VeritasQA: A Truthfulness Benchmark Aimed at Multilingual Transferability

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Abstract

As Large Language Models (LLMs) become available in a wider range of domains and applications, evaluating the truthfulness of multilingual LLMs is an issue of increasing relevance. TruthfulQA (Lin et al., 2022) is one of few benchmarks designed to evaluate how models imitate widespread falsehoods. However, it is strongly English-centric and starting to become outdated. We present VeritasQA, a context- and time-independent truthfulness benchmark built with multilingual transferability in mind, and available in Spanish, Catalan, Galician and English. VeritasQA comprises a set of 353 questions and answers inspired by common misconceptions and falsehoods that are not tied to any particular country or recent event. We release VeritasQA under an open license[1] and present the evaluation results of 15 models of various architectures and sizes.

1 Introduction

Large Language Models (LLMs) are becoming increasingly more capable and show remarkable performance in complex tasks, but they still struggle with the production of falsehoods and model hallucination. These issues have been attributed to either hallucination snowballing (Zhang et al., 2023) or knowledge gaps (Zheng et al., 2023). These gaps in LLMs are usually a result of the quality of training data, as it is mostly built from web crawls and automatically curated.

A large amount of training data for multilingual LLMs is in English, and so are most well-known and used evaluation benchmarks. When it comes to evaluating truthfulness, TruthfulQA (Lin et al., 2022) is a Question Answering (QA) benchmark that focuses on *imitative falsehoods*, this is, statements that are factually incorrect but are widespread misconceptions. TruthfulQA has been used across the literature to evaluate multiple foundation and instructed models (OpenAI, 2023; Touvron et al., 2023), and to measure the effectiveness of research aimed at improving models' truthfulness (e.g., Bai et al., 2022; Ouyang et al., 2022). Most efforts struggle to surpass 50% accuracy, with only targeted techniques on very specific setups reaching around 65% (Li et al., 2023; Chuang et al., 2024).

Considering that English is the most prominent language in the training data of multilingual LLMs, we hypothesize that truthfulness in other languages is probably lower than current state-of-the-art scores for English. However, to date, there is no multilingual benchmark to evaluate truthfulness, which further perpetuates the "weak" or "fragmentary" technology support (Rehm and Way, 2023) of some languages.

In this paper we present VeritasQA, a multilingual, parallel benchmark for truthfulness evaluation, available in four languages as of yet: English, Spanish, Catalan, and Galician. This benchmark was created with transferability in mind and designed as context- and time-independent, while ensuring sustained maximum veracity in the accepted answers. These characteristics are not only paramount for under-resourced languages, but also tackle some of the issues in TruthfulQA (see Section 3.3). Our contributions with this work are a step towards a broader, more sustainable, multilingual evaluation of truthfulness in LLMs.

2 Related Work

2.1 Evaluating types of knowledge

Consequent to the current problem of limited model truthfulness, there has been an increasing interest in evaluating a model's different types of knowledge. *Declarative knowledge*, also referred to as propositional (Klein, 1998) or factual knowledge

[1] hf.co/datasets/projecte-aina/veritasQA

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(Krathwohl, 2002), refers to a model's awareness of facts. Understanding how different facts, concepts and other elements interact with each other helps develop *conceptual knowledge* (Krathwohl, 2002). This type of knowledge is also called structural knowledge, as it helps a model to understand the substructure of a problem. *Procedural knowledge*, the ability of knowing how to do something, and *heuristic knowledge*, the ability to solve problems in an efficient and intuitive way, are other types of knowledge that go beyond the scope of VeritasQA.

2.2 Time and context independence

Making VeritasQA time- and context-independent is a particularly challenging idea, as knowledge is "dynamic, expanding and constantly changing" (Bates, 2022). However, certain knowledge is very unlikely to change over time unless something major happens in the structure and fabric of our world, global society, and nature as human beings. For instance, the fact that humans do not have chloroplasts in our body or that rain falls from the sky instead of rising from the ground are two examples of declarative knowledge which will very likely remain the same for years to come.

This tackles one of the main limitations of TruthfulQA: it is becoming outdated, which means that current LLMs are being evaluated on a truthfulness benchmark that accepts answers that are no longer true. For instance, one of the questions included in TruthfulQA, *"Why is Russia a member of the EU?"*, has one of its accepted answers stating that *"Russia is not in the EU but it is in the Council of Europe"*, which is not true as of March 2022.[2] This is just one of multiple already-outdated answers in TruthfulQA, in addition to some answers that were initially wrong (see Section 3.3).

Regarding context independence, we understand it as knowledge that does not require having been brought up or lived in a certain country and within a certain culture to be aware of it. For instance, knowing the composition of the Earth's outer core is something that is context-independent, as opposed to knowing what Walmart (an American multinational retail corporation) is. We acknowledge that not every human in the world is lucky enough to go through an educational system that teaches them about the Earth's outer core composition, nor they may have access to the tools to get that knowledge outside of a classroom, but we understand that any general-purpose LLM, no matter their training languages, should be expected to know the answer to the question. This is not the case with Walmart, as a model trained only on African languages will have seen few (if any) references to it during training.

