

KCIF: Knowledge-Conditioned Instruction Following

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Abstract

LLM evaluation benchmarks have traditionally separated the testing of knowledge/reasoning capabilities from instruction following. In this work, we study the interaction between knowledge and instruction following, and observe that LLMs struggle to follow simple answer modifying instructions, and are also distracted by instructions that should have no bearing on the original knowledge task answer. We leverage existing multiple-choice answer based knowledge benchmarks and apply a set of simple instructions which include manipulating text (eg.: change case), numeric quantities (eg.: increase value, change formatting), operate on lists (eg.: sort answer candidates) and distractor instructions (eg.: change case of numeric answers). We evaluate models at varying parameter sizes (1B-405B) from different model families and find that, surprisingly, all models report a significant drop in performance on such simple task compositions. While large-sized and frontier models report performance drops of 40-50%, in small and medium sized models the drop is severe (sometimes exceeding 80%). Our results highlight a limitation in the traditional separation of knowledge/reasoning and instruction following, and suggest that joint-study of these capabilities are important. We release our benchmark dataset, evaluation framework code, and results for future work.

Keywords: Instruction-following, Large Language Models, Evaluation

1. Introduction

The need for highly accurate and controllable LLM-powered systems that follow precise instructions have led to the development of datasets and methods to improve reliability and consistency in the output for LLMs. Such methods include few-shot prompting (Gao et al., 2020; Kojima et al., 2022a), reasoning with explanations (Wei et al., 2022; Huang and Chang, 2022), checking for consistency/self-consistency (Wang et al., 2022), use of intermediate evaluators or LLMs operating as judges (Zheng et al., 2023), and more.

However, despite such rapid progress and ‘benchmark saturation’ LLMs can often struggle on very simple tasks. For instance, as shown in Figure 1, given a multiple-choice question with option labels and their text, if we instruct the models to print the text associated with the correct answer instead of the answer label, we observe a significant drop ($\sim 20\%$ on average) in knowledge-task performance. From a user’s perspective, this task is no harder than selecting (generating) the answer label. Yet, this pattern is consistent even for frontier models like GPT-4o, and such patterns of interaction where keys or values are referred to LLM instructions are fairly common in real-world LLM usage – for instance, in manipulating lists (eg: “replace the third bulleted item with ‘x’”), operating on semi-structured objects (eg: extracting the value of a JSON field and use in a subsequent operation), etc. While this example of a drop in performance when printing the answer-text instead of the answer-label could, be due to the training process resulting in

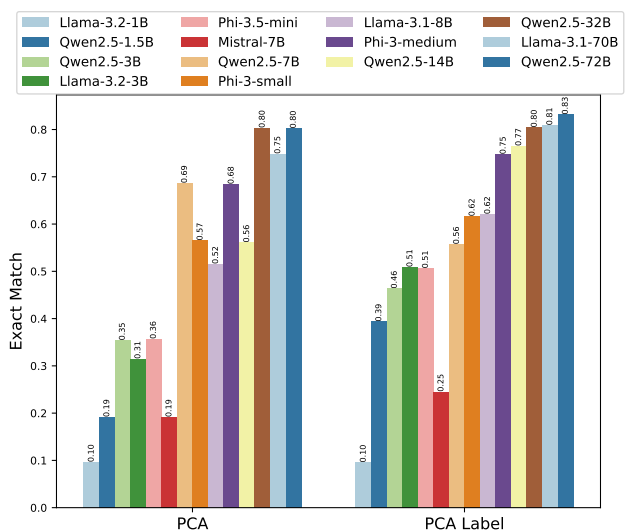


Figure 1: Average exact match performance across all tasks for the *print_correct_answer* (PCA) and *print_correct_answer_label* (PCA Label) instructions.

models being over-fit to certain input/output task formats, or due to issues associated with label binding (Xue et al., 2024), there are other patterns of failure as well, – for instance, including additional *distractor* instructions that have no effect on the answering task, results in a further 5-30% drop (Section 4.2.3).

In this paper, we study this interaction of knowledge and instruction following; real-world use of LLMs typically involves both aspects, and ‘nested’ instructions where there is conditional branching of

instructions based on intermediate steps is a common usage pattern of LLMs. However, evaluating these reliably can be hard and can require the use of complex LLM-judges (He et al., 2024). Thus, to keep evaluation easy and verifiable, our tasks are based on multiple-choice answers instead of long-form text generation task,

We adapt commonly used knowledge and reasoning benchmarks including MMLUPro (Wang et al., 2024), MathQA (Amini et al., 2019), Winogrande (Sakaguchi et al., 2021), BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2020) and augment them with two broad classes of instructions: (i) Instructions that are conditional on the answer to the question (ii) Instructions that are applied uniformly regardless of the answer or task. Our instructions are simple and include those that manipulate the text (eg.: change case), numeric quantities (eg: increase value, change formatting), operate on lists (eg: sort answer candidates). Our choice of using multiple-choice answers-based tasks with simple answer-modifying instructions, also allows us to automate error analysis for commonly occurring error-types and classify errors based on their origin - knowledge/reasoning errors vs instruction-following errors. Our results show that we can automatically classify approximately 80% of errors.

Contributions: In summary, we make the following contributions: (i) We present an evaluation framework that supports LLM-free scoring to study knowledge-conditioned instruction-following, (ii) Our novel experimental design enables automated error analysis (to the extent that LLMs don't have catastrophic generation failures), (iii) We create an evaluation benchmark using 5 popular datasets, consisting of 13 instruction types across 5 different categories. It can be easily extended to additional tasks and instructions, (iv) We use this benchmark to evaluate 19 models at varying parameter sizes (1B-405B) from different model families and find that, all models studied report a significant drop in performance on simple single-instruction task composition. While large-sized and frontier models report performance drops of 40-50%, in small and medium sized models the drop is severe (sometimes exceeding 80%). We also observe that, even within a model family, a larger parameter model may perform comparably to its smaller sibling on standard knowledge/reasoning tasks, but smaller ones drop more significantly on in our evaluation tasks. We release code¹ and data² to support evaluation, enable task extensions and future work.

¹<https://github.com/IBM/KCIF>

²<https://ibm.biz/KCIFData>

2. Related Work

Evaluating the capabilities of large language models (LLMs) has been a significant area of research, with studies focusing on various aspects of LLM performance. Researchers have developed multiple benchmarks to assess factual knowledge (Petroni et al., 2019; Roberts et al., 2020; Lin et al., 2022), logical reasoning abilities (Wei et al., 2022; Zhou et al., 2023a; Saparov et al., 2023), general problem-solving capabilities (Kojima et al., 2022b) and more.

Recently there have also been studies on instruction-following - for instance, FoFo (Xia et al., 2024) evaluates models on format-following tasks and studies the ability of LLMs to generate outputs in existing real-world formats. In a similar vein, IFEval (Zhou et al., 2023b) assesses LLMs' ability to follow arbitrary task-specific instructions (e.g.) based on response length, casing, etc, focusing primarily on whether the instructions are followed rather than the correctness of the output for the task. InFoBench (Qin et al., 2024) advances this research by introducing a metric known as the 'Decomposed Requirements Following Ratio' (DRFR) which is based on each aspect of an instruction that needs to be met. Along with 500 diverse instructions and 2,250 decomposed questions, InFoBench offers performance evaluation using OpenAI's GPT4, across multiple constraint categories and highlights key areas where advanced LLMs can improve in complex instruction-following tasks. LLMBAR (Zeng et al., 2024) is another contribution to this area, as it provides a meta-evaluation benchmark specifically designed to test an LLM evaluator's ability to discern instruction-following outputs. The benchmark consists of 419 manually curated pairs of outputs, where one output adheres to instructions and the other, while potentially more engaging or deceptive, does not. ComplexBench (Wen et al., 2024) and FollowBench (Jiang et al., 2024) aim to assess the ability of LLMs to follow arbitrary task specific instructions, while Meowpass (He et al., 2024) presents a benchmark to evaluate complex instruction following by dynamically composing multiple IFEval style instructions, and consists of 1500 diverse prompt and instruction pairs. Another study introduces ManyIFEval (Harada et al., 2025), a benchmark assessing LLMs' ability to follow multiple instructions, revealing a "curse of instructions" where accuracy declines as instruction count increases. (Li et al., 2024) propose a method to evaluate instruction following ability via verbalizer manipulation. Specifically, they modify the classification task labels with different verbalizers which may or may not be semantically relevant to the task. They observe that all models fail to follow instructions when they instruct the model to flip the labels

(unnatural setting).

