

Charting the European LLM Benchmarking Landscape: A New Taxonomy and a Set of Best Practices

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Abstract

While new benchmarks for large language models (LLMs) are being developed continuously to catch up with the growing capabilities of new models and AI in general, using and evaluating LLMs in non-English languages remains a little-charted landscape. We give a concise overview of recent developments in LLM benchmarking, and then propose a new taxonomy for the categorization of benchmarks that is tailored to multilingual or non-English use scenarios. We further propose a set of best practices and quality standards that could lead to a more coordinated development of benchmarks for European languages. Among other recommendations, we advocate for a higher language and culture sensitivity of evaluation methods.

Keywords: large language models, benchmarking, taxonomy, cultural competence, quality recommendations

1. Introduction

The rapid advancement of large language models (LLMs) has brought unprecedented capabilities in natural language understanding and generation, reasoning, coding, and more. With the global race in raising the bar, commercial models are approaching artificial general intelligence (AGI) and exhibit more and more agency as they engage in strategic planning, independently interact with other applications, and carry out larger tasks. While open-source models generally score lower on most leaderboards, they too grow larger and smarter.

In the brief history of LLMs, many evaluation frameworks have been set up – both human and automatic – to assess their evolving performance across different linguistic and non-linguistic tasks of growing complexity. While new benchmarks emerge almost on a daily basis in order to measure these expanding abilities, the overwhelming majority of evaluation datasets are developed primarily for English, creating a significant evaluation gap for other languages and varieties.

To evaluate the performance of LLMs in non-English contexts, a widely used approach so far has been to translate existing English benchmarks using machine translation, with or without human revision. This might seem reasonable: several major international benchmarks or benchmark collections (e.g., SuperGLUE (Wang et al., 2019), MMLU (Hendrycks et al., 2021), Hellaswag (Zellers et al., 2019) exist together with their parallel (translated) versions, and this allows for a direct comparison of LLMs across a wide range of tasks and languages. However, Global-MMLU (Singh et al.,

2024) revealed that success in MMLU depends heavily on learning Western-centric concepts, with 28% of all questions requiring culturally sensitive knowledge. Moreover, for questions requiring geographic knowledge, an astounding 84.9% focus on either North American or European regions. Such cultural biases are not uncommon in other widely used benchmarks, and their machine-translated versions potentially overlook language- and culture-specific phenomena, exhibit skewed performance which does not accurately reflect true multilingual capabilities, or simply fail to address issues which may be critical for users of an LLM in a particular language.

On the other spectrum of multilingual evaluation, there are several cases of language- and culture-specific benchmarks, such as those included in the Hungarian HuLu (Ligeti-Nagy et al., 2024) evaluation framework, BenCzechMark (Fajcik et al., 2025), PLCC (Dadas et al., 2025), or BertaQA (Etxaniz et al., 2024), which have been developed specifically for a particular language or community of speakers. Such benchmarks provide a deeper insight into a model’s performance for that language, but typically do not allow us to assess the model’s multilingual capacities.

Despite the proliferation of evaluation platforms, research projects, and benchmarking initiatives across the multilingual landscape, the field lacks a comprehensive overview that synthesizes current practices, identifies critical gaps, and provides clear guidance for developing more inclusive and effective evaluation methodologies for LLMs in non-English contexts. We thus make a case for the creation of a European benchmarking registry that

collects structured benchmark data according to a universal and inclusive taxonomy of benchmarks. The proposed registry would include rich descriptive metadata and provide a clear overview of both existing benchmarks and the gaps in the current European benchmarking landscape.

The remainder of this paper is structured as follows: In Section 2, we present some recent developments in LLM benchmarking, focusing on evaluations of linguistic and cultural competence in a multilingual context and on emerging trends. In Section 3, we proceed with a proposal for a categorization of benchmarks that could serve as a foundation for charting ongoing and future LLM evaluation activities in Europe and beyond. We finally propose some recommendations as to how existing benchmarks can be documented, and how future benchmarks can be made both more culture-aware and more in tune with the needs of different language communities.