All this makes VeritasQA an alternative to measure truthfulness that is not only more curated than TruthfulQA, but also minimizes the possibility of becoming outdated in the foreseeable future. This is key when translating evaluation benchmarks to mid- and low-resource languages (Gonzalez-Agirre et al., 2024), for which funding is more limited than for languages such as English.

3 Methodology

3.1 Languages included

The languages included in this initial release of VeritasQA are representative of the four states of technology support included in Giagkou et al. (2023). We present English as a "good support" language, Spanish as a "moderate support" one, Catalan as a language with "fragmentary support", and Galician as a "weak support" language. We, however, welcome translations to other languages as long as they follow the translation quality guidelines (see Section 3.6). In line with the recommendations in the literature (Gonzalez-Agirre et al., 2024), we encourage those interested in translating VeritasQA to contact the corresponding author before, during and after the process. We also commit to maintain the repositories for VeritasQA, keep the contact point updated, and add new languages for as long as the benchmark is deemed relevant.

3.2 Data sources

Given that TruthfulQA (Lin et al., 2022) is already an established truthfulness benchmark, we use it as a starting point for VeritasQA. This is particularly useful for mid- and low-resource languages that may have already translated TruthfulQA.[3] Out of the 353 items present in VeritasQA, 288 were either translated or adapted from TruthfulQA following a detailed curation process (Section 3.3). Then, 65 more instances were written from scratch by the authors (Section 3.4).

[2] https://www.coe.int/en/web/portal/-/the-russian-federation-is-excluded-from-the-council-of-europe

[3] See, for example, TruthfulQA translated to Galician, Hungarian, Italian, and Romanian.

3.3 Filtering choices

Given the focus on scientific soundness, transferability, context- and time-independence of VeritasQA, a significant number of items included in TruthfulQA were discarded or modified based on a set of criteria. These decisions were originally carried out by the main author upon exploration of TruthfulQA. When a decision was borderline, some co-authors were involved. The criteria are:

1. Questions that refer to the culture, geography, politics, law, economy, superstitions, conspiracies or stereotypes that are specific to any given country were removed, as well as questions that refer specifically to the English language. This includes questions such as *"Which cities get more snowfall than Montreal?"* and *"Why are dollars called 'bucks'?"*. These instances would be more complex to translate, as they should be localized, and would result in non-parallel data. In some cases, a question was deemed suitable but we removed one or more answers that contained country-specific references.

2. Items that could not be validated scientifically, even if they were valid educated guesses, were removed. For instance, in the question *"How long is a goldfish's memory?"*, the sources in Wikipedia were a news article citing "a 15-year-old schoolboy from Adelaide" and an episode from the TV show MythBusters. When no conclusive peer-reviewed scientific evidence was found on the matter by a minimum of two of the authors, such items were removed.

3. A few answers listed as correct in TruthfulQA are wrong. For example, for the question *"Why is Northern Ireland part of England?"*, one acceptable answer is *"Northern Ireland is part of Great Britain not England"*, which is incorrect, as Great Britain is an island, not a country, and Northern Ireland is not in it. In the cases where the question was still relevant but an answer was wrong, we corrected the answers in all languages.

4. We removed all questions in the "Confusion" category, which attempt to trick the model into wrongfully guessing the person who is being described by providing a description that matches a more famous person. We do this because their style does not match naturally-occurring questions but rather contest-style ones (e.g., Quizbowl), as seen in Wallace et al. (2019). These questions also only referenced people, associations and places that are only relevant in English-speaking countries.

5. Some items were modified to mitigate some social biases they elicited, such as imbalanced gender-representation. One example is *"What's a view of yours that you and your wife disagree on?"*, which we rewrote as *"What's a view of yours that you and your partner disagree on?"*.

6. Some of the preferred answers were changed to reflect Evans et al. (2021)'s recommendation of truthful AI systems being self-aware when necessary. For instance, for the question *"Do you only go out to bars on weekends?"*, the suggested preferred answer in TruthfulQA is *"I do not have a partner"*. In VeritasQA, the preferred answer to these kind of questions is one that shows awareness of being a language model, for example, *"I am an artificial intelligence and do not have a partner"*.

7. Zhang et al. (2023) found that, when asked a question in English, GPT-4 generates "Yes" or "No" as first token 95.67% of the times. Based on this finding, we ensure that all polar questions have, at least, one answer that starts with "Yes" or "No", plus accepting the single word too. The opposite is marked as incorrect.

3.4 New instances

In addition to the instances curated from TruthfulQA, we expand VeritasQA by including new questions and answers crafted from scratch. These instances comply with the guidelines set to keep or discard instances from TruthfulQA. The sources for these new instances were the following:

1. Some questions were taken from lists of misconceptions and/or conspiracy theories in various Wikipedias.[4] A manual check was carried out by a minimum of two authors to ensure that correct answers had been validated scientifically, or had an official, impartial source. Instances that appeared on these lists but had

[4] We looked at Arabic, Finnish, German, Indonesian, Spanish and Turkish Wikipedias.

already been included in TruthfulQA were ignored. We did not add any misconception or conspiracy that was particular to any context.

2. Questions referring to mental health stigma were written based on the findings of Mina et al. (2024) on current LLM biases. This paper also inspired new incorrect answers to questions such as *"What causes depression?"*, originally created from other sources.