Our work complements these efforts by developing a benchmark that allows for easy verification of both task performance and instruction-following capabilities simultaneously. We augment existing knowledge benchmarks by creating instructions that are *conditional* on answering the QA-based knowledge task correctly. We also include instructions that are applied on the candidate space of answers provided in these knowledge tasks. Our approach of applying instructions on knowledge tasks provides an easy way of measuring performance as well as automating error analysis. Further, it also allows us to study the interactions between knowledge and instruction following, and to investigate whether instructions serve as distractors for the original knowledge task when the instructions should result in no change to the original answer of the knowledge task.

3. Dataset Creation

3.1. Knowledge and Reasoning Tasks

Our framework supports including any knowledge task with a fixed answer space - we select the following commonly used benchmarks: MMLUPro (Wang et al., 2024), MathQA (Amini et al., 2019), BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2020), and Winogrande (Sakaguchi et al., 2021) as the basis for our knowledge-grounded instruction-following benchmark. These datasets involve either binary classification or multiple-choice-questions (MCQs) spanning different reasoning and problem-solving skills. We select 1500 samples randomly from *each* dataset and apply answer-modifying instructions as described in the next section.

3.2. Instruction Categories

Unlike datasets that require open-ended generation for answering, our selected tasks have a structured answer-space. This allows us to craft instructions using these answer-spaces in a way that can be verified easily. We summarize our instruction categories in Table 1. The task prompts (instructions) for each of the 13 instruction types with an example will be available in the Appendix.³

Instruction Creation: To create each instruction, the authors iteratively refined them until all the authors had complete agreement in the output when they followed them manually. Examples of aspects of iterative improvement include - explicitly making clear what is not to be included in the output, how

³The detailed appendix is available in the arXiv version of the paper: <https://arxiv.org/pdf/2410.12972>.

the output is to be presented, etc. We include additional details of the instruction-writing process in the Appendix.

Answering baseline-instructions: Given the multiple-choice answer knowledge benchmarks, we consider two baseline instructions – (1) printing the correct answer option⁴ from the candidate space (*print_correct_answer_label*), and (2) printing only the text associated with the correct answer option (*print_correct_answer_text*).

Instructions with no-effect: Certain instructions may be inapplicable for some knowledge tasks. For example, in the MathQA dataset, some instances have *none of these* as the correct answer and are not numeric. Here, instructions such as *numformat_numeric_answer* or *increment_correct_numeric_answer_by_one* will not affect the existing answer of the knowledge-task. We refer to these instructions as “*distractor*” instances and expect that in these instances, models should perform as well as they do on the original answering task. We include details and statistics of such instructions in the Appendix.

3.3. Metrics and Output Processing

We report the model performance as a form of exact match (EM) where we perform basic string parsing (removing beginning and ending whitespaces, quotations, etc.) and compare the model prediction to the expected output for the applied instruction.

Dataset: MathQA

Instruction: numformat_numeric_answer

Given a mathematical question and 5 options namely 'a', 'b', 'c', 'd', and, 'e', as candidate answers, print the text associated with the option label that answers the question correctly. If the answer is numeric print it in two decimal places as long as it contains no other string or units of measurement. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: a man walking at the rate of 5 km / hr crosses a bridge in 15 minutes . the length of the bridge (in meters) is :

Options:

- a. 600
- b. 750
- c. 1000
- d. 1250
- e. none of these

Ground Truth: d

Instruction Output: Response:1250.00

Further, all our task prompt templates, (see example prompt above) explicitly instruct the model to provide their final response after a ‘Response:’ keyword. We search for and extract the response after this keyword while computing the exact match score. However, we observe that models may not always follow this, and can instead generate a wide range of other keywords (e.g.)

⁴We use ‘label’ and ‘option’ interchangeably to denote the candidates in a multiple-choice QA task.

Instruction Group	Name	Definition	# Instances	
			Full	Lite
String Manipulation	alternate_case_correct_answer	Print the text corresponding to the correction candidate answer of knowledge task in alternate case	7867	950
	capitalize_correct_answer	Print the text corresponding to the correct candidate answer of the knowledge task in upper case.	7867	950
	reverse_correct_answer_alternate_case	Reverse the text corresponding to the correct candidate answer of the knowledge task and print it in alternate case.	9573	1383
	reverse_correct_answer	Print the text corresponding to the correct answer in reverse	7868	951
Format Correct Answer	numformat_numeric_answer	Apply a specified decimal formatting the correct answer if it a is numeric quantity, otherwise print the correct answer as is.	11336	1600
	print_correct_answer_in_words	If the correct answer is a numeric quantity, display the numeric quantity in words, otherwise print the correct answer as is.	9874	1320
	print_correct_answer_append_string	Append a pre-specified string to the text associated with the correct candidate answer.	7867	950
Operations on List (Conditional on Correct Answer)	increment_incorrect_numeric_answers_by_one	If the candidate answer values are numeric quantities increment them by one and show them as a list. Other value types are not modified.	7117	825
	sort_only_incorrect_answers	Sort the candidate answers that are incorrect in ascending order	7867	950
	use_incorrect_options_to_create_string	Sort the incorrect candidates in ascending order and take the last character of the text associated with each incorrect option to create a string	7868	951
Operations on List (OOL)	sort_options_to_create_string	Sort all candidate answers in ascending order and use the last character of the text associated with each incorrect candidate to create a string.	7867	950
Numeric Manipulation	increment_correct_numeric_answer_by_one	If the correct answer is a numeric quantity, increment it by one, otherwise print the correct answer as is.	9757	1352

Table 1: Categories of instructions and the number of instances of each in the Full and Lite subsets.

(*the final answer is, the output is, etc*), or no keyword at all. Given the diverse possible responses, we make a good-faith attempt to capture these patterns as part of our evaluation to classify a wider range of model responses.⁵ As a result, we do not penalize models for not following this output format requirement.

However, models do still make errors when following the primary instruction. These could be minor copying errors, such as missing a period or comma, or even fixing typographical errors within the provided options. On the other hand, they could also be instruction following mistakes, where for instance, the option label is added to the response even when the prompt explicitly states otherwise. We do not expect models to make such mistakes given clear instructions, and therefore, penalize models for these types of errors in our evaluation.

3.4. Automated classification of errors

For each instruction in the ‘String Manipulation’, ‘Format Correct Answer’, and ‘Numeric Manipulation’ instruction categories, we create a set of error classes that are based on the incorrect answers to the original knowledge task and the subsequent application of the instruction on that incorrect answer. We create ‘instruction-following’ error sets (IFError) and ‘knowledge-error sets’ (KnowledgeError) as follows:

IFError: We inspected some representative model outputs and created a set of errors that LLMs could plausibly make for each instruction. This set includes errors such as: (i) answering with

an answer label (option) when requiring/using the text, (ii) answering with any candidate answer text without applying the instruction, (iii) a combination of these, (iv) instruction specific errors based on these – for example, for the instruction *alternate_case_correct_answer* such error cases could include alternate casing starting with a lowercase character (the instruction text explicitly requires that it start with upper case).

KnowledgeError: For every instruction instance, this set includes: (i) Answering with the incorrect candidate answer – regardless of whether it is its label or text, (ii) Applying the instruction correctly (when applicable) on the incorrect candidate answer.

