Understanding LLMs' Cross-Lingual Context Retrieval: How Good It Is And Where It Comes From

Changjiang Gao[♣], **Hankun Lin**[♣], **Xin Huang**[◇], **Xue Han**[◇], **Junlan Feng**[◇], **Chao Deng**[◇], **Jiajun Chen**[♣], **Shujian Huang**[♣*]
[♣]National Key Laboratory for Novel Software Technology, Nanjing University
[◇]China Mobile Research Beijing, China
{gaocj,linhk}@smail.nju.edu.cn, {chenjj,huangsj}@nju.edu.cn
{huangxinyjy,hanxueai,fengjunlan,dengchao}@chinamobile.com

Abstract

Cross-lingual context retrieval (extracting contextual information in one language based on requests in another) is a fundamental aspect of cross-lingual alignment, but the performance and mechanism of it for large language models (LLMs) remains unclear. In this paper, we evaluate the cross-lingual context retrieval of over 40 LLMs across 12 languages, using cross-lingual machine reading comprehension (xMRC) as a representative scenario. Our results show that post-trained open LLMs show strong cross-lingual context retrieval ability, comparable to closed-source LLMs such as GPT-4o, and their estimated oracle performances greatly improve after post-training. Our mechanism analysis shows that the cross-lingual context retrieval process can be divided into two main phases: question encoding and answer retrieval, which are formed in pre-training and post-training respectively. The phasing stability correlates with xMRC performance, and the xMRC bottleneck lies at the last model layers in the second phase, where the effect of post-training can be evidently observed. Our results also indicate that larger-scale pretraining cannot improve the xMRC performance. Instead, larger LLMs need further multilingual post-training to fully unlock their cross-lingual context retrieval potential. [1]

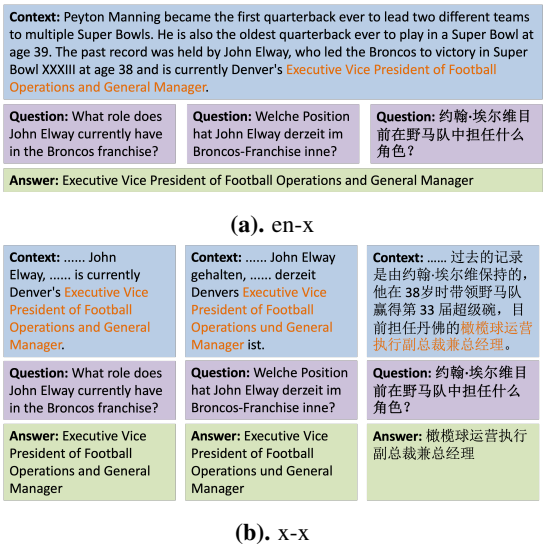

Figure 1: Examples of our en-x and x-x testing scenarios. The figures show examples in English (en), German (de), and Chinese (zh).

1 Introduction

Since the rise of Large language models (LLMs), many models have demonstrated their strong capability in various NLP tasks (Chang et al., 2024), e.g. ChatGPT[2], Claude[3], Gemini (Gemini Team et al., 2024), LLaMA (Grattafiori et al., 2024), Qwen (Qwen et al., 2025), DeepSeek (DeepSeek-AI et al., 2024b), etc. However, due to the dominance of English training data, most of these LLMs show their best performance in English (Lai et al., 2023b). To improve their performance and efficiency in non-English languages, cross-lingual alignment has become a major research topic for multilingual LLMs (Qi et al., 2023; Wang et al., 2024), which encourages LLMs to share capabilities across languages. For example, given requests with the same semantics but in different languages, LLMs should give consistent answers.

Such alignment has been shown challenging when the task requires recalling trained knowledge (Gao et al., 2024; Hu et al., 2025). Thus, a follow-up question is that, when the knowledge is presented in the context in one language (e.g. English), could LLMs retrieve it when answering requests in the another language? Note that this is different from multilingual context retrieval (the context and the request are in the same language) and cross-lingual information retrieval (retrieving

*Corresponding author
[1]Our code and results are available at https://github.com/NJUNLP/Cross-Lingual-Context-Retrieval
[2]https://chatgpt.com
[3]https://claude.ai

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queried text from a database). However, evaluation and mechanism analysis of this ability in LLMs are not fully explored.

In this paper, we evaluate cross-lingual context retrieval of SOTA multilingual LLMs, and analyze the mechanism of it. We use cross-lingual machine reading comprehension (xMRC) (Cui et al., 2019) as a simplified but representative scenario because: (1) It is a representative NLP task where models need to retrieve cross-lingual knowledge within the context; (2) The target knowledge to be retrieved is entirely within the context, so minimal extra knowledge recall is needed; (3) The model only has to copy part of the context as the answer, simplifying evaluation and mitigating other factors such as low-resource language generation errors.

Furthermore, we conduct in-depth analysis of the performance bottleneck, oracle performance, and mechanism of LLMs doing the xMRC task, using suitable tools and specially designed metrics. Specifically, we propose a hypothesis of two-phased xMRC process in LLMs, and verify our hypothesis with experimental evidence.

Our main findings are:

- Post-trained open-source LLMs, especially 7-9B versions, show strong xMRC ability, catching up with closed-source models. Larger models show higher English MRC performance, but larger gap between English and non-English.
- Post-training significantly improves the estimated oracle performance to almost saturate in all tested languages, setting space for improvement of real performance, while the effect of extended pre-training is minor.
- The xMRC process can be divided into two phases within the model: question encoding and answer retrieval. The former forms in pre-training, and its stability correlates with the base model capability, as well as xMRC performance; the latter forms in post-training, and serves as a bottleneck.
- One reason for the larger language gap observed on larger post-trained open-source LLMs might be insufficient and language-biased post training.

2 Methods

2.1 Evaluation methods

2.1.1 Scenarios

We use English to non-English (en-x) as a typical and common cross-lingual scenario, where the context and answer are in English, and the question is in non-English, because it avoids the requirement of non-English generation fluency that is not related to cross-lingual context retrieval, and keeps the answers always in English which makes answer verification easier and fairer. Meanwhile, non-English monolingual (x-x) is used as comparison to ablate the effect of non-English understanding. Figure 1 shows examples of the testing scenarios.

2.1.2 Metrics

Performance metrics. We use the F1 score to evaluate xMRC performance, as adopted by XQuAD (Artetxe et al., 2020). Exact match (EM) is not used because it tends to under-estimate the performance due to unnecessary source text in the answers (see Appendix A.1).

Cross-lingual performance metrics. To measure performance alignment between English and non-English, we calculate the average performance on all the non-English languages divided by English (en-x/en-en, x-x/en-en).

2.1.3 Performance bottleneck analysis

Error type ablation. Based on observation of model responses, we distinguish error types as:

- **Language**: answering in x instead of en;
- **Generation**: generation errors including gibberish, refusal and blank answers;
- **Content**: meaningful but incorrect answers in the correct language;

For example, the language error rate for test setting en-x is calculated as:

$$E_{\text{lang}}(\text{en},\text{x}) = \sum_{(r,a)\in W_{\text{en,x}}} \frac{\mathbb{I}(\text{Lang}(r)=\text{en})\mathbb{I}(\text{Lang}(a)=\text{x})}{|W_{\text{en,x}}|}$$

where r is the reference answer, a is the model prediction, and $\text{Lang}(\cdot)$ is a language detector for given text. Meanwhile, a generation error rate, e.g. gibberish, will be:

$$E_{\text{gib}}(\text{en},\text{x}) = \sum_{(r,a)\in W_{\text{en,x}}} \frac{\mathbb{I}(\text{Type}(r)=\text{Gibberish})}{|W_{\text{en,x}}|}$$

where $\text{Type}(\cdot)$ is an LLM-based error type classifier for generation errors.

Oracle performance estimation The xMRC score can be affected by errors in the generation process, under-estimating LLMs' cross-lingual context retrieval ability. To ablate this effect, we estimate the oracle retrieval performance of LLMs

by perturbation-based attribution[4] on contextual sentences or spans. If the sentence/span with the correct answer receives the largest attribution score, we consider the model's oracle retrieval on this testing sample correct.

2.2 Mechanism analysis methods

2.2.1 Layer-wise attribution to reflect forward process

To better understand the forward process of LLMs performing xMRC, we need layer-wise attribution to observe information flow from context parts into the residual stream (Voita et al., 2024) at each layer. Here we adopt AttentionLRP (Achtibat et al., 2024), an attribution method based on Taylor Decomposition on attention, FFN and normalization modules of LLMs, that can calculate the relevance of token representations in each layer to the output.

Based on the attribution results, we define the **Major Relevance Depth (MRD)** to estimate the maximum depth to which a token representation x needs to be encoded, by calculating the layer number corresponding to the 95th percentile of its attributed relevance to model m's output:

$$\mathrm{MRD}(m,x) = \min_{1\leqslant n\leqslant N} n$$
$$\text{s.t.} \sum_{i=1}^{n} r_{\text{out}}(x,i) \geqslant 0.95 \sum_{i=1}^{N} r_{\text{out}}(x,i)$$

where $r_{\text{out}}(x,i)$ refers to the normalized relevance score of token representation x in layer i to the final output given by AttentionLRP. A token-MRD of $\hat{n}$ indicates that the token information participates in the context retrieval process only in the first $\hat{n}$-th layers. Then, for parts of the input, i.e., task description, demonstrations, question and context, we take the maximum token-MRD of each to represent them, and calculate the mean part-MRD.

2.2.2 Hidden state similarity to measure cross-lingual alignment

To observe the cross-lingual alignment of internal xMRC process, we collect the hidden states in all model layers and calculate their cross-lingual similarity, and define a cross-lingual similarity ratio $S(\text{en,x})$ between English and language x:

$$S(\text{en,x}) = \overline{\text{Sim}}(E,X)/\overline{\text{Sim}}(X,X)$$
$$= \frac{(K-1)\sum_{e_k\in E, x_k\in X}\text{Sim}(e_k,x_k)}{2\sum_{x_i,x_j\in X}\text{Sim}(x_i,x_j)}$$

where $\overline{\text{Sim}}$ denotes the mean cosine similarity, $\text{Sim}(x,y) = x\cdot y/|x||y|$. E and X denotes en-en and en-x hidden states. K is the total number of samples, e_k and x_k are the hidden states from the k-th parallel sample pair between English and language x, x_i, x_j are the hidden states from every two different samples in language x.

3 Experiment Settings

3.1 Dataset

We use the XQuAD dataset (Artetxe et al., 2020) to measure the xMRC performance of LLMs, because its testing samples are parallel in all the 12 included languages[5] and thus suitable for cross-lingual transforming. The dataset has 1190 parallel samples for each language and an average context length of 702.50 words. It also covers diverse language families, scripts, and resource levels.

3.2 Models and tools

We adopt a variety of SOTA open and business LLMs, including LLaMA-3.1 (Grattafiori et al., 2024), Mistral (Jiang et al., 2023), Qwen-2.5 (Qwen et al., 2025), Gemma-2 (Team et al., 2024), DeepSeek V2&3 (DeepSeek-AI et al., 2024a,b), GPT-3.5, and GPT-4o, in smaller and larger sizes. Table 4 in Appendix B.1 shows a full list of all the tested models. We also tune the LLaMA-3.1-8B model with the TULU-v3 dataset (Lambert et al., 2025) into a model called LLaMA-3.1-Tuned-8B (Appendix C.3 for details) to verify the effect of post-training.

For language error detection, we use Lingua[6] with its high-accuracy mode, the accuracy of which is satisfactory in our tested languages (see Appendix A.2). For generation errors detection, we use Qwen-2.5-72B-Instruct (prompt shown in Appendix A.3) to identify generation errors. To rule out the potential bias induced by Qwen judging itself, we adopt Gemini-2.5-Flash-Lite [7] as another judge for cross-validation (see Appendix B.4).

3.3 Prompts

In our xMRC evaluation, we try two different prompt templates and use the one with higher performance for each model (see Appendix A.3). Our main evaluation and analysis uses 2-shot for higher

[4] We use Captum to perform the attribution (https://github.com/pytorch/captum)

[5] en, de, es, vi, zh, hi, ar, el, ro, ru, th, tr

[6] https://github.com/pemistahl/lingua

[7] https://gemini.google.com

	F1 scores					Error rates		
	en-en	mean en-x	mean x-x	en-x / en-en	x-x / en-en	mean language	mean generation	en-en generation
LLaMA-3.1-8B	75.97	49.01	70.28	0.64	0.93	0.32	8.88	5.60
LLaMA-3.1-70B	82.39	58.68	74.73	0.71	0.91	60.21	2.63	1.20
Mistral-V0.3-7B	79.57	58.74	64.92	0.74	0.82	21.24	14.25	0.49
Qwen-2.5-7B	62.42	57.51	66.11	0.92	1.06	0.96	3.29	1.51
Qwen-2.5-72B	86.03	78.92	81.16	0.92	0.94	10.90	2.53	0.00
Gemma-2-9B	80.42	66.82	72.90	0.83	0.91	1.91	4.11	1.02
DeepSeek-V2-Lite-16B	73.81	44.65	57.66	0.61	0.78	12.97	8.45	1.87
LLaMA-3.1-Instruct-8B	77.89	72.13	65.02	0.93	0.83	0.89	2.53	0.85
LLaMA-3.1-Tuned-8B	78.80	70.80	66.84	0.90	0.85	0.80	3.28	0.87
LLaMA-3.1-Instruct-70B	83.29	73.07	74.13	0.88	0.89	0.23	1.87	1.85
Mistral-V0.3-Instruct-7B	62.01	56.63	49.39	0.91	0.80	2.77	3.30	1.77
Qwen-2.5-Instruct-7B	81.83	76.43	71.61	0.93	0.88	0.67	3.21	2.75
Qwen-2.5-Instruct-72B	77.12	66.04	70.29	0.86	0.91	4.58	1.62	0.38
Gemma-2-IT-9B	83.69	78.72	75.53	0.94	0.90	0.17	2.47	1.95
DeepSeek-V2-Chat-Lite-16B	70.30	54.03	49.95	0.77	0.71	2.36	5.92	0.58
DeepSeek-V3	82.21	78.55	76.80	0.96	0.93	0.18	1.60	0.00
GPT-3.5-Turbo-0125	81.74	68.75	72.04	0.84	0.88	0.16	2.80	0.00
GPT-4o	83.29	78.76	75.68	0.95	0.91	0.10	1.40	0.00

Table 1: 2-shot F1 scores on en-x and x-x tasks, and 2-shot language error and generation error rates (%) on en-x tasks.

performance, and 0-shot results can be found in Appendix B.2.

4 Results

4.1 Evaluation results

Table 1 summarizes the en-x and x-x MRC performances of the main-list models (see more results in Appendix B.2).