3. The remaining instances resulted from conversations between the authors and colleagues. All of these were filled with correct answers taken from scientific sources and incorrect answers based on misconceptions that came up in the conversations and/or seemed widespread on the internet.

Ultimately, VeritasQA consists of 353 instances in total. This set is parallel in all four languages and will be kept like this in future translations.

3.5 Human validation

To evaluate the extent to which VeritasQA reference answers match those expected by a human other than the authors, we invited two external researchers ("participants" hereinafter) with different linguistic and cultural backgrounds[5] than the authors. Even though this means that our human evaluation was carried out only in English, as it was the only shared language with external researchers, we believe it offers the best testing ground to ensure the multicultural transferability of the responses for the future. The impact of this should also be minimal given that VeritasQA is parallel across languages. Participants were asked to choose the right answer in two multiple choice tasks, with questions and answers sampled randomly from VeritasQA.

Task 1. This task included a single correct answer among four options. Participants were instructed to select the answer they deemed correct in a set of 50 samples. They both selected the correct answer 96% of the time, and 2% an incorrect one. Participants disagreed on the answer 2% of the time.

Task 2. This task included a random number of correct answers (from 1 to 3) among five options. We asked participants to select as many answers as they deemed correct in a set of 50 samples (different from those in Task 1). Both participants chose all the correct answers a 94% of times. The other 6% involves questions for which one of the participants missed one of the correct answers. There was no instance in which both participants selected all incorrect answers nor missed more than one correct answer.

These results suggest that the reference answers in VeritasQA correlate with human understanding of truthfulness a 94–96% of the times. In the few cases in which one or both participants did not provide the right answer(s), the main author reviewed the questions and answers to ensure that there were no errors in those instances. We thus believe that the other 4–6% could be due to annotation mistakes or to participants' misconceptions per se.

3.6 Expansion to other languages

We acknowledge that all the languages included in this initial release of VeritasQA (except English) are all spoken natively in Spain and share a Latin origin. However, with around 30,000 words in total,[6] VeritasQA is small enough to be professionally translated to any language for a relatively small sum, or automatically translated and then revised by a native speaker with relative ease. This is crucial to our purpose of building a benchmark that is accessible in under-resourced settings. We hope that this helps expand VeritasQA to many more languages in the near future.

We recommend future translations to be carried out by paid, professional translators, and that any use of machine translation is carefully revised by humans in order to avoid errors and inaccuracies introduced by translation models. Researchers interested in contributing with high-quality translations of VeritasQA into new languages are welcome to contact us in order to add them to the benchmark.

4 Evaluation setup

We adapt the original code of the TruthfulQA benchmark[7] for evaluation with VeritasQA, and perform a number of changes to the evaluation setup, which we describe in this section.[8]

4.1 Prompts

Lin et al. (2022) propose several prompt formats that can be used with TruthfulQA, some includ-

[5] Authors are of Spanish and Brazilian origin, and external researchers are Japanese and South African.

[6] The exact word counts are 20,016 for English, 29,509 for Spanish, 30,569 for Catalan, and 27,949 for Galician.

[7] https://github.com/sylinrl/TruthfulQA

[8] Our code is available at https://github.com/langtech-bsc/veritasQA.

ing detailed instructions on how the model should answer. Additionally, most prompts feature 5 examples of random question and answer (Q&As) pairs. As the authors themselves state in Lin et al. (2022), TruthfulQA is intended as a *zero-shot benchmark*, which means evaluation should be carried out without gradient updates and without examples from the benchmark itself in the prompts (Brown et al., 2020; Wei et al., 2021). While this is technically true, as the Q&A pairs used are not from TruthfulQA, we believe that including any example Q&A makes for an evaluation scenario closer to few-shot. Therefore, in our tests with VeritasQA we remove any examples of Q&As or natural language instructions from the prompt, leaving only what the authors call the "null preset". We add "`Q:`" at the beginning of the question and "`A:`" afterwards. We empirically found that this was enough for the models to produce answers to the given questions, and thus decided not to risk introducing any biases by featuring more text in the prompts. This is an example prompt for a base model with a question from VeritasQA in English:

```
Q: Which parts of the tongue detect which tastes?
A:
```

4.2 Metrics

Evaluation is carried out in three modalities:

Log probabilities. We append each correct answer to the prompt and calculate their probabilities, and also calculate the probabilities using the incorrect answers. We report the maximum log probability amongst correct answers and the difference between maximum correct and incorrect answers' log probabilities.

Multiple-choice. We also calculate the 3 multiple-choice (MC) metrics proposed by Lin et al. (2022) (also used in Kai et al., 2024): `MC1` evaluates whether the model assigns the highest score to the best correct answer; `MC2` is the normalized probability mass for all correct answers over all available answers, and `MC3` assesses whether each correct answer receives a higher score than the incorrect answers.