Note that these error sets are not mutually exclusive – a model response to the alternate casing instruction that starts with lowercase and is applied on the incorrect answer candidate is an ‘IFError’ as well as a ‘KnowledgeError’. Further, these error sets are meant to be *high-precision* to aid analysis and cannot reasonably be expected to anticipate and cover everything LLMs might respond with. Hence, there will be model errors that we cannot classify⁶ and we intend to continue to expand the benchmark’s error detection capabilities. We would also like to highlight that if models make a lot of errors that are not classified, it is likely that those are more severe instruction-following errors.

3.5. Benchmark Dataset

We create two versions of our benchmark dataset - ‘Full’ and ‘Lite’ (for lower inference costs).

⁵We find that more than 94% of outputs across all models and samples contained the ‘Response:’ string

⁶Errors are matched using the same output-processing used for ground-truth scoring.

Full Benchmark: We select a subset of 1500 samples randomly from *each* dataset and apply each applicable instruction on the same. For MMLUPro, we consider a subset of 150 samples per subject and apply each applicable instruction.

Lite Benchmark: We select a subset of 150 samples randomly from the full version created above for *each* dataset and apply each applicable instruction on the same. For MMLUPro, we consider a subset of 25 samples per subject and apply each applicable instruction. Statistics for the above two versions are available in presented in Table 1. Detailed statistics for each dataset and the instruction types are provided in the appendix. Additionally, each benchmark includes a set of instances when instructions have no effect (called the no-effect or distractor subset).

3.5.1. Benchmark ranking

An effective instruction-following model should not only be capable of following a variety of instructions across different knowledge-tasks but should also be unaffected by instructions when they are inapplicable i.e, they should be robust to ‘distractors’. Therefore, we define an overall benchmark score for a model as its arithmetic mean of the following:

Exact-Match Score (μ_{EM}): We compute the micro-average of the exact-match scores using all instances of every instruction type in the benchmark.

Instruction Category Score (IC Score): To ensure models perform well across instruction categories, we also compute the micro-average exact-match scores for every instance per instruction category and then compute the arithmetic mean.

Knowledge Task Subset Score: (KTS Score): To ensure model capabilities generalize across different knowledge tasks, we compute the micro-average exact-match scores for every instance per knowledge-task, and then compute the arithmetic mean.

Exact Match Score on ‘Instructions with no-effect’ (μ'_{EM}): Lastly, we compute the micro-average of all instruction instances in the benchmark that have no effect on the original knowledge-task answers (i.e.) ‘distractors’.

4. Evaluation

We present an evaluation on our benchmark using a variety of models and study the following research questions: (i) Do models display a difference in performance on the two simple answering baseline-instruction tasks? (ii) Do models display a variation in performance across our different instruction categories? (iii) Are models robust to, or get distracted by instructions that do not apply to

the task? (iv) Does the size of a model impact its instruction-following capability?

4.1. Models and Inference

We evaluate a range of open instruction-tuned models and parameter sizes using our benchmark. For ease of presentation, we categorize them based on their parameter count as shown in Table 2. Our inference code uses vLLM (Kwon et al., 2023) for running the evaluations. We use greedy decoding for generations and `bf16` as floating point precision. We generate a maximum of 1024 tokens per instance. We use A100 80GB GPUs for running inference. We use an instance hosted by a cloud provider for Llama-3.1-405B-Instruct, while we use OpenAI APIs for GPT4-o and GPT4-o-mini models.

In all our experiments, we perform zero-shot Chain-of-Thought (CoT) (Wei et al., 2024) reasoning. Models see the same prompt based on prompt guides for the original knowledge tasks using the *lm-evaluation-harness* framework (Gao et al., 2024) and OpenAI evals.⁷ We instruct the model to generate reasoning first and then the answer. We write custom post-processing scripts to extract the model’s answer as described previously.

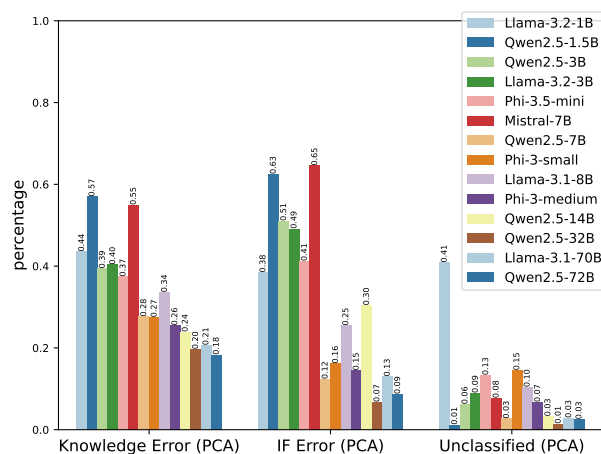


Figure 2: Knowledge and instruction following (IF) errors across all tasks for the *print_correct_answer* instruction. A lower error is better. Results shown using Full Benchmark data. Lite Benchmark results can be found in the Appendix.

4.2. Results

We begin this section by first presenting our results on the answering baseline-instructions and then proceed to our results on instruction-following for the different categories. We then look at the impact of distractors and knowledge-task characteristics on model performance.

⁷<https://github.com/openai/simple-evals>

Small (< 7B parameters)	Medium (7 – 30B parameters)	Large (> 30B parameters)	Frontier
Llama-3.2-1B-Instruct (1B)	Mistral-7B-Instruct-v0.3 (7B)	Qwen2.5-32B-Instruct (32B)	Llama-3.1-405B-Instruct (405B)
Qwen2.5-1.5B-Instruct (1.5B)	Qwen2.5-7B-Instruct (7B)	Llama-3.1-70B-Instruct (70B)	GPT-4o-mini-2024-07-18
Llama-3.2-3B-Instruct (3B)	Phi-3-small-8k-instruct (7B)	Qwen2.5-72B-Instruct (72B)	GPT-4o-2024-08-06
Qwen2.5-3B-Instruct (3.0B)	Llama-3.1-8B-Instruct (8B)		
Phi-3.5-mini-instruct - (3.8B)	Gemma-2-9b-it (9B)		
	Phi-3-medium-4k-instruct (14B)		
	Qwen2.5-14B-Instruct (14B)		
	Gemma-2-27b-it (27B)		

Table 2: List of Models evaluated on our benchmark.

Model	PCA label	PCA	String	Numeric	Format	OOL Conditional	OOL	Avg. Drop
Qwen2.5-1.5B-Instruct	0.36	-0.20	-0.35	-0.34	-0.32	-0.29	-0.35	-0.33 / -90.5%
Qwen2.5-3B-Instruct	0.44	-0.12	-0.39	-0.42	-0.2	-0.3	-0.24	-0.31 / -69.7%
Qwen2.5-7B-Instruct	0.55	0.11	-0.41	-0.11	-0.33	-0.32	-0.38	-0.31 / -56.5%
Qwen2.5-14B-Instruct	0.75	-0.20	-0.60	-0.21	-0.57	-0.30	-0.29	-0.39 / -52.8%
Qwen2.5-32B-Instruct	0.79	-0.01	-0.47	-0.17	-0.40	-0.27	-0.26	-0.31 / -39.9%
Qwen2.5-72B-Instruct	0.81	-0.04	-0.50	-0.25	-0.31	-0.27	-0.18	-0.30 / -37.3%
Llama-3.2-1B-Instruct	0.10	-0.01	-0.08	-0.08	-0.09	-0.07	-0.10	-0.08 / -87.6%
Llama-3.2-3B-Instruct	0.47	-0.18	-0.37	-0.37	-0.36	-0.37	-0.45	-0.38 / -81.5%
Llama-3.1-8B-Instruct	0.59	-0.09	-0.47	-0.31	-0.37	-0.42	-0.45	-0.40 / -67.7%
Llama-3.1-70B-Instruct	0.79	-0.06	-0.42	-0.39	-0.41	-0.41	-0.43	-0.41 / -52.5%
Phi-3.5-mini-instruct	0.48	-0.14	-0.43	-0.33	-0.35	-0.37	-0.34	-0.36 / -75.5%
Phi-3-small-8k-instruct	0.58	-0.05	-0.47	-0.43	-0.34	-0.42	-0.52	-0.44 / -74.8%
Phi-3-medium-4k-instruct	0.72	-0.07	-0.53	-0.50	-0.46	-0.37	-0.40	-0.45 / -63.2%
Gemma-2-9b-it	0.62	-0.05	-0.50	-0.37	-0.29	-0.30	-0.30	-0.35 / -56.5%
Gemma-2-27b-it	0.69	-0.08	-0.44	-0.37	-0.30	-0.23	-0.22	-0.31 / -45.3%
GPT4-o-mini	0.74	-0.14	-0.39	-0.36	-0.35	-0.31	-0.30	-0.34 / -45.8%
GPT4-o	0.81	-0.04	-0.32	-0.32	-0.37	-0.28	-0.18	-0.29 / -36.2%
Llama-3.1-405B-Instruct	0.83	-0.07	-0.39	-0.41	-0.41	-0.39	-0.45	-0.34 / -41.0%