2. Recent Developments in LLM Benchmarking

Several comprehensive overviews of LLM benchmarking have recently been published, including Chang et al. (2023) and Ni et al. (2025). Both surveys clearly show trends in both the development of datasets and the evolution of evaluation metrics. However, they lack a focus on non-English and multilingual scenarios, which is the main motivation for this work.

2.1. Major Benchmarks

By major or global, we refer to benchmarks most frequently used in current evaluation platforms and leaderboards. These benchmarks are without exception in English. The ones that evaluate generic language understanding and commonsense reasoning have their origins in the 2018–2022 period, when the challenges still roughly corresponded to natural language processing (NLP) research areas. Some of these benchmarks have seen multiple revisions, extensions and updates, and can be seen as “parent” datasets on which many adaptations, translations, or local versions are based.

Some of the most prominent for language understanding and reasoning include MMLU (Hendrycks et al., 2021) and its derivatives MMLU-Pro (Wang et al., 2024), MMLU-Prox (Xuan et al., 2025) and Global MMLU (Singh et al., 2024); the SuperGLUE benchmark collection comprising BoolQ (yes/no questions, Clark et al., 2019), CommitmentBank (textual entailment, De Marneffe et al., 2019), COPA (Choice of Plausible Alternatives for causal reasoning, Roemmele et al., 2011), MultiRC (multi-sentence reading comprehension, Khashabi

et al., 2018), ReCoRD (reading comprehension with commonsense reasoning, Zhang et al., 2018), RTE (Recognizing Textual Entailment, Giampiccolo et al., 2007), WiC (Words in Context, Pilehvar and Camacho-Collados, 2019), and WSC (Winograd Schema Challenge, Levesque et al., 2012); ARC (Clark et al., 2018) with multiple-grade science questions; Hellaswag (Zellers et al., 2019) and its recent derivative GoldenSwag (Chizhov et al., 2025). An attempt to create a more challenging benchmark collection is BIG-bench (Beyond the Imitation Game Benchmark, Srivastava et al., 2023), a massive collaborative benchmark consisting of 204 tasks contributed by more than 450 authors across 132 institutions, designed to probe large language models on tasks believed to be beyond their current capabilities. Finally, SUPERB (Speech processing Universal PERformance Benchmark, Yang et al., 2021) is a unified speech-focused benchmark for evaluating self-supervised and general-purpose speech representations across a wide spectrum of speech processing tasks. It organizes 10 core tasks – including automatic speech recognition, speaker identification, keyword spotting, emotion recognition, and intent classification – spanning content, speaker, semantics, and paralinguistics.

2.2. Multilingual Benchmarks

Most state-of-the art models have multilingual capabilities, but since the precise amounts of non-English data used in their pre-training are usually obscure, it is hard to say to what extent the language competence of a model in a particular language is in correlation with the amount of language-specific data it has seen. In addition to this, models differ in their representations of intermediate layers, which may result in cultural conflicts between latent internal and target output language (Zhong et al., 2024).

Since many authors observe a marked decline in performance for low-resource languages, benchmarks are now being developed both as parallel evaluation sets based on existing “parent” datasets to allow for direct comparison of LLM capabilities across a number of languages, and as language-specific benchmarks, usually aimed at assessing LLM performance in a particular linguistic community and/or culture (see Section 2.4 for the latter).

Although the datasets in the first category are parallel, they may differ considerably in the methods used for their creation. Some were translated using machine translation or LLMs, for example, EU20-MMLU, EU20-HellaSwag, EU20-ARC, EU20-TruthfulQA, and EU20-GSM8K (Theermann et al., 2024); or MMLU-Prox (Xuan et al., 2025). Other multilingual benchmarks were created with a special focus on cultural sensitivity by dividing the original subsets into culturally sensitive and culturally

agnostic ones (Global MMLU, Singh et al., 2024), or by using professional translators or multiple rounds of revision to raise the quality of the dataset, e.g., BenchMax (Huang et al., 2025), Flores-101 and FLORES-200 (Goyal et al., 2022) and Belebele (Bandarkar et al., 2024).

