Linguini: A benchmark for language-agnostic linguistic reasoning

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Abstract

We propose a new benchmark to measure a language model's linguistic reasoning skills without relying on pre-existing language-specific knowledge. The test covers 894 questions grouped in 160 problems across 75 (mostly) extremely low-resource languages, extracted from the International Linguistic Olympiad corpus. To attain high accuracy on this benchmark, models don't need previous knowledge of the tested language, as all the information needed to solve the linguistic puzzle is presented in the context. We find that, while all analyzed models rank below 25% accuracy, there is a significant gap between open and closed models, with the best-performing proprietary model at 24.05% and the best-performing open model at 8.84%.

1 Introduction

Recently, language models have shown impressive multilingual skills (Xu et al., 2024), achieving state of the art results in several tasks, such as machine translation (OpenAI, 2024), bilingual lexicon induction (Brown et al., 2020) and cross-lingual classification (Xue et al., 2021). However, the sometimes steep increase in performance of these tasks has led to saturation of popular benchmarks, such as MMLU (Hendrycks et al., 2021), where SotA performance has gone from 60% in December 2021 (Rae et al., 2022) to 90% in December 2023 (Gemini Team, 2024), providing diminishing returns when it comes to quantifying differences between models.

Moreover, in the case of linguistic reasoning, the task of evaluating a model's linguistic skills is often tied to the comprehensive knowledge a model has of a certain language (most commonly, English), making it difficult to evaluate a model's underlying linguistic skills beyond language-specific knowledge.

To address these issues, we introduce Linguini[1], a linguistic reasoning benchmark. Linguini consists of linguistic problems which require metalinguistic awareness and deductive reasoning capabilities to be solved instead of pre-existing language proficiency. Linguini is based on problems extracted from the International Linguistic Olympiad (IOL)[2], a secondary school level contest where participants compete in solving Rosetta Stone-style problems (Derzhanski and Payne, 2010) relying solely on their understanding of linguistic concepts. An example of the type of challenges and the reasoning steps needs to solve it can be seen in Figure 2.

We evaluate a list of open and proprietary models on Linguini, showing a noticeable gap between open and closed language models, in favor of the latter. We also conduct a series of experiments aiming at understanding the role of the contextual information in the accuracy obtained in the benchmark, performing both form (transliteration) and content (removing context) ablations, with results showing a main reliance of the context to solve the problems, minimizing the impact of language or task contamination in the models' training sets.

2 Related Work

There has been an increasing number of articles focusing on evaluating reasoning in language models (Chang et al., 2024). In the area of mathematical reasoning, (Qin et al., 2023) analyze models' arithmetic reasoning, while (Frieder et al., 2023) leverage publicly-available problems to build GHOSTS, a comprehensive mathematical benchmark in natural language. (Bang et al., 2023) include symbolic reasoning in their multitask, multilingual and multimodal evaluation suite. (Wu et al., 2024)

[1] The dataset is available at `redacted`

[2] The problems are shared only for research purposes under the license CC-BY-SA 4.0.

and (Hartmann et al., 2023) show that current language models have profound limitations when performing abstract reasoning, but (Liu et al., 2023) indicate promising logical reasoning skills; however, performance is limited on out-of-distribution data. Multi-step reasoning is assessed by Chain-of-Thought Hub (Fu et al., 2023) and ThoughtSource (Ott et al., 2023), pointing out the limitations of language models in complex reasoning tasks.

Coverage of linguistic reasoning, which can be defined as the ability to understand and operate under the rules of language, has been limited in evaluation datasets for language models. One of the earliest examples is PuzzLing Machines (Şahin et al., 2020), which presents 7 different patterns from the Rosetta Stone paradigm (Bozhanov and Derzhanski, 2013) for models to perform exclusively machine translation. (Chi et al., 2024) replicate (Şahin et al., 2020)'s approach, manually creating a number of examples to avoid data leakage. Recently, some approaches have leveraged long context capabilities of language models to include in-context linguistic information (e.g. a grammar book (Tanzer et al., 2024) and other domain-specific sources (Zhang et al., 2024)) to solve different linguistic tasks. For large-scale linguistic reasoning evaluation, Big-Bench (Lewkowycz et al., 2022) includes a task linguistic mappings[3], relying on arbitrary artificial grammars to perform logical deduction. This approach is limited by its reliance on constructed languages instead of natural languages, which overlooks more complex underlying properties of languages, such as voicing rules. Finally, (Waldis et al., 2024) present Holmes, a comprehensive benchmark for linguistic competence in English language.

3 Benchmarking linguistic reasoning

To overcome the previous limitations, we built a dataset where, in most cases, a model has no information about task language outside of the given context. To achieve this, we worked with problems extracted from the International Linguistic Olympiad.

