La Leaderboard: A Large Language Model Leaderboard for Spanish Varieties and Languages of Spain and Latin America

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Abstract

Leaderboards showcase the current capabilities and limitations of Large Language Models (LLMs). To motivate the development of LLMs that represent the linguistic and cultural diversity of the Spanish-speaking community, we present LA LEADERBOARD [1], the first open-source leaderboard to evaluate generative LLMs in languages and language varieties of Spain and Latin America. LA LEADERBOARD is a community-driven project that aims to establish an evaluation standard for everyone interested in developing LLMs for the Spanish-speaking community. This initial version combines 66 datasets in Basque, Catalan, Galician, and different Spanish varieties, showcasing the evaluation results of 50 models. To encourage community-driven development of leaderboards in other languages, we explain our methodology, including guidance on selecting the most suitable evaluation setup for each downstream task. In particular, we provide a rationale for using fewer few-shot examples than typically found in the literature, aiming to reduce environmental impact and facilitate access to reproducible results for a broader research community.

1 Introduction

The evaluation of multilingual Large Language Models (LLMs) is challenging. LLMs are expected to perform a large variety of tasks, from problem-solving to text summarization, all in multiple languages (Guo et al., 2023). In this context,

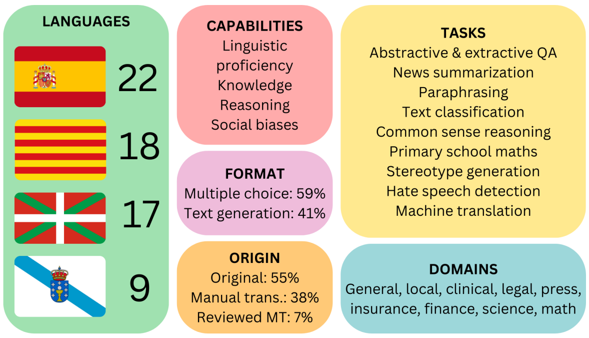

Figure 1: Summary of the evaluation datasets included in LA LEADERBOARD . Disclaimer: A country does not represent a language; flags are used for simplicity.

leaderboards have emerged as one of the standard approaches for evaluating and comparing LLMs in a transparent manner. As we cannot improve what we cannot measure, it is important to develop leaderboards that enable a more comprehensive evaluation of LLMs across linguistic boundaries, contributing to the development of culturally aware AI systems that can serve diverse global linguistic communities.

Spanish is one of the most spoken languages worldwide, with more than 600 million speakers (Fernández and Mella, 2024). It is the predominant language in 21 countries, where it coexists with other languages. Many people use Spanish and the local language in their daily activities. Spain has four official languages: Spanish, Catalan, Basque, and Galician. While Catalan and Galician are Romance languages closely related to Spanish, Basque is one of the world's few language isolates (Campbell, 2010). In Latin America (LATAM),

[1]https://hf.co/spaces/la-leaderboard/la-leaderboard

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there are hundreds of indigenous languages, such as Guarani and Náhuatl, which have influenced local Spanish varieties (Lustig, 1996). From a sociolinguistic point of view, this creates a unique scenario for multilingual LLM evaluation. Moreover, knowing which LLMs perform best in these languages can have deep implications for multilingual communication (Strassel and Tracey, 2016).

Existing leaderboards predominantly focus on English or a small set of high-resource languages (Fourrier et al., 2024; Mialon et al., 2023; Pal et al., 2024; Contributors, 2023). While Spanish is often included in multilingual leaderboards, evaluation datasets are typically limited and translated, either by machines (Barth et al., 2024), failing to capture the linguistic richness of the language (Plaza et al., 2024) or by humans[2], still failing to represent the target culture (Singh et al., 2024) Moreover, despite the growing presence of LLMs in multilingual settings, no leaderboard currently evaluates a combination of languages spoken in Spain and Latin America. This lack of representation limits the development of models that can truly serve these communities (Mager et al., 2018).

To address this gap, we introduce LA LEADERBOARD , the first open-source leaderboard designed to evaluate generative LLMs based on the needs of the Spanish-speaking community. Beyond the initial set of languages that includes Spanish and the official languages of Spain (Basque, Catalan, and Galician), LA LEADERBOARD is designed to evolve, gradually expanding to encompass more languages and linguistic varieties, ensuring it reflects the rich diversity of the global community. This new leaderboard consists of a diverse set of evaluation tasks (see Figure 1) designed in a way that reflects the nuances and actual usage of the target languages. It is a community-driven initiative launched by the #Somos600M Project (Grandury, 2024), aiming to foster the development of LLMs that better represent the linguistic and cultural diversity of the Spanish-speaking world. We share our approach to inspire other linguistic communities to create similar leaderboards.

The main contributions of this work are:

- We present the community-based methodology used to create the first open-source leaderboard for evaluating generative LLMs in Spanish and the official languages of Spain, with a scalable framework designed to include more languages and language varieties over time.
- We introduce a logical and resource-efficient approach to few-shot configurations, enabling accessible and reproducible evaluations for the wider community.
- We provide a comprehensive analysis of state-of-the-art (SOTA) LLMs, providing insights into their strengths and limitations in Spanish, Catalan, Basque, and Galician.

[2] https://hf.co/datasets/openai/MMMLU

By addressing the linguistic and cultural diversity of Spain and LATAM, LA LEADERBOARD sets a new standard for multilingual LLM evaluation, which encourages the development of models that are not only linguistically competent but also culturally aware.

2 Related Work

Benchmarks Several benchmarks have been developed to evaluate the performance of LLMs in tasks like language understanding (Wang et al., 2019), general knowledge (Hendrycks et al., 2021a), reasoning (Sakaguchi et al., 2019), or mathematical problem solving (Hendrycks et al., 2021b). There are also efforts to develop holistic benchmarks or evaluation suites that provide a comprehensive evaluation of different capabilities of LLMs (Liang et al., 2023; Gao et al., 2021; Fourrier et al., 2023, 2024; Srivastava and et al, 2023).

Multilingual and multicultural benchmarks LLMs are now trained in multiple high-resource languages at the same time (Ali et al., 2024; Martins et al., 2024; Qwen Team, 2024; Jiang et al., 2023), which means that the benchmarks must reflect this linguistic diversity. A common approach is machine translating English tests (Holtermann et al., 2024; OpenAI, 2023). However, translation errors may add noise to the results, making them less reliable (Plaza et al., 2024). Furthermore, each language has its nuances, preferred styles, and cultural background, which unrevised machine translation may fail to capture (Plaza-del-Arco et al., 2020; Singh et al., 2024). Ideally, specific test sets should be originally written in the target language or manually adapted (Nangia et al., 2020) to capture the richness and cultural and linguistic subtleties associated with it. This is slowly becoming the trend as shown by the recently released language-specific (Mercorio et al., 2024; Quercia et al., 2024) and multilingual culturally aware (Romanou et al., 2024; Salazar et al., 2025; Myung et al., 2025; Romero et al., 2024) benchmarks.

Leaderboards Benchmarks are the pieces of the LLM evaluation puzzle that provide valuable but fragmented information on their performance. Leaderboards and arenas use these evaluation sets to compare the performance of LLMs in a neutral, third-party manner through automatic evaluations (Mialon et al., 2023) or human judgments (Chiang et al., 2024). On some community-oriented leaderboards (Fourrier et al., 2024), anyone can submit their LLMs for evaluation, and the tools, tests, and results are open, allowing for reproducibility. This represents a good way to drive progress in LLM development by enabling people with limited compute to compare their models to the current SOTA.

Multilingual leaderboards Leaderboards exhibit the same shortcomings as benchmarks when evaluating languages other than English. To address this problem, specific leaderboards are being developed in different languages such as Italian (Mercorio et al., 2024), Korean (Kim et al., 2024), Chinese (Contributors, 2023), Arabic (Elfilali et al., 2024) or Polish (Jassem et al., 2025).

Spanish leaderboards Focusing on the Spanish language, the ODESIA leaderboard[3] by UNED NLP features 14 bilingual Spanish-English datasets from discriminative shared tasks. The team evaluates 10 LLMs. While submissions are open, the evaluation datasets are private, avoiding task contamination (Salido et al., 2025) but making it impossible to reproduce the results locally. Regarding text generation, Spanish is represented in the Chatbot Arena[4], which features a dedicated category, and in SCALE's private leaderboard[5]. However, both exclusively evaluate a fixed set of models. The only existing leaderboard including a language from Spain or Latin America other than Spanish is CLUB[6], developed by the BSC as part of the AINA Project, which combines 8 Catalan datasets and evaluates 5 BERT and RoBERTa-based models.

In this work, we present the methodology used to create a comprehensive, fully open-source leaderboard for languages and language varieties from Spain and Latin America that assesses different capabilities of generative models, including domain knowledge, information extraction, linguistic proficiency, and ethical aspects. LA LEADERBOARD aims to serve as a reference for the Spanish-speaking scientific community, fostering the development of more robust and culturally adequate LLMs.

[3]https://leaderboard.odesia.uned.es
[4]https://lmarena.ai
[5]https://scale.com/leaderboard/spanish
[6]https://club.aina.bsc.es

3 LA LEADERBOARD

LA LEADERBOARD is a community-driven initiative that brings together 66 datasets in Spanish, Catalan, Basque, and Galician, covering diverse tasks and domains. Public since September 23, 2024, LA LEADERBOARD has received over 15,000 visits in four months and currently showcases evaluation results from 50 models.

3.1 Data Collection

Most of the datasets in LA LEADERBOARD were donated by 13 research groups. Initially, these contributions were received through a publicly shared Google Form (Appendix E) or direct outreach. In particular, 7 datasets were specifically created for LA LEADERBOARD (AQuAS, ClinTreatES, ClinDiagnosES, HumorQA, SpaLawEx, TELEIA, and RAGQuAS). We also included widely used open-source benchmarks such as Belebele.

LA LEADERBOARD keeps expanding with dataset contributions such as CONAN-EUS and VeritasQA. These new connections are bidirectional: we actively share this initiative in relevant conferences and reach out to research groups, while others contact us upon discovering LA LEADERBOARD . Beyond collecting existing datasets, we are also fostering collaborations to enhance the representation of languages and linguistic varieties across Latin America.

To thank research groups for their donations, we include in LA LEADERBOARD 's interface the corresponding logo and dataset citation. Moreover, the dataset authors are acknowledged in this paper.

3.2 Task Construction

3.2.1 Datasets

Including diverse evaluation datasets is essential for building a comprehensive leaderboard. This section discusses the key axes that guided their selection. Table 1 enumerates the datasets organized by language and task type, while Table 2 shows the upcoming datasets that have been recently donated and not yet evaluated. In Appendix A, we provide the citations and further details about the datasets, including origin and domain.

Languages La Leaderboard contains 22 evaluation datasets in Spanish, including the varieties of Spain, Mexico, Argentina, Chile, and Uruguay. It also gathers datasets in all the official languages of Spain, with 18 datasets in Catalan, 17 in Basque, and 9 in Galician.

Origin We aim to evaluate models with high-quality datasets that reflect the cultural and linguistic idiosyncrasies of each language. For this reason, we only include datasets that have been annotated or revised by at least one native speaker of the language. We prioritize the inclusion of datasets originally created in the language they evaluate, which constitute 55% of the leaderboard. When this is not possible and translation is required, we prioritize datasets translated by human professionals. Not only does this prevent the loss of linguistic nuances that happens with machine translation (Plaza et al., 2024), but it also allows translators to adapt the text to the target culture (Nangia et al., 2020) and to identify errors in the source datasets and ensure that no extra hints regarding the answer are given in the input prompt (Baucells et al., 2025). In La Leaderboard , 38% of the datasets have been manually translated from an existing English benchmark. We also acknowledge that, given the low-resource nature of some languages we cover, machine translation is more affordable than human translation. However, we only include such datasets if the automatic translation was comprehensively reviewed by a person proficient in the target language. Only 7% of the datasets in La Leaderboard are manual reviews of machine-translated datasets.

Format The multiple-choice question-answering (MCQA) format is widely used for automatic evaluations due to its simplicity. Thus, MCQA is the format of 59% of the tasks included in La Leaderboard . We acknowledge that the literature has identified some issues with MCQA tasks, such as models' sensitivity to answer order (Pezeshkpour and Hruschka, 2024; Mina et al., 2025) or lack of task understanding (Khatun and Brown, 2024). Moreover, some suggest that this type of task does not reflect the actual models' responses and capabilities (Li et al., 2024; Wang et al., 2024a). To address this issue, we also include text generation tasks, such as summarization, evaluated using NoticIA for Spanish, caBreu for Catalan, and Summarization-GL for Galician. We evaluate long-form question-answering in Spanish using the AQuAS and RagQuAS datasets. Finally, we assess counter-narrative generation with RefutES in Spanish and CONAN in Basque and Spanish.

Domains La Leaderboard includes well-known generalist datasets aimed at evaluating a model's capability to understand and complete a task, such as Belebele, WNLI, and XStoryCloze. We also include evaluation datasets focused on truthfulness assessment, such as VeritasQA and the Galician translation of TruthfulQA. There are, in addition, several domains represented in La Leaderboard , such as the medical (e.g., ClinTreatES), legal (e.g., SpaLawEx), and press (e.g., caBreu, NoticIA). We also include ethics-oriented datasets, evaluating stereotype generation in Spanish and Catalan with CrowsPairs.

Tasks The types of tasks chosen for our leaderboard extend those usually included in well-known leaderboards (e.g., reasoning, natural language inference, question answering or summarization) to other task types for which high-quality datasets exist in our target languages (e.g., counter-narrative generation or linguistic acceptability). For consistent performance comparisons across languages, we prioritize tasks available in multiple languages.

3.2.2 Metrics

The MCQA tasks are evaluated by measuring the logarithmic probabilities (LogProbs) of models' outputs among a restricted list of options. For text generation tasks, we compare the expected (*gold-standard*) and given responses using various metrics depending on the original authors' implementation, including BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and Semantic Answer Similarity (SAS, Risch et al., 2021). Furthermore, following the recent trend of evaluating text generation tasks using LLMs, we are adapting an automated Judge-LLM metric from Zubiaga et al. (2024). Since SAS and LLM-based metrics are not currently supported in the evaluation suite we use, the LM Evaluation Harness (Gao et al., 2021), we implement them in our open-source fork[7].

