Test Set Quality in Multilingual LLM Evaluation

Kranti Chalamalasetti¹, Gabriel Bernier-Colborne², Yvan Gauthier², Sowmya Vajjala²,

¹University of Potsdam, Germany, ²National Research Council, Canada

kranti.chalamalasetti@uni-potsdam.de, gabriel.bernier-colborne@nrc-cnrc.gc.ca {yvan.gauthier, sowmya.vajjala}@nrc-cnrc.gc.ca

Abstract

Several multilingual benchmark datasets have beendeveloped in a semi-automatic manner in the recent past to measure progress and understand the state-of-the-art in the multilingual capabilities of Large Language Models. However, there is not a lot of attention paid to the quality of the datasets themselves, despite the existence of previous work in identifying errors in even fully human-annotated test sets. In this paper, we manually analyze recent multilingual evaluation sets in two languages - French and Telugu, identifying several errors in the process. We compare the performance difference across several LLMs with the original and revised versions of the datasets and identify large differences (almost 10% in some cases) in both languages). Based on these results, we argue that test sets should not be considered immutable and should be revisited, checked for correctness, and potentially versioned. We end with some recommendations for both the dataset creators as well as consumers on addressing the dataset quality issues.

1 Introduction

Achieving multilingual fairness in AI systems that incorporate large language models (LLMs) requires not only careful curation of pre-training data and post-training data, but also (and perhaps more importantly) evaluation data, as only the latter can enable us to accurately track progress of these systems on the various tasks they perform.

There has been a lot of recent work on the development of evaluation datasets across several languages (Huang et al., 2023; Yüksel et al., 2024; Son et al., 2025; Hupkes and Bogoychev, 2025; Tran et al., 2025; Sibaee et al., 2025). In most cases, these evaluation sets are automatically extracted from web sources followed by varying degrees of manual oversight. They are then used as benchmarks to compare performances of LLMs. From past NLP research, we know that even high

quality task-specific data sources created with expert human annotations are prone to errors (Boyd et al., 2008; Bernier-Colborne and Vajjala, 2024; Reiss et al., 2020). More recently, Gema et al. (2025) discuss errors in MMLU (Hendrycks et al., 2021), a popular LLM evaluation dataset that has since been translated into multiple languages (from English) and is being used as a multilingual LLM performance benchmark (Singh et al., 2024). This kind of scrutiny is mostly restricted to English test sets, though.

In this background, we took a closer look at two recent multilingual datasets and performed a manual analysis for one French and two Telugu test subsets. A comparison of various LLMs between the original and cleaned versions of the test sets reveal large variations (up to 10%) in both languages, raising questions about the quality of the resources. Based on these results, we provide some recommendations on how to address test set quality. We hope this discussion will serve as a starting point leading to a broader discussion around multilingual evaluation and test set creation.

2 Related Work

Datasets for various tasks have been the subject of denoising or re-annotation studies in NLP research of the past, including part-of-speech tagging (Silberztein, 2018), dependency parsing (Alzetta et al., 2017; Wisniewski, 2018), entity linking (Jha et al., 2017) and named entity recognition (Wang et al., 2019; Reiss et al., 2020; Muthuraman et al., 2021; Stanislawek et al., 2019; Bernier-Colborne and Vajjala, 2024) Most of this work focused on English, but other languages have been studied, such as Hindi (Saha et al., 2009), Japanese (Ichihara et al., 2015), and Uyghur (Abudukelimu et al., 2018) in the case of NER. Some past work looked at Swedish, Czech and German datasets in the context of parsing (Boyd et al., 2008).

In the context of LLM evaluation, recent work by Gema et al. (2025) looked at the well-known MMLU dataset for English, finding that over 6% of its questions contain errors such as ambiguous phrasing, incorrect ground truths, or unclear options. Plaza et al. (2024) examine MMLU's Spanish version and reveal that many test item failures are due to automated translation errors (including mistranslated names, technical terms, cultural mismatches, and grammatical issues). Cengiz et al. (2025) evaluate 17 Turkish benchmarks across six quality dimensions (including answer, grammar correctness, cohesion and coherence), finding that about 70% fail to meet their proposed quality standards. We follow this lead, but look into other multilingual datasets and languages in this paper.

3 Our Approach

Our approach can be summarized as comprising the follow steps: a) we manually analyzed French and Telugu versions of a test set, b) compared the performance of 10 LLMs in terms of the difference in accuracy between the two versions of the test set for each language, and c) replicated this setup with another dataset, for Telugu. Details of the process are described below:

Dataset: We used Include44 from Romanou et al. (2024), a multilingual LLM evaluation dataset comprised of multiple-choice questions automatically extracted academic and professional exam questions compiled from the web as our test dataset, as it is a recent multilingual test set and is not a translated version of English. We chose French and Telugu, the native languages spoken by the authors, to ensure two annotators per language.