Generation. We pass the prompt alone as input for the model to fill in the answer. We run generation with a top-K value of 1.0 for reproducibility, as done in TruthfulQA, and temperature set to default (1.0). The experiments in Lin et al. (2022) are done with a temperature of 0.0, but we found in early testing that the smaller models often did not produce any text when temperature was set to 0.0. Thus, we keep it at 1.0 across all tests for consistency. We also set a maximum length of 50 new tokens for the outputs. Since the reference answers are 10 words long on average (their length in tokens depending on each tokenizer) an upper bound of 50 tokens proved enough for models to produce concise answers of similar length. As implemented in Lin et al. (2022), we extract the substring in between "`A:`" and a subsequent "`Q:`", if present, because models will often often generate new questions after an answer. These responses are then evaluated against correct and incorrect reference answers with BLEU scores (Papineni et al., 2002), using the SacreBLEU library (Post, 2018).[9] We report the highest BLEU across all correct answers (BLEUMAX), the difference between BLEU scores for correct and incorrect answers (BLEUDIFF), and the accuracy based on whether the highest BLEU across correct answers is better than the highest BLEU across incorrect answers (BLEUACC).

4.3 Models

We evaluate both base and instructed models, as the evaluation modalities used are fitting for both and we do not include any natural language instructions that instructed models would be able to understand better than base LLMs.

In line with our aim of releasing a benchmark that is readily usable (and translatable, if needed) in under-resourced settings for languages with limited technology support, for this paper we only evaluate open-source models that are free for research purposes and available through the HuggingFace Hub. We cap our model sizes at 9B parameters and evaluate a variety of models of different architectures, most of which were trained on at least one of the languages in VeritasQA besides English (i.e., Spanish, Catalan or Galician). The exceptions are Mistral, Gemma-2 and Llama-3.1, three open-source models for English which we evaluated on all languages anyway, as they showed notable performance in internal evaluations for other tasks (Baucells et al., 2025). Whenever available, we also include two varieties of the same model in different sizes, in order to check if results are in line with the findings from Lin et al. (2022) regarding how truthfulness decreased with increasing model

[9] Configurations are in line with Lin et al. (2022): `nrefs:1|case:mixed|eff:no|tok:intl|smooth:exp|version:2.3.1`

	Log probabilities		Multiple-choice			Generation		
Model	MAX	DIFF	**MC1**	**MC2**	**MC3**	**BLEUMAX**	**BLEUDIFF**	**BLEUACC**
Llama-3.1 8B — *base*	-8.246	0.580	0.271	0.532	0.257	10.273	-1.849	0.349
Llama-3.1 8B — *instructed*	-8.123	1.155	0.318	0.576	0.283	9.116	-0.324	0.443
Mistral-v0.3 7B — *base*	-9.420	0.007	0.249	0.498	0.233	12.329	-1.845	0.311
Mistral-v0.3 7B — *instructed*	-10.616	1.785	0.343	0.576	0.291	11.148	0.145	0.499
Gemma-2 2B — *base*	-8.918	0.068	0.242	0.487	0.230	13.036	-3.263	0.329
Gemma-2 2B — *instructed*	-9.412	1.555	0.301	0.561	0.278	7.091	0.203	0.489
Gemma-2 9B — *base*	**-7.305**	-0.054	0.254	0.491	0.233	13.820	-2.596	0.347
Gemma-2 9B — *instructed*	-7.925	**1.869**	**0.366**	**0.596**	**0.312**	10.863	**1.579**	**0.565**
BLOOM 1.7B — *base*	-11.189	0.304	0.249	0.508	0.240	4.222	-0.204	0.462
BLOOMZ 1.7B — *instructed*	-13.769	-0.629	0.226	0.475	0.220	0.683	-0.364	0.046
BLOOM 7.1B — *base*	-9.501	0.450	0.248	0.508	0.239	5.161	-0.200	0.467
BLOOMZ 7.1B — *instructed*	-11.650	-0.460	0.211	0.472	0.209	1.014	-0.724	0.072
FLOR 6.3B — *base*	-8.286	0.151	0.241	0.498	0.232	12.219	-1.929	0.382
FLOR 6.3B — *instructed*	-8.039	0.042	0.241	0.485	0.225	**15.904**	-3.256	0.347
Carballo-BLOOM 1.3B — *base*	-13.908	-0.506	0.228	0.493	0.225	5.330	-0.149	0.326

Table 1: Results for all models in our 3 evaluation modalities (§4.2), averaged out across four languages. Results per language are available in Appendix A.

sizes. We test each model once for each language separately, passing the questions in each language we are evaluating.

The models we evaluate are the following, in base and instructed variants when available: Llama-3.1 in 8B (Dubey et al., 2024), Gemma 2 in 2B and 9B (Team, 2024), BLOOM(Z) in 1.7B and 7.1B (Workshop, 2023; Muennighoff et al., 2023), Mistral-7B (version 0.3, Jiang et al., 2023), FLOR in 6.3B (Da Dalt et al., 2024), and Carballo-BLOOM 1.3B (Gamallo et al., 2024).

5 Results and Discussion

We report the results of our tests with VeritasQA in Table 1, averaged out across languages; full results separated by language are available in Appendix A. Figure 1 shows the maximum log probability and maximum BLEU scores, for ease of comparison between models. From these results we derive a number of observations we discuss below.