3.1 IOL

The International Linguistic Olympiad (IOL)[4] is a contest for students up to secondary school level, where contestants must compete solving problems based on their understanding of linguistics (Derzhanski and Payne, 2010). The presented problems are formulated following the Rosetta Stone paradigm and present participants with challenges related to a variety of (mainly) extremely low-resource languages that students are not expected to be familiar with. The goal is for participants to leverage their linguistic skills rather than their foreign language knowledge. The IOL has been held yearly since 2003 (with the exception of 2020), and every year includes 5 short problems (to be solved individually) and 1 long, multipart problem (to be solved in groups). Problems are formulated in English and in several languages (up to 25 languages for the 2023 edition). The IOL corpus is available on their website in different formats of PDF with questions and correct answers, explanations of some answers and total marks for each problem. Beyond IOL, there are regional contests (e.g. Asia Pacific Linguistic Olympiad[5] and The Australian Computational and Linguistics Olympiad[6]) that award places for the IOL.

3.2 Selecting problems for our benchmark

To select the types of questions for the dataset, we built a taxonomy exploring the IOL from 2003 to 2023. We excluded all instances for which their category only appears once; those where the question includes an image or those where the response is only an explanation. The remaining problems require solving different linguistic reasoning tasks, such as morphosyntactic segmentation (eg., verb conjugation), morphosemantic alignment (e.g., noun negation), derivation (e.g., finding cognates in related languages), morphophonological segmentation (e.g., pluralization) or graphophonemic transcription (e.g., transcription from one script to another). In total, Linguini is composed by 894 questions grouped in 160 problems across 75 (mostly) extremely low-resource language. A list of languages can be found in Appendix A. We classify the problems included in Linguini into the three categories according to their content: sequence transduction, fill-in-blanks and number transliteration. Figure 1 shows one example of each.

Sequence transduction This category includes sequence production (identified in the benchmark as `` `translation' ``) and sequence matching (iden-

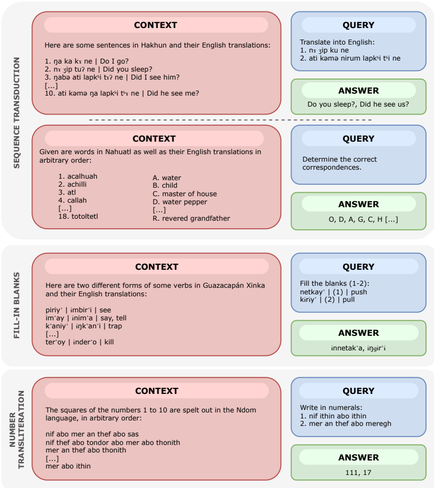
[3] https://github.com/google/BIG-bench/blob/main/bigbench/benchmark_tasks/linguistic_mappings/

[4] https://ioling.org

[5] https://aplo.asia

[6] https://ozclo.org.au

Figure 1: Examples of Linguini entries covering the three problems included in the dataset: sequence transduction, fill-in-blanks, number transliteration.



tified as `match_letter'). The problems require the model to transform a sequence into a different space (e.g., language, phonetic representation, script) based on few examples. In some cases, basic phonetic/phonological knowledge is needed. For example, the model should be able to reason over principles of voicing and their implementation in situations of coarticulation. Some problems require to know that consonants come in voiced-voiceless pairs, and that one element of the pair may in some cases be a substitute for the other element in the pair under certain circumstances.

Fill-in blanks Fill-in blanks are mainly morphophonological derivation tasks, and they are identified in the benchmark as `fill_blanks'. Models need to understand what are the morphophonological rules that make it possible to go from the first form of a word to its second form. This can usually be applied to verbal (e.g., verb tense conjugation), nominal or adjectival (e.g., case declension) derivation. It involves understanding affixation rules and morpheme swapping rules, which often come with phonological rules if there are different coarticulation phenomena with different affixes or phonotactic phenomena such as consonantal mutations.

Digit/text number transliteration These problems are identified by the labels `text_to_num' and `num_to_text'. In them, models have to produce a digit or text equivalent, respectively. They require a model's understanding of morphological analysis and morpheme order.

Figure 2: A subset of the context of a problem in Terenâ language and the reasoning steps needed to solve it. To correctly answer the question, the model must notice that (a) voiced *d* mutates to voiceless paired sound *t* (fortition), (b) *n* is dropped because there are no voiceless nasal alveolar sounds and (c) an epenthetic vowel has to be added between the mutation consonant and the rest of the word (a root), and that the vowel that gets added matches the aperture of the vowel in the root. If the aperture is closed, the epenthetic vowel is the closed front vowel *i*; if the aperture is mid, the epenthetic vowel is the mid front vowel *e*.

4 Experiments

We perform zero-shot to few-shot (0-5 in-context examples) evaluation across the whole dataset for an array of open and proprietary LLMs. Given the size of the benchmark, we employ a leave-one-out cross-validation scheme to maximize the number of in-context candidates per task. For every given inference, we include examples of the same format (e.g., `translation', `match_letter'), but we exclude in-content examples of the same language to avoid language contamination.

