher need to cover the total cost of the trip for all students?	240
45	Rachel and Shauna go out to dinner. Dinner costs \$68.25 in total (without taxes). Rachel's meal costs 1/3 of the total price, while Shauna's meal costs 2/3 of the total price. How much did Shauna's meal cost (round to the nearest dollar)?	46
46	Olivia owns a local hotel and needs to drive up business. She is planning to give a special deal to anyone who signs up for a membership card. Her idea is to give them 20% off their first night and 10% off on every night they stay after that. If her first new customer pays \$616 for their stay, and each night costs \$140 before discounts, how many nights did they stay at the hotel?	5
47	Johnny has 8 green balls. He has five fewer than twice that number in red balls. How many total balls does Johnny have?	19
48	30 students are in a class. 1/5 of them are 12 years old, 1/3 are 13 years old. 1/10 of them are 11 years old. How many of them are not 11, 12, or 13 years old?	11
49	Francis loves sandwiches. He gets his usual from his favorite deli: two "Big Boy" sandwiches, and a glass-bottled soda. A "Big Boy" costs \$15.25 and the soda costs \$3.75. His friend Lars calls him and asks for a double-sweet soda that's \$4.75. If Francis pays all of this with \$40 and asks for his change back in only quarters, how many quarters will he get?	4
50	A factory needs to produce 960 pieces of toy boats. They are only able to produce 1/6th of their goal a day. 5 toy boats make up a case and 4 cases make up a box. If a toy shop comes to pick up what is available on the fourth day and finds an extra 8 boxes left for them that were forgotten from a previous pickup, how many boxes of toy boats will they be able to take?	40

F Additional Plots From Log-Likelihood Experiments

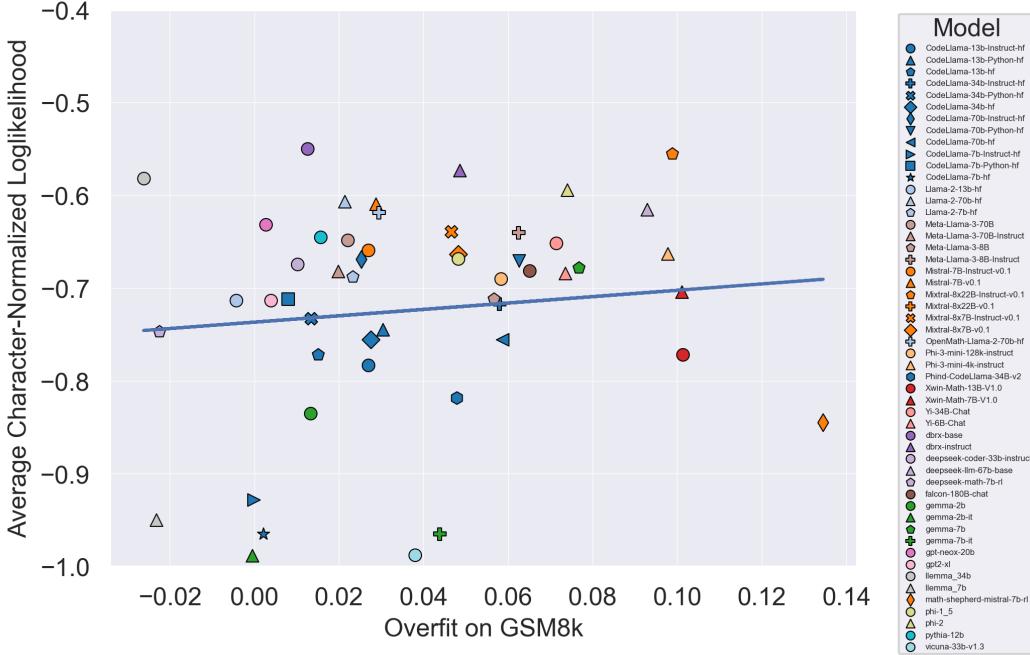


Figure 10: Log-likelihood of models on GSM1k (ours). As expected, we observe almost no correlation between the model’s probability of generating GSM1k and its level of overfit. This is because GSM1k is newly created and not on the internet.