For speech, ML-SUPERB (Multilingual Speech processing Universal PERformance Benchmark, Shi et al., 2023) extends the English SUPERB speech benchmark to 143 languages, evaluating self-supervised speech representations on automatic speech recognition and language identification. FLEURS (Conneau et al., 2022) is a speech-based extension of the FLORES multilingual benchmark, with focus on language identification, automatic speech recognition, and retrieval evaluation. DIALECTBENCH (Faisal et al., 2024) is the first large-scale benchmark for language variety understanding, aggregating 10 text-level tasks for 281 varieties.

2.3. Dynamic Benchmarks

Recent developments emphasize dynamic and contamination-resistant evaluation. The period 2022–2025 has witnessed fundamental shifts toward more sophisticated evaluation approaches. One such attempt is LiveBench (White et al., 2024), the first benchmark designed to resist training data contamination through frequently updated questions from recent sources, automatic scoring, and monthly updates. This dynamic approach remains challenging, with the top models achieving accuracy below 80%.

2.4. Language- and Culture-Specific Benchmarks

Focusing on different approaches to the evaluation of LLM performance in non-English European languages, we find a broad array of language- and culture-specific benchmarks developed with various methodologies and serving different purposes, of which we present the ones we find most interesting.

Many European languages have established evaluation frameworks dedicated to language-specific benchmarks, and in most cases such frameworks combine traditional datasets translated from English, and native more culture-aware benchmarks. Examples include HuLu¹ for Hungarian (Ligeti-Nagy et al., 2024), which covers a number of well-known tasks such as plausible alternatives (HuCoPa), textual entailment (HuRTE) and linguistic acceptability (HuCoLa), of which the latter was originally constructed using sentences from selected Hungarian linguistics books. BenCzechMark for

Czech (Fajcik et al., 2025) is a complex benchmark collection comprising 50 tasks, of which 14 were newly created and only 10% of the collective instances were machine-translated. The authors also employ multiple evaluation metrics including duel scoring. Another recent benchmark for Czech, Ukrainian and Slovak called CUS-QA (Libovický et al., 2025) focuses specifically on cultural competence and crafts questions, both textual and visual, from Wikipedia articles which exist in only one of the languages.

For Iberian languages, a comprehensive and extensible framework has been established under IberBench (González et al., 2025), spanning 22 task categories and addressing both generic and industry-relevant tasks. In parallel and under a similar name, IberoBench (Baucells et al., 2025) offers 62 tasks of which several were created from scratch from native data, and others were included only if they satisfied rather strict quality criteria.

For Slovenian, the SloBENCH² evaluation framework offers natural language inference (SI-NLI), machine translation, speech recognition, Slovene SuperGLUE, and two pragmatics benchmarks: SloPragMega and SloPragEval. To create the latter, full localization of the originally English dataset was performed, by adapting cultural references and occasionally completely rewriting examples to better match the linguistic and cultural context. A similar approach has been taken while translating and adapting the COPA benchmark (Roemmele et al., 2011) to four standard languages and three dialects of the South Slavic language group, resulting in the DIALECT-COPA (Ljubešić et al., 2024) benchmark collection. While proper cultural adaptation did take place, the overall popularity and age of the parent COPA benchmark surely makes it prone to LLM contamination. Regardless of that, today’s best-performing proprietary models still score only halfway between random and optimal on dialectal data (Chifu et al., 2024).

A fully native benchmark is ITALIC for Italian (Seveso et al., 2025), which comprises 10,000 instances from 12 domains and was built entirely from exam materials offered by various public institutions or government bodies.