Annotation Process: Based on some preliminary analysis, for both the language subsets, we identified three primary issues in the test sets: unanswerable questions, incorrect question/answer pairs; question or answer being in English instead of the target language. Two annotators (native speakers) per language manually analyzed the French and Telugu language test sets to mark each sample with any of these three concerns or as "no concerns"; Only samples unanimously marked as "no concerns" were included in the final cleaned dataset. Table 1 shows a summary of the datasets before and after cleanup. A qualitative analysis of this dataset is presented in Section 4.1.

Almost half of the Telugu samples, and about

| Test Subset | # Orig. | # Clean |
|-------------|---------|---------|
| French | 419 | 327 |
| Telugu | 548 | 285 |

Table 1: # samples in original and cleaned test sets

25% of the French samples were removed in the cleaned version. Note that our approach to discard is aggressive, as we remove all samples where at least one annotator expressed a concern.¹

LLM Evaluation: We evaluated 10 LLMs in total, considering both open weight and proprietary LLMs as well as small and large LLMs. All the larger LLMs (>15B - GPT4o, Claude-3.7, Gemini-2.0-Flash, LLama3.3-70B, Gemma3-27B) that cannot be hosted on a laptop are accessed via OpenRouter² and the smaller (<15B - Gemma3-12B, Aya-Expanse:8B, Qwen2.5-7B, LLama3.2-7B, Gemma2-9B) models are downloaded and run locally on a laptop, via Ollama³ in their 4-bit quantized versions. Table 4 in the appendix gives more details about the LLMs we used.

All the evaluations were conducted through the Inspect LLM evaluation framework⁴ with its default prompts. Most evaluated models list French among supported languages (e.g., Claude, LLaMA 3, Qwen, Aya). Gemini, Gemma3, and GPT-40 do not have published language lists. In contrast, none of the models explicitly list Telugu as supported. Some (e.g., Gemma3) claim broad multilingual coverage, but do not provide language lists. Since the dataset is in the multiple-choice format, we considered accuracy as the evaluation measure and used it to compare the difference between original and cleaned test sets. Section 4.2 discusses the results of this evaluation.

Additionally, we did a replication experiment using another Telugu test set, from the MILU dataset (Verma et al., 2024), which is comparable in size to Include44's Telugu test set. This experiment was designed to compare trends in dataset quality and LLM evaluation performance. More details are provided in Section 4.3.

¹Our revised versions of the datasets with comments will be shared publicly.

²https://openrouter.ai/

³https://ollama.com/

⁴https://inspect.aisi.org.uk/

4 Results

We first present a qualitative analysis of the Include 44 test sets, followed by quantitative performance comparisons between the original and cleaned versions, and conclude with a replication study.

4.1 Qualitative Analysis of the Datasets

In both languages, we noticed several cases of "unanswerable questions", questions that miss information such as the year, country, etc. For example, the Telugu dataset has a question: "Who won the recent Asia Under-14 Tennis Championship?", giving four female names as the possible options. The right answer as per the dataset is true in 2018, and we annotated such questions as "unanswerable" as we would need that context to answer correctly. There were questions with missing context, for instance questions that are geography-specific but had no region or location specified in the question. There were also examples of incomplete questions, undefined symbols in choices, or incorrect answers in both languages. There were several question and/or answers in English, in the Telugu subset. We present examples of the identified issues in French and Telugu in Tables 5 and 6, respectively, in the appendix, along with further discussion of these issues (Section B).

Many quality issues that we observe can be explained by how the dataset was compiled. The authors of the dataset (Romanou et al., 2024) describe a process of automatic extraction, followed by manual check by native speakers to check if the extraction is correct, filtering out questions with images or tables, and adding some meta-data. This automated process can inadvertently generate questions for which there are multiple valid answers, where the context of the question is insufficient (e.g., if an image was removed), or if the question is not time-specific enough to be correctly answered years later.

The type of concerns with the questions varies by language. In French, the concerns are more evenly distributed between incorrect questions, incorrect answers, and unanswerable questions – with only a single question in the wrong language. In Telugu, however, the large majority of concerns were around english-text questions, and there were very few incorrect questions or answers (see Figure 1 in the Appendix).

In French, the annotators were provided with

an initial set of four categories, e.g. incorrect language, incorrect question or choices or answer, unanswerable question, and no concerns. They were asked to adjudicate cases where they disagreed on the category. The discussion led them to define several specific error types. Some of these are illustrated in Table 5. Besides these, the annotators found one duplicate question (with same choices and answer). Among the most frequent problems identified were questions that were about one specific country or jurisdiction (i.e., France) without mentioning that country or jurisdiction. If such questions were used outside of that country or jurisdiction to assess LLM safety, they could lead to incorrect conclusions. There were also several questions where more than one choice was assessed to be valid, or the correct answer was incorrect or at least debatable. In some cases, problems seem to have arisen due to the way in which questions and choices were extracted from their sources – this includes questions where the choices assume a different number of blanks that the question presents, and questions that refer to some figure or additional context that is not included in this dataset.

