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The Hallucinations Leaderboard – An Open Effort to Measure Hallucinations in Large Language Models

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Abstract

Large Language Models (LLMs) have transformed the Natural Language Processing (NLP) landscape with their remarkable ability to understand and generate human-like text. However, these models are prone to “hallucinations” — outputs that do not align with factual reality or the input context. This paper introduces the Hallucinations Leaderboard, an open initiative to quantitatively measure and compare the tendency of each model to produce hallucinations. The leaderboard uses a comprehensive set of benchmarks focusing on different aspects of hallucinations, such as factuality and faithfulness, across various tasks, including question-answering, summarisation, and reading comprehension. Our analysis provides insights into the performance of different models, guiding researchers and practitioners in choosing the most reliable models for their applications.

1 Introduction

Large Language Models (LLMs) have emerged as powerful language generators, i.e. generating fluent and topically coherent text, and few-shot task instruction followers (Radford et al., 2019; Brown et al., 2020; Wei et al., 2022; Ouyang et al., 2022; Liu et al., 2023). Because they are trained on large amounts of textual data, they are also a prominent source of knowledge (Petroni et al., 2019; Roberts et al., 2020; Safavi and Koutra, 2021; Heinzerling and Inui, 2021; Jiang et al., 2020). Thus, they are perfect backbone models for text generation and knowledge-intensive downstream tasks, such as question answering (QA). Despite their success,

*Equal contribution. GH conducted the first draft of the paper and the analyses in Section 3. APG contributed to the first version of the leaderboard and corresponding [blog post](#). RS contributed to the summarisation tasks. XD contributed to the knowledge memorisation tasks. LPB contributed to the writing and experimental design. MR contributed to prompt robustness evaluation and writing. PM and CF created the first version of the leaderboard and corresponding [blog post](#).

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these models are prone to generate text that is factually incorrect or inconsistent with a provided instruction or knowledge source; such generations are usually referred to as *hallucinations* (Ji et al., 2023; Zhang et al., 2023c; Bang et al., 2023).

In recent years, an overwhelming number of LLMs have been made available. They differ in the training approach (language modelling, instruction following, human feedback), training data used, and the number of parameters. Given the large-scale setting (i.e., number of models, their size and number of downstream tasks), it becomes difficult to gauge performance differences amongst LLMs. To systematically quantify the impact of hallucinations in several downstream tasks, we present the *Hallucinations Leaderboard*¹, a platform for evaluating the hallucination tendencies of LLMs.

We aim to reveal the hallucination tendencies of LLMs in their role as backbone models on different generative and knowledge-intensive tasks. We distinguish two scenarios for LLM hallucinations (Huang et al., 2023). One is related to *faithfulness*, i.e., whether an LLM generation adheres to the given source of information (e.g. when summarising a document). The other is related to *factuality*, i.e. whether LLMs generate factually correct content according to world knowledge based on knowledge acquired during training (e.g., in closed-book general domain QA tasks). [Figure 1](#) (left-top) shows an example of faithfulness hallucination where the generated summary contradicts the input document; and an example of factuality hallucination (right-top) in question answering where the model answers that *Charles Lindbergh* was the first person to walk on the moon. Concretely, we use a set of tasks, listed in [Figure 1](#) (bottom), to assess LLMs’ hallucination behaviour in terms of factuality and faithfulness. We evaluate 20 LLMs

¹Available at <https://huggingface.co/spaces/hallucinations-leaderboard/leaderboard>

