

One ruler to measure them all: Benchmarking multilingual long-context language models

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Abstract

We present ONERULER,¹ a multilingual benchmark designed to evaluate long-context language models across **26 languages**. ONERULER adapts the English-only RULER benchmark (Hsieh et al., 2024) by including seven synthetic tasks that test both retrieval and aggregation, including new variations of the “needle-in-a-haystack” task that allow for the possibility of a *nonexistent* needle. We create ONERULER through a two-step process, first writing English instructions for each task and then collaborating with native speakers to translate them into 25 additional languages. Experiments with both open-weight and closed LLMs reveal a widening performance gap between low- and high-resource languages as context length increases from 8K to 128K tokens. Surprisingly, English is not the top-performing language on long-context tasks (ranked 6th out of 26), with Polish emerging as the top language. Our experiments also show that many LLMs (particularly OpenAI’s o3-mini-high) incorrectly predict the absence of an answer, even in high-resource languages. Finally, in cross-lingual scenarios where instructions and context appear in different languages, performance can fluctuate by up to 20% depending on the instruction language. We hope the release of ONERULER will facilitate future research into improving multilingual and cross-lingual long-context training pipelines.

1 Introduction

Long-context language understanding is essential for real-world applications of LLMs such as summarization and question answering. However, it is difficult and expensive to conduct realistic evaluations for these tasks (Kim et al., 2024; Karpinska et al., 2024), which motivates the use of synthetic benchmarks as proxy diagnostics. One popular example is the “needle-in-a-haystack” (NIAH) task (Kamradt, 2023), in which a codeword is inserted into a long document and subsequently queried for. The RULER benchmark (Hsieh et al., 2024) contains several variants of NIAH (e.g., multiple needles and queries) as well as other synthetic tasks to test aggregation and variable tracing. Unfortunately, RULER and other similar benchmarks mostly test long-context understanding in either just English or in a small number of languages (Bai et al., 2024; Hengle et al., 2024); as such, it remains unclear how well LLMs perform in *multilingual* and *cross-lingual* long-context scenarios.

In this paper, we create ONERULER, a multilingual adaptation of RULER that includes seven synthetic tasks (five variants of NIAH as well as two aggregation tasks) in **26 different languages**, including both low- and high- resource languages. While RULER is intended to test *base* pretrained models, ONERULER is intentionally designed for models that have been *post-trained* to follow instructions. Our data collection process involved first writing instructions for all six tasks in English, and then hiring native speakers of the other 25 languages to translate these instructions. Unlike prior work, our NIAH instructions also allow for the **possibility of a nonexistent needle**, where models get credit for identifying that

¹Dataset and code available at <https://github.com/mungg/OneRuler>.

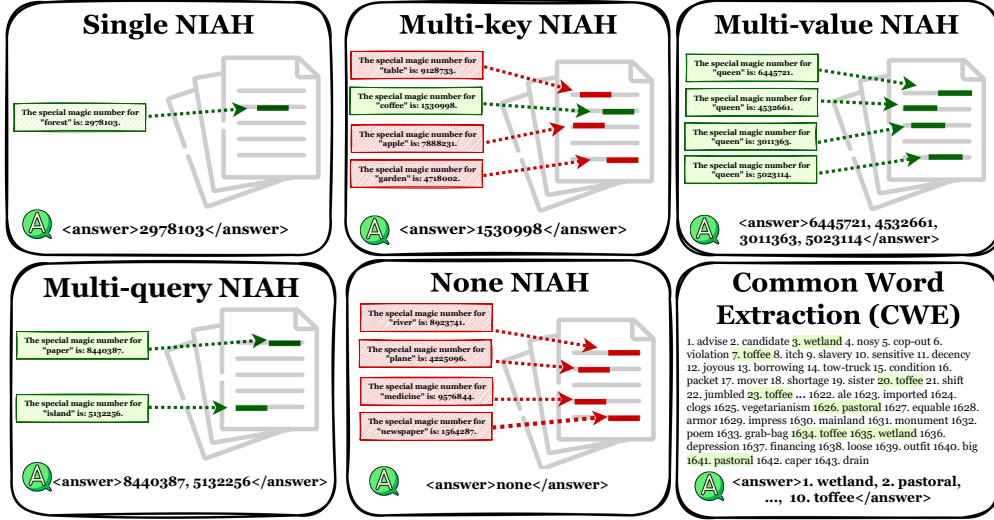


Figure 1: The seven tasks included in ONERULER. Spans highlighted in red are distractors, while green spans contain answers that need to be produced for credit. CWE appears twice (in easy and hard versions with differing frequencies) but shares the same format, hence only one version is shown here. The NONE-NIAH task is a novel variant in which the needle does not exist in the input context.

there is no answer. We show that this simple change dramatically lowers the performance of models even on the vanilla NIAH task.

We benchmark four recently-released open-weight LLMs of different sizes, Qwen2.5 (7B and 72B), Llama 3.1 (8B), and Llama 3.3 (70B), as well as two closed-source LLMs (OpenAI’s o3-mini-high and Google’s Gemini 1.5 Flash). Overall, Gemini 1.5 Flash is the strongest tested model in aggregate, followed by Qwen2.5 72B; o3-mini-high, despite its powerful reasoning capabilities, struggles badly on longer contexts. Interestingly, we observe a widening gap in accuracy (averaged over all tasks and models) between low- and high-resource languages as context length increases (Figure 6), suggesting a disparity between languages in long-context pretraining and instruction tuning data.

Our experiments yield several surprising and counterintuitive results. For one, English is *not* the highest-performing language across all models; in fact, it is the sixth-best language out of the 26 when evaluated at long-context lengths (64k & 128k), while Polish takes the top spot.² Also surprising is the difficulty of even the vanilla NIAH task when we add the potential of the needle not existing in the context, especially given the near-perfect vanilla NIAH results observed in RULER and subsequent long-context LLM papers.³ In fact, a large percentage of errors occur because models incorrectly decide that no needle exists.⁴ The most difficult task in ONERULER is the aggregation task, which requires listing the ten most common words in a long list of words: interestingly, reasoning models (o3-mini-high and DeepSeek-r1) “overthink” mightily on this task by producing thousands of reasoning tokens. Finally, in the *cross-lingual* setting, where the instructions and context are in different languages, we observe that the accuracy can change to 20% depending on the language of instructions.

²Overall, the top-performing language families are Slavic, Romance, and Germanic, while Bantu languages fare poorly despite having over 350M speakers.

³See e.g., Figure 2 of the Qwen2.5 paper (Qwen Team, 2025), which shows a now-familiar bright green rectangle exhibiting perfect NIAH performance.

⁴This result is reminiscent of the added challenge posed by SQuAD 2.0’s unanswerable questions upon its release (Rajpurkar et al., 2018).

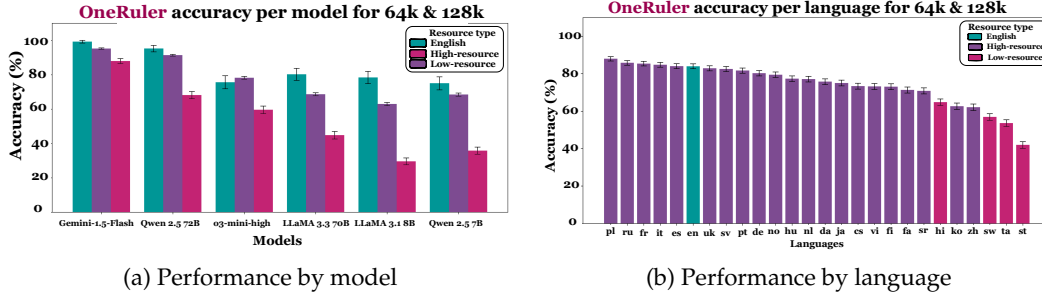


Figure 2: NIAH performance across models and languages by language resource group for long-context tasks (64K and 128K). Gemini 1.5 Flash demonstrates the best long-context performance, while English and Chinese are surprisingly not among the top five languages.

2 Creating the ONERULER benchmark

ONERULER spans seven tasks, all of which are directly adapted from RULER (Hsieh et al., 2024). Five are variants of the needle-in-a-haystack *retrieval* task, differing in the number (and existence) of needles and queries. The final two tasks both require *aggregation*: finding words repeated frequently in a long list of words, with two different distractor word frequencies. For each task, models are evaluated using four context lengths (8K, 32K, 64K, 128K) with 50 examples per language across 26 languages, resulting in a total of 5.2K prompts per task per model. In this section, we outline our data curation pipeline and provide detailed descriptions of each task.

Languages: We include 26 diverse languages: Chinese (zh), Czech (cs), Danish (da), Dutch (nl), English (en), Finnish (fi), French (fr), German (de), Hindi (hi), Hungarian (hu), Italian (it), Japanese (ja), Korean (ko), Norwegian (no), Persian (fa), Polish (pl), Portuguese (pt), Russian (ru), Serbian (sr), Sesotho (st), Spanish (es), Swahili (sw), Swedish (sv), Tamil (ta), Ukrainian (uk), and Vietnamese (vi). These languages provide a solid representation of different language families and writing systems (e.g., Latin, Cyrillic, logographic)⁵ and exhibit a range of typological features, such as variations in word order and morphological complexity. For fair comparison in retrieval and cross-lingual tasks, we also translated a consistent set of 100 vocabulary words into all 26 languages.

High vs. low resource languages: Many of our experiments present comparisons between *high-resource* and *low-resource* languages. To define what constitutes a low-resource language, we rely on the official article count of Wikipedia articles per language (Joshi et al., 2020; Ranathunga & de Silva, 2022),⁶ defining a minimum threshold of 250K articles for a language to be considered high resource. Per this definition, we identify four low-resource languages for our study: Hindi, Sesotho, Swahili, and Tamil.