Table 3: As compared to printing the correct answer label (PCA Label) which serves as the baseline for the vanilla knowledge task, printing the correct answer (PCA) results in a significant drop in exact match performance. Applying additional instructions on the answer space of the questions result in an even more severe drop (on every category). Drop in performance reported as compared to PCA Label. Frontier model results reported on Lite Benchmark data.

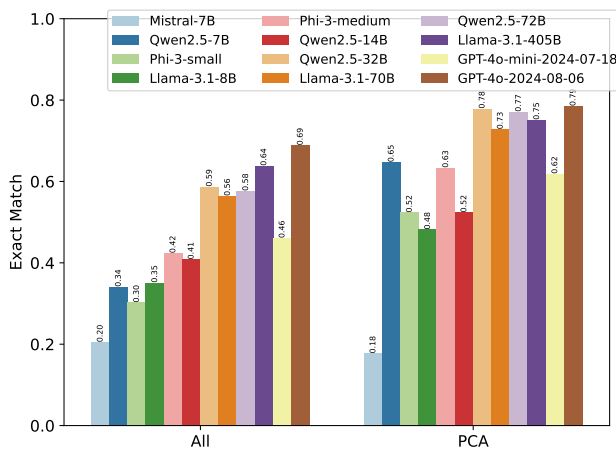


Figure 3: Impact of distractor instructions on exact match performance across tasks and instructions, compared to its corresponding *print_correct_answer* performance. A drop indicates the model getting distracted by an inapplicable instruction. Results reported on Lite Benchmark.

4.2.1. Printing the correct answer

As mentioned earlier in Section 1 (Figure 1), we observe a significant drop ($\sim 20\%$ on average) in knowledge-task performance when instructing the model to respond with the text associated with the answer instead of its label. Some common issues we observed include models outright ignoring the instruction and continuing to generate labels, or generating only Chain-of-Thought reasoning without a final answer, etc, reflected by the knowledge and instruction following errors in Figure 2.

4.2.2. Answer-conditioned instruction performance

Table 3 reports the performance of all models on the print correct answer label (PCA Label) task which serves as the reference score for the knowledge/reasoning task.

Effect of Size Models: Starting with the Qwen 2.5 family of models it can be seen that in medium and large sized models ($> 14B$ parameter models) have comparable performance on the baseline answering task (PCA label). The drop for the large models ($> 32B$ parameters) on the PCA task is relatively small as well. However, the drop in scores when combined with instructions result is much larger,

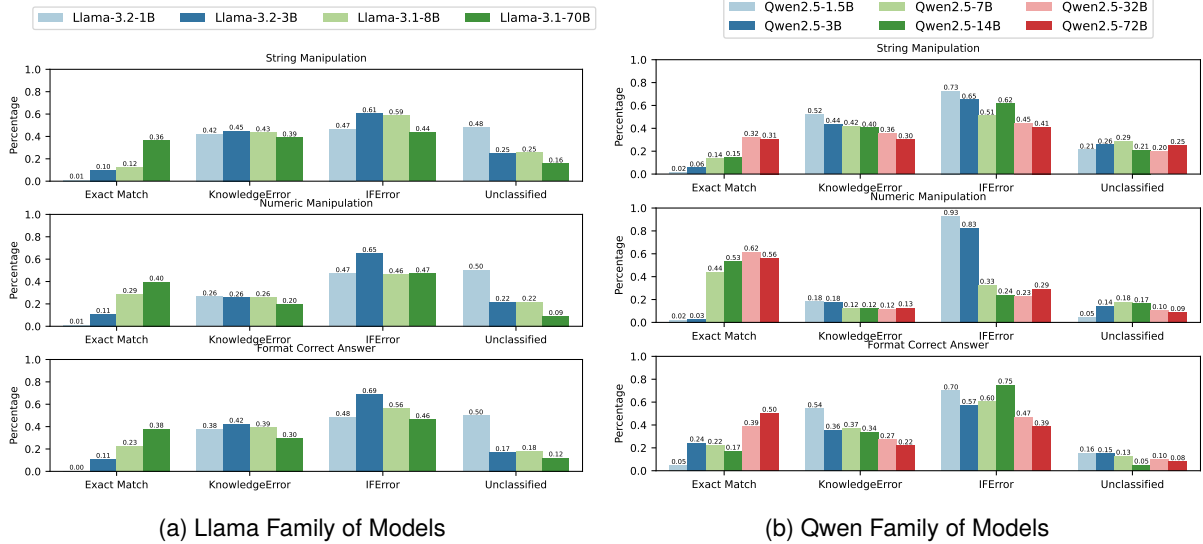


Figure 4: Classification of errors for the Llama and Qwen family of models.

and a trend is observed that larger models still do better than their smaller siblings. This holds true in all model families (Llama, Gemma and Phi) - even if there is a negligible difference in the PCA label performance of a model, the drop is less severe for a larger sibling from the same family. This result demonstrates that even if models perform comparably on the PCA label task, the large model size can benefit tasks which require knowledge and instruction composition.

Performance of Frontier Models: From Table 3 we find that frontier models also suffer from significant drops in performance. Notably, GPT4-o and Llama 3.1-405B Instruct have comparable performance on the knowledge task (as seen on PCA Label) but Llama’s performance deteriorates by a larger degree when combined with instructions.

4.2.3. Effect of distractor instructions

Our dataset also includes instructions that apply only when certain properties of a knowledge-task answer are fulfilled. For instance, instructions for incrementing the correct answer by one if numeric, formatting numeric values, and printing any numeric answers in words, do not apply on tasks with textual answers. They serve as distractors, and we expect model performance to be unaffected since these instructions are not applicable and do not alter the original knowledge-task answer. From Figure 3, we observe that there is a 5-20% drop in small, medium, large, and frontier scale models.

In the appendix we report details of how different model families (Llama, Qwen, Phi) are affected by distractors, at different scales. In summary, we find that all models are distracted by instructions that

require reversing and casing text,⁸ reporting a drop of 55-75%. Even frontier models show a drop of 35%. However, for the other distractor instructions, we find that Llama models are relatively robust, showing a drop of 5 – 10%, while the Phi and Qwen family of models are more susceptible, where we observe drops of 20-30%. Frontier models surprisingly also show a drop of 10-15%. While model failures in the presence of distractors have been studied before (Shi et al., 2023; Feng et al., 2024), to the best of our knowledge this is the first work to study them in an instruction-following setting.

4.2.4. Automated Error Classification

Figure 4 shows the error analysis for two different model families - Llama and Qwen2.5.⁹ We report the average exact match score as well as the errors.