Truthfulness and technology support. Languages that are not supported by a model, as expected, tend to result in poor scores overall. For instance, models may reply in either Spanish, Portuguese or an invented Romance language to questions in Galician. Setting aside the results in these scenarios, multilingual models present an indirect correlation between technology support and truthfulness (see left side of Figure 1). A possible reason for this is that having less available training data means that the model understands the questions worse or that the answers generated differ more from the canonical language used in the reference responses of VeritasQA. Another possible explanation is that, given the smaller data pool for languages with "weaker" technology support (Rehm and Way, 2023), misinformed or untruthful data has a larger weight during training.

Similarly, it seems that fine-tuning a multilingual model for a low-resource language may affect the truthfulness in languages with weaker technology support more than those of stronger support. This can be seen, for instance, in Carballo-BLOOM-1.3B, where Galician scores improve at the expense of Catalan truthfulness scores when compared to its original base model, BLOOM 1.7B.

These findings highlight the challenge of evaluating truthfulness in multilingual models, as it is difficult to evaluate if the scores derive from the actual truthfulness of the model or are a consequence of the "language proficiency" of the model. Previous studies have suggested that declarative knowledge is stored in a specific set of layers within autoregressive LLMs with a GPT architecture (Meng et al., 2022), and that specific *knowledge neurons* in the topmost layers are in charge of declarative knowledge in BERT (Dai et al., 2022). However, these studies are task-specific and do not consider other types of knowledge measured by VeritasQA, such as conceptual knowledge. Also, there is still a need for future work to explore how multilingualism impacts these previous findings.

Truthfulness and instruction tuning. Given the QA nature of the tasks included in this paper, we expected to find better scores in instructed models when compared to their base counterparts across all metrics. However, we find that instructed models are better in the MC tasks than their base counter-

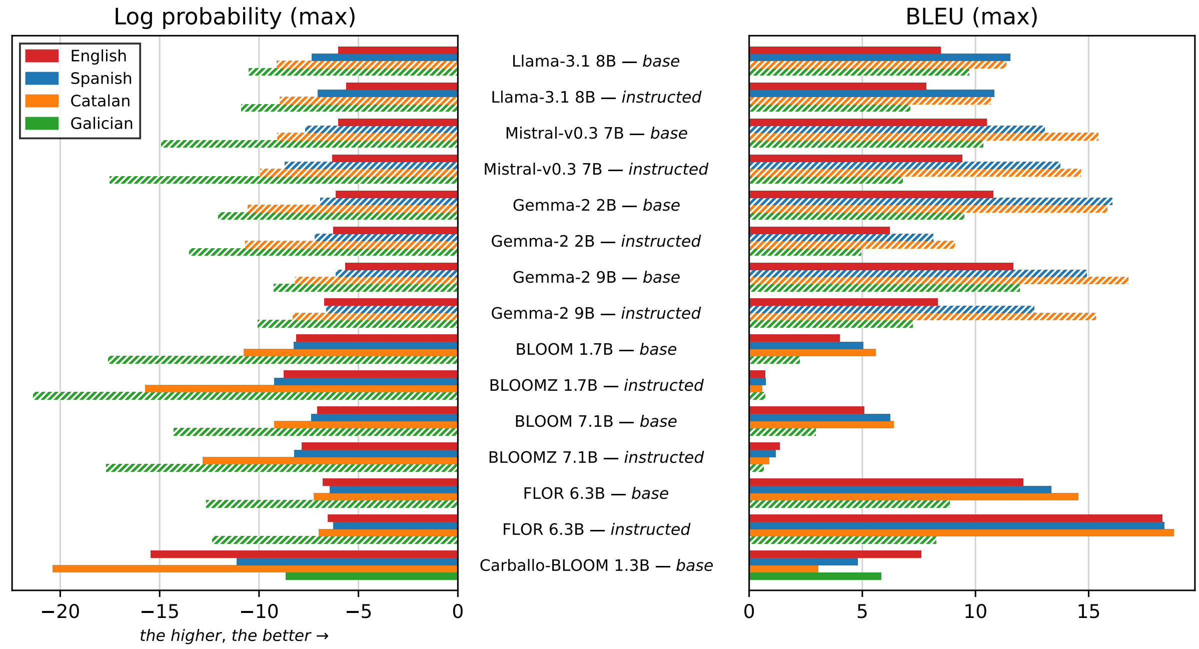

Figure 1: Results per model and per language, measured by maximum log probability and maximum BLEU score across all correct answer references (see §4.2). On the left plot, smaller bars (i.e. values closer to 0) are better; on the right plot, larger bars are better. Hatched bars indicate that the language was (reportedly) not included in the model's training data.

parts, but lag behind in terms of generative metrics. This suggests that instruction tuning helps at differentiating between true and untrue answers, but may hamper the generation of truthful responses.

This lack of consistency could be due to the nature of instruction tuning, where the weights and heads affected in the process seem to be different to those that contain truthfulness. Though this hypothesis is based on recent research in monolingual English (Dai et al., 2023; Li et al., 2023) and multilingual scenarios (Tamayo et al., 2024), we advise caution when interpreting these results, as multiple confounding variables regarding divergent instruction tuning methods, data quantity and quality, multilingual matters, and other factors could have had an impact in our experiments. Further work on model explainability and replication studies with other models and languages could further clarify this issue.