4.2 Performance variation across LLMs between the dataset versions

Table 2 shows the performance of the various LLMs on the modified version of the dataset, with change from the original dataset indicated in the parentheses, for the two languages we considered. Detailed accuracies and standard errors per model, per dataset can be seen in Table 8 in the appendix.

| Model | French | Telugu | |
|------------------|------------------------|------------------------------|--|
| GPT-4o | 0.88 (†9.2%) | 0.66 (†3.2%) | |
| Claude3.7-Sonnet | $0.89(\uparrow 7.4\%)$ | $0.71 (\uparrow 5.7\%)$ | |
| Gemini2.0-Flash | $0.83(\uparrow 6.5\%)$ | $0.76(\uparrow 4.7\%)$ | |
| Llama-3.3-70B-it | 0.77(\dagger5\%) | 0.59 (†9.5 %) | |
| Gemma3-27B-it | $0.74(\uparrow 5.4\%)$ | $0.57(\uparrow 3.7\%)$ | |
| Gemma3-12B | $0.71(\uparrow 7.1\%)$ | $0.34(\uparrow 0.8\%)$ | |
| Aya-Expanse:8b | $0.66(\uparrow 4.4\%)$ | $0.27(\uparrow 0.9\%)$ | |
| Qwen2.5-7B | $0.66(\uparrow 5.8\%)$ | $0.32(\uparrow 0.5\%)$ | |
| LLama3.2-7B | 0.52(\dagger3\%) | $0.29(\uparrow 0.9\%)$ | |
| Gemma2-9B | 0.68(†6%) | $0.47(\uparrow 6.9\%)$ | |

Table 2: Performance with the cleaned versions of Include 44 for French and Telugu test sets (and the change from original test set)

Not surprisingly, accuracy tends to be higher with larger models, in both languages. We no-

tice that even the large and very large LLMs see large increases in the performance with the cleaned dataset compared to the original dataset for both French and Telugu. Interestingly, three of the five small, local language models too had an over 5% increase with the cleaned version of the French test set, but the increases were modest (under 1%) in the case of Telugu, where the original performance was already quite poor. The increases are also not uniform between the two languages even with the larger models. For example, GPT-40 sees a 9% increase for French, but only a 3% increase for Telugu. Yet, these fluctuations are large enough to warrant probing further into a central question: what are we evaluating against? They also serve as a reminder to report differences across languages more specifically.

4.3 Replication

The evaluation so far dealt with two languages and different web sources, but the test sets were both constructed in a similar manner. To understand if the quality issues are due to the method of data collection, we replicated the analysis using a dataset from a different source, for one language, Telugu. MILU (Verma et al., 2024) is a multi-task Indian language understanding benchmark covering 11 languages and is intended to be used as an evaluation dataset with LLMs. The dataset spans a range of domains and subjects and is collected by scraping websites that publish questions and answers from various past competitive exams, similarly to INCLUDE44. The cleaning process is automatic and a sample from the dataset was manually evaluated for quality in the original paper. We took a sample of 500 test items (out of the total 7.3K) for our manual analysis.

While we notice similar issues to Include44 (incomplete questions, unanswerable questions, incorrect questions, questions in English, etc), there is less disagreement between the two annotators on "No Concerns" and 383/500 (77%) are retained in the cleaned version. Examples of the removed samples can be found in the Appendix (Table 7). Table 3 shows the performance difference of the LLMs on the cleaned version along with the difference from the original version. The variations seem to be lesser for this dataset compared to Include44, and there are also cases where the performance with the cleaned dataset is slightly lower than the original dataset.

| Model | Accuracy (% Diff) |
|------------------|------------------------------|
| GPT-4o | 0.74 (†4.4 %) |
| Claude3.7-Sonnet | $0.74 (\uparrow 3.1\%)$ |
| Gemin2.0-Flas | $0.84(\uparrow 2.3\%)$ |
| Llama-3.3-70B-it | $0.64(\uparrow 2.4\%)$ |
| Gemma3-27B-it | $0.66(\uparrow 3.6\%)$ |
| Gemma3-12B | $0.33(\downarrow 0.2\%)$ |
| Aya-Expanse:8b | $0.29 (\downarrow 0.1\%)$ |
| Qwen2.5-7B | $0.33 (\downarrow 1.7\%)$ |
| LLama3.2-7B | $0.26(\downarrow 1.7\%)$ |
| Gemma2-9B | $0.45(\uparrow 1.2\%)$ |

Table 3: Performance with the cleaned version of MILU-Te subset compared to original subset

5 Conclusions and Discussion

Our analysis revealed quality issues in the datasets we analyzed. LLM evaluations on the original and cleaned versions of the datasets revealed large differences in performance between the two versions, sometimes amounting to almost 10%, in both languages. A replication experiment with a dataset from another source had similar issues, but to a lesser degree. Moreover, the type of concerns we identified in the datasets varied widely depending on the language. This limits how much one can infer from the performance of LLMs across languages when using unverified, uncleaned datasets.

Based on these experiments, we recommend the following as a call for further research on dataset quality:

- Test sets should not be considered immutable and should be subject to further quality assurance, either by the creators or by others using them for conducting LLM evaluations.
- Test set developers should have a provision to version them and evaluation studies should consider reporting results with cleaner, modified versions where possible.
- Model developers can consider adding small scale qualitative analyses for languages they can read, to identify potential limitations of their models as well as the test datasets used.
- More research should go into automatic or semi-automatic identification of dataset quality, potentially utilizing the recent developments in LLM-as-a-judge approaches.