4.1.1 Cross-lingual performance

Generally, the English MRC performance of most models are high (over 70 out of 100), but the en-x scores ranges (from 45 to 78), showing the **performance gap in context retrieval with English and non-English queries**. Down into individual models, while GPT-4o shows the highest cross-lingual performance and smallest language gap, several post-trained open LLMs, such as Gemma-2-IT, Qwen-2.5-Instruct and LLaMA-3.1-Instruct, show performance levels and small language gaps comparable to the commercial models.

An interesting observation is that, for LLaMA-3.1 and Gemma-2, the en-en performances remains close after post-training, but en-x greatly improve. This phenomenon is **more prominent in smaller (7-9B) than larger models**, bring the former a smaller performance gap between English and non-English, which is also observed on Qwen2.5 with growing parameter sizes (See Appendix B.3).

4.1.2 Comparison with Monolingual performance

In general, the performance gaps between en-en and x-x are much smaller for most models than en-x, and the Qwen models even show higher non-English performance than English. This suggests that **non-English language fluency is not the main challenge of xMRC**.

Also, for base models and post-trained larger models ($\sim$70B), **the x-x performances are always higher than en-x**. A possible explanation to this may be the cross-lingual task is less frequent in training, and more difficult because it requires cross-lingual understanding.

However, for post-trained, smaller models (7-9B), the pattern flips, where x-x performances become consistently lower than en-x, suggesting that **these models use their English context processing ability to assist non-English retrieval**, overcoming the difficulty and low-frequency of the cross-lingual task. Also, since larger LLMs tend to be better at instruction following and understanding, this further highlights that post-training better elicits the cross-lingual context retrieval ability on smaller LLMs.

4.2 Performance bottleneck analysis

4.2.1 Error type ablation

The right part of Table 1 shows error rates of different types (see details in Appendix B.4).

Language and generation errors. The language error rates of post-trained models (lower part of the table) are significantly lower than base models (upper part of the table), since the former can better follow the cross-lingual task format. Meanwhile, the error rate is low for all the post-trained models, so it cannot be viewed as a bottleneck of xMRC. The generation error rates are minor for most models, regardless of size and post-training, marking it not the bottleneck of xMRC either.

Model	Step		Sequence	
Language	en-en	en-x	en-en	en-x
LLaMA-3.1-8B	66.55	67.59	35.14	36.39
LLaMA-3.1-70B	47.47	54.92	47.89	56.97
LLaMA-3.1-Instruct-8B	89.86	83.42	93.75	86.66
LLaMA-3.1-Tuned-8B	86.49	81.04	89.53	83.07
LLaMA-3.1-Instruct-70B	92.82	90.67	95.44	93.54

Table 2: Oracle performance estimated for LLaMA models in en-en and en-x (average) scenarios. The estimation is performed with one generation step (left) and with the whole generated sequence, respectively.

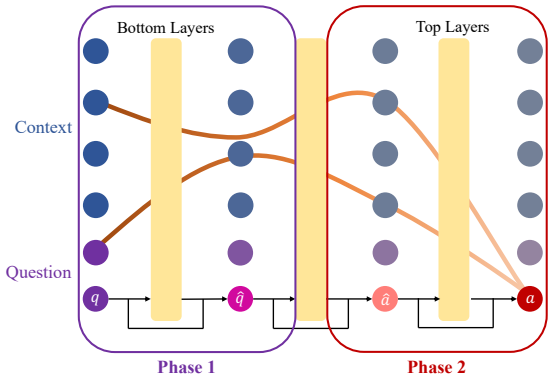
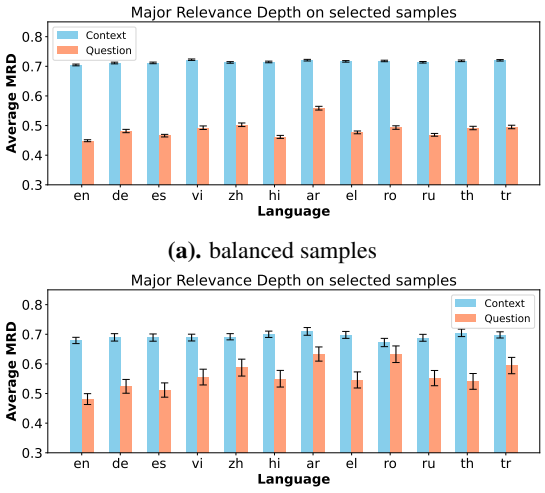


Figure 2: Illustration of the hypothesized two-phased xMRC process. Through layers, the last question token will be transferred to the first answer token in two phases, between which is a cross-lingual question representation.



(a). balanced samples

(b). en-superior samples

Figure 3: Mean MRD of the context and question parts for LLaMA-3.1-Instruct-8B.

4.2.2 Estimated oracle performance

Table 2 shows the estimated oracle performances of the LLaMA-3.1 models. "Step" means the attribution is done when generating the first answer token, and "Sequence" means the attribution is done on whole-sequence generation until EOS.

First, **the estimated oracle performances of post-trained models are significantly higher than the base models**, both for en-en and en-x, suggesting the importance of post-training to improving xMRC. However, 70B models show no substantial advantage over 8B, indicating extended pretraining contributes less to xMRC.

Second, the estimated oracle performance for en-x is close to en-en for all the LLaMA-3.1 models, and the oracle for post-trained models are basically over 90%. This is much higher than the actual performance, suggesting the **models have the potential to locate correct answers with high accuracy, but the ability needs to be further elicited**.

5 Two-phased mechanism of xMRC

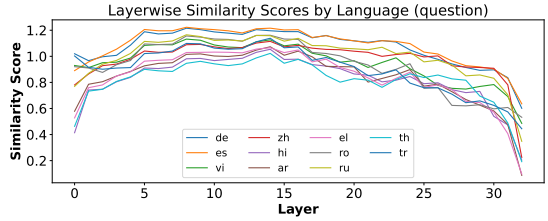
Besides evaluation of xMRC performance and bottlenecks, the mechanism of how LLMs do xMRC also worth exploring. Considering the model forward process from the input prompt to the output answer, we come up with a two-phase hypothesis of the xMRC process (taking en-x as an example):

1. **Question encoding.** The non-English queries will be encoded into a shared semantic space, where queries in different languages are aligned and understood in a language-neutral way;
2. **Answer retrieval.** The encoded queries will be used to match the answer in the English context according to the task description and format, then the answer is generated by copying from the original context.

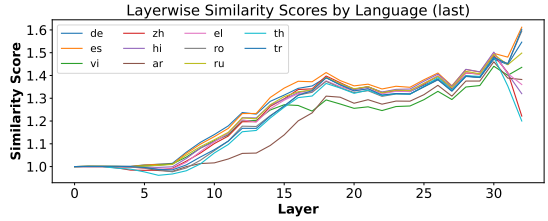
Figure 2 shows an illustration of the hypothesized process, which aligns with previous studies (Tang et al., 2024; Wendler et al., 2024; Zhao et al., 2024). If the hypothesis holds, then we will be able to extract cross-lingual representations in the middle layers and steer them to control the model retrieval behaviors. We test our hypothesis from attribution and hidden-state views with LLaMA-3.1-Instruct-8B, which shows high performance alignment across languages and is widely used. To further ensure the effect of post-training, we also conduct finetuning and compare the model behavior before and after it.

5.1 Evidence from attribution view

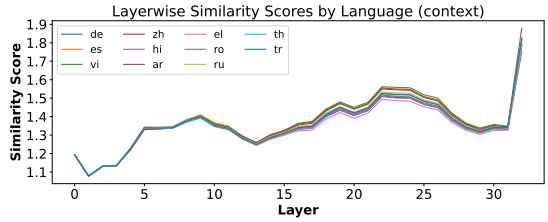
Figure 3 shows the mean MRD (§2.2.1) of the contexts and the questions for the LLaMA-3.1-Instruct-8B on testing samples that are identified as either "balanced" or "en-superior" in all tested languages. We identify a sample as "balanced" if the model F1 score on it is above 0.5 in all directions; and a sample as "en-superior" if the F1 score in English



(a). Question



(b). Last token



(c). Context

Figure 4: Question, last token and context hidden state similarity between English and other languages in each layer of the LLaMA-3.1-Instruct-8B model on the "balanced" samples.

is higher than the average of other languages with a margin greater than 0.5.

We find that the mean question MRD is significantly and substantially lower than the mean context MRD in all tested languages and across the LLaMA models, especially for the "balanced" samples (Figure 3), revealing a clear phased behavior.

Also, the MRDs of "balanced" samples (Figures 3a) are more stable than those of "en-superior" samples (Figure 3b), suggesting correlation between the higher xMRC performance and clearer phasing.

These patterns are consistent for different LLaMA models regardless of prompt formats, except much weaker for LLaMA-2-Chat-7B, which has smaller pre-training capacity and weaker multilingual ability (see Appendix C.1 for mode details).

In summary, **the attribution results supports the two-phase hypothesis**, and indicates that the phased behavior is already formed after pre-training, regardless of model size and prompt format. The phasing strength correlates with the pre-training capacity and the xMRC task performance.

5.2 Evidence from hidden states view

The hidden state similarity results also support our hypothesis. Figure 4 shows the en-x hidden state similarity of the question, last input token (predicting the start of the answer) and context parts for the LLaMA-3.1-Instruct-8B model (more results are in Appendix C.2). The observed trends are consistent:

- For question representations, they all show a shared arc-shaped trend, where the highest similarity to English appears at the relative depth of around 1/3;
- For context representations, a consistent double-peak trend can be observed, with a "turning point" around the relative depth of 0.4 (matching the question MRD) and the second, higher peak at around 0.7 (matching the context MRD);
- For last input token representations, one can see a consistent "plateau" of similarity starting at around a relative depth of 0.5, which also matches the mean question MRD.

It is worth noticing that, though the context parts are all English, there are 2-shot demonstrations with non-English questions, making the representations not identical. The context similarity curves can represent the degree of semantic encoding compared with formal encoding.

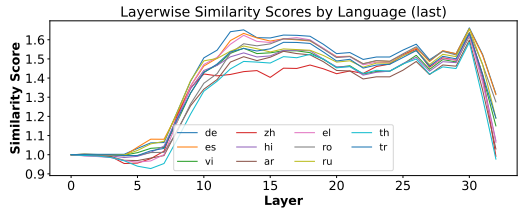
Again, for the less powerful model LLaMA-2-Chat-7B (Figure 20 in Appendix C.2), the trends are weaker: its question similarity to English varies much across languages, and the "plateau" of answer similarity to English starts later than other models, which is after the mean question and context MRDs.

These results suggest that **the hidden states similarity through the xMRC process also undergo two main phases with evident distinction**. This phased behavior already exists in pre-trained LLMs, and is preserved in post-training. Also, the phasing strength correlates with the model capability built during pre-training.

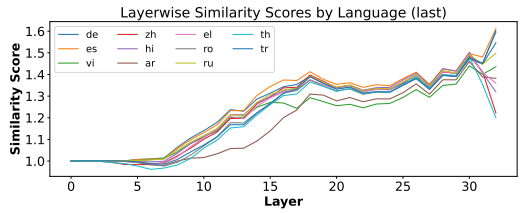
5.3 Importance of post-training

Our evaluation results show that post-training is crucial to enhancing xMRC performance. Here, we show the significance of post-training to xMRC from the hidden-state view.

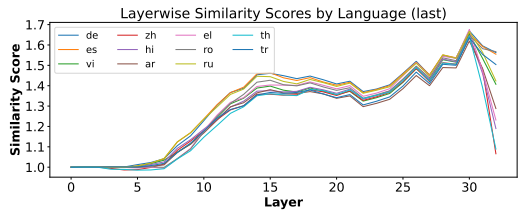
The first evidence comes from the last-input-token similarity results. One can observe from Figure 5a and 7a that, **the last-input-token similarity of base models experience severe and consistent decline in the last few layers**, across all



(a). LLaMA-3.1-8B

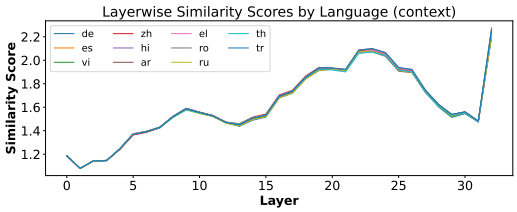


(b). LLaMA-3.1-Instruct-8B

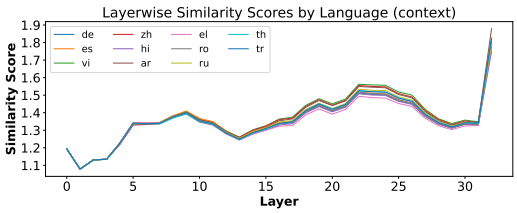


(c). LLaMA-3.1-Tuned-8B

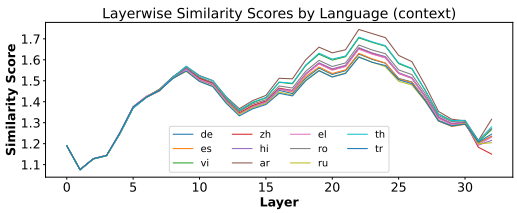
Figure 5: Change in last-input-token hidden state similarity between English and other languages in each layer of LLaMA-3.1-8B, LLaMA-3.1-Instruct-8B and LLaMA-3.1-Tuned-8B on the "balanced" samples.



(a). LLaMA-3.1-8B



(b). LLaMA-3.1-Instruct-8B



(c). LLaMA-3.1-Tuned-8B

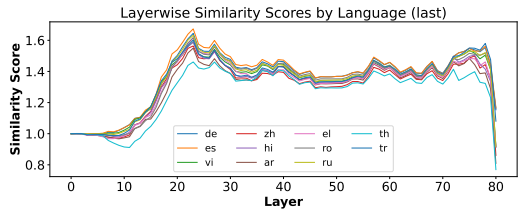
Figure 6: Change in context hidden state similarity between English and other languages in each layer of LLaMA-3.1-8B, LLaMA-3.1-Instruct-8B and LLaMA-3.1-Tuned-8B on the "balanced" samples.

non-English languages. Since we expect the same English output for all tested languages, this drop in cross-lingual similarity can directly affect the performance and its cross-lingual alignment. However, **after post-training on 8B models** (Figure 5b, 5c and 7b), **the decline significantly narrows**, and even turns into increase for languages with Latino alphabets, especially on the 8B models (Figure 5). Since this enhancement in similarity can directly turn into the narrowing of language performance gap, this indicates that post-training is especially essential to enhancing the cross-lingual alignment xMRC ability, by taking effect in the last few layers and the final calculation steps. However, **for the 70B model** (Figure 7), **the decline is still severe** after post-training, partly explaining why they show larger xMRC gap between English and non-English.