Annotator instructions: We hired 17 annotators from Upwork⁷ and recruited 6 volunteers to translate the English instructions and a list of 100 vocabulary words⁸ into 25 languages. All annotators were native speakers of the target languages with strong English proficiency.⁹ They were provided with the context about the task and its objectives to ensure high-quality translations. Annotators were instructed to translate and localize the instructions to make

⁵Details of language family and script for each language are in §A.

⁶https://meta.wikimedia.org/wiki/List_of_Wikipedias

⁷<https://www.upwork.com/>

⁸To prevent homonyms from being translated as different words, we provided descriptions for each word generated using the GPT-4o mini model.

⁹Two annotators were native speakers of multiple languages and translated both of those languages (Polish & Japanese, Russian & Ukrainian).

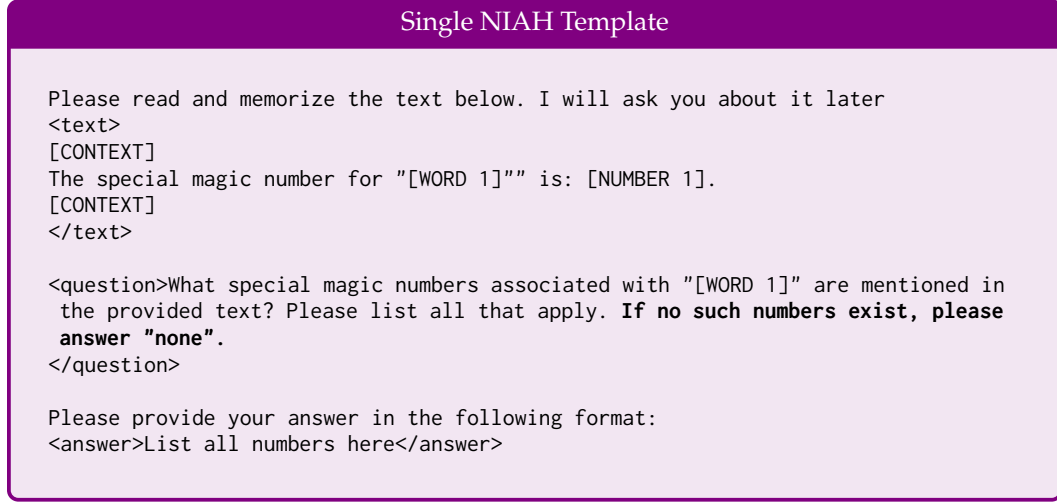


Figure 3: Prompt template for our “Single NIAH” task with one magic number. The bolded sentence introduces the possibility of no answer existing, which we show significantly hurts model accuracies, even for this Single NIAH task where the answer always exists.

the prompts sound as natural as possible.¹⁰ After completing the initial translations, each annotator reviewed the full set of instructions and made any necessary adjustments. All annotators were paid **\$25 USD** per language to translate instructions and vocabulary words. The total cost of obtaining these translations was **\$492 USD**.

Tokenization: It is difficult to conduct a fair comparison across models because they use different tokenizers: for example, one of our Tamil documents is 42,124 tokens using Gemini’s tokenizer and 103,990 tokens using Qwen’s tokenizer. This discrepancy presents us with a choice of either (1) ensuring that the *input text* shown to each model is identical, even if they have differing token counts across models; or (2) ensuring that the *total number of tokens* shown to each model is identical, even if this means some models see more text than others. We decide to report our main results using the second setting to focus specifically on the effect of sequence length on model performance. However, we also report results of experiments run under the first configuration in §D, noting that our conclusions about relative model rankings and language-specific performance do not change significantly.

2.1 Retrieval tasks

We propose five retrieval tasks to assess the model’s ability to extract information from extended contexts. Each task is based on the needle-in-a-haystack paradigm (Kamradt, 2023), where a target sentence is embedded within a longer text and the model must retrieve specific details. Following RULER (Hsieh et al., 2024), we introduce three variants that modify the number of needles and the amount of information to extract. However, we deviate by reformatting all tasks for *instruction-following* models (instead of base pretrained models) and also by introducing the possibility of the answer not existing. For each task, we vary the position of the needle between prompts and pay special attention to injecting the target sentence cleanly, respecting the spacing and punctuation conventions of the given language. To create plausible contexts for needle injection, we collect and clean 26 open-domain non-copyrighted books, one per language.¹¹ Below are descriptions of each task:

¹⁰We pay special attention to the grammar of each language to ensure that any swap of variables will not result in ungrammatical sentences.

¹¹Each book was processed to remove the front and back matter. See Table 4 for the complete list of books in the dataset.

- **Single-NIAH (S-NIAH):** This task follows the classic needle-in-a-haystack framework, where a single target sentence (the needle) is embedded in a book-length context. The model must locate this sentence and retrieve the specific number (“value”) associated with the keyword (“key”). In S-NIAH, only one needle is present with no distractors. Unlike NIAH configurations in prior work, our prompt template (Figure 3) allows for the possibility of a nonexistent needle, although in S-NIAH the needle always exists. This wording is present in each of our NIAH variants, and we ablate its impact on performance in §4.
- **Multi-key NIAH (MK-NIAH):** This variant embeds multiple needles with different keys into the context, where only one needle contains the correct key. Specifically, we insert 4 needles with unique keys, where 3 serve as distractors (Figure 11). The model must identify the needle containing the target key and return its corresponding value.
- **Multi-value NIAH (MV-NIAH):** In contrast to MK-NIAH, this variant inserts 4 needles that share the same key but have different values (Figure 12). To successfully complete the task, the model must retrieve all four values associated with the common key.
- **Multi-query NIAH (MQ-NIAH):** While sharing the same needle structure as MK-NIAH, this variant presents multiple queries within each question (Figure 13). The model’s response is considered correct only if it accurately retrieves all required information for every query. This tests the model’s ability to maintain context awareness across multiple retrieval operations.
- **None-NIAH (NONE-NIAH):** This novel variant tests a model’s ability to recognize when *no* correct answer exists. The context contains four embedded needles that all function as distractors. This challenges models to acknowledge the absence of a correct response rather than forcing an incorrect selection.

2.2 Aggregation tasks

Unlike our retrieval tasks, which focus on extracting specific information from large and irrelevant contexts, aggregation tasks require models to synthesize information across the entire context to generate accurate responses. We adapt RULER’s Common Word Extraction (CWE) task, which requires identifying the n most frequent words from a context. We extracted word lists for 26 languages from GitHub repositories (§3) dedicated to language wordlists, using part-of-speech tagging to identify nouns, adjectives, and verbs. Our two CWE settings are:

- **CWE-easy:** The most frequent words in the list appear exactly 30 times each, while other distractor words appear 3 times each. This replicates the parameters from RULER, chosen because the task proves easy in short context settings but difficult in longer contexts.
- **CWE-hard:** We also examine a more difficult setting that changes only the word frequencies. In this setting, the most frequent words appear 20 times each while distractor words appear 10 times each. This setting challenges models in both short and long context settings because of the reduced frequency gap between answer words and distractors.

3 Experiments

We evaluate 7 different models on ONERULER across four context lengths (Figure 5), reporting *micro-accuracy* across models, languages, and tasks on the subset of returned responses.¹² While most models perform near perfectly on vanilla NIAH for English, accuracies on low resource languages and those that use non-Latin scripts is drastically lower, especially at

¹²We discard refusals and instances where reasoning models run out of generation tokens before returning an answer.

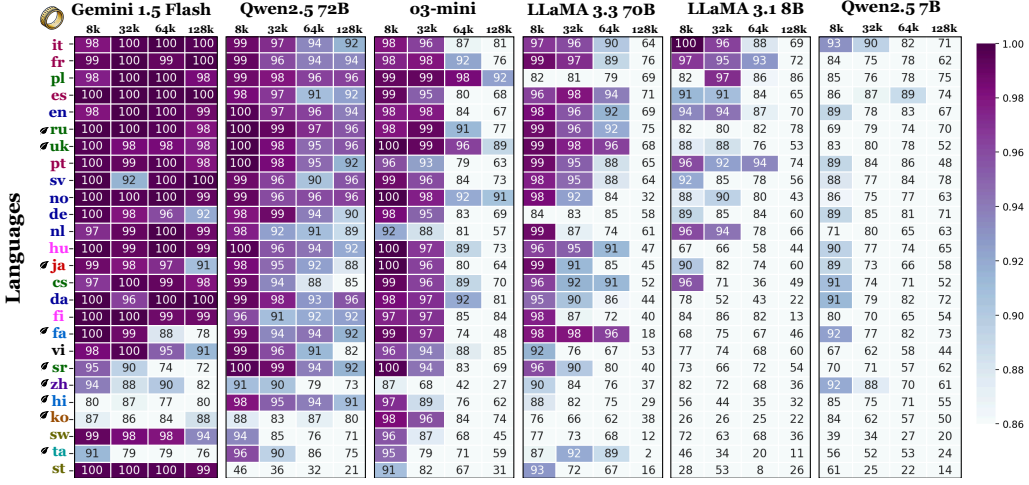


Figure 4: Micro-accuracy across context-lengths and languages for all NIAH tasks. We find that Romance languages perform the best across all context lengths, along with languages like Polish and Russian. All models struggle on languages that use non-Latin or Cyrillic scripts. Gemini-1.5 Flash does surprisingly well on Sesotho in comparison to other models.

longer context lengths. Only Gemini-1.5 and Qwen2.5 72B perform well on NIAH tasks at long contexts (128K) on aggregate, but they still have room for improvement especially on low resource languages. Our CWE aggregation tasks are difficult for all models, especially the CWE-hard task: none of the test models achieves an accuracy above 1%.