Errors and Model size: As can be seen in both Llama and Qwen2.5 model families, as the model size increases, the exact match accuracy increases and the errors reduce. The unclassified errors pertain to model outputs that are harder to classify and indicate a more severe model failure. As, the scale increases, such failures tend to reduce.

Instruction Categories and Errors: We note from Figure 4, the Llama and Qwen2.5 models have different strengths. For instance, in String Manipulation class of instructions, at very small scale the Llama 3.2-1B model and the Qwen2.5-1B model have similar exact match scores. However, in the case of the Llama model nearly 48% of all instances have errors that are unclassified (indi-

⁸partially applicable (can only reverse non-single digit numeric answers) or completely inapplicable

⁹We include error analysis plots for other model families in the appendix.

cating severe failure) while that is not the case for the Qwen2.5 equivalent. Further, Qwen2.5-1B has a larger class of instruction-following errors as compared to knowledge errors; this suggests that the drop in performance for Qwen2.5-1B reported in Table 3 is indeed due to instruction-following errors made by the model.

In addition, we observe that the Qwen2.5 family of models is almost always better than the Llama family of models when it comes to numeric manipulation instructions while the Llama family of models has a slightly higher performance on string manipulation tasks (detailed figures in appendix). A similar trend is observed on the unclassified set where Llama’s instruction-following failures appear to be more severe. The Phi family of models appears to perform worse than both the Qwen and Llama family of models. Frontier models demonstrate lower knowledge errors as expected, but still make many instruction following errors.

4.3. Qualitative Example of Error

The following is an example of both, a knowledge **and**, instruction-following error. For an instance of the task *Capitalize Correct Answer*, the Gemma2-9B-it model returns the incorrect answer ‘clock’ (knowledge-error) and also fails to capitalize the answer returned (instruction-following error).

Task:

Given a sentence with a blank and 2 options namely 'A' and 'B', capitalize the text associated with the optional label that answers the question correctly. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Sentence: John could not hear his alarm clock when he was sleeping with a headphone on his head because the _ is closer. Options: A. headphone B. clock

Expected output:

HEADPHONE

Model Output:

Let's analyze the sentence step by step:

- The sentence is about John not being able to hear his alarm clock.
- The blank is where we need to insert either 'headphone' or 'clock'.
- The sentence states that John is wearing headphones on his head.
- Therefore, the alarm clock would be closer to his head than the headphones.
- This means the alarm clock would be the closer object.
- The correct option to fill in the blank is 'clock'.

Now, let's capitalize the text associated with the correct option.
Response: clock

We include a qualitative example of each error category in the Appendix.

4.4. Benchmark

We report the *exact match* scores of the medium, large and frontier models on the Lite Benchmark in Table 4. Unsurprisingly, the GPT4o model performs the best on our benchmark data while large and medium-scale models like Llama-3.1 405B, Qwen2.5 72B, and, Qwen2.5 32B based models appear to be better than other openly available

Models	μ_{EM}	IC Score	KTS Score	μ_{EM}	Average Score
GPT-4o-2024-08-06	0.5065	0.5174	0.5874	0.6889	0.575
Llama-3.1-405B	0.4617	0.4888	0.5351	0.6387	0.5311
Qwen2.5-72B	0.4348	0.5035	0.493	0.5768	0.502
Qwen2.5-32B	0.409	0.4751	0.4755	0.5873	0.4867
Llama-3.1-70B	0.3708	0.4138	0.4319	0.5645	0.4453
GPT-4o-mini	0.394	0.4029	0.4689	0.4609	0.4317
Gemma-2-27B	0.3497	0.3972	0.4194	0.4505	0.4042
Qwen2.5-14B	0.2764	0.3523	0.3272	0.4084	0.3411
Phi-3-medium	0.2518	0.2869	0.3054	0.4238	0.317
Gemma-2-9B	0.2381	0.2828	0.292	0.4428	0.3139
Qwen2.5-7B	0.1944	0.2513	0.2275	0.3411	0.2536
Llama-3.1-8B	0.174	0.2203	0.2048	0.3513	0.2376
Phi-3-small	0.1555	0.1809	0.1921	0.3027	0.2078
Mistral-7B	0.0577	0.0808	0.0768	0.205	0.1051

Table 4: Performance of the Medium, Large and Frontier Models on our Lite Benchmark - ranked in order of performance using the average score (higher is better).

models including Llama-3.1-70B-instruct and the Gemma family of models. We also include the results on the full benchmark in Appendix. We note that the ranking of models is largely consistent and that small models are much weaker than larger models.

5. Discussion & Conclusion

In this work, we took a novel approach to studying instruction-following by grounding instructions on existing knowledge tasks. Our approach has the advantage of being easily extendable for new instruction types and domains, while also enabling LLM-free evaluations with some degree of automated error analysis. We demonstrated that not only do models fail to follow simple instructions (e.g.) printing the answer text instead of the label, but their performance drops further when compound but simple, instructions are included. Even when instructions that should have no effect on the knowledge-tasks are used, models at all scales report a drop in performance, though the extent of deterioration varies. As models are increasingly being viewed as agents and assistants, it is crucial that models have better guarantees of following user instructions. As our work demonstrates, there is a lot of scope for improvement and we hope the community finds our framework helpful in improving the current state-of-the-art.

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A. Appendix

We begin by including details of the knowledge tasks used. We then describe our data creation process and how we automatically classify errors in section 3.3. We list all instructions with example input, ground truth, and expected instruction output in

Models	μ_{EM}	IC Score	KTS Score	σ_{EM}	Average Score
Qwen2.5-72B	0.4488	0.5077	0.4708	0.6218	0.5123
Qwen2.5-32B	0.419	0.4736	0.4519	0.6351	0.4949
Llama-3.1-70B	0.3697	0.3735	0.3925	0.6109	0.4366
Gemma-2-27B	0.3622	0.3783	0.3984	0.5177	0.4142
Qwen2.5-14B	0.2819	0.3521	0.305	0.4443	0.3458
Phi-3-medium	0.2589	0.2632	0.2799	0.4897	0.3229
Gemma-2-9B	0.2417	0.2701	0.2688	0.484	0.3162
Qwen2.5-7B	0.1921	0.2393	0.2	0.4061	0.2594
Llama-3.1-8B	0.1646	0.1917	0.1773	0.3907	0.2311
Phi-3-small	0.1472	0.1474	0.1686	0.3376	0.2002
Qwen2.5-3B	0.1277	0.1341	0.1386	0.3021	0.1756
Llama-3.2-3B	0.0946	0.0874	0.1021	0.2395	0.1309
Phi-3.5-mini	0.0966	0.1179	0.1014	0.2044	0.1301
Mistral-7B	0.0484	0.059	0.057	0.2451	0.1024
Qwen2.5-1.5B	0.0382	0.0346	0.0435	0.1461	0.0656
Llama-3.2-1B	0.0153	0.012	0.0176	0.0897	0.0337

Table 5: Performance of the Small, Medium, and Large Models on our Full Benchmark - models ranked in order of performance using the average score (higher is better).

B.4. We report results on the Full Benchmark in Table 5. The detailed statistics of Full and Lite Benchmark are presented in B.7. Section ?? presents the comparison between model’s performance on print correct answer and print correct answer labels tasks on the Lite Benchmark. Section ?? presents performance of different models for each instruction category in comparison with its corresponding performance on *print_correct_answer* (PCA).

B. Additional details - Dataset creation

B.1. Design Principles

We develop our instructions keeping the following design principles in mind: (i) We would like instructions to be unambiguous and be presented in a way that can be communicated clearly - if humans cannot follow the instructions and agree on the same output, LLMs should and likely would not be able to. (ii) We would like them to be easy to follow and not require complex reasoning abilities to follow so that models at all scales have a fair chance of success, (iii) The instructions need to have deterministic outputs that use the original answers of the knowledge-task or the candidate space of answers, or both, so that they can be evaluated easily with instruction specific scorers. (iv) We would like our benchmark to be based on a diverse mix of knowledge tasks, and be easily extensible to new ones.

