HELMET: HOW TO EVALUATE LONG-CONTEXT LANGUAGE MODELS EFFECTIVELY AND THOROUGHLY

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ABSTRACT

There have been many benchmarks for evaluating long-context language models (LCLMs), but developers often rely on synthetic tasks like needle-in-a-haystack (NIAH) or arbitrary subsets of tasks. It remains unclear whether they translate to the diverse downstream applications of LCLMs, and the inconsistency further complicates model comparison. We investigate the underlying reasons behind current practices and find that existing benchmarks often provide noisy signals due to low coverage of applications, insufficient lengths, unreliable metrics, and incompatibility with base models. In this work, we present **HELMET** (**H**ow to **E**valuate **L**ong-context **M**odels **E**ffectively and **T**horoughly), a comprehensive benchmark encompassing seven diverse, application-centric categories. We also address many issues in previous benchmarks by adding controllable lengths up to 128k tokens, model-based evaluation for reliable metrics, and few-shot prompting for robustly evaluating base models. Consequently, we demonstrate that HELMET offers more reliable and consistent rankings of frontier LCLMs. Through a comprehensive study of 59 LCLMs, we find that (1) synthetic tasks like NIAH are not good predictors of downstream performance; (2) the diverse categories in HELMET exhibit distinct trends and low correlation with each other; and (3) while most LCLMs achieve perfect NIAH scores, open-source models significantly lag behind closed ones when the task requires full-context reasoning or following complex instructions—the gap widens with increased lengths. Finally, we recommend using our RAG tasks for fast model development, as they are easy to run and more predictive of other downstream performance; ultimately, we advocate for a holistic evaluation across diverse tasks.[1]

1 INTRODUCTION

Long-context language models (LCLMs) unlock a myriad of applications, from summarizing long documents to learning new tasks on the fly with thousands of examples. Many recent benchmarks sought to evaluate language models' long-context abilities (Zhang et al., 2024b; An et al., 2024; Shaham et al., 2023; Bai et al., 2024, *inter alia*). However, recent developments on long contexts (Chen et al., 2023; Xiong et al., 2023; Peng et al., 2024; Fu et al., 2024) still rely on either perplexity or synthetic needle-in-a-haystack tasks (NIAH; Kamradt, 2024; Hsieh et al., 2024). Frontier LCLMs (Dubey et al., 2024; Team et al., 2024c; OpenAI, 2023; Team et al., 2024a) also mostly

Table 1: Most LCLMs evaluate on synthetic (Syn.) tasks. ♭: base models. ∞: ∞BENCH.

Model	Syn.	PPL	∞		ZEROSCROLLS					RAG	ICL
			QA	All	NQA	QS	QL	SQ	All		
Gemini-1.5	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
GPT-4	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Claude-3.5	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Llama-3.1	✓	✗	✓	✗	✗	✓	✓	✓	✗	✗	✗
Phi-3	✓	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗
Jamba-1.5	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
Qwen2	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Command R	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗
Xiong et al.	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗	✗
Chen et al.♭	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Peng et al.♭	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Fu et al.♭	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗

[1]Our data and code are available at https://princeton-nlp.github.io/HELMET/.

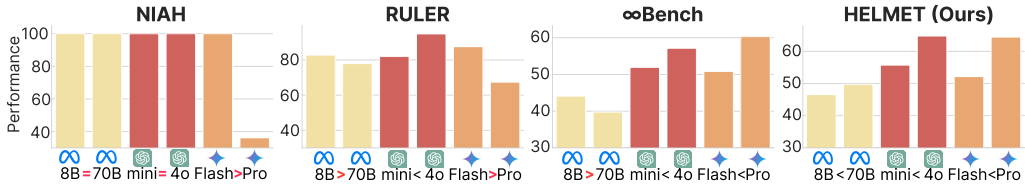


Figure 1: Long-context benchmark results of frontier LCLMs (Llama-3.1 8B/70B, GPT-4o-mini, GPT-4o-08-06, and Gemini-1.5 Flash/Pro) at 128k input length. NIAH is saturated for almost all models; RULER (Hsieh et al., 2024) and ∞BENCH (Zhang et al., 2024b) show unexpected trends for Llama-3.1 (Dubey et al., 2024). In contrast, HELMET demonstrates more consistent rankings of these frontier models.

report NIAH, sometimes with arbitrary subsets of other datasets, as shown in Table 1. Such inconsistency complicates comparisons between different models. It is also unclear whether synthetic NIAH tasks or the few chosen datasets can provide a holistic picture of models' long-context abilities and their performance in real-world applications.

Why don't model developers agree on these evaluations? We take a closer look and find that existing benchmarks have many critical design flaws, including:

- **Insufficient coverage of downstream tasks**: Existing benchmarks either focus on synthetic tasks (Hsieh et al., 2024) or add simple question answering (Zhang et al., 2024b). Other works study particular aspects of LCLMs, such as summarization (Chang et al., 2024), in-context learning (Li et al., 2024c), and retrieval-augmented generation (RAG; Lee et al., 2024), but they do not provide a holistic evaluation of LCLMs.
- **Inadequate lengths**: Most natural language datasets in existing benchmarks (Shaham et al., 2023; An et al., 2024, Table 4) are too short to test frontier long-context abilities (usually $\geq$128k).
- **Unreliable metrics**: For commonly used long-document QA and summarization tasks, most existing benchmarks still rely on metrics like ROUGE (Lin, 2004), which can be noisy and unreliable (Goyal et al., 2023; Deutsch et al., 2022; Chang et al., 2024).
- **Incompatibility with base models**: Many LCLM developments focus on base models without instruction tuning, but most existing benchmarks require models to be instruction-tuned—hence developers can only rely on synthetic tasks or perplexity.

Consequently, existing benchmarks either are not applicable to long-context works (inadequate lengths or incompatibility) or provide very noisy signals (insufficient coverage or unreliable metrics). We summarize the shortcomings of many of the benchmarks in Table 2. For the three benchmarks that support 128k[2] context length (NIAH, RULER, and ∞BENCH), we use them to evaluate 6 frontier models and report the numbers in Figure 1. We see that NIAH does not reflect differences across models; RULER and ∞BENCH show unexpected trends—on RULER, Gemini Flash is stronger than Gemini Pro; on ∞BENCH, the 70B Llama model is weaker than the 8B one. This raises concerns about the reliability of the benchmarks and how they can differentiate long-context models, which likely contributes to the lack of use of these benchmarks in model development.

To address these challenges, we present **HELMET** (**H**ow to **E**valuate **L**ong-context **M**odels **E**ffectively and **T**horoughly). We curate a *diverse* set of application-centric long-context tasks across seven categories. Beyond widely adopted categories like *synthetic recall*, *long-document question answering (QA)*, and *summarization*, we also add *many-shot in-context learning* (ICL), *retrieval-augmented generation* (RAG), *passage re-ranking*, and *generation with citations* (Gao et al., 2023). We further address the shortcomings of existing benchmarks: (1) we ensure all datasets support input lengths of 128k and are easily extendable to more tokens (§2.1); (2) we introduce reference-based model evaluation for QA and summarization and show that it drastically improves over n-gram overlap metrics (§2.2); (3) we refine the prompts and in-context demonstrations used for all tasks, reducing the evaluation noise by different output formats and allowing base models to be evaluated on most of the categories robustly (§2.3). Together, HELMET enables a holistic evaluation of

[2]Throughout the paper, we use binary prefixes k= 2^{10}.

Table 2: Comparison of long-context benchmarks: ZeroSCROLLS (Shaham et al., 2023), LongBench (Bai et al., 2024), L-Eval (An et al., 2024), RULER (Hsieh et al., 2024), ∞BENCH (Zhang et al., 2024b), and our HELMET. L: input tokens. †: All datasets have $L < 128$k except one dataset. ‡: L-Eval uses LLMs to compute reference-free, pairwise win-rates; we design reference-based model evaluation for specific tasks.

	Type of tasks							Benchmark features		
	Cite	RAG	Re-rank	Long-QA	Summ	ICL	Synthetic Recall	Robust Eval.	$L \geq 128$k	Controllable L
ZeroSCROLLS	✗	✗	✗	✓	✓	✗	✗	✗	✗†	✗
LongBench	✗	✓	✗	✓	✓	✓	✓	✗	✗†	✗
L-Eval	✗	✓	✗	✓	✓	✗	✗	✓‡	✗†	✗
RULER	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
∞BENCH	✗	✗	✗	✓	✓	✗	✓	✗	✓	✓
HELMET (Ours)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

long-context capabilities and provides more reliable signals for model development. Figure 1 shows that HELMET can clearly differentiate models at different capabilities and reflect comparisons consistent with human perception. More discussions on the improvement of HELMET over previous benchmarks and direct comparisons are in §A.

To understand the progress of LCLMs and how different long-context capabilities correlate with one another, we evaluate a thorough list of 59 LCLMs of various architectures, scales, and training strategies. Our analysis reveals that (1) synthetic tasks are poor indicators of downstream performance (§3.1), (2) different categories in HELMET show distinctive trends (§3.2), and (3) open-source models significantly lag behind closed ones on tasks that require reasoning over long contexts or following complex instructions—the gap further widens with increased lengths (§3.3). Finally, we find that the RAG category strikes a good balance between ease of use, better correlation with downstream tasks, and compatibility with base models. Ultimately, it is imperative to evaluate LCLMs over a diverse spectrum of categories. We hope that our insights offer a more effective way to evaluate LCLMs for future model development and benchmarking.

2 OUR BENCHMARK: HELMET

In this work, we seek to overcome the shortcomings of existing benchmarks by meeting the following desiderata: (1) diverse coverage across different tasks and capabilities of LCLMs, (2) controllable lengths that support more than 128k input tokens, and (3) reliable evaluation for both base and instruction-tuned models. In this section, we describe the datasets used in HELMET and how they improve upon existing evaluation benchmarks in terms of settings and metrics.

2.1 REALISTIC AND DIVERSE LONG-CONTEXT APPLICATIONS

Retrieval-augmented generation (RAG). We use open-domain question answering (ODQA)—which requires retrieving from a knowledge corpus and then generating correct answers (Chen et al., 2017)—as a representation of retrieval-augmented generation (RAG) applications. We use Natural Questions (NQ; Kwiatkowski et al., 2019), TriviaQA (TQA; Joshi et al., 2017), HotpotQA (Yang et al., 2018), and PopQA (Mallen et al., 2023). We use the gold passage (the passage with the answer) from Petroni et al. (2021), or otherwise use any passage that contains the answer.

For a particular input length L, we first determine the number of passages k that can fit within L tokens, then retrieve k passages[3] from the corpus[4] that *do not contain the answer* as *distractors*. This differs from previous works that *randomly sample passages* from the corpus (Lee et al., 2024) and is more realistic and challenging. For NQ, TQA, and PopQA, we take the top $k - 1$ distractors and insert the gold passage at six evenly distributed positions following Liu et al. (2023). For

[3]We use `Alibaba-NLP/gte-large-en-v1.5` for retrieval (Zhang et al., 2024a).

[4]We use Wikipedia 2019-8-01 dump, split into 100-word passages (Petroni et al., 2021).

Table 3: Overview of evaluation datasets. We select datasets that cover various important long-context capabilities. SubEM: substring exact match.

Category	Dataset	Metrics	Description
Retrieval-augmented generation	Natural Questions	SubEM	Factoid question answering
	TriviaQA	SubEM	Trivia question answering
	PopQA	SubEM	Long-tail entity question answering
	HotpotQA	SubEM	Multi-hop question answering
Passage re-ranking	MS MARCO	NDCG@10	Rerank passage for a query
Generation with citations	ALCE ASQA	Recall, Cite	Answer ambiguous questions with citations
	ALCE Qampari	Recall, Cite	Answer factoid questions with citations
Long-document QA	NarrativeQA	Model-based	Book and movie script QA
	∞BENCH QA	ROUGE F1	Novel QA with entity replacement
	∞BENCH MC	Accuracy	Novel multiple-choice QA with entity replacement
Summarization	∞BENCH Sum	Model-based	Novel summarization with entity replacement
	Multi-LexSum	Model-based	Summarizing multiple legal documents
Many-shot in-context learning	TREC Coarse	Accuracy	Question type classification, 6 labels
	TREC Fine	Accuracy	Question type classification, 50 labels
	NLU	Accuracy	Task intent classification, 68 labels
	BANKING77	Accuracy	Banking intent classification, 77 labels
	CLINC150	Accuracy	Intent classification, 151 labels
Synthetic recall	JSON KV	SubEM	Retrieve a key in JSON dictionary
	RULER MK Needle	SubEM	Retrieve the needle (a number) within noisy needles
	RULER MK UUID	SubEM	Retrieve the needle (a UUID) within noisy needles
	RULER MV	SubEM	Retrieve multiple values for one needle (key)

HotpotQA, which requires two gold passages, we combine them and the top $k-2$ distractors and randomly shuffle them into three permutations. We use substring exact match (SubEM; whether the answer is included in the output), following previous work (Mallen et al., 2023; Asai et al., 2024a). §B.1 offers more details.

Generation with citations (Cite). We leverage ALCE (Gao et al., 2023) to evaluate LCLMs on a realistic application of answering questions while providing correct attributions (Bohnet et al., 2022). Given multi-faceted questions and relevant passages, models are required to generate a long-text answer and cite supporting passage IDs at the end of each sentence. This tests models' ability to utilize the passages in the context and also to follow the instructions about citation formats. We use the ASQA (Stelmakh et al., 2022) and QAMPARI (Rubin et al., 2022) subsets from ALCE. For an input length L, we first determine the number of passages k, and use the top k retrieved passages from Wikipedia as contexts. The model's generations are evaluated on correctness and citation quality, and we report the average across all metrics. See §B.2 for more details.

Long-document question answering (LongQA). We use NarrativeQA (Kočiský et al., 2018) and the English book QA and multiple choice (MC) subsets from ∞BENCH (Zhang et al., 2024b) for evaluating long-document QA. We select those tasks for their abundant context lengths (Table 4). We truncate the document from the end based on L. We use ROUGE F1 for ∞BENCH QA (answers are mostly entity names) and accuracy for ∞BENCH MC. For NarrativeQA, where the answers can be long text and open-ended, we use a model-based evaluation (§2.2).

Summarization (Summ). Summarization tests LCLMs' ability to aggregate information across the contexts. We choose Multi-LexSum (legal document summarization) and the English summarization task from ∞BENCH (novel summarization) for their long lengths (Table 4). We truncate the document from the end based on the evaluation length L. We use our model-based evaluation (§2.2) for both datasets instead of the commonly used ROUGE, as it better reflects human judgment.

Table 4: Dataset lengths.