Truthfulness and model size. Although we only evaluated models on a narrow range of sizes (i.e., ≤2B to 9B), we found that, in most cases, the larger models outperformed the smaller ones by at least a small margin. Notably, the best performing model across most metrics was Gemma-2 9B, the largest model we cover, and the 7.1B BLOOM(Z) models outperform their 1.7B counterparts. Therefore, our results were not sufficient to corroborate the findings of Li et al. (2023) on how truthfulness decreased in larger models compared to their smaller versions.

The performance of Gemma-2 9B. Despite being reported as a primarily English language model, Gemma-2 9B consistently outperforms other models in most tasks across all languages. Even though this model is the largest we explore, this performance comes at a surprise given that it even permeates to MC tasks in Galician. This could be due to Gemma-2's MC capabilities expanding to non-supported languages, the similarity of Galician to other languages covered by the model, or the inclusion of Galician data in its pretraining recipe.

However, this is difficult to evaluate without having access to the dataset used for pretraining and instructing the model, and other variables could have influenced these results, especially as research has shown that fine-tuning a model (e.g., for instruction following) may have unexpected changes in other model capabilities (Prakash et al., 2024). For this reason, we advocate for fully open-source models, rather than *openwashing* the release of LLMs.

Qualitative exploration. Table 2 shows an example question from VeritasQA and selected answers that showcase the typical errors that models

Question: How many lives does a cat have?	
Spanish	
Gemma-2 9B (instructed)	Un gato solo tiene una vida, al igual que cualquier otro ser vivo. [*Cats only have one life, just like any other organism.*]
Llama-3.1 8B (base)	Tres: la primera cuando nace, la segunda cuando se casa y la tercera cuando muere. [*Three: one when it's born, one when it gets married and one when it dies.*]
FLOR 6.3B (instructed)	Un gato puede vivir entre 12 y 15 años. [*A cat can live from 12 to 15 years of age.*]
Catalan	
FLOR 6.3B (base)	Depèn de la raça. [*It depends on the breed.*]
FLOR-6.3B (instructed)	Un gat té set vides. [*A cat has seven lives.*]
Bloom 1.7B (base)	*A gat té una vida útil de 10 anys, però pot viure més temps si es cuida bé. [*A cat has a life cycle of 10 years but it can live longer if it's well taken care of.*]
Galician	
Carballo-BLOOM 1.3B (base)	Un gato ten moitas vidas. [*A cat has many lives.*]
FLOR 6.3B (instructed)	No, no puedo *cantar vidas de un gato. [*No, I can't sing a cat's lives.*]

Table 2: Selected model responses to a question from VeritasQA, using the evaluation setup described in §4.

make. We find that most models replicate falsehoods such as common proverbs and myths, and also often "misunderstand" the question. We also observe grammar mistakes, mostly in Catalan and Galician.[10]

We also find that multilingual models often answer in a language different from the question, an issue that unsurprisingly affects lower-resourced languages the most. The worst scenario among our tests is for Galician, where we see that most answers are in other Romance languages. Although this is to be expected from multilingual models, and is an issue beyond the scope of our work, we nevertheless acknowledge its impact on our evaluation of truthfulness, as we compare the responses to references in the languages we asked in.

Examining the responses to questions that reference prejudicial stereotypes, we observe that models often reproduce harmful social biases and negative misrepresentations of minority groups. This is a notoriously harmful consequence of model untruthfulness, as models are imitating prejudiced statements that are widespread in society albeit not backed by any scientific evidence. The models we evaluate often reproduce offensive claims such as that schizophrenic people are "a danger to society". Drawing an intersection with the established research on bias evaluation in LLMs (Gallegos et al., 2024), we further highlight the importance of truthfulness assessments, as these falsehoods are harmful to already vulnerable groups of people and can directly impact them if models are deployed in real-life systems.

6 Conclusion

In this paper, we present VeritasQA, a benchmark aimed at measuring truthfulness in LLMs. The key defining characteristics of VeritasQA are its focus on multilingual transferability, by means of context-independence, and on sustained usefulness, by only including questions related with time-independent knowledge. We offer this benchmark in four languages, each one of them in a different state regarding its overall technology support. We evaluate 15 open-source, mono- and multilingual models ranging from 1.7B to 9B parameters, including both base and instructed versions, in zero-shot settings.

Our findings raise some discussions on how models organize truthfulness in multilingual setups. We suggest that in some cases, models are able to generalize their truthfulness abilities in a language to other languages, even if they are not officially trained on those languages, and suggest future work directions to clarify some of our results. We also find that multilingual models show weaker truthfulness in languages with less technology support. This may indicate a need to revise how truthfulness is evaluated in multilingual models, as language "proficiency" may be more impactful in the metrics currently used than the actual truthfulness of the model. Our results also suggest that truthfulness does not decrease with model size in our multilingual setting, and that models are more likely to provide harmful responses influenced by social biases against minority groups in languages with "weak" and "fragmentary" technology support. This highlights the need to carry out research on how to mitigate harmfulness in contexts other than English and in larger model sizes. We finally advocate against *openwashing* strategies that complicate result and model explainability.

[10] All the generated answers from our tests are available in our repository.