Setup and Models We prompt models with an instruction, a context that provides information to unambiguously solve the linguistic problem and the problem itself. Scores of answers to each item of a problem are averaged to provide a single score (0-100) per task. We evaluate several major open LLMs and commercially available (behind API) SotA LLMs at the publication of this work. For open models, we conduct inference experiments in an 8 A100 GPUs node. An exhaustive list can be found in Appendix B.

Evaluation We use exact match (accuracy) as main evaluation criterion. Given the almost null performance on exact match of certain models, we also include chrF (Popović, 2015) as a *softer* metric. A low ChrF score indicates extremely low performance models, e.g. not understanding the domain of the task at hand.

5 Results and Discussion

Table 1 shows there's a gap between the best performing open model and the best performing proprietary model, with several tiers of proprietary models above the best open model (*llama-3-70b*). We also find mixed impact of in-context examples in the performance of the models. While some models benefit from it (such as *llama-3-70b-it*), other models' performance degrades as the number of examples increases (such as *claude-3-opus*). This disparity might be due to the two factors introduced by the ICEs: from one side, they set an answer format that could be useful for models that can't infer it directly from a single natural language instruction and, from another side, they introduce tokens of languages potentially unrelated to the evaluated problem. It is possible that for models more capable of instruction following, only the second factor plays a role in the model's performance. We include results with chrF in Appendix D for reference.

Table 1: Exact match results with Linguini for 0-5 ICEs.

Model	0	1	2	3	4	5	Best(↑)
claude-3-opus	24.05	20.58	21.36	19.91	17.00	15.1	24.05
gpt-4o	14.65	12.98	13.87	12.98	13.98	13.76	14.65
gpt-4	6.38	9.96	11.52	12.98	11.74	13.31	12.98
claude-3-sonnet	12.30	8.95	10.29	10.40	9.28	8.72	12.30
gpt-4-turbo	8.72	9.40	9.96	7.49	8.61	9.96	9.96
llama-3-70b	8.17	5.93	7.72	8.84	8.72	6.60	8.84
llama-3-70b-it	4.81	5.93	7.16	7.38	6.82	8.39	8.39
claude-3-haiku	6.04	7.61	4.36	6.04	6.94	7.05	7.61
llama-2-70b	4.70	2.24	2.57	3.24	3.36	3.58	3.58
mistral-0.1-8x7b	2.46	3.47	3.91	3.02	3.24	3.47	3.91
llama-2-70b-it	0.89	1.45	2.80	3.02	3.13	2.80	3.13
gemma-2b	0.34	2.01	1.90	1.34	1.45	1.90	2.01
qwen-1.5-110b-it	1.45	1.23	1.34	1.45	1.45	1.68	1.68

In addition to our main experiments, we performed a series of ablation studies to get a better insight of how language models perform linguistic reasoning.

5.1 No-Context Prompting

Given that we don't have information about training data for the majority of the analyzed models, we performed a series of experiments to study the degree in which models rely on the given context to provide correct answers. Models that have not been trained on any data of the task language should have a null-adjacent performance when not given the context necessary to solve the task. We analyze the impact of ignoring the context provided in the benchmark as a proxy of possible data contamination. The results are shown in Table 2.

Table 2: No context results.

Model	Zero-shot	No context	Δ
llama-3-70b-it	4.81	1.12	-3.69
gpt-4-turbo	8.72	1.45	-7.27
gpt-4	6.38	1.34	-5.04
claude-3-sonnet	12.30	2.01	-10.29
mistral-0.1-8x7b	2.46	1.98	-0.48
claude-3-haiku	6.04	1.12	-4.92
qwen-1.5-110b-it	1.45	0.43	-1.02
gemma-2b	0.34	0.09	-0.25
llama-2-70b	4.70	1.07	-3.63
llama-2-70b-it	0.89	0.56	-0.33
llama-3-70b	8.17	1.67	-6.50
claude-3-opus	24.05	1.23	-22.82
gpt-4o	14.65	1.45	-13.20

We find steep performance drops for every model, which points towards a low likelihood of the language (or the training examples) being present in the models' training sets.

5.2 Character-wise substitution

Since most problems are presented in Latin script, we wanted to understand whether the script in which the task languages are presented impact the performance on Linguini. But given that all information needed to solve the task is present in the context, the script should not have a major impact on the performance beyond encoding constraints. In other words, if the model doesn't rely on instances of the language (or the problem) in its training set, it should be able to solve the task in a non-Latin script as well. We selected the best performing model (*claude-3-opus*) and transcribed the best performing problems (those where the accuracy >= 75) into 4 non-Latin alphabetical scripts (Cyrilic, Greek, Georgian and Armenian)[7]. An example of a transliterated problem can be found in

[7]The mappings from Latin script to the rest can be found at https://github.com/barseghyanartur/transliterate/

Figure 3. Given the difficulty of uniformly transcribing a diverse set of orthographic systems and diacritics, we opted for performing a character/bi-character-wise substitution of the standard Latin alphabet character, leaving non-standard characters with their original Unicode symbol. We filtered 17 well performing problems, and excluded one with a non-Latin script task language (English Braille). We performed transcriptions on the remaining 16 problems.