An exceptionally active approach to language- and culture-specific benchmarking can be observed for Polish³, with a range of generic and domain-specific evaluations for Polish including multi-turn conversation (MT-Bench), emotional intelligence (EQ-Bench), comprehensive text understanding (CPTUB⁴), medical domain benchmark,

²<https://slobench.cjvt.si>

³<https://huggingface.co/spaces/speakleash/polish-llm-benchmarks>

⁴https://huggingface.co/spaces/speakleash/cptu_bench

¹<https://hulu.nytud.hu>

linguistic and cultural competency (PLCC, [Dadas et al., 2025](#)), educational (LLMs Behind the School Desk), cultural vision benchmark, and legal QA tasks. Most of these benchmarks were developed anew, by carefully selecting tasks and examples, verifying them by experts and collecting human annotations. The CPTUB is composed of two parts, the first evaluating implicatures (implied meaning, sarcasm, idiomatic expressions) and the second testing on tricky questions (logical puzzles, semantic ambiguity, logical inconsistencies, absurdity, humor). Similarly, the PLCC consists of 600 manually crafted questions and is divided into six categories: history, geography, culture and tradition, art and entertainment, grammar, and vocabulary. The leaderboard results⁵ indicate that even the largest models still reach mediocre performance in Polish grammar and vocabulary, thus justifying the need for detailed assessment of linguistic competence for other European languages as well. A final example of a culturally specific benchmark is the Polish Cultural Vision Benchmark⁶, a collection of images with text descriptions to evaluate the cultural competence of multimodal models. The dataset is part of a citizen science project aimed at collecting 1 million culturally specific images⁷ and recruiting user donations under the slogan of “technopatriotism.” While similar platforms have been established before to collect text data, this is a positive example of a contemporary and at the same time participatory benchmark.

3. Categorization of Benchmarks

Since this paper makes a case for a European database of LLM benchmarks, we propose a new taxonomy which would allow a better categorization and labeling of benchmarks for non-English languages. This would allow us to better compare LLMs across languages; gain deeper insight into the strengths and weaknesses of current and future LLMs in a specific language, use case, modality or domain; set common priorities and work towards filling the evaluation and performance gaps.

The proposed taxonomy should serve as a (tentative) *hierarchy of labels* to organize or classify benchmarks; many (or indeed most) belong to more than a single category. For this reason, a natural choice to store and query the European benchmarking activities is a database, in which benchmarks are described according to this proposal. Thus, the

benchmarks are assigned non-exclusive categories and are richly described with metadescritions.

While alignment, including trustworthiness, truthfulness and safety of LLMs, are central topics to the development of LLMs, they constitute another level of evaluation. Many elements of AI ethics partly overlap, or are entailed, in other benchmarks (e.g., bias is revealed in translation or language generation; trustworthiness is related to reasoning performance, etc.). This is another reason why multiple categories per benchmark are considered typical and expected.

Since LLMs tend to perform worse in non-English languages, and especially non-standard varieties, over a spectrum of tasks, we propose that the language- and culture-related abilities receive more attention, and therefore a more fine-grained taxonomy than they do in existing taxonomies. The list can be expanded as needed.

3.1. Existing Taxonomies

As new benchmarks are continuously presented to evaluate the emerging capabilities of LLMs, many attempts have been made to organize them in a structured and logical way.

The [AI Verify Foundation](#) has established one of the most systematic approaches to LLM benchmark categorization globally. In their October 2023 publication “Cataloguing LLM Evaluations” ([AI Verify Foundation, 2023](#)), LLM benchmarks are organized into 5 top categories (further divided into subcategories). These are *General Capabilities* (natural language understanding, natural language generation, reasoning, knowledge and factuality, tool use effectiveness, multilingualism, and context length handling); *Domain Specific Capabilities* (specialized industry performance across various domains); *Safety and Trustworthiness*; *Extreme Risks*; and *Undesirable Use Cases*.

The catalogue represents a comprehensive and valuable contribution to the field, and has many positive features: The taxonomy is based on LLM capabilities, occasionally also referred to as tasks, which seems intuitively most pragmatic as this is usually the way we think about (and evaluate) human performance too. Complex benchmarks can appear in several categories simultaneously (e.g., BigBench as a massive collaborative benchmark appears in almost all taxonomy categories), and the recommendations for future LLM evaluations are a solid starting point to reinforce minimum quality standards for fair and trustworthy LLM assessment.