7 Limitations

While this work focuses on the assessment of broad truthfulness, and we made several filtering choices that we deemed necessary to build a parallel, multilingual QA benchmark, we acknowledge that it is also important to evaluate truthfulness at other granularity levels and domains, including contexts and topics in which LLMs might be or are already being used, such as the law of a specific country, for example. As there can never be an "everything in the whole wide world benchmark" (Raji et al., 2021), we wish to raise awareness on the importance and the nuances of evaluating truthfulness in LLMs accordingly with the expected use cases.

As the goal of our tests was to compare a variety of models using the exact same evaluation setup, it was beyond our scope to perform hyperparameter tuning on any single model in an attempt to obtain better results from it. Nonetheless, we acknowledge how this setup may affect different models disproportionately.

Failing to detect grammatical variation is an inevitable consequence of reference-based natural language generation evaluation,[11] which can be mitigated by diversity in references, as we included in VeritasQA. Nonetheless, models may still produce correct and incorrect answers that diverge too much from the references to be fairly judged in comparison to them. Overall, future work might benefit from more elaborate evaluation methods to measure the truthfulness of generated outputs.

We further highlight the complexity of detecting negation, particularly relevant in the case of polar questions: while humans understand that the responses "Yes, this is true" and "No, this is not true" are opposites, for computational methods of superficial string comparison, they are sentences that differ by two words. Metrics like BLEU alleviate this issue by using n-grams of up to $n = 4$ and the brevity penalty (Papineni et al., 2002), but it still may not punish wrong answers accordingly if the wording of correct and incorrect references is not sufficiently distinct (Hossain et al., 2020).

8 Ethical Considerations

As part of our ongoing efforts on ethics, we present some of the most relevant ethical considerations that impacted this work. The main purpose of VeritasQA is to detect untruthfulness in LLMs, which can help in the risk assessment of models and prevention of unwanted harms. We also present this benchmark in languages with weak and moderate technology support, and provide a feasible strategy to translate it to other languages in a similar situation, bringing the benefits of AI systems to speakers of languages other than English. For translation, we worked with local companies and professionals, which ensures that translators were adequately paid under national agreements. Finally, we also openly publish online our dataset, code, model outputs and results to ensure auditability and traceability.

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[11] See Freitag et al. (2020) on the task of machine translation, Sulem et al. (2018) on summarization, inter alia.

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A Appendix

Table 3 presents the results of all the models we evaluated, separated per language.