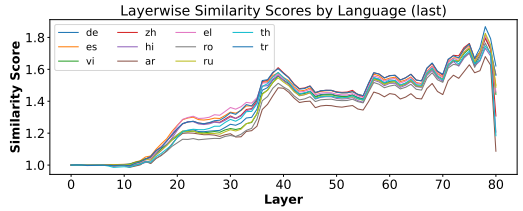
Another evidence comes from the context similarity results. One can see from Figure 6 and 8 that, the context similarity value significantly decreases after post-training, and the peak value diverges among languages. Based on our understanding of the score, **lower context similarity means its contextual representations become more customized for the demonstrations** with non-English questions, which is potentially beneficial for xMRC. This also partly explains the enhancement of xMRC after post-training. However, **the divergence among languages means that this driving effect of demonstrations varies in different languages**, contributing to the performance gap between languages. It is especially evident for the 70B model (Figure 8) that, better-xMRC-performing languages (e.g. de, es) tend to show lower peak values, while worse-xMRC-performing languages (e.g. ar, th) tend to show higher. This corresponds with the reasoning that lower context similarity correlates with higher xMRC performance, and adds to the explanation why 70B models have larger performance gaps between languages.

Based on these findings, we propose a possible reason for the larger language gap for 70B post-trained models that **their post-training is insufficient to reshape the answer retrieving phase, and is biased to certain languages**, which causes the near-base behavior in last-token similarity and the larger divergence in context similarity. With more sufficient and language-balanced post-training, we expect the Instruct-70B model

to reveal similar patterns in last-input-token and context hidden states similarity as Instruct-8B.

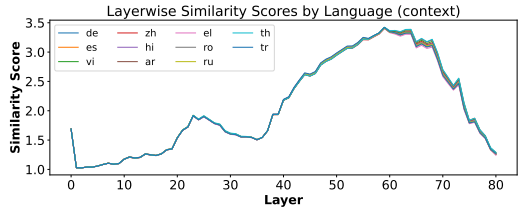


(a). LLaMA-3.1-70B

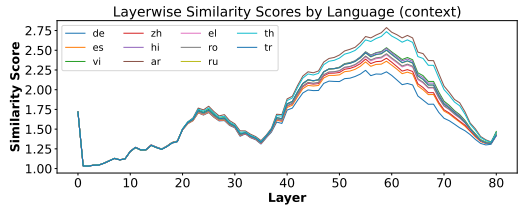


(b). LLaMA-3.1-Instruct-70B

Figure 7: Change in last-input-toke hidden state similarity between English and other languages in each layer of LLaMA-3.1-70B and LLaMA-3.1-Instruct-70B on the "balanced" samples.



(a). LLaMA-3.1-70B



(b). LLaMA-3.1-Instruct-70B

Figure 8: Change in context hidden state similarity between English and other languages in each layer of LLaMA-3.1-70B and LLaMA-3.1-Instruct-70B on the "balanced" samples.

6 Related Work

6.1 Cross-lingual alignment of LLMs

Previous studies have shown a misalignment of LLMs with English and other languages. With respect to performance, Lai et al. (2023b), Ahuja et al. (2024) and Wang et al. (2024) demonstrated that SOTA LLMs performed better in English, and showed inconsistency when dealing with non-English queries. Etxaniz et al. (2024) found that LLMs performed worse with non-English prompts than with self-translated English prompts. Beyond performance, Qi et al. (2023) demonstrated the low cross-lingual consistency of factual knowledge does of LLMs, and Gao et al. (2024) showed that multilingual pre-training and instruction tuning could only enhance superficial levels of cross-lingual alignment. Zhao et al. (2024) demonstrated that multilingual LLMs employ shared and language-specific circuits to process different languages when needed. These papers mostly focus on same-language queries, and our work focuses on cross-lingual queries.

There have also been many techniques to enhance LLMs' cross-lingual alignment. For example, adding parallel data in the pre-training stage (Lample and Conneau, 2019; Jiang et al., 2022; Wei et al., 2023; Lu et al., 2024); and the post-training stage, including instruction tuning (Li et al., 2023b; Zhang et al., 2025; Li et al., 2023a; Cahyawijaya et al., 2023; Chai et al., 2024; Kuulmets et al., 2024; Shaham et al., 2024; Kew et al., 2024) and preference tuning (Lai et al., 2023a; She et al., 2024). Especially, extra translation training is commonly used (Zhang et al., 2023; Yang et al., 2023; Li et al., 2024; Ranaldi et al., 2024; Zhu et al., 2024; Lu et al., 2024). In this paper, we examine the effect of some of these techniques by comparing various SOTA models.

6.2 Cross-lingual machine reading comprehension

xMRC is a relatively new task of natural language understanding. Cui et al. (2019) proposed the task, in order to improve non-English MRC performance by introducing English resources. There are some representative datasets in this area, such as XQA (Liu et al., 2019), BiPaR (Jing et al., 2019), MLQA (Lewis et al., 2020), and XQuAD (Artetxe et al., 2020). Ushio et al. (2023) also proposes a pipeline for multilingual QA generation. However, previous work on the xMRC task mainly focuses on enhancing the performance of task-specific models using techniques such as data augmentation (Bornea et al., 2021; Xiang et al., 2024), knowledge injection (Duan et al., 2021), constractive learning (Chen et al., 2022) and knowledge transfer (Cao et al., 2023; Xu et al., 2023). In this paper, we study the xMRC of multilingual LLMs under the larger topic of cross-lingual alignment.

7 Conclusion

This paper investigates the performance and mechanism of cross-lingual context retrieval of LLMs within the xMRC scenario. For evaluation, we demonstrate the strong xMRC abilities of post-trained models, and study their bottlenecks and oracle performances. For mechanism, we verify a two-phased hypothesis of the xMRC process, identifying the effect of post-training, and finding a possible explanation to the language gap for larger post-trained models. We hope our research will inspire future study to foster the cross-lingual alignment of LLMs in a broader scope.

Limitations

While this study provides insights of the cross-lingual context retrieval abilities of LLMs, there are also some limitations.

First, the scope of our empirical evaluation is constrained by available resources and time. This necessarily limits the breadth of our testing, preventing us from exhaustively covering the rapidly expanding landscape of LLMs. Besides, while we test across 12 diverse languages, a more comprehensive analysis would ideally include an even wider range of languages, as well as grouping them according to their levels of resource, in order to improve the generalizability of our findings across linguistic diversity.

Second, although we identify a two-phased feature of xMRC and confirm its correlation with pre-training and post-training, the precise factors within these training processes that drive this outcome remain unclear. Future work could delve deeper into the data and strategies of these training stages to locate factors contributing to the emergence and strength of the phasing.

Finally, within the two major phases we discover, we observe hints of more fine-grained changes in model behavior, particularly in the hidden state similarity curves. These preliminary observations suggest the potential for a more nuanced understanding of the xMRC process. Future studies could further investigate these finer-grained dynamics within each phase to gain a more detailed and complete picture of how LLMs achieve cross-lingual context retrieval.

Beyond these limitations, it is also important to consider potential risks associated with this work. While our research is foundational and not directly tied to specific applications, advancements in cross-lingual context retrieval, like any technology, could be misused. For example, improved cross-lingual capabilities might inadvertently contribute to the spread of misinformation if models are used to retrieve and amplify biased or inaccurate information across languages. Furthermore, if deployed without careful consideration, these technologies could exacerbate existing inequalities by favoring languages and knowledge systems already dominant in LLM training data, potentially marginalizing less-represented languages and perspectives. Future work should consider these dual-use aspects and explore mitigation strategies to ensure responsible development and deployment of cross-lingual NLP technologies, paying special attention to fairness and inclusivity across diverse linguistic communities.

Ethics Statements

This research adheres to ethical principles in its use of language models and data. All language models evaluated and finetuned in this study are accessed and utilized in compliance with their respective licenses and terms of service. Furthermore, the XQuAD dataset employed for evaluation, and the TULU-v3 dataset used for finetuning LLaMA-3.1-8B, are both publicly available datasets intended for research purposes. Based on our review and the documented nature of these datasets, we have determined that they are not designed to collect or contain personally identifiable information or offensive content. To the best of our knowledge, and as indicated in their public documentation, neither dataset includes data that names or uniquely identifies individual people, nor do they present offensive content.

Our use of these existing artifacts, including both language models and datasets, is aligned with their intended use within research contexts. Specifically, derivatives of data accessed for research purposes, such as model outputs and analysis results, are used solely within the bounds of academic inquiry and are not disseminated or utilized outside of these research contexts, in accordance with responsible data handling practices.