[7]`https://github.com/somosnlp/lm-evaluation-harness`

Task Type	Spanish	Catalan	Basque	Galician
Common-sense reasoning	copa_es xstorycloze_es	copa_ca xstorycloze_ca	xcopa_eu xstorycloze_eu	xstorycloze_gl
Ethics	crows_pairs_es	crows_pairs_ca	–	–
Linguistic acceptability	escola	catcola	–	galcola
Math	mgsm_direct_es	mgsm_direct_ca	mgsm_direct_eu	mgsm_direct_gl
NLI	wnli_es xnli_es	teca wnli_ca xnli_ca	epec_koref_bin qnli_eu, wiceu wnli_eu, xnli_eu	xnli_gl
Paraphrasing	paws_es parafrases_sushi	parafraseja paws_ca	–	parafrases_gl paws_gl
Question answering	aquas clindiagnoses clintreates spalawex teleia ragquas xquad_es	arc_ca catalanqa coqcat openbookqa_ca piqa_ca siqa_ca xquad_ca	bertaqa bhtc_v2 eus_exams eus_proficiency eus_trivia vaxx_stance	openbookqa_gl
Reading comprehension	belebele_spa_Latn	belebele_cat_Latn	belebele_eus_Latn eus_reading	belebele_glg_Latn
Summarization	noticia xlsum_es	cabreu	–	summarization_gl
Text classification	humorqa fake_news_es offendes	catalonia_ independence	bec2016_eu	–

Table 1: Datasets of LA LEADERBOARD as of February 2025 organized by task type and language.

Task Type	Dataset	Languages
Adaptation	*phrases*	Catalan, Spanish, Valencian
Common-sense reasoning	*xstorycloze_gl*	Galician
Counter-narrative generation	*conan_eus/mt_es* *refutes*	Basque, Spanish Spanish
Ethics	*h4rmony_eval*	Spanish
Text classification	*haha*	Spanish
Natural language inference	*americasnlp_nli* *meta4xnli*	Aymara, Asháninka, Bribri, Guarani, Náhuatl, Otomí, Quechua, Rarámuri, Shipibo-Konibo, Wixarika Spanish
Question answering	*paes_cl* *voces_originarias* *medexpqa* *quales*	Spanish Aymara, Guarani, Tehuelche, Náhuatl, Quechua Spanish Spanish
Translation	*flores* *americasnlp_mt* *tradu_latam*	Spanish, Catalan, Basque, Galician Spanish, Aymara, Asháninka, Bribri, Guarani, Náhuatl, Otomí, Quechua, Rarámuri, Shipibo-Konibo, Wixarika Spanish, Aymara, Gurananí, Tehuelche, Náhuatl, Quechua
Truthfulness	*truthfulqa* *veritasqa*	Spanish, Catalan, Basque, Galician Spanish, Catalan, Galician

Table 2: Datasets that have been recently donated to LA LEADERBOARD and are not yet included in the evaluation results, including benchmarks involving American Indigenous languages.

3.3 Code Bases

3.3.1 Backend

We acknowledge the cost of running evaluations and want to ensure that any researcher or developer can compare their models to the state-of-the-art and follow their evolution. This is why submitting a model for evaluation is open to the whole community. Once a model has been added to the evaluation queue, the last commit of the model is stored for reproducibility and to enable future comparisons of different versions. The results from the LM Evaluation Harness (Gao et al., 2021) are normalized according to the following formula:

$$\text{normalized\_value} = \frac{\text{raw\_value} - \text{random\_baseline}}{\text{max\_value} - \text{random\_baseline}} \quad (1)$$

where $random\_baseline$ is 0 for generative tasks and $1/n$ for MCQA tasks with n choices.

3.3.2 Frontend

The implementation of La Leaderboard is based on the HuggingFace leaderboard template[8]. The frontend is developed using Gradio (Abid et al., 2019) and presents the evaluation results categorized by language. To ensure transparency and reproducibility, we share the evaluation command and normalization formula. To bring the tool closer to the community, the information and submission guidelines are available in English and Spanish.

3.3.3 License

Since we want to motivate other communities to create their own, La Leaderboard is published under the permissive Apache 2.0 license[9].

3.4 Efficiency Considerations

3.4.1 Number of Few-Shot Examples

Recent literature reveals significant inconsistency in the number of examples (shots) used when evaluating large language models (LLMs). While early research demonstrated notable performance improvements with 3-5 in-context examples (Brown et al., 2020), current evaluation practices vary considerably across different models and benchmarks. For instance, the Open LLM Leaderboard employs 0-5 shots depending on the task, Mistral-7B generally follows this range with an exception of 8 shots for GSM8K (Cobbe et al., 2021), and Llama 3 and OLMo models focus primarily on zero-shot evaluation. In contrast, Gemini models use a broader range of 0-10 shots, including "variable-shot" configurations. This variation extends to language-specific models, with Salamandra[10] and Latxa (Etxaniz et al., 2024) families using different shot configurations in their evaluations, typically ranging from 0 to 5 shots.

Given this myriad of options, when choosing the number of shots to use in La Leaderboard , we take into consideration the following aspects:

A. Base vs. instruct models The number of shots should allow for a fair evaluation of the base models without helping instruct models too much. Also, the availability of structured datasets in specific evaluation formats—such as MCQA—is very low in mid- and low-resource languages. This means that models trained on English-heavy corpora are more likely to have encountered these structured formats in English than in other languages, potentially biasing their performance.

B. Cognitive bias Models suffer from cognitive bias depending on the order and options presented as few-shots (Zhao et al., 2021; Pezeshkpour and Hruschka, 2024; Mina et al., 2025). Thus, we ensure that, in MCQA tasks, all possible correct options are included in the in-context learning instances. For example, in an MCQA task with four possible answers, we evaluate on a 4-shot setting, with each shot showing one of the four options as correct, in random order. This is done unless it interferes with item A.

C. Context windows The context window limitations of language models vary significantly based on hardware constraints and architectural choices, affecting their ability to process long-form tasks such as summarization and reading comprehension. For example, while the Spanish government's 40B-parameter ALIA model[11] operates with a 4,096-token context window, Meta's Llama 3.2 1B model can handle up to 128K tokens[12]. To ensure fair evaluation across models with different context window capacities, few-shot examples are employed with a maximum limit of 2,048 tokens, following the methodology established in previous research on LLM analysis (Biderman et al., 2023).

D. Prompt format The evaluation methodology employed task-specific prompts from the LM

[8] https://hf.co/spaces/demo-leaderboard-backend/leaderboard

[9] https://www.apache.org/licenses/LICENSE-2.0

[10] https://hf.co/BSC-LT/salamandra-7b-instruct

[11] https://hf.co/BSC-LT/ALIA-40b

[12] https://ai.meta.com/blog/llama-3-2-connect-2024-vision-edge-mobile-devices

Evaluation Harness, with new prompts created for previously unimplemented tasks following established formats and validated by dataset authors. The number of few-shots varied based on prompt complexity: convoluted prompts (e.g., paraphrasing with PAWS and reasoning with COPA) used 3 in-context examples to allow models to understand the task while complying with items A and C (Brown et al., 2020); straightforward question-answering tasks employed 2-shot evaluation, while tasks with explicit, naturally structured prompts (like ClinDiagnosES and NoticIA) and those evaluating sentence continuation probability (e.g., XStoryCloze) were conducted using 0-shot evaluation.

3.4.2 Measuring Model Efficiency

The evaluation was performed using two NVIDIA H100 GPUs with Hopper architecture and 64 GB of HBM memory in the MareNostrum 5 High-Performance Computer[13], maintaining identical configurations across instances to ensure consistent measurements. Performance metrics included task execution time and energy consumption, tracked using the Energy Aware Runtime (EAR) package[14], with all tasks running at a batch size of 1.

Task execution duration, which includes token prediction time, response length, and tokenizer efficiency, was measured to assess model speed for time-sensitive applications. The duration of task execution is influenced by multiple factors beyond token prediction time, including the response length generated and the language-specific tokenization efficiency (Conde et al., 2024).

Energy consumption was recorded in kWh and converted to CO_2 equivalents using the European Commission's conversion ratio for Spain (0.158 kg CO_2/kWh), as the evaluation was conducted in Barcelona (Lottick et al., 2019).

4 Evaluation Results and Analysis

We focus on evaluating models accessible to the broader community. We select 50 open-weights models from various families, primarily ranging from 1B to 9B parameters, while including larger quantized models. We consider multilingual models trained by large technological companies and startups like Meta-Llama (Grattafiori et al., 2024) and Mistral (Jiang et al., 2023) as well as models such as EuroLLM (Martins et al., 2024) and Salamandra[15], which have been designed by European and Spanish research groups specifically to process our target languages more efficiently and capture cultural nuances. We assess both the base and instruction-tuned versions when available (Appendix C). Each model-task pair was evaluated once, and the raw, pre-normalization results analyzed in this work are publicly available[16].

Model	Top10	ES	CA	EU	GL
gemma-2-9b-it	**43**	61.69	57.30	**54.13**	46.49
gemma-2-9b	**43**	57.21	**59.60**	53.80	48.58
Meta-Llama-3.1-8B-IT	41	59.03	57.01	49.87	45.07
Qwen2.5-32B-IT-GPTQ-Int4	38	**64.06**	56.80	49.23	**52.52**
Qwen2.5-14B-IT-GPTQ-Int8	35	60.59	54.08	49.05	52.13
EuroLLM-9B *	30	55.00	57.32	38.92	46.36
Meta-Llama-3.1-8B	28	55.62	56.52	46.90	44.90
salamandra-7b *	26	52.17	54.13	45.80	39.88
salamandra-7b-instruct *	25	51.41	53.22	46.19	41.65
Qwen2.5-7B	25	58.79	57.28	42.51	46.82
aya-expanse-8b	20	55.42	53.99	41.99	43.38
salamandra-2b *	**8**	46.60	41.05	39.28	34.99
Qwen2.5-1.5B	**8**	52.60	47.88	38.13	38.79
gemma-2-2b-it	5	**54.85**	**48.27**	**50.27**	**39.79**
Qwen2.5-1.5B-IT	5	54.38	45.09	39.04	39.27
salamandra-2b-instruct *	3	43.83	43.28	38.57	34.53
gemma-2-2b	2	51.59	**50.22**	39.81	39.29
leniachat-qwen2-1.5B-v0 *	2	51.14	40.97	38.29	36.16
EuroLLM-1.7B-IT *	2	47.92	45.28	36.19	34.67

Table 3: Best performing models ranked by the number of tasks in which they achieved a top-10 placement (see "Top10" column), showing their average language performance. Target language–optimized models are indicated by an asterisk (*). Complete per-language top-10 frequencies can be found in Figure 4, and full average scores for all models are shown in Figure 3.

4.1 Model performance

Table 3 shows that the models most consistently ranking in the top 10 across languages are Gemma-2-9B base and instructed, Llama-3.1-8B-IT, and the quantized versions of Qwen-2.5-IT 14B and 32B. When prioritizing transparency, EuroLLM-9B stands out, followed by Salamandra-7B. For resource-constrained settings, Salamandra-2B and Qwen-2.5-1.5B offer the best performance.

Performance per task As illustrated in Figure 2, the evaluation results are generally better for NLI tasks, including textual entailment and paraphrasing, and worse for language proficiency tests, with all four languages having similar performance on both tasks. Within the language proficiency tests, which combine reading comprehension, linguistic

[13] https://www.bsc.es/ca/marenostrum/marenostrum-5

[14] https://www.bsc.es/research-and-development/software-and-apps/software-list/ear-energy-management-framework-hpc

[15] https://hf.co/collections/BSC-LT/salamandra-66fc171485944df79469043a

[16] https://hf.co/datasets/la-leaderboard/results

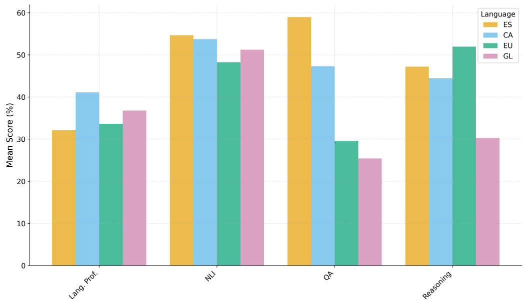

Figure 2: Results per type of task type and language.

acceptability, and summarization, results are particularly low for summarization tasks. In question answering and reasoning tasks, there is a larger inter-language difference, with Galician having significantly lower scores overall, while Basque obtains the best results for reasoning but the second worst for question answering. While commonsense reasoning results are generally good, math reasoning yields the lowest results, which could be related to a too strict metric (exact match). Further analysis is needed to understand whether these differences are due to the datasets used or indeed to the models' performance. The poor results on language proficiency tests also warrant a detailed examination to understand their implications, as they may indicate fundamental limitations in the models' knowledge across languages.

Performance per language Regarding specific models, the same five (Gemma2, Llama3.1, and quantized Qwen2.5) consistently rank among the top ten performers. However, we find that some models stand out for specific language-task pairs. In Spanish, AYA-Expanse-8B joins the top three for QA, EuroLLM-9B for reasoning, and RigoChat-7B is in the top four for language proficiency. In Catalan, EuroLLM ranks among the top three for both QA and reasoning tasks. For Basque, Salamandra-7B-IT is the second-best QA model, while Latxa-7B and Salamandra-7B occupy the first and second positions in reasoning and the third and second positions in classification, respectively. In Galician, EuroLLM-9B is the best model for QA, followed by its instructed version, Salamandra-7B ranks third in reasoning, and AYA-Expanse-8B takes second place in NLI.

Performance by training data configuration It is valuable to compare the different language configuration strategies in training. Salamandra and EuroLLM, by distributing tokens fairly among languages, achieve homogeneous performance and, in particular, reinforce Galician and Basque, but lose ground in Spanish and Catalan to models supported by high-resource corpora. Gemma2, which prioritizes volume over linguistic diversity, stands out for just the opposite; training on a large but linguistically imbalanced dataset allows the model to transfer patterns learned from English, maths, and code, and consistently rank among the top models overall. This shows that, sometimes, breadth of knowledge can compensate for the lack of language specific data.

The results confirm that the strategy of pre-training from scratch on a large multilingual corpus is the one that offers the most consistent and homogeneous coverage. Qwen-2.5, trained on 29 languages, and Llama-3.1, trained on 8, rank high in all languages. Moreover, systems that use continuous pre-training - adding large-scale data in a new language plus some English data to avoid catastrophic forgetting - achieve peak scores in the target language; e.g., Latxa holds the second-highest mark in Basque reasoning. Finally, models that just fine-tune on target language data without extending the pre-training (e.g., RigoChat or some Instruct variants) gain fluency and style, but the improvement in reasoning and QA tasks is modest, and models rarely enter the top 10. In summary, the earlier and deeper the model is exposed to the target languages, the higher its average scores; a posteriori strategies function as beneficial reinforcers, especially in less-resourced languages, but do not replace the power of extensive multilingual pre-training.