Limitations

This study suffers from at least two specific limitations. Firstly, we chose only two languages, and small test sets as we opted for manual annotations - but we don't see this exercise as an end in itself and hope that this will lead into more discussion and more effort in this direction. Secondly, our annotation guidelines too were somewhat loosely defined and we just took "no concerns" samples without attempting to fix the source for the other samples. The results of this study should be considered along with these limitations of the annotation approach.

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References

- Halidanmu Abudukelimu, Abudoukelimu Abulizi, Boliang Zhang, Xiaoman Pan, Di Lu, Heng Ji, and Yang Liu. 2018. Error analysis of Uyghur name tagging: Language-specific techniques and remaining challenges. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, Miyazaki, Japan. European Language Resources Association (ELRA).
- Chiara Alzetta, Felice Dell'Orletta, Simonetta Montemagni, and Giulia Venturi. 2017. Dangerous relations in dependency treebanks. In *Proceedings of the 16th International Workshop on Treebanks and Linguistic Theories*, pages 201–210, Prague, Czech Republic.
- Gabriel Bernier-Colborne and Sowmya Vajjala. 2024. Annotation errors and ner: A study with ontonotes 5.0. *Preprint*, arXiv:2406.19172.
- Adriane Boyd, Markus Dickinson, and W Detmar Meurers. 2008. On detecting errors in dependency treebanks. *Research on Language and Computation*, 6:113–137.
- Ayse Aysu Cengiz, Ahmet Kaan Sever, Elif Ecem Ümütlü, Naime Seyma Erdem, Burak Aytan, Büsra Tufan, Abdullah Topraksoy, Esra Darici, and Cagri Toraman. 2025. Evaluating the quality of benchmark datasets for low-resource languages: A case study on turkish. *CoRR*, abs/2504.09714.
- Aryo Pradipta Gema, Joshua Ong Jun Leang, Giwon Hong, Alessio Devoto, Alberto Carlo Maria Mancino, Rohit Saxena, Xuanli He, Yu Zhao, Xiaotang Du, Mohammad Reza Ghasemi Madani, Claire Barale, Robert McHardy, Joshua Harris, Jean Kaddour, Emile Van Krieken, and Pasquale Minervini. 2025. Are we done with MMLU? In *Proceedings of the*

- 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pages 5069–5096, Albuquerque, New Mexico. Association for Computational Linguistics.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2021. Measuring massive multitask language understanding. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net.
- Yuzhen Huang, Yuzhuo Bai, Zhihao Zhu, Junlei Zhang, Jinghan Zhang, Tangjun Su, Junteng Liu, Chuancheng Lv, Yikai Zhang, Jiayi Lei, Yao Fu, Maosong Sun, and Junxian He. 2023. C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models. In Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 16, 2023.
- Dieuwke Hupkes and Nikolay Bogoychev. 2025. Multiloko: a multilingual local knowledge benchmark for llms spanning 31 languages. *CoRR*, abs/2504.10356.
- Masaaki Ichihara, Kanako Komiya, Tomoya Iwakura, and Maiko Yamazaki. 2015. Error analysis of named entity recognition in bccwj. *Recall*, 61:2641.
- Kunal Jha, Michael Röder, and Axel-Cyrille Ngonga Ngomo. 2017. All that glitters is not gold–rule-based curation of reference datasets for named entity recognition and entity linking. In *European Semantic Web Conference*, pages 305–320. Springer.
- Karthik Muthuraman, Frederick Reiss, Hong Xu, Bryan Cutler, and Zachary Eichenberger. 2021. Data cleaning tools for token classification tasks. In *Proceedings of the Second Workshop on Data Science with Human in the Loop: Language Advances*, pages 59–61, Online. Association for Computational Linguistics.
- Irene Plaza, Nina Melero, Cristina del Pozo, Javier Conde, Pedro Reviriego, Marina Mayor-Rocher, and María Grandury. 2024. Spanish and LLM benchmarks: is MMLU lost in translation? *CoRR*, abs/2406.17789.
- Frederick Reiss, Hong Xu, Bryan Cutler, Karthik Muthuraman, and Zachary Eichenberger. 2020. Identifying incorrect labels in the conll-2003 corpus. In *Proceedings of the 24th conference on computational natural language learning*, pages 215–226.
- Angelika Romanou, Negar Foroutan, Anna Sotnikova, Zeming Chen, Sree Harsha Nelaturu, Shivalika Singh, Rishabh Maheshwary, Micol Altomare, Mohamed A Haggag, Alfonso Amayuelas, and 1 others. 2024. Include: Evaluating multilingual language understanding with regional knowledge. *arXiv preprint arXiv:2411.19799*.

Sujan Kumar Saha, Sudeshna Sarkar, and Pabitra Mitra. 2009. Hindi named entity annotation error detection and correction. *Language forum*, 35(2):73–93.