However, the catalogue also has some drawbacks which render it unsuitable for our purposes. Firstly, to no fault of its authors, it has not been updated since 2023 and hence does not include many benchmarks which have since become mainstream, nor does it address recent developments

⁵<https://huggingface.co/spaces/sdadas/plcc>

⁶https://huggingface.co/spaces/speakleash/Polish_Cultural_Vision_Benchmark

⁷<https://obywatel.bielik.ai>

in LLMs and AI in general. Secondly, although it includes Multilinguality as a separate category, it falls short in capturing some aspects of LLM performance which may be critical for the evaluation of European models; i.e., models specifically developed to be used in region-, language-, culture- or domain-specific contexts. Thirdly, and this is less of a drawback but simply an observation, the taxonomy and the quality recommendations are primarily focused on the safety and trustworthiness of LLMs, in the context of AI governance and alignment research. While these are indeed crucial priorities especially for the so-called “frontier models” and capabilities, the European landscape of LLM development and evaluation is – at least for now – gyrating around a different set of goals, such as how to reach state-of-the-art levels of understanding and generation in non-English languages, or how to de-bias English-centric models.

Other approaches to taxonomization include HELM (Holistic Evaluation of Language Models), also referred to as the Stanford approach (Liang et al., 2022). The authors introduce the concept of scenarios (what we want to evaluate) and metrics (which performance aspects are measured, and how), then propose a taxonomy of scenarios and desiderata. Today, the framework⁸ includes a number of leaderboards with support for multimodality and model-graded evaluation. While the scenarios proposed in HELM and the framework itself leave room for continuous extension, they do not in fact offer a hierarchical structure with sufficient focus on multilinguality and issues related to the use of LLMs in non-English contexts.

Similarly, Chang et al. (2023) provide an overview of existing LLM evaluations, which they examine from three aspects: what, where, and how to evaluate. They divide the evaluations tasks into eight top-level non-exclusive categories, namely *Natural language processing*; *Robustness, ethics, biases and trustworthiness*; *Social sciences*; *Natural science and engineering*; *Medical applications*; *Agent applications*; and *Other applications*.

Huber and Niklaus (2025) present a cognitive-based view on benchmarking by mapping the well-known Bloom’s taxonomy of cognitive abilities to LLM capabilities across six hierarchical cognitive levels: *Remember*, *Understand*, *Apply*, *Analyze*, *Evaluate*, and *Create*, revealing significant gaps in the coverage of higher-order thinking skills.

Another comprehensive attempt at taxonomizing benchmarks is by Guo et al. (2023) who introduce a three-pillar framework that categorizes LLM evaluation into three major groups: *Knowledge and capability evaluation*, *Alignment evaluation*, and *Safety evaluation*.

⁸<https://crfm.stanford.edu/he1m/>

3.2. New Taxonomy Proposal

As already outlined in the sections above, the proposed taxonomy is intended for the categorization of (mainly) European LLM benchmarks and is based on AI Verify Foundation’s catalogue, but with the following modifications:

- We merge all **language-related tasks and scenarios** under a single top-level category called Language capabilities.
- We further **merge the traditional NLP divide between natural language understanding and natural language generation** into a single subcategory. The fact is that state-of-the-art LLMs more often than not combine these two capabilities, and even straight-forward tasks such as question answering or text summarization involve both.
- We **expand the category for general linguistic competence** with further subcategories for style, conversation and pragmatics, and allow for other more fine-grained aspects of measuring the grammaticality, stylistic appropriateness or coherence of generated outputs.
- We **expand the category of specific linguistic competence** to include creativity, atypical communication, the use of domain-specific language etc.
- We also **expand and redefine the category of multilinguality** to include code-switching, multilingual interaction, and dialectal flexibility.
- We introduce **cultural competence** as a separate category.
- We introduce **speech** as a separate category to include benchmarks specifically aimed at performing tasks unique to spoken language as input or output.⁹
- We add **agency** as a form of long-term, consistent or strategic reasoning.