Figure 3: Example of transliteration of a problem into Cyrillic, Greek, Georgian and Armenian scripts.

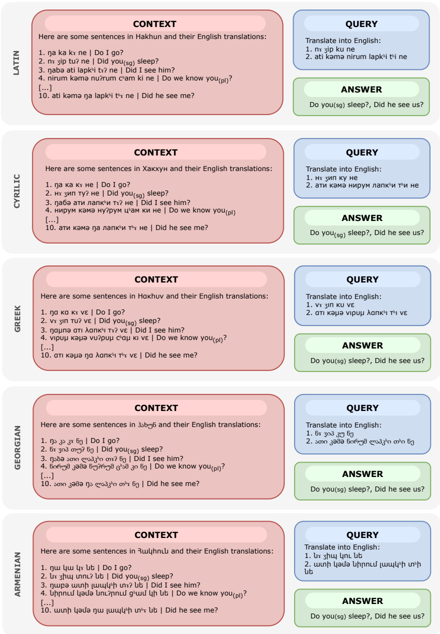


Table 3: Scores of selected problems with different language scripts for *claude-3-opus*.

Problem code & language	Latn	Cyrl	Grek	Geor	Armn
012023010100 (qda-gua)	75.00	100.00	75.00	100.00	0.00
012021020500 (zun)	100.00	0.00	100.00	0.00	0.00
012012030100 (eus)	78.57	7.14	92.86	0.00	0.00
012018020100 (nst-hkn)	83.33	83.33	66.67	83.33	100.00
012007050100 (tur)	75.00	75.00	50.00	37.50	50.00
012006020100 (cat)	75.00	50.00	50.00	58.33	33.33
012003030200 (eus)	100.00	100.00	75.00	100.00	100.00
012004010100 (txu)	100.00	100.00	66.67	66.67	33.33
012007030100 (kat)	80.00	13.33	6.67	100.00	0.00
012009050100 (nci)	83.33	83.33	83.33	83.33	50.00
012015020100 (kbd-bes)	100.00	66.67	100.00	66.67	83.33
012012050100 (rtm)	100.00	100.00	100.00	100.00	100.00
012011040200 (nci)	100.00	50.00	75.00	75.00	0.00
012013010200 (yii)	100.00	100.00	100.00	75.00	100.00
012012030200 (eus)	100.00	50.00	0.00	0.00	0.00
012012030300 (eus)	100.00	50.00	100.00	0.00	0.00
Average	85.71	56.12	65.31	63.27	38.78

Table 3 shows that the model retains the capacity to perform linguistic reasoning even after changing scripts, which backs the hypothesis of the model relying mainly on the presented context and not on spurious previous knowledge. The fact that for 13 our of 16 of the given problems there's at least one non-Latin script in which the model can solve the problem with greater or equal performance than with Latin script further supports this claim. Performance disparity among scripts could be related to either the difference in tokenization of different scripts or to the inherent limitations of our transliteration strategy (e.g. the Armenian script might lack a specific consonant cluster that needs to be developed to provide the right answer, and character/bi-character-wise substitution doesn't take this nuance into account).

5.3 Language resourcefulness and accuracy

We were also interested in assessing whether higher-resource languages perform, on average, better than lower-resource languages. We use two metrics as proxies of language resourcefulness: number of speakers (Figure 4) and online presence (Figure 5), measured by Google searches).

Figure 4: Accuracy vs. number of speakers. Data points are clustered for readability.

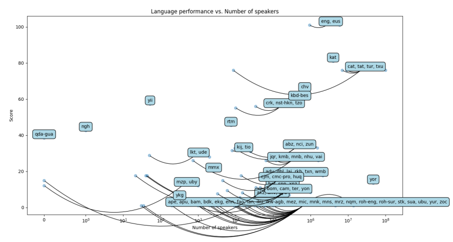
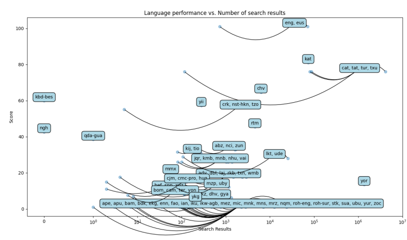


Figure 5: Accuracy vs. number of Google searches. Data points are clustered for readability.