Serry Sibaee, Omer Nacar, Adel Ammar, Yasser Al-Habashi, Abdulrahman Al-Batati, and Wadii Boulila. 2025. From guidelines to practice: A new paradigm for arabic language model evaluation. *arXiv preprint arXiv:2506.01920*.

Max Silberztein. 2018. Using linguistic resources to evaluate the quality of annotated corpora. In *Proceedings of the First Workshop on Linguistic Resources for Natural Language Processing*, pages 2–11, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Shivalika Singh, Angelika Romanou, Clémentine Fourrier, David I. Adelani, Jian Gang Ngui, Daniel Vila-Suero, Peerat Limkonchotiwat, Kelly Marchisio, Wei Qi Leong, Yosephine Susanto, Raymond Ng, Shayne Longpre, Wei-Yin Ko, Madeline Smith, Antoine Bosselut, Alice Oh, Andre F. T. Martins, Leshem Choshen, Daphne Ippolito, and 4 others. 2024. Global mmlu: Understanding and addressing cultural and linguistic biases in multilingual evaluation. *Preprint*, arXiv:2412.03304.

Guijin Son, Hanwool Lee, Sungdong Kim, Seungone Kim, Niklas Muennighoff, Taekyoon Choi, Cheonbok Park, Kang Min Yoo, and Stella Biderman. 2025. KMMLU: measuring massive multitask language understanding in korean. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL 2025 - Volume 1: Long Papers, Albuquerque, New Mexico, USA, April 29 - May 4, 2025*, pages 4076–4104. Association for Computational Linguistics.

Tomasz Stanislawek, Anna Wróblewska, Alicja Wójcicka, Daniel Ziembicki, and Przemyslaw Biecek. 2019. Named entity recognition - is there a glass ceiling? In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pages 624–633, Hong Kong, China. Association for Computational Linguistics.

Khanh-Tung Tran, Barry O'Sullivan, and Hoang D Nguyen. 2025. Irlbench: A multi-modal, culturally grounded, parallel irish-english benchmark for open-ended llm reasoning evaluation. *arXiv* preprint *arXiv*:2505.13498.

Sshubam Verma, Mohammed Safi Ur Rahman Khan, Vishwajeet Kumar, Rudra Murthy, and Jaydeep Sen. 2024. Milu: A multi-task indic language understanding benchmark. *arXiv preprint arXiv:2411.02538*.

Zihan Wang, Jingbo Shang, Liyuan Liu, Lihao Lu, Jiacheng Liu, and Jiawei Han. 2019. CrossWeigh: Training named entity tagger from imperfect annotations. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference

on Natural Language Processing (EMNLP-IJCNLP), pages 5154–5163, Hong Kong, China. Association for Computational Linguistics.

Guillaume Wisniewski. 2018. Errator: a tool to help detect annotation errors in the Universal Dependencies project. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, Miyazaki, Japan. European Language Resources Association (ELRA).

Arda Yüksel, Abdullatif Köksal, Lütfi Kerem Senel, Anna Korhonen, and Hinrich Schütze. 2024. Turkishmmlu: Measuring massive multitask language understanding in turkish. In *Findings of the Association for Computational Linguistics: EMNLP 2024, Miami, Florida, USA, November 12-16, 2024*, pages 7035–7055. Association for Computational Linguistics.

A Details about LLMs

| LLM | Open? | Provider |
|----------------------------|-------|-------------------------|
| GPT-4o (gpt-4o-2024-08-06) | No | OpenAI ^{OR} |
| Claude-3.7-Sonnet | No | Anthropic ^{OR} |
| Gemini-2.0-Flash | No | $Google^{OR}$ |
| LLama3.3-70B-Instruct | Yes | $Meta^{OR}$ |
| Gemma3-27B-Instruct | Yes | $Google^{OR}$ |
| Gemma3-12B | Yes | $Google^{OL}$ |
| Aya-Expanse-8B | Yes | Cohere ^{OL} |
| Qwen-2.5-7B | Yes | Alibaba OL |
| LLama-3.2-7B | Yes | Meta^{OL} |
| Gemma2-9B | Yes | $Google^{OL}$ |

Table 4: Details about the LLMs compared. Superscripts indicates how we accessed the models. OR indicates OpenRouter, and OL indicates Ollama.

B Include44 Examples

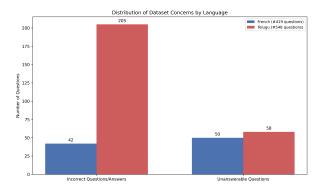


Figure 1: Distribution of concerns across French and Telugu datasets in Include44 test set.