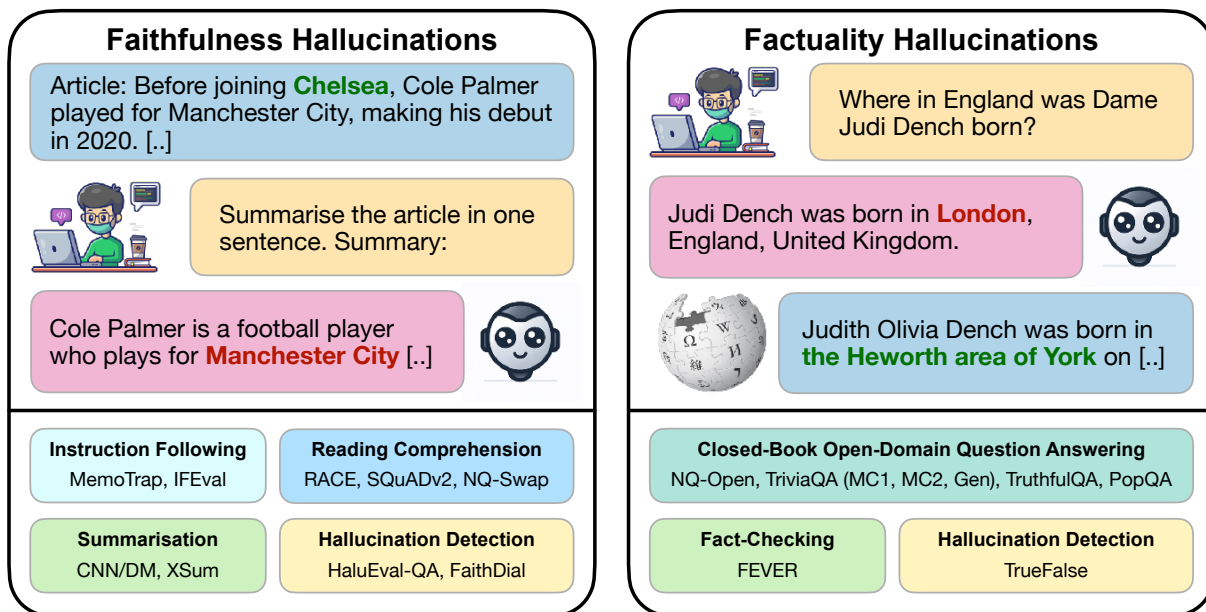


Figure 1: Example of LLM factuality hallucination and factuality evaluation tasks in the Hallucination Leaderboard (left). Faithfulness hallucination example and tasks on the right.

across 15 tasks, and each model is evaluated with no training in a zero- or very few-shot in-context examples.

Our results show variances across models and tasks, offering insights into the strengths and weaknesses of different LLMs in handling hallucinations. These results are critical for understanding the current capabilities and limitations of LLMs in various applications. The Hallucinations Leaderboard represents a significant step towards addressing the challenge of hallucinations in LLMs. It will not only aid researchers and engineers in selecting more reliable models but also drive the development of LLMs. The project welcomes contributions and feedback, indicating its evolving nature and commitment to continuous improvement.

2 Evaluation Framework

The Hallucinations Leaderboard leverages the EleutherAI Language Model Evaluation Harness (Gao et al., 2023), a framework for zero-shot and few-shot language model evaluation via in-context learning on a wide array of tasks. The leaderboard covers a range of tasks, including Closed-book Open-domain QA, Summarisation, Reading Comprehension, Instruction Following, Fact-Checking, Hallucination Detection, and Self-Consistency. Each task is designed to target specific aspects of hallucination in LLMs.

These tasks are generally categorised into two

classes based on the type of hallucinations the models may generate: factuality hallucination and faithfulness hallucination.

2.1 Factuality Evaluation

Closed-book Question Answering This category involves evaluating the LLM’s ability to answer questions without external knowledge sources. Natural Questions (Kwiatkowski et al., 2019; Lee et al., 2019) and TriviaQA (Joshi et al., 2017) demand the generation of answers to real-world or trivia questions, assessed against the gold standard answers. PopQA (Mallen et al., 2023) poses a new challenge by introducing questions about long-tail entities, which enables a fine-grained analysis of LLM’s memorisation of factual knowledge. In addition, we measure the ability of LLMs to answer questions about the truthfulness of a statement on TruthfulQA (Lin et al., 2022). Models are evaluated by accuracy on the multi-label classification task (MC2) in TruthfulQA.

Fact-Checking These tasks evaluate the LLM’s ability to verify the authenticity of statements. Each instance in FEVER (Thorne et al., 2018) comprises a claim and a label (SUPPORTS and REFUTES), and the model’s task is to predict the label based on the claim, akin to a closed-book open-domain QA setting. The evaluation is conducted in a 16-shot setting, emphasising the model’s discernment and verification capabilities.

Hallucination Detection True-False (Azaria and Mitchell, 2023) assesses the model’s ability to distinguish between factual and false statements across various domains. We measure the performance of LLMs by accuracy.

2.2 Faithfulness Evaluation

Summarisation Summarisation tasks test the LLM’s capability to generate concise summaries that faithfully reflect the information in the input article. XSum (Narayan et al., 2018) targets single-sentence summarisation of news articles, while CNN/DM (CNN/Daily Mail; See et al., 2017) involves generating multi-sentence summaries of news articles. Models are evaluated based on ROUGE-L (Lin, 2004), which assesses n-gram overlap with reference summaries.