We find the distribution to follow a uniform trend with respect to both metrics of language resourcefulness, which suggests that the accuracy isn't largely correlated to to its likelihood of being included in the training set. Notable exceptions to this trend are a number of very high-resource languages (e.g., cat, eus, kat, tur), which are very likely to be included in the model's training set, given their institutional status.

5.4 One-Book Prompting

Previous studies (Tanzer et al., 2024) have shown the capacity of language models to acquire some proficiency in the task of machine translation for an unseen language only through an in-context textbook. We leverage publicly available textbooks to scale Tanzer et al. (2024)'s analysis in number of languages and types of tasks. We convert the textbooks in PDF format to raw text using the pdftotext library[8] and include them as context without any pre-processing. A list of textbooks employed can be found in Appendix C.

Table 4: Scores for a subset of examples evaluated with no context, with context, with a textbook and with a combination of both.

Language code	No-context	Context	Textbook	Context + Textbook
akz	0.00	5.13	0.00	3.85
apu	0.00	0.00	0.00	16.67
mnk	0.00	0.00	0.00	0.00
Average	0.00	1.71	0.00	6.84

Even thought in many cases the orthography of the task language greatly varies from the textbook to the problem and the PDF to text conversion introduces errors for highly diacritical text (as shown in Figure 6), the results in Table 4 show that a model can learn to model linguistic phenomena relying on a single in-context textbook.

6 Conclusions

We presented Linguini, a new linguistic reasoning evaluation dataset. Our experiments show that Linguini provides a compact and effective benchmark to assess linguistic reasoning without relying on a substrate of existing language-specific knowledge. There's a considerable gap between open source and proprietary LLMs in linguistic reasoning. Subsequent experiments also show very low likelihood of dataset contamination in the analyzed models. Limitations and broader impact of the dataset are discussed in Appendix 7.

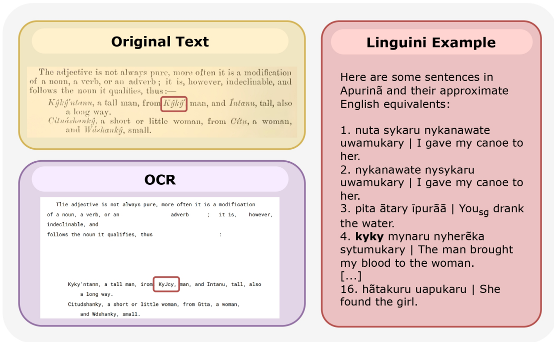
7 Limitations, further work and broader impact

Evaluation of long in-context learning for linguistic reasoning is limited in this paper to a few languages, given the difficulties of finding publicly available grammar books. We plan to scale up the number of covered languages in further versions of the benchmark to perform a better encompassing analysis of long in-context learning.

Our dataset also lacks a curated list of explanations for each problem, which could be used as a basis to run chain-of-thought experiments and improve lingusitic reasoning skills of language models. We intend to engage with linguists and IOL organizers to fill this gap.

This benchmark intends to address and quantify the root of multilingualism, which in turn can impact the support of language models for the majority of world languages.

Figure 6: Example of transliteration of a problem into Cyrillic, Greek, Georgian and Armenian scripts. The discrepancies between the term *kyky* (English: *man*) in the original document (a scan from a 1894 grammar book of Apurinã language), its OCR conversion and the text of a problem in the benchmark are highlighted. In spite of the noise introduced by different orthographies and imperfect OCR, performance for Apurinã increases from 0% 16.67% with the full OCR text in-context.



[8] https://github.com/jalan/pdftotext

References

AI@Meta. 2024. Llama 3 model card.

Anthropic AI. 2024. The claude 3 model family: Opus, sonnet, haiku. *Claude-3 Model Card*.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. Qwen technical report.

Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, Quyet V. Do, Yan Xu, and Pascale Fung. 2023. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity.

Bozhidar Bozhanov and Ivan Derzhanski. 2013. Rosetta stone linguistic problems. In *Proceedings of the Fourth Workshop on Teaching NLP and CL*, pages 1–8, Sofia, Bulgaria. Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners.

Yupeng Chang, Xu Wang, Jindong Wang, Yuan Wu, Linyi Yang, Kaijie Zhu, Hao Chen, Xiaoyuan Yi, Cunxiang Wang, Yidong Wang, Wei Ye, Yue Zhang, Yi Chang, Philip S. Yu, Qiang Yang, and Xing Xie. 2024. A survey on evaluation of large language models. *ACM Trans. Intell. Syst. Technol.*, 15(3).

Nathan Chi, Teodor Malchev, Riley Kong, Ryan Chi, Lucas Huang, Ethan Chi, R. McCoy, and Dragomir Radev. 2024. ModeLing: A novel dataset for testing linguistic reasoning in language models. In *Proceedings of the 6th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*, pages 113–119, St. Julian's, Malta. Association for Computational Linguistics.