Model selection: We evaluate 5 open-source models: (DeepSeek-AI, 2025), Llama 3.3-70B (Llama Team, 2024), Llama 3.1-7B (Llama Team, 2024), Qwen2.5 (Qwen Team, 2025) in 7B and 72B variants), and Deepseek-R1,¹³ the latter only for an analysis experiment in English. We also compare to 2 closed-source models: Gemini 1.5 Flash and o3-mini-high. Notably, Qwen was trained on 3 trillion tokens of multilingual data with a particular focus on English and Chinese. We evaluate Llama and Qwen with vLLM (Kwon et al., 2023) and we use up to 4 A100 GPUs for running evaluation. Model specifications can be found in Figure 5 and detailed comparisons are provided in §B.1.

Model	# Param	Ctx len	# Vocab
Gemini 1.5 Flash	~1.1T	1M	256K
o3-mini-high	~1.1T	200K	200K
Deepseek-R1	685B	128K	129k
Llama3.3	70B	128K	128K
Llama3.1	8B	128K	128K
Qwen2.5-72B	72B	128K	152K
Qwen2.5-7B	7B	128K	152K

Figure 5: Closed-source () and open-weights () models used in the experiments. We report models’ parameters count, claimed context length, and vocabulary size.

3.1 Results

Figure 2b shows that ONERULER accuracy aggregated over all NIAH tasks and context lengths is (unsurprisingly) higher for high-resource languages than low-resource languages. We do see some correlation between model size and aggregate accuracy on low-resource languages, with the difference in accuracy between high and low resource languages shrinking as model size increases (Figure 6a). We highlight several more interesting findings below:

¹³Although Deepseek-R1 is an open-source model, it requires 16 A100-80GB GPUs for inference, which exceeds our available resources. Therefore, we utilized the Fireworks API (<https://fireworks.ai/>) for evaluation. Due to cost constraints, we limited our Deepseek-R1 experiments to English.

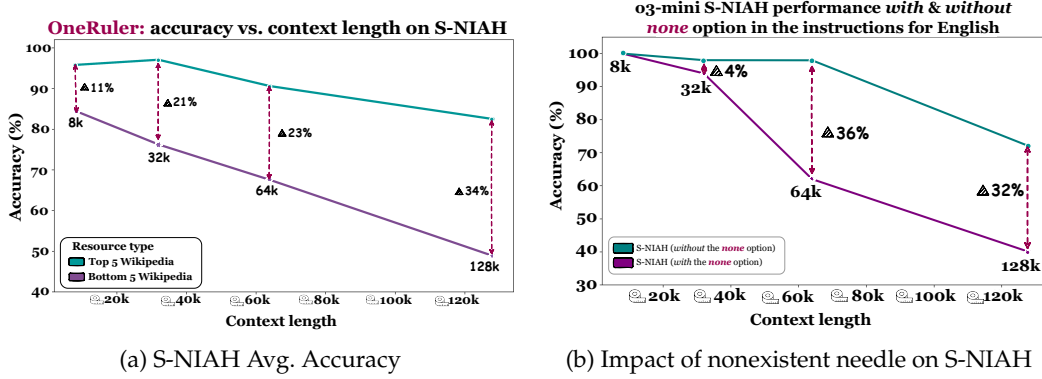


Figure 6: (A) Micro-accuracy of all models on the S-NIAH task for the top 5 and bottom 5 languages by Wikipedia size. As context length increases, the performance gap between high-resource and low-resource languages increases. (B) The average accuracy of all models on the S-NIAH task, with and without the inclusion of the “None” answer in the prompt. Models are much more likely to produce errors at long contexts when they think there is a chance of the needle not existing.

The gap between high- and low-resource languages widens as context size increases: As context size increases from 8K to 128K, Figure 6a shows that aggregate ONERULER accuracy between the top five and bottom five languages by Wikipedia size widens considerably. Specifically, the difference in aggregate accuracy increases from 11% with a context length of 8K to 34% with context length of 128K. We speculate that the widening gap might be due to a lack of low-resource data used during long context extension (Gao et al., 2024; Lenz et al., 2025; Llama Team, 2024): it is possible that long-context capabilities do not easily transfer across languages.

Low-resource languages are challenging even at short contexts: All models demonstrate strong aggregate ONERULER accuracy with a context length of 8K, as shown in Figure 2a. However, they still struggle with low-resource languages like Swahili and Sesotho. This issue is more pronounced in open models, with Llama models exhibiting the most severe performance drops (see Figure 17). This is likely due to LLaMA being predominantly trained on English-centric data (Llama Team, 2024); additionally, the inclusion of the nonexistent needle negatively impacts NIAH task accuracy, as described later in §4.

English and Chinese are *not* the highest-performing languages: English is the dominant pretraining language for most models, with Qwen also emphasizing Chinese in their data mixture, and so we might expect these to be the top-performing models on ONERULER, especially at longer contexts. However, at context lengths of 64K and 128K, we unexpectedly observe that Polish is the top performer on NIAH tasks with an average accuracy of 88% across all models, as depicted in Figure 2b. English is only the 6th best language out of the 26, with an average NIAH accuracy of 83.9%. More shockingly, Chinese is the 4th *worst* language on ONERULER, with an average NIAH accuracy of 62.1%. While there seems to be some correlation between resource availability and performance (all 4 low-resource languages rank in the bottom 6 languages), it remains unclear why some high-resource languages like Chinese fare worse than anticipated. In contrast, the top 10 positions are occupied by Slavic, Romance, and Germanic languages, all of which have substantial resources, as indicated by the number of Wikipedia articles (Figure 9). Notably, none of these languages rank among the bottom 10, with Czech performing the worst among them.

Individual model performance varies: Figure 4 displays the aggregate accuracy of different models on all ONERULER NIAH tasks as a function of language and context size. While Gemini 1.5 Flash outperforms all other models across all context lengths, we observe that Qwen2.5 72B is consistently better than LLaMA 3.3 70B across all context lengths, with notably higher performance in the 64k and 128k context-length settings. Also interesting is

the low average performance of o3-mini-high: it achieves only 67% accuracy on English at a context length of 128K, compared to 92% on Polish and 89% on Ukrainian.

CWE is much more challenging than NIAH:

Compared to the NIAH tasks, on which all models consistently achieve above 80% accuracy on high-resource languages, the CWE task presents a substantially greater challenge. As seen in Figure 7, average English accuracy over all models is only 36.4% for the CWE_easy task¹⁴. The CWE_hard setting proves unsolvable with nearly 0% accuracy across all models,¹⁵ indicating that LLMs have significant room for improvement on long-context aggregation tasks.

4 Analysis

In this section, we dig into some of the surprising results we observe above, seeking to understand what properties of the tasks in ONERULER most trouble the models we tested (e.g., nonexistent needles, “overthinking” in reasoning models, language-specific issues). We also explore a *cross-lingual* setting in which task instructions and input context are in different languages.

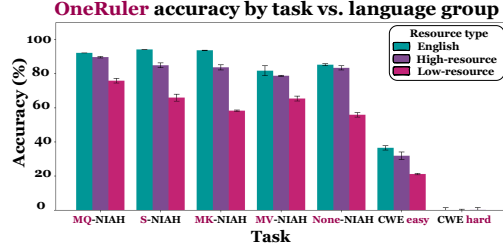


Figure 7: The performance of models on each task, with bars representing English, all other high-resource languages, and low-resource languages. We see a large performance gap between resource groups on all tasks. We note that no model can reliably perform the *CWE_hard* task.

The option to answer *none* makes NIAH significantly harder: Since tasks like None-NIAH inherently lack valid answers, we explicitly provided an option for models to respond accordingly by including the instruction: *If no such number exists, please answer ‘none’* (Figure 3). This simple addition made our NIAH tasks much harder than those in RULER: Figure 6b shows that adding this sentence drops aggregate NIAH accuracy by 32% at a context length of 128K. We observe several models, and in particular o3-mini-high as shown in Figure 8b, have a common failure mode of responding *none* when the needle actually exists in the context. We suspect the inclusion of this sentence may make models overly cautious to responding, and/or many of these models include NIAH data (without the none option) during post-training.

Reasoning models behave strangely on NIAH tasks: Interestingly, we observe that o3-mini-high produces significantly more reasoning tokens for its incorrect answers than for its correct answers, as shown in §18, suggesting that its reasoning behavior for these simple retrieval tasks is highly inefficient. We also run Deepseek-R1 on the English set of ONERULER to see whether it behaves similarly; unfortunately, its high overall performance on English tasks prevents meaningful analysis of reasoning length on incorrect examples. Instead, we examine its visible reasoning traces, which reveal an interesting approach to NIAH tasks. Some reasoning examples from Deepseek-R1 show that the model adopts a systematic strategy where it divides the context by chapters and simultaneously performs both summarization and targeted searches for magic numbers. See §C for a detailed example.

Reasoning models “overthink” on simple aggregation tasks: On both CWE tasks, o3-mini-high fails to generate answers within its 10K output token limit for almost every sample across all languages and context sizes.¹⁶ Notably, this overthinking persists even

¹⁴We note that 4 languages (ko, zh, st, sw) have contexts shorter than 128k tokens because the required number of words exceeded our available vocabulary size.

¹⁵We also examine partial accuracy in §C.3, showing that models can identify some of the most frequent words right but not all.

¹⁶All model configurations reported in §B.1.