Datasets	Medium	Max
ZeroSCROLLS		
QASPER	6k	12k
GovReport	12k	33k
QuALITY	9k	11k
SQuALITY	8k	10k
HELMET		
NarrativeQA	73k	518k
∞BENCH QA	191k	835k
∞BENCH MC	167k	835k
∞BENCH Sum	154k	835k
Multi-LexSum	90k	5m

Passage re-ranking (Re-rank). Re-ranking retrieved passages based on their relevance to the query is an important application of LCLMs (Sun et al., 2023). The task requires the model to retrieve relevant information and compare and reason over different parts of the contexts. We use the MS MARCO dataset (Bajaj et al., 2018), where each instance contains a query and passages retrieved by BM25 (Robertson & Zaragoza, 2009) from the Internet. Each passage has annotations of a relevance label—perfect, highly relevant, or not relevant. We determine the number of passages k from the input length L, and randomly sample k passages with balanced labels for each test query. The model is prompted with the query and the shuffled k passages and is instructed to output the top-10 document IDs ranked by relevance. We report NDCG@10. Details are in §B.3.

Many-shot in-context learning (ICL). In-context learning (ICL) is a key ability that enables LLMs to adapt to new tasks on the fly (Brown et al., 2020). Ratner et al. (2023); Xu et al. (2024); Li et al. (2024c); Bertsch et al. (2024) explore performing many-shot ICL (with thousands of examples) with LCLMs. Following Bertsch et al. (2024), we focus on datasets with large label spaces: TREC-coarse, TREC-fine (Li & Roth, 2002), BANKING77 (Casanueva et al., 2020), CLINC150 (Larson et al., 2019), and NLU (Liu et al., 2019). We adjust the number of shots to control the input length L, and the number of examples in each class is balanced. We report the accuracy on the test set.

One *difference* from previous works is that we map original natural language labels (e.g., *location*) into numbered labels (i.e., *0*, *1*) to test how well a model can learn new tasks instead of relying on its pre-trained priors (Wei et al., 2023; Pan et al., 2023; Min et al., 2022). More details are in §B.4.

Synthetic recall. Synthetic recall tasks, such as needle-in-a-haystack (NIAH), stress test models' ability to recall relevant information (needle) from long contexts. They gain popularity for being easy to use (can test any arbitrary length) and easy to control (can put the "needle" at any position). For this category, we select multiple synthetic recall tasks from RULER (a more comprehensive version of NIAH; Hsieh et al., 2024) and also add a JSON KV retrieval task (Liu et al., 2023), which we find more challenging. Following previous works, we report the percentage of the ground truth answers that are substrings in the generation (SubEM). Refer to §B.5 for more details.

2.2 Reliable evaluation metrics

Existing long-context benchmarks (Zhang et al., 2024b; Shaham et al., 2023) largely rely on n-gram overlap metrics like ROUGE (Lin, 2004) that have been shown to correlate poorly with human judgment for tasks with long outputs, such as summarization (Goyal et al., 2023; Deutsch et al., 2022; Krishna et al., 2023). L-Eval (An et al., 2024) uses LLMs to score reference-free "win-rates", which neglects the available answer annotations and always requires evaluating model pairs. Instead, we design *reference-based model evaluation* for long-document QA and summarization that are more reliable and easy to use.

Question answering. In NarrativeQA, we prompt GPT-4o[5] with the question, the ground truth, and the model output to check for fluency and correctness. The fluency score is either 0 (incoherent or repetitive) or 1 (fluent), and the correctness score takes on the value of 0 (incorrect), 1 (partly correct), 2 (correct but not fully relevant), and 3 (correct and relevant). We take the product of the two as the final score and normalize it to a range of $[0, 100]$.

Summarization. Following previous works (Kamoi et al., 2023; Zhang & Bansal, 2021), we first decompose the gold summary into atomic claims and use GPT-4o to check if each claim is supported by the generation (recall) and if each sentence in the generation is supported by the reference summary (precision). We then calculate the F1 score from the recall and precision scores. We also ask GPT-4o to check for fluency (0 or 1) and take its product with the F1 score as the final score. In each of the above steps, we prompt GPT-4o with handwritten examples.

Empirically, our reference-based model evaluation reflects more consistent trends, as shown in Figure 2: (1) Llama-3.1-8B-Inst achieves similar ROUGE scores to GPT-4o, while our evaluation shows a significant gap. (2) Our metric better identifies incoherent generations and shows lower performance for models with smaller context windows, such as the Mistral models. (3) Our metric shows a substantially more positive trend for GPT-4o as input length increases, whereas ROUGE-L

[5] `GPT-4o-2024-05-13`

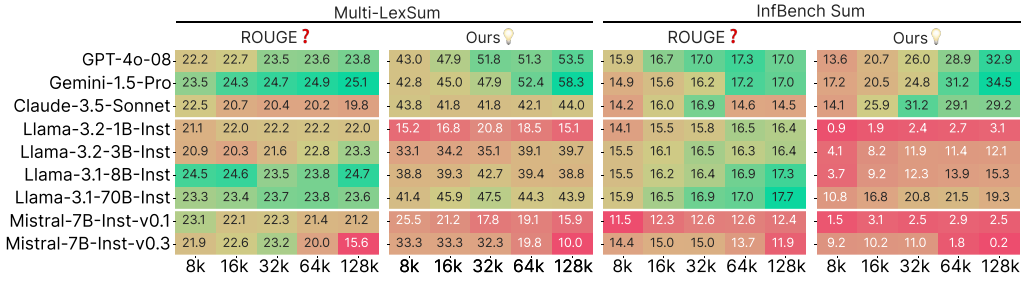


Figure 2: Comparison between ROUGE-L F1 and our model-based evaluation metric on summarization tasks. Our metric shows more consistent trends: it reflects the performance gain on GPT-4o with increased input length, while ROUGE remains almost the same; our metric also clearly distinguishes models while ROUGE shows little difference.

remains within a difference of 2 absolute points. We further validate the model-based evaluation through human studies, which suggests that our new metrics highly agree with human judgments: for example, on ∞BENCH Sum, our metric reaches a human-model agreement of Cohen's $\kappa = 0.91$ and $\kappa = 0.76$ on summary precision and recall, respectively. More details on the human validation studies can be found in §B.

2.3 ROBUST PROMPTING AND CONTROLLED EVALUATION SETTINGS

Robust prompting reduces noise and enables evaluation on base models. Many long-context benchmarks require models to follow instructions and only support evaluating instruction-tuned models (Zhang et al., 2024b; Shaham et al., 2023). However, many model developments do not apply instruction tuning (Chen et al., 2023; Fu et al., 2024) and these models can only rely on perplexity or synthetic tasks. To support long-context research efforts, we design our benchmark so that at least a portion of the datasets supports evaluating base models.

Existing benchmarks mostly use zero-shot prompting (Shaham et al., 2023; Zhang et al., 2024b), which leads to noisy output formats, especially for base models. For example, the model may output a long answer in RAG when a short answer is required. We add two-shot demonstrations in the prompt for all tasks to address this problem.[6] For long-document QA and summarization, we replace the original document with a placeholder phrase to reduce the number of input tokens in the ICL example. As shown in Table 8, we observe that both base and instruct models substantially benefit from the demonstrations.

Furthermore, we employ the length-instruction-enhanced evaluation from L-Eval for long-generation tasks (i.e., summarization), which is shown to have substantially more consistent and reliable evaluations (An et al., 2024). As a result, we find that our reproduction of previous datasets, such as ∞BENCH QA tasks, better reflects the capabilities of LCLMs, as shown in Table 7. The use of demonstration and better instructions thus better depicts how models perform in real applications.

Controlled input length and difficulty. An important dimension to consider when evaluating LCLMs is the input length L, as longer inputs can provide more information while challenging the model's ability to process distracting contexts. As we discussed in §2.1, we can control the input length L for each task by either adjusting the number of retrieved passages, the number of demonstrations, or truncating the document text to fit within the specified lengths. Consequently, we are able to study model performance at or beyond the length of current frontier LCLMs ($\geq$ 128k).

As shown in Figure 1 and 2, HELMET provides rankings more consistent with human perception of model performance. The diverse tasks, controllable lengths, and robust metrics and prompting enable a thorough examination of LCLMs across multiple dimensions.

[6]Except for ICL (the number of shots varies) and RULER (we follow the original formatting).

3 ANALYSIS

We evaluate 59 LCLMs with HELMET. To our best knowledge, this is the most thorough and controlled comparison of long-context models on diverse applications. These models cover closed-source models, such as GPT-4, Claude, and Gemini, as well as open-source model families, such as Llama (Dubey et al., 2024), Mistral (Jiang et al., 2023), Phi (Abdin et al., 2024), and Qwen (Qwen et al., 2025). We also consider models that use different architectures—full-attention transformers (Vaswani et al., 2017), sliding-window attention (Beltagy et al., 2020), and hybrid models with SSM modules (Dao & Gu, 2024). We also benchmark position extrapolation models such as YaRN (Peng et al., 2024) and LongRoPE (Ding et al., 2024). We list all the models evaluated in Table 15. We evaluate each model at input lengths: $L \in \{8k, 16k, 32k, 64k, 128k\}$, where L is the number of Llama-2 tokens (Touvron et al., 2023), and use greedy decoding for all models for consistency. We randomly sample 100 to 600 examples from each dataset; more details are in §D.

3.1 SIMPLE SYNTHETIC TASKS ARE POOR PREDICTORS OF REAL-WORLD PERFORMANCE

Many model developers rely on simple synthetic tasks, such as NIAH, for evaluating long-context language models, but it is unclear if these tasks are representative of real-world performance. To this end, we calculate Spearman's rank correlation ρ with the performance of 35 instruction-tuned models between synthetic and real-world tasks. First, Figure 3 shows that none of the synthetic tasks achieves an average correlation higher than 0.8. We also make the following observations.

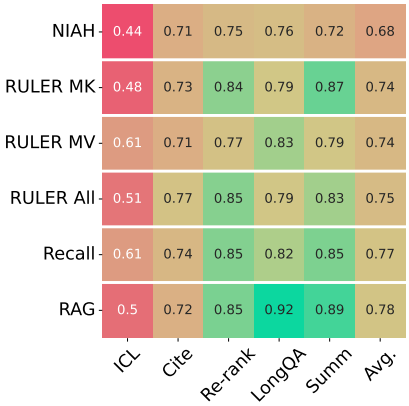


Figure 3: Spearman's rank correlation at 128k input length, calculated across 35 instruction-tuned models.

Not all synthetic tasks are created equal. The original NIAH, which places a needle in the middle of unrelated essays and asks the model to retrieve it, does not correlate well with real-world tasks: all correlations are ≤ 0.8. Using the popular RULER average score—which contains not only NIAH variants but also synthetic aggregation, multi-hop tracing, and QA—also does not give strong correlations (all < 0.85).

We take a closer look at different RULER tasks and find that harder recall-type tasks are more reflective of real-world categories—such as RULER MK, which places distracting needles around the target needle. Despite the overall low correlation, we believe they can still serve as a useful *sanity check* during model development. We put together several such RULER tasks, along with JSON KV, to form the HELMET synthetic recall set (more discussions on this in §E.1).

Tasks with noisier, more distracting contexts better differentiate models. To understand why synthetic tasks poorly correlate with real-world tasks, we plot the performance of different models on NIAH, RULER MK (one of our recall tasks), and HotpotQA (one of our RAG tasks) in Figure 4. We use ∞BENCH QA as a representative real-world task. We find that most models achieve either perfect or near-zero performance on the original NIAH, leaving few data points in the middle and resulting in poor separability between models. On the other hand, RULER MK, whose contexts are more distracting, better distributes the models between 0 and 100% performance.

RAG is a better proxy for real-world tasks. Finally, we find that RAG datasets, such as HotpotQA, consistently achieve higher correlation with other real-world tasks. We also see from Figure 4 that HotpotQA enjoys an almost linear relationship with the QA dataset. Similar to synthetic tasks, RAG tasks are easy to control and also test models' recall abilities; yet since all the passages are retrieved and relevant to the query, RAG contexts are more distracting and hence harder to saturate.

3.2 DIVERSE LCLM APPLICATIONS CALL FOR DIVERSE EVALUATION

In long-context language modeling, realistic tasks are often only used in isolated settings (Karpinska et al., 2024; Li et al., 2024c; Dubey et al., 2024), which limits the understanding of LCLMs in a

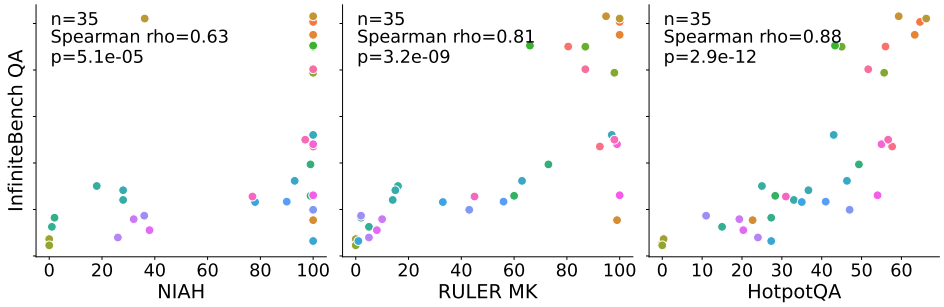


Figure 4: Distribution of instruction-tuned models' performance on ∞BENCH QA with respect to NIAH, RULER MK, and HotpotQA.

broader context. In this work, we cross-examine model performance over a wide range of real tasks, and find that different categories do not always correlate with each other, as shown in Figure 5.

Naturally, RAG and passage re-ranking moderately correlate due to the shared retrieval component. However, the added complexity of generating citations in ALCE leads to lower correlation with other categories. As shown in Figure 9, generating correct answers and valid citations are not well correlated, which suggests that instruction following and recalling facts with long contexts are distinct capabilities.

Furthermore, some categories—generation with citations and in-context learning—do not correlate well with other categories. Intuitively, summarization tests for the model's ability to aggregate information across the whole input while ICL tests for the model's ability to learn new tasks from many examples. Such capabilities are orthogonal to recall facts in long contexts. Therefore, model developers should evaluate across these distinct axes to draw a more holistic picture of the model's capabilities. Additional analysis are in §E.2.

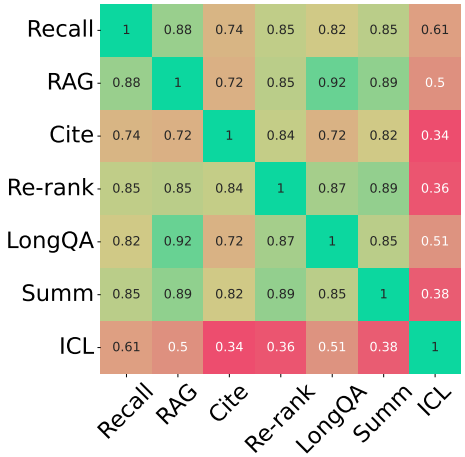


Figure 5: Spearman rank correlation between different categories at L =128k.

3.3 MODEL PERFORMANCE ACROSS TASKS AND LENGTHS

We show the performance of instruction-tuned models on HELMET at five different lengths in Figure 6, and the full results are illustrated in Figure 10. We analyze the model performance across two critical dimensions of long-context language modeling: task complexity and input length.