Ivan Derzhanski and Thomas Payne. 2010. The linguistics olympiads: Academic competitions in linguistics for secondary school students. *Linguistics at school: language awareness in primary and secondary education*, pages 213–26.

D Eberhard, G Simons, and C Fennig. 2020. Ethnologue: Languages of the world. twenty-third edition. dallas, texas: Sil international. online version:[internet]. ethnologue.

Simon Frieder, Luca Pinchetti, Alexis Chevalier, Ryan-Rhys Griffiths, Tommaso Salvatori, Thomas Lukasiewicz, Philipp Christian Petersen, and Julius Berner. 2023. Mathematical capabilities of chatgpt.

Yao Fu, Litu Ou, Mingyu Chen, Yuhao Wan, Hao Peng, and Tushar Khot. 2023. Chain-of-thought hub: A continuous effort to measure large language models' reasoning performance.

Gemini Team. 2024. Gemini: A family of highly capable multimodal models.

Gemma Team. 2024. Gemma: Open models based on gemini research and technology.

Jochen Hartmann, Jasper Schwenzow, and Maximilian Witte. 2023. The political ideology of conversational ai: Converging evidence on chatgpt's pro-environmental, left-libertarian orientation.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2021. Measuring massive multitask language understanding.

Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, et al. 2024. Mixtral of experts. *arXiv preprint arXiv:2401.04088*.

Aitor Lewkowycz, Ambrose Slone, Anders Andreassen, Daniel Freeman, Ethan S Dyer, Gaurav Mishra, Guy Gur-Ari, Jaehoon Lee, Jascha Sohl-dickstein, Kristen Chiafullo, et al. 2022. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. Technical report, Technical report.

Hanmeng Liu, Ruoxi Ning, Zhiyang Teng, Jian Liu, Qiji Zhou, and Yue Zhang. 2023. Evaluating the logical reasoning ability of chatgpt and gpt-4.

Karen Jacque Lupardus. 1982. *The language of the Alabama Indians*. University of Kansas.

OpenAI. 2024. Gpt-4 technical report.

Simon Ott, Konstantin Hebenstreit, Valentin Liévin, Christoffer Egeberg Hother, Milad Moradi, Maximilian Mayrhauser, Robert Praas, Ole Winther, and Matthias Samwald. 2023. Thoughtsource: A central hub for large language model reasoning data. *Scientific Data*, 10(1).

Jacob Evert Resyek Polak. 1894. *A Grammar and a Vocabulary of the Ipuriná Language*. 1. Published for the Fund By Kegan Paul, Trench, Trübner.

Maja Popović. 2015. chrF: character n-gram F-score for automatic MT evaluation. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 392–395, Lisbon, Portugal. Association for Computational Linguistics.

Chengwei Qin, Aston Zhang, Zhuosheng Zhang, Jiaao Chen, Michihiro Yasunaga, and Diyi Yang. 2023. Is chatgpt a general-purpose natural language processing task solver?

Jack W. Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, Eliza Rutherford, Tom Hennigan, Jacob Menick, Albin Cassirer, Richard Powell, George van den Driessche, Lisa Anne Hendricks, Maribeth Rauh, Po-Sen Huang, Amelia Glaese, Johannes Welbl, Sumanth Dathathri, Saffron Huang, Jonathan Uesato, John Mellor, Irina Higgins, Antonia Creswell, Nat McAleese, Amy Wu, Erich Elsen, Siddhant Jayakumar, Elena Buchatskaya, David Budden, Esme Sutherland, Karen Simonyan, Michela Paganini, Laurent Sifre, Lena Martens, Xiang Lorraine Li, Adhiguna Kuncoro, Aida Nematzadeh, Elena Gribovskaya, Domenic Donato, Angeliki Lazaridou, Arthur Mensch, Jean-Baptiste Lespiau, Maria Tsimpoukelli, Nikolai Grigorev, Doug Fritz, Thibault Sottiaux, Mantas Pajarskas, Toby Pohlen, Zhitao Gong, Daniel Toyama, Cyprien de Masson d'Autume, Yujia Li, Tayfun Terzi, Vladimir Mikulik, Igor Babuschkin, Aidan Clark, Diego de Las Casas, Aurelia Guy, Chris Jones, James Bradbury, Matthew Johnson, Blake Hechtman, Laura Weidinger, Iason Gabriel, William Isaac, Ed Lockhart, Simon Osindero, Laura Rimell, Chris Dyer, Oriol Vinyals, Kareem Ayoub, Jeff Stanway, Lorrayne Bennett, Demis Hassabis, Koray Kavukcuoglu, and Geoffrey Irving. 2022. Scaling language models: Methods, analysis & insights from training gopher.

Gözde Gül Şahin, Yova Kementchedjhieva, Phillip Rust, and Iryna Gurevych. 2020. PuzzLing Machines: A Challenge on Learning From Small Data. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1241–1254, Online. Association for Computational Linguistics.