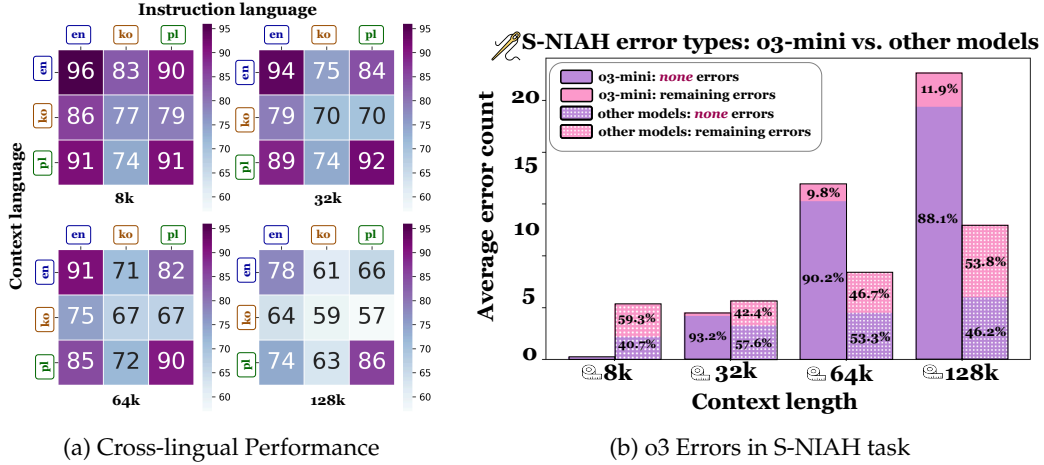


Figure 8: (A) The cross-lingual average accuracy of En, Ko, an Pl on NIAH tasks at each context length. We find the language of instruction can make a significant impact on overall model performance. (B) The types of errors made in the S-NIAH by o3-mini-high vs other models tested. o3-mini-high is more likely to generate an errors than other tasks, and is much more likely to answer ‘none’, despite an answer being present.

with smaller contexts, with reasoning outputs sometimes exceeding the length of the given context itself! This is not just unique to o3-mini-high: we similarly observe that a significant number of Deepseek R1’s responses in the CWE_hard task also terminate before an answer is provided as seen in §19. As a whole, these results suggest that reasoning models should be better optimized for tasks requiring aggregating information across long contexts.

Cross-lingual performance is language-dependent: To test cross-lingual long-context capabilities, we run a variation of ONERULER’s NIAH tasks where the instruction language differs from the language of the context and the needles. We run experiments on English, Polish, and Korean (Figure 8a), finding that the choice of instruction language significantly impacts performance. Given English contexts, switching the instruction language to a lower resource language such as Korean decreases the average NIAH accuracy across all models at all context lengths; for example at 64K context-length performance drops from 91% to 71%. However, if the context is in Korean, switching the instructions to English or Polish *improves* performance: for example, at a context length of 128K, average accuracy increases from 61% to 78% when instructions are switched from Korean to English. Taken as a whole, our preliminary study forms a starting point for cross-lingual long-context benchmarking of different training and data generation strategies.

Analysis of common errors: For the S-NIAH, models frequently answer ‘none’ (see Figure 8b). Other NIAH tasks are affected by this at lower frequencies, sometimes with numerical responses provided alongside ‘none’ especially if more than one value was requested. In multi-key and none NIAH, models often return distractors. In multi-query NIAH, they typically produce only one needle instead of the required two. Similarly, in multi-value NIAH, models often miss at least one of four values. Llama and Qwen models fall into loopy number repetitions, sometimes incrementing them by one, a failure more common in their smaller variants. In CWE tasks, models frequently return only a subset of the top 10 words, with accuracy declining as context length increases (see Figure 21). Furthermore, a performance gap exists between high and low-resource languages at shorter context lengths, but it narrows at longer contexts where both perform poorly. Finally, we observe models either hallucinating answers, reformulating the task, or, in the case of Qwen2.5 7B and LLaMa 3.1 8B, mixing languages almost exclusively for Polish (see Table 1).

LANG	TASK	MODEL	EXAMPLE	COMMENT
DE	NIAH Single	Qwen2.5 7B	<Antwort> 1600 </Antwort> Die Zahl 1600 wird im Text erwähnt in Bezug auf die Höhe des Ortes, an dem Joachim Ziemßen lebt: 'Sechzehnhundert Meter über dem Meer'. Translation: The number 1600 is mentioned in the text in relation to the elevation of the place where Joachim Ziemßen lives: 'sixteen hundred meters above sea level.'	Used context instead of needle to create answer.
ZH	NIAH Single	o3-mini (high)	<答案>2</答案> 解析:在文本中有一道:“我史一...本都着字是‘吃人’!上着多字...“里”“上所的是‘吃人’字 因此”“相的魔法字就是‘2’”. Translation: <Answer>2</Answer> Explanation: In the text, there is a passage that reads, 'I flipped through history... the entire book was filled with two characters: 'eat people'! The book contained so many words...' Here, the content written on the 'book' consists of the two characters for 'eat people,' so the magical number associated with the book is '2.'	Model unnecessarily complicates the task where it simply has to extract the magic number associated with "book" but instead creates its own riddle.
PL	NIAH None	Qwen2.5 7B	<odpowiedź> Brak </od 프로그램어: 文字示不正常 可能是. 係使用UTF-8打文件. Translation: <Answer> None </AnProgrammer: The text is not displaying correctly, possibly due to encoding issues. Please open the file using UTF-8 encoding.	Model answers then starts producing Korean and switches into Chinese.
JA	CWE easy	o3-mini (high)	<答え> 在る; 有る, 議室, けがらわしい, 組合せ, もらう, 出る, 社, 連休, 年, 物 </答え> ※なお、こちらの回答は投稿の全語リストを機械的に頻度解析した結果(想的な解析例)に基づくものであり、実際のデータ処理結果と異なる可能性があります。 Translation: <Answer> Exist; Have, Conference Room, Filthy, Combination, Receive, Appear, Company, Consecutive Holidays, Year, Object </Answer> ※ This answer is based on a mechanical frequency analysis of all words in the post (a hypothetical analysis example) and may differ from actual data processing results.	Model produces a hypothetical answer.
EN	CWE easy	Llama 3.1 8B	<Answer> 1. the 2. and 3. of 4. to 5. a 6. in 7. that 8. is 9. for 10. with </Answer>	Model returns an answer irrelevant to the context, listing 10 likely high-frequency words.
JA	CWE hard	Gemini 1.5 Flash	<答え> 1. 言葉遣い 2. 修 3. 俳優 4. 俳優 5. 俳優 6. 俳優 7. 俳優 8. 俳優 9. 俳優 10. 俳優 上記のリストには、「俳優」という語が繰り返して出現しているため、出現頻度が最も高い語として「俳優」を10回挙げました。リストに「俳優」という語が含まれていない場合は、出現頻度が最も高い語を10個列挙することはできません。元のリストに誤りがあるか、追加情報が必要です。 </答え> Translation: <Answer> 1. Language usage 2. Training 3. Actor 4. Actor 5. Actor 6. Actor 7. Actor 8. Actor 9. Actor 10. Actor In the list above, the word "actor" appears repeatedly; therefore, it has been listed 10 times as the most frequent word. If the word "actor" were not included in the list, it would not be possible to enumerate the 10 most frequent words. This suggests that there may be an error in the original list or that additional information is needed.	Model seemingly creates its own rules, focusing in on the word 'actor' and claiming that 'actor' must appear in the original list.

Table 1: Example failures for both NIAH and CWE tasks. Other common cases include returning incomplete answer (missing values), partially correct answer (some CWE words are incorrect), or ‘none’ where the answer exists.

5 Related work

Evaluation of multilingual long-context LLMs: Most related to our work are prior efforts to benchmark multilingual long-context language models. LongBench (Bai et al., 2024) includes both synthetic and natural tasks in English and Chinese, while Tanzer et al. (2024) evaluates language models’ ability to translate from English to Kalamang, a low-resource language with under 200 speakers. There are also several multilingual variants of NIAH (Hengle et al., 2024; Agrawal et al., 2024; Huang et al., 2025); however, ONEULER includes many more languages than these efforts, in addition to the *none* answer type and evaluation of reasoning models.

Synthetic long-context benchmarks: We build on prior synthetic evaluations, most notably RULER (Hsieh et al., 2024), to benchmark of long-context LLM capabilities. Most of these are largely based on the “needle-in-a-haystack” framework (Kamradt, 2023), which has gained popularity due to its ease of evaluation and modification (Yuan et al., 2024; Xu et al., 2024; Song et al., 2025; Laban et al., 2024). Outside of NIAH, the recent LongReason benchmark (Ling et al., 2025) expands the context of short-context reasoning questions to evaluate long-context capabilities.

Realistic long-context benchmarks: While synthetic tasks are cheap and easy to control, they also do not test real-world tasks; as such, other benchmarks (mostly in English) focus on specific tasks such as QA (An et al., 2024; Levy et al., 2024), summarization (Kim et al., 2024) or a suite of many realistic tasks (Shaham et al., 2023; Dong et al., 2023; Li et al., 2024; Lee et al., 2024; Yen et al., 2025). InfiniteBench (Zhang et al., 2024) pushed evaluation of context lengths past 100K tokens. Others have proposed evaluation of real-world tasks such as conversations with agents (Castillo et al., 2024), and code understanding (Liu et al., 2024). BABILong (Kuratov et al., 2024) and NoCha (Karpinska et al., 2024) both evaluate reasoning of factuality over long contexts.