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Arnold, Vijay Vasudevan, Shubham Agrawal, Jason Riesa, Dmitry Lepikhin, Richard Tanburn, Srivatsan Srinivasan, Hyeontaek Lim, Sarah Hodkinson, Pranav Shyam, Johan Ferret, Steven Hand, Ankush Garg, Tom Le Paine, Jian Li, Yujia Li, Minh Giang, Alexander Neitz, Zaheer Abbas, Sarah York, Machel Reid, Elizabeth Cole, Aakanksha Chowdhery, Dipanjan Das, Dominika Rogozińska, Vitaliy Nikolaev, Pablo Sprechmann, Zachary Nado, Lukas Zilka, Flavien Prost, Luheng He, Marianne Monteiro, Gaurav Mishra, Chris Welty, Josh Newlan, Dawei Jia, Miltiadis Allamanis, Clara Huiyi Hu, Raoul de Liedekerke, Justin Gilmer, Carl Saroufim, Shruti Rijhwani, Shaobo Hou, Disha Shrivastava, Anirudh Baddepudi, Alex Goldin, Adnan Ozturel, Albin Cassirer, Yunhan Xu, Daniel Sohn, Devendra Sachan, Reinald Kim Amplayo, Craig Swanson, Dessie Petrova, Shashi Narayan, Arthur Guez, Siddhartha Brahma, Jessica Landon, Miteyan Patel, Ruizhe Zhao, Kevin Villela, Luyu Wang, Wenhao Jia, Matthew Rahtz, Mai Giménez, Legg Yeung, James Keeling, Petko Georgiev, Diana Mincu, Boxi Wu, Salem Haykal, Rachel Saputro, Kiran Vodrahalli, James Qin, Zeynep Cankara, Abhanshu Sharma, Nick Fernando, Will Hawkins, Behnam Neyshabur, Solomon Kim, Adrian Hutter, Priyanka Agrawal, Alex Castro-Ros, George van den Driessche, Tao Wang, Fan Yang, Shuo yiin Chang, Paul Komarek, Ross McIlroy, Mario Lučić, Guodong Zhang, Wael Farhan, Michael Sharman, Paul Natsev, Paul Michel, Yamini Bansal, Siyuan Qiao, Kris Cao, Siamak Shakeri, Christina Butterfield, Justin Chung, Paul Kishan Rubenstein, Shivani Agrawal, Arthur Mensch, Kedar Soparkar, Karel Lenc, Timothy Chung, Aedan Pope, Loren Maggiore, Jackie Kay, Priya Jhakra, Shibo Wang, Joshua Maynez, Mary Phuong, Taylor Tobin, Andrea Tacchetti, Maja Trebacz, Kevin Robinson, Yash Katariya, Sebastian Riedel, Paige Bailey, Kefan Xiao, Nimesh Ghelani, Lora Aroyo, Ambrose Slone, Neil Houlsby, Xuehan Xiong, Zhen Yang, Elena Gribovskaya, Jonas Adler, Mateo Wirth, Lisa Lee, Music Li, Thais Kagohara, Jay Pavagadhi, Sophie Bridgers, Anna Bortsova, Sanjay Ghemawat, Zafarali Ahmed, Tianqi Liu, Richard Powell, Vijay Bolina, Mariko Iinuma, Polina Zablotskaia, James Besley, Da-Woon Chung, Timothy Dozat, Ramona Comanescu, Xiance Si, Jeremy Greer, Guolong Su, Martin Polacek, Raphaël Lopez Kaufman, Simon Tokumine, Hexiang Hu, Elena Buchatskaya, Yingjie Miao, Mohamed Elhawaty, Aditya Siddhant, Nenad Tomasev, Jinwei Xing, Christina Greer, Helen Miller, Shereen Ashraf, Aurko Roy, Zizhao Zhang, Ada Ma, Angelos Filos, Milos Besta, Rory Blevins, Ted Klimenko, Chih-Kuan Yeh, Soravit Changpinyo, Jiaqi Mu, Oscar Chang, Mantas Pajarskas, Carrie Muir, Vered Cohen, Charline Le Lan, Krishna Haridasan, Amit Marathe, Steven Hansen, Sholto Douglas, Rajkumar Samuel, Mingqiu Wang, Sophia Austin, Chang Lan, Jiepu Jiang, Justin Chiu, Jaime Alonso Lorenzo, Lars Lowe Sjösund, Sébastien Cevey, Zach Gleicher, Thi Avrahami, Anudhyan Boral, Hansa Srinivasan, Vittorio Selo, Rhys May, Konstantinos Aisopos, Léonard Hussenot, Livio Baldini Soares, Kate Baumli, Michael B. 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thée Lottaz, Qi Li, Vikas Yadav, Luyao Xu, Alex Chinien, Rakesh Shivanna, Aleksandr Chuklin, Josie Li, Carrie Spadine, Travis Wolfe, Kareem Mohamed, Subhabrata Das, Zihang Dai, Kyle He, Daniel von Dincklage, Shyam Upadhyay, Akanksha Maurya, Luyan Chi, Sebastian Krause, Khalid Salama, Pam G Rabinovitch, Pavan Kumar Reddy M, Aarush Selvan, Mikhail Dektiarev, Golnaz Ghiasi, Erdem Guven, Himanshu Gupta, Boyi Liu, Deepak Sharma, Idan Heimlich Shtacher, Shachi Paul, Oscar Akerlund, François-Xavier Aubet, Terry Huang, Chen Zhu, Eric Zhu, Elico Teixeira, Matthew Fritze, Francesco Bertolini, Liana-Eleonora Marinescu, Martin Bölle, Dominik Paulus, Khyatti Gupta, Tejasi Latkar, Max Chang, Jason Sanders, Roopa Wilson, Xuewei Wu, Yi-Xuan Tan, Lam Nguyen Thiet, Tulsee Doshi, Sid Lall, Swaroop Mishra, Wanming Chen, Thang Luong, Seth Benjamin, Jasmine Lee, Ewa Andrejczuk, Dominik Rabiej, Vipul Ranjan, Krzysztof Styrc, Pengcheng Yin, Jon Simon, Malcolm Rose Harriott, Mudit Bansal, Alexei Robsky, Geoff 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Héctor Fernández Alcalde, Peter Makarov, Will Chen, Antonio Stella, Liselotte Snijders, Michael Mandl, Ante Kärrman, Paweł Nowak, Xinyi Wu, Alex Dyck, Krishnan Vaidyanathan, Raghavender R, Jessica Mallet, Mitch Rudominer, Eric Johnston, Sushil Mittal, Akhil Udathu, Janara Christensen, Vishal Verma, Zach Irving, Andreas Santucci, Gamaleldin Elsayed, Elnaz Davoodi, Marin Georgiev, Ian Tenney, Nan Hua, Geoffrey Cideron, Edouard Leurent, Mahmoud Alnahlawi, Ionut Georgescu, Nan Wei, Ivy Zheng, Dylan Scandinaro, Heinrich Jiang, Jasper Snoek, Mukund Sundararajan, Xuezhi Wang, Zack Ontiveros, Itay Karo, Jeremy Cole, Vinu Rajashekhar, Lara Tumeh, Eyal Ben-David, Rishub Jain, Jonathan Uesato, Romina Datta, Oskar Bunyan, Shimu Wu, John Zhang, Piotr Stanczyk, Ye Zhang, David Steiner, Subhajit Naskar, Michael Azzam, Matthew Johnson, Adam Paszke, Chung-Cheng Chiu, Jaume Sanchez Elias, Afroz Mohiuddin, Faizan Muhammad, Jin Miao, Andrew Lee, Nino Vieillard, Jane Park, Jiageng Zhang, Jeff Stanway, Drew 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Shuangfeng Li, Olivier Dousse, Fan Yang, Jeff Piper, Nathan Ie, Rama Pasumarthi, Nathan Lintz, Anitha Vijayakumar, Daniel Andor, Pedro Valenzuela, Minnie Lui, Cosmin Paduraru, Daiyi Peng, Katherine Lee, Shuyuan Zhang, Somer Greene, Duc Dung Nguyen, Paula Kurylowicz, Cassidy Hardin, Lucas Dixon, Lili Janzer, Kiam Choo, Ziqiang Feng, Biao Zhang, Achintya Singhal, Dayou Du, Dan McKinnon, Natasha Antropova, Tolga Bolukbasi, Orgad Keller, David Reid, Daniel Finchelstein, Maria Abi Raad, Remi Crocker, Peter Hawkins, Robert Dadashi, Colin Gaffney, Ken Franko, Anna Bulanova, Rémi Leblond, Shirley Chung, Harry Askham, Luis C. 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Ser tan Girgin, Hui Li, Jiayu Ye, Ofir Roval, Reiko Tojo, Michael Kwong, James Lee-Thorp, Christopher Yew, Danila Sinopalnikov, Sabela Ramos, John Mellor, Abhishek Sharma, Kathy Wu, David Miller, Nicolas Sonnerat, Denis Vnukov, Rory Greig, Jennifer Beattie, Emily Caveness, Libin Bai, Julian Eisenschlos, Alex Korchemniy, Tomy Tsai, Mimi Jasarevic, Weize Kong, Phuong Dao, Zeyu Zheng, Frederick Liu, Fan Yang, Rui Zhu, Tian Huey Teh, Jason Sanmiya, Evgeny Gladchenko, Nejc Trdin, Daniel Toyama, Evan Rosen, Sasan Tavakkol, Linting Xue, Chen Elkind, Oliver Woodman, John Carpenter, George Papamakarios, Rupert Kemp, Sushant Kafle, Tanya Grunina, Rishika Sinha, Alice Talbert, Diane Wu, Denese Owusu-Afriyie, Cosmo Du, Chloe Thornton, Jordi Pont-Tuset, Pradyumna Narayana, Jing Li, Saaber Fatehi, John Wieting, Omar Ajmeri, Benigno Uria, Yeongil Ko, Laura Knight, Amélie Héliou, Ning Niu, Shane Gu, Chenxi Pang, Yeqing Li, Nir Levine, Ariel Stolovich, Rebeca Santamaria-Fernandez, Sonam Goenka, Wenny Yustalim, Robin Strudel, Ali Elqursh, Charlie Deck, Hyo Lee, Zonglin Li, Kyle Levin, Raphael Hoffmann, Dan Holtmann-Rice, Olivier Bachem, Sho Arora, Christy Koh, Soheil Hassas Yeganeh, Siim Põder, Mukarram Tariq, Yanhua Sun, Lucian Ionita, Mojtaba Seyedhosseini, Pouya Tafti, Zhiyu Liu, Anmol Gulati, Jasmine Liu, Xinyu Ye, Bart Chrzaszcz, Lily Wang, Nikhil Sethi, Tianrun Li, Ben Brown, Shreya Singh, Wei Fan, Aaron Parisi, Joe Stanton, Vinod Koverkathu, Christopher A. Choquette-Choo, Yunjie Li, TJ Lu, Abe Ittycheriah, Prakash Shroff, Mani Varadarajan, Sanaz Bahargam, Rob Willoughby, David Gaddy, Guillaume Desjardins, Marco Cornero, Brona Robenek, Bhavishya Mittal, Ben Albrecht, Ashish Shenoy, Fedor Moiseev, Henrik Jacobsson, Alireza Ghaffarkhah, Morgane Rivière, Alanna Walton, Clément Crepy, Alicia Parrish, Zongwei Zhou, Clement Farabet, Carey Radebaugh, Praveen Srinivasan, Claudia van der Salm, Andreas Fidjeland, Salvatore Scellato, Eri Latorre-Chimoto, Hanna Klimczak-Plucińska, David Bridson, Dario de Cesare, Tom Hudson, Piermaria Mendolicchio, Lexi Walker, Alex Morris, Matthew Mauger, Alexey Guseynov, Alison Reid, Seth Odoom, Lucia Loher, Victor Cotruta, Madhavi Yenugula, Dominik Grewe, Anastasia Petrushkina, Tom Duerig, Antonio Sanchez, Steve Yadlowsky, Amy Shen, Amir Globerson, Lynette Webb, Sahil Dua, Dong Li, Surya Bhupatiraju, Dan Hurt, Haroon Qureshi, Ananth Agarwal, Tomer Shani, Matan Eyal, Anuj Khare, Shreyas Rammohan Belle, Lei Wang, Chetan Tekur, Mihir Sanjay Kale, Jinliang Wei, Ruoxin Sang, Brennan Saeta, Tyler Liechty, Yi Sun, Yao Zhao, Stephan Lee, Pandu Nayak, Doug Fritz, Manish Reddy Vuyyuru, John Aslanides, Nidhi Vyas, Martin Wicke, Xiao Ma, Evgenii Eltyshev, Nina Martin, Hardie Cate, James Manyika, Keyvan Amiri, Yelin Kim, Xi Xiong, Kai Kang, Florian Luisier, Nilesh Tripuraneni, David Madras, Mandy Guo, Austin Waters, Oliver Wang, Joshua Ainslie, Jason Baldridge, Han Zhang, Garima Pruthi, Jakob Bauer, Feng Yang, Riham Mansour, Jason Gelman, Yang Xu, George Polovets, Ji Liu, Honglong Cai, Warren Chen, XiangHai Sheng, Emily Xue, Sherjil Ozair, Christof Angermueller, Xiaowei Li, Anoop Sinha, Weiren Wang, Julia Wiesinger, Emmanouil Koukoumidis, Yuan Tian, Anand Iyer, Madhu Gurumurthy, Mark Goldenson, Parashar Shah, MK Blake, Hongkun Yu, Anthony Urbanowicz, Jennimaria Palomaki, Chrisantha Fernando, Ken Durden, Harsh Mehta, Nikola Momchev, Elahe Rahimtoroghi, Maria Georgaki, Amit Raul, Sebastian Ruder, Morgan Redshaw, Jinhyuk Lee, Denny Zhou, Komal Jalan, Dinghua Li, Blake Hechtman, Parker Schuh, Milad Nasr, Kieran Milan, Vladimir Mikulik, Juliana Franco, Tim Green, Nam Nguyen, Joe Kelley, Aroma Mahendru, Andrea Hu, Joshua Howland, Ben Vargas, Jeffrey Hui, Kshitij Bansal, Vikram Rao, Rakesh Ghiya, Emma Wang, Ke Ye, Jean Michel Sarr, Melanie Moranski Preston, Madeleine Elish, Steve Li, Aakash Kaku, Jigar Gupta, Ice Pasupat, Da-Cheng Juan, Milan Someswar, Tejvi M., Xinyun Chen, Aida Amini, Alex Fabrikant, Eric Chu, Xuanyi Dong, Amruta Muthal, Senaka Buthpitiya, Sarthak Jauhari, Nan Hua, Urvashi Khandelwal, Ayal Hitron, Jie Ren, Larissa Rinaldi, Shahar Drath, Avigail Dabush, Nan-Jiang Jiang, Harshal Godhia, Uli Sachs, Anthony Chen, Yicheng Fan, Hagai Taitelbaum, Hila Noga, Zhuyun Dai, James Wang, Chen Liang, Jenny Hamer, Chun-Sung Ferng, Chenel Elkind, Aviel Atias, Paulina Lee, Vít Listík, Mathias Carlen, Jan van de Kerkhof, Marcin Pikus, Krunoslav Zaher, Paul Müller, Sasha Zykova, Richard Stefanec, Vitaly Gatsko, Christoph Hirnschall, Ashwin Sethi, Xingyu Federico Xu, Chetan Ahuja, Beth Tsai, Anca Stefanoiu, Bo Feng, Keshav Dhandhania, Manish Katyal, Akshay Gupta, Atharva Parulekar, Divya Pitta, Jing Zhao, Vivaan Bhatia, Yashodha Bhavnani, Omar Alhadlaq, Xiaolin Li, Peter Danenberg, Dennis Tu, Alex Pine, Vera Filippova, Abhipso Ghosh, Ben Limonchik, Bhargava Urala, Chaitanya Krishna Lanka, Derik Clive, Yi Sun, Edward Li, Hao Wu, Kevin Hongtongsak, Ianna Li, Kalind Thakkar, Kuanysh Omarov, Kushal Majmundar, Michael Alverson, Michael Kucharski, Mohak Patel, Mudit Jain, Maksim Zabelin, Paolo Pelagatti, Rohan Kohli, Saurabh Kumar, Joseph Kim, Swetha Sankar, Vineet Shah, Lakshmi Ramachandruni, Xiangkai Zeng, Ben Bariach, Laura Weidinger, Tu Vu, Alek Andreev, Antoine He, Kevin Hui, Sheleem Kashem, Amar Subramanya, Sissie Hsiao, Demis Hassabis, Koray Kavukcuoglu, Adam Sadovsky, Quoc Le, Trevor Strohman, Yonghui Wu, Slav Petrov, Jeffrey Dean, and Oriol Vinyals. 2024. 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A Additional experiment information

A.1 Example of unnecessary source text in outputs

We do not use exact matching (EM) as the main performance metric because it can be easily affected by unnecessary source text in the model outputs. Here is an example:

> Context: "The Panthers defense gave up just 308 points, ranking sixth in the league, while also leading the NFL in interceptions with 24 and boasting four Pro Bowl selections. Pro Bowl defensive tackle Kawann Short led the team in sacks with 11, while also forcing three fumbles and recovering two. Fellow lineman Mario Addison added 6½ sacks. The Panthers line also featured veteran defensive end Jared Allen, a 5-time pro bowler who was the NFL's active career sack leader with 136, along with defensive end Kony Ealy, who had 5 sacks in just 9 starts. Behind them, two of the Panthers three starting linebackers were also selected to play in the Pro Bowl: Thomas Davis and Luke Kuechly. Davis compiled 5½ sacks, four forced fumbles, and four interceptions, while Kuechly led the team in tackles (118) forced two fumbles, and intercepted four passes of his own. Carolina's secondary featured Pro Bowl safety Kurt Coleman, who led the team with a career high seven interceptions, while also racking up 88 tackles and Pro Bowl cornerback Josh Norman, who developed into a shutdown corner during the season and had four interceptions, two of which were returned for touchdowns."
>
> Question: How many Panthers defense players were selected for the Pro Bowl?
>
> Reference: four
>
> Model Answer: four Pro Bowl selections.

The reference is "four", which is consistent with the model output, but the "Pro Bowl selections." in the model output is unnecessary and will cause the EM metric to give a 0 result.

A.2 Accuracy of language detection tool

We use Lingua with its high accuracy mode in this work to detect the language of model outputs. Table 3 shows its reported accuracies on the tested languages, which is satisfactory to serve in our experiments.

Code	Language	Average Acc (high accuracy mode)
en	English	81
de	German	89
es	Spanish	70
vi	Vietnamese	91
zh	Chinese	100
hi	Hindi	73
ar	Arabic	98
el	Greek	100
ro	Romanian	87
ru	Russian	90
th	Thai	99
tr	Turkish	94

Table 3: Detection accuracies of the tested language with Lingua in its high-accuracy mode, adapted from their GitHub page (https://github.com/pemistahl/lingua).

A.3 Prompt used in evaluation and error type detection

We use the default system prompt and chat templates assigned in the `tokenizer.config` files of the model repositories. Then, we apply these configurations to two prompt formats which we call v1 and v2.

The v1 prompt format is:

> {system prompt}
>
> Below is a reading comprehension task. There will be paragraphs of context, each followed by a question related to its content. You should only present your answer to the last question by strictly copying the corresponding part of the context. Please provide a direct answer in English without extra output. Your answer should be in the form of "Answer: {Your Answer}"
>
> Context: {demo context 1}
>
> Question: {demo question 1}
>
> Answer: {demo answer 1}
>
> Context: {demo context 2}
>
> Question: {demo question 2}
>
> Answer: {demo answer 2}
>
> Your task starts here:
>
> Context: {text context}
>
> Question: {text question}

The v2 prompt format is:

{system prompt}

Context: {demo context 1}

Question: {demo question 1}

Answer: {demo answer 1}

Context: {demo context 2}

Question: {demo question 2}

Answer: {demo answer 2}

Your task starts here:

Context: {text context}

Question: {text question}
You should only present your answer to the last question by strictly copying the corresponding part of the context. Please provide a direct answer in English without extra output. Your answer should be in the form of "Answer: {Your Answer}"

The prompt for error type detection is:

<|im_start|>system
You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<|im_end|>
<|im_start|>user
You are tasked with identifying the type of a given raw answer. You will be provided with a question and a raw answer. Your job is to determine whether the raw answer falls into one of the following categories based on the given question:

0. Reasonable Answer: The answer seems like some attempt to answer the question, regardless of whether it is correct or not.

1. Blank Answer: No response is provided.

2. Gibberish: Incoherent text with no clear meaning or cannot be seen as some kind of answer to the question, e.g. "{Your Answer}".