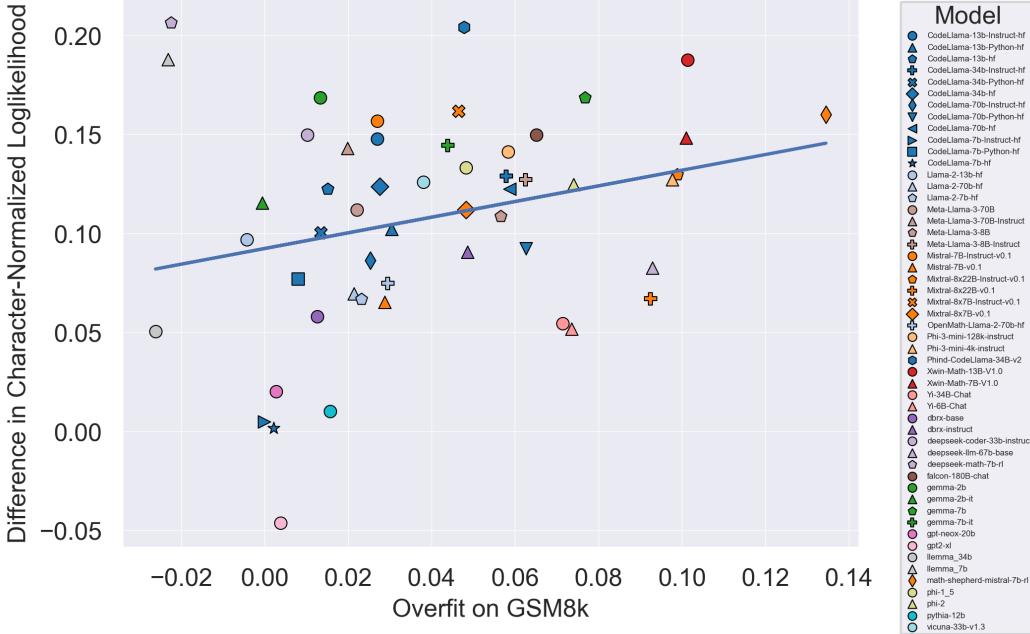


Figure 11: Difference between log-likelihood of GSM1k (ours) and GSM8k.

G Bar Chart of Performance Gaps Between GSM8k and GSM1k Across All Model Accuracies

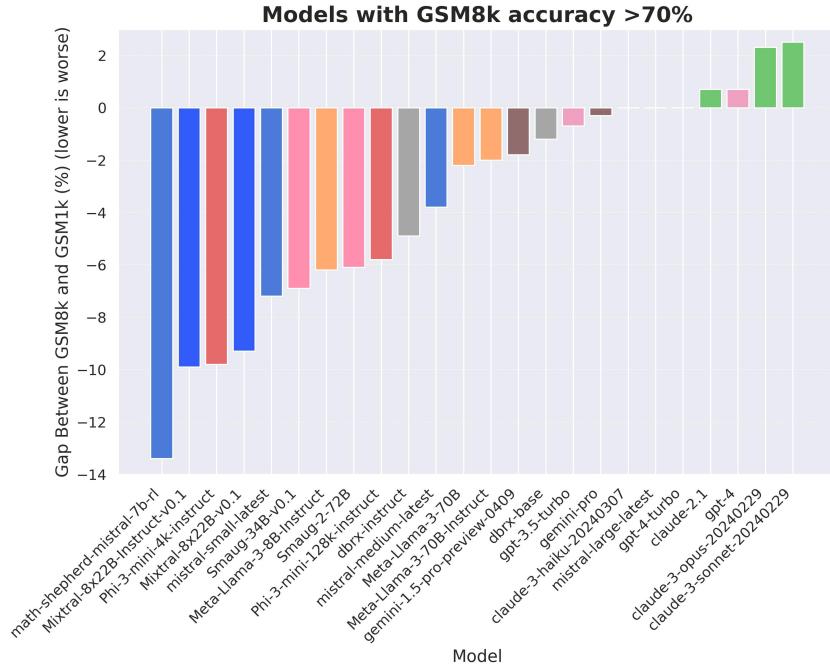


Figure 12: Models with over 70% accuracy on GSM8k. We observe that some models (e.g. Mistral, Phi) are overfit, while other models show little to no evidence of overfitting.