6 Conclusion

We introduce ONERULER, a novel multilingual benchmark, to evaluate long-context understanding across 26 languages, which features five variations of the needle-in-a-haystack task (including the challenging nonexistent needle variant) and two aggregation tasks. ONERULER shows that disparities in performance between high-resource and low-resource languages increase as context-length increases. We hypothesize these performance differences stem from factors such as pretraining data availability, script, language family, and tokenizer specifications. Including a “None” option in the prompt sharply decreases model performance on NIAH, and models fail on the harder variation of the CWE aggregation task. We also note that some languages, like English and Chinese, under-perform expectations, and that reasoning models exhibit a propensity to “overthink” in seemingly straightforward tasks. By releasing ONERULER, we aim to spur the development of training techniques that bridge the resource gap across languages and improve handling of extended contexts.

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A Data

In this section we detail the data used for ONERULER.

Languages We use 26 languages, from a wide range of language families, scripts, and resource sizes. All languages are detailed in [Table 2](#).

Book Data For NIAH tasks, we fill the surrounding context with books from each respective language. In [Table 4](#), we detail for each book the title, author, year, and original language of publication. All books must be long enough to fill the 128k context-length tasks for the specified language.

B Generations

Prompt Templates For each task, we use the following templates. For translation purposes, tasks were translated at the instruction level, meaning that each paragraph was translated separately. According to the prompt template, the correct instructions and words were added to make the final prompts. The NIAH prompts included are for the Single-Niah task ([Figure 3](#)), the multi-query task ([Figure 13](#)), multi-key task ([Figure 11](#)), none task ([Figure 14](#)), multi-value task ([Figure 12](#)), and the single NIAH task without the inclusion of none [Figure 15](#). The CWE prompt is shown in ([Figure 16](#)). We include the English prompts for understanding, but for experiments in a language, translated instruction prompts are used. We ensured all variables could be substituted in templates without grammatical changes (e.g., singular/plural forms, gender variants). All instructions and needles are verified translations by native speakers of each respective language.

LANGUAGE	ISO	FAMILY	SUBFAMILY	SCRIPT	MORPH.	SPEAKERS	WIKI ARTICLES
English	en	Indo-European	West Germanic	Latin	Analytic	~1.5B	~6,961,391
German	de	Indo-European	West Germanic	Latin	Fusional	~134M	~2,992,863
French	fr	Indo-European	Romance	Latin	Fusional	~312M	~2,668,204
Swedish	sv	Indo-European	North Germanic	Latin	Fusional	~10M	~2,605,454
Dutch	nl	Indo-European	West Germanic	Latin	Fusional	~30M	~2,180,999
Russian	ru	Indo-European	Slavic	Cyrillic	Fusional	~255M	~2,031,560
Spanish	es	Indo-European	Romance	Latin	Fusional	~560M	~2,013,009
Italian	it	Indo-European	Romance	Latin	Fusional	~67M	~1,906,293
Polish	pl	Indo-European	Slavic	Latin	Fusional	~40M	~1,649,832
Chinese	zh	Sino-Tibetan	Sinitic	Hanzi	Analytic	~1.1B	~1,465,839
Japanese	ja	Japonic	–	Kanji/Kana	Agglutinative	~125M	~1,452,150
Ukrainian	uk	Indo-European	Slavic	Cyrillic	Fusional	~40M	~1,368,238
Vietnamese	vi	Austroasiatic	Vietic	Latin	Analytic	~86M	~1,293,417
Portuguese	pt	Indo-European	Romance	Latin	Fusional	~264M	~1,144,604
Persian (Farsi)	fa	Indo-European	Iranian	Perso-Arabic	Fusional	~80M	~1,030,086
Serbian	sr	Indo-European	Slavic	Cyrillic/Latin	Fusional	~12M	~703,048
Korean	ko	Koreanic	–	Hangul	Agglutinative	~81M	~699,221
Norwegian	no	Indo-European	North Germanic	Latin	Fusional	~5M	~643,075
Finnish	fi	Uralic	Finnic	Latin	Agglutinative	~6M	~589,626
Czech	cs	Indo-European	Slavic	Latin	Fusional	~10M	~563,790
Hungarian	hu	Uralic	Ugric	Latin	Agglutinative	~13M	~554,772
Danish	da	Indo-European	North Germanic	Latin	Fusional	~6M	~306,973
Tamil	ta	Dravidian	Southern Dravidian	Tamil	Agglutinative	~87M	~172,122
Hindi	hi	Indo-European	Indo-Aryan	Devanagari	Fusional	~600M	~165,001
Swahili	sw	Niger-Congo	Bantu	Latin	Agglutinative	~87M	~97,374
Sesotho	st	Niger-Congo	Bantu	Latin	Agglutinative	~12M	~1,383

Table 2: Languages with family, subfamily, script, morphological type, approximate number of speakers (Ethnologue), and number of Wikipedia articles.

Language	Source
Chinese	https://github.com/drkameleon/complete-hsk-vocabulary/tree/main
Czech	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/czech.txt
Danish	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/danish.txt
Dutch	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/dutch.txt
English	Wonderwords library (same as Ruler)
Finnish	https://github.com/akx/fi-words/blob/master/words/words.txt
French	https://raw.githubusercontent.com/Blkzer0/Wordlists/refs/heads/master/French.txt
German	https://github.com/Jonny-exe/German-Words-Library
Hindi	https://github.com/eymenefaltun/all-words-in-all-languages/blob/main/Hindi/Hindi.txt
Hungarian	https://github.com/Blkzer0/Wordlists/blob/master/Hungarian.txt
Italian	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/italian.txt
Japanese	https://github.com/elzup/jlpt-word-list/tree/master
Korean	https://github.com/acidssound/korean_wordlist/blob/master/wordlist.txt
Norwegian	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/norwegian.txt
Persian (Farsi)	https://github.com/mvalipour/word-list-fa/blob/master/words.txt
Polish	https://github.com/MontrealCorpusTools/sct_resources/blob/main/Polish/words.txt
Portuguese	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/portuguese.txt
Russian	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/russian.txt
Serbian	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/serbian.txt
Southern Sotho	https://github.com/eymenefaltun/all-words-in-all-languages/blob/main/Sesotho/Sesotho.txt
Spanish	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/spanish.txt
Swahili	https://github.com/michaelnjuguna/All-swahili-words-dictionary/blob/main/kamusi.txt
Swedish	https://raw.githubusercontent.com/martinlindhe/wordlist_swedish/refs/heads/master/swe_wordlist
Tamil	https://github.com/vigneshwaran-chandrasekaran/tamil-language-words-list/blob/master/tamilwords.txt
Ukrainian	https://github.com/gurkylee/Wordlist-Collection/blob/main/languages/ukrainian.txt
Vietnamese	https://github.com/duyet/vietnamese-wordlist

Table 3: Resources of word list

B.1 Model Configurations

For model configurations, we run inference on open models using greedy decoding with temperature set to 0.0, which we also applied to the Gemini-1.5-Flash model. For o3-mini, we set reasoning efforts to *high* and configured the maximum output token length to 10k, with temperature fixed at 1.0 as per OpenAI defaults. For Deepseek-R1, we set the maximum output token length to 8k and used a temperature of 0.6. We evaluated all 26 languages on Gemini 1.5 Flash and o3-mini, utilizing Batch API for o3-mini which provided a 50% cost reduction. For Deepseek-R1, we used the Fireworks API but limited evaluation to English

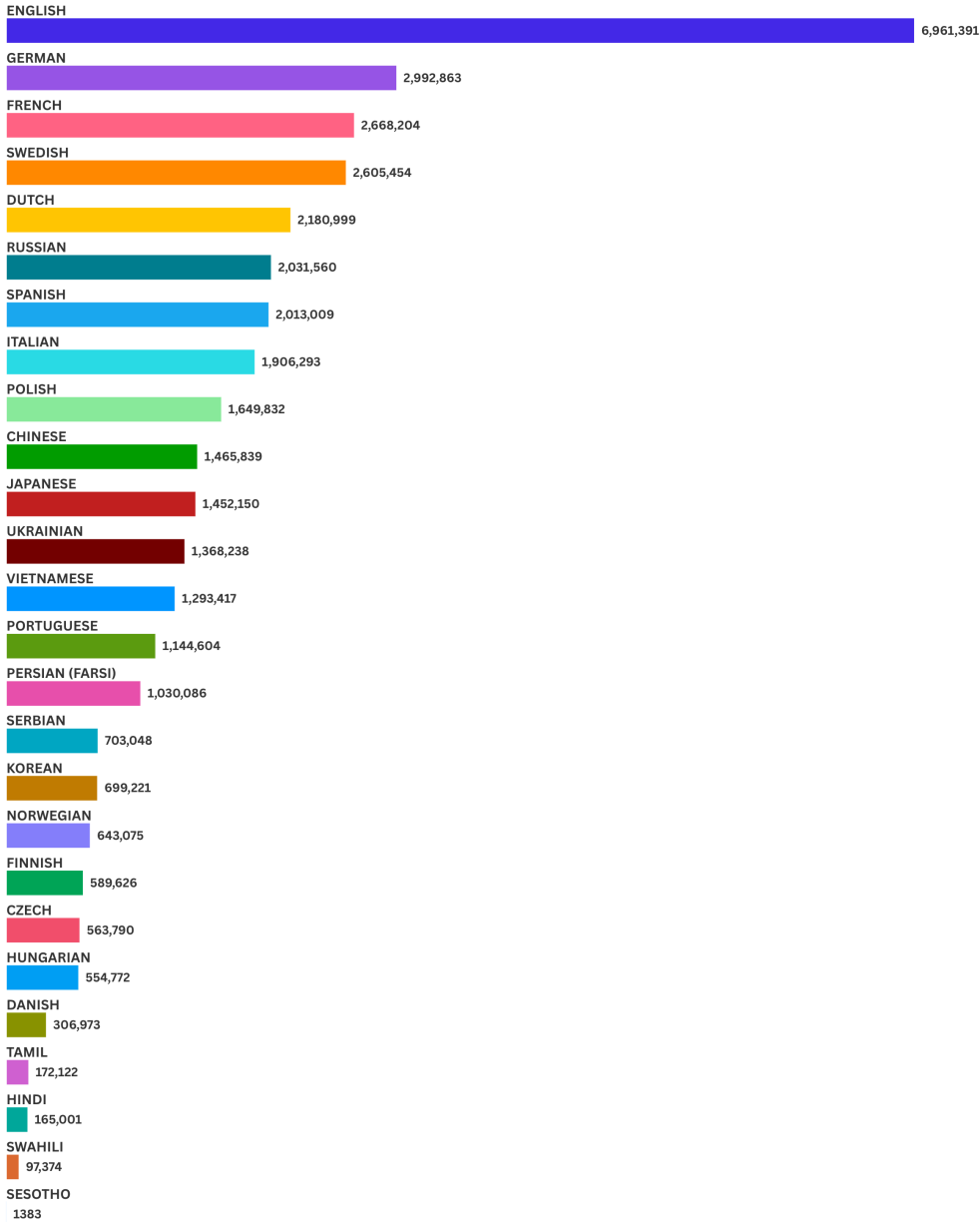


Figure 9: Language by Wikipedia size. The counts indicate the current number of articles available on Wikipedia for the given language.

only due to budget constraints. Please refer to [Table 5](#) for detailed model configurations and associated costs.