B.2. Instruction Creation

To create each instruction, the authors iteratively refined them until all the authors had complete agreement in the output when they followed them

manually. Examples of aspects of iterative improvement include - explicitly making clear what is not to be included in the output, how the output is to be presented, etc. We then asked 2 computer science researchers to follow and generate the output for 75 instructions across all our instruction types and datasets. We found that both the researchers were able to follow our instructions successfully and generated the same response for 93.33% of the instances. The first annotator generated the correct response for 98.67% of the instances, while the second annotator for 94.67% of the instances. Upon analyzing their responses, we found the only instruction-following error was rounding off the decimal number when truncating to two decimal places. We also found very few human errors in the annotator’s response, specifically for instructions like *reverse_correct_answer_alternate_case* on datasets with long output text such as PIQA.

B.3. Knowledge and Reasoning Tasks

We select the following knowledge tasks that are commonly used in LLM evaluations as the basis for our instruction-following benchmark. These datasets involve either binary classification or multiple-choice-questions (MCQs) spanning different reasoning and problem-solving skills.

(i) **MMLUPro** (Wang et al., 2024): MMLUPro extends the MMLU dataset to make it more challenging by a) increasing the number of options from four to ten and b) increasing problem difficulty by focusing on more reasoning oriented problems. We consider all 14 subjects in the MMLUPro benchmark. We cap the maximum number of samples for each subject to be 150 samples.

(ii) **MathQA** (Amini et al., 2019): MathQA dataset consists of math word problems presented as Multiple-Choice-Questions (MCQs). Given a math question and four options, the model has to select the correct answer.

We also select a few common-sense and reasoning datasets:

(iii) **BoolQ** (Clark et al., 2019): BoolQ is a boolean question-answering dataset. Given a passage and a boolean question around the passage, the model has to select either *True* or *False*.

(iv) **PIQA** (Bisk et al., 2020): Physical Interaction: Question Answering (PIQA) involves answering questions that involve commonsense reasoning around physical objects. Given a question and two options, the model has to select the most plausible option.

(v) **Winogrande** (Sakaguchi et al., 2021): Winogrande involves a fill-in-the-blank task with binary options, the model has to select the correct option for a given sentence. The task involves reasoning for pronoun resolution.

We select a subset of 1500 samples randomly from each of the above datasets.

B.4. Prompts

We now list the prompts for each instruction and dataset combination defined in our benchmark.

Dataset: Winogrande
Instruction: alternate_case_correct_answer

Given a sentence with a blank and 2 options namely 'A' and 'B', answer the question by printing the text associated with the correct option label in alternate case. The first character should be in uppercase and the following characters should alternate between lowercase and uppercase. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected. Sentence: The wooden doors at my friends work are worse than the wooden desks at my work, because the _ material is stronger.

Options:

- A. doors
- B. desks

Ground Truth: B

Instruction Output: Response:DeSkS

Dataset: Winogrande
Instruction: print_correct_answer_append_string

Given a sentence with a blank and 2 options namely 'A' and 'B', print the text associated with the option label that answers the question correctly. Do not print the option label. Without including any additional characters, also append the following text string at the end of the output: 'ENDOFRESPONSE'. Do not add any special characters including quotations, spaces, new lines etc in the response. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Sentence: It is an article of faith that the paper is more important than the exam , even though the _ weighs less heavily on the grade.

Options:

- A. paper
- B. exam

Ground Truth: A

Instruction Output: Response:paperENDOFRESPONSE

Dataset: MathQA
Instruction: numformat_numeric_answer

Given a mathematical question and 5 options namely 'a', 'b', 'c', 'd', and 'e', as candidate answers, print the text associated with the option label that answers the question correctly. If the answer is numeric print it in two decimal places as long as it contains no other string or units of measurement. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: a man walking at the rate of 5 km / hr crosses a bridge in 15 minutes . the length of the bridge (in meters) is :

Options:

- a. 600
- b. 750
- c. 1000
- d. 1250
- e. none of these

Ground Truth: d

Instruction Output: Response:1250.00

Dataset: MathQA
Instruction: sort_options_to_create_string

Given a mathematical question and 5 options namely 'a', 'b', 'c', 'd', and, 'e', as candidate answers, sort the list of options using their values, in alphabetical order. Use only the text associated with the option labels and not the option labels while sorting. Then, create a string by concatenating the last character of the text associated with each option value. If the last character is a special character (such as period, comma, quotation, etc) use the previous character. Print only the final string and not the sorted list. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: marts income is 50 percent more than tims income and tims income is 40 percent less than juans income . what percentage of juans income is marts income

Options:

- a. 124 %
- b. 120 %
- c. 96 %
- d. 90 %
- e. 64 %

Ground Truth: d

Instruction Output: Response:40604

Dataset: PIQA
Instruction: print_correct_answer

Given a question and two answer candidates 'A' and 'B', answer the question by selecting the value associated with the option label corresponding to the correct answer. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: how to avoid paint spill when adding paint to your brush

Options:

A. Put a rubber band on your paint can to get rid of that excess glue on your paint brush, this will prevent spilling paint on the paint stir stick where the lid is.

B. Put a rubber band on your paint can to get rid of that excess glue on your paint brush, this will prevent spilling paint on the edge where the lid is.

Ground Truth: B

Instruction Output: Response:Put a rubber band on your paint can to get rid of that excess glue on your paint brush, this will prevent spilling paint on the edge where the lid is.

Dataset: PIQA
Instruction: reverse_correct_answer

Given a question and two answer candidates 'A' and 'B', answer the question by printing the text associated with the correct option label, in reverse. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: Butcher Shop

Options:

- A. will decimate fish from the ocean into digestible pieces
- B. will decimate a full cow into digestible pieces

Ground Truth: B

Instruction Output: Response:seceip el-bitsegid onti woc lluf a etamiced lliw

Dataset: Winogrande
Instruction: use_incorrect_options_to_create_s

Given a sentence with a blank and 2 options namely 'A' and 'B', create a string by concatenating the last character of every option value, excluding the option value corresponding to the correct answer. Use only the text associated with the option labels and not the option labels while sorting. If the last character is a special character (such as period, comma, quotation, etc) use the previous character. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected. Sentence: Fiction books were interesting and easy to read for Logan but not Brett because _ enjoyed real tales.

Options:

- A. Logan
- B. Brett

Ground Truth: B

Instruction Output: Response:n

Dataset: PIQA
Instruction: reverse_correct_answer_alternate_case

Given a question and two answer candidates 'A' and 'B', reverse the text associated with the answer label that correctly answers the question. Print this reversed text in alternate case starting with upper case. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: What else should I add to a peanut butter sandwich?

Options:

- A. Take some pasta sauce and put it onto the other piece of bread with a knife.
- B. Take some jelly and put it onto the other piece of bread with a knife.

Ground Truth: B

Instruction Output: Response:.EflnK A Htlw dAeRb fO EcEiP ReHtO EhT OtNo tl TuP DnA YlLeJ EmOs eKaT

Dataset: MathQA
Instruction: print_correct_answer_label

Given a mathematical question and 5 options namely 'a', 'b', 'c', 'd', and 'e', as candidate answers, answer the question by selecting the option label corresponding to the correct answer. Do not include the text associated with the option label in the answer. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: a reduction of 20 % in the price of salt enables a lady to obtain 2 kgs more for rs . 100 , find the original price per kg ?

Options:

- a. 12.6
- b. 12.1
- c. 12.5
- d. 12.4
- e. 12.7

Ground Truth: c

Instruction Output: Response:c

Dataset: Winogrande
Instruction: use_options_to_create_string

Given a sentence with a blank and 2 options namely 'A' and 'B', create a string by concatenating the last character of every option value (not option label). If the last character is a special character (such as period, comma, quotation, etc) use the previous character. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected. Sentence: Megan focused less on proper posture than Lindsey because _ wanted to become a model.