3. Denial of Answer: A statement indicating inability to answer, such as "I apologize, but I cannot answer this question because...".

You must provide your response as a SINGLE number representing the category (0, 1, 2, or 3) without extra output.

B More evaluation results

B.1 Full list of models evaluated

A comprehensive list of all models evaluated during this study, including older versions and alternative sizes, is available in Table 4 to supplement the main list.

B.2 Detailed evaluation results

Table 6 presents the complete evaluation results from our 0-shot experiments, encompassing both the English-to-NonEnglish (en-x) and non-English monolingual (x-x) tasks in all models and languages tested. Table 7 further presents detailed F1 scores for en-x and x-x tasks in the 2-shot setting.

Name	Modes	Sizes
LLaMA 2	Base / Chat	7B / 13B / 70B
LLaMA 3	Base / Instruct	8B / 70B
LLaMA 3.1	Base / Instruct	8B / 70B
LLaMAX-2-Alpaca	-	7B
LLaMAX-3-Alpaca	-	8B
Mistral V0.1	Base / Instruct	7B
Mistral V0.3	Base / Instruct	7B
Qwen 1.5	Base / Chat	7B / 14B / 72B
Qwen 2	Base / Instruct	7B / 72B
Qwen 2.5	Base / Instruct	7B / 72B
DeepSeek V2	Base / Chat	Lite (16B)
Gemma 2	Base / IT	9B
GPT-3.5-Turbo-0125	-	-
GPT-4o	-	-

Table 4: Full list of models evaluated. This table presents a complete list of all models tested in this study, encompassing older versions and alternative sizes.

B.3 Performance vs. parameter size

To observe the effect of increasing model size on xMRC performance, we evaluate the Qwen-2.5 models from 1.5B to 72B, showing results in Table 5. The trend is consistent with our findings in the main body, and an advantage of the 7B model stands out.

B.4 Detailed language error and generation error rates

Tables 8 and 9 show detailed language and generation error rates across all tested languages. Note that Table 9 contain the results judged by both Qwen-2.5-Instruct-72B and Gemini-2.5-Flash-Lite, which are consistent to each other. Meanwhile, Table 10 provides a more granular view of the generation errors discussed in the main text.

While Table 9 presents the aggregated rate of these errors, Table 10 is further subdivided into three separate tables: Table 10a, Table 10b, and Table 10c. These tables individually display the error rates for gibberish errors, refusal errors, and blank errors, respectively, across all tested models and languages in the 2-shot en-x xMRC task setting.

C Two-phased xMRC Analysis

C.1 Further analysis on MRD

C.1.1 Example of attribution results

Figure 9 shows an example of the attribution outcome for LLaMA-3.1-Instruct-8B.

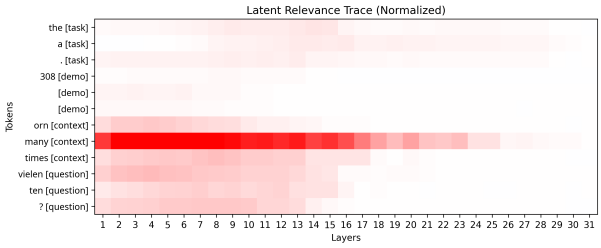
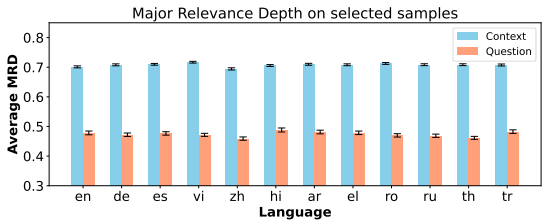


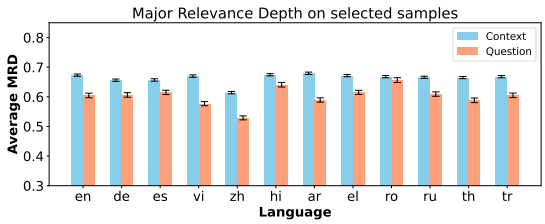
Figure 9: An example output of layer-wise attribution with LLaMA-3.1-Instruct-8B, where only the top 3 tokens from each input part are shown.

C.1.2 MRD for other LLaMA models

Figures 10, 11 and 12 provide further illustrative examples of the mean MRD for context and question components, specifically for LLaMA-3.1-8B, LLaMA-3.1-Instruct-70B and LLaMA-2-Chat-7B. These figures complement the MRD analysis presented in the main body of this paper.



(a). balanced samples



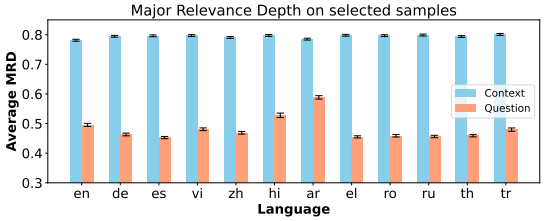
(b). en-superior samples

Figure 10: Mean MRD of the context and question parts for LLaMA-3.1-Base-8B.

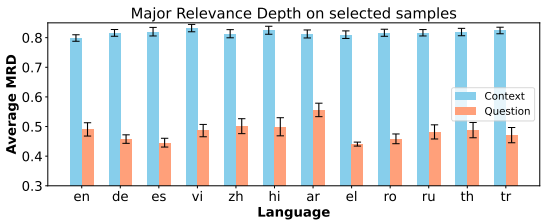
C.1.3 Analysis of task descriptions and demonstrations

Analyzing the MRD of task descriptions and demonstrations in our 2-shot setting (Figures 13-15) reveals a general trend where demonstrations tend to exhibit a comparable or slightly higher MRD than task descriptions across the LLaMA model family, suggesting demonstrations are at least as important as, if not slightly more impactful than, task descriptions in guiding the models. This could indicate that providing concrete examples is a particularly effective way to communicate the desired behavior for cross-lingual context retrieval to these models.

However, the precise relationship is not uniform and varies across models. For example, while LLaMA-3.1-Instruct-8B shows a relatively balanced MRD between task descriptions and demonstrations, LLaMA-2-Chat-7B consistently demonstrates a higher MRD for demonstrations, which implies that older or smaller models might lean more heavily on the provided in-context examples.

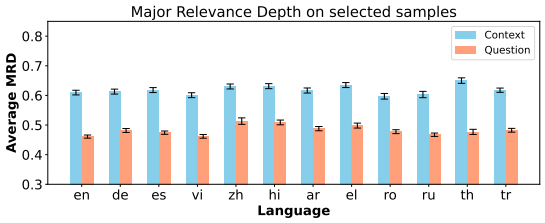


(a). balanced samples

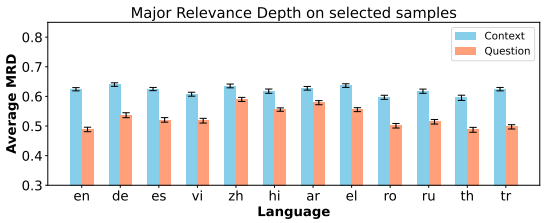


(b). en-superior samples

Figure 11: Mean MRD of the context and question parts for LLaMA-3.1-Instruct-70B.



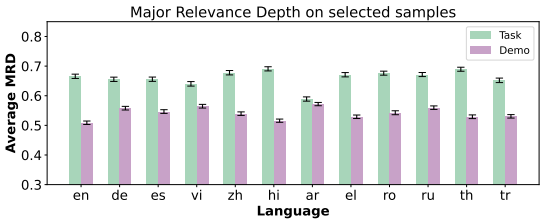
(a). balanced samples



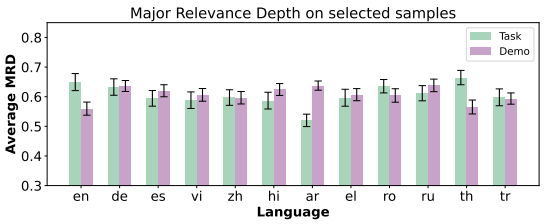
(b). en-superior samples

Figure 12: Mean MRD of the context and question parts for LLaMA-2-Chat-7B.

In contrast, LLaMA-3.1-Instruct-70B exhibits the most pronounced difference, with a significantly elevated MRD for task descriptions across all languages and sample types, suggesting that larger models can become highly attuned to and reliant on user-specified task commands.

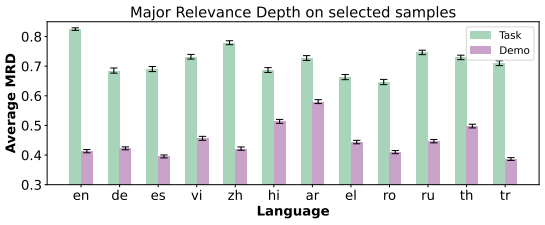


(a). balanced samples

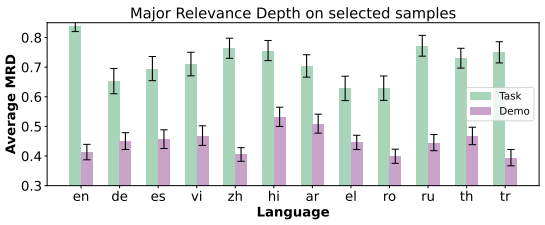


(b). en-superior samples

Figure 13: Mean MRD of the task descriptions and demonstrations parts for LLaMA-3.1-Instruct-8B.



(a). balanced samples

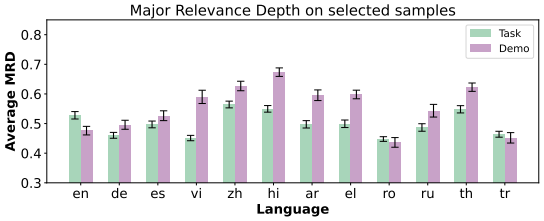


(b). en-superior samples

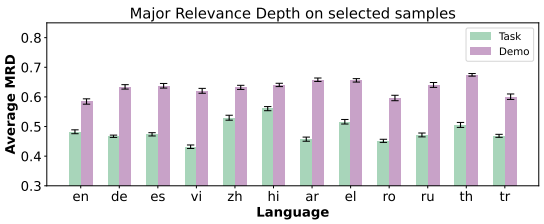
Figure 14: Mean MRD of the task descriptions and demonstrations parts for LLaMA-3.1-Instruct-70B.

C.1.4 Influence of prompt format on MRD pattern

We test the influence of different prompt formats (v1, v2) on LLaMA-3.1-Instruct-8B, and by comparing the results in Figure 16 and Figure 3, which present results obtained using the prompt format v1 and v2, respectively, it is clear that the fundamental pattern observed in the mean MRD is consistent across both formats. Therefore, the trend of the mean question MRD being consistently and substantially lower than the mean context MRD is maintained regardless of the prompt format employed.

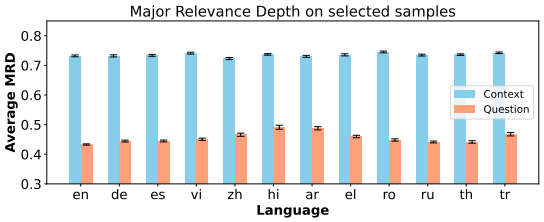


(a). balanced samples

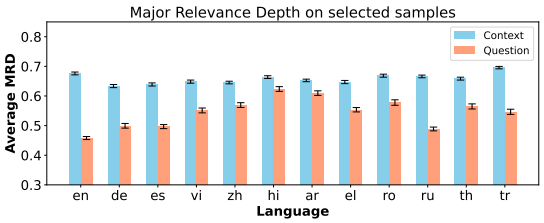


(b). en-superior samples

Figure 15: Mean MRD of the task descriptions and demonstrations parts for LLaMA-2-Chat-7B.



(a). balanced samples

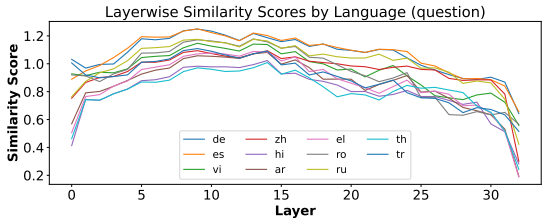


(b). en-superior samples

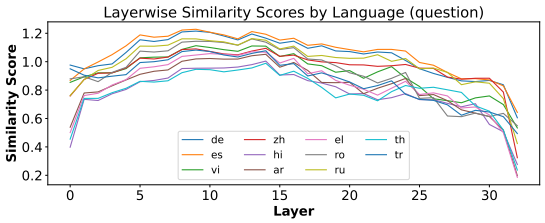
Figure 16: Mean MRD for LLaMA-3.1-Instruct-8B on both "balanced" and "en-superior" samples in v1 prompting format. Only the results of context and question parts of the prompt are displayed.

C.2 Hidden state similarity results for other LLaMA models

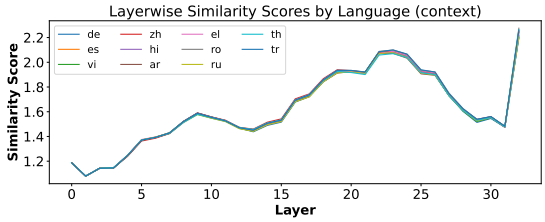
Figures 17–20 present the hidden state similarity results for additional LLaMA models, complementing the analysis of the LLaMA-3.1-Instruct-8B model discussed in the main body of the paper.



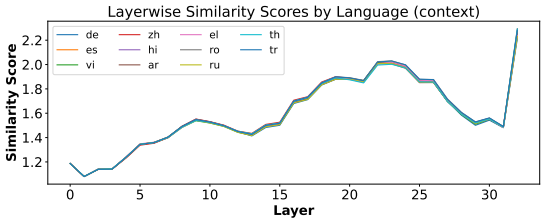
(a). Question hidden state similarity for balanced samples.



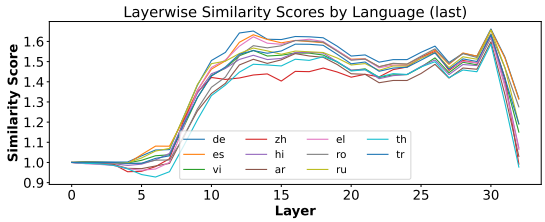
(b). Question hidden state similarity for en-superior samples.



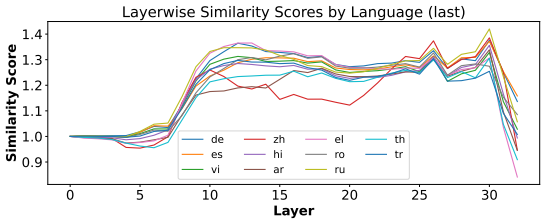
(c). Context hidden state similarity for balanced samples.