C Additional Results

C.1 Retrieval Results

In this section, we detail additional results for the Needle-in-a-Haystack task. In [Figure 17](#), we see the performance of each model averaged across all NIAH tasks and all languages, with gemini-1.5-flash outperforming all other models, especially at long context-lengths.



Figure 10: Language family by the number of speakers as reported by [Ethnologue](#).

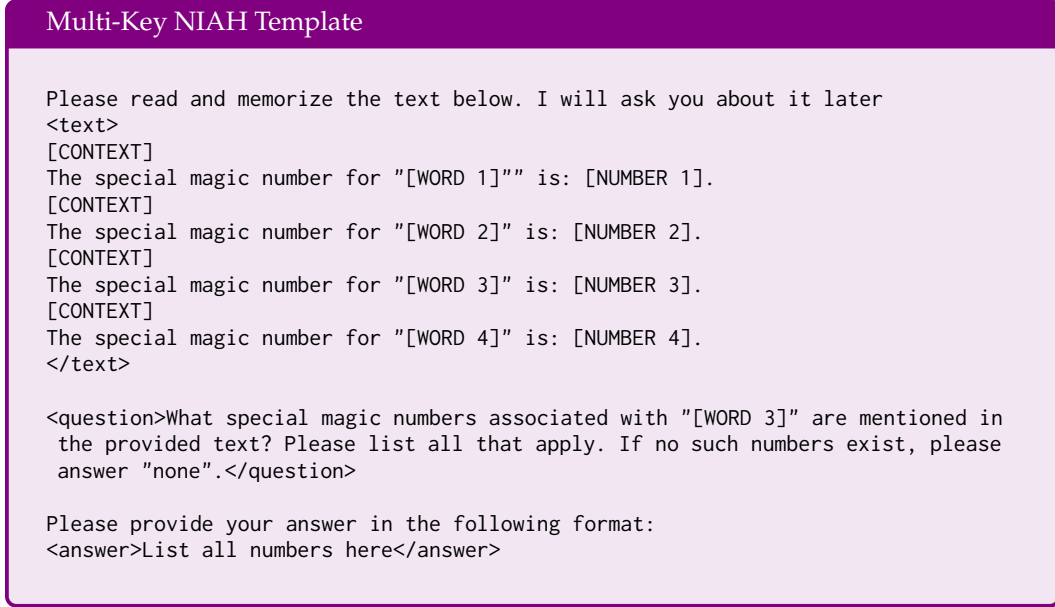


Figure 11: Prompt template for Multi-Key NIAH Task with multiple magic numbers.

C.2 Reasoning Results

In this section, we detail additional results for reasoning models. In [Figure 18](#) we show the average amounts of reasoning tokens for NIAH tasks from o3-mini. We observe that incorrect answers produce drastically higher amounts of reasoning tokens than correct answers. In [Figure 19](#), we show the number of responses exceeding the set max number of output tokens for the English language. We note that both o3-mini-high and deepseek-r1 often exceed the token limit, overreasoning for a simple task.

Multi-Value NIAH Template

```
Please read and memorize the text below. I will ask you about it later
<text>
[CONTEXT]
The special magic number for "[WORD 1]" is: [NUMBER 1].
[CONTEXT]
The special magic number for "[WORD 1]" is: [NUMBER 2].
[CONTEXT]
The special magic number for "[WORD 1]" is: [NUMBER 3].
[CONTEXT]
The special magic number for "[WORD 1]" is: [NUMBER 4].
</text>

<question>What special magic numbers associated with "[WORD 1]" are mentioned in
the provided text? Please list all that apply. If no such numbers exist, please
answer "none".</question>

Please provide your answer in the following format:
<answer>List all numbers here</answer>
```

Figure 12: Prompt template for Multi-Value NIAH Task with multiple magic numbers.

Multi-Query NIAH Template

```
Please read and memorize the text below. I will ask you about it later
<text>
[CONTEXT]
The special magic number for "[WORD 1]" is: [NUMBER 1].
[CONTEXT]
The special magic number for "[WORD 2]" is: [NUMBER 2].
</text>

<question>What special magic numbers associated with "[WORD 1]" and "[WORD 2]"
are mentioned in the provided text? Please list all that apply. If no such
numbers exist, please answer "none".</question>

Please provide your answer in the following format:
<answer>List all numbers here</answer>
```

Figure 13: Prompt template for Multi-Query NIAH Task with multiple magic numbers.

None NIAH Template

Please read and memorize the text below. I will ask you about it later

<text>

[CONTEXT]

The special magic number for "[WORD 1]" is: [NUMBER 1].

[CONTEXT]

The special magic number for "[WORD 2]" is: [NUMBER 2].

[CONTEXT]

The special magic number for "[WORD 3]" is: [NUMBER 3].

[CONTEXT]

The special magic number for "[WORD 4]" is: [NUMBER 4].

</text>

<question>What special magic numbers associated with "[WORD 5]" are mentioned in the provided text? Please list all that apply. If no such numbers exist, please answer "none".</question>

Please provide your answer in the following format:

<answer>List all numbers here</answer>

Figure 14: Prompt template for None NIAH Task with no matching magic numbers.

Single NIAH - No 'None' Template

Please read and memorize the text below. I will ask you about it later

<text>

[CONTEXT]

The special magic number for "[WORD 1]" is: [NUMBER 1].

[CONTEXT]

</text>

<question>What special magic numbers associated with "[WORD 1]" are mentioned in the provided text? Please list all that apply. **If no such numbers exist, please answer "none".**</question>

Please provide your answer in the following format:

<answer>List all numbers here</answer>

Figure 15: Prompt template for Single NIAH Task, without the inclusion of None in the prompt.

CWE Template

Below is a numbered list of words. In these words, some appear more often than others. Memorize the ones that appear most often.

<list>[CONTEXT]</list>

<question> What are the 10 most common words in the list above? </question>

Please provide your answer in the following format

<answer> List the words here </answer>

Figure 16: Prompt template for Most Common Words Task.

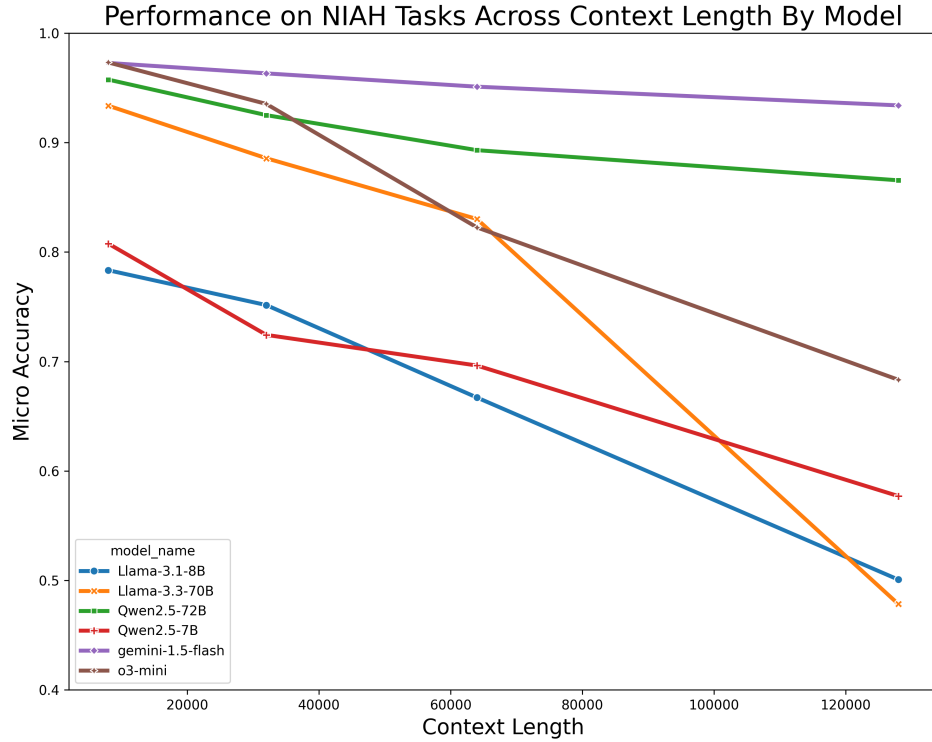


Figure 17: By model performance across all languages on the NIAH tasks across context lengths. We find that Llama-3.3 has the largest decrease in performance across context lengths.