Figure 1 shows the four top-level taxonomy categories with subcategories. The full taxonomy along with fine-grained third-level categories will be added as Appendix A into the camera-ready version of this paper.

⁹We propose Modality as one of the metadeccriptors, allowing for any benchmark to be implemented in any of the modes. The Speech category refers to evaluations targeted at speech-related activities.

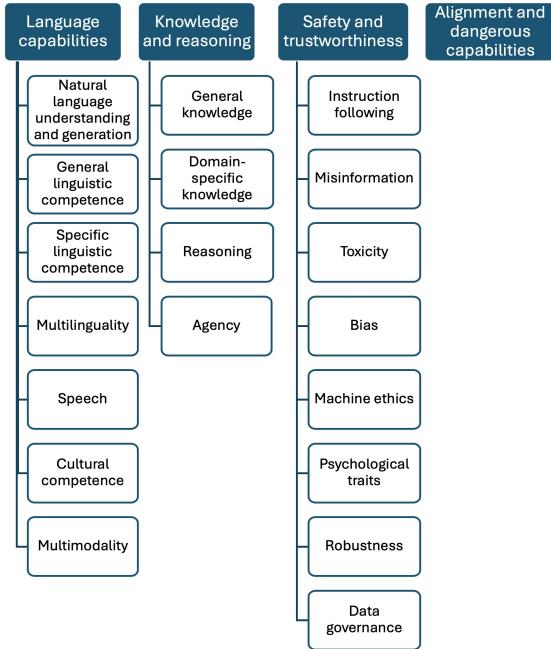


Figure 1: Top-level categories with subcategories.

4. Quality Standards and Metadata

If we conceive of a European benchmarking registry as a searchable database which may help the LLM development community in setting priorities, exchanging knowledge and standardizing evaluation practices, we should be able to define some desiderata around how a particular benchmark is presented, described and distributed. Below we discuss some of these aspects.

4.1. Provenance

While it is clear that the development of original and sufficiently complex benchmarking datasets is highly time-consuming and costly, the drawbacks of automatically translated and culturally maladapted benchmarks have been clearly pointed out (Singh et al., 2024; Xuan et al., 2025). We should thus strive towards clearer – even if more complex – descriptors which indicate how a dataset or benchmark was created. We propose the following descriptors:

- **Original** Applies to datasets which have been originally created in the language they appear in, *by any method other than translation* (e.g., collecting original exam questions, employing experts to provide domain-specific tasks, adapting authentic texts in a particular language to create tasks in that language).
- **Machine translation** Applies to datasets created *by any automated translation service*, including those created by LLMs using any kind

of prompt scenario, and workflows with machine revision. The tools and workflows must be specified.

- **Machine translation and Human revision** Applies to datasets where the result of *automated translation was revised by a human* professional or non-professional translator or reviewer. Since many non-English benchmarks are created by machine translating the – usually – English original, followed by human revision of only a small portion of the dataset, the recommendation would be to use all labels that apply.
- **Human translation** Used only for datasets which have been *fully translated and revised by humans*. Only a few European non-English datasets satisfy this criterion.
- **Full localization** Used for datasets which have not only been translated professionally, but for which a *full linguistic and cultural adaptation* was performed. This might mean the replacement of culturally-specific or untranslatable tasks with new ones, or removing parts of the dataset deemed culturally unsuitable.
- **Other** If several of the above scenarios were used, the dataset should be labeled with all that apply. Other methods and scenarios used in the creation of a dataset should be specified here.

4.2. Accessibility

The tension between open benchmarking and data contamination poses a significant challenge for AI evaluation. While public datasets enable reproducible research and fair comparisons, they risk contamination when models train on test data, inflating performance scores and undermining benchmark validity. Private evaluation sets offer a potential solution by keeping data hidden from training processes, ensuring cleaner performance measurements.

- **Public** Applies to fully open datasets shared with labels through common platforms.
- **Public without labels** Applies to datasets where labels are not distributed to prevent direct training.
- **Private (academic/research access)** Where authors encourage reproducibility but wish to prevent contamination.
- **Private (closed/proprietary)** Where datasets are typically not shared as they are used for internal or industry-specific evaluation.