Reading Comprehension These tasks examine the LLM’s proficiency in understanding and extracting information from given passages. RACE (Lai et al., 2017) entails answering questions from English exam passages, while SQuAD 2.0 (Rajpurkar et al., 2018) contains answerable and unanswerable questions about Wikipedia articles, requiring the LLM to discern when provided information is insufficient or ambiguous. A faithful LLM should be able to identify unanswerable questions and refuse to provide fabricated answers. Models are evaluated using Exact Match (EM) on SQuAD-v2 and by accuracy on RACE, respectively.

A main cause of faithfulness hallucination is that LLMs tend to rely on the memorisation of training data. We measure the tendency of LLMs to rely on parametric knowledge using NQ-Swap (Longpre et al., 2021), a dataset derived from Natural Questions (Kwiatkowski et al., 2019; Lee et al., 2019), where the gold answer in the input document is replaced by a random entity of the same entity type. A faithful model is required to generate the replaced answer given the perturbed context. Models are evaluated by exact match based on substituted answer entities.

Instruction Following Faithful LLMs are expected to follow instructions provided by the user. We assess the LLM’s fidelity in adhering to specific instructions by the following tasks. Memo-Trap (Liu and Liu, 2023) involves completing text, translation, or answering questions without relying on memorised text or concepts, gauging the model’s creative adherence to the given prompts in a zero-shot setting. IFEval (Zhou et al., 2023)

presents a more complex challenge, requiring the execution of a set of detailed instructions, testing the model’s compliance and accuracy in following multi-faceted directives in a zero-shot evaluation. We measure the performance of LLMs on these tasks by accuracy.

Hallucination Detection These tasks are explicitly designed to detect hallucinations in LLM-generated content. FaithDial (Dziri et al., 2022) focuses on detecting faithfulness in dialogues. HaluEval (Li et al., 2023a) extends this to QA, dialogue, and summarisation tasks, requiring models to identify hallucinated content in responses based on given knowledge snippets. In the leaderboard, we only consider the QA task from HaluEval, which contains human-annotated hallucinated samples created from HotpotQA (Yang et al., 2018). Models are evaluated by accuracy on these tasks.

2.3 Overall Evaluation Metrics

We propose two scores, namely the *factuality score* and the *faithfulness score*, to measure the overall performance of LLMs on each type of hallucination. The scores are computed by averaging all the evaluation metrics on each category of tasks.

2.4 Large Language Models

The leaderboard encompasses open-source LLMs of various sizes, and categorised into pre-trained, fine-tuned, and instruction-tuned models².

Base Models *Base models* refers to LLMs that have been pre-trained on a large dataset. We selected multiple variants of pre-trained models of different sizes: GPT-J-6B (Wang and Komatsuzaki, 2021), GPT-Neo 125M/1.3B/2.7B (Black et al., 2021), Bloom-560M/1.7B/7.1B (BigScience Workshop et al., 2022), Llama-2-7B/13B (Touvron et al., 2023), Mistral-7B (Jiang et al., 2023), and Falcon-7B (Almazrouei et al., 2023).

Fine-tuned Models *Fine-tuned models* are pre-trained models that have been further fine-tuned on a specific dataset and task to improve certain capabilities. One variation of fine-tuning techniques is *instruction fine-tuning*, which further fine-tunes a base model on a dataset of instructions³, aiming to enhance their ability to follow

²For our analyses, we selected only a subset of models and tasks; however, the hallucination leaderboard encompasses a wider array of task metrics and models

³A chat or instructions dataset

human directives. We selected several instruction-tuned models such as Llama-2-7b/13b-chat (Touvron et al., 2023) and Vicuna-7b-v1.5 (Zheng et al., 2023), which are instruction-tuned versions of Llama-2 models. Falcon-7b-instruct (Almazrouei et al., 2023) and Mistral-7b-instruct (Jiang et al., 2023) are instruction-tuned versions of Falcon-7b and Mistral-7b, respectively. Another fine-tuning technique is Reinforcement Learning with Human Feedback (RLHF), for example, via Direct Preference Optimisation (DPO, Rafailov et al., 2023). We selected zephyr-7b-beta (Tunstall et al., 2023) as a representative model that is fine-tuned via RLHF.

The leaderboard aims to analyse the effect of scale and type on the LLMs’ tendency to hallucinate. For simplicity, we undertake experiments and analyses solely on a selected few representative models from each scale and type.