Tables 5 and 6 and show examples of problematic questions and choices from the test set, annotated with explanations. Note that, in the case

of French, the annotators also spotted one duplicate questions (with identical choices and answer). Figure 1 showcases the distribution of problematic questions. Out of the total, French had 42 Incorrect Q/A cases and 50 Unanswerable questions, while Telugu had 205 and 235 respectively. Unanswerable questions are further categorized as:

- 1. Timeline Sensitivity: Questions whose answers change depending on the timeline.(e.g., ఇటీవల జరిగిన ఆసియా అండర్–14 టెన్నిస్ ఛాంపి యన్ష్మ్ విజేత ఎవరు? EN: Who won the recent Asian Under-14 Tennis Championship?)
- Geographic Dependency: Questions whose answers vary across countries. (e.g., Les documents obligatoires à présenter en cas de contrôle de police sont: – EN: The mandatory documents to be presented in the event of a police check are:)
- 3. Missing Context: Questions that require additional information to answer correctly. (e.g., J'arrive en premier sur le lieu de cet accident, en attendant les secours je peux : EN: I arrive first at the scene of this accident, while waiting for help I can:) or (e.g., క్రింది పై చిత్రాన్ని గమనించి దిగువ ప్రశ్నలకు సమాధానాలివ్వండి EN: Observe the 'Pi' picture below and answer the questions below. no image is provided in the question.)

Incorrect Q/A questions can be further categorized as follows:

1. Incorrect questions: These are questions where the phrasing, logic, or structure leads to misleading or mismatched answer options. Questions like, సుల్తానుల సాంకేతిక పరిజ్ఞానాన్ని, వారి పద్ధతులను పాటించి నిర్మించబడిన కట్టడం? – EN: A building built using the technology and methods of the Sultans?), where the majority of the given answer choices describe buildings that were constructed using such methods. To answer correctly, the question should have included a negation, such as "was not built using..." to match the intent of the answers.). Similarly in questions such as Dans une économie à deux acteurs, il y a une offre excessive sur le marché des produits si: - EN: In an economic system with two agents, there is oversupply in the commodities market if, but the answer options use undefined variables like C, S, I, Y.

- 2. Multiple acceptable answers: Questions where more than one choice is valid (e.g., Ma consommation de carburant augmente si : EN: My fuel consumption increases if: with options like ["J'adopte une conduite nerveuse.", "Il pleut.", "Mes pneus sont sous gonflés.", "J'utilise la climatisation."], all of which are potentially correct)
- 3. Code-mixed or English-only questions: These include questions or answer choices that are wholly or partially in English, despite being in a regional language context. For example: To which category does a TV belong as a teaching aid? a question intended for a Telugu context but presented entirely in English. Choices like ['between 30°C to 50°C', 'between 21°C to 27°C', 'Less than 25°C', 'More than 25°C'] or ['b, c', 'a, c', 'a, b, c', 'b మాత్రమే'], where mixing languages disrupts consistency.

C MILU-Te Examples

Table 7 shows examples from the MILU-Te dataset and the associated errors/concerns.

D Detailed Performance Table

Table 8 shows the detailed accuracy and standard error statistics for all the LLMs, across the original and cleaned versions of the three datasets (Include44-Te, Include44-Fr, MILU-Te).

| Question | Choices | Concern | |
|--|---|--|--|
| Membre de l'Union Européenne: (Mem- | [Italie, Allemagne, Finlande, Norvège] | Multiple valid answers. | |
| ber of the European Union:) | [Italy, Germany, Finland, Norway] | | |
| Territoire densément peuplé de la Terre (Densely populated area on Earth) | [les territoires entre les 20 0 et 23 0 de latitude nord., les régions situées sur l'équateur., les régions de plaines de la zone tempérée., les versants sud des hautes montagnes.] [areas between 20 and 23 latitude North, areas along the equator, temperate plains, the southern slope of mountains] | vided answer here conflicts with source we consulted). vided answer here conflicts with source we consulted). vided answer here conflicts with source we consulted). | |
| J'ai mon permis depuis 8 mois. Je peux circuler à (<i>I got my license 8 months ago. I can drive at</i>) | [130km/h, 110km/h, 100km/h, 90km/h] | Country-specific, but country is not mentioned. | |
| Combien de pays compte l'Afrique ? (How many countries are there in Africa?) | [40, 60, 57, 75] | Time-specific, but time is not mentioned. | |
| Classez ces planètes de la plus éloignée du soleil à la plus proche : (Sort these planets from furthest to closest to the sun:) | [1-3-2-4, 2-4-1-3, 3-4-1-2, 4-1-2-3] | Insufficient context (e.g. missing figure). | |
| Remplissez les blancs avec la bonne suite de mots : Distribue ces flyers dans les magasins de la ville (Fill in the blanks: Distribute these flyers in the stores in town) | ["diférents-différants-différant-différend", "différents-différents-différents-différents-différents-différents-différents-différents-différents-différents-différents-différents-différents-différents-différent"] | Incorrect number of blanks. | |
| Dans une économie à deux acteurs, il y a une offre excessive sur le marché des produits si (In an economic system with two agents, there is oversupply in the commodities market if) Une carte routière est à l'échelle | ["C+I <y", "s+c='I",' "s+i="">Y", "S<i"] 10="" 100="" 25="" [1="" km,="" km]<="" td=""><td>Undefined variables/symbols in choices. Incomplete or unclear question.</td></i"]></y",> | Undefined variables/symbols in choices. Incomplete or unclear question. | |
| 1/250 000 (A road map has a scale of 1/250,000) | [1 Kili, 23 Kili, 100 Kili, 10 Kili] | incomplete of uncrear question. | |
| La sclérose est : (Sclerosis is:) | ["Une induration anormale d'un tissu ou d'un organe", "1+2+3", "1+3", "2+4"] ["Abnormal hardening of body tissue", "1+2+3", "1+3", "2+4"] | Choices make no sense. | |
| Parmi les recettes suivantes, laquelle est affectée aux collectivités locales ? (Among these revenues, which goes to local governments?) | ["Le droit de consommation sur les tabacs manufacturés", "Les droits de douanes", "Réponse: A : Aucune des réponses n'est correcte", "L'impôt sur le revenu"] ["Excise duties on tobacco products", "Customs duties", "Answer: A: None of these answers are correct", "Income tax"] | Biased choices (e.g. only one choice is prefixed by "Réponse"). | |
| L'un des facteurs de la demande en devises est (One factor of currency demand is) | [aucune des deux, toutes les deux, l'exportation de marchandises, l'importation de capital] [neither, both, commodity exports, capital imports] | Awkward order of choices. | |
| Mediterrán éghajlat uralkodik ezen a tájon: | [Chypre, La Sicile, Crète, Dalmatie] | Question not in French. | |