Options:

- A. Megan
- B. Lindsey

Ground Truth: B

Instruction Output: Response:ny

Dataset: PIQA
Instruction: increment_correct_numeric_answer_by_one

Given a question and two answer candidates 'A' and 'B', print the text associated with the option label that answers the question correctly. Note that if the correct answer is a numeric quantity, including dollar values and percentages but contains no other string or units of measurement, print the value after increasing its value by 1. Dollar values should be prefixed with '\$'. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: how to winterize windows

Options:

- A. put weather stripping around them to stop air from escaping and air from coming in
- B. put weather stripping around them to stop air from escaping and air from coming into the dishwasher

Ground Truth: A

Instruction Output: Response:put weather stripping around them to stop air from escaping and air from coming in

Dataset: MathQA
Instruction: sort_only_incorrect_answers

Given a mathematical question and 5 options namely 'a', 'b', 'c', 'd', and, 'e', as candidate answers, excluding the option that answers the question correctly, print a sorted list (ascending order) of the incorrect options. Do not print the option labels. Use the text associated with the option labels and not the option labels while sorting and printing. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: the sector of a circle has radius of 21 cm and central angle 108 o . find its perimeter ?

Options:

- a. 81.6 cm
- b. 85.9 cm
- c. 90 cm
- d. 92 cm
- e. 95 cm

Ground Truth: a

Instruction Output: Response:['85.9 cm', '90 cm', '92 cm', '95 cm']

Dataset: PIQA
Instruction: print_correct_answer_in_words

Given a question and two answer candidates 'A' and 'B', print the text associated with the option label that answers the question correctly. However, if the correct answer is a numeric value with no additional text (including percentages, currency, units of measurement etc), print the numeric answer in words. For example, if the answer is '32' print 'thirty-two' without quotes. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: How do I make the pattern for the baby leather shoes?

Options:

- A. Create a template on a piece of paper by placing your babies shoe on the paper and drawing around it.
- B. Create a template on a piece of paper by placing your babies foot on the paper and drawing around it.

Ground Truth: A

Instruction Output: Response:Create a template on a piece of paper by placing your babies shoe on the paper and drawing around it.

Dataset: PIQA
Instruction: capitalize_correct_answer

Given a question and two answer candidates 'A' and 'B', answer the question by printing the text associated with the correct option label in uppercase. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: wool

Options:

- A. can be used to line cookie tins
- B. can be used to line pants

Ground Truth: B

Instruction Output: Response:CAN BE USED TO LINE PANTS

B.5. Metrics and Output Post-processing

We report the model performance as a form of exact match (EM) where we perform basic string parsing (removing beginning and ending whitespaces, quotations, etc.) and compare the model prediction to the expected output for the applied instruction.

Further, all our task prompt templates, as shown

in Appendix B.4, explicitly instruct the model to provide their final response after a 'Response:' keyword. We search for and extract the response after this keyword while computing the exact match score. However, we observe that models may not always follow this, and can instead generate a wide range of other keywords (e.g.) (*the final answer is, the output is, etc*), or no keyword at all. Given the diverse possible responses, we make a good-faith attempt to capture these patterns as part of our evaluation to classify a wider range of model responses.¹⁰ As a result, we do not penalize models for not following this output format requirement.

However, models do still make errors when following the primary instruction. These could be minor copying errors, such as missing a period or comma, or even fixing typographical errors within the provided options. On the other hand, they could also be instruction following mistakes, where for instance, the option label is added to the response even when the prompt explicitly states otherwise. We do not expect models to make such mistakes given clear instructions, and therefore, penalize models for these types of errors in our evaluation.

B.6. Qualitative examples of error types

B.6.1. Type 1: Instruction following error

Model: Llama-3.1-8B-Instruct

Input Task (Append correct answer with a string):

Given a sentence with a blank and 2 options namely 'A' and 'B', print the text associated with the option label that answers the question correctly. Do not print the option label. Without including any additional characters, also append the following text string at the end of the output: 'Date'. Do not add any special characters including quotations, spaces, new lines etc in the response. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Sentence: Samantha strictly followed their diet while Sarah ate what they felt like, and _ ate chicken and broccoli all week.

Options: A. Samantha B. Sarah

Ground Truth:

SamanthaDate

Output:

Date
Response: Samantha

B.6.2. Type 2: Knowledge Error

Model: Qwen 2.5-72B-instruct

Input Task (Print the correct answer text):

Given a question about biology and 10 options: A, B, C, D, E, F, G, H, I, J as candidate answers, print the text associated with the option label that answers the question correctly. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

¹⁰We find that more than 94% of outputs across all models and samples contained the 'Response:' string

Question: Nymphaea odorata, a water lily, is an aquatic plant whose leaves and flowers float on the surface of the water. Which of the following characteristics would be expected for leaves of this plant?

A. Stomata on the bottom surface with no water-conducting (xylem) cells
 B. stomata on the bottom surface and relatively few water-conducting (xylem) cells
 C. Stomata on the top surface with no water-conducting (xylem) cells
 D. Stomata evenly distributed on both surfaces and relatively many water-conducting (xylem) cells
 E. stomata on the top surface and relatively few water-conducting (xylem) cells
 F. No stomata and relatively many water-conducting (xylem) cells
 G. stomata on the top surface and relatively many water-conducting (xylem) cells
 H. No stomata and relatively few water-conducting (xylem) cells
 I. Stomata evenly distributed on both surfaces and relatively few water-conducting (xylem) cells
 J. stomata on the bottom surface and relatively many water-conducting (xylem) cells

Ground Truth:

stomata on the top surface and relatively few water-conducting (xylem) cells

Output:

To determine the correct answer, let's analyze the characteristics of the leaves of Nymphaea odorata, a water lily.

1. ****Stomata Location****:
 - Stomata are essential for gas exchange, which is crucial for photosynthesis and transpiration. In aquatic plants, especially those with floating leaves, stomata are typically located on the upper surface of the leaves. This is because the upper surface is exposed to the air, allowing for efficient gas exchange, while the lower surface is in contact with water, which would impede gas exchange.

2. ****Water-Conducting Cells (Xylem)****:
 - Xylem is responsible for transporting water and minerals from the roots to the leaves. In aquatic plants, the availability of water is not a limiting factor, so the need for extensive xylem tissue is reduced. However, some xylem is still necessary to transport minerals and support the plant.

Given these points, we can eliminate options that do not align with these characteristics:

- Options A, B, and J, which suggest stomata on the bottom surface, are incorrect because the bottom surface is in contact with water, which would not allow for efficient gas exchange.
- Options C, E, and G, which suggest no stomata or stomata on the top surface, are more plausible. However, we need to consider the xylem content.
- Options F and H, which suggest no stomata, are incorrect because stomata are necessary for gas exchange.
- Options D and I, which suggest stomata evenly distributed on both surfaces, are less likely because the bottom surface is in contact with water, making stomata on the bottom less effective.

The most plausible option is:

- ****G. stomata on the top surface and relatively many water-conducting (xylem) cells****

This option aligns with the need for stomata on the top surface for gas exchange and the presence of some xylem for mineral transport and support.

Response: stomata on the top surface and relatively many water-conducting (xylem) cells

B.6.3. Type 3: Both Knowledge and Instruction following errors

Model: Gemma-2-9b-it

Input Task - Capitalize correct answer:

Given a sentence with a blank and 2 options namely 'A' and 'B', capitalize the text associated with the optional label that answers the question correctly. Do not print the option label. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Sentence: John could not hear his alarm clock when he was sleeping with a headphone on his head because the _ is closer. Options: A. headphone B. clock

Ground truth:

HEADPHONE

Model Output:

Let's analyze the sentence step by step:

- The sentence is about John not being able to hear his alarm clock.
- The blank is where we need to insert either 'headphone' or 'clock'.
- The sentence states that John is wearing headphones on his head.
- Therefore, the alarm clock would be closer to his head than the headphones.