3 Results

To gain a deeper understanding of hallucinations in LLMs, we conducted a comprehensive analysis of the models and tasks introduced in Section 2. In Figure 2, we display the results of models for each task in the form of a heatmap. The value of each cell in the heatmap follows the metric of the corresponding task, and the dendrogram-shaped clusters are formed after applying min-max normalisation by task (y-axis) and model (x-axis). The hierarchical clustering is computed using the Ward variance minimisation linkage method (Ward Jr, 1963) and Euclidean distance to group similar data points based on their mean pairwise distances, organising them into a tree structure.

Figure 2 shows the task-related hallucination tendency of LLMs. We observe that LLMs are better at judging factuality and faithfulness than what they are at producing factual and faithful generations. Llama-2 models (Touvron et al., 2023) show the stronger opposite behaviour, i.e., they perform relatively well in FEVER, FaithDial and true-false while quite poorly in QA tasks such as NQ-open. Mistral models perform slightly better on the TriviaQA task. This agrees with the findings in Li et al. (2023b) and Zhang et al. (2023b) where authors find that models have better internal representations of truthfulness than what they often surface. Second, tasks that mostly require completing a text sequence (e.g., MemoTrap or TruthfulQA-MC2) reflect slightly better performance than those that involve reading a longer input context (e.g. XSum) or

Models	Faithfulness	Factuality
Llama-2-7b	37.94 (+0.0)	40.12 (+0.0)
Llama-2-7b-Chat	38.69 (+0.8)	42.48 (+2.4)
Vicuna-7b-v1.5	37.13 (-0.8)	51.42 (+11.3)
Llama-2-13b	39.75 (+0.0)	44.49 (+0.0)
Llama-2-13b-Chat	42.32 (+2.6)	44.60 (+0.1)
Mistral-7B-v0.1	38.62 (+0.0)	55.41 (+0.0)
Mistral-7B-Instruct-v0.1	43.26 (+4.6)	50.74 (-4.7)
Zephyr-7b-beta	36.14 (-2.5)	55.11 (-0.3)
OpenHermes-2.5-Mistral-7B	43.88 (+5.3)	57.41 (+2.0)
Falcon-7b	32.81 (+0.0)	41.74 (+0.0)
Falcon-7b-Instruct	33.61 (+0.8)	38.90 (-2.8)

Table 1: Comparison between the faithfulness and factuality scores (introduced in Section 2.3) produced by the base models and their corresponding fine-tuned models. Performance differences are against the base models.

answering a question based on memorised knowledge (e.g. NQ-open).

By examining how models are clustered, it becomes evident that the hallucination tendency is less dependent on the model type (Section 2.4) and more on their belonging to the same family — e.g. Llama-2 (Touvron et al., 2023), GPT-Neo (Black et al., 2021), Bloom (BigScience Workshop et al., 2022). This observation can be attributed to the fact that while models from different families may possess distinct training data and structures, those within the same family generally share architectures and are based on the same pre-training data. This finding has inspired us to analyse the impact of instruction fine-tuning and the influence of model size within the same family, as elaborated in Sections 3.1 and 3.2.

3.1 Impact of Instruction Fine-Tuning on Hallucinations

Table 1 shows a comparison of pre-trained models with their corresponding instruction fine-tuned variants across two metrics: *faithfulness score* and *factuality score* (Section 2.3). We can observe that instruction fine-tuned models achieve higher Faithfulness scores than their base counterparts. This is indicative of their enhanced ability to retain fidelity to the given input or the specific instructions given (e.g. "Answer the following question based on the provided context").

Unlike Faithfulness, Factuality scores across the models show a trend of either marginal improvement or, in some cases, a decline, with the notable exception of the Llama-2-7b model. While these models become better at adhering to instructions