Table 5: Examples of some issues in a sample from the French test set.

| Question | Choices | Concern |
|--|--|--|
| To which category does a TV belong as | [Audio aid, *Audio-visual aid*, Authen- | Question/Answer in English. |
| a teaching aid? | tic aid, Visual aid] | |
| ఇటీవల జరిగిన ఆసియా అండర్–14 టెన్నిస్ | [కుమ్ కుమ్ సీలా, *సంజన సిరిమల్ల*, మల్లిక, | Unanswerable Question- Year needs to |
| ఛాంపియన్ష్మ్ విజేత ఎవరు? (Who won the | ప్రియాంశి సంకేత్] [Kumkum Neela, San- | be specified. This seems to be from |
| recent Asia under-14 Tennis Champi- | jana Sirimalla, Mallika, Priyanshi San- | 2018. |
| onship?) | ket] | |
| చిప్కా ఉద్యమం ఏ రాష్ట్రము లో ప్రారంభమైం | [ఉత్తరప్రదేశ్, మధ్యప్రదేశ్, *ఉత్తరాఖండ్*, సి | Ambiguous Answer - A is right when |
| ది? (In which state did the Chipko move- | క్కిం] | the incident happened, but it falls into |
| ment start?) | [Uttar Pradesh, Madhya Pradesh, Ut- | the state in answer C according to to- |
| | tarkhand, Sikkm] | day's division which came into being in 2000s. |
| సుల్తానుల సాంకేతిక పరిజ్ఞానాన్ని, వారి పద్దతుల | [పంచ్ మహల్, అష్ట బిహిష్ట్, హుమాయూన్ | Incorrect Question - Missing negation |
| ను పాటించి నిర్మించబడిన కట్టడం.? (Which | సమాధి, *పద్మ మహల్*] [Panch Mahal, | in the question results in all other an- |
| structure followed the technology and | Hasth Bihisht, Humayun Tomb, Padma | swers except the gold standard one be- |
| conventions of the Sultans?) | Mahal] | ing correct. |
| Given thatFind the value of | [36.164, 36.304, 37.164, *37.304*] | Incomplete question, and in English. |

Table 6: Examples of quality issues in the Telugu subset of the *Include44* test set. Each row shows a question, its answer options, and the annotation team's concern.

| Question | Choices | Concern |
|---|--|--|
| భారత ప్రభుత్వం ట్రాన్స్ జెండర్ వ్యక్తుల కోసం జా తీయ మండలిని ఏర్పాటు చేసింది. మండలికి సంబంధించి క్రింది ప్రకటనలు సరైనవా? (The Government of India has set up a Na- tional Council for Transgender Persons. Are the following statements correct re- garding the Council?) | [కేవలం 2 మరియు 3; కేవలం 1 మరియు 2; కేవలం 1 మరియు 3; 1, 2 మరియు 3] [Only 2 and 3; Only 1 and 2; Only 1 and 3; 1,2, and 3] | Incomplete Question. Options are not provided in the question. |
| ఇచ్చిన పై చార్ట్ ని అధ్యయనం చేసి, ఈ క్రింది ప్రశ్న కు సమాధానం ఇవ్వండి. 4 సంవత్సరాల మొత్తం ఆదాయం రూ. 75,00,000. సంవత్సరం 2 నుండి 3 సంవత్సరం వరకు మొత్తం ఆదాయం ఎంత? (Answer the following question after studying the given pie-chart. If the income for four years in total is Rs. 75,00,000, what is the income from year 2 to year 3?) | [రూ. 43,00,000; రూ. 42,00,000; రూ. 45,00,000; రూ. 42,50,000] | Incomplete question. No pie-chart provided. |
| గ్రామరీకల్గా సరైన వాక్యాన్ని గుర్తించండి. (Identify the grammatical sentence.) | ["No other boy is as taller as Sub- hash" "Gold is one of the more precious metal." "Mohan is the young boy in the class." "The metrological department says 'this year, Hyderabad will face the hottest summer in the decade'."] | Question tests English knowledge. |
| ప్రస్తుతం క్యూబా అధ్యక్షుడు ఎవరు? (Who is the current president of Cuba?) | [రాల్ కాస్ట్రే; ఫిడేల్ కాస్ట్రే; అల్బెర్ట్లో హెర్రెరా; టో మస్ ఎస్ట్రాడా పాల్మా] [[Ralph Castro; Fidel Castro; Alberto Herrera; Tomas Estrada Palma]] | Unanswerable Question - Year needs to be specified. None of the answers are correct in 2025. |
| ఒక పట్టణ ప్రస్తుత జనాభా 3,00,000. జనా భా వృద్ధిరేటు రానున్న సంవత్సరాల్లో వరుసగా ప్ర స్తుత జనాభా ఆధారంగా 6%, 7 1 2 %, 9%, 10 1 2 %, గా ఉండవచ్చునని భావిస్తున్నా రు. 8 సంవత్సరముల తర్వాత జనాభా అంచ నా (The current population of a city is 3,00,000. The population growth rate expected in the coming years is 6%, 7 1 2%, 9% and 10 1 2% respectively. What is the estimated population after 8 years?) | [5,70,000; 5,50,000; 5,30,000; 5,10,000] | Incorrect Question. There seems to be some formatting issue, perhaps missing decimal points. |