Performance by training compute Regarding the computational budget and the hardware used, public data is scarce. Regarding large tech companies we can consider Llama-3.1-8B, which was trained for 1.5M GPU-h. By contrast, other evaluated models required three to four orders of magnitude fewer. As expected, the results confirm that teams with access to GPUs/TPUs and high-end accelerators (TPUv5p, H100 or A100 in large clusters) can apply the strategies that we highlighted in the previous section as the most successful - massive multilingual pre-training and continuous pre-training - reflecting in significantly higher average scores. However, the same results also nuance the linear relationship between investment and performance as Salamandra-7B, despite its large budget (600 k GPU-h), falls in the middle of the table. Overall, the dashboard illustrates that computational abundance enables impactful techniques, but that dataset quality and fine-tuning remain decisive levers for converting that power into real performance.

Performance vs. size In general, our experiments show some correlation between performance and size, with models in the range of 1-2B parameters achieving better scores for their size. This is particularly true for Gemma-2-2B and Qwen-2.5-1.5B, both base and instructed models. Among the top 10 models, we find that all have between 8 and 9 billion parameters, except for the quantized versions from the Qwen family.

Performance per model type For the same VRAM requirement, quantized models with more parameters outperform full-precision models with fewer parameters. We don't observe any correlation between performance and whether the model is pre-trained or instruction-tuned, as this varies depending on the model.

4.2 Energy consumption

The total computational resources amount to 660.87 hours of processing time and 582.84 kWh of energy consumption, resulting in 92.09 kg of CO_2 emissions. On average, each model consumes 9.25 kWh (median 6.88, SD 8.42), showing a wide variety in energy usage. The models that consume the most energy are Grommeanuer-7B-IT, Qwen-2.5-32B-IT-GPTQ-Int4, and Qwen-2.5-14B-IT-GPTQ-Int8, each exceeding 30 kWh. On the other hand, Salamandra-2b, FLOR-1.3B-IT, and LLama-3.2-1B-IT are the most energy-efficient, consuming less than 2.1 kWh each.

Energy consumption vs. size As expected, a strong correlation between model size and energy dissipation is observed, as the number of arithmetic operations required to predict a token is related to the number of parameters of the model. However, some outliers are observed, such as Qwen, which consumes significantly more energy across all its sizes compared to other models. Conversely, models like FLOR exhibit considerably lower energy consumption across their different sizes relative to other models of similar scale.

Energy consumption vs. task Similarly, as anticipated, text generation tasks such as summarization require more energy for evaluation. Since LLMs generate text token by token and their prediction speed remains constant (assuming the same hardware and stable conditions), the most energy-intensive tasks are expected to be those that require the generation of larger amounts of text.

Energy consumption vs. performance Our experiments show a strong correlation between the energy consumed at inference and the model performance. For one of the overall top models, Gemma-2-9B, its instruction-tuned version excels with a third of the energy consumed by the base version. We observe a trend of instructed models consuming less energy, due to the verbosity of base models.

5 Conclusions and Future Work

In this paper, we propose a methodology to create community-driven leaderboards, including key points to gather diverse datasets and the rationale behind a more efficient and accessible evaluation setup. In doing so, we hope to inspire the creation of more leaderboards that fulfil the needs of diverse linguistic communities.

In particular, we present LA LEADERBOARD , the first open-source leaderboard to evaluate LLMs in languages from Spain and Latin America. It is the result of a collaboration among 13 research groups. LA LEADERBOARD consists of 66 datasets in Spanish, Catalan, Basque, and Galician, and covers a wide range of task types and domains. The results of evaluating 50 LLMs suggest that the top-performing models in the target languages are Gemma-2-9B base and instruct, Llama-3.1-8B-IT, and the quantized versions of Qwen-2.5-IT 14B and 32B. However, for domain-specific applications, particular linguistic contexts, or deployment scenarios with computational constraints or transparency requirements, alternative models (e.g., Salamandra-7B and EuroLLM-9B) demonstrate competitive performance metrics.

Our planned next steps include evaluating the recently donated datasets, with a special focus on indigenous languages. We will also add larger open models and proprietary models. Moreover, we are organizing a hackathon to create a benchmark to measure cultural adequacy in each Spanish-speaking country. Finally, we welcome any person or organization interested in joining our effort. This way, we hope that LA LEADERBOARD will keep evolving to include more languages, language varieties, and use cases that motivate the development of LLMs that better serve our diverse community.

Limitations

Indigenous languages We acknowledge that indigenous languages from Latin America are not yet included among the evaluation results of La Leaderboard . However, we have ongoing collaborations to include existing benchmarks and create new ones to keep extending La Leaderboard to be as inclusive as possible and reflect the diversity of the Spanish-speaking community.

Spanish language varieties Currently, the leaderboard includes datasets in the Spanish varieties of Spain, Mexico, Argentina, Chile, and Uruguay. Although we don't know the exact origin of all the samples from some third-party datasets, we estimate that less than 25% of all the Spanish datasets in the leaderboard come from LATAM. We plan to increase this percentage by collaborating with LATAM research groups in the creation of an open hackathon.

Large and proprietary models To improve the coverage of the state-of-the-art language models for the use cases included in La Leaderboard , it would be interesting to evaluate larger language models as well as proprietary models.

Contamination Another pending task is to analyse potential contamination (Sainz et al., 2023) within our leaderboard. We have not addressed this yet because a high percentage of the datasets used are very recent and niche, making it unlikely that they have been incorporated into training data, unlike more established benchmarks such as MMLU (Hendrycks et al., 2021a; Wang et al., 2024b; Taghanaki et al., 2024) that serve as primary pillars in model evaluation in every model report. Nevertheless, we have started to evaluate contamination to ensure in the short-term future that we provide high-quality results.

For the datasets specifically created for La Leaderboard , we advised the corresponding authors to release them gated to avoid being unintentionally included in training datasets by web scraping; AQuAS and RagQuAS are gated. The authors of TELEIA decided to release an adaptation of their dataset and keep the original private to be able to analyze contamination through time.

Ethical Considerations

Fair representation Since our objective is to establish an evaluation standard for Latin America and Spain, it is important to properly represent the linguistic and cultural diversity of the community in order to avoid the perpetuation, or even amplification, of stereotypes and inequalities.

Third-party datasets Some of the evaluation datasets included in La Leaderboard were created by organizations other than our data contributors. As a result, we acknowledge the possibility that some of these datasets may have been developed using practices that could be considered unethical. These concerns range from potential legal violations to extractive data collection methods that may impact disadvantaged communities.

Environmental impact Evaluating 50 language models on 66 tasks required 660.87 hours of compute, translating to 92.09 kg of CO_2. However, we hope that by publishing a comprehensive evaluation of the available models, La Leaderboard will contribute to reducing the total environmental impact of individual private evaluations.

Misuse of La Leaderboard We welcome model submissions from everyone. This could potentially lead to overuse, with people sending many different versions of the same model. We plan to mitigate this behaviour by following the spam mitigation strategies from the Open LLM Leaderboard (Fourrier et al., 2024).

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A Evaluation Datasets

The datasets are used only for evaluation, aligning with their intended uses.

Spanish datasets

The Spanish datasets in La Leaderboard are: AQuAS (Instituto de Ingeniería del Conocimiento, 2024a), Belebele (Bandarkar et al., 2024), EsCoLA (Bel et al., 2024a), Fake News ES (Posadas-Durán et al., 2019), FLORES-200 (Costa-jussà et al., 2022), ClinTreatES and ClinDiagnosES (LenguajeNatural.AI, 2024b), HumorQA (LenguajeNatural.AI, 2024a), MGSM (Shi et al., 2023), MultiLingualCrowsPairs (Nangia et al., 2020), NoticIA (García-Ferrero and Altuna, 2024), OffendES (Plaza-del-Arco et al., 2021), RagQuAS (Instituto de Ingeniería del Conocimiento, 2024b), SpaLawEx (LenguajeNatural.AI, 2024c), TELEIA (Mayor-Rocher et al., 2025), WNLI (Gonzalez-Agirre et al., 2024; Baucells et al., 2025)[17], XL-Sum (Hasan et al., 2021), XStoryCloze (Lin et al., 2022; Baucells et al., 2025), and XQuAD (Artetxe et al., 2020).

Catalan datasets

The Catalan datasets in La Leaderboard are: caBREU, CatalanQA, COPA-ca, CoQCat, PAWS-ca, TE-ca, WNLI-ca and XNLI-ca (Gonzalez-Agirre et al., 2024), IberoBench (Baucells et al., 2025), CatCoLA (Bel et al., 2024b), FLORES-200 (Costa-jussà et al., 2022), MGSM (Shi et al., 2023), XStoryCloze (Lin et al., 2022), XQuAD-ca (Armengol-Estapé et al., 2021), XStoryCloze (Lin et al., 2022; Baucells et al., 2025), Parafraseja[18], PAWS-X (Yang et al., 2019), and VeritasQA (Aula-Blasco et al., 2025).

Basque datasets

The Basque datasets in La Leaderboard are: EusExams, EusReading, EusProficiency and EusTrivia from Etxaniz et al. (2024); BEC2016eu, BHTCv2, EpecKorrefBin, QNLIeu, WiCeu from BasqueGlue (Urbizu et al., 2022); QNLI-eu (Urbizu et al., 2022), VaxxStance (Agerri et al., 2021), XNLIeu (Heredia et al., 2024), FLORES-200 (Costa-jussà et al., 2022), MGSM (Shi et al., 2023), and XStoryCloze (Lin et al., 2022; Baucells et al., 2025).

[17]For Spanish, see https://hf.co/datasets/PlanTL-GOB-ES/wnli-es.

[18]https://hf.co/datasets/projecte-aina/Parafraseja

Galician datasets

The Galician datasets in La Leaderboard are: FLORES-200 (Costa-jussà et al., 2022), GalCoLA (de Dios-Flores et al., 2023), TruthfulQA-GL[19], and XStoryCloze (Lin et al., 2022; Baucells et al., 2025)[20].

Datasets created for La Leaderboard

The 7 datasets specifically created for the initial version of La Leaderboard are AQuAS, ClinDiagES, ClinTreatES, HumorQA, RagQuAS, SpaLawEx, and TELEIA. Their corresponding datasheets are included in Appendix F.

Newly donated datasets

The new datasets donated will be evaluated shortly. These include CONAN-EUS (Bengoetxea et al., 2024), RefutES[21], TruthfulQA in Basque, Catalan, Galician and Spanish (Figueras et al., 2025), VeritasQA (Aula-Blasco et al., 2025), PAES Chile (Latam-GPT, 2025), meta4xnli (Sanchez-Bayona and Agerri, 2024), MedExpQA (Alonso et al., 2024), Catalonia Independence Corpus (CIC) in Catalan and Spanish (Zotova et al., 2021), HAHA humor detection and analysis in Spanish (Chiruzzo et al., 2021), QuALES for question-answering in Spanish in the COVID-19 domain (Rosá et al., 2022), AmericasNLP-MT (Mager et al., 2021), AmericasNLI (Ebrahimi et al., 2021), TraduLATAM, and VocesOriginarias evaluating indigenous languages.

Evaluation dataset details

The Tables 4 (Spanish), 5 (Catalan), 6 (Basque), and 7 (Galician) list these datasets, providing additional information about their task type, domain, and origin. We run the evaluations using our fork of the LM Evaluation Harness[22], synced with the main repository on commit 6ccd520f3fb2b5d74c6f14c05f9d189521424719. The tables mentioned also include details about the evaluation configuration, providing the Harness task ID, metric, and number of shots.

[19]https://hf.co/datasets/proxectonos/truthfulqa_gl

[20]For Galician, see https://hf.co/datasets/proxectonos/xstorycloze_gl.

[21]https://hf.co/datasets/SINAI/RefutES

[22]https://github.com/somosnlp/lm-evaluation-harness

Dataset	Task	Metric	Domain	Origin	#Examples	#Shots
AQuAS	Abstractive QA, Long Form QA	sas_encoder	Miscellaneous	Original	87	1
Belebele Spa	Reading Comprehension	acc	Miscellaneous	Human translation	900	2
ClinDiagnosES	Long Form QA	sas_encoder	Clinical	Original	62	0
ClinTreatES	Long Form QA	sas_encoder	Clinical	Original	62	0
COPA_es	Commonsense Reasoning	acc	Lang. prof., Misc.	Human translation	500	3
Crows Pairs Spanish	Stereotype Detection	pct_stereotype	Ethics, Hate speech	Original	1509	0
EsCoLA	Linguistic Acceptability	mcc	Language proficiency	Original	1060	2
Fake News ES	Fake News Detection	acc	Press	Original	572	2
HumorQA	Humor Classification	acc	Language proficiency	Original	51	0
MGSM_es	Math Reasoning	exact_match	Math	Human translation	250	2
NoticIA	Summarization	rouge1	Lang. prof., Press	Original	100	0
OffendES	Hate Speech Detection	acc	Hate speech	Original	13600	2
OpenBookQA_es	Multiple Choice QA	acc	General knowledge	Human translation	500	0
PAWS-X_es	Paraphrasing	acc	Lang. prof., Misc.	Original	2000	3
RagQuAS	Abstractive QA, Long Form QA	sas_encoder	Miscellaneous	Original	201	1
SpaLawEx	Multiple Choice QA	acc	Legal	Original	119	0
TELEIA	Multiple Choice QA	acc	Gen. knowl., Lang. prof.	Original	100	2
WNLI ES	Natural Language Inference	acc	Lang. prof., Misc.	Human translation	146	2
XL-Sum_es	Summarization	bleu	Press	Original	4763	1
XNLI_es	Natural Language Inference	acc	Miscellaneous	Original	5010	3
XQuAD_es	Extractive QA	f1	Miscellaneous	Original	1190	2
xStoryCloze_es	Commonsense Reasoning	acc	Miscellaneous	Human translation	1510	0

Table 4: Details of the evaluation datasets in Spanish (ES).