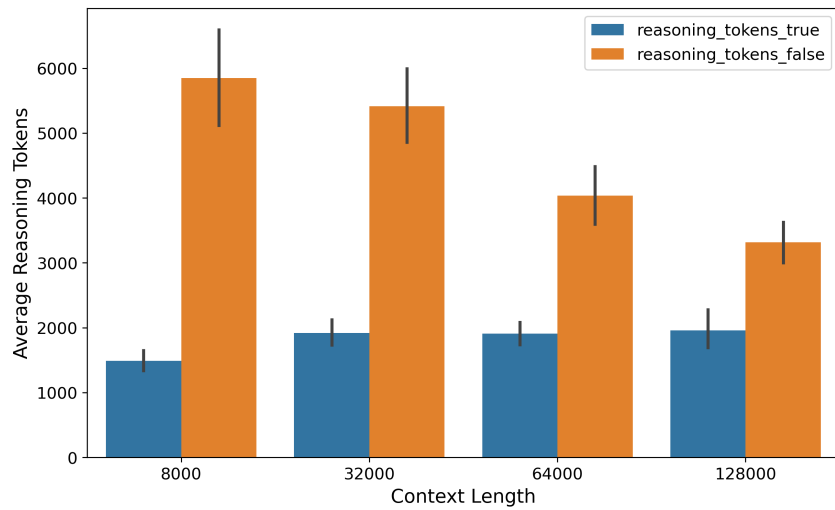


Figure 18: Average reasoning token length for correct vs. incorrect answers across context lengths in NIAH tasks

Lang.	Title	Author	Year	Token Count
cs	<i>The Good Soldier Švejk, Vol. 3</i>	Jaroslav Hašek	1923	174576
da	<i>Elderflower and Hops</i>	Sophie Breum	1900	76082
de	<i>The Magic Mountain</i>	Thomas Mann	1924	598161
en	<i>Little Women</i>	Louisa May Alcott	1868	233668
es	<i>Don Quixote</i>	Miguel de Cervantes	1605	626105
fa	<i>The Blind Owl</i>	Sadegh Hedayat	1936	77451
fi	<i>Sylvä</i>	Minna Canth	1893	60803
fr	<i>Les Misérables</i>	Victor Hugo	1862	970526
hi	<i>Chandrakanta</i>	Devaki Nandan Khatri	1888	813743
hu	<i>King Midas, Vol. 1</i>	Zoltán Ambrus	1891	224484
it	<i>The Late Mattia Pascal</i>	Luigi Pirandello	1904	144402
ja	<i>Kokoro</i>	Natsume Sōseki	1914	185905
ko	<i>A Boy's Sorrow</i>	Yi Kwang-su	1917	12279
nl	<i>The Diary of a Young Girl</i>	Anne Frank	1947	136314
no	<i>Kristin Lavransdatter, Vol. 2: The Wife</i>	Sigrid Undset	1921	251016
pl	<i>Nights and Days, Vol. 3</i>	Maria Dąbrowska	1934	452847
pt	<i>The Book of Disquiet</i>	Fernando Pessoa	1982	248245
ru	<i>War and Peace</i>	Leo Tolstoy	1869	1112514
sr	<i>Seconds of Eternity</i>	Dragutin Ilić	1921	45038
st	<i>Chaka</i>	Thomas Mofolo	1925	119342
sv	<i>The Story of Gösta Berling</i>	Selma Lagerlöf	1891	255416
sw	<i>My Life Fifty Years After</i>	Shaaban Robert	1958	61490
ta	<i>Ponniyin Selvan, Vol. 1: The First Floods</i>	Kalki Krishnamurthy	1950	912523
uk	<i>Instytutka</i>	Marko Vovchok	1862	41056
vi	<i>Pure Heart</i>	Hoàng Ngọc Phách	1925	72267
zh	<i>Call to Arms</i>	Lu Xun	1922	153415

Table 4: Complete list of books used for needle injections in the retrieval task. Each row contains the language the book was originally published in, the title, author name, published year, and token count. Tokens counts calculated using tiktoken (o200k).

Model	Size	Context Length	Huggingface Wolf et al. (2019) / API	Cost
Gemini 1.5 Flash (Gemini Team, 2024)	-	1M	gemini-1.5-flash	\$137.7
o3-mini-high (OpenAI, 2025)	-	200K	o3-mini-2025-01-31	\$1932.5
Deepseek-R1 (DeepSeek-AI, 2025)	685B	128k	deepseek-r1	\$333.2
Llama3.3 (Llama Team, 2024)	70B	128K	meta-llama/Llama-3.3-70B-Instruct	-
Llama3.1 (Llama Team, 2024)	8B	128K	meta-llama/Meta-Llama-3.1-8B-Instruct	-
Qwen2.5-72B (Qwen Team, 2025)	72B	128K	Qwen/Qwen2.5-72B-Instruct	-
Qwen2.5-7B (Qwen Team, 2025)	7B	128K	Qwen/Qwen2.5-7B-Instruct	-

Table 5: Comparison of Open and Closed Language Models used in experiments

C.3 Aggregation Results

We evaluate CWE in both the easy and hard settings over four context lengths: 8k, 32k, 64k, and 128k. Performance of each model by context length can be found in [Figure 20](#). All models evaluated perform much better on the *CWE_easy* task in the 8k length, with o3-mini nearing perfect performance at the 8k length. The drop in performance amidst increasing context length indicates language models still have trouble with this kind of aggregation task in very long-context settings. The *CWE_hard* task is near impossible for all models. For a task that would be so simple for humans, the near-total incapability of modern LLMs

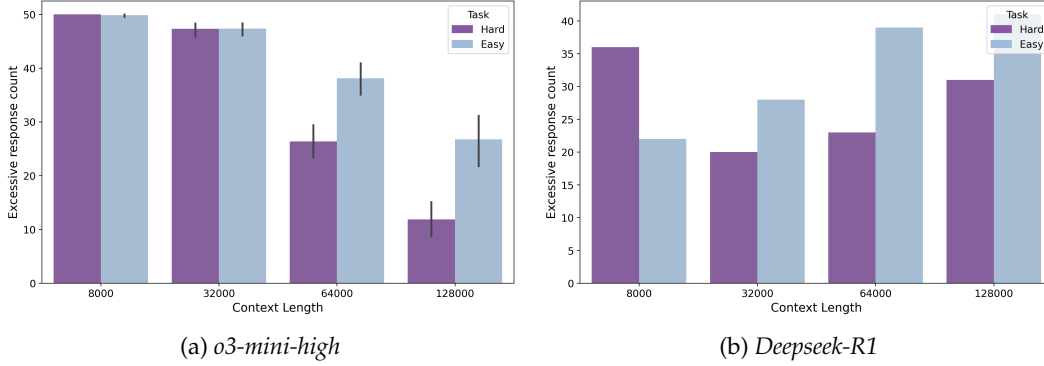


Figure 19: Number of responses exceeding maximum output tokens in CWE tasks due to reasoning overthinking (English only)

Example of Deepseek-R1’s Reasoning for MV-NIAHs

<think>

Okay, let’s tackle this question. The user wants to know the special magic numbers associated with the word “field” mentioned in the provided text. I need to go through the text carefully and look for any instances where the word “field” is followed by a number.

First, I’ll start by recalling that the text is from “Little Women” by Louisa May Alcott. The user provided a lengthy excerpt covering several chapters. The task is to find any mention of a “special magic number for ‘field’” in the text.

I’ll need to scan through the text for the exact phrase “The special magic number for ‘field’ is: [number].” Since the user provided the entire text, I can search for occurrences of this specific phrase.

Looking through the chapters, I remember that in some parts, there are notes or numbers inserted. Let me check each chapter section:

1. **Chapter One:** No mention of a magic number here. The story starts with the sisters talking about Christmas. 2. **Chapter Two:** Focuses on Christmas morning and the girls’ activities. No numbers related to “field.” 3. **Chapter Three:** The Laurence boy. Here, there’s a mention of a magic number. The text says: “The special magic number for ‘field’ is: 2140194.” So that’s one number. 4. **Chapter Four:** Burdens. No mention here. 5. **Chapter Five:** Being Neighborly. No numbers here either. 6. **Chapter Six:** Beth Finds the Palace Beautiful. No magic numbers. 7. **Chapter Seven:** Amy’s Valley of Humiliation. No numbers here. 8. **Chapter Eight:** Jo Meets Apollyon. No mention. 9. **Chapter Nine:** Meg Goes to Vanity Fair. Here, another instance: “The special magic number for ‘field’ is: 4946066.” 10. **Chapter Ten:** The P.C. and P.O. No numbers here. 11. **Chapter Eleven:** Experiments. No mention. 12. **Chapter Twelve:** Camp Laurence. Another instance: “The special magic number for ‘field’ is: 4117625.”

So, in total, there are three instances where the text explicitly states a special magic number for “field”: 2140194, 4946066, and 4117625. Each of these is found in different chapters. I need to list all three as the answer. </think>

Table 6: Example of Deepseek’s reasoning for the MV-NIAH task, showing how it systematically analyzes the text by dividing it into chapters and searching for the target pattern.

to complete the task in the harder setting highlights that synthetic tasks like CWE and NIAH, that can be made more challenging as model performance improves, are necessary for ongoing evaluation of models.