- **Other** This may include dynamic benchmarks where tasks are continually updated (such as White et al., 2024).

4.3. Language Coverage

This category indicates the prominence, reach or scale of a benchmark in terms of its presence on major leaderboards, coverage, global spread, but also purpose. We are aware that the boundaries between the proposed buckets may be fuzzy.

- **Major global benchmark** See section 2.1 for examples.
- **Multilingual benchmark** This category can be used for benchmarks derived from the above, for instance by developing a multilingual variant of a well-known benchmark for a set of new languages. Examples include XCOPA (Ponti et al., 2020), MMLU-Prox (Xuan et al., 2025) or xHumanEval (Raihan et al., 2025).
- **Language-group or region-specific benchmark** This category is used for language-specific benchmarks as well as benchmarks that cover multiple languages from a similar language group or target a certain geographical region. Examples include IberoBENCH (Baucells et al., 2025) and DIALECT-COPA (Ljubešić et al., 2024).
- **Other**

4.4. Evaluation Type

An important factor for present and future benchmarks is the divide between **closed-ended** types of tasks, most prominently multiple-choice questions, but also other types of tasks where the solution is included in the task, and **open-ended** tasks, typically generation of text, speech, image, or multimodal output. Few benchmarks to date address the latter, despite the fact that generative LLMs are now mainstream and the vast majority of application scenarios exploit generative abilities.

4.5. Evaluation Metrics and Frameworks

The performance of an LLM can be evaluated in several ways, depending on the type of task. For multiple choice questions, text classification tasks or cloze tests, where the correct answer is deterministic, **accuracy** or **F1** can be used. However, to evaluate longer, more complex responses resulting from generative tasks, many other methods were proposed. In reference-based evaluation, the LLM response is compared to a reference using various distance measures (e.g., **BERTScore**, **Rouge-1**, **METEOR**), while in reference-less contexts, the

quality of the response is directly assessed (e.g., by an **LLM-as-a-judge**). As we have seen, recently developed benchmarks employ more complex evaluation methodologies, and a common alternative to algorithmic benchmarks is human preference voting (in so-called chatbot arenas, e.g., <https://lmarena.ai/>).

Another important element is the existence of a human baseline, and its quality. Important factors to consider are participant selection (demographic sampling, expertise), participant training, task design and instructions (to ensure fair comparison between humans and LLMs), control for attention, bias or fatigue, and the collection of participant demographics to facilitate reproducibility and interpretation of results. Human annotators or participants can also provide relevant insight into the overall quality of the benchmark, thus some campaigns actively collect human feedback to be used in revised versions of the evaluation dataset.

If the benchmark or dataset is integrated into an evaluation framework, this should be indicated together with a link or other reference to the evaluation site.

4.6. Metadescritors

We propose collecting rich metadata for each benchmark that allows researchers to quickly understand its content, characteristics, and provenance. Such metadescritors facilitate dataset discovery, comparison, and reuse. Below, we summarize the metadata fields currently envisaged in the proposed registry:

- **Description:** A short summary of the dataset's content and purpose.
- **Benchmark family:** The broader benchmark initiative or collection to which the dataset belongs. For example, the COPA benchmark family would include the English COPA (Roemmele et al., 2011) and its many parallel variants such as the COPA datasets in Hungarian (Ligeti-Nagy et al., 2024), Croatian (Ljubešić and Lauc, 2021), South Slavic dialects (Ljubešić et al., 2024) etc.
- **Number of test instances:** The total number of instances in the test set, enabling quick comparison of dataset scale.
- **Language:** The language(s) in which the dataset is provided.
- **Language type:** Specification of whether the language of the dataset is standard, non-standard, or a dialect.
- **Modality:** The input modality of the dataset, such as text, speech, sign language, or audio-visual signal.