Dataset	Task	Metric	Domain	Origin	#Examples	#Shots
ARC_ca	Multiple Choice QA	acc	Science	Human translation	869	2
Belebele Cat	Reading Comprehension	acc	Miscellaneous	Human translation	900	2
caBREU	Summarization	bleu	Press	Original	301	1
CatalanQA	Extractive QA	f1	Miscellaneous	Original	2135	2
CatCoLA	Linguistic Acceptability	mcc	Language proficiency	Original	1020	2
COPA_ca	Commonsense Reasoning	acc	Lang. prof., Misc.	Human translation	500	3
CoQCat	Extractive QA	f1	Miscellaneous	Original	8986	1
MGSM_ca	Math Reasoning	exact_match	Math	Human translation	250	2
OpenBookQA_ca	Multiple Choice QA	acc	General knowledge	Human translation	500	0
Parafraseja	Paraphrasing	acc	Language proficiency	Original	21984	3
PAWS_ca	Paraphrasing	acc	Lang. prof., Misc.	Human translation	2000	3
PIQA_ca	Multiple Choice QA	acc	General knowledge	Human translation	1838	2
SIQA_ca	Multiple Choice QA	acc	General knowledge	Human translation	1954	2
TE-ca	Natural Language Inference	acc	Lang. prof., Misc.	Original	2117	3
WNLI_ca	Natural Language Inference	acc	Lang. prof., Misc.	Human translation	146	2
XNLI_ca	Natural Language Inference	acc	Lang. prof., Misc.	Human translation	5010	3
XQuAD_ca	Extractive QA	f1	Miscellaneous	Human translation	1190	2
xStoryCloze_ca	Commonsense Reasoning	acc	Miscellaneous	Human translation	1510	0

Table 5: Details of the evaluation datasets in Catalan (CA).

Dataset	Task	Metric	Domain	Origin	#Examples	#Shots
BEC2016eu	Sentiment Analysis	f1	Politics, Twitter	Original	1302	3
Belebele Eus	Reading Comprehension	acc	Miscellaneous	Human translation	900	2
BertaQA	Multiple Choice QA	acc	Cultural Knowledge	Original	4760	3
BHTCv2	Topic Classification	f1	Press	Original	1854	2
EpecKorrefBin	Natural Language Inference	acc	Press	Original	587	3
EusExams	Multiple Choice QA	acc	Miscellaneous	Original	16000	4
EusProficiency	Multiple Choice QA	acc	Language proficiency	Original	5169	4
EusReading	Reading Comprehension	acc	Miscellaneous	Original	352	1
EusTrivia	Multiple Choice QA	acc	General knowledge	Original	1715	4
MGSM_eu	Math Reasoning	exact_match	Math	Human translation	250	2
QNLIeu	Natural Language Inference	acc	Miscellaneous	Original	238	2
VaxxStance	Stance Detection	f1	Politics, Twitter	Original	312	3
WiCeu	Natural Language Inference	acc	Language proficiency	Original	1400	2
WNLI_eu	Natural Language Inference	acc	Lang. prof., Misc.	Human translation	146	2
XCOPA_eu	Commonsense Reasoning	acc	Lang. prof., Misc.	Human translation	500	3
XNLI_eu	Natural Language Inference	acc	Lang. prof., Misc.	Reviewed MT	5010	3
xStoryCloze_eu	Commonsense Reasoning	acc	Miscellaneous	Human translation	1510	0

Table 6: Details for evaluation datasets in Basque (EU).

Dataset	Task	Metric	Domain	Origin	#Examples	#Shots
Belebele Glg	Reading Comprehension	acc	Miscellaneous	Reviewed MT	900	2
GalCoLA	Linguistic Acceptability	mcc	Language proficiency	Original	1710	2
MGSM_gl	Math Reasoning	exact_match	Math	Reviewed MT	250	2
OpenBookQA_gl	Multiple Choice QA	acc	General knowledge	Reviewed MT	500	0
ParafrasesGL	Paraphrasing	acc	Language proficiency	Original	294	3
PAWS_gl	Paraphrasing	acc	Lang. prof., Misc.	Reviewed MT	2000	3
SummarizationGL	Summarization	bleu	Press	Original	8080	1
XNLI_gl	Natural Language Inference	acc	Lang. prof., Misc.	Reviewed MT	5010	3
xStoryCloze_gl	Commonsense Reasoning	acc	Miscellaneous	Human translation	1510	0

Table 7: Details for evaluation datasets in Galician (GL).

B Frontend Detailed Description

The implementation of La Leaderboard is based on the HuggingFace leaderboard template. [23] The frontend is developed using Gradio (Abid et al., 2019) and divided into four tabs:

- The landing tab, named "La Leaderboard", is divided into five sub-tabs, each containing tables with all the evaluated models and their corresponding average results. These sub-tabs include overall and language-specific results for Spanish, Catalan, Basque, and Galician. The results are aggregated by averaging the scores across all tasks for each language.
- For transparency and reproducibility purposes, the second tab, "Info", includes the command we use to evaluate the models and also the normalization formula. In the acknowledgements section, we list the institutions and every person who contributed to the project.
- The next tab describes all the "Tasks" included in La Leaderboard .
- Finally, there is a tab where everyone can submit their model for evaluation.

The text of the information and submission tabs is available both in English and Spanish to bring the tool closer to the community.

In the footer, we can find the citation information for the software, all the included datasets, and the evaluation suite. Below are the fourteen logos from all the collaborating institutions. The entities in the acknowledgements are ordered chronologically by the date they joined the project to thank early adopters, whereas the logos in the footer are ordered by the number of datasets donated.

C Models Evaluated

Table 8 details the 50 models evaluated, including the following families: Aitana[24], BERTIN (la Rosa et al., 2022), Carballo (Gamallo et al., 2024), FLOR (Da Dalt et al., 2024), LeniaChat[25], RigoChat (Instituto de Ingeniería del Conocimiento, 2025), Salamandra[26], Occiglot[27], EuroLLM (Martins et al., 2024), Aya (Dang et al., 2024), DeepSeek (DeepSeek-AI et al., 2025), Gemma (Riviere et al., 2024), Llama (Grattafiori et al., 2024), Mistral (Jiang et al., 2023), Phi (Li et al., 2023), SmolLM (Allal et al., 2025), and Qwen (Qwen Team, 2024).

D Evaluation Results

This section detailed visualizations of the evaluation results, comparing models, languages, and tasks, considering metrics such as performance and energy efficiency.

Figure 3 presents the full list of average results of the models evaluated, overall and by language. Moreover, since a very bad or good score in a few tasks can lower or raise the average score for a model and distort the comparison, we show the results in terms of the number of tasks for which a model is in the top 10 in Figure 4. This provides an alternative view of the results, focusing on the number of tasks for which the performance of the model is good. Figure 5 provides a comprehensive view of all the evaluation results by language, size, and model type.

Figure 6 represents the total energy consumed by each model. On average, each model consumed 9.25 kWh (median = 6.88, SD = 8.42), showing a wide variety in energy usage. Figure 7 shows which tasks consume more energy, with the text generation tasks on the top of the list. Figure 8 presents a comparison between model size and energy consumption. Finally, Figure 9 shows the relation between performance and energy consumption.

[23] https://hf.co/spaces/demo-leaderboard-backend/leaderboard

[24] https://hf.co/gplsi/Aitana-6.3B

[25] https://hf.co/LenguajeNaturalAI/leniachat-gemma-2b-v0

[26] https://hf.co/collections/BSC-LT/salamandra-66fc171485944df79469043a

[27] https://hf.co/collections/occiglot/occiglot-eu5-7b-v01-65dbed502a6348b052695e01

Family	Model ID	Model Type	Size (B)
Aitana	gplsi/Aitana-6.3B	pretrained	6.25
BERTIN	bertin-project/bertin-gpt-j-6B	pretrained	6.06
BERTIN	bertin-project/Gromenauer-7B	pretrained	7.24
BERTIN	bertin-project/Gromenauer-7B-Instruct	instruction-tuned	7.24
Carballo	proxectonos/Carballo-bloom-1.3B	pretrained	1.31
FLOR	projecte-aina/FLOR-1.3B	pretrained	1.31
FLOR	projecte-aina/FLOR-1.3B-Instructed	instruction-tuned	1.31
FLOR	projecte-aina/FLOR-6.3B	pretrained	6.25
FLOR	projecte-aina/FLOR-6.3B-Instructed	instruction-tuned	6.25
Latxa	HiTZ/latxa-7b-v1.2	pretrained	7.00
LeniaChat	LenguajeNaturalAI/leniachat-gemma-2b-v0	instruction-tuned	2.51
LeniaChat	LenguajeNaturalAI/leniachat-qwen2-1.5B-v0	instruction-tuned	1.54
RigoChat	IIC/RigoChat-7b-v2	instruction-tuned	7.62
Salamandra	BSC-LT/salamandra-2b	pretrained	2.25
Salamandra	BSC-LT/salamandra-2b-instruct	instruction-tuned	2.25
Salamandra	BSC-LT/salamandra-7b	pretrained	7.77
Salamandra	BSC-LT/salamandra-7b-instruct	instruction-tuned	7.77
EuroLLM	utter-project/EuroLLM-1.7B	pretrained	1.70
EuroLLM	utter-project/EuroLLM-1.7B-Instruct	instruction-tuned	1.70
EuroLLM	utter-project/EuroLLM-9B	pretrained	9.15
EuroLLM	utter-project/EuroLLM-9B-Instruct	instruction-tuned	9.15
Occiglot	occiglot/occiglot-7b-es-en	pretrained	7.24
Occiglot	occiglot/occiglot-7b-es-en-instruct	instruction-tuned	7.24
Occiglot	occiglot/occiglot-7b-eu5	pretrained	7.24
Occiglot	occiglot/occiglot-7b-eu5-instruct	instruction-tuned	7.24
Aya	CohereForAI/aya-expanse-8b	pretrained	8.03
DeepSeek	deepseek-ai/DeepSeek-R1-Distill-Qwen-1.5B	instruction-tuned	1.78
DeepSeek	deepseek-ai/DeepSeek-R1-Distill-Qwen-7B	instruction-tuned	7.62
DeepSeek	unsloth/DeepSeek-R1-Distill-Qwen-14B-bnb-4bit	instruction-tuned	14.8 (8.37)
Gemma	google/gemma-2-2b	pretrained	2.61
Gemma	google/gemma-2-2b-it	instruction-tuned	2.61
Gemma	google/gemma-2-9b	pretrained	9.24
Gemma	google/gemma-2-9b-it	instruction-tuned	9.24
Llama	meta-llama/Llama-3.2-1B	pretrained	1.24
Llama	meta-llama/Llama-3.2-1B-Instruct	instruction-tuned	1.24
Llama	meta-llama/Meta-Llama-3.1-8B	pretrained	8.03
Llama	meta-llama/Meta-Llama-3.1-8B-Instruct	instruction-tuned	8.03
Mistral	mistralai/Mistral-7B-Instruct-v0.3	instruction-tuned	7.25
Mistral	mistralai/Mistral-7B-v0.3	pretrained	7.25
Phi	microsoft/phi-1_5	pretrained	1.42
SmolLM	HuggingFaceTB/SmolLM2-1.7B	pretrained	1.71
SmolLM	HuggingFaceTB/SmolLM2-1.7B-Instruct	instruction-tuned	1.71
Qwen	Qwen/Qwen2.5-1.5B	pretrained	1.54
Qwen	Qwen/Qwen2.5-1.5B-Instruct	instruction-tuned	1.54
Qwen	Qwen/Qwen2.5-7B	pretrained	7.62
Qwen	Qwen/Qwen2.5-7B-Instruct	instruction-tuned	7.62
Qwen	Qwen/Qwen2.5-14B-Instruct-GPTQ-Int8	instruction-tuned	14.80 (4.99)
Qwen	Qwen/Qwen2.5-32B-Instruct-GPTQ-Int4	instruction-tuned	32.80 (5.74)

Table 8: Models evaluated in LA LEADERBOARD as of February 2025. The table is divided into sections starting at the top with models optimized for the languages of Spain, followed by models created by European projects, and finally models trained by international large technological companies and startups. The size is specified in billions of parameters, as appears in the SafeTensors information of the corresponding Hugging Face model page. For quantized models, the SafeTensors equivalent size of the model is added in parenthesis after the size of the base model.

Model Name	**Training Tokens (B)**	**Languages Included**	**Tokens (B) per Language**	**Hardware**	**Training Time (h)**
Aitana-6.3B	2.6	CA	2.6	4 A100	80
bertin-gpt-j-6B	65	ES	65	1 v3-8	4320
Gromenauer-7B	14.5	ES	14.5	-	-
Gromenauer-7B-Instruct	14.5+	ES, CA	14.5+, -	-	-
Carballo-bloom-1.3B	2.1	GL	2.1	5 A100	-
FLOR-1.3B	26	ES, CA	10.8, 10.9	Cerebras CS-2	-
FLOR-1.3B-Instructed	26+	ES, CA	10.8, 10.9+	Cerebras CS-2	-
FLOR-6.3B	140	ES, CA	46.7, 46.8	16 Cereb. CS-2	60
FLOR-6.3B-Instructed	140+	ES, CA	46.7, 46.8+	16 Cereb. CS-2	60+
latxa-7b-v1.2	4.2	EU	4.2	4 A100	953
leniachat-gemma-2b-v0	-	ES	-	-	-
leniachat-qwen2-1.5B-v0	-	ES	-	-	-
RigoChat-7b-v2	-	ES	-	1 A100	8.5
salamandra-2b	12875000	ES, CA, GL, EU	2075k, 253k, 39k, 30k	256 Hopper	221k
salamandra-2b-instruct	12875000+	ES, CA, GL, EU	2075k, 253k, 39k, 30k+	256 Hopper	221k+12
salamandra-7b	12875000	ES, CA, GL, EU	2075k, 253k, 39k, 30k	512 Hopper	602k
salamandra-7b-instruct	12875000+	ES, CA, GL, EU	2075k, 253k, 39k, 30k+	512 Hopper	602k+16
EuroLLM-1.7B	4000	ES, CA, GL	240, 12, 4	256 H100	-
EuroLLM-1.7B-Instruct	4000+	ES, CA	240, 12, 4+	256 H100	-
EuroLLM-9B	4000	ES, CA, GL	240, 12, 4	400 H100	-
EuroLLM-9B-Instruct	4000+	ES, CA	240, 12, 4+	400 H100	-
occiglot-7b-es-en	112	ES	58.2	128 A100	-
occiglot-7b-es-en-instruct	112+0.16	ES	58.2+0.08	+8 H100	-
occiglot-7b-eu5	293	ES	58.6	128 A100	-
occiglot-7b-eu5-instruct	293+0.40	ES	58.6+0.08	+8 H100	-
aya-expanse-8b	-	ES	-	-	-
DeepSeek-R1-Dist-Qwen-1.5B	-	-	-	-	-
DeepSeek-R1-Dist-Qwen-7B	-	-	-	-	-
DeepSeek-R1-Dist-Qwen-14B-4bit	-	-	-	-	-
gemma-2-2b	2000	-	-	v5p	-
gemma-2-2b-it	2000+	-	-	v5p	-
gemma-2-9b	8000	-	-	v5p	-
gemma-2-9b-it	8000+	-	-	v5p	-
Llama-3.2-1B	9000	ES	-	H100	370k
Llama-3.2-1B-Instruct	9000+	ES	-	H100	370k+
Llama-3.1-8B	15000	ES	-	H100	1460k
Llama-3.1-8B-Instruct	15000+	ES	-	H100	1460k+
Mistral-7B-v0.3	-	-	-	-	-
Mistral-7B-Instruct-v0.3	-	-	-	-	-
phi-1_5	150	none	0	32 A100	192
SmolLM2-1.7B	11000	none	0	256 H100	-
SmolLM2-1.7B-Instruct	11000+	none	0	256 H100	-
Qwen2.5-1.5B	18000	ES	-	-	-
Qwen2.5-1.5B-Instruct	18000	ES	-	-	-
Qwen2.5-7B	18000	ES	-	-	-
Qwen2.5-7B-Instruct	18000	ES	-	-	-
Qwen2.5-14B-Instruct-GPTQ-Int8	18000	ES	-	-	-
Qwen2.5-32B-Instruct-GPTQ-Int4	18000	ES	-	-	-

Table 9: Public details about the training corpus and compute resources of the models evaluated on LA LEADERBOARD : total number of tokens in the training data, target languages included in the training data, number of tokens per language, hardware type, and hours of training time.