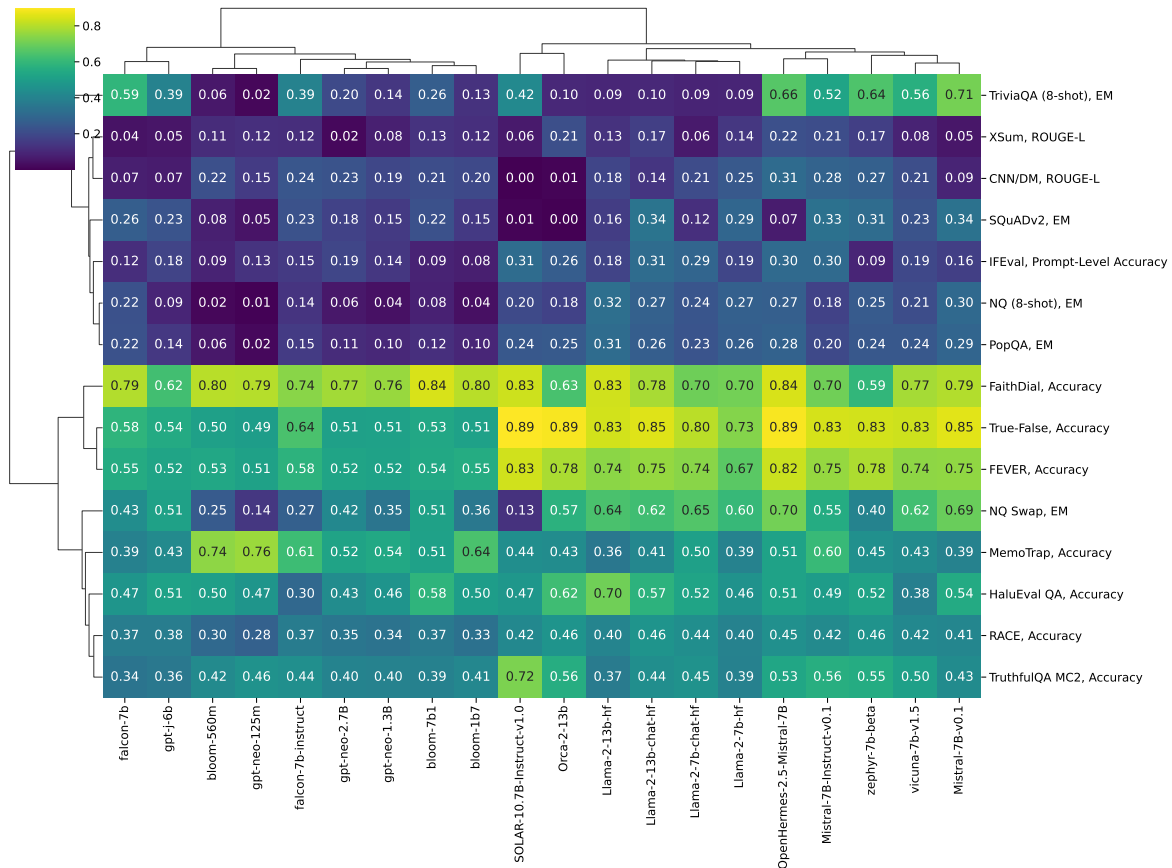


Figure 2: The heatmap of results for various tasks of selected models. Each value in the heatmap follows the corresponding task’s metric while clustering on the x -axis and y -axis was done after model/task normalisation.

or the input, which is reflected in the improved Faithfulness scores, their capacity to produce factually accurate information does not consistently improve in the same way. This pattern suggests a trade-off between Faithfulness and Factuality in instruction fine-tuning: enhancing a model’s ability to follow instructions closely (Faithfulness) might not always lead to improvements in the accuracy of the information produced (Factuality).

To analyse the impact of instruction fine-tuning on hallucinations further, in Figure 4, we compare Mistral-7B models (Jiang et al., 2023) with and without instruction fine-tuning in different categories of tasks defined in Section 2. We can see that the improvement in faithfulness is mainly attributed to the improvement in instruction fine-tuning and summarisation tasks, while the decrease in factuality is caused by the degradation of question-answering and hallucination-detection tasks.

3.2 Impact of Model Size on Hallucinations

To explore the impact of model size on Faithfulness and Factuality hallucinations, we provide Faithful-

Models	Faithfulness	Factuality
GPT-Neo-125m	32.08 (+0.0)	25.04 (+0.0)
GPT-Neo-1.3B	33.91 (+1.8)	28.36 (+3.3)
GPT-Neo-2.7B	34.28 (+2.2)	29.91 (+4.9)
Bloom-560m	34.32 (+0.0)	26.52 (+0.0)
Bloom-1b7	35.18 (+0.9)	28.80 (+2.3)
Bloom-7b1	38.38 (+4.1)	32.07 (+5.6)
Llama-2-7b	37.94 (+0.0)	40.12 (+0.0)
Llama-2-13b	39.75 (+1.8)	44.49 (+4.4)
Llama-2-chat-7b	38.69 (+0.0)	42.48 (+0.0)
Llama-2-chat-13b	42.32 (+3.6)	44.60 (+2.1)

Table 2: Comparison between the faithfulness and factuality scores produced by models of different scales, where differences are against the smallest models.

ness and Factuality scores across various model sizes in Table 2. While an increase in model size generally enhances both Faithfulness and Factuality, it is noteworthy that Factuality tends to exhibit more substantial improvements compared to Faithfulness, with the Llama-2-chat models being a notable exception to this trend.