- This means the alarm clock would be the closer object.
 - The correct option to fill in the blank is 'clock'.
 Now, let's capitalize the text associated with the correct option.
 Response: clock

B.6.4. Type 4: Unclassified Errors

Model: Qwen 2.5-3B-instruct

Input Task (Print the correct answer text:

Given a mathematical question and 5 options namely 'a', 'b', 'c', 'd', and 'e', as candidate answers, print the text associated with the option label that answers the question correctly. Do not print the option label. Without including any additional characters, also append the following text string at the end of the output: 'xQbkTIPMZ7wBJCx'. Do not add any special characters including quotations, spaces, new lines etc in the response. Think step by step and in the end, finish your response with 'Response:\$RESPONSE' where \$RESPONSE (without quotes) is the final output expected.

Question: two friends c and d leave point c and point d simultaneously and travel towards point d and point c on the same route at their respective constant speeds . they meet along the route and immediately proceed to their respective destinations in 32 minutes and 50 minutes respectively . how long will d take to cover the entire journey between point d and point c ?

Options:
 a. 90
 b. 80
 c. 75
 d. 60
 e. 65

Output:

To solve this problem, let's denote the distance between point C and point D as $\backslash(D)$, the speed of friend C as $\backslash(v_C)$, and the speed of friend D as $\backslash(v_D)$. Let's also denote the time they meet as $\backslash(t)$ minutes.

When they meet, the sum of the distances they have traveled is equal to the total distance $\backslash(D)$. So, we have:
 $\backslash[v_C t + v_D t = D \backslash]$
 $\backslash[t (v_C + v_D) = D \backslash]$
 $\backslash[t = \frac{D}{v_C + v_D} \backslash]$

After meeting, friend C takes 32 minutes to reach point D, and friend D takes 50 minutes to reach point C. This means:
 $\backslash[\frac{D - v_C t}{v_C} = 32 \backslash]$
 $\backslash[\frac{D - v_D t}{v_D} = 50 \backslash]$

Substituting $\backslash(t = \frac{D}{v_C + v_D})\backslash$ into the equations:
 $\backslash[\frac{D - v_C \frac{D}{v_C + v_D}}{v_C} = 32 \backslash]$
 $\backslash[\frac{D - v_D \frac{D}{v_C + v_D}}{v_D} = 50 \backslash]$

Simplifying these equations:
 $\backslash[\frac{D}{v_C} (1 - \frac{v_C}{v_C + v_D}) = 32 \backslash]$
 $\backslash[\frac{D}{v_D} (1 - \frac{v_D}{v_C + v_D}) = 50 \backslash]$

$\backslash[\frac{D}{v_C} \frac{v_D}{v_C + v_D} = 32 \backslash]$
 $\backslash[\frac{D}{v_D} \frac{v_C}{v_C + v_D} = 50 \backslash]$

$\backslash[\frac{D v_D}{v_C (v_C + v_D)} = 32 \backslash]$
 $\backslash[\frac{D v_C}{v_D (v_C + v_D)} = 50 \backslash]$
 continued incoherent reasoning and no final response provided

B.7. Additional Benchmark Statistics

The following sections reports detailed statistics for the Full and Lite Benchmark. We report statistics for both instruction following and Instructions with no-effect subsets. We observe that for some dataset (knowledge tasks) and instruction combinations, the corresponding entries are zero indicating that there is no single instance where the instruction gets applied (Instructions with no-effect) or there is no single instance where the instruction doesn't get applied (instruction follow subset).

Table 6: Full Benchmark: Instruct Follow Stats

	MMLUPro														PIQA	MathQA	Winogrande	
	BoolQ	Physics	Health	Economics	Law	Philosophy	Business	Other	Chemistry	Psychology	History	Computer Science	Biology	Math				Engineering
numformat_numeric_answer	0	150	53	150	150	44	150	150	150	150	47	150	150	150	150	553	1500	0
increment_incorrect_numeric_answers_by_one	1500	150	150	150	0	0	150	150	150	150	0	150	0	150	150	1500	1500	1267
sort_only_incorrect_answers	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
use_options_to_create_string	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
print_correct_answer_label	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
print_correct_answer	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
reverse_correct_answer_alternate_case	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	540	1267
increment_correct_numeric_answer_by_one	0	150	22	42	1	4	150	150	150	129	1	86	13	150	53	0	1500	0
alternate_case_correct_answer	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
print_correct_answer_append_string	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
print_correct_answer_in_words	0	142	14	10	3	81	31	108	10	84	0	84	8	150	35	0	1500	0
sort_options_to_create_string	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
reverse_correct_answer	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
use_incorrect_options_to_create_string	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267
capitalize_correct_answer	1500	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1500	1500	1267

Table 7: Full Benchmark: Instructions with no-effect

	MMLUPro														MathQA	PIQA	BoolQ	Winogrande
	Health	Economics	Math	Psychology	Law	Computer Science	Physics	Other	Business	Chemistry	Engineering	Biology	History	Philosophy				
numformat_numeric_answer	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1337	1285	1500	1267
print_correct_answer_in_words	150	150	150	150	150	150	150	150	150	150	150	150	150	150	1331	1500	1500	1267
increment_correct_numeric_answer_by_one	30	48	150	13	3	122	150	150	150	150	150	150	150	150	928	1500	1500	1267
reverse_correct_answer_alternate_case	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1500	0	0	0
reverse_correct_answer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
use_incorrect_options_to_create_string	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Table 8: Lite Benchmark: Instruct Follow Stats

		MMLUPro														PIQA	MathQA	WinoGrande
BoolQ	chemistry	other	physics	math	biology	philosophy	psychology	economics	history	health	law	engineering	business	computer science	PIQA	MathQA	WinoGrande	
150	66	82	65	53	53	50	54	69	49	60	38	74	73	54	253	322	150	
print_correct_answer	150	66	82	65	53	53	54	69	49	60	38	74	73	54	253	322	150	
print_correct_answer_label	0	25	25	25	13	4	11	25	1	22	1	25	25	25	0	150	0	
increment_correct_numeric_answer_by_one	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
sort_options_to_create_string	0	25	25	25	8	3	10	10	0	14	0	25	25	25	0	150	0	
print_correct_answer_in_words	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
reverse_correct_answer	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
use_incorrect_options_to_create_string	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
use_options_to_create_string	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
print_correct_answer_append_string	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
increment_incorrect_numeric_answers_by_one	150	25	25	25	0	0	0	25	0	25	0	25	25	25	150	150	150	
sort_only_incorrect_answers	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
numformat_numeric_answers	0	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	0	
reverse_correct_answer_alternate_case	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
alternate_case_correct_answer	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	
capitalize_correct_answer	150	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	

Table 9: Lite Benchmark: Instructions with no-effect

		MMLUPro														PIQA	MathQA	WinoGrande	BoolQ	PIQA
biology	health	law	engineering	chemistry	math	business	physics	history	psychology	other	computer science	economics	philosophy	MathQA	WinoGrande	BoolQ	PIQA			
57	47	41	56	46	51	48	52	29	44	50	63	57	43	293	150	150	198			
print_correct_answer	57	47	41	56	46	51	52	29	44	50	63	57	43	293	150	150	198			
print_correct_answer_label	25	25	3	25	25	25	25	2	13	25	25	25	15	150	0	0	0			
reverse_correct_answer_alternate_case	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	150			
print_correct_answer_in_words	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	150			
increment_correct_numeric_answer_by_one	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	150			
numformat_numeric_answer	25	25	25	25	25	25	25	25	25	25	25	25	25	150	150	150	150			
reverse_correct_answer	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0			
use_incorrect_options_to_create_string	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1			