(d). Context hidden state similarity for en-superior samples.



(e). Last-input-token hidden state similarity for balanced samples.



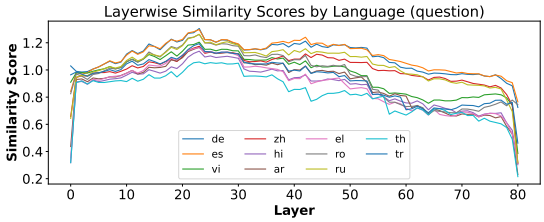
(f). Last-input-token hidden state similarity for en-superior samples.

Figure 17: Hidden state similarity between English and other languages on different parts of the selected samples in each layer of the LLaMA-3.1-8B model.

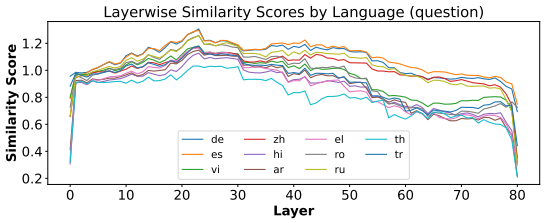
C.3 Training details and evaluation results of our finetuned LLaMA-3.1-8B

We tune the LLaMA-3.1-8B base model on TULU-V3 for 1 epoch with 8 * H800 GPUs for 15 hours using the LLaMA-Factory repository. The data cut-off length is 2048, batch size per device is 8, learning rate is 1.0e-5, and the warm-up ratio is 0.1 with cosine learning rate scheduling.

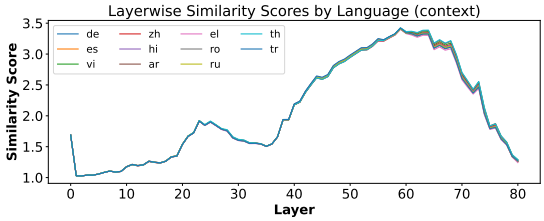
Regarding evaluation, Table 11 summarizes the performance of our finetuned model on both en-x cross-lingual and x-x monolingual MRC tasks. Furthermore, Figure 21 illustrates the hidden state similarity between English and other tested languages across layers, focusing on question, context, and last-input-token representations derived from balanced samples.



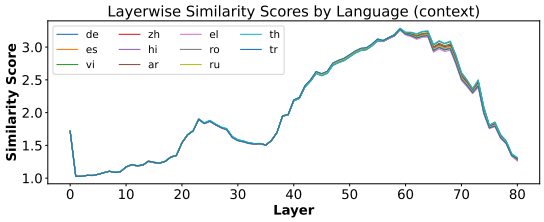
(a). Question hidden state similarity for balanced samples.



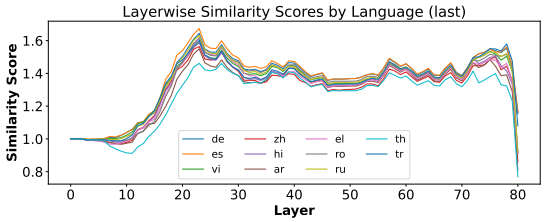
(b). Question hidden state similarity for en-superior samples.



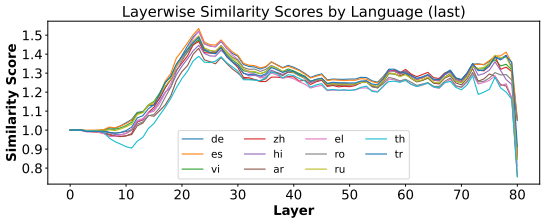
(c). Context hidden state similarity for balanced samples.



(d). Context hidden state similarity for en-superior samples.



(e). Last-input-token hidden state similarity for balanced samples.



(f). Last-input-token hidden state similarity for en-superior samples.

Figure 18: Hidden state similarity between English and other languages on different parts of the selected samples in each layer of the LLaMA-3.1-70B model.

Version	Size	en-en	mean en-x	mean x-x	en-x / en-en	x-x / en-en
Base	1.5B	61.26	47.10	54.55	0.77	0.89
	3B	71.09	58.75	60.00	0.83	0.84
	7B	62.42	57.51	66.11	**0.92**	**1.06**
	14B	76.71	69.04	74.60	0.90	0.97
	32B	80.37	73.23	74.02	0.91	0.92
	72B	**86.03**	**78.92**	**81.16**	**0.92**	0.94
Instruct	1.5B	70.63	55.21	58.11	0.78	0.82
	3B	71.65	64.41	60.39	0.90	0.84
	7B	**81.83**	**76.43**	71.61	**0.93**	0.88
	14B	80.91	67.64	**72.95**	0.84	0.90
	32B	80.97	73.77	71.90	0.91	0.89
	72B	77.12	66.04	70.29	0.86	**0.91**

Table 5: xMRC performances of Qwen-2.5 models with increasing parameter sizes.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	28.49	26.39	23.70	16.97	21.76	21.68	19.66	24.96	22.27	22.69	27.73	15.71
LLaMA-3.1-70B	49.92	38.32	36.22	41.34	45.13	24.62	27.40	37.73	38.49	34.87	47.90	33.95
Mistral-V0.3-7B	20.50	21.43	19.50	10.84	8.66	11.60	14.87	14.20	12.44	18.32	16.13	10.67
Qwen-2.5-7B	38.66	36.05	37.31	48.32	42.02	38.91	42.44	34.87	35.55	38.57	45.63	41.60
Qwen-2.5-72B	63.95	56.55	56.72	53.19	52.86	55.97	56.30	52.27	54.03	55.55	55.29	51.68
DeepSeek-V2-Lite-16B	12.35	11.26	4.12	4.20	9.58	9.58	4.79	7.73	7.06	10.84	5.80	4.96
Gemma-2-9B	15.21	5.97	14.87	14.87	26.47	7.40	11.43	4.62	13.70	20.42	32.27	17.31
LLaMA-2-Chat-7B	34.96	26.81	24.54	19.50	22.52	19.58	20.00	20.50	22.10	25.04	13.95	16.55
LLaMA-3.1-Instruct-8B	40.92	25.55	28.82	28.24	33.95	27.65	24.87	20.42	19.24	29.66	29.75	30.42
LLaMA-3.1-Instruct-70B	57.82	47.23	47.23	45.88	49.16	39.33	42.86	46.72	43.19	41.51	51.93	44.20
Mistral-V0.3-Instruct-7B	3.19	2.61	2.69	5.13	2.86	2.02	4.12	3.11	2.35	3.87	4.54	3.36
Qwen-2.5-Instruct-7B	53.28	40.17	35.97	36.13	40.67	36.22	35.46	33.70	38.99	35.71	36.22	38.24
Qwen-2.5-Instruct-72B	36.89	27.98	26.81	23.53	23.28	22.94	23.45	23.19	31.01	24.37	23.03	23.95
DeepSeek-V2-Chat-Lite-16B	16.30	18.24	13.87	8.24	15.13	11.01	11.09	13.95	13.87	12.61	9.75	12.61
Gemma-2-IT-9B	57.06	46.30	42.77	42.86	42.35	44.37	40.25	41.85	39.24	42.69	44.96	43.87
GPT-3.5-Turbo-0125	32.18	24.12	22.61	21.34	21.93	17.48	22.44	23.70	23.87	21.43	20.34	20.42
GPT-4o	51.01	39.58	36.97	40.50	41.18	37.48	36.05	37.82	36.97	39.33	39.16	39.66

(a). 0-shot Exact Match (EM) scores (%) on en-x tasks.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	37.60	34.11	33.87	21.86	35.12	36.97	30.11	36.66	30.82	30.37	39.43	21.79
LLaMA-3.1-70B	68.03	58.29	56.22	60.33	55.20	50.63	41.23	56.41	57.13	55.87	62.87	54.32
Mistral-V0.3-7B	40.07	27.17	31.26	19.26	13.19	17.94	23.98	19.16	18.23	28.26	21.86	18.63
Qwen-2.5-7B	59.02	55.58	55.61	64.37	60.26	56.32	60.61	53.14	51.21	56.72	63.23	55.52
Qwen-2.5-72B	80.50	73.73	74.48	72.48	71.37	73.60	73.23	70.59	71.44	73.36	72.78	68.18
DeepSeek-V2-Lite-16B	24.88	25.14	11.07	13.25	18.55	14.01	13.69	15.32	14.72	23.10	9.28	13.73
Gemma-2-9B	24.08	11.12	24.96	20.17	36.04	10.03	16.04	8.68	21.19	32.67	43.05	24.34
LLaMA-2-Chat-7B	56.83	45.97	44.45	37.78	36.50	33.65	32.13	34.03	39.14	45.51	25.18	30.64
LLaMA-3.1-Instruct-8B	64.47	50.69	53.41	52.33	57.10	50.09	48.61	45.36	43.46	54.14	53.88	52.72
LLaMA-3.1-Instruct-70B	78.28	70.13	68.39	64.43	68.91	56.20	60.19	67.79	65.78	64.72	67.69	62.13
Mistral-V0.3-Instruct-7B	35.19	32.41	32.68	30.23	32.15	28.49	30.21	29.42	28.93	32.51	31.48	29.23
Qwen-2.5-Instruct-7B	73.03	59.69	56.82	56.99	60.64	56.99	55.54	53.93	58.27	56.62	57.08	59.22
Qwen-2.5-Instruct-72B	59.84	46.79	46.86	43.46	36.20	43.82	40.01	44.46	50.91	43.98	44.68	44.28
DeepSeek-V2-Chat-Lite-16B	43.24	35.99	32.46	26.34	38.20	27.90	29.16	35.33	29.12	32.53	30.33	29.19
Gemma-2-IT-9B	76.80	67.91	64.91	64.74	64.83	65.31	62.35	63.89	61.29	64.94	65.84	64.10
GPT-3.5-Turbo-0125	60.08	51.06	50.45	47.23	49.06	41.58	48.90	50.57	50.90	49.32	46.66	46.22
GPT-4o	74.24	64.38	58.94	65.71	65.40	62.48	58.81	64.00	62.15	64.82	64.60	64.95

(b). 0-shot F1 Scores on en-x tasks.

	de-de	es-es	vi-vi	zh-zh	hi-hi	ar-ar	el-el	ro-ro	ru-ru	th-th	tr-tr
LLaMA-3.1-8B	24.87	19.16	18.66	33.95	16.05	17.31	10.00	18.15	17.90	33.87	14.37
LLaMA-3.1-70B	42.94	37.23	42.86	50.08	30.00	40.17	36.30	40.76	35.13	57.06	37.40
Mistral-V0.3-7B	27.31	25.29	20.17	34.62	7.98	21.09	17.73	22.69	11.93	23.45	12.44
Qwen-2.5-7B	29.50	35.04	38.57	57.23	23.11	42.94	21.09	31.85	32.18	53.95	31.51
Qwen-2.5-72B	46.89	46.39	51.93	78.32	41.18	50.67	36.64	50.67	43.03	63.78	41.34
DeepSeek-V2-Lite-16B	4.87	2.44	1.01	7.56	2.02	1.43	4.03	3.19	2.02	5.13	2.94
Gemma-2-9B	2.02	14.03	8.91	12.10	8.66	1.43	1.43	4.62	10.92	9.66	13.28
LLaMA-2-Chat-7B	22.86	18.82	15.55	4.54	1.68	4.79	6.05	22.86	11.93	3.78	10.59
LLaMA-3.1-Instruct-8B	25.71	26.97	36.64	48.40	27.06	33.03	13.70	28.32	26.22	35.63	29.83
LLaMA-3.1-Instruct-70B	40.25	35.29	47.31	57.65	35.71	44.96	30.92	40.76	38.66	59.50	40.84
Mistral-V0.3-Instruct-7B	2.69	2.44	4.29	0.92	0.84	3.70	1.51	3.11	1.43	4.29	2.61
Qwen-2.5-Instruct-7B	32.86	30.92	30.42	47.40	24.71	27.90	21.68	36.05	27.82	42.44	30.67
Qwen-2.5-Instruct-72B	29.41	24.45	26.97	45.71	20.42	32.18	15.88	32.02	25.29	36.30	21.51
DeepSeek-V2-Chat-Lite-16B	12.18	7.48	10.08	7.82	7.65	9.24	8.40	7.73	9.41	11.93	7.31
Gemma-2-IT-9B	42.94	40.92	46.97	51.09	41.93	43.03	37.98	45.97	42.52	56.13	36.30
GPT-3.5-Turbo-0125	23.53	23.19	30.50	38.32	25.71	28.74	24.03	27.31	25.80	39.41	26.47
GPT-4o	40.34	34.87	44.37	54.29	32.10	42.10	26.22	38.94	37.82	52.79	30.59

(c). 0-shot Exact Match (EM) scores (%) on x-x tasks

	de-de	es-es	vi-vi	zh-zh	hi-hi	ar-ar	el-el	ro-ro	ru-ru	th-th	tr-tr
LLaMA-3.1-8B	37.62	34.52	36.04	43.66	41.18	34.54	32.58	34.61	35.68	47.38	28.02
LLaMA-3.1-70B	62.66	59.02	61.54	55.26	56.81	63.43	56.52	59.81	55.99	70.20	57.39
Mistral-V0.3-7B	41.31	47.37	39.40	41.73	24.04	42.28	35.43	37.91	29.51	37.70	28.32
Qwen-2.5-7B	49.22	58.04	62.82	68.32	46.19	63.63	44.78	52.10	52.96	68.59	54.30
Qwen-2.5-72B	70.77	72.81	74.95	84.33	68.09	72.94	64.72	73.17	68.56	78.50	67.79
DeepSeek-V2-Lite-16B	12.56	8.24	7.64	9.73	8.35	6.98	9.59	9.39	7.79	9.03	8.89
Gemma-2-9B	4.16	20.57	13.66	14.74	15.58	2.53	3.07	6.96	18.84	14.14	23.02
LLaMA-2-Chat-7B	40.12	40.37	32.22	10.68	13.62	17.59	18.83	38.52	26.51	10.64	23.93
LLaMA-3.1-Instruct-8B	51.95	58.67	62.55	54.15	52.86	56.45	45.21	55.02	52.99	56.89	55.40
LLaMA-3.1-Instruct-70B	68.60	68.79	73.54	66.32	62.66	70.97	66.97	68.90	65.53	73.91	66.35
Mistral-V0.3-Instruct-7B	24.81	26.71	26.83	11.22	15.57	20.21	22.81	25.11	20.37	30.99	21.98
Qwen-2.5-Instruct-7B	57.65	57.89	56.71	57.29	50.26	53.38	50.18	59.65	53.25	63.81	55.85
Qwen-2.5-Instruct-72B	54.08	51.89	52.80	57.27	45.64	57.66	45.27	56.80	50.74	62.11	48.48
DeepSeek-V2-Chat-Lite-16B	35.78	34.43	34.37	15.75	25.36	29.23	33.21	32.04	34.46	28.91	28.62
Gemma-2-IT-9B	68.38	68.84	71.81	65.03	67.91	66.82	67.78	69.48	66.19	73.71	64.21
GPT-3.5-Turbo-0125	53.58	56.26	58.50	52.01	50.36	57.77	58.48	56.60	55.95	57.45	54.36
GPT-4o	67.90	67.79	71.45	65.72	61.33	69.67	62.12	66.61	66.59	74.43	62.68

(d). 0-shot F1 Scores on x-x tasks.