This suggests that as model size increases, the

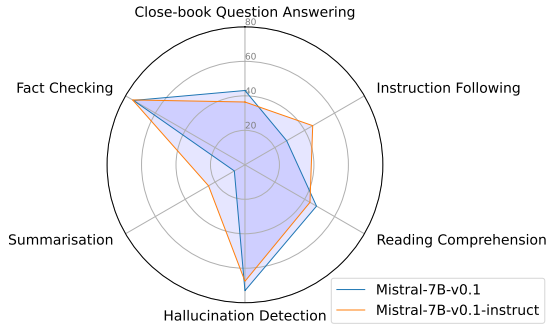


Figure 4: Comparison of models with and without instruction fine-tuning.

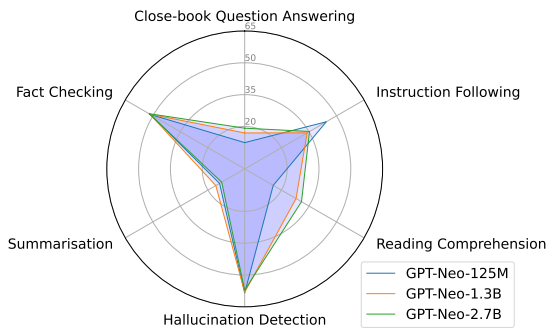


Figure 5: Comparison of models with different sizes.

accumulation of parametric knowledge during the training phrase becomes more extensive, leading to a reduced dependence on context. This observation aligns with the findings of existing research, such as "Imitative Falsehoods" (Lin et al., 2022) or "Strong Prior" (McKenzie et al., 2022), expanding upon them across various models and tasks.

In Figure 5, we show the evaluation results of different sizes of GPT-Neo on different categories of tasks. We observe that GPT-Neo can obtain higher accuracy on question-answering and open-book question-answering tasks when the model’s size is increased, contributing to improved factuality. We can also see that GPT-Neo-125M is more accurate on instruction-following tasks than larger models, which is mainly due to the "Strong Prior" phenomenon, as we discussed above.

4 Related Work

Much work has focused on hallucination detection for summarisation tasks (Maynez et al. 2020; Kryscinski et al. 2020; Scialom et al. 2021; Ribeiro et al. 2022; Laban et al. 2022; Utama et al. 2022; Schuster et al. 2022). For instance, Laban et al. (2022) propose SummaC, which examines faithfulness through a Natural Language Inference frame-

work. Far from solved, this problem takes a broader scope in the context of LLMs (Huang et al., 2023; Ye et al., 2023). Factual and faithfulness evaluations are carried out for LLMs’ diverse downstream tasks and by LLM evaluators. For instance, Chen et al. (2023) propose a benchmark covering question answering, reasoning, maths, and writing recommendation tasks. Chuang et al. (2024) propose a decoding strategy to improve factuality on multiple choice and open-ended generation tasks. Some work proposes LLM-based hallucination evaluators (Cohen et al., 2023; Zhang et al., 2023a; Manakul et al., 2023). For instance, Cohen et al. (2023) propose a multi-turn iterative examination between LLMs where one LLM formulates claims and the other asks questions to uncover inconsistencies. Our Hallucination Leaderboard supports this research gathering for evaluation LLMs and downstream tasks.

Leaderboards have arisen in 2023 as a way to quickly get insights on model capabilities, by comparing models in equivalent and reproducible setups (Beeching et al., 2023; Wang et al., 2023). They contribute significantly to our understanding of LLMs’ capabilities and limitations in specific areas. Looking at the same domain, the Hughes Hallucination Evaluation Model (HHEM) leaderboard (Hughes and Bae, 2023) focuses on a summarisation tasks, and uses a model as a judge approach to evaluate hallucinations. Our study and leaderboard aim to broaden the scope by evaluating hallucinations in LLMs across-the-board, using a wide variety of tasks and metrics. We aim to complement and extend the insights gained from existing studies, providing a more comprehensive understanding of LLMs