Open-source models lag behind closed-source models on complex tasks. First, we consider the performance of frontier LCLMs at the longest input length of 128k tokens. We find that the closed-source models—notably GPT-4o-08 and Gemini-1.5-Pro—stand out as the strongest LCLMs. Other than ICL, the closed-source models outperform the open-source models on all tasks. The gap is relatively small on synthetic recall and LongQA, where the task is to retrieve information from the context. There is a stark contrast in the generation with citations and re-ranking performance, where the closed-source models are 30 to 40 absolute points better than the best open-source models.

Performance degradation with longer inputs is category-dependent. Most frontier models largely retain performance on recall and RAG with longer inputs; however, even the best models significantly degrade with more contexts on tasks like re-ranking and generation with citations. As illustrated in Figure 7, with increased task complexity from left to right, performance degradation at longer lengths is more pronounced. On generation with citations, open-source models completely collapse at 128k while GPT-4o stays roughly the same. This underscores the importance of evaluating on more complex and realistic long-context applications.

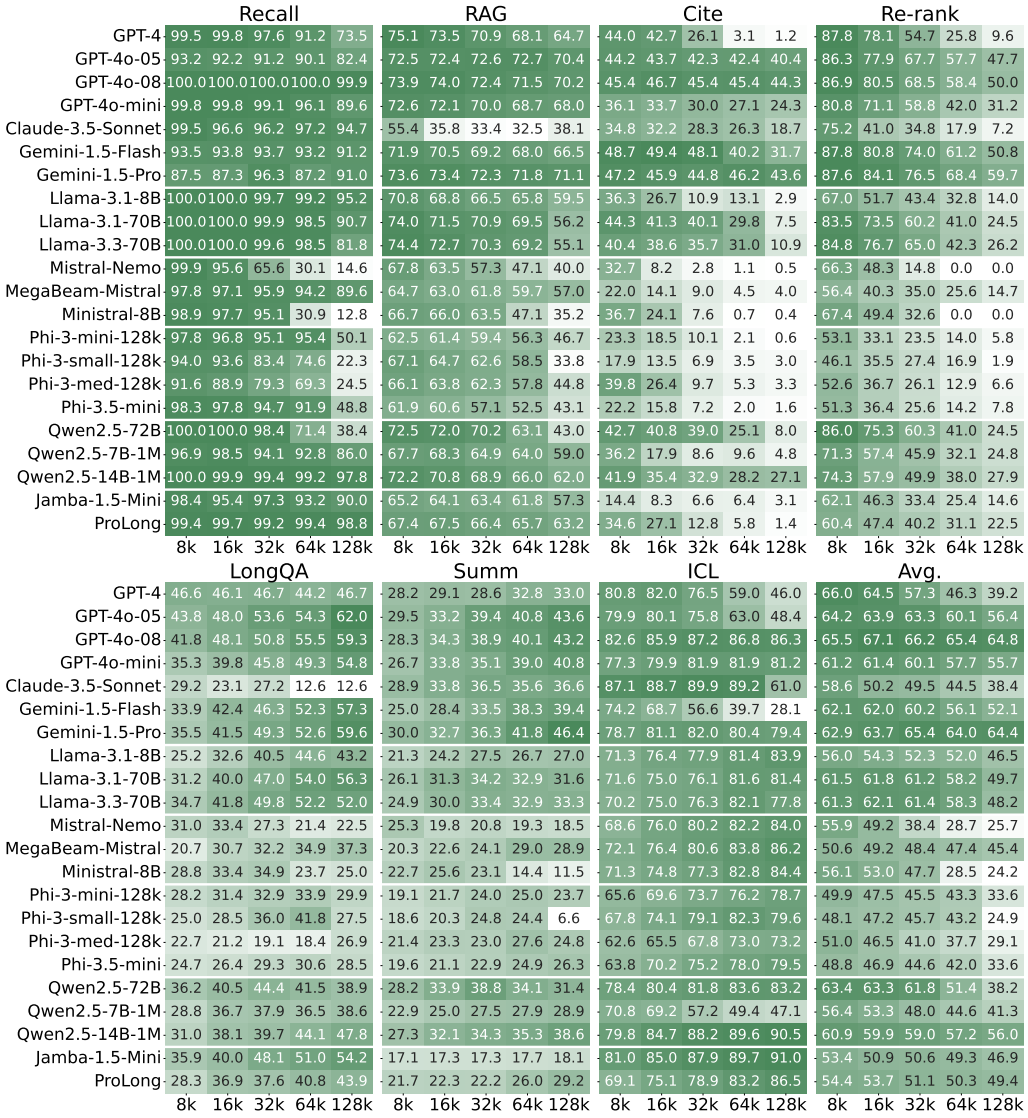


Figure 6: Results of HELMET. All models are instruction-tuned and have a claimed context window of 128k tokens or more.

No clear winner across all categories. As we observe from the previous sections, the different categories are not always correlated with each other. This is evident in the different winners across different categories: for instance, GPT-4o is stronger on recall and generation with citations, while Gemini is stronger on passage re-ranking and long-document QA. Furthermore, many open-source models outperform the closed-source models on ICL, potentially because heavy instruction tuning hurts ICL, and we provide qualitative examples in Table 19. Thus, it is critical to evaluate models across multiple axes. In the appendix, we also present additional analysis, such as the performance of positional extrapolation methods (§E.3), the lost-in-the-middle phenomenon (§E.4), and the performance of Claude (§E.6).

4 Related Works

Long-context language models. Frontier models such as GPT-4 (OpenAI, 2023), Gemini, and Claude claim to have expanded their context window beyond 100k tokens. In the open-source community, there are also efforts to train models with longer input lengths (Dubey et al., 2024;

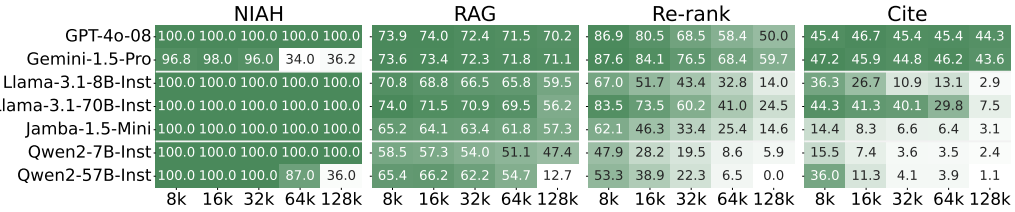


Figure 7: Results of selected instruct models on various lengths and increasing complexity of tasks. Notably, Qwen2 relies on position extrapolation, while other open-models are trained at or greater than 128k context window.

Fu et al., 2024; AI et al., 2024), explore position extrapolation techniques (Peng et al., 2024; Chen et al., 2023; Ding et al., 2024), and experiment with efficient architectures (Gu & Dao, 2023; Dao & Gu, 2024; Bertsch et al., 2023; Beltagy et al., 2020; Yen et al., 2024; Lieber et al., 2024, *inter alia*).

Synthetic tasks. Synthetic tasks are often used to evaluate LCLMs since they can be procedurally generated, thereby enabling arbitrarily long input lengths and controlled "needle" placement (Tay et al., 2021; Liu et al., 2023). In particular, Needle-in-a-Haystack (NIAH; Kamradt, 2024) inserts a "needle" at specific depths of a long essay (i.e., the haystack) and asks the model to recall the fact. Recent works have expanded upon it and designed new procedures to test different aspects of LCLMs (Hsieh et al., 2024; Li et al., 2024b; Levy et al., 2024; Arora et al., 2023; Laban et al., 2024; Goldman et al., 2024). However, they do not study how results on synthetic tasks transfer to real applications. In contrast, we evaluate both synthetic and downstream tasks and investigate how they correlate with each other.

Long-context benchmarks. As discussed in the main paper, existing benchmarks either are limit to relatively short context lengths (Shaham et al., 2022; 2023; Li et al., 2024a; An et al., 2024; Bai et al., 2024; Dong et al., 2024; Kwan et al., 2024) or lack rigorous evaluation methods (Zhang et al., 2024b; Yuan et al., 2024). Many works instead focus on specific domains, such as question answering (Wang et al., 2024b; Karpinska et al., 2024; Wang et al., 2024a;c), in-context learning (Li et al., 2024c; Bertsch et al., 2024; Xu et al., 2024; Anil et al., 2024; Agarwal et al., 2024), summarization (Chang et al., 2024; Kim et al., 2024; Shen et al., 2022), or RAG (Lee et al., 2024). In this work, we construct a comprehensive benchmark that tests across diverse downstream tasks at long input lengths and also present a unified comparison and analysis across 59 LCLMs.

5 Conclusion

In this work, we first identify the shortcomings of long-context evaluation settings and existing benchmarks—over-reliance of synthetic tasks, low coverage of realistic applications, and unreliable metrics among others. We seek to address these issues by constructing HELMET, an application-centric benchmark with diverse domains and reliable evaluation settings. We then present a comprehensive evaluation of 59 frontier LCLMs across multiple dimensions, including different tasks, input lengths, and model types. Our analysis shows that synthetic tasks are poor predictors of downstream performance and different categories exhibit distinct capabilities and trends. Thus, it is critical to evaluate models on a diverse set of real-world tasks. Furthermore, open-source models still lag behind closed-source models on complex tasks at long lengths. Finally, we hope that our benchmark and subsequent comprehensive evaluation can serve as a valuable resource for future research in long-context language modeling.

Reproducibility Statement

We have publicly released all of our code and data to ensure reproducibility. Experimental settings are outlined in the main text (§3) and the appendix (§D), and we will provide additional details and instructions in the code repository. Furthermore, we plan on releasing the model generated outputs and statistics to enable further analysis and comparison.

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A COMPARISON WITH OTHER BENCHMARKS

Due to the lack of large-scale human studies on long-context language models, it may be challenging to discern the true rankings of LCLMs. Thus, we rely on previous works and intuition to guide our expectations. Specifically, the Gemini 1.5 report observes a trend of large models performing better at long contexts—the larger models beating the smaller models both qualitatively and quantatively across the Gemini, GPT, and Claude model families (Section 5.2, Tables 4 and 5 Team et al., 2024b). Although the evaluation suite is not publicly available, the results align with our intuition, which is commonly observed in other uses of language models. Since we do not have access to a ground truth ranking of models and acquiring one via human evaluation is nearly impossible due to the associated costs, relying on such a commonly-accepted intuition is reasonable. In this section, we further examine the improvement of HELMET over existing benchmarks through direct comparison of model rankings and performance as well as careful ablation studies.

A.1 RESULTS

We build upon previous datasets and update evaluation settings to reflect the capabilities of the model better. Specifically, we evaluate models on ∞BENCH, another benchmark that evaluates long-context at 128k tokens. We show the results reproduced from the original authors' code in Table 6. The numbers for Figure 1 are shown in Table 5.

We take a closer look at a set of open-sourced models' ranking and performance on HELMET and ∞BENCH in Table 9. In addition to the previously noted performance discrepancy between Llama-3.1-8B-Instruct and Llama-3.1-70B-Instruct, we observe that all Llama-3.2 models degenerate in performance on ∞BENCH at input length 128k. However, on HELMET, we find that the Llama-3.2 models, especially Llama-3.2-3B-Instruct, rank well against other open-source models. Upon qualitative examination, we find that the Llama 3.2 models are able to produce coherent and useful generation at long contexts with better prompting strategies from HELMET, such as adding in-context learning examples.

We further ablate the impact of few-shot demonstrations on model performance in Table 8, and find that the 2-shot demonstrations significantly improve the performance of base models, which is a more realistic evaluation of how the models are used in practice. The improvement in instructions and prompting strategies are illustrated in 7, where we show that the smaller Llama-3.2 models are able to compete against some of the larger models when the instructions are improved. Thus, HELMET provides a better and more realistic reflection of how these models would be used in practice over previous benchmarks.

Table 5: Results with 128k input length across different benchmarks.

Model	Claimed Length	NIAH	RULER	∞BENCH	HELMET
GPT-4o-mini	128000	**100.0**	80.8	51.9	54.1
GPT-4o-08	128000	**100.0**	**93.3**	57.1	**63.8**
Gemini-1.5-Flash	1048576	**100.0**	86.6	50.8	50.7
Gemini-1.5-Pro	2097152	45.3	65.3	**60.3**	62.7
Llama-3.1-8B-Inst	131072	**100.0**	81.3	44.1	47.0
Llama-3.1-70B-Inst	131072	**100.0**	75.8	39.7	49.3

A.2 DISCUSSIONS

Many existing long-context language modeling benchmarks are studied in isolated settings, such as synthetic tasks (Hsieh et al., 2024; Li et al., 2024b; Levy et al., 2024; Laban et al., 2024), in-context learning (Anil et al., 2024; Bertsch et al., 2024; Li et al., 2024c; Agarwal et al., 2024), summarization (Chang et al., 2024; Kim et al., 2024), and retrieval-augmented settings (Lee et al., 2024). However, these works lack a unified evaluation across diverse downstream tasks.

There are also benchmarks that sought to unify different datasets, such as ∞BENCH (Zhang et al., 2024b), LongBench (Bai et al., 2024), L-Eval (An et al., 2024), LV-Eval (Yuan et al., 2024), and

Table 6: Results on ∞BENCH(Zhang et al., 2024b). We report numbers from running the original authors repo: https://github.com/OpenBMB/InfiniteBench. The original code did not support evaluation of the Gemini and Llama 3 models at the time of access, so we evaluate them by following the script and template for GPT-4 and open-source models, respectively. We exclude coding tasks from the evaluation suite since it is out of the scope for general long-context language modeling tasks.

Model	MC	QA	Sum	Diag	Calc	Find	Number	PassKey	KV	Avg.
GPT4	75.9	23.7	10.7	18.5	0.0	47.1	100.0	100.0	58.8	44.9
GPT-4o-05	88.2	37.9	23.7	28.5	0.0	58.6	100.0	100.0	94.2	55.4
GPT-4o-08	86.5	26.0	21.5	51.0	0.0	58.9	100.0	100.0	99.8	57.1
GPT-4o-mini	78.2	19.1	24.8	21.5	0.0	69.7	100.0	100.0	80.4	51.9
Gemini-1.5-Flash	76.0	42.1	30.0	55.8	0.0	47.4	100.0	100.0	31.4	50.8
Gemini-1.5-Pro	77.5	27.7	29.0	97.5	0.0	58.0	100.0	100.0	70.4	60.3
Llama-3.1-8B	56.8	8.8	14.3	0.5	0.0	22.0	99.7	100.0	18.8	33.0
Llama-3.1-8B-Inst	67.2	15.5	26.7	23.0	0.0	33.1	99.5	100.0	55.0	44.1
Llama-3.1-70B	66.4	9.2	17.5	8.5	0.0	32.3	100.0	100.0	13.4	35.1
Llama-3.1-70B-Inst	75.5	23.3	31.3	18.0	0.0	43.1	99.7	100.0	2.6	39.7
Llama-3.2-1B	2.2	1.4	8.6	4.5	0.0	0.0	1.5	0.0	0.0	2.0
Llama-3.2-1B-Instruct	3.5	1.4	12.5	5.5	0.0	0.0	0.0	0.0	0.0	2.4
Llama-3.2-3B	1.3	1.2	7.6	4.5	0.0	0.0	1.7	0.0	0.0	1.9
Llama-3.2-3B-Instruct	2.2	1.6	13.3	4.5	0.0	0.0	1.7	1.7	0.0	2.8

Table 7: We compare the results on ∞BENCH multiple-choice (MC) and question answering (QA) tasks between the original authors and HELMET. In our implementation, we leverage refined prompts and carefully crafted parsing scripts to ensure robust and fair evaluation. For example, we find that Llama-3.2 models are actually much better long-context language models than ∞BENCH would suggest.