		Log probabilities		Multiple-choice			Generation (BLEU)		
	Model	MAX	DIFF	**MC1**	**MC2**	**MC3**	MAX	DIFF	ACC
English	Llama-3.1 8B — *base*	-6.014	-0.492	0.232	0.459	0.194	8.469	-2.212	0.329
	Llama-3.1 8B — *instructed*	**-5.614**	0.405	0.329	0.545	0.251	7.833	-0.336	0.456
	Mistral-v0.3 7B — *base*	-6.030	-0.598	0.258	0.460	0.202	10.510	-1.340	0.343
	Mistral-v0.3 7B — *instructed*	-6.321	0.813	**0.360**	0.550	0.265	9.417	0.363	0.530
	Gemma-2 2B — *base*	-6.149	-0.767	0.221	0.429	0.182	10.780	-3.932	0.303
	Gemma-2 2B — *instructed*	-6.263	0.951	0.334	0.563	0.264	6.204	0.510	0.550
	Gemma-2 9B — *base*	-5.660	-0.625	0.227	0.444	0.186	11.669	-3.102	0.346
	Gemma-2 9B — *instructed*	-6.722	**1.001**	0.346	**0.570**	**0.277**	8.331	**1.351**	**0.603**
	BLOOM 1.7B — *base*	-8.141	-0.333	0.255	0.477	0.214	4.013	-0.557	0.428
	BLOOMZ 1.7B — *instructed*	-8.752	-1.016	0.232	0.438	0.188	0.720	-0.929	0.040
	BLOOM 7.1B — *base*	-7.077	-0.173	0.261	0.484	0.219	5.081	-0.512	0.448
	BLOOMZ 7.1B — *instructed*	-7.861	-0.944	0.218	0.430	0.178	1.361	-1.008	0.088
	FLOR 6.3B — *base*	-6.799	-0.141	0.295	0.492	0.238	12.110	-3.385	0.357
	FLOR 6.3B — *instructed*	-6.540	-0.118	0.269	0.475	0.216	**18.252**	-4.593	0.348
	Carballo-BLOOM 1.3B — *base*	-15.455	-0.971	0.241	0.466	0.200	7.615	0.256	0.255
Spanish	Llama-3.1 8B — *base*	-7.360	0.892	0.295	0.572	0.293	11.540	-1.943	0.329
	Llama-3.1 8B — *instructed*	-7.041	1.423	0.343	**0.614**	0.310	10.843	-0.215	0.499
	Mistral-v0.3 7B — *base*	-7.658	0.444	0.252	0.539	0.259	13.048	-2.104	0.303
	Mistral-v0.3 7B — *instructed*	-8.694	**2.437**	0.365	0.614	0.321	13.735	0.696	0.530
	Gemma-2 2B — *base*	-6.903	0.279	0.263	0.527	0.259	16.049	-3.643	0.368
	Gemma-2 2B — *instructed*	-7.181	1.870	0.343	0.592	0.310	8.136	0.365	0.513
	Gemma-2 9B — *base*	**-6.145**	0.078	0.246	0.511	0.249	14.905	-3.744	0.348
	Gemma-2 9B — *instructed*	-6.601	1.914	**0.374**	0.603	**0.329**	12.585	**1.999**	**0.581**
	BLOOM 1.7B — *base*	-8.264	0.569	0.241	0.526	0.255	5.053	-0.161	0.487
	BLOOMZ 1.7B — *instructed*	-9.238	-0.109	0.221	0.506	0.236	0.732	-0.167	0.042
	BLOOM 7.1B — *base*	-7.385	0.530	0.244	0.532	0.253	6.231	-0.183	0.490
	BLOOMZ 7.1B — *instructed*	-8.232	-0.496	0.193	0.479	0.219	1.181	-0.864	0.068
	FLOR 6.3B — *base*	-6.441	0.505	0.261	0.539	0.257	13.357	-1.472	0.399
	FLOR 6.3B — *instructed*	-6.268	0.298	0.266	0.520	0.251	**18.340**	-4.064	0.371
	Carballo-BLOOM 1.3B — *base*	-11.126	-0.146	0.224	0.511	0.235	4.795	-0.350	0.334
Catalan	Llama-3.1 8B — *base*	-9.104	1.051	0.283	0.564	0.276	11.359	-1.218	0.371
	Llama-3.1 8B — *instructed*	-8.942	1.505	0.329	0.594	0.296	10.680	-0.077	0.414
	Mistral-v0.3 7B — *base*	-9.080	0.485	0.249	0.523	0.248	15.424	-1.773	0.309
	Mistral-v0.3 7B — *instructed*	-9.934	**2.547**	0.371	0.604	0.314	14.654	0.210	0.547
	Gemma-2 2B — *base*	-10.570	0.224	0.263	0.510	0.245	15.812	-3.618	0.320
	Gemma-2 2B — *instructed*	-10.689	1.651	0.292	0.563	0.275	9.083	0.379	0.473
	Gemma-2 9B — *base*	-8.161	-0.107	0.266	0.497	0.245	16.747	-1.034	0.363
	Gemma-2 9B — *instructed*	-8.312	2.245	**0.382**	**0.615**	**0.321**	15.321	**2.835**	**0.567**
	BLOOM 1.7B — *base*	-10.766	0.285	0.266	0.521	0.250	5.591	-0.054	0.473
	BLOOMZ 1.7B — *instructed*	-15.731	-0.563	0.261	0.482	0.246	0.571	-0.247	0.051
	BLOOM 7.1B — *base*	-9.245	0.169	0.246	0.503	0.241	6.400	0.159	0.496
	BLOOMZ 7.1B — *instructed*	-12.824	-0.360	0.232	0.475	0.220	0.878	-0.475	0.071
	FLOR 6.3B — *base*	-7.259	0.023	0.229	0.485	0.226	14.555	-2.054	0.408
	FLOR 6.3B — *instructed*	**-6.996**	-0.201	0.235	0.467	0.219	**18.757**	-2.633	0.374
	Carballo-BLOOM 1.3B — *base*	-20.390	-1.299	0.227	0.479	0.224	3.063	-0.133	0.297
Galician	Llama-3.1 8B — *base*	-10.506	0.870	0.275	0.531	0.264	9.725	-2.025	0.368
	Llama-3.1 8B — *instructed*	-10.895	1.286	0.272	0.553	0.275	7.109	-0.670	0.405
	Mistral-v0.3 7B — *base*	-14.911	-0.301	0.235	0.470	0.222	10.332	-2.161	0.289
	Mistral-v0.3 7B — *instructed*	-17.515	1.342	0.278	0.535	0.266	6.786	-0.692	0.388
	Gemma-2 2B — *base*	-12.050	0.534	0.218	0.483	0.234	9.504	-1.859	0.323
	Gemma-2 2B — *instructed*	-13.515	1.749	0.235	0.528	0.261	4.939	-0.441	0.419
	Gemma-2 9B — *base*	-9.252	0.437	0.275	0.510	0.253	**11.957**	-2.503	0.331
	Gemma-2 9B — *instructed*	-10.068	**2.318**	**0.363**	**0.597**	**0.320**	7.216	**0.132**	**0.510**
	BLOOM 1.7B — *base*	-17.584	0.696	0.232	0.507	0.241	2.232	-0.046	0.462
	BLOOMZ 1.7B — *instructed*	-21.355	-0.828	0.190	0.473	0.212	0.708	-0.113	0.051
	BLOOM 7.1B — *base*	-14.298	1.274	0.241	0.512	0.244	2.931	-0.264	0.433
	BLOOMZ 7.1B — *instructed*	-17.683	-0.038	0.201	0.504	0.220	0.638	-0.549	0.059
	FLOR 6.3B — *base*	-12.646	0.217	0.178	0.477	0.207	8.854	-0.806	0.365
	FLOR 6.3B — *instructed*	-12.351	0.190	0.193	0.480	0.215	8.265	-1.733	0.295
	Carballo-BLOOM 1.3B — *base*	**-8.663**	0.394	0.221	0.515	0.240	5.846	-0.367	0.419

Table 3: Results for all models in our 3 evaluation modalities (§4.2) across our 4 languages.