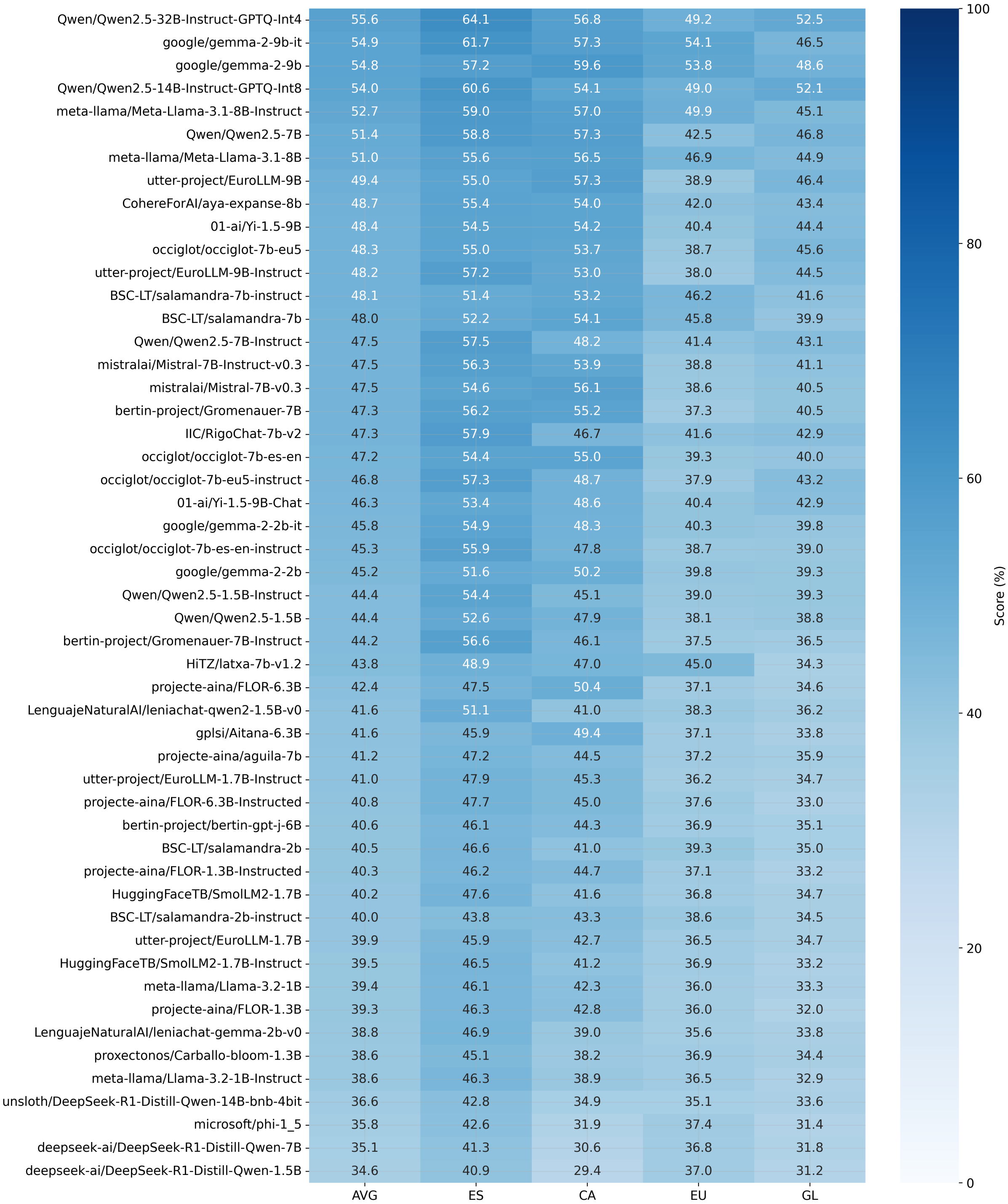

Figure 3: Average results of the first set of models evaluated on LA LEADERBOARD , overall and by language.

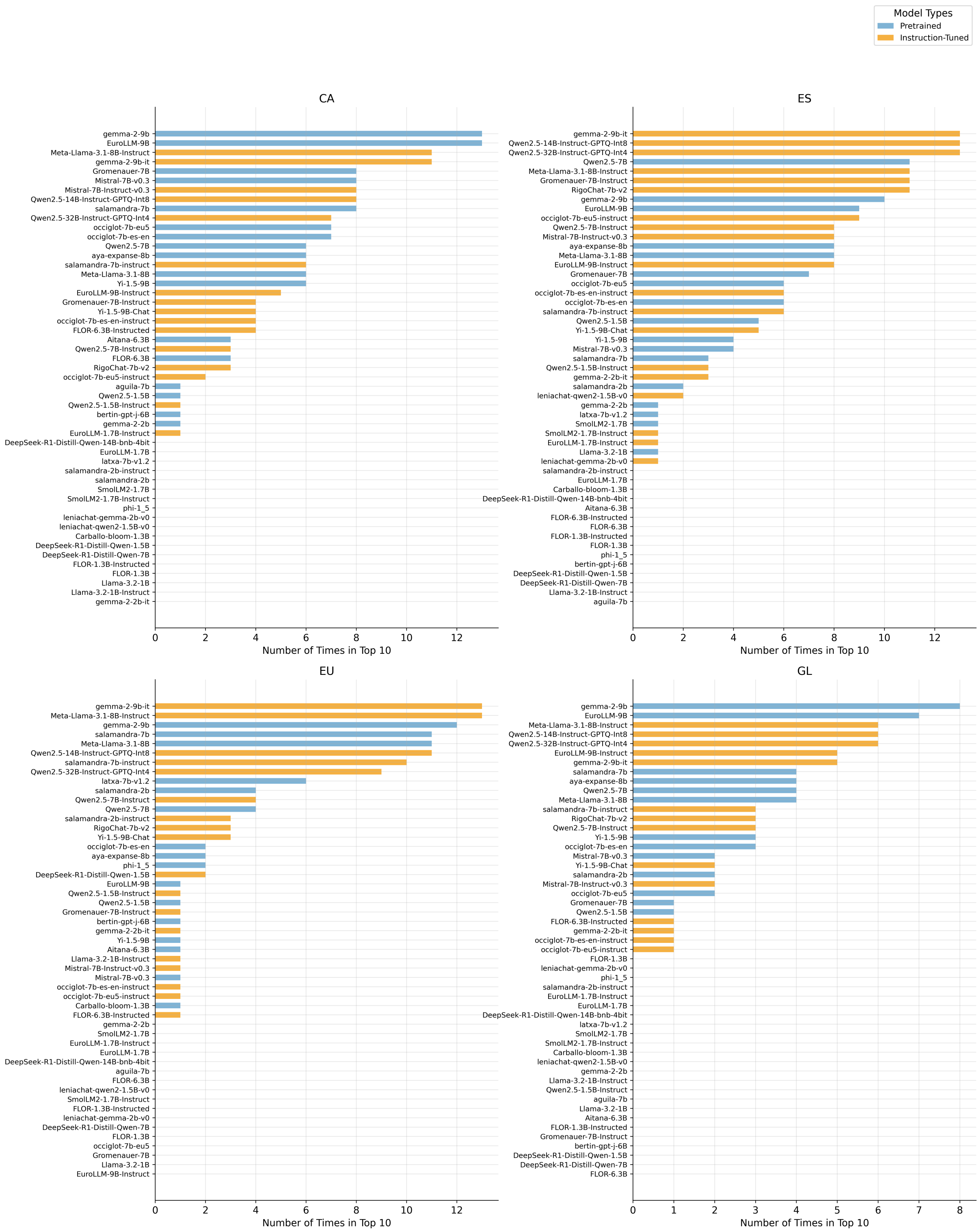

Figure 4: Number of tasks in which a model is among the top 10 models, by language.

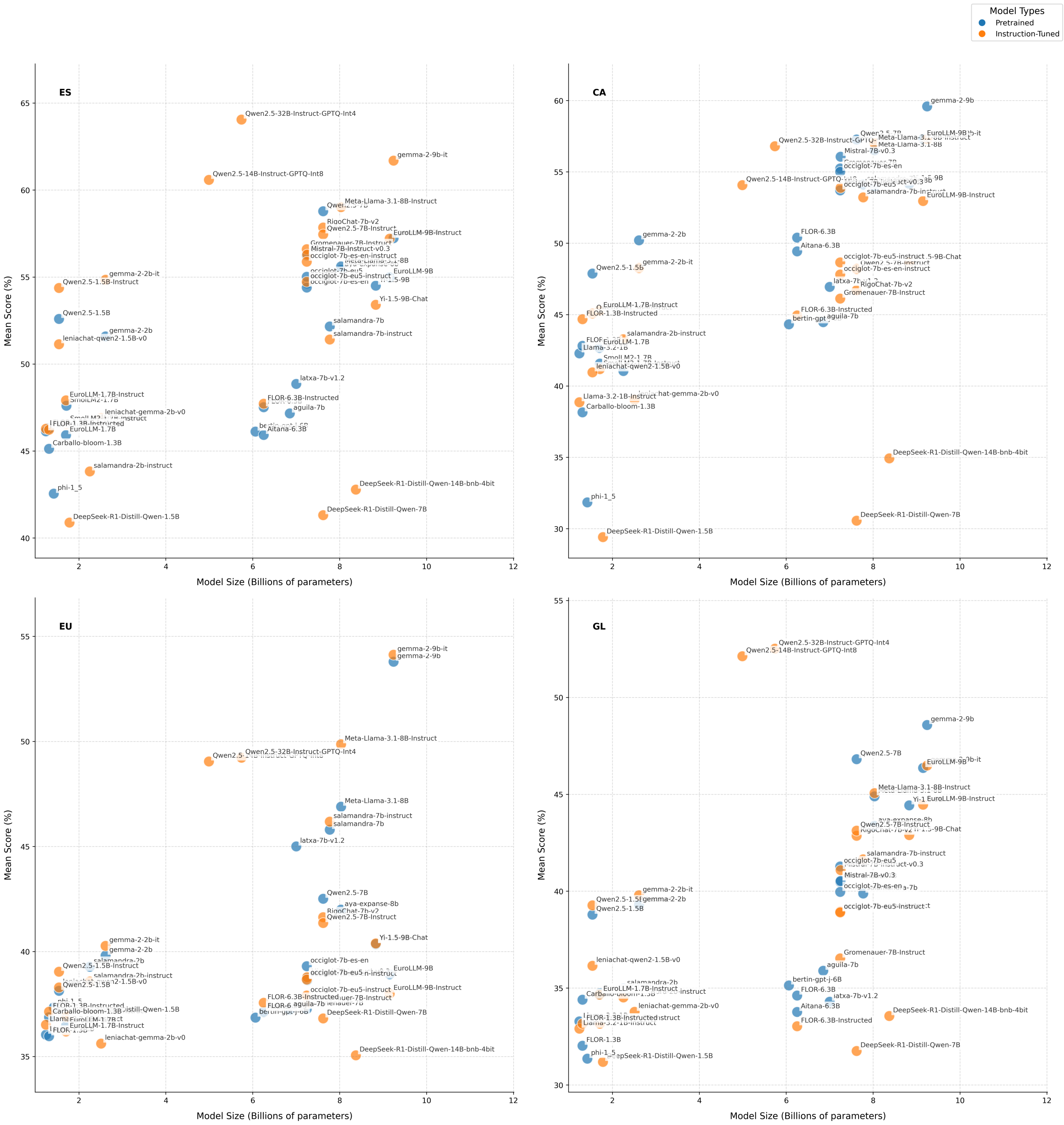

Figure 5: Results of the first set of models evaluated on LA LEADERBOARD organized by language, size, and model type.

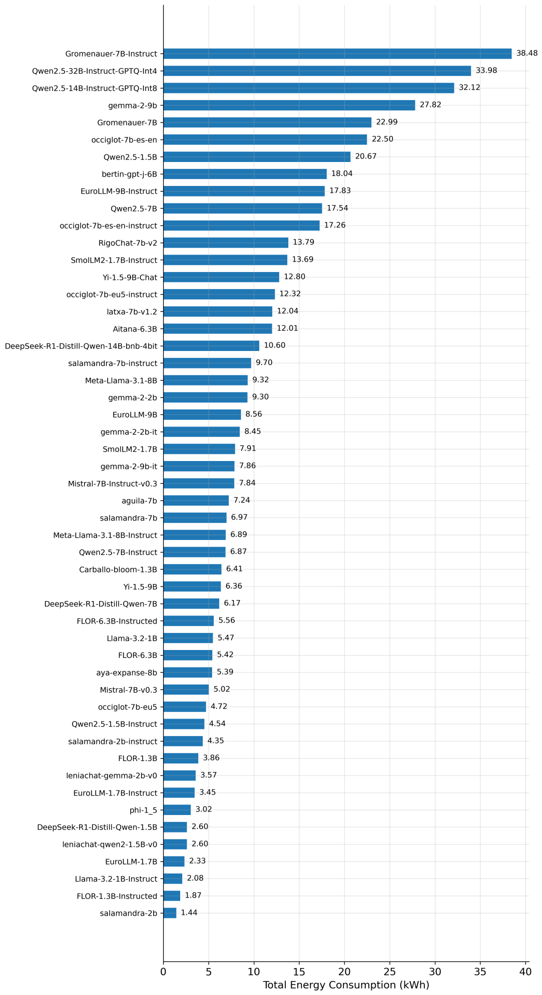

Figure 6: Distribution of results of models evaluated on LA LEADERBOARD organized by energy consumption.