		Original		**HELMET**	
Model	**Claimed Length**	**MC**	**QA**	**MC**	**QA**
GPT-4o-mini	128000	88.2	37.9	71.0	44.5
GPT-4o-05	128000	86.5	26.0	76.0	53.0
GPT-4o-08	128000	78.2	19.1	73.0	47.9
Gemini-1.5-Flash	1048576	76.0	42.1	79.1	51.7
Gemini-1.5-Pro	2097152	77.5	27.7	83.3	50.9
Llama-3.1-8B	131072	56.8	8.8	54.0	38.8
Llama-3.1-8B-Inst	131072	67.2	15.5	49.0	40.3
Llama-3.2-1B	131072	2.2	1.4	21.0	17.6
Llama-3.2-1B-Inst	131072	3.5	1.4	16.0	13.3
Llama-3.2-3B	131072	1.3	1.2	36.0	31.0
Llama-3.2-3B-Inst	131072	2.2	1.6	42.0	20.6

ZeroSCROLLS (Shaham et al., 2023). Many of these benchmarks are still limited by the context length, evaluation metrics, or both. Most similar to our work, ∞BENCHZhang et al. (2024b) also evaluates models at context lengths at 128k tokens. However, their evaluation settings are limited to a few domains—synthetic, QA, and summarization. Although they also evaluate coding tasks, the domain is limited to code-specialized models outside of the realm of general-purposed language models. Furthermore, their summarization evaluations lack robust evaluation and still rely on ROUGE scores. Similarly, LV-Eval (Yuan et al., 2024) evaluates long-context models across different lengths but is limited to the QA tasks. Furthermore, we are the first to evaluate existing LCLMs comprehensively—we evaluate over 50 models of different sizes and architectures, which enables previously unavailable insights into the correlation across tasks and the landscape of current models.

To summarize, HELMET improves upon existing benchmarks by providing a comprehensive evaluation across diverse tasks and carefully designed evalution metrics and prompting strategies. Consequently, HELMET provides a more accurate reflection of the models' capabilities in practice.

Table 8: We evaluate the performance of models on a subset of HELMET tasks with 0-shot and 2-shot demonstrations at 128k input length to understand the impact of ICL on model performance, averaged across three random seeds. The standard deviation across three runs are shown in the subscript. We observe that the performance is generally higher for 2-shot demonstrations compared to 0-shot demonstrations. Crucially, the 2-shot examples enable base models to achieve higher results that reflect the model's long-context capabilities in realistic settings, such as for MSMARCO and JSON KV. ♭denotes base models.

	JSON KV		NQ		MSMARCO		∞BENCH MC		∞BENCH QA	
Model	**0 shot**	**2 shot**	**0 shot**	**2 shot**	**0 shot**	**2 shot**	**0 shot**	**2 shot**	**0 shot**	**2 shot**
GPT-4o-mini	$92.3_{5.5}$	$93.7_{2.1}$	$57.8_{1.1}$	$60.4_{2.6}$	$24.8_{0.7}$	$31.4_{1.1}$	$72.0_{2.6}$	$69.3_{4.7}$	$28.8_{1.9}$	$47.1_{4.4}$
GPT-4o-05	$99.3_{0.6}$	$36.7_{7.1}$	$59.4_{4.0}$	$63.0_{2.1}$	$42.7_{0.9}$	$46.8_{1.3}$	$73.7_{0.6}$	$76.3_{0.6}$	$49.1_{1.9}$	$51.3_{3.4}$
GPT-4o-08	$100.0_{0.0}$	$100.0_{0.0}$	$58.5_{2.0}$	$61.9_{4.5}$	$46.6_{0.3}$	$48.7_{1.0}$	$75.3_{2.5}$	$72.7_{0.6}$	$29.8_{0.9}$	$48.6_{1.5}$
Gemini-1.5-Flash	$98.3_{0.6}$	$99.0_{1.0}$	$53.7_{5.9}$	$51.5_{4.5}$	$44.9_{3.0}$	$49.9_{0.9}$	$73.9_{2.3}$	$77.1_{3.2}$	$48.2_{4.7}$	$49.9_{2.6}$
Gemini-1.5-Pro	$97.7_{0.6}$	$93.7_{2.3}$	$62.2_{2.6}$	$59.2_{2.7}$	$57.1_{0.9}$	$58.4_{0.3}$	$83.6_{2.8}$	$83.3_{0.7}$	$46.4_{1.8}$	$47.2_{3.2}$
Llama-3.1-8B♭	$77.3_{2.1}$	$98.0_{1.0}$	$45.7_{2.1}$	$44.9_{3.9}$	$0.1_{0.0}$	$7.5_{0.5}$	$55.3_{5.5}$	$53.3_{8.0}$	$36.1_{2.0}$	$36.6_{2.1}$
Llama-3.1-8B-Inst	$96.0_{1.0}$	$95.7_{0.6}$	$48.4_{1.3}$	$48.9_{2.6}$	$5.4_{0.0}$	$13.8_{1.1}$	$49.7_{2.1}$	$52.0_{2.6}$	$29.1_{2.0}$	$37.9_{2.6}$
Llama-3.2-1B♭	$34.0_{3.5}$	$34.3_{2.1}$	$25.1_{0.7}$	$23.2_{2.8}$	$0.3_{0.0}$	$4.8_{0.5}$	$23.0_{2.6}$	$22.7_{1.5}$	$18.9_{2.5}$	$18.9_{3.3}$
Llama-3.2-1B-Inst	$6.3_{1.5}$	$9.3_{3.2}$	$23.3_{4.4}$	$22.9_{1.4}$	$0.0_{0.0}$	$0.5_{0.3}$	$16.0_{2.6}$	$16.3_{2.5}$	$12.6_{0.4}$	$12.7_{0.5}$
Llama-3.2-3B♭	$30.3_{2.1}$	$54.0_{8.9}$	$40.2_{2.0}$	$42.3_{4.1}$	$0.1_{0.0}$	$6.0_{1.3}$	$43.0_{1.0}$	$40.7_{7.2}$	$31.3_{1.1}$	$31.6_{2.2}$
Llama-3.2-3B-Inst	$31.3_{2.3}$	$36.7_{2.5}$	$44.2_{2.5}$	$42.8_{3.8}$	$0.2_{0.0}$	$0.9_{0.2}$	$36.0_{2.0}$	$40.0_{3.5}$	$17.8_{1.2}$	$19.7_{0.8}$

Table 9: Comparison of model rankings on HELMET and ∞BENCH.

Model	**HELMET**	**Model**	**InfBench**
Llama-3.1-70B-Inst	49.3	Llama-3.1-8B-Inst	46.7
Llama-3.1-8B-Inst	47.0	Llama-3.1-70B-Inst	43.7
Llama-3.1-70B	41.3	Yi-34B-200k	43.1
Yi-34B-200k	38.3	Llama-3.1-70B	38.6
Llama-3.2-3B-Inst	36.9	Yi-9B-200k	37.6
Llama-3.1-8B	35.6	Llama-3.1-8B	35.7
Yi-9B-200k	33.0	Yi-6B-200k	32.0
Llama-3.2-3B	31.9	Llama-3.2-3B-Inst	2.8
Yi-6B-200k	26.3	Llama-3.2-1B-Inst	2.6
Llama-3.2-1B-Inst	24.6	Llama-3.2-1B	2.0
Llama-3.2-1B	21.2	Llama-3.2-3B	1.8

B DATASETS

B.1 RETRIEVAL-AUGMENTED GENERATION

Natural Questions (NQ; Kwiatkowski et al., 2019) is a large-scale dataset for open-domain questions answering with real user queries. TriviaQA (TQA; Joshi et al., 2017) is a dataset of trivia questions with answers. HotpotQA (Yang et al., 2018) is a dataset of questions that require reasoning over multiple passages. We obtain these datasets from KILT (Petroni et al., 2021), where each query is annotated with a set of gold passages that the answer is located in.

PopQA (Mallen et al., 2023) is a dataset with questions about long-tail entities. We filter the original dataset to only include the subject entities with a popularity of less than 1000 to ensure that models are unlikely to have memorized the fact during training. We do not have access to the gold passages for PopQA, so we use the ground truth answer to classify each retrieved passage into positive or negative by simply checking if the gold answer is in the passage.

It is important to note that we fill the context with *hard negative passages* that are retrieved from the same corpus as the positive passages with a real retriever, making it much harder for the model to identify the answer than randomly sampled passages filled the context. We believe that this is a more realistic setting for retrieval-augmented generation tasks, as models are often required to distinguish between relevant and irrelevant information in real-world applications.

B.2 GENERATION WITH CITATIONS

Generation with citations is an important and realistic task for making language models more trustworthy and verifiable (Bohnet et al., 2022; Gao et al., 2023; Asai et al., 2024b). Thus, we use ALCE to evaluate the models' ability to generate text with correct citations. Following the original work, we use Wikipedia as the retrieval corpus and GTR (Ni et al., 2022) as the retriever. We do not evaluate the fluency of the generated text using MAUVE, as we find that models are often able to generate fluent text, and when it does not, the other scores are also near zero. Thus, we only evaluate correctness and citation quality and report their average.

B.3 PASSAGE RE-RANKING

We test the models' ability to process and re-rank passages in the context (Sun et al., 2023) with the MS MARCO passage ranking dataset (Bajaj et al., 2018). We use the datasets with annotations from the TREC Passage Re-ranking challenge (Craswell et al., 2020). Each instance in the dataset is consisted of a query and a list of passages with relevance scores. The queries are sourced from Bing user queries and the passages are retrieved by BM25 from Internet web pages. The relevance labels are either perfect, highly relevant, or not relevant. We first calculate the number of passages k from the input L. We balance the number of labels between the passages and shuffle them to prevent positional biases. We then shuffle the k passages into three different permutations to construct the inputs. The performance is evaluated with NDCG@10. Although we may evaluate NDCG@k, we find it expensive to generate hundreds of passage IDs during inference, and thus we only evaluate NDCG@10.

B.4 IN-CONTEXT LEARNING

For in-context learning, we use a label mapping to force the model to leverage the in-context learning examples as opposed to relying on their learned priors for classification tasks. To this end, each label is first randomly mapped into an integer $l \in \{0, 1, \ldots, n-1\}$ where n is the number of unique labels in the dataset, following previous works (Pan et al., 2023). Then, we simply replace all label texts with their corresponding integers in the dataset. Furthermore, we put examples into round of demonstrations similar to (Li et al., 2024c), where each round contains exactly one example from each label and the order is shuffled. We then construct the input by concatenating rounds of demonstrations together until we meet a certain input length L. We evaluate 500 samples for each ICL dataset in contrast to the 100 samples in other categories.

B.5 SYNTHETIC TASKS

For the RULER tasks, we generate the data using the original authors' scripts (Hsieh et al., 2024). To standardize the amount of texts input to all models, we use the Llama-2 tokenizer (Touvron et al., 2023) when generating the data. The RULER suite of tasks are consisted of these tasks:

- Three variants of NIAH Single: NIAH (variant 2, which is the most similar to the original NIAH), NIAH Single Repeat (variant 1, where the context is repeated phrase instead of Paul Graham essays), and NIAH Single UUID (variant 3, same as variant 2 but with UUIDs as the value to retrieve)
- Three variants of NIAH MultiKey (MK): NIAH MK Essay (variant 1, where there are 3 irrelevant keys and 1 gold key to retrieve and the context is Paul Graham Essays), NIAH MK Needle (variant 2, where the context are all needles), and NIAH MK UUID (variant 3, same as variant 2 but with UUIDs as the value to retrieve for every needle)
- NIAH MultiValue (MV): There is one key but is associated with four different numbers that the model needs to retrieve. The context is irrelevant essays.
- NIAH MultiQuery (MQ): There are four keys, each of which is associated with a different value, and the model needs to retrieve the correct value for each key. The context is irrelevant essays.
- Variable Tracking (VT): the model needs to track the value of a variable through a series of operations.

- Common word extraction (CWE) and frequent word extraction (FWE): The model needs to extract the words that occurs the most often.
- Question answering: SQuAD (variant 1; Rajpurkar et al., 2016) and HotpotQA (variant 2; Yang et al., 2018). The key difference between our RAG tasks and these QA datasets is that our context is filled with *retrieved* passages from the corpus instead of a random sample of the corpus. Thus, this makes the task more realistic and challenging.

For more details, please refer to the original paper (Hsieh et al., 2024).

For the JSON KV tasks, we randomly generate a JSON dictionary where each key and value is a randomly generated UUID. Then, we query the model with the key at six evenly spaced depths in the context, asking it to retrieve the corresponding value.

B.6 MODEL-BASED EVALUATION

Automatic evaluation metrics, such as ROUGE, are known to be unreliable and uncorrelated with human judgments (Goyal et al., 2023; Chang et al., 2024). However, existing long-context benchmarks still largely rely on these metrics (Bai et al., 2024; Zhang et al., 2024b). In this work, we seek to more reliably evaluate language models at long-contexts by leveraging LLMs as judges, inspired by previous works (Zheng et al., 2023). For all model-based evaluations, we use `GPT-4o-2024-05-13` as the judge.

Long document question answering. For NarrativeQA, we found that the models can often output answers that are correct but have little surface form or lexical overlaps with the ground truth answers in preliminary experiments, resulting in lower-than-expected performance. This is often due to the long lengths of the ground truth answers, which gives more possibilities of how to write it than a simple named entity that is often the case of other QA datasets.

Therefore, we employ an LLM to judge if the model output is fluent and semantically similar to the ground truth. Given the question, the ground truth answer, and the model-generated output, we ask the LLM to judge if (1) the model output is fluent and (2) the generated output is correct and relevant to the question with the ground truth as a reference. The detailed prompts, precise definitions, and instructions are found in Table 10.

In Table 14, we also find that model evaluation can be useful in catching extremely cases. For example, Claude scores low in terms of F1 due to its tendency to output extra, assistant-like text, which is penalized by the n-gram overlap metric, and appears to be worse than the much smaller Llama-3.2-3B-Inst model. However, the model-based evaluation is able to catch this issue, and Claude scores higher than Llama-3.2-3B-Inst, which users might have expected given the model sizes.

Summarization. At a high level, we ask the model to check for three properties: fluency, precision, and recall. Fluency can take on a value of either 0 (incoherent, incomplete, and/or repetitive) or 1 (fluent and coherent). Precision is the percentage of model-generated sentences that are supported by the gold summary (we use the long summary from Multi-LexSum here). Recall is the percentage of the key points that are supported by the model-generated output. We calculate the F1 score from precision and recall and multiply it with the fluency score for the final score.