- **Authors:** The creators or curators of the dataset.
- **Paper link:** Reference to the main publication describing the dataset.
- **Access info:** Information on how to obtain the dataset, e.g., a link to a website from where the dataset can be acquired, or an e-mail of the dataset owner if the dataset is not published online.
- **Last revised:** The date of the most recent update or revision of the dataset.
- **More information:** Additional notes, links, or resources relevant to the dataset.

5. Recommendations and Future Directions

Several challenges of LLM evaluation have been pointed out by a number of studies (e.g., [Laskar et al., 2024](#) or [AI Verify Foundation, 2023](#): p. 16–22), most notably reproducibility, reliability (including contamination, obscure evaluation methods and unfair comparisons), and robustness. There are numerous parallel activities in progress to set the course of the European LLM evaluation landscape, agree on common principles and establish a dialogue between different stakeholders. While a full review of the above-mentioned challenges is beyond the scope of this paper, we list some priorities which apply in particular for the European benchmarking landscape and evaluations in non-English settings.

1. **Cultural sensitivity** The prevalent framing of toxicity, bias, but also factual knowledge and reasoning, tends to be Western-centric. Evaluation concepts should be expanded to include diverse global perspectives and values.
2. **Language sensitivity** Under this term, we refer to the fact that LLMs find applications in multilingual and multicultural settings, and that the performance of an LLM may depend heavily on the language it is used in. Benchmarks for bias and toxicity, but also some common benchmarks for language understanding and inference, are not trivial to transfer across languages and linguistic structures.
3. **Comparability vs. specificity** Many European and other non-English languages still have a limited number of benchmark datasets. To provide a common ground for the evaluation of LLMs across languages, major global benchmarks are still being translated to facilitate international comparability. It is recommended that such translation and adaptation

procedures acknowledge the complexity of the task and, even if performed automatically, consider employing different tools, prompt strategies, LLM revision techniques and human evaluation of random samples.

4. **Additional modalities** Many benchmarks have been developed recently to include different modalities, but there is still a gap in benchmarks for speech, sign language, audiovisual communication, and combinations thereof.
5. **Human baseline** While frontier LLMs already surpass humans in many areas, it is of paramount importance, especially in high-risk domains, to have a solid foundation for the evaluation of LLMs by comparing the results to human performance on a specific task, acknowledging that every benchmark is a limited representation of a task.
6. **Transparent implementation** The details of the evaluation process should be published in a transparent manner, including the exact specification of prompting strategies and hyperparameters used, such as temperature. If possible, evaluation scripts should also be made public, and results validated through multiple runs in the case of smaller datasets.
7. **Context-specific evaluation** There is a lack of nuanced, context-specific evaluations that address the multi-faceted nature of real-world LLM deployments. This includes domain-specificity, but also other elements of attuning evaluation to the users it serves.

We believe that the rapidly evolving benchmarking landscape for European languages would benefit from a catalogue where each benchmark is categorized and documented according to the above principles. We conceive of such a catalogue in the form of a database, accommodating the fact that the proposed taxonomy categories and metadescritors may overlap, so that each entry can be labeled with all which apply.

6. Conclusion

We have presented recent trends in LLM benchmarking for European languages and proposed a new taxonomy for their categorization, intended to be implemented alongside a range of metadescritors in the context of a European catalogue of LLM benchmarks. Our taxonomization strategy focuses on the linguistic, cultural, factual and reasoning capabilities of models and also incorporates emerging abilities. The proposed considerations follow the wide-spread belief amongst European researchers and developers that the traditional Western-centric,

likely contaminated and linguistically inappropriate datasets no longer satisfy our needs, and that targeted efforts should be invested in filling the evaluation gaps for all European languages.

The initiative presented in this paper is the result of a series of discussions and reflections within the framework of several international research communities, collecting and integrating feedback from a number of researchers, developers and benchmark creators. With the rapid advancement of the field, we envisage continuous extensions and revisions both of the taxonomy and the associated set of metadescritors and recommendations.

Acknowledgements

This work is supported by the LLM4DH project, funded by the Slovenian Research and Innovation Agency (ARIS) under the grant agreement GC-0002.

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