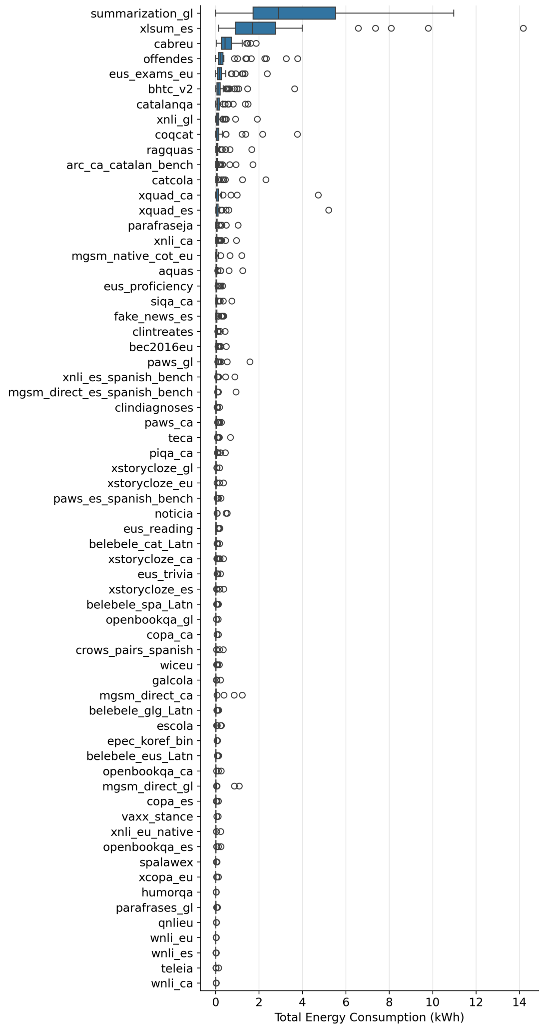

Figure 7: Energy consumption for the tasks evaluated on LA LEADERBOARD . The top three tasks (summarization_gl, xlsum_es, and cabreu) correspond to text summarization tasks, which require the generation of many tokens. The next tasks correspond to QA tasks with thousands of questions.

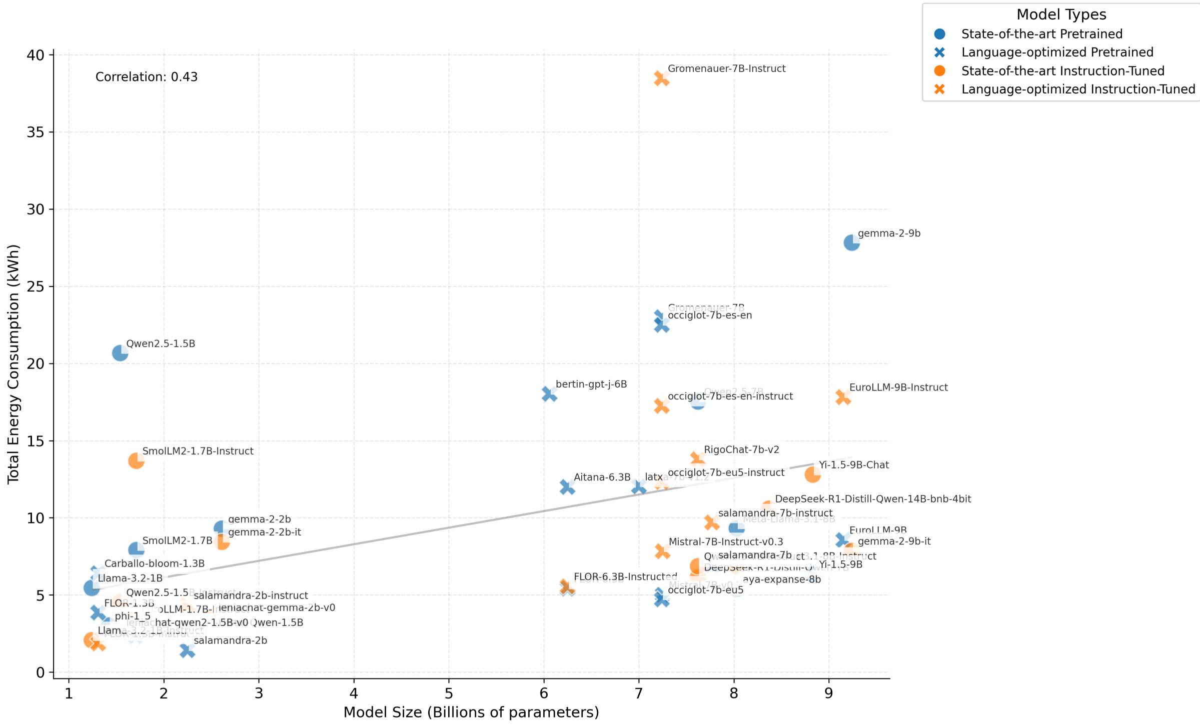

Figure 8: Distribution of results of models evaluated on LA LEADERBOARD comparing energy consumption versus size. The plot shows some correlation between model size and energy consumed, with a Pearson correlation coefficient of 0.43.

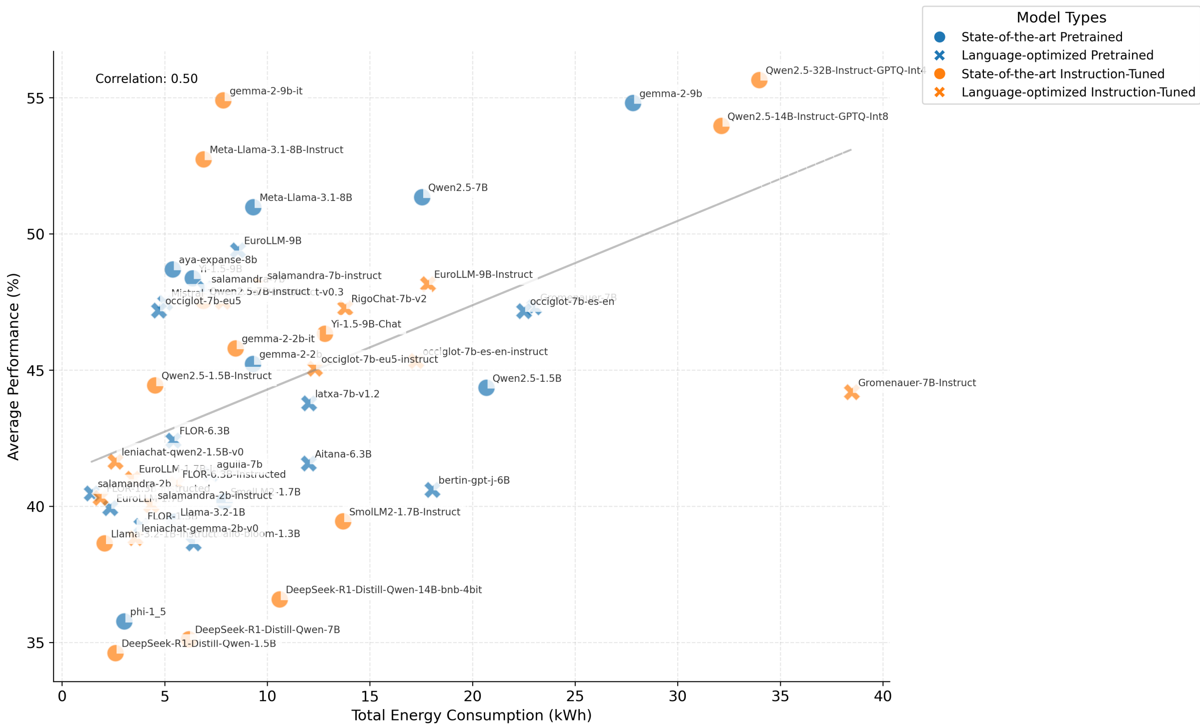

Figure 9: Distribution of results of models evaluated on LA LEADERBOARD comparing energy consumption versus performance. The plot shows a high correlation between model performance and energy consumed, with a Pearson correlation coefficient of 0.50.

E Data Collection Campaign

Below are the questions, translated into English, corresponding to the Google Form used in the open data collection campaign.

1. Email *
2. Data source (Select one option) *
   (a) The dataset is public
   (b) Instructions to recreate it are available
   (c) The dataset is private but access can be requested on a website
   (d) The dataset is currently private, but we want to open it as a donation
   (e) The dataset is private, but you should try contacting the organization that created it
3. Dataset link * This can be the dataset link, the instructions to recreate it, or the corresponding organization's website if private.
4. If your dataset is not uploaded to Hugging Face, would you like us to take care of uploading it? (Select one option)
   (a) Yes, upload it to the SomosNLP organization
   (b) Yes, help me create my own organization and upload it
   (c) No, I prefer to create my own organization and upload it myself
5. Modality * (Select one option)
   (a) Text
   (b) Audio
   (c) Image (e.g., images with descriptions)
6. Language(s) * (Select all that apply)
   (a) Spanish
   (b) Other: _____
7. Country(ies) * Country(ies) of origin of the data and/or the people who annotated it. A region can also be specified if known. The more information, the better.
8. Tasks * (Select all that apply)
   (a) Language modeling (unannotated)
   (b) Question answering (QA)
   (c) Classification
   (d) Token classification (e.g., NER, PoS)
   (e) Translation
   (f) Summarization
   (g) Semantic similarity
   (h) Multimodal (e.g., text-to-image, audio-to-text)
9. Subtask For example, subtasks of "text classification" could be "sentiment analysis" or "hate speech detection."
10. Domain * (Select all that apply)
    (a) Legal
    (b) Clinical or biomedical
    (c) Academic or technical
    (d) Literature or music
    (e) Social media or forums
    (f) News or articles
    (g) Dialogues
    (h) General
11. Number of examples Enter the exact number of examples if known, otherwise provide a range.
12. License type *
    (a) Commercial
    (b) Non-commercial
13. License link
14. Link to the dataset documentation or any other relevant information: description, annotation and cleaning process, ethical considerations... *
15. Link to the script/repository on GitHub to download or process the dataset
16. Thank you very much for your contribution! To publicly acknowledge your contribution, you may share your name and/or affiliation to be displayed on the website. If this is a donation, we will contact you soon—thank you!
17. Name
18. Affiliation
19. How could we improve this campaign? Who would you recommend we contact? Anything else you'd like to tell us?

F Datasheets

We present the datasheets (Gebru et al., 2021) corresponding to each of the datasets specifically created for LA LEADERBOARD : AQuAS, ClinDiagnosES, ClinTreatES, HumorQA, RagQuAS, SpaLawEx, TELEIA. Moreover, we propose an adaptation for leaderboards and fill it for LA LEADERBOARD .

La Leaderboard

Motivation for Leaderboard Creation

Why was the leaderboard created? LA LEADERBOARD is the first open-source leaderboard to evaluate generative LLMs in languages of Spain and Latin America. By aiming to address the linguistic and cultural diversity of the Spanish-speaking community, LA LEADERBOARD aims to set a new standard for multilingual LLM evaluation. Our goal is to encourage the development of models that are not only linguistically competent but also culturally aware, ultimately driving progress in Natural Language Processing (NLP) for the benefit of our whole community.

Who funded the creation of the leaderboard? LA LEADERBOARD is an initiative launched by an international open-source community and was promoted by volunteers. The funding of each of the individual datasets donated to LA LEADERBOARD will be disclosed after review.

Leaderboard Composition

What are the instances? LA LEADERBOARD consists of 66 evaluation datasets. All the evaluation datasets in the leaderboard consist solely of text instances.

Are relationships between instances made explicit in the data There are no known relationships between instances.

How many instances of each type are there? Summing all the instances of the 66 evaluation datasets, the leaderboard consists of 149,782 examples.

Is everything included or does the data rely on external resources? Everything is included in the datasets.

Are there recommended data splits or evaluation measures? The splits used in LA LEADERBOARD are the corresponding test splits of each dataset.

Data Collection Process

How was the data collected? The datasets were collected through an open data collection campaign.

Who was involved in the data collection process? How were they compensated? Professional researchers from academia and industry. The logo and names of the donators are included in the user interface, and the creators of the datasets are acknowledged in the paper.

Over what time-frame was the data collected? During 2024.

Does the dataset contain all possible instances? The evaluations are launched including all the available test instances for each donated dataset.

If the dataset is a sample, then what is the population? Not applicable.

Is there information missing from the dataset and why? No

Are there any known errors, sources of noise, or redundancies in the data? No.

Leaderboard Distribution

How is the leaderboard distributed? The leaderboard is available in the HuggingFace hub[28].

When will the leaderboard be released/first distributed? The leaderboard was released in September 2024.

What license (if any) is it distributed under? The leaderboard is licensed under "Apache 2.0".

Are there any fees or access/export restrictions? There are no fees or restrictions.

Leaderboard Maintenance

Who is supporting/hosting/maintaining the leaderboard? The leaderboard is hosted at HuggingFace[29], and the community can be contacted

[28] https://hf.co/spaces/la-leaderboard/la-leaderboard

[29] https://hf.co/spaces/la-leaderboard/la-leaderboard

through the "Discussions" tab in the interface or via email[30].

Will the leaderboard be updated? How often and by whom? Yes, every time there is a new donation, the maintainer will update the leaderboard and communicate the update on the usual communication channels of the open-source community.

Is there a repository to link to any/all papers/systems that use this leaderboard? Yes, all the datasets and tools used by LA LEADERBOARD are referenced in the "Citation" section of the interface[31].

Legal & Ethical Considerations

If the dataset relates to people or was generated by people, were they informed about the data collection? Not applicable.

If it relates to other ethically protected subjects, have appropriate obligations been met? Not applicable.

If it relates to people, were there any ethical review applications/reviews/approvals? Not applicable.

If it relates to people, were they told what the dataset would be used for and did they consent? Not applicable.

If it relates to people, could this dataset expose people to harm or legal action? Not applicable.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? Not applicable.

If it relates to people, were they provided with privacy guarantees? Not applicable.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? Yes, it complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No.

Does the dataset contain information that might be considered inappropriate or offensive? No.