We first ask the model to generate a list of key points or atomic claims from the gold summary, following previous works that show that LLMs can accurately decompose long texts (Kamoi et al., 2023; Gao et al., 2023). We manually checked 105 claims originating from 25 Multi-LexSum summaries and found that the claims were all factually correct. Although we found one out of 25 instances where the model missed a possible key point in the given summary, we found that GPT-4o is almost always reliable for the decomposition task. For Multi-LexSum, we use the short summary to obtain the key point as the annotation contains both a long and a short summary. These key points are then saved for Multi-LexSum and ∞BENCH Sum.

We show the detailed prompts for the summarization tasks in Table 11, 12, and 13, which are modeled after previous works (Kamoi et al., 2023; Chang et al., 2024; Kim et al., 2024). These previous works have shown that LLMs can effectively judge model outputs (Zheng et al., 2023), but we conduct human analysis to further verify the evaluation metric.

From qualitative analysis, we found that the model is consistently able to distinguish between fluent and non-fluent outputs, where we agree with the model judgments 100% of the time for randomly sampled Multi-LexSum and ∞BENCH Sum outputs. We then check if the GPT-4o judgments for precision and recall agree with human judgments. To this end, we sample 10 generated summaries for Multi-LexSum and ∞BENCH each (from Gemini-1.5-Pro and Llama-3.1-70B-Inst) and check five key point evaluations for each summary. We follow a similar procedure where we check if the model output supports the key point. We observed Cohen's $\kappa = 0.76$ for ∞BENCH Sum and $\kappa = 0.72$ for Multi-LexSum, suggesting substantial agreement. For precision, we conduct a similar human evaluation, and found a $\kappa = 0.91$ for ∞BENCH Sum and $\kappa = 0.83$ for Multi-LexSum, suggesting near-perfect agreement.

Inspecting the disagreements, we find that that most of them arise from the partially supported cases. For instance, the key point may include specific details, such as the names of government departments or Court Justices' names, that are not explicitly mentioned in the generated summary, and the model judge is typically more lenient about the exclusion of these small details while humans are more strict. However, this is also subjective to the preference of the human.

Qualitatively, We find that model-based evaluation can catch cases where the model is overly repetitive and scores high ROUGE-L score as a result, such as Mistral-7B-Inst-v0.3 on ∞BENCH Sum. For instance, the Mistral model may generate an output consisted of the sentence "The author's object is to show that the study of grammar is necessary part of education" repeated for hundreds of times. This summary would receive an ROUGE-L score of 12.3 while the GPT-4o judge would penalize the model for being overly repetitive and incoherent and assign the output a final score of 0.0. Thus, our GPT-4o judge penalizes the model for being overly repetitive, and the final metric reflects this issue.

C MODELS

Please see Table 15 for the detailed information of the models used in this work.

D EXPERIMENTAL SETUP

As previously described, we are able to evaluate models across different input lengths. Thus, we evaluate all models at $L \in \{8192, 16384, 32768, 65536, 131072\}$. For the proprietary models, GPT, Gemini, and Claude, we rely on the provider's API. For all open-source models, we evaluate on a H100 GPUs with 80GB of memory. We use the HuggingFace framework (Wolf et al., 2020) to load and generate model outputs. We apply instruction-tuned models' chat template whenever applicable. We use FlashAttention2 (Dao, 2023) and BF16 for faster inference. Our compute is limited to 8 H100 GPUs; thus, we are not able to run some of the larger models, such as Command-R or Jamba-1.5-Large, at 128k tokens. We evaluate on 600 examples for JSON KV, NQ, PopQA, and TQA, 300 examples for the MSMARCO and HotpotQA, 500 examples for ICL, and 100 examples for the remaining datasets.

E ADDITIONAL RESULTS

E.1 CORRELATION BETWEEN SYNTHETIC AND DOWNSTREAM TASKS

We show the correlation between all synthetic and RAG datasets with other downstream tasks in Figure 8. We see that the synthetic tasks are generally less correlated with the downstream tasks, whereas the RAG datasets are more correlated with the downstream tasks. Furthermore, there appears to be a pattern between the complexity of the synthetic task and its correlation with other tasks—the more complex the task, the more correlated it is with the downstream tasks. Furthermore, noisier variants tend to be more reflective of real-world applications, as seen in the difference between RULER MK Essay, where the context is irrelevant essays, and RULER MK Needle, where the context is other distracting needles. Upon closer inspection, we note that Needle MK Needle/UUID, JSON KV, and NIAH MV generally have relatively high correlation with other realistic datasets, and are able to test the recall abilities of the model. Thus, we select these four datasets as part of the HELMET synthetic recall subset. We validate this selection by checking the correlation

Table 10: Model-based evaluation prompt for long-document question answering.

```
Please act as an impartial judge and evaluate the quality of the
provided answer which attempts to answer the provided question based on
a provided context.  Although you are not given the context, you will be
given a set of correct answers that achieves full scores on all metrics,
and you need to assess the provided answers using the correct answers.

Below is your grading rubric:


Fluency:  - Score 0 (incoherent, repetitive, or incomplete):  Incoherent
sentences, repetitive sentences (even if not by exact words), incomplete
answers, or gibberish.  Note that even if the answer is coherent, if it
is repetitive or incomplete, it should be given a score of 0.  - Score 1
(coherent, non-repetitive answer):  Coherent, non-repetitive, fluent,
grammatically correct answers.


Correctness:  - Score 0 (Incorrect):  The answer does not agree with the
provided correct answers at all.  - Score 1 (partly correct):  Partly
agree with one of the provided correct answers (for example, the
question asks for a date and a person; the answer gets the date right
but the person wrong).  - Score 2 (correct but not fully relevant):
Fully agrees with one of the provided correct answers but mentions other
completely irrelevant information.  Note that extra details provided in
the answer, even if not mentioned in the correct answers, should NOT be
seen as irrelevant as long as they are relevant to the question to a
reasonable extend.  - Score 3 (correct and relevant):  Fully agrees with
one of the provided correct answers and only provides information
relevant to the question.  Note that if the answer is longer than the
correct answer, as long as everything in the answer is relevant to the
question, it should still be given score 3.  For example, if the correct
answer is ''the North Pole'' and the answer is ''They are headed for the
North Pole'', it should still be given a score of 3.


Now, read the following question, answer, and correct answers.  First
think step-by-step and provide your reasoning and assessment on the
answer.  Then output your score in the following json format:
{{''fluency'':  0, ''correctness'':  1}}.

Question:  {question}
Correct answers:  {correct_answers}
Answer:  {parsed_output}
```

between this set and other downstream tasks, and found that it generally has higher correlation than using synthetic datasets individually. There may be more optimal methods for selecting synthetic datasets, and we leave this as future work.

E.2 Correlation between datasets

We plot the correlation between all HELMET datasets in Figure 9. In general, the datasets in each category are strongly correlated with each other. One exception to this observation is the lack of correlation between the ALCE datasets. This suggests that writing the correct citations is a different skill from answering questions with facts. We also observe some low correlation between datasets for long-document QA and ICl, but this is likely due to the diversity within each categories.

Table 11: Model-based evaluation prompt for summarization fluency score.

```
Please act as an impartial judge and evaluate the fluency of the
provided text. The text should be coherent, non-repetitive, fluent, and
grammatically correct.


Below is your grading rubric: - Score 0 (incoherent, repetitive, or
incomplete): Incoherent sentences, repetitive sentences (even if not by
exact words), incomplete answers, or gibberish. Note that even if the
answer is coherent, if it is repetitive or incomplete, it should be
given a score of 0. - Examples: - Incomplete: ''Summary:'' -
Incoherent: ''Summary: The plaintiff the the the the able the the the
the the the the the the the able the the the the the '' - Repetitive:
''Summary: The U.S. government brought a criminal case against four
defendants. Summary: The U.S. government brought a criminal case
against four defendants. Summary: The U.S. government brought a
criminal case against four defendants. Summary: The U.S. government
brought a criminal case against four defendants.''


- Score 1 (coherent, non-repetitive answer): Coherent, non-repetitive,
fluent, grammatically correct answers. If the text is coherent,
non-repetitive, and fluent, but the last sentence is truncated, it
should still be given a score of 1. - Examples: - ''This case is about
an apprenticeship test that had a disparate impact on Black
apprenticeship applicants. The Equal Employment Opportunity Commission
(EEOC) filed this lawsuit on December 27, 2004, in U.S. District Court
for the Southern District of Ohio.'' - ''The plaintiffs sought
declaratory and injunctive relief, as well as attorneys' fees and costs,
under the Americans with Disabilities Act, the Rehabilitation Act of
1973, the Social Security Act, and the Nursing Home Reform Act. The
case was certified as a class action on behalf of all Medicaid-eligible
adults with disabilities in Cook County, Illinois, who are being, or may
in the future be, unnecessarily confined to nursing facilities and with
appropriate supports and services may be able to live in a community
setting. The defendants denied the allegations and argued that the
plaintiffs' claims were not typical of the class and that the class
definition was too broad. The case is ongoing, with discovery and
expert testimony scheduled for the fall of''

Now, read the provided text, and evaluate the fluency using the rubric.
Then output your score in the following json format: {{''fluency'':
1}}.

Text: ''{text}''
```

E.3 Positional embedding extrapolation remains a challenge

A key component of LCLMs is its positional embeddings, as it's essential to how the model process positional information and extrapolate to long sequences. Thus, we also consider models that leverages positional extrapolation during inference. Specifically, we show Llama-3-Inst with the original RoPE embedding and changing the Theta base to 8M during inference, and Qwen2-Inst with YaRN scaling. Formally, RoPE defines $\theta_d = b^{-2d/|D|}$, where θ_d is the angle at the d-th hidden state, b is a constant called the base, and $|D|$ is the size of the hidden state (Su et al., 2021). Llama-3 sets $b = 500,000$ during training, and we evaluate with both the original base and setting $b = 8,000,000$.

We find that existing positional embeddings still struggle at out-of-distribution length, with both families of models dropping sharply in performance past $L = 32768$, show in Figure 7. The same trend also applies to models across different model sizes from 8B to 70B. Finally, altering the positional embedding may lead to degradation at shorter lengths, which is evident for Llama-3-8B-Inst

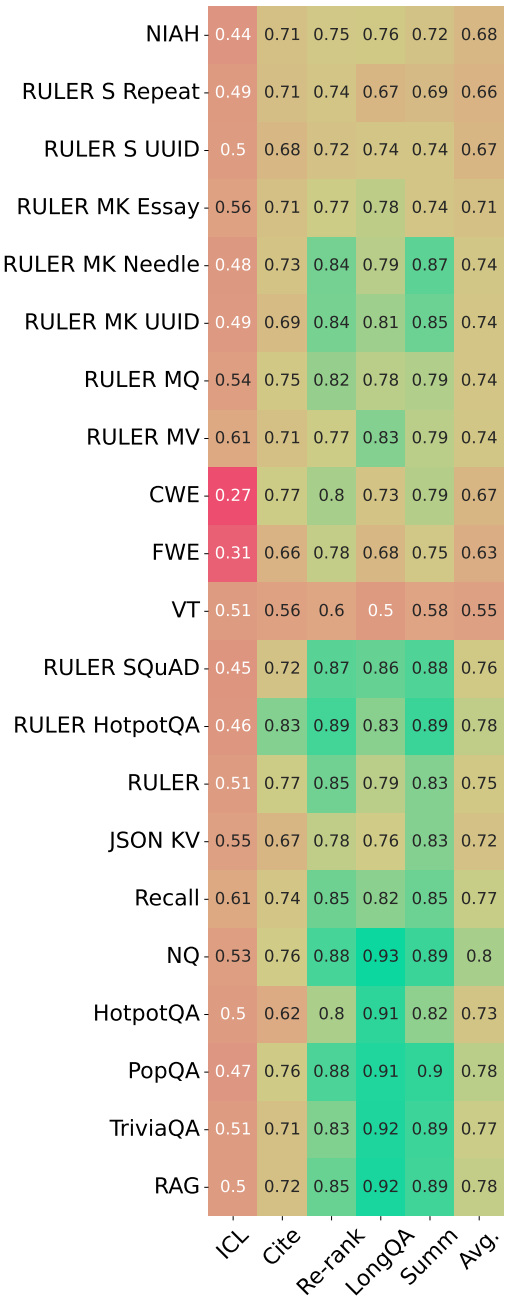


Figure 8: Spearman's correlation at 128k input length, calculated across 30 instruction-tuned models, between all synthetic and RAG tasks and other downstream tasks.

on ODQA and ICL. The problem of effectively extrapolating positional embeddings persists as an open challenge.

E.4 Presence of Lost in the Middle

Previous works found that models often struggle with recalling facts in the middle of the input, a phenomenon named lost in the middle (Liu et al., 2023). In this work, we extend the previous analysis to input length up to 128k tokens. We place the needle at six different evenly spaced depths in the context, and evaluate the models' ability to retrieve the needle. In our study, the needle may

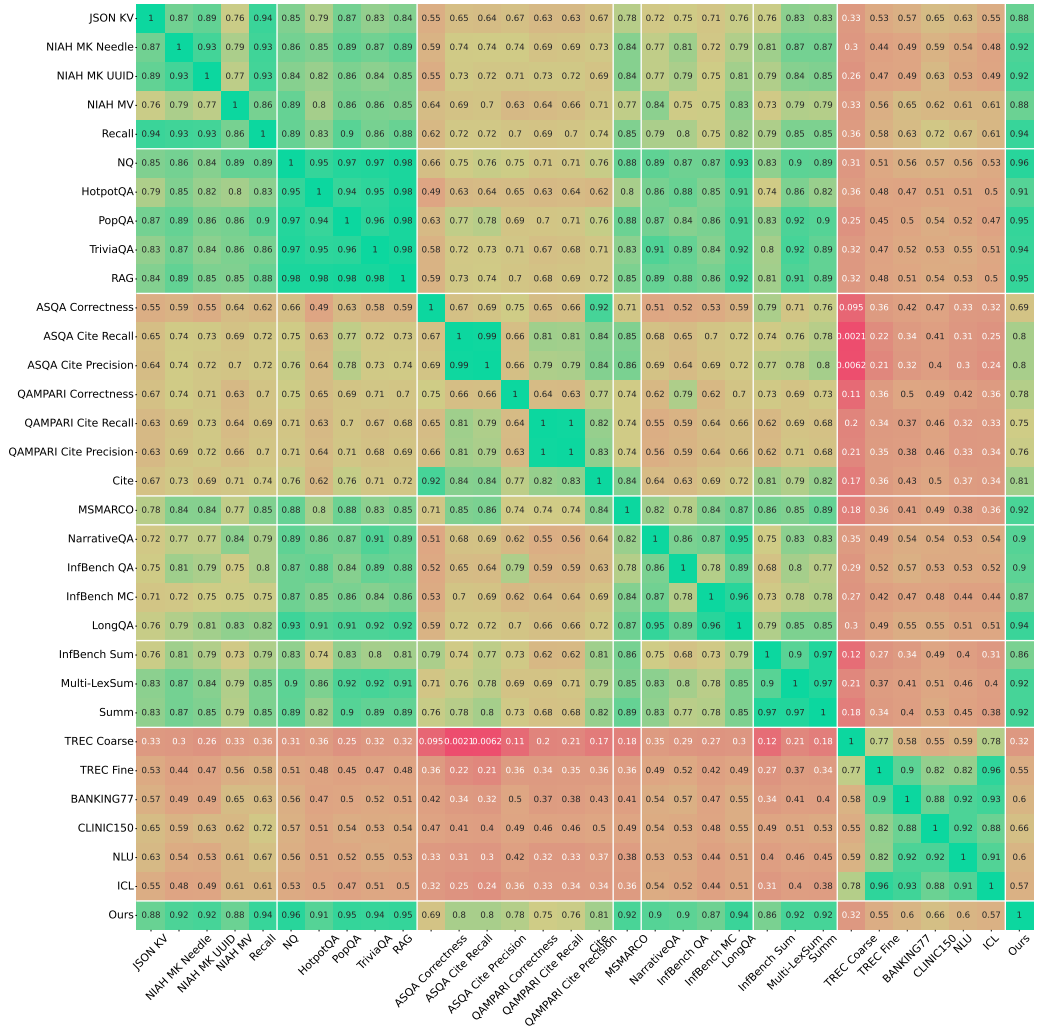


Figure 9: Spearman's correlation at 128k input length, calculated across 35 instruction-tuned models, between all HELMET datasets and category averages.

be either a key in the JSON dictionary or the answer to a question. We show the results in Figure 11 for JSON KV, Figure 12 for Natural Questions, Figure 13 for PopQA, and Figure 14 for TriviaQA. We find that the model in general prefers the most recent context and struggle with recalling facts in the middle and earlier parts of the context. Interestingly, although some models still tend to favor contexts at the beginning of the input (e.g., Llama-3 and Llama-3.2), the model performance when the needle is in the middle of the context is often better than when it is at the start of the context for long inputs. We leave further investigation for future work.