Richard Alan Spears. 1965. *The Structure of Faranah-Maninka*. Indiana University.

Garrett Tanzer, Mirac Suzgun, Eline Visser, Dan Jurafsky, and Luke Melas-Kyriazi. 2024. A benchmark for learning to translate a new language from one grammar book.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models.

Andreas Waldis, Yotam Perlitz, Leshem Choshen, Yufang Hou, and Iryna Gurevych. 2024. Holmes: Benchmark the linguistic competence of language models.

Zhaofeng Wu, Linlu Qiu, Alexis Ross, Ekin Akyürek, Boyuan Chen, Bailin Wang, Najoung Kim, Jacob Andreas, and Yoon Kim. 2024. Reasoning or reciting? exploring the capabilities and limitations of language models through counterfactual tasks.

Yuemei Xu, Ling Hu, Jiayi Zhao, Zihan Qiu, Yuqi Ye, and Hanwen Gu. 2024. A survey on multilingual large language models: Corpora, alignment, and bias.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mT5: A massively multilingual pre-trained text-to-text transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 483–498, Online. Association for Computational Linguistics.

Kexun Zhang, Yee Man Choi, Zhenqiao Song, Taiqi He, William Yang Wang, and Lei Li. 2024. Hire a linguist!: Learning endangered languages with in-context linguistic descriptions.

A Languages of Linguini

Table 5: Languages and their characteristics

Lang. Code	Language	No. Speakers[9]	No. Search Results[10]	Language Family	Script
abz	Abui	16,000	263	Trans-New Guinea	Latin
ady	Adyghe	425,000	2,370	Abkhaz-Adyghe	Latin
akz	Alabama	370	1,350	Muskogean	Latin
abz	Mountain Arapesh	16,000	98	Torricelli	Latin
apu	Apurinã	2800	264	Maipurean	Latin
bam	Bambara	14000000	7150	Niger-Congo	N'Ko
bdk	Budukh	200	126	Nakh-Daghestanian	Latin
bef	Bena Bena	45000	107	Trans-New Guinea	Latin
bom	Birom	1000000	115	Niger-Congo	Latin
cam	Cemuhî	3300	6	Austronesian	Latin
cat	Catalan	9200000	87100	Indo-European	Latin
chv	Chuvash	700000	6260	Turkic	Latin
cjm	Phan Rang Cham	491448	2	Austronesian	Latin
cmc-pro[11]	Proto-Chamic	0	267	Austronesian	Latin
crk	Plains Cree	34000	5290	Algic	Latin
dbl	Dyirbal	21	2900	Australian	Latin
dhv	Drehu	13,000	216	Austronesian	Latin
ekg	Ekari	100000	141	Trans-New Guinea	Latin
eng	English Braille	6000000	728	Indo-European	Latin
enn	Engenni	20000	185	Niger-Congo	Latin
eus	Basque	936,812	71100	Isolate	Latin
fao	Faroese	69000	23800	Indo-European	Latin
gya	Northwest Gbaya	267000	8	-	Latin
huq	Tsat	4500	128	Austronesian	Latin
ian	Iatmül	46000	9	Papua New Guinea	Latin
iku	Inuktitut	39,000	12500	Eskimo-Aleut	Latin
ikw-agb[11]	Agbirigba	30	1	Niger-Congo	Latin
jqr	Jaqaru	725	101	Aymaran	Latin
kat	Georgian	4000000	73700	Kartvelian	Latin
kbd-bes[11]	Besleney Kabardian	516000	0	Abkhaz-Adyghe	Latin
kij	Kilivila	25000	271	Austronesian	Latin
kmb	Kimbundu	1600000	1130	Niger-Congo	Latin
laj	Lango	2100000	1490	Nilo-Saharan	Latin
lkt	Lakhota	2000	25300	Siouan-Catawban	Latin
mez	Menominee	2000	2240	Algic	Latin
mic	Micmac	11000	774	Algic	Latin
mmx	Madak	2600	57	Austronesian	Latin
mnb	Muna	270000	1020	Austronesian	Latin
mnk	Maninka	4600000	478	Niger-Congo	N'Ko
mns	Mansi	2229	1490	Uralic	Latin
mrz	Coastal Marind	9000	100	Trans-New Guinea	Latin
mzp	Movima	1000	72	Isolate	Latin
nci	Classical Nahuatl	1500000	1690	Uto-Aztecan	Latin
ngh	Nluuki	1	0	Tuu	Latin
nhu	Nooni	64000	82	Niger-Congo	Latin
nqm	Ndom	1200	154	Trans-New Guinea	Latin
nst-hkn[11]	Hakhun	10000	5	Sino-Tibetan	Latin
qda-gua[11]	Guazacapán Xinka	0	1	Xincan	Latin
rkb	Rikbaktsa	40	54	Isolate	Latin
roh-eng[10]	Engadine	60000	7	Indo-European	Latin
roh-sur[11]	Sursilvan	60000	3	Indo-European	Latin
rtm	Rotuman	7500	4560	Austronesian	Latin
spp	Supyire	460000	45	Niger-Congo	Latin
stk	Arammba	1000	36	South-Central Papuan	Latin
sua	Sulka	3500	107	Isolate	Latin
tat	Tatar	7000000	79700	Turkic	Latin
ter	Terêna	15,000	115	Maipurean	Latin
tio	Teop	8000	81	Austronesian	Latin
tur	Turkish	100000000	4130000	Turkic	Latin
txn	West Tarangan	14,000	4	Austronesian	Latin
txu	Kayapo	8600	116	Jean	Latin
tzo	Tzotzil	550000	1160	Mayan	Latin
ubu	Umbu-Ungu	32,000	90	Trans-New Guinea	Latin
uby	Ubykh	0	1180	Abkhaz-Adyghe	Latin
ude	Udihe	50	108	Tungusic	Latin
vai	Vai	120000	1380	Niger-Congo	Latin
wmb	Wambaya	43	112	Australian	Latin
xnz	Kunuz Nubian	35000	2	Nilo-Saharan	Latin
yii	Yidiny	52	280	Australian	Latin
ykg	Tundra Yukaghir	320	206	Yukaghir	Latin
yon	Yonggom	6,000	48	Trans-New Guinea	Latin
yor	Yoruba	47000000	1360000	Niger-Congo	Latin
yur	Yurok	35	2830	Algic	Latin
zoc	Copainalá Zoque	10000	10	Mixe-Zoquean	Latin
zun	Zuni	9500	1610	Isolate	Latin