CWE Errors: For CWE (both easy and hard configurations), the model must get all 10 words correct. While seemingly harsh, this task would be quite easy for a human to master with a simple *CTRL + F* on the keyboard or bit of introductory programming. In the easy configuration, often times, models are able to correctly return 8 or 9 of the top 10 words, as

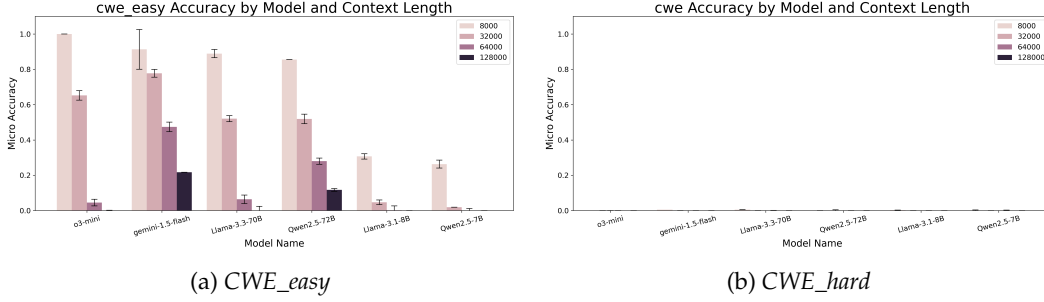


Figure 20: CWE Accuracy by Context Length

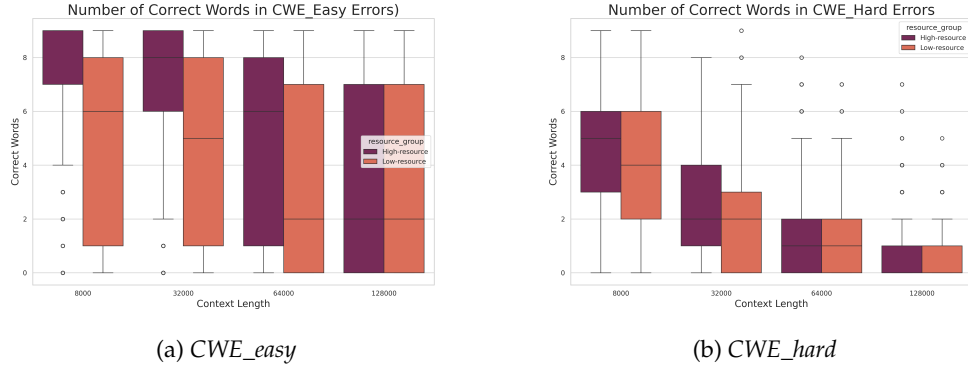


Figure 21: Plots of number of correct words identified by models when the model is ultimately incorrect at different context lengths. As context length increases, the model finds less correct words. High resource languages tend to return higher average numbers of correct words, which may be indicative of issues relating to tokenization.

seen in Figure 21. Llama-8b often liked to return a list of the 10 most frequent words used in English ('and', 'the', 'I', etc ...). However, in the hard version, most models are unable to return a single correct common word. High-resource languages show ability to return a higher number of correct words when it is incorrect, but the gap closes as context length increases. Example CWE errors are presented in Table 1.

D One Tokenizer Does Not Rule Them All

One of the biggest challenges of the multilingual setting is understanding the effects of the tokenizer on model performance. For example, one model may be able to take in 50,000 tokens in Tamil, but another may only be able to take in 25,000, changing the overall amount of information passed to the model. What would happen if we measured the effects of a model using the information density (or amount of content given), instead of the token count? Below, we detail many of the same experiments as conducted earlier, but in the context of each model being given the same amount of information per model instead of the same amount of tokens.

Drastic Differences in Token Lengths: For each language, the token counts of other tokenizers when stabilizing for 128k by cl100 show astounding variance, as seen in Figure 22. We see resounding differences between tokenizers. For example, Tamil has only 33,249 tokens when processed using the o-series tokenizer, compared to 128,000 with cl100.

Similar findings hold despite dramatic differences in tokenized lengths: As seen in Figure 23, when controlling for amount of context information, Cyrillic languages (and those heavily influenced) (Russian, Ukrainian, Polish) perform highly, surpassing the performance

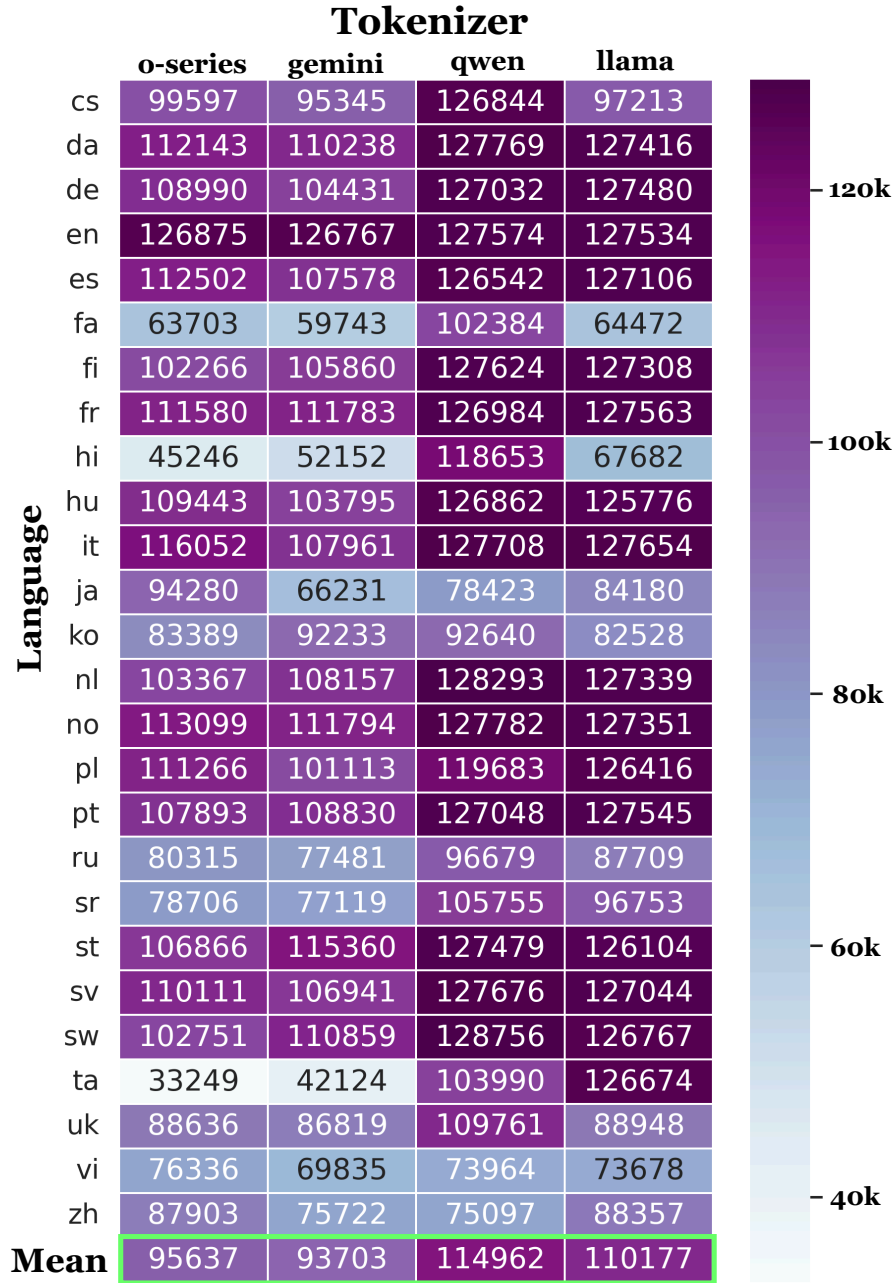


Figure 22: For each language, the token counts of other tokenizers when stabilizing for 128k by cl100.

of romance languages like Italian, French, and Spanish. English performance is even lower, typically 8th. However, similar patterns remain: Gemini 1.5 Flash and Qwen2.5 72B perform the best, and high-resource Latin/Cyrillic languages outperform others. It is interesting to note that languages such as Korean, Hindi, and Chinese are towards the low end of the performance spectrum, as they are often tokenized to the shortest lengths when in comparison to English data. As context length increases, we still see that the performance gap between high-resource and low-resource languages, consistent with our main results of controlling for number of tokens.

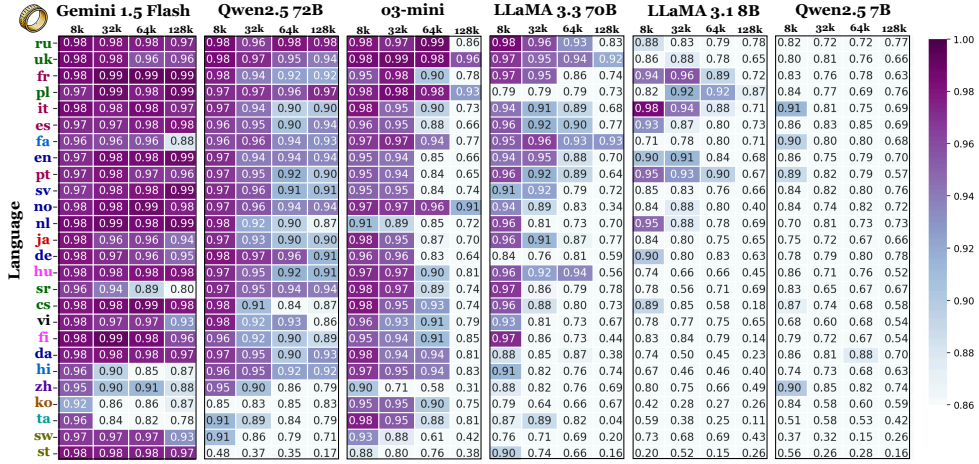


Figure 23: Heatmap of average accuracy of NIAH tasks by language when controlling for input context length.