Table 6: 0-shot evaluation results on en-x and x-x tasks.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	75.97	45.97	43.90	50.71	47.70	48.41	50.98	50.40	47.22	49.12	59.77	44.94
LLaMA-3.1-70B	82.39	60.46	60.00	59.57	62.68	57.38	51.50	59.43	54.28	56.15	66.54	57.48
Mistral-V0.3-7B	79.57	66.94	67.57	59.82	53.66	48.36	52.56	47.83	67.30	70.62	48.56	62.94
Qwen-2.5-7B	62.42	56.68	56.45	59.15	58.84	55.85	62.94	50.62	54.43	58.37	61.61	57.72
Qwen-2.5-72B	86.03	77.24	79.22	80.16	80.14	79.09	78.70	76.72	80.41	80.77	78.48	77.16
DeepSeek-V2-Lite-16B	73.81	46.34	47.65	52.75	41.77	34.45	44.61	46.18	50.39	51.91	34.58	40.57
Gemma-2-9B	80.42	60.13	61.74	64.76	71.33	64.55	68.84	75.81	65.49	72.09	70.59	59.72
LLaMA-3.1-Instruct-8B	77.89	74.81	73.50	73.29	72.78	68.59	69.66	70.41	72.24	73.40	73.60	71.20
LLaMA-3.1-Instruct-70B	83.29	73.58	72.98	73.97	73.79	70.87	75.96	72.91	71.69	72.73	75.30	70.00
Mistral-V0.3-Instruct-7B	62.01	59.06	60.98	54.81	58.84	47.16	60.51	57.49	59.80	60.81	55.63	47.86
Qwen-2.5-Instruct-7B	81.83	77.37	77.02	76.06	78.82	73.70	76.11	74.70	76.80	77.44	77.05	75.69
Qwen-2.5-Instruct-72B	77.12	67.65	68.89	64.34	52.67	70.35	59.59	69.52	69.81	70.19	67.01	66.40
DeepSeek-V2-Chat-Lite-16B	70.30	55.96	58.96	51.21	62.05	48.39	52.04	54.80	52.86	57.04	50.01	51.01
Gemma-2-IT-9B	83.69	78.72	78.13	79.38	79.17	77.86	76.53	79.82	79.96	79.80	79.28	77.24
GPT-3.5-Turbo-0125	81.74	71.98	72.81	71.53	68.63	63.20	65.77	63.05	70.86	70.70	65.21	72.54
GPT-4o	83.29	78.31	74.51	80.29	79.40	77.64	78.29	80.03	78.10	80.23	79.56	80.00

(a). 2-shot F1 scores on en-x tasks.

	de-de	es-es	vi-vi	zh-zh	hi-hi	ar-ar	el-el	ro-ro	ru-ru	th-th	tr-tr
LLaMA-3.1-8B	71.67	74.17	73.19	64.96	71.91	68.20	69.35	74.65	67.17	70.89	66.89
LLaMA-3.1-70B	76.24	78.68	76.90	71.67	75.85	76.43	72.41	78.06	68.43	76.70	70.67
Mistral-V0.3-7B	71.02	72.91	69.91	66.65	56.73	58.25	62.81	71.73	63.57	62.08	58.44
Qwen-2.5-7B	58.74	57.36	72.29	73.38	63.74	72.74	67.24	58.82	64.12	77.89	60.84
Qwen-2.5-72B	81.29	81.15	82.82	89.08	79.12	79.53	77.83	82.18	77.49	85.00	77.29
DeepSeek-V2-Lite-16B	65.26	67.33	64.81	63.68	48.64	46.98	51.04	65.73	56.19	49.43	55.20
Gemma-2-9B	75.62	76.34	73.60	66.92	73.90	72.51	71.87	78.14	67.38	74.20	71.43
LLaMA-3.1-Instruct-8B	66.22	69.74	69.38	61.99	66.00	66.19	58.81	68.18	61.08	66.18	61.43
LLaMA-3.1-Instruct-70B	75.26	76.36	78.83	71.09	74.05	72.34	72.10	77.23	70.01	76.23	71.98
Mistral-V0.3-Instruct-7B	55.84	53.27	57.29	39.27	34.57	45.94	44.52	59.13	52.33	55.19	45.97
Qwen-2.5-Instruct-7B	73.75	75.24	78.26	70.21	67.08	70.82	67.65	75.61	67.99	73.89	67.23
Qwen-2.5-Instruct-72B	73.09	71.26	73.36	71.12	64.14	69.76	64.70	75.14	69.13	73.92	67.60
DeepSeek-V2-Chat-Lite-16B	56.24	59.33	56.18	50.06	41.19	42.46	44.03	54.63	56.10	40.71	48.52
Gemma-2-IT-9B	76.22	77.12	79.86	72.25	75.47	74.44	74.89	77.32	72.64	78.57	72.04
GPT-3.5-Turbo-0125	75.68	77.58	73.09	70.49	67.64	70.09	71.03	77.17	71.55	67.00	71.12
GPT-4o	76.94	78.78	77.25	71.37	72.02	76.17	73.40	77.66	77.34	80.00	71.58

(b). 2-shot F1 scores on x-x tasks

Table 7: Detailed 2-shot F1 scores on en-x and x-x tasks in each language.

	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	0.68	0.00	1.28	0.00	0.10	0.10	0.00	0.00	0.19	0.10	1.10
LLaMA-3.1-70B	60.20	54.59	63.73	48.90	69.09	66.86	56.83	67.88	56.69	56.09	61.50
Mistral-V0.3-7B	2.11	1.78	16.39	23.80	61.82	54.17	6.96	2.65	1.02	46.35	16.63
Qwen-2.5-7B	2.42	1.01	0.43	0.43	0.00	0.00	0.00	1.15	0.00	0.00	5.17
Qwen-2.5-72B	7.39	6.35	11.22	0.98	5.74	2.82	19.78	11.36	3.59	27.01	23.64
DeepSeek-V2-Lite-16B	8.90	1.87	1.69	26.75	46.80	4.76	3.68	2.27	0.47	35.17	10.31
Gemma-2-9B	0.00	0.10	9.78	2.37	0.50	0.20	0.34	3.15	0.00	2.23	2.37
LLaMA-2-Chat-7B	3.07	0.45	0.72	2.25	0.27	0.00	0.32	1.55	0.00	0.12	1.62
LLaMA-3.1-Instruct-8B	1.15	1.87	0.37	0.36	0.59	0.00	0.00	1.75	0.36	0.37	3.01
LLaMA-3.1-Instruct-70B	0.79	0.76	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.34
Mistral-V0.3-Instruct-7B	4.30	1.73	12.79	0.00	0.35	0.00	0.44	3.12	0.00	0.67	7.03
Qwen-2.5-Instruct-7B	1.89	0.71	0.76	0.38	0.00	0.00	0.00	0.68	0.00	0.00	2.91
Qwen-2.5-Instruct-72B	6.31	1.13	5.68	9.73	2.46	7.51	2.61	4.41	1.96	0.35	8.18
DeepSeek-V2-Chat-Lite-16B	5.43	2.35	0.90	0.41	4.47	1.33	0.94	4.09	0.65	0.66	4.74
Gemma-2-IT-9B	0.96	0.00	0.31	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.28
GPT-3.5-Turbo-0125	1.12	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.32
GPT-4o	0.39	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00

Table 8: 2-shot language error rates (%) on en-x xMRC tasks.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	5.60	6.77	8.55	10.97	5.00	9.59	8.37	10.56	9.64	7.94	9.74	10.52
LLaMA-3.1-70B	1.20	1.98	2.41	2.19	2.62	4.12	2.33	2.35	1.71	1.57	2.70	4.94
Mistral-V0.3-7B	0.49	4.85	4.93	17.66	10.00	32.00	13.97	18.50	4.86	5.25	26.43	18.33
Qwen-2.5-7B	1.51	2.03	1.30	5.72	1.96	2.26	3.11	6.09	2.10	3.99	2.85	4.77
Qwen-2.5-72B	0.00	1.19	1.35	0.97	1.82	3.69	2.62	3.16	1.91	2.94	4.93	3.29
DeepSeek-V2-Lite-16B	1.87	3.26	2.33	11.97	2.39	20.61	10.10	8.04	4.27	2.76	15.97	11.23
Gemma-2-9B	1.02	1.34	1.38	5.39	2.60	6.51	4.69	4.98	3.68	2.64	5.05	6.98
LLaMA-2-Chat-7B	6.18	9.59	16.79	22.45	17.69	60.33	55.46	46.73	10.01	8.93	62.89	21.38
LLaMA-3.1-Instruct-8B	0.85	2.51	1.73	1.36	1.99	1.66	2.58	2.37	6.48	2.67	1.03	3.43
LLaMA-3.1-Tuned-8B	0.87	2.44	2.60	5.07	2.15	2.80	3.77	2.80	4.55	3.44	2.83	3.63
LLaMA-3.1-Instruct-70B	1.85	1.06	0.68	1.78	2.94	1.53	1.54	1.75	2.91	2.07	2.26	2.10
Mistral-V0.3-Instruct-7B	1.77	2.03	2.18	7.79	2.25	1.81	4.00	1.80	2.71	2.78	5.61	3.37
Qwen-2.5-Instruct-7B	2.75	2.47	3.20	3.42	4.04	2.78	5.38	3.25	2.36	2.56	2.04	3.80
Qwen-2.5-Instruct-72B	0.38	1.58	1.09	1.19	0.54	1.71	1.68	1.35	2.77	1.65	1.30	3.00
DeepSeek-V2-Chat-Lite-16B	0.58	4.28	2.93	9.77	3.27	6.80	4.98	6.31	6.69	8.60	6.15	5.39
Gemma-2-IT-9B	1.95	2.26	1.76	1.92	3.30	3.03	3.73	1.47	3.43	2.84	0.94	2.52
GPT-3.5-Turbo-0125	0.00	0.65	2.35	1.61	3.49	2.15	2.60	1.44	2.89	3.70	5.17	4.73
GPT-4o	0.00	0.45	0.86	1.56	0.50	0.00	0.92	1.00	3.57	2.56	0.00	4.00
DeepSeek-V3	0.00	1.84	0.94	0.43	0.49	1.72	2.29	1.48	1.40	3.09	0.84	3.08

(a). Qwen-judged results

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	4.80	4.85	7.53	7.61	4.18	6.06	5.88	7.77	7.70	6.44	5.98	8.31
LLaMA-3.1-70B	0.00	0.22	0.22	0.00	0.72	1.24	0.36	0.64	0.19	0.99	1.08	0.83
Mistral-V0.3-7B	0.49	1.35	0.81	4.86	4.15	9.38	6.43	5.33	1.35	0.00	9.43	7.38
Qwen-2.5-7B	1.08	1.11	0.37	0.84	0.39	0.19	0.24	1.18	0.35	1.00	0.44	1.59
Qwen-2.5-72B	0.00	0.00	0.00	0.00	0.45	0.46	0.00	1.19	0.48	0.49	0.90	0.82
DeepSeek-V2-Lite-16B	1.12	1.46	1.34	3.69	0.30	10.63	4.83	1.93	1.78	2.20	5.89	3.50
Gemma-2-9B	0.00	0.44	0.23	1.88	0.97	1.25	0.29	1.15	1.31	0.00	1.27	1.96
LLaMA-2-Chat-7B	5.67	5.92	12.93	20.38	16.46	34.95	33.13	37.56	7.78	6.40	58.56	7.92
LLaMA-3.1-Instruct-8B	0.85	0.72	1.39	1.02	0.66	0.83	1.14	1.19	2.59	1.34	0.68	1.56
LLaMA-3.1-Tuned-8B	1.85	0.71	0.34	0.36	1.33	0.31	0.78	1.05	0.64	0.34	0.76	1.50
LLaMA-3.1-Instruct-70B	2.43	1.22	1.09	1.82	1.02	0.76	1.56	0.80	3.47	0.85	1.74	2.14
Mistral-V0.3-Instruct-7B	0.55	0.41	0.40	0.38	0.00	0.35	0.38	0.72	0.39	0.85	0.00	0.00
Qwen-2.5-Instruct-7B	0.00	0.00	0.27	0.00	0.00	0.85	0.63	0.54	1.11	0.55	0.52	0.75
Qwen-2.5-Instruct-72B	0.58	2.33	0.84	2.87	0.93	2.43	1.89	2.41	4.01	4.21	1.49	1.52
DeepSeek-V2-Chat-Lite-16B	0.65	0.90	0.88	0.48	0.00	0.00	0.82	0.00	1.47	0.95	0.47	1.26
Gemma-2-IT-9B	0.57	0.32	0.78	0.32	0.87	1.20	1.82	0.72	0.00	0.93	0.78	1.69
GPT-3.5-Turbo-0125	0.00	0.00	0.00	0.52	0.00	0.00	0.00	0.00	0.89	0.00	0.00	0.00
GPT-4o	0.58	0.92	0.47	0.00	0.00	0.43	0.46	0.00	0.47	1.33	0.42	0.44
DeepSeek-V3	0.44	0.70	0.58	1.26	0.61	0.84	0.54	0.28	0.91	0.62	0.62	0.61