E.5 Comparison between base and instruction-tuned models

Previous benchmarks largely focus on evaluating instruction-tuned models (Shaham et al., 2023; Zhang et al., 2024b). As a result, developers of long-context base models often turn to perplexity and synthetic tasks to evaluate their models (Fu et al., 2024; Yen et al., 2024; AI et al., 2024). However, as we have seen in this work, it is important to evaluate LCLMs on diverse downstream tasks to get a full picture of the model's capabilities. Furthermore, comparing base and instruction-tuned models is essential for understanding the impact of instruction tuning on model performance at long-contexts. Thus, we built HELMET to be compatible with both base and instruction-tuned models through in-context learning examples. Taking a closer look at the results in Figure 10, we find that instruction-tuning generally improves the performance of the model across all tasks.

Instruction-tuning at long contexts may yield more benefits than simply scaling up the model sizes; for example, Llama-3.1-8B-Inst outperforms Llama-3.1-70B on most tasks.

E.6 Performance of Claude

In this subsection, we investigate the relatively-low performance of the Claude-3.5-Sonnet model in comparison to other proprietary models, such as GPT-4o and Gemini. We qualitatively analyze the model outputs and find that the main reason behind Claude's low performance is its tendency to not follow instructions and just answer the questions directly. For example, it often does not output the citation markers for Cite (Table 17), does not output the passage re-rankings task (Table 18), and does not output the classification label for ICL (Table 18). Sometimes it even refuses to answer the question due to copyright concerns (Table 17). Thus, it has a lower score on these tasks. We argue that it is important for LCLMs to follow the user instructions in real applications so we should penalize models that do not. Sometimes, the output may be truncated due to the restriction on the maximum number of generated tokens (Table 16). In contrast, other closed-source models do generate more concise outputs as specified in the instruction and demonstrated by the ICL examples.

E.7 Full results

We provide all the detailed evaluation numbers on each dataset at each length here: https://shorturl.at/5wjVl.

Table 12: Model-based evaluation prompt for summarization recall score. here we show the demonstrations for Multi-LexSum.

```
Please act as an impartial judge and evaluate the quality of the
provided summary of a civil lawsuit. The summary is based on a set of
legal documents, and it should contain a short description of the
background, the parties involved, and the outcomes of the case. The
text should contain all the major points in the expert-written summary,
which are given to you.
Below is your grading rubric: Recall: - Evaluate the provided summary
by deciding if each of the key points is present in the provided
summary. A key point is considered present if its factual information
is well-supported by the provided summary. - Score: the number of key
points present in the provided summary. - Examples: use the following
examples to guide your evaluation.
Example 1:
Key points: 1. The case challenged curfews in Los Angeles and San
Bernardino, California. 2. The curfews were issued in response to the
nationwide protests following the police killing of George Floyd in
Minneapolis. 3. The complaint argued that the curfews violated free
speech, free assembly, free movement, and Due Process. 4. The
complaint also argued that the San Bernardino curfew violated the
Establishment Clause. 5. The complaint sought injunctive and
declaratory relief. 6. The plaintiffs voluntarily dismissed the case
on July 7, 2020. 7. The dismissal occurred because the city had
rescinded the curfews and not attempted to reinstate them.
Summary: ''In June 2020, Black Lives Matter - Los Angeles and several
individuals filed a lawsuit in the U.S. District Court for the Central
District of California against Los Angeles Mayor Eric Garcetti, other
city officials, and the City of San Bernardino, challenging the
constitutionality of curfew orders imposed during protests against
police violence. The plaintiffs, represented by the ACLU of Southern
California, argued that the curfews violated their First Amendment
rights to free speech and assembly, as well as their freedom of
movement, by suppressing political protests and other activities. The
lawsuit also claimed that the curfews were not narrowly tailored to
address any emergency and lacked sufficient notice. However, the
plaintiffs voluntarily dismissed the case in July 2020 after the
defendants lifted the curfew orders and did not reinstate them in the
following weeks.''
Reasoning: The summary states that the plaintiffs challenged the
constitutionality of curfew orders against Los Angeles and San
Bernadino, so key point 1 is present. The summary does not mention that
the curfew orders were issued in response to the nationwide protest that
resulted from the police killing of George Floyd in Minneapolis, so key
point 2 is missing. The summary does mention that the complaint argued
that the curfews violated the First Amendment rights to free speech and
assembly, so key point 3 is present. The summary does not mention that
the complaint argued that the San Bernardino curfew violated the
Establishment Clause, so key point 4 is missing. The summary does not
mention that the complaint sought injunctive and declaratory relief, so
key point 5 is missing. The summary mentions that the plaintiffs
voluntarily dismissed the case in July 2020 after the defendants lifted
the curfew orders and did not reinstate them in the following weeks, so
key point 6 and 7 are present. Finally, key points 1, 3, 6, and 7 are
present in the summary, so the recall score is 4.
Output: {{''recall'': 4}}
Example 2: [omitted for brevity]
Now, read the provided summary and key points, and evaluate the summary
using the rubric. First, think step-by-step and provide your reasoning
and assessment on the answer. Then output your score in the following
json format: {{''recall'': 2}}.
Key points: {keypoints}
Summary: ''{summary}''
```

Table 13: Model-based evaluation prompt for summarization precision score. Here we show the demonstrations for Multi-LexSum.

```
Please act as an impartial judge and evaluate the quality of the
provided summary of a civil lawsuit. The summary is based on a set of
legal documents, and it should contain a short description of the
background, the parties involved, and the outcomes of the case.
Below is your grading rubric: Precision: - Evaluate the provided
summary by deciding if each sentence in the provided summary is
supported by the information provided in the expert summary. A sentence
is considered supported if its major facts align with the information in
the expert summary. A sentence is still considered supported even if
some of its minor details, such as dates, entity names, or the names of
laws and previous court cases, are not explicitly mentioned in the
expert summary. A sentence is not supported if its major facts are not
mentioned or contradicted in the expert summary. - Score: the number
of sentences in the provided summary that are supported by the expert
summary. - Examples: use the following examples to guide your
evaluation.
Example 1:
Expert summary: ''This lawsuit, brought in the the U.S. District Court
for the Central District of California, was filed on June 3, 2020. The
plaintiffs were represented by attorneys from the ACLU of Southern
California. This lawsuit followed nation-wide protests that occurred in
response to the killing of George Floyd by a police officer in
Minneapolis. While most protests were peaceful, some ended in violence,
property destruction, rioting, and looting. Many cities, including Los
Angeles and San Bernardino, issued curfews in an attempt to quell these
riots. [omitted for brevity]''
Provided summary: ''In June 2020, Black Lives Matter - Los Angeles and
several individuals filed a lawsuit in the U.S. District Court for the
Central District of California against Los Angeles Mayor Eric Garcetti,
other city officials, and the City of San Bernardino, challenging the
constitutionality of curfew orders imposed during protests against
police violence. The plaintiffs, represented by the ACLU of Southern
California, argued that the curfews violated their First Amendment
rights to free speech and assembly, as well as their freedom of
movement, by suppressing political protests and other activities. The
lawsuit also claimed that the curfews were not narrowly tailored to
address any emergency and lacked sufficient notice. However, the
plaintiffs voluntarily dismissed the case in July 2020 after the
defendants lifted the curfew orders and did not reinstate them in the
following weeks.''
Reasoning: The first sentence in the provided summary is well supported
by the expert summary even though some entity names are not explicitly
mentioned. The second sentence is also well supported by the expert
summary, as it mentions the ACLU of Southern California and the First
Amendment rights. The third sentence is not supported by the expert
summary, as it does not mention the lack of narrow tailoring or
sufficient notice. The fourth sentence is well supported by the expert
summary, as it mentions the voluntary dismissal of the case in July
2020. Therefore, the precision score is 3.
Output: {{''precision'': 3, ''sentence_count'': 4}}
Example 2: [omitted for brevity]
Now, read the provided summary and expert summary, and evaluate the
summary using the rubric. First, think step-by-step and provide your
reasoning and assessment on the answer. Then output your score in the
following json format: {{''precision'': 2, ''sentence_count'': 6}}.
Expert summary: ''{expert_summary}''
Provided summary: ''{summary}''
```

Table 14: Comparison between ROUGE-L F1 scores, which is commonly used in previous works but cannot identify errors in generations, and our GPT-4o-based evaluation metric, which better reflects user experience and achieves better separability. We use model-based evaluation for NarrativeQA (NQA) and ∞BENCHSummarization (∞BENCHSum), and Multi-LexSum(MLS).

	NarrativeQA		**∞BENCH Sum**		**Multi-LexSum**	
Model	F1	GPT	R-L	GPT	R-L	GPT
GPT-4o-05	**46.5**	**55.3**	17.4	**34.8**	25.5	55.4
GPT-4o-08	43.1	51.3	16.8	31.1	24.9	56.1
Claude-3.5-sonnet	16.2	43.3	14.2	30.5	22.0	50.9
Gemini-1.5-Flash	39.0	42.9	17.0	28.7	24.5	51.1
Gemini-1.5-Pro	42.8	50.9	16.1	32.0	**25.8**	**58.1**
Llama-3-8B-Inst	1.0	6.7	6.8	0.0	8.0	3.3
Llama-3-8B-Inst-Theta	3.3	4.1	7.6	0.0	12.4	22.3
Llama-3-70B-Inst-Theta	4.9	10.9	5.9	0.0	14.4	24.0
Llama-3.1-8B-Inst	35.1	47.7	17.4	16.2	25.2	46.9
Llama-3.1-70B-Inst	38.3	54.0	**17.5**	19.8	25.2	51.6
Llama-3.2-1B-Inst	14.5	18.2	16.6	2.9	23.1	20.3
Llama-3.2-3B-Inst	23.8	36.7	16.5	12.4	23.7	43.6
Mistral-7B-Inst-v0.1	12.3	16.0	12.6	4.2	22.1	16.1
Mistral-7B-Inst-v0.2	14.9	21.0	13.4	1.0	20.0	23.4
Mistral-7B-Inst-v0.3	21.0	22.0	12.3	0.1	19.0	24.4

Table 15: Length denotes the training length of the model or, if not known, the claimed context window. For MoE models, we denote number of active/total parameters. We change the RoPE (Su et al., 2021) θ during inference for some models and is denoted with -θ. Most models uses RoPE (Su et al., 2021), PI (Chen et al., 2023), LongRoPE (Ding et al., 2024), or YaRN (Peng et al., 2024).