[30] maria.grandury@somosnlp.org

[31] `https://hf.co/spaces/la-leaderboard/la-leaderboard`

AQuAS

The Abstractive Question-Answering in Spanish (AQuAS) dataset (Instituto de Ingeniería del Conocimiento, 2024a), developed by Instituto de Ingeniería del Conocimiento, is a monolingual Spanish dataset designed for abstractive question-answering. It contains 107 examples covering a diverse range of topics, including finance, insurance, healthcare, music, and law. Each example consists of a context passage, a related question, and a human-crafted answer. The dataset is aimed at evaluating the ability of large language models (LLMs) to generate well-formed, coherent, and informative responses.

Motivation for Dataset Creation

Why was the dataset created? AQuAS was created to provide high-quality examples of pairs of questions and answers with a related context that can be used to evaluate the ability of large language models (LLMs) to generate well-formed, coherent, and informative responses (abstractive question answering).

What (other) tasks could the dataset be used for? There are no recommended uses for this dataset other than evaluation.

Who funded the creation of the dataset? If there is an associated grant, provide the grant number. The dataset was created and funded by the research institute.

Dataset Composition

What are the instances? Each instance is a pair of a question and an answer accompanied by the related context on which the answer has been based and the corresponding topic.

Are relationships between instances made explicit in the data There are no known relationships between instances.

How many instances of each type are there? The dataset consists of 107 examples.

What data does each instance consist of? The instances consist of text data and are labelled with the corresponding topic.

Is everything included or does the data rely on external resources? Everything is included in the dataset.

Are there recommended data splits or evaluation measures? Since the dataset is intended for testing, there is no recommended split.

Data Collection Process

How was the data collected? The data for the contexts was gathered from different sources on the web using software to crawl those sites. The rest of the dataset (question-answer pairs) was curated and created manually.

Who was involved in the data collection process? How were they compensated? The data was collected by computational linguists and data scientists from a research institute.

Over what time-frame was the data collected? The data was collected during 2023, when the dataset was created.

How was the data associated with each instance acquired? The question-answer pairs were created and revised by computational linguists.

Does the dataset contain all possible instances? The dataset is composed of selected instances of different datasets created by a research institute.

If the dataset is a sample, then what is the population? This dataset is a 24,5% sample of the original complete datasets. The instances were randomly selected from the original datasets.

Is there information missing from the dataset and why? There is no data missing.

Are there any known errors, sources of noise, or redundancies in the data? There are no known errors because the revision process ensured the data is as clean and error-free as possible.

Data Preprocessing

What preprocessing/cleaning was done? The text contained in the "context" part of each instance in the dataset has not undergone any preprocessing or changes. There was no need to apply any cleaning to the question-answer pairs because they were created manually by computational linguists following a rigorous methodology and were subjected to revision afterwards.

Was the "raw" data saved in addition to the preprocessed/clean data? No, the text in the dataset is the raw data.

Is the preprocessing software available? No preprocessing software was used.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes, the collection procedure ensures the dataset is sufficiently varied so it can be used to evaluate a model on a wide range of topics. However, there are some potential limitations in the dataset which might slightly bias the data towards particular topics, because not all topics included have the exact same representation in the dataset, and obviously it was not possible to cover all topics in existence.

Dataset Distribution

How is the dataset distributed? The dataset is available in HuggingFace[32].

When will the dataset be released/first distributed? The dataset was released in 2024.

What license (if any) is it distributed under? The dataset is licensed under CC BY-NC-SA 4.0.

Are there any fees or access/export restrictions?
There are no fees or restrictions.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? How does one contact the owner/curator/manager of the dataset?
The dataset is hosted at HuggingFace, and the research institute can be contacted through email contacto.iic@iic.uam.es.

Will the dataset be updated? How often and by whom? How will updates/revisions be documented and communicated? Is there an erratum?
It is not planned to update the dataset at the moment.

Is there a repository to link to any/all papers/systems that use this dataset? No.

Legal & Ethical Considerations

If the dataset relates to people or was generated by people, were they informed about the data collection? Not applicable. The data was collected from public web sources, and does not contain sensitive personal information.

[32] https://hf.co/datasets/IIC/AQuAS

If it relates to other ethically protected subjects, have appropriate obligations been met? Not applicable.

If it relates to people, were there any ethical review applications/reviews/approvals? Not applicable.

If it relates to people, were they told what the dataset would be used for and did they consent? Not applicable.

If it relates to people, could this dataset expose people to harm or legal action? Not applicable.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? Not applicable.

If it relates to people, were they provided with privacy guarantees? Not applicable.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? The dataset complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No.

Does the dataset contain information that might be considered inappropriate or offensive? No.

ClinTreatES

The ClinTreatES (LenguajeNatural.AI, 2024b) dataset consists of clinical cases collected directly from doctors in various medical specialties (cardiology, traumatology, emergency, psychiatry, neurology, dermatology, ENT-laryngology, and anaesthesia) across European medical centers. It was developed through a joint collaboration between LenguajeNatural.AI and healthcare professionals. The dataset is intended for evaluating the ability of large language models (LLMs) to generate effective treatment plans based on provided clinical cases and diagnoses.

Motivation for Dataset Creation

Why was the dataset created? ClinTreatES was created to evaluate LLMs' capability to design appropriate treatments from real clinical cases and their corresponding diagnoses.

What (other) tasks could the dataset be used for? In addition to treatment planning, the dataset may be used to study medical reasoning and decision-making; however, it is not recommended for diagnostic tasks.

Who funded the creation of the dataset? The dataset was developed through a collaboration between an NLP startup and healthcare professionals.

Dataset Composition

What are the instances? Each instance comprises a clinical case description and its associated diagnosis.

Are relationships between instances made explicit in the data? No, there are no explicit relationships between instances.

How many instances of each type are there? The dataset contains 62 examples.

What data does each instance consist of? Each instance includes text data: a clinical case and its corresponding diagnosis, which serves as the basis for generating a treatment plan.

Is everything included or does the data rely on external resources? The dataset is self-contained with no reliance on external resources.

Are there recommended data splits or evaluation measures? No specific splits are recommended; the dataset is intended primarily for evaluation purposes.

Data Collection Process

How was the data collected? Data was collected directly from healthcare professionals across various specialities in European medical centers.

Who was involved in the data collection process? Medical professionals from cardiology, traumatology, emergency medicine, psychiatry, neurology, dermatology, ENT-laryngology, and anesthesia contributed to the dataset.

Over what time-frame was the data collected? The data was collected in 2024.

How was the data associated with each instance acquired? Clinical cases and their corresponding diagnoses were directly provided by the contributing healthcare professionals.

Does the dataset contain all possible instances? It is a curated collection and does not cover every possible clinical case.

If the dataset is a sample, then what is the population? The dataset represents a curated sample of clinical cases from European medical centers.

Is there information missing from the dataset and why? No, all relevant information is included.

Are there any known errors, sources of noise, or redundancies in the data? The data has been carefully curated and reviewed to minimize errors and noise.

Data Preprocessing

What preprocessing/cleaning was done? The clinical texts were formatted according to a standardized template; only minimal preprocessing was applied.

Was the "raw" data saved in addition to the preprocessed/clean data? Yes, the dataset contains the original clinical texts as provided by the contributors.

Is the preprocessing software available? No specific preprocessing software was used.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes, the collection and curation process ensures the dataset is suitable for evaluating treatment design tasks by LLMs.

Dataset Distribution

How is the dataset distributed? The dataset is available on HuggingFace[33].

When will the dataset be released/first distributed? The dataset was released in March 2024.

What license (if any) is it distributed under? It is distributed under the CC BY-NC-SA 4.0 license.

Are there any fees or access/export restrictions? There are no fees or restrictions.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? The dataset is hosted on HuggingFace and maintained by the NLP startup.

Will the dataset be updated? How often and by whom? No updates are planned at this time.

Is there a repository to link to any/all papers/systems that use this dataset? The dataset is available on HuggingFace[34].

Legal & Ethical Considerations

If the dataset relates to people, were they informed about the data collection? The clinical cases were provided by healthcare professionals; any personal details have been removed to ensure anonymity. They were anonymized by the healthcare professionals themselves, before transferring the data to the NLP startup.

If it relates to other ethically protected subjects, have appropriate obligations been met? Yes, all obligations have been met and ensured in the data collection process.

If it relates to people, were there any ethical review applications/reviews/approvals? Yes, healthcare professionals ensured the ethical review was complete.

If it relates to people, were they told what the dataset would be used for and did they consent? Yes, patients were told in advance about the objective of data collection and they provided their consent for this use.

[33] https://hf.co/datasets/LenguajeNaturalAI/ClinTreatES

[34] https://hf.co/datasets/LenguajeNaturalAI/ClinTreatES

If it relates to people, could this dataset expose people to harm or legal action? No, as the data is anonymized by the healthcare professionals.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? No.

If it relates to people, were they provided with privacy guarantees? Yes, all personal information has been removed by the healthcare professionals.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? Yes, it complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No, all potentially sensitive or confidential information has been removed.

Does the dataset contain information that might be considered inappropriate or offensive? No.

ClinDiagnosES

The ClinDiagnosES (LenguajeNatural.AI, 2024b) dataset comprises clinical cases accompanied by corresponding diagnoses, collected directly from healthcare professionals across multiple specialties in Europe. It is intended for evaluating LLMs' diagnostic reasoning abilities.

Motivation for Dataset Creation

Why was the dataset created? ClinDiagnosES was created to assess the ability of LLMs to generate accurate diagnoses based on clinical case descriptions.

What (other) tasks could the dataset be used for? Besides diagnostic evaluation, it can be used to study medical reasoning; however, it is not suitable for treatment planning tasks.

Who funded the creation of the dataset? The dataset was developed through a collaboration between LenguajeNatural.AI and healthcare professionals.

Dataset Composition

What are the instances? Each instance consists of a clinical case description along with its corresponding diagnosis.

Are relationships between instances made explicit in the data? No, there are no explicit relationships between instances.

How many instances of each type are there? The dataset contains 62 examples.

What data does each instance consist of? Each instance includes text data representing a clinical case and its associated diagnosis.

Is everything included or does the data rely on external resources? The dataset is self-contained.

Are there recommended data splits or evaluation measures? No specific splits are recommended; it is intended for evaluation purposes.

Data Collection Process

How was the data collected? Data was collected directly from healthcare professionals across various medical specialties.

Who was involved in the data collection process? Healthcare professionals from fields such as cardiology, traumatology, emergency medicine, psychiatry, neurology, dermatology, ENT-laryngology, and anesthesia contributed.

Over what time-frame was the data collected? The data was collected in 2024.

How was the data associated with each instance acquired? Each clinical case was accompanied by a diagnosis provided by a medical expert.

Does the dataset contain all possible instances? It is a curated collection and does not encompass every possible clinical case.

If the dataset is a sample, then what is the population? The dataset represents a curated sample of clinical cases from European medical centers.

Is there information missing from the dataset and why? No, all necessary information is included.

Are there any known errors, sources of noise, or redundancies in the data? The dataset has been reviewed to minimize errors and inconsistencies.

Data Preprocessing

What preprocessing/cleaning was done? The clinical cases and diagnoses were formatted using a standardized template with minimal cleaning.

Was the "raw" data saved in addition to the preprocessed/clean data? Yes, the raw clinical texts and diagnoses are preserved.

Is the preprocessing software available? No specific preprocessing software was utilized.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes, the procedure ensures the dataset is suitable for evaluating diagnostic reasoning in LLMs.

Dataset Distribution

How is the dataset distributed? The dataset is available on HuggingFace[35].

When will the dataset be released/first distributed? It was released in March 2024.

What license (if any) is it distributed under? It is distributed under the CC BY-NC-SA 4.0 license.

Are there any fees or access/export restrictions? There are no fees or restrictions.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? The dataset is hosted on HuggingFace and maintained by the NLP startup.

Will the dataset be updated? How often and by whom? No updates are planned at this time.

Is there a repository to link to any/all papers/systems that use this dataset? The dataset is available on HuggingFace[36].

Legal & Ethical Considerations

If the dataset relates to people, were they informed about the data collection? The clinical cases were provided by healthcare professionals; any personal details have been removed to ensure anonymity. They were anonymized by the healthcare professionals themselves, before transferring the data to the NLP startup.

If it relates to other ethically protected subjects, have appropriate obligations been met? Yes, all obligations have been met and ensured in the data collection process.

If it relates to people, were there any ethical review applications/reviews/approvals? Yes, healthcare professionals ensured the ethical review was complete.

If it relates to people, were they told what the dataset would be used for and did they consent? Yes, patients were told in advance about the objective of data collection and they provided their consent for this use.

If it relates to people, could this dataset expose people to harm or legal action? No, as the data is anonymized by the healthcare professionals.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? No.

If it relates to people, were they provided with privacy guarantees? Yes, all personal information has been removed by the healthcare professionals.

[35] https://hf.co/datasets/LenguajeNaturalAI/ClinDiagnosES

[36] https://hf.co/datasets/LenguajeNaturalAI/ClinDiagnosES

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? Yes, it complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No, all potentially sensitive or confidential information has been removed.

Does the dataset contain information that might be considered inappropriate or offensive? No.

HumorQA

The HumorQA dataset (LenguajeNatural.AI, 2024a), developed collaboratively by LenguajeNatural.AI and Human Profit Consulting, focuses on humor classification. It consists of jokes paired with labels indicating the joke type: C/E (Comparison/Exaggeration), JP (Wordplay), R3 (Rule of Three) and AI (Animating the Inanimate). The data set is based on a study involving 94 executives and is intended to evaluate the ability of LLMs to understand and classify humor.

Motivation for Dataset Creation

Why was the dataset created? HumorQA was created to assess the ability of LLMs to recognize and classify different types of humor.

What (other) tasks could the dataset be used for? It can also be used for research on sentiment analysis and humor recognition, although its primary purpose is humor classification.

Who funded the creation of the dataset? The dataset was developed through a collaboration between an NLP startup and a psychology consulting firm.

Dataset Composition

What are the instances? Each instance comprises a joke and its corresponding humor-type label.

Are relationships between instances made explicit in the data? No, there are no explicit relationships between instances.

How many instances of each type are there? The dataset contains 51 examples.

What data does each instance consist of? Each instance includes text data representing a joke and a label indicating its humor category.

Is everything included or does the data rely on external resources? The dataset is self-contained.

Are there recommended data splits or evaluation measures? No specific splits are recommended; it is intended for evaluation purposes.

Data Collection Process

How was the data collected? Jokes were collected and curated as part of a research study involving humor workshops and interviews with 94 executives.

Who was involved in the data collection process? The data collection involved humor experts at Human Profit Consulting along with participating executives.