(b). Gemini-judged results

Table 9: 2-shot generation error rates (%) on en-x xMRC tasks judged by Qwen and Gemini.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	4.80	4.03	1.83	7.08	2.83	5.38	3.56	2.99	2.45	2.70	6.42	7.81
LLaMA-3.1-70B	0.60	1.32	2.19	1.31	2.14	3.50	2.15	1.93	1.33	1.18	2.43	4.12
Mistral-V0.3-7B	0.00	3.77	4.11	16.78	9.62	31.16	12.50	18.17	4.32	4.94	26.43	16.90
Qwen-2.5-7B	1.29	1.11	1.11	4.45	1.57	1.69	2.63	5.41	1.75	3.59	2.63	4.17
Qwen-2.5-72B	0.00	1.19	1.35	0.97	1.82	3.69	2.62	3.16	1.91	2.45	4.93	2.88
DeepSeek-V2-Lite-16B	1.87	2.77	2.00	10.31	2.24	19.72	8.24	6.27	3.20	2.02	15.84	10.79
Gemma-2-9B	1.02	1.12	0.92	5.16	1.95	5.51	3.52	3.83	2.89	2.31	3.79	6.54
LLaMA-2-Chat-7B	5.41	8.78	16.60	3.98	3.23	60.21	55.46	45.03	3.28	8.74	6.37	20.64
LLaMA-3.1-Instruct-8B	0.00	2.15	0.69	1.02	1.99	0.83	2.01	1.78	5.83	2.34	1.03	3.43
LLaMA-3.1-Instruct-70B	0.00	0.35	0.34	1.42	2.67	1.22	0.77	0.70	1.94	1.38	1.51	0.90
Mistral-V0.3-Instruct-7B	0.00	1.22	1.09	7.07	1.02	1.36	2.67	1.20	0.39	1.93	4.84	1.53
Qwen-2.5-Instruct-7B	1.65	1.65	2.80	3.04	3.14	1.74	3.85	3.25	1.97	2.13	2.04	3.80
Qwen-2.5-Instruct-72B	0.00	1.05	0.82	0.95	0.54	0.57	1.26	0.81	1.66	1.10	0.78	2.00
DeepSeek-V2-Chat-Lite-16B	0.58	3.70	2.30	8.25	2.80	5.67	4.81	5.75	6.19	7.89	5.65	4.72
Gemma-2-IT-9B	0.65	1.36	0.88	0.96	2.83	3.03	2.90	0.98	2.45	1.90	0.47	0.84
GPT-3.5-Turbo-0125	0.00	0.65	2.35	1.61	2.91	1.67	2.60	1.44	2.89	3.70	4.65	4.05
GPT-4o	0.00	0.45	0.86	1.56	0.50	0.00	0.92	1.00	3.57	2.56	0.00	4.00

(a). Gibberish error.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	0.00	0.16	0.00	0.00	0.00	0.34	0.18	0.18	0.00	0.00	0.22	0.00
LLaMA-3.1-70B	0.00	0.00	0.00	0.22	0.00	0.00	0.18	0.21	0.00	0.00	0.27	0.41
Mistral-V0.3-7B	0.00	0.00	0.00	0.00	0.19	0.17	1.10	0.00	0.00	0.31	0.00	0.00
Qwen-2.5-7B	0.22	0.92	0.19	0.21	0.39	0.38	0.48	0.34	0.35	0.40	0.22	0.20
Qwen-2.5-72B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DeepSeek-V2-Lite-16B	0.00	0.00	0.00	0.37	0.00	0.38	0.62	0.16	0.00	0.37	0.13	0.00
Gemma-2-9B	0.00	0.00	0.00	0.00	0.65	0.25	0.88	0.38	0.00	0.33	0.63	0.00
LLaMA-2-Chat-7B	0.77	0.61	0.19	18.31	14.31	0.12	0.00	1.70	6.56	0.19	56.42	0.59
LLaMA-3.1-Instruct-8B	0.85	0.36	1.04	0.00	0.00	0.55	0.57	0.59	0.65	0.00	0.00	0.00
LLaMA-3.1-Instruct-70B	1.23	0.00	0.00	0.00	0.27	0.00	0.00	0.35	0.32	0.00	0.00	0.60
Mistral-V0.3-Instruct-7B	1.77	0.61	0.65	0.54	0.82	0.45	1.33	0.60	2.13	0.64	0.00	1.84
Qwen-2.5-Instruct-7B	0.55	0.41	0.40	0.38	0.45	0.35	1.15	0.00	0.00	0.43	0.00	0.00
Qwen-2.5-Instruct-72B	0.38	0.53	0.27	0.24	0.00	1.14	0.21	0.54	0.83	0.55	0.52	1.00
DeepSeek-V2-Chat-Lite-16B	0.00	0.19	0.21	1.01	0.47	0.81	0.17	0.56	0.33	0.53	0.33	0.67
Gemma-2-IT-9B	0.00	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.47	0.00	0.84
GPT-3.5-Turbo-0125	0.00	0.00	0.00	0.00	0.29	0.24	0.00	0.00	0.00	0.00	0.26	0.00
GPT-4o	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(b). Refusal error.

	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-8B	0.80	2.58	6.72	3.89	2.17	3.87	4.63	7.39	7.19	5.24	3.10	2.71
LLaMA-3.1-70B	0.60	0.66	0.22	0.66	0.48	0.62	0.00	0.21	0.38	0.39	0.00	0.41
Mistral-V0.3-7B	0.49	1.08	0.82	0.88	0.19	0.67	0.37	0.33	0.54	0.00	0.00	1.43
Qwen-2.5-7B	0.00	0.00	0.00	1.06	0.00	0.19	0.00	0.34	0.00	0.00	0.00	0.40
Qwen-2.5-72B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.00	0.41
DeepSeek-V2-Lite-16B	0.00	0.49	0.33	1.29	0.15	0.51	1.24	1.61	1.07	0.37	0.00	0.44
Gemma-2-9B	0.00	0.22	0.46	0.23	0.00	0.75	0.29	0.77	0.79	0.00	0.63	0.44
LLaMA-2-Chat-7B	0.00	0.20	0.00	0.16	0.15	0.00	0.00	0.00	0.17	0.00	0.10	0.15
LLaMA-3.1-Instruct-8B	0.00	0.00	0.00	0.34	0.00	0.28	0.00	0.00	0.00	0.33	0.00	0.00
LLaMA-3.1-Instruct-70B	0.62	0.71	0.34	0.36	0.00	0.31	0.77	0.70	0.65	0.69	0.75	0.60
Mistral-V0.3-Instruct-7B	0.00	0.20	0.44	0.18	0.41	0.00	0.00	0.00	0.19	0.21	0.77	0.00
Qwen-2.5-Instruct-7B	0.55	0.41	0.00	0.00	0.45	0.69	0.38	0.00	0.39	0.00	0.00	0.00
Qwen-2.5-Instruct-72B	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.00	0.28	0.00	0.00	0.00
DeepSeek-V2-Chat-Lite-16B	0.00	0.39	0.42	0.51	0.00	0.32	0.00	0.00	0.17	0.18	0.17	0.00
Gemma-2-IT-9B	1.30	0.45	0.88	0.96	0.47	0.00	0.83	0.49	0.49	0.47	0.47	0.84
GPT-3.5-Turbo-0125	0.00	0.00	0.00	0.00	0.29	0.24	0.00	0.00	0.00	0.00	0.26	0.68
GPT-4o	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(c). Blank error.

Table 10: Detailed percentages (%) of generation error types (gibberish error, refusal error, and blank error) on 2-shot en-x tasks.

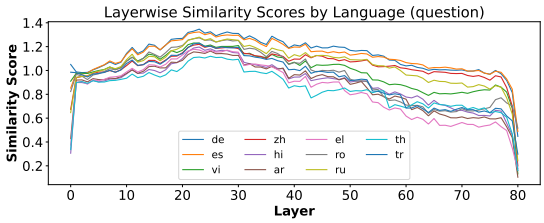
	en-en	en-de	en-es	en-vi	en-zh	en-hi	en-ar	en-el	en-ro	en-ru	en-th	en-tr
LLaMA-3.1-Tuned-8B	78.80	74.07	69.85	72.12	71.03	69.23	67.57	69.35	71.54	71.86	71.12	71.02

(a). en-x

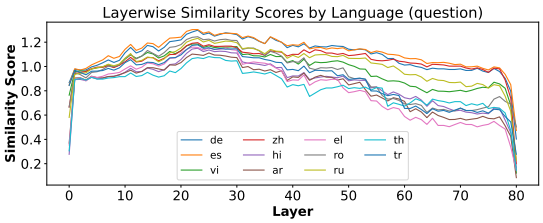
	de-de	es-es	vi-vi	zh-zh	hi-hi	ar-ar	el-el	ro-ro	ru-ru	th-th	tr-tr
LLaMA-3.1-Tuned-8B	69.28	71.16	73.73	63.71	67.48	64.35	61.84	73.03	65.66	62.34	62.63

(b). x-x

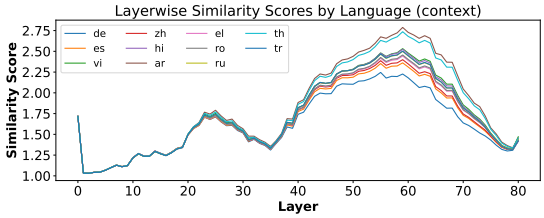
Table 11: 2-shot F1 scores on en-x and x-x tasks for our finetuned LLaMA-3.1-8B.



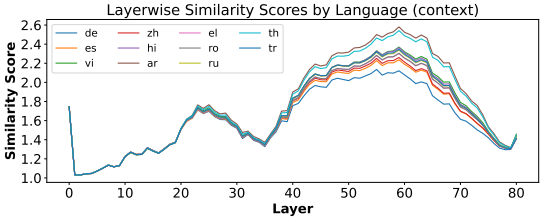
(a). Question hidden state similarity for balanced samples.



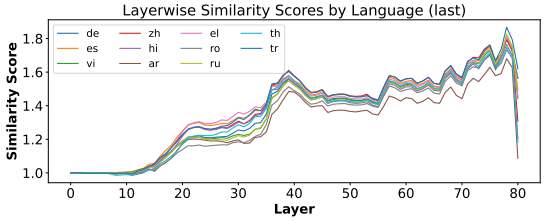
(b). Question hidden state similarity for en-superior samples.



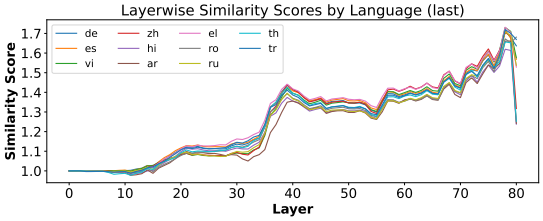
(c). Context hidden state similarity for balanced samples.



(d). Context hidden state similarity for en-superior samples.

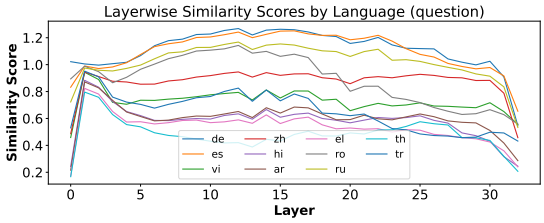


(e). Last-input-token hidden state similarity for balanced samples.

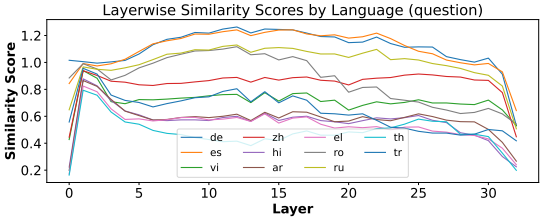


(f). Last-input-token hidden state similarity for en-superior samples.

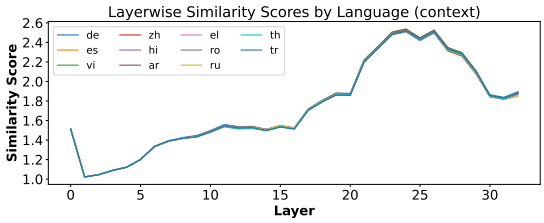
Figure 19: Hidden state similarity between English and other languages on different parts of the selected samples in each layer of the LLaMA-3.1-Instruct-70B model.



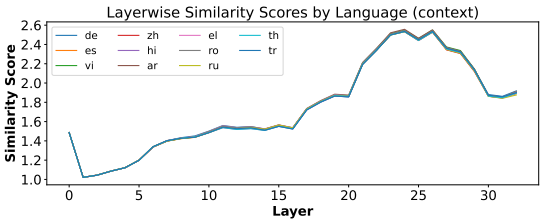
(a). Question hidden state similarity for balanced samples.



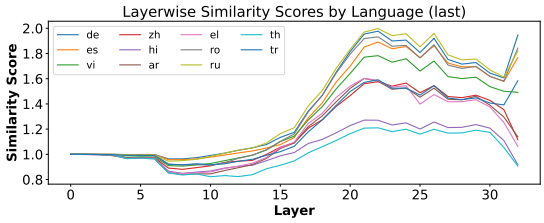
(b). Question hidden state similarity for en-superior samples.



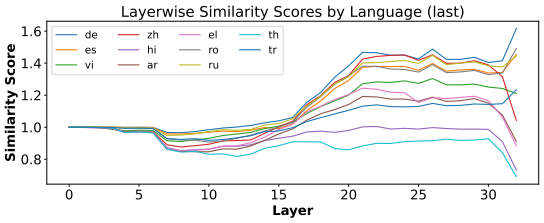
(c). Context hidden state similarity for balanced samples.



(d). Context hidden state similarity for en-superior samples.

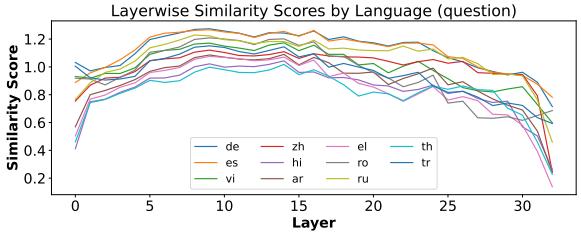


(e). Last-input-token hidden state similarity for balanced samples.

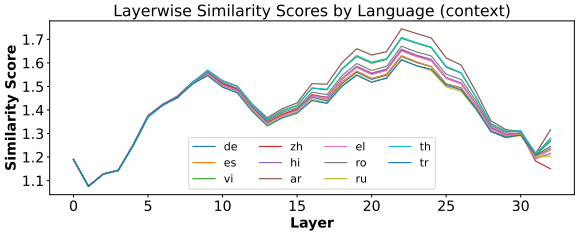


(f). Last-input-token hidden state similarity for en-superior samples.

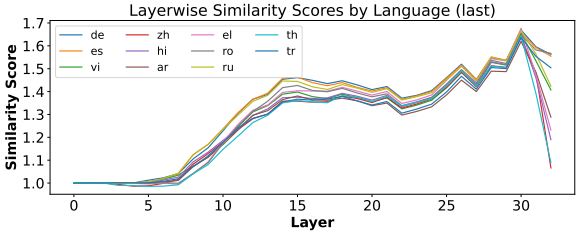
Figure 20: Hidden state similarity between English and other languages on different parts of the selected samples in each layer of the LLaMA-2-Chat-7B model.



(a). Question hidden state similarity.



(b). Context hidden state similarity.



(c). Last-input-token hidden state similarity.

Figure 21: Hidden state similarity between English and other languages on different parts of the balanced samples in each layer for our finetuned LLaMA-3.1-8B model.