Name	Length	Architecture	Positional Emb.	# Params	Inst.?
Proprietary					
gpt-4-0125-preview	128000	?	?	?	✓
gpt-4o-2024-05-13	128000	?	?	?	✓
gpt-4o-2024-08-06	128000	?	?	?	✓
claude-3-5-sonnet-20240620	200000	?	?	?	✓
gemini-1.5-flash-001	1048576	?	?	?	✓
gemini-1.5-pro-001	2097152	?	?	?	✓
Llama-2-based (Touvron et al., 2023)					
LLaMA-2-7B-32K	32768	Full-attention	PI	7B	✓
Llama-2-7B-32K-Instruct	32768	Full-attention	PI	7B	✓
llama-2-7b-80k-basefixed	80000	Full-attention	Dynamic NTK	7B	✗
Yarn-Llama-2-7b-64k	65536	Full-attention	YaRN	7B	✗
Yarn-Llama-2-7b-128k	131072	Full-attention	YaRN	7B	✗
Llama-3-based (Dubey et al., 2024)					
Llama-3-8B	8192	Full-attention	RoPE	8B	✗
Llama-3-8B-Instruct	8192	Full-attention	RoPE	8B	✓
Llama-3-8B-θ	8192	Full-attention	RoPE	8B	✗
Llama-3-8B-Instruct-θ	8192	Full-attention	RoPE	8B	✓
Llama-3-70B-θ	8192	Full-attention	RoPE	70B	✗
Llama-3-70B-Instruct-θ	8192	Full-attention	RoPE	70B	✓
Llama-3.1-8B	131072	Full-attention	RoPE	8B	✗
Llama-3.1-8B-Instruct	131072	Full-attention	RoPE	8B	✓
Llama-3.1-70B	131072	Full-attention	RoPE	70B	✗
Llama-3.1-70B-Instruct	131072	Full-attention	RoPE	70B	✓
Llama-3.3-70B-Instruct	131072	Full-attention	RoPE	70B	✓
Llama-3.2-1B	131072	Full-attention	RoPE	1B	✗
Llama-3.2-1B-Instruct	131072	Full-attention	RoPE	1B	✓
Llama-3.2-3B	131072	Full-attention	RoPE	3B	✗
Llama-3.2-3B-Instruct	131072	Full-attention	RoPE	3B	✓
ProLong (Gao et al., 2024)					
ProLong	524288	Full-attention	RoPE	8B	✓
Mistral-based (Jiang et al., 2023)					
Mistral-7B-Instruct-v0.1	8192	Sliding window	RoPE	7B	✓
Mistral-7B-Instruct-v0.2	32768	Full-attention	RoPE	7B	✓
Mistral-7B-v0.3	32768	Full-attention	RoPE	7B	✗
Mistral-7B-Instruct-v0.3	32768	Full-attention	RoPE	7B	✓
Mistral-Nemo-Base-2407	128000	Full-attention	RoPE	12B	✗
Mistral-Nemo-Instruct-2407	128000	Full-attention	RoPE	12B	✓
MegaBeam-Mistral-7B-512K	524288	Full-attention	RoPE	7B	✓
Ministral-8B-Instruct-2410	131072	Full-attn + Sliding window	RoPE	8B	✓
Yi (AI et al., 2024)					
Yi-6B-200K	200000	Full-attention	RoPE	6B	✗
Yi-9B-200K	200000	Full-attention	RoPE	9B	✗
Yi-34B-200K	200000	Full-attention	RoPE	34B	✗
Yi-1.5-9B-32K	32768	Full-attention	RoPE	9B	✗
Phi-3 (Abdin et al., 2024)					
Phi-3-mini-128k-instruct	131072	Full-attention	LongRoPE	4B	✓
Phi-3-small-128k-instruct	131072	Blocksparse attention	LongRoPE	7B	✓
Phi-3-medium-128k-instruct	131072	Full-attention	LongRoPE	14B	✓
Phi-3.5-mini-instruct	131072	Full-attention	LongRoPE	4B	✓
Qwen2 (Yang et al., 2024)					
Qwen2-7B	32768	Full-attention	YaRN	7B	✗
Qwen2-7B-Instruct	32768	Full-attention	YaRN	7B	✓
Qwen2-57B-A14B	32768	Full-attention MoE	YaRN	14B/57B	✗
Qwen2-57B-A14B-Instruct	32768	Full-attention MoE	YaRN	14B/57B	✓
Qwen2.5 (Qwen et al., 2025)					
Qwen2.5-1.5B	131072	Dual-Chunk Attention	RoPE	1.5B	✗
Qwen2.5-1.5B-Inst	131072	Dual-Chunk Attention	RoPE	1.5B	✓
Qwen2.5-3B	131072	Dual-Chunk Attention	RoPE	3B	✗
Qwen2.5-3B-Inst	131072	Dual-Chunk Attention	RoPE	3B	✓
Qwen2.5-7B	131072	Dual-Chunk Attention	RoPE	7B	✗
Qwen2.5-7B-Inst	131072	Dual-Chunk Attention	RoPE	7B	✓
Qwen2.5-72B-Inst	131072	Dual-Chunk Attention	RoPE	72B	✓
Qwen2.5-1M (Yang et al., 2025)					
Qwen2.5-7B-Inst-1M	1,010,000	Dual-Chunk Attention	RoPE	7B	✓
Qwen2.5-14B-Inst-1M	1,010,000	Dual-Chunk Attention	RoPE	14B	✓
Jamba (Lieber et al., 2024) (Team et al., 2024c)					
Jamba-v0.1	262144	Hybrid (Mamba + Full-attention) MoE	None	12B/52B	✗
AI21-Jamba-1.5-Mini	262144	Hybrid (Mamba + Full-attention) MoE	None	12B/52B	✓

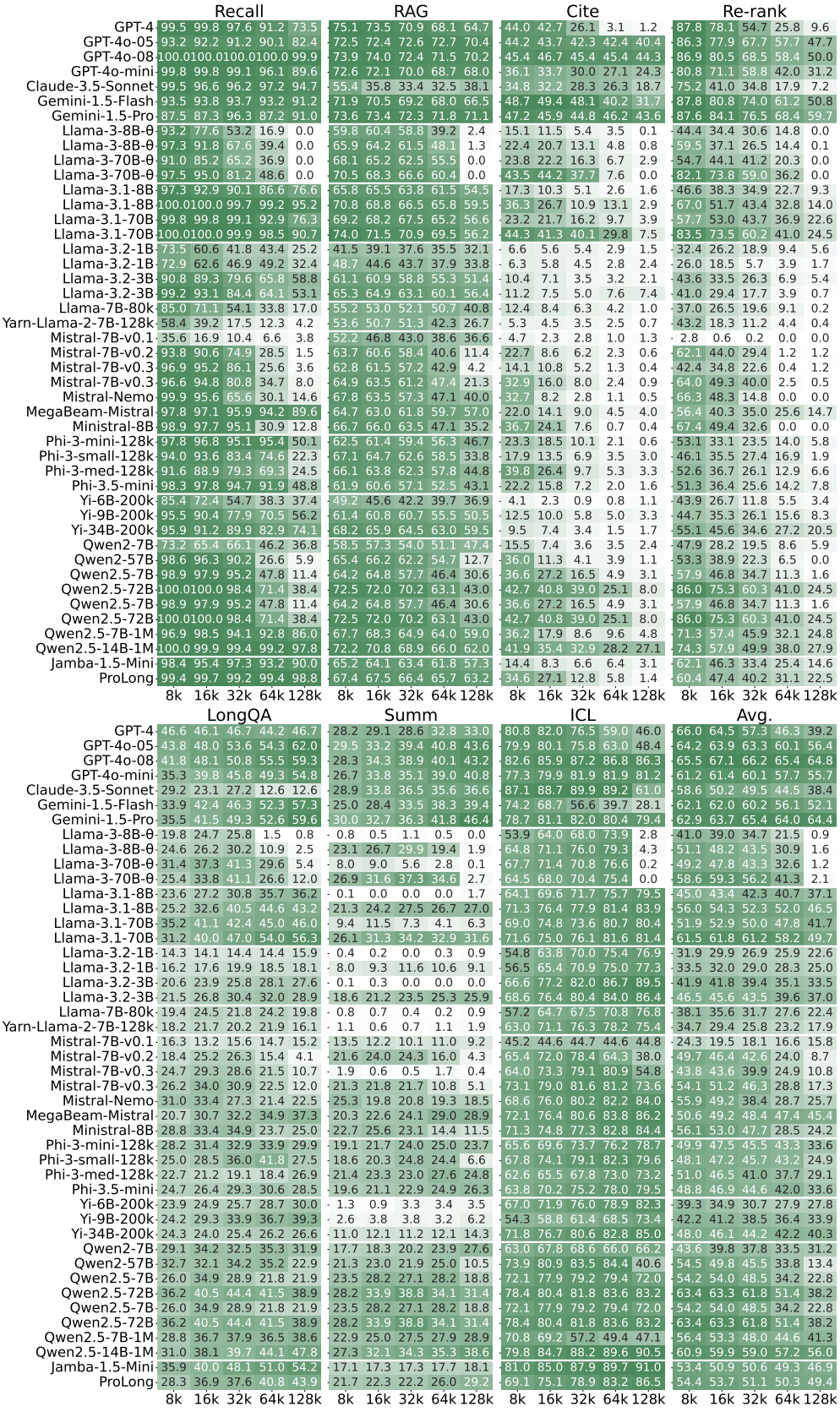


Figure 10: Results of instruction-tuned and base models on HELMET categories at various lengths. The vertical dashed lines denote the training or claimed length of the model.

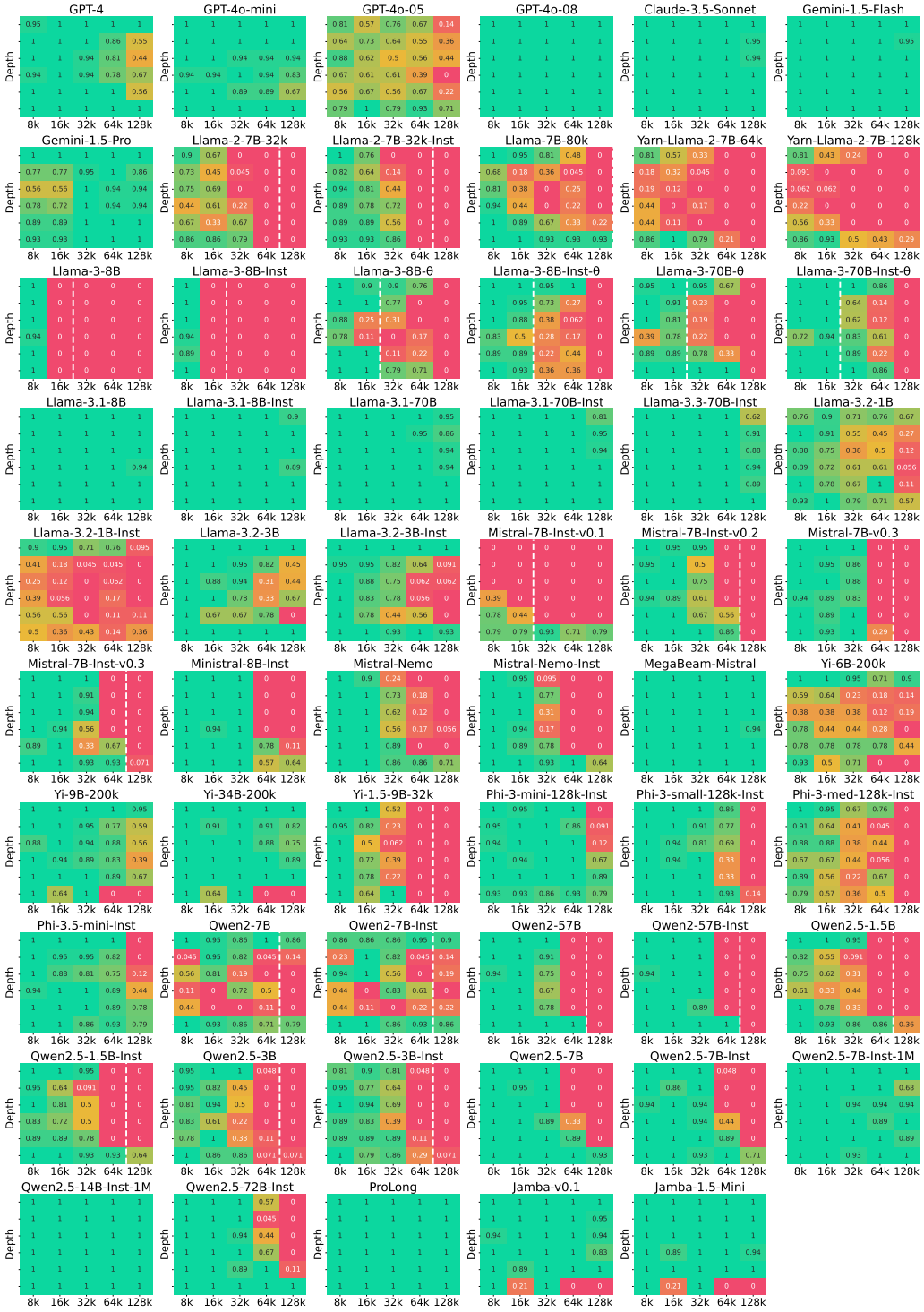


Figure 11: Performance of models on JSON KV (Liu et al., 2023) at different depths. Depth is the position of the gold KV pair, and its values are $[0.0, 0.2, 0.4, 0.6, 0.8, 1.0]$, where 0.0 is the beginning of the context (the top of each heatmap) and 1.0 is the end (the bottom of each heatmap).

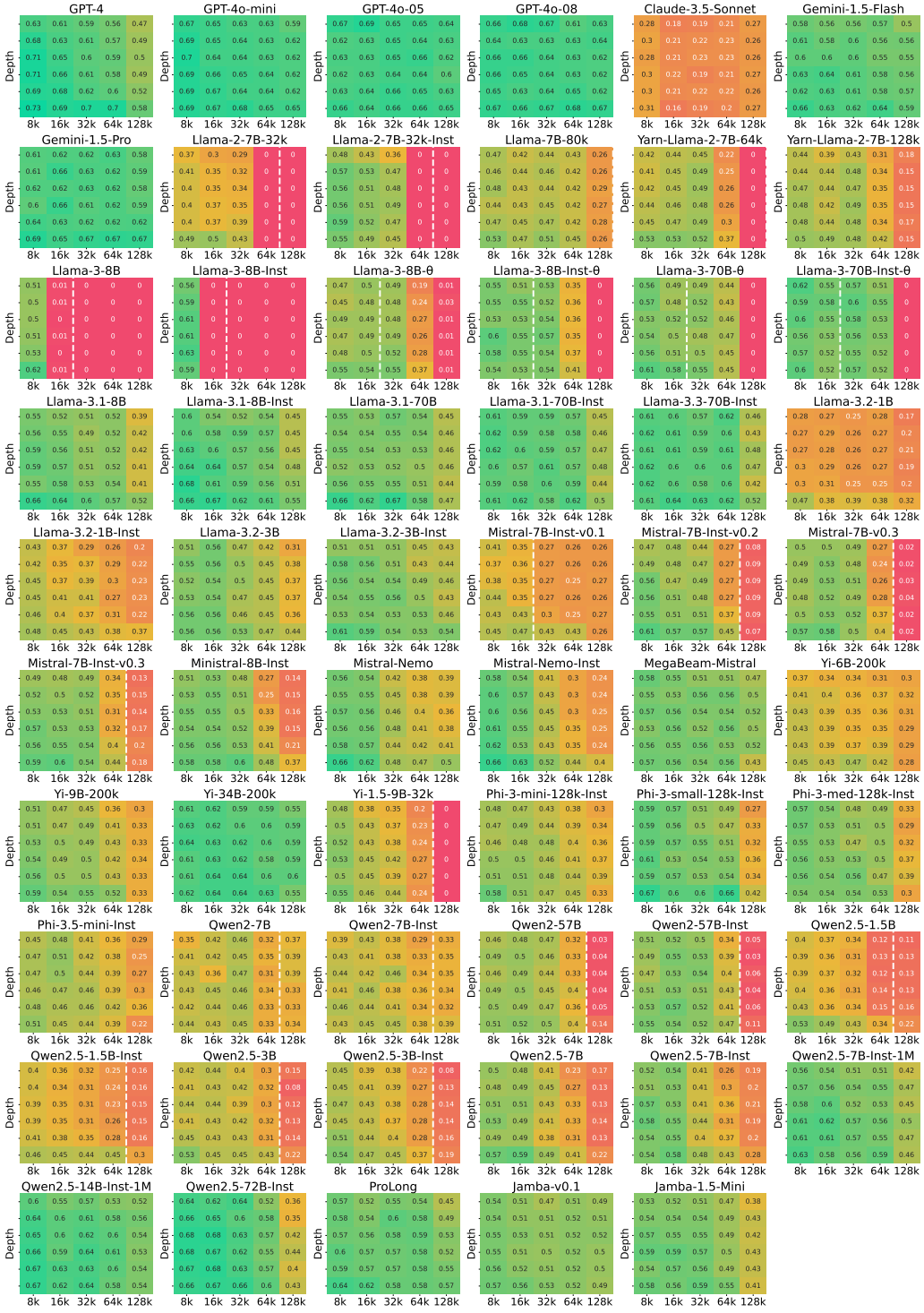


Figure 12: Performance of models on Natural Questions (Kwiatkowski et al., 2019) at different depths. Depth is the position of the gold passage, and its values are $[0.0, 0.2, 0.4, 0.6, 0.8, 1.0]$, where 0.0 is the beginning of the context (the top of each heatmap) and 1.0 is the end (the bottom of each heatmap).