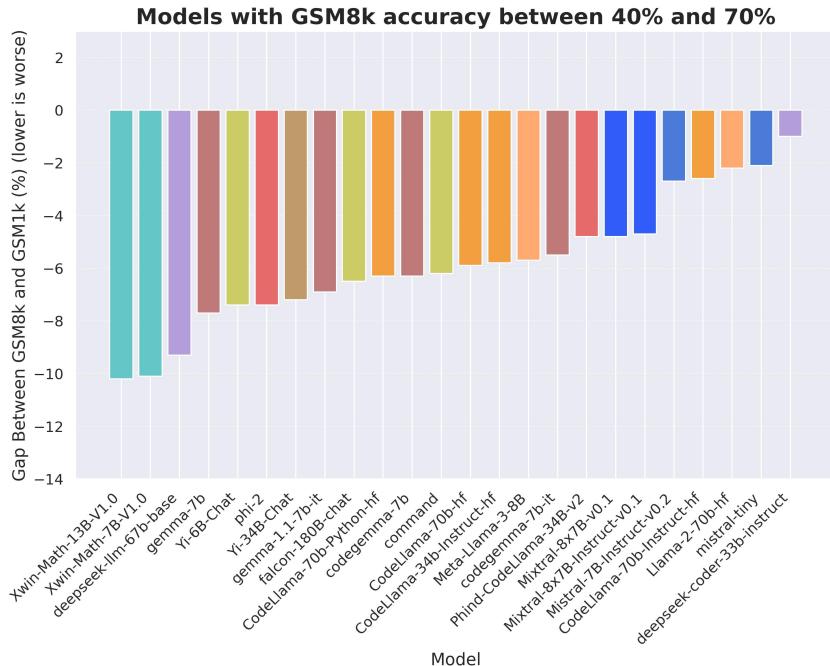


Figure 13: Comparison of models with between 40 and 70% accuracy on GSM8k. We observe that all models seem to fall below the line in this regime of model performance, though some models (e.g. Llama-2-70b) do much better than others.

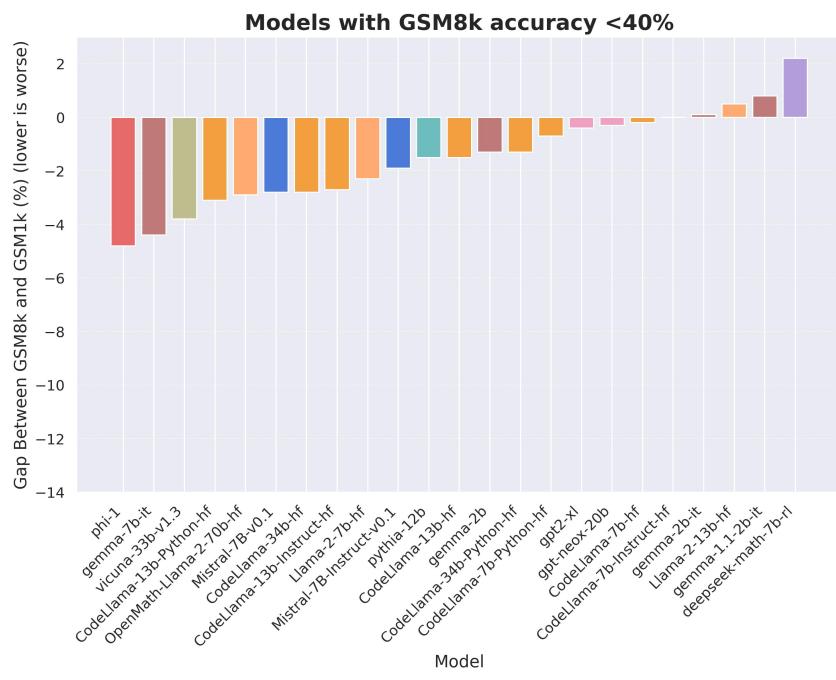


Figure 14: Models with less than 40% accuracy on GSM8k.