Over what time-frame was the data collected? The data was collected in 2024.

How was the data associated with each instance acquired? Jokes were labeled according to a predefined categorization based on the study's methodology.

Does the dataset contain all possible instances? It is a curated sample representing various humor styles.

If the dataset is a sample, then what is the population? The sample represents humorous content identified in a study with executives from diverse sectors.

Is there information missing from the dataset and why? No, all relevant information is included.

Are there any known errors, sources of noise, or redundancies in the data? The dataset has been thoroughly reviewed; no significant errors or redundancies have been identified.

Data Preprocessing

What preprocessing/cleaning was done? The jokes and labels were formatted into a standardized template with minimal preprocessing.

Was the "raw" data saved in addition to the preprocessed/clean data? Yes, the original joke texts are preserved.

Is the preprocessing software available? No specific preprocessing software was used.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes, the curation process supports the evaluation of humor classification by LLMs.

Dataset Distribution

How is the dataset distributed? The dataset is available on HuggingFace[37].

When will the dataset be released/first distributed? It was released in March 2024.

What license (if any) is it distributed under? It is distributed under the CC BY-NC-SA 4.0 license.

Are there any fees or access/export restrictions? There are no fees or restrictions.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? The dataset is hosted on HuggingFace by the NLP startup.

Will the dataset be updated? How often and by whom? No updates are planned at this time.

Is there a repository to link to any/all papers/systems that use this dataset? The dataset is available on HuggingFace[38].

Legal & Ethical Considerations

If the dataset relates to people, were they informed about the data collection? The dataset is based on humorous content and research; it does not involve personal data.

If it relates to other ethically protected subjects, have appropriate obligations been met? Not applicable.

If it relates to people, were there any ethical review applications/reviews/approvals? Not applicable.

If it relates to people, were they told what the dataset would be used for and did they consent? Not applicable.

If it relates to people, could this dataset expose people to harm or legal action? No.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? No.

If it relates to people, were they provided with privacy guarantees? Not applicable.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? Yes, it complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No.

Does the dataset contain information that might be considered inappropriate or offensive? No.

[37] https://hf.co/datasets/LenguajeNaturalAI/HumorQA

[38] https://hf.co/datasets/LenguajeNaturalAI/HumorQA

RagQuAS

The Retrieval-Augmented-Generation and Question-Answering in Spanish (RagQuAS) dataset (Instituto de Ingeniería del Conocimiento, 2024b), created by Instituto de Ingeniería del Conocimiento, is a high-quality monolingual Spanish dataset designed to evaluate models in retrieval-augmented generation (RAG) and question-answering tasks. It consists of 201 examples covering a wide range of knowledge domains, such as hobbies, linguistics, health, astronomy, and customer service. Each example includes a question, multiple context passages extracted from different documents, and a gold-standard answer. This dataset is particularly useful for assessing a model's ability to retrieve relevant information from multiple sources and generate accurate, contextually appropriate responses.

Motivation for Dataset Creation

Why was the dataset created? (e.g., were there specific tasks in mind, or a specific gap that needed to be filled?) RagQuAS was created to provide high-quality examples of questions and answers with related contexts that can be used to evaluate models in retrieval-augmented generation (RAG) and question-answering tasks.

What (other) tasks could the dataset be used for? Are there obvious tasks for which it should not be used? There are no recommended uses for this dataset other than evaluation.

Who funded the creation of the dataset? If there is an associated grant, provide the grant number. The dataset was created and funded by Instituto de Ingeniería de Conocimiento.

Dataset Composition

What are the instances? (that is, examples; e.g., documents, images, people, countries) Are there multiple types of instances? (e.g., movies, users, ratings; people, interactions between them; nodes, edges) Each instance consists of several categories of text: the topic, a question, an indicator of the variant of the question (this represents questions with linguistic differences but pertaining to the same contexts than other questions), an answer, one to five contexts, one to five complete documents from where the contexts were extracted and the links to these documents.

Are relationships between instances made explicit in the data (e.g., social network links, user/movie ratings, etc.)? There are no known relationships between instances.

How many instances of each type are there? The dataset consists of 201 examples.

What data does each instance consist of? "Raw" data (e.g., unprocessed text or images)? Features/attributes? Is there a label/target associated with instances? If the instances are related to people, are subpopulations identified (e.g., by age, gender, etc.) and what is their distribution? The instances consist of text data and are labeled with the corresponding topic.

Is everything included or does the data rely on external resources? Everything is included in the dataset.

Are there recommended data splits or evaluation measures? Since the dataset is intended for testing, there is no recommended split.

Data Collection Process

How was the data collected? The data for the contexts was gathered from different sources manually with the help of generative models (to suggest web searches and results). The rest of the dataset was curated and created manually.

Who was involved in the data collection process? How were they compensated? The data was collected by computational linguists and data scientists from the research institute.

Over what time-frame was the data collected? The data was collected during 2023, when the dataset was created.

How was the data associated with each instance acquired? The question-answer pairs were created and revised by computational linguists.

Does the dataset contain all possible instances? The dataset is composed of selected instances of a dataset created by the research institute.

If the dataset is a sample, then what is the population? This dataset is a 24% sample of the original complete datasets. The instances were randomly selected from the original dataset.

Is there information missing from the dataset and why? There is no data missing.

Are there any known errors, sources of noise, or redundancies in the data? There are no known errors because the revision process ensured the data is as clean and error free as possible.

Data Preprocessing

What preprocessing/cleaning was done? The text contained in context and document part of each instance in the dataset has not undergone any preprocessing or changes. The questions were created manually by computational linguists following a rigorous methodology and were subjected to revision afterwards. The answers were carefully curated and revised by linguists from generated texts.

Was the "raw" data saved in addition to the preprocessed/clean data? No, the text in the dataset is the raw data.

Is the preprocessing software available? No preprocessing software was used.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes, the methodology used when creating the dataset ensures it is sufficiently varied so it can be used to evaluate a model on a wide range of topics. However, there are some potential limitations in the dataset which might slightly bias the data towards particular topics, because not all topics included have the exact same representation in the dataset, and obviously it was not possible to cover all topics in existence.

Dataset Distribution

How is the dataset distributed? The dataset is available in HuggingFace[39].

When will the dataset be released/first distributed? The dataset was released in 2024.

What license (if any) is it distributed under? Are there any copyrights on the data? The dataset is licensed under CC BY-NC-SA 4.0.

Are there any fees or access/export restrictions? There are no fees or restrictions.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? How does one contact the owner/curator/manager of the dataset? The dataset is hosted at HuggingFace, and the research institute can be contacted through email contacto.iic@iic.uam.es.

Will the dataset be updated? How often and by whom? How will updates/revisions be documented and communicated? Is there an erratum? It is not planned to update the dataset at the moment.

Is there a repository to link to any/all papers/systems that use this dataset? No.

Legal & Ethical Considerations

If the dataset relates to people or was generated by people, were they informed about the data collection? Not applicable. The data was collected from public web sources, and does not contain sensitive personal information.

If it relates to other ethically protected subjects, have appropriate obligations been met? Not applicable.

If it relates to people, were there any ethical review applications/reviews/approvals? Not applicable.

If it relates to people, were they told what the dataset would be used for and did they consent? Not applicable.

If it relates to people, could this dataset expose people to harm or legal action? Not applicable.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? Not applicable.

If it relates to people, were they provided with privacy guarantees? Not applicable.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? The dataset complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No.

Does the dataset contain information that might be considered inappropriate or offensive? No.

[39] https://hf.co/datasets/IIC/RagQuAS

SpaLawEx

The SpaLawEx dataset (LenguajeNatural.AI, 2024c) consists of multiple-choice legal questions extracted from Spanish Bar Examination papers of 2022 and 2023. Each instance includes a legal question along with four answer options (A, B, C, and D).

Motivation for Dataset Creation

Why was the dataset created? SpaLawEx was created to evaluate the legal reasoning and knowledge of LLMs within the context of Spanish law using multiple-choice questions.

What (other) tasks could the dataset be used for? In addition to benchmarking legal question answering systems, it may be used for legal education; it is not intended for non-legal tasks.

Who funded the creation of the dataset? The dataset was developed by an NLP startup, with contributions from legal experts.

Dataset Composition

What are the instances? Each instance is a multiple-choice legal question accompanied by four answer options.

Are relationships between instances made explicit in the data? No, there are no explicit relationships between instances.

How many instances of each type are there? The dataset contains 119 examples.

What data does each instance consist of? Each instance comprises text data, including a legal question and its four answer options (A, B, C, and D).

Is everything included or does the data rely on external resources? The dataset is self-contained, extracted from publicly available examination papers.

Are there recommended data splits or evaluation measures? No specific splits are recommended; the dataset is intended for evaluation purposes.

Data Collection Process

How was the data collected? Data were extracted from official Spanish Bar Examination papers from 2022 and 2023.

Who was involved in the data collection process? The extraction was performed by the developers at an NLP startup, with input from legal experts.

Over what time-frame was the data collected? The data was collected in 2024.

How was the data associated with each instance acquired? Questions and answer options were directly extracted from exam documents.

Does the dataset contain all possible instances? It is a comprehensive collection of questions from the specified examination periods. However, it is not exhaustive and it does not contain all possible instances.

If the dataset is a sample, then what is the population? It represents the pool of questions from the Spanish Bar Examinations of 2022 and 2023.

Is there information missing from the dataset and why? No, all relevant information is included.

Are there any known errors, sources of noise, or redundancies in the data? The dataset has been checked for accuracy; any minor extraction errors are not known to be significant.

Data Preprocessing

What preprocessing/cleaning was done? The exam questions and answer options were formatted into a standardized template with minimal cleaning.

Was the "raw" data saved in addition to the preprocessed/clean data? Yes, the original extracted text is preserved.

Is the preprocessing software available? No specific preprocessing software was used.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes, the process ensures the dataset is suitable for evaluating legal reasoning in LLMs.

Dataset Distribution

How is the dataset distributed? The dataset is available on HuggingFace[40].

When will the dataset be released/first distributed? It was released in March 2024.

[40]https://hf.co/datasets/LenguajeNaturalAI/SpaLawEx

What license (if any) is it distributed under? It is distributed under the CC BY-NC-SA 4.0 license.

Are there any fees or access/export restrictions? There are no fees or restrictions.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? The dataset is hosted on HuggingFace by the NLP startup.

Will the dataset be updated? How often and by whom? No updates are planned at this time.

Is there a repository to link to any/all papers/systems that use this dataset? No repository has been provided.

Legal & Ethical Considerations

If the dataset relates to people, were they informed about the data collection? The dataset is derived from public examination materials and does not involve personal data.

If it relates to other ethically protected subjects, have appropriate obligations been met? Not applicable.

If it relates to people, were there any ethical review applications/reviews/approvals? Not applicable.

If it relates to people, were they told what the dataset would be used for and did they consent? Not applicable.

If it relates to people, could this dataset expose people to harm or legal action? No.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? No.

If it relates to people, were they provided with privacy guarantees? Not applicable.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? Yes, it complies with GDPR.

Does the dataset contain information that might be considered sensitive or confidential? No.

Does the dataset contain information that might be considered inappropriate or offensive? No.

TELEIA

The TELEIA (Mayor-Rocher et al., 2025) dataset is intended for the evaluation of Spanish language knowledge focusing on reading comprehension and grammatical competence. The dataset is designed as a set of multiple-choice questions that have the same format and level as those used in several Spanish evaluation tests for humans. The questions are divided into three blocks which resemble existing tests of Spanish for foreign learners and University access. In total, one hundred questions are included that have been prepared and revised by experts on Spanish language, and that have been validated by comparing the results with the original exams.

Motivation for Dataset Creation

Why was the dataset created? The main motivation was to have a simple test to evaluate the competence of LLMs in Spanish, similar to tests used with humans.

What (other) tasks could the dataset be used for? The test also checks reading comprehension and thus can be used to evaluate natural language understanding.

Who funded the creation of the dataset? The development of the dataset was supported by the FUN4DATE (PID2022-136684OB-C22) project funded by the Spanish Agencia Estatal de Investigación (AEI) 10.13039/501100011033.

Dataset Composition

What are the instances? The test is made of multiple-choice questions.

Are relationships between instances made explicit in the data No.

How many instances of each type are there? The dataset consists of 100 questions.

What data does each instance consist of? Each question has a text presenting the question and four answer options, of which only one is correct.

Is everything included or does the data rely on external resources? Everything is included in the dataset.

Are there recommended data splits or evaluation measures? No.

Data Collection Process

How was the data collected? Questions were formulated and peer-reviewed by experts in Spanish.

Who was involved in the data collection process? Experts in Spanish who participated as researchers in our group.

Over what time-frame was the data collected? The questions were created during the spring of 2024.

How was the data associated with each instance acquired? Data was created by experts.

Does the dataset contain all possible instances? Questions are examples, and many other similar questions can be formulated.

If the dataset is a sample, then what is the population? Not applicable.

Is there information missing from the dataset and why? No.

Are there any known errors, sources of noise, or redundancies in the data? No.

Data Preprocessing

What preprocessing/cleaning was done? None.

Was the "raw" data saved in addition to the preprocessed/clean data? Not applicable.

Is the preprocessing software available? Not applicable.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? Yes.

Dataset Distribution

How is the dataset distributed? Websites.

When will the dataset be released/first distributed? Data is available since July 2024.

What license (if any) is it distributed under? No license or restrictions are applicable.

Are there any fees or access/export restrictions? No.

Dataset Maintenance

Who is supporting/hosting/maintaining the dataset? The dataset is hosted at Zenodo[41] providing contact details for all the authors.

Will the dataset be updated? No updates are expected, but the repository supports versioning.

Is there a repository to link to any/all papers/systems that use this dataset? No.

Legal & Ethical Considerations

If the dataset relates to people (e.g., their attributes) or was generated by people, were they informed about the data collection? Not applicable.

If it relates to other ethically protected subjects, have appropriate obligations been met? Not applicable.

If it relates to people, were there any ethical review applications/reviews/approvals? Not applicable.

If it relates to people, were they told what the dataset would be used for and did they consent? Not applicable.

If it relates to people, could this dataset expose people to harm or legal action? Not applicable.

If it relates to people, does it unfairly advantage or disadvantage a particular social group? Not applicable.

If it relates to people, were they provided with privacy guarantees? Not applicable.

Does the dataset comply with the EU General Data Protection Regulation (GDPR)? Yes.

Does the dataset contain information that might be considered sensitive or confidential? No.

Does the dataset contain information that might be considered inappropriate or offensive? No.

[41] https://zenodo.org/records/12571763