Table 7: Examples of some issues in a sample from the Telugu test set of MILU (Verma et al., 2024)

| Include44-Te | ORIG-548 Samples | | CLEAN-285Samples | |
|------------------------|------------------|--------------|--------------------------|--------|
| Model | acc | stderr | acc | stderr |
| Gpt-4o | 0.631 | 0.0206 | 0.663 | 0.028 |
| Claude3.7-Sonnet | 0.655 | 0.0203 | 0.712 | 0.0269 |
| Gemin2.0-Flash | 0.714 | 0.0173 | 0.761 | 0.0253 |
| Llama 3.3 70B Instruct | 0.498 | 0.0214 | 0.593 | 0.0292 |
| Gemma3-27B-it | 0.538 | 0.0213 | 0.575 | 0.0293 |
| Gemma3-12B | 0.336 | 0.0202 | 0.344 | 0.0282 |
| Aya-Expanse:8b | 0.265 | 0.0189 | 0.274 | 0.0265 |
| Qwen2.5-7B | 0.318 | 0.0199 | 0.323 | 0.028 |
| LLama3.2-3B | 0.286 | 0.0193 | 0.295 | 0.0271 |
| Gemma2-9B | 0.398 | 0.0209 | 0.467 | 0.0296 |
| Include44-Fr | ORIG | -419 Samples | CLEAN-327 Samples | |
| Model | acc | stderr | acc | stderr |
| Gpt-4o | 0.792 | 0.198 | 0.884 | 0.0177 |
| Claude3.7-Sonnet | 0.816 | 0.0189 | 0.89 | 0.0173 |
| Gemin2.0-Flash | 0.77 | 0.0206 | 0.835 | 0.0206 |
| Llama 3.3 70B Instruct | 0.721 | 0.0219 | 0.771 | 0.0233 |
| Gemma3-27B-it | 0.683 | 0.0228 | 0.737 | 0.0244 |
| Gemma3-12B | 0.642 | 0.0234 | 0.713 | 0.0251 |
| Aya-Expanse:8b | 0.613 | 0.0238 | 0.657 | 0.0263 |
| Qwen2.5-7B | 0.606 | 0.0239 | 0.664 | 0.0262 |
| LLama3.2-7B | 0.487 | 0.0244 | 0.517 | 0.0277 |
| Gemma2-9B | 0.616 | 0.0238 | 0.676 | 0.0259 |
| | | | | |
| MILU-Te | ORIG | -500 Samples | CLEAN-383 Samples | |
| Model | acc | stderr | acc | stderr |
| Gpt-4o | 0.7 | 0.0205 | 0.744 | 0.0223 |
| Claude3.7-Sonnet | 0.708 | 0.0204 | 0.739 | 0.0225 |
| Gemin2.0-Flash | 0.82 | 0.0172 | 0.843 | 0.0186 |
| Llama 3.3 70B Instruct | 0.618 | 0.0218 | 0.642 | 0.0245 |
| Gemma3-27B-it | 0.622 | 0.0217 | 0.658 | 0.0243 |
| Gemma3-12B | 0.328 | 0.021 | 0.326 | 0.024 |
| Aya-Expanse:8b | 0.296 | 0.0204 | 0.295 | 0.0233 |
| Qwen2.5-7B | 0.346 | 0.0213 | 0.329 | 0.024 |
| LLama3.2-3B | 0.278 | 0.0201 | 0.261 | 0.0225 |
| Gemma2-9B | 0.442 | 0.022 | 0.454 | 0.0255 |

Table 8: Detailed Performance For All The Models/Datasets