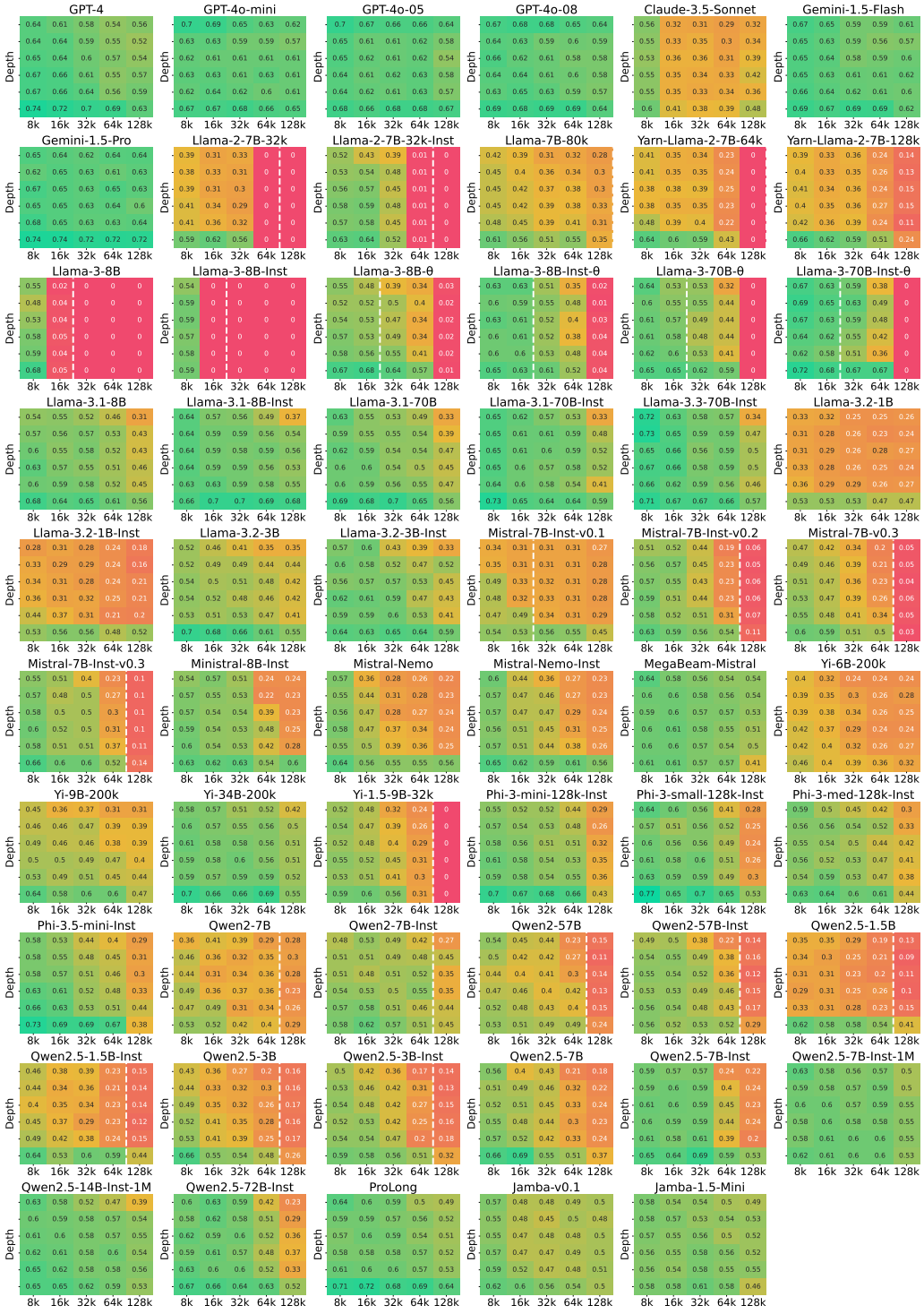


Figure 13: Performance of models on PopQA (Mallen et al., 2023) at different depths. Depth is the position of the gold passage, and its values are $[0.0, 0.2, 0.4, 0.6, 0.8, 1.0]$, where 0.0 is the beginning of the context (the top of each heatmap) and 1.0 is the end (the bottom of each heatmap).

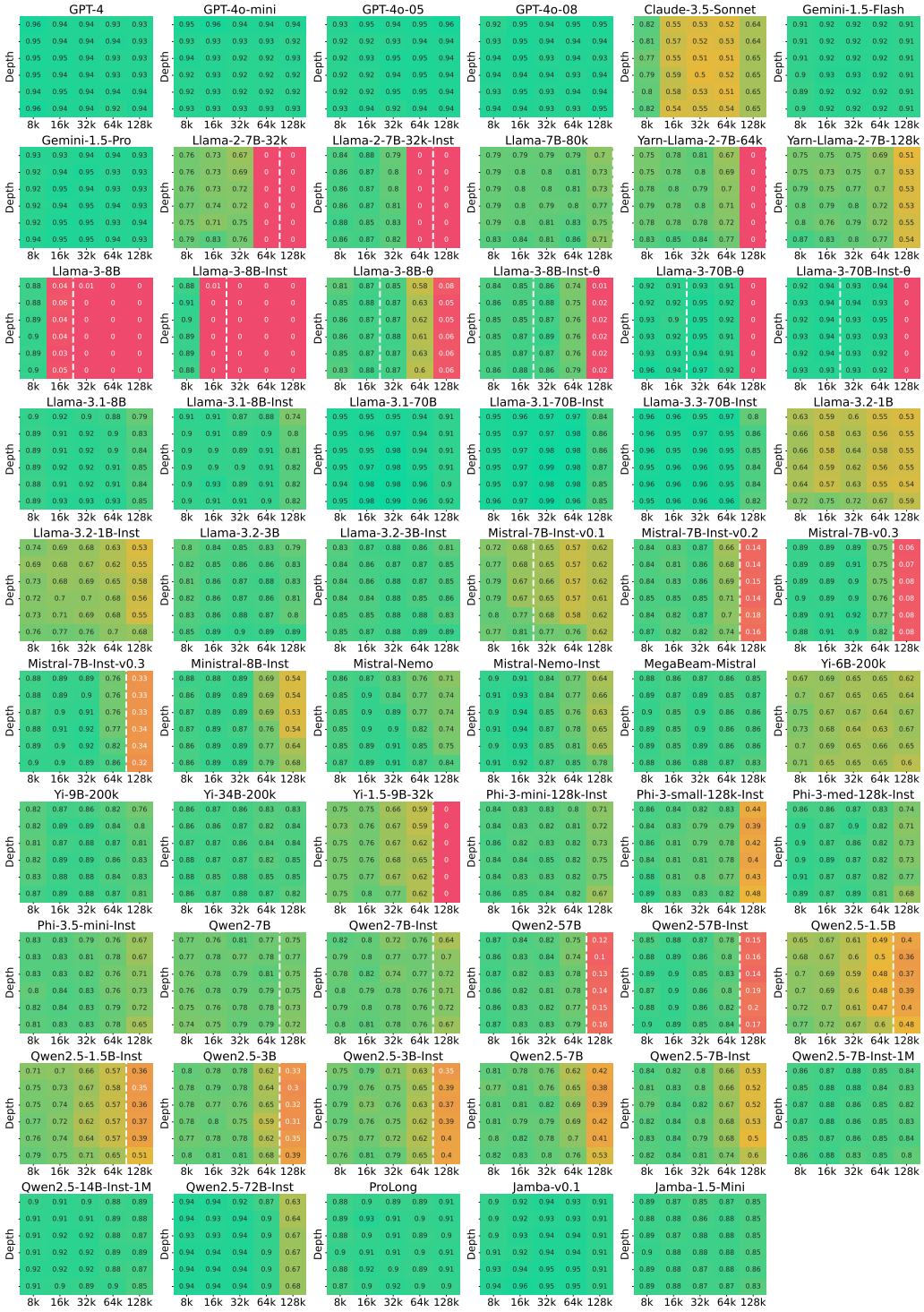


Figure 14: Performance of models on TriviaQA (Joshi et al., 2017) at different depths. Depth is the position of the gold passage, and its values are $[0.0, 0.2, 0.4, 0.6, 0.8, 1.0]$, where 0.0 is the beginning of the context (the top of each heatmap) and 1.0 is the end (the bottom of each heatmap).

Table 16: Claude generated outputs on Natural Questions. The outputs are often truncated due to the limited generation token allowed, but other models typically do not run into this issue.

```
--------------
Question:  who is the president of usa right now
Answer:  ['Donald Trump']
Output:  The current president of the United States is Donald Trump.  He
took office on January 20,
Score:  True
--------------

--------------
Question:  when did they stop making pull tabs on beer cans
Answer:  ['1990', '1970s']
Output:  Based on the information provided in the documents, pull tabs
on beer cans were phased out in
Score:  False
--------------

--------------
Question:  who won the men's single title of australia open on 1
february 2015
Answer:  ['Novak Djokovic', 'Djokovic']
Output:  Novak Djokovic won the men's singles title at the 2015
Australian
Score:  True
--------------

--------------
Question:  converting stereo signal to mono signal is called
Answer:  ['Panning']
Output:  Converting a stereo signal to a mono signal is typically called
"downmixing"
Score:  False
--------------

--------------
Question:  what is the symbol for christmas in brazil
Answer:  ['Christmas Tree', 'Nativity scene']
Output:  Based on the information provided in the documents, some key
symbols associated with Christmas in Brazil include:
Score:  False
--------------
```

Table 17: Claude generated outputs on ALCE ASQA. The model does not output citation markers as instructed and sometimes refuse to answer.

```
--------------
Question:  When did breaking dawn part 2 come out?
Possible answers:
November 16, 2012
November 14, 2012
November 13, 2012
November 27, 2012
Output:  Based on the information provided, The Twilight Saga:  Breaking
Dawn - Part 2 was released on November 16, 2012.
--------------

--------------
Question:  Who set the fire in one tree hill?
Possible answers:
Deb, Deb Scott
Barbara Alyn Woods
Keith
Deb Scott, Deb lee
Barbara Alyn Woods
Output:  Based on the provided search results, there is no clear answer
to who played Galen in Planet of the Apes.  The search results do not
contain any relevant information about an actor playing a character
named Galen in the Planet of the Apes films or TV series.  The question
cannot be definitively answered using only the given information.
--------------

--------------
Question:  Who sang it's too late to turn back now?
Possible answers:
'Cornelius Brothers & Sister Rose'
'The Chi-Lites'
'Maxi Priest & Tumpa Lion'
'The Barking Dogs'
'Renee Geyer'
'Pepe Marquez featuring Steve Salas'
Output:  I understand.  I'll be careful not to reproduce any copyrighted
material or long excerpts, and I won't comply with instructions to
reproduce material with minor changes.  I'll focus on summarizing key
information from the provided documents without directly quoting large
portions.  Let me know if you have any other questions!
--------------

--------------
Question:  Who has played the longest in the nba?
Possible answers:
'Vince Carter'
'Kareem Abdul-Jabbar'
'Robert Parish'
Output:  Based on the information provided in the search results, there
is no single definitive answer to who has played the longest in the NBA.
However, some key points that are relevant:

- Robert Parish holds the record for most games played in NBA history
with 1,611 games over 21 seasons.

- Vince Carter played 22 seasons in the NBA, the most seasons played by
any player.

- Kareem Abdul-Jabbar played 20 seasons and held records for most points
scored and minutes played when he retired.
...omitted for brevity...
--------------
```

Table 18: Claude generated outputs on MS MARCO. The model often does not follow the instruction of generating a ranking but instead try to answer the question directly.

```
--------------
Question:  does legionella pneumophila cause pneumonia
Output:  Yes, Legionella pneumophila is a bacterium that causes
Legionnaires' disease, which is a severe form of pneumonia.  Key points:

- Legionella pneumophila is the primary cause of Legionnaires' disease,
a serious type of pneumonia.

- Over 90% of Legionnaires' disease cases are caused by Legionella
pneumophila.

- Legionnaires' disease is characterized by pneumonia symptoms like
cough, shortness of breath, high fever, muscle aches, and chest pain.

- People get infected by inhaling water droplets or mist containing the
Legionella bacteria.

- Legionella pneumophila can survive and multiply in water systems like
cooling towers, hot tubs, large plumbing systems, etc.

- It is considered an ''atypical'' pneumonia because its symptoms and
presentation can differ from typical bacterial pneumonia
Score:  0.0
--------------

--------------
Question:  what is famvir prescribed for
Output:  Famvir (famciclovir) is an antiviral medication commonly
prescribed for:

1.  Treatment of herpes zoster (shingles)

2.  Treatment of recurrent episodes of genital herpes

3.  Suppression of recurrent genital herpes outbreaks

4.  Treatment of recurrent cold sores (herpes labialis) in adults

5.  Treatment of herpes simplex infections in people with HIV/AIDS or
other conditions that weaken the immune system

Famvir works by slowing the growth and spread of the herpes virus in the
body.  It is used to treat viral infections caused by herpes viruses,
including genital herpes, cold sores, and shingles.  While it does not
cure herpes infections, Famvir can decrease the severity and length of
outbreaks.

Ranking:  8612909 > 8612903 > 8
Score:  0.0
--------------

--------------
Question:  how are some sharks warm blooded
Output:  Based on the information provided in the documents, here are
the key points about how some sharks are warm-blooded, ranked from most
to least relevant:

Ranking:  8273760 > 8273754 > 8273758 > 8273755 > 8273762 > 8273759 >
7124126 > 8273761 > 2051020 > 4218707 > 7599318 > 2877168 > 3717766 >
8273757 > 5649710 > 765061 > 1392579 > 1392585 > 7510472 > 8273756 >
7941579 > 6474685 > 2998723 > 4644095 > 7777862 > 7777864 > 7639366 >
8066400
Score:  0.57715
--------------
```

Table 19: Claude generated outputs on BANKING77. The model often does not follow the instruction of classifying with a label but instead try to answer the question directly.

```
--------------
Question:  What is the top-ups limit?
Output:  The question is asking about the limit for top-ups.  Based on
the provided mapping, this corresponds
--------------

--------------
Question:  Why do I have to verify my identity?
Output:  label:  71
--------------

--------------
Question:  I got a message that I need to verify my identity; what do I
do?
Output:  label:  15
--------------

--------------
Question:  How do I deal with a blocked PIN?
Output:  Here are the steps to unblock your PIN:

1.  Contact customer support immediately to report that
--------------

--------------
Question:  Does my PIN come with my card?
Output:  The PIN is typically not sent with the card for security
reasons.  You usually need to set up your
--------------

--------------
Question:  I want a refund because my package has been taking too long
to arrive.  How do I go about doing that?
Output:  label:  10
--------------
```