[11]Language code not in ISO-639-3

B Models

Table 6: Overview of Large Language Models

Model ID	API Version	Organization	Model Size[12]	Open	Reference
claude-3-opus	claude-3-opus-20240229	Anthropic	-	✗	(Anthropic AI, 2024)
gpt-4o	gpt-4o-2024-05-13	OpenAI	-	✗	(OpenAI, 2024)
gpt-4	gpt-4-0125-preview	OpenAI	-	✗	(OpenAI, 2024)
claude-3-sonnet	claude-3-sonnet-20240229	Anthropic	-	✗	(Anthropic AI, 2024)
gpt-4-turbo	gpt-4-turbo-2024-04-09	OpenAI	-	✗	(OpenAI, 2024)
llama-3-70b	-	Meta	70.6	✓	(AI@Meta, 2024)
llama-3-70b-it	-	Meta	70.6	✓	(AI@Meta, 2024)
claude-3-haiku	claude-3-haiku-20240307	Anthropic	-	✗	(Anthropic AI, 2024)
llama-2-70b	-	Meta	69.0	✓	(Touvron et al., 2023)
mistral-0.1-8x7b	-	Mistral	46.7	✓	(Jiang et al., 2024)
llama-2-70b-it	-	Meta	69.0	✓	(Touvron et al., 2023)
gemma-2b	-	Google	2.5	✓	(Gemma Team, 2024)
qwen-1.5-110b-it	-	Alibaba	111.0	✓	(Bai et al., 2023)

C Books

Table 7: Overview of Grammar Books

Language	Book Title	Citation
akz	The Language of the Alabama Indians	(Lupardus, 1982)
apu	A Grammar and a Vocabulary of the Ipuriná Language	(Polak, 1894)
mnk	The Structure of Faranah-Maninka	(Spears, 1965)

D chrF Results

Table 8: chrF results with Linguini for 0-5 ICEs

Model	0	1	2	3	4	5
llama-3-70b-it	45.35	42.65	43.89	45.99	48.07	51.08
gpt-4-turbo	52.89	50.82	50.03	50.94	49.98	51.79
gpt-4	44.62	55.05	58.47	57.36	57.62	58.18
claude-3-sonnet	54.97	45.32	50.91	47.35	46.51	42.06
mistral-0.1-8x7b	42.0	34.8	38.01	37.57	37.64	37.63
claude-3-haiku	47.74	50.75	41.02	45.38	42.32	41.83
qwen-1.5-110b-it	2.57	0.0	0.22	0.78	1.12	2.8
gemma-2b	33.72	27.19	24.62	26.04	27.04	27.63
llama-2-70b	45.3	35.39	34.06	35.54	36.21	36.44
llama-2-70b-it	43.55	41.42	39.73	41.42	39.69	39.34
llama-3-70b	37.25	36.04	41.83	41.21	41.92	41.63
claude-3-opus	63.96	58.26	58.5	53.17	49.01	46.55
gpt-4o	57.68	58.13	57.32	58.86	58.99	58.22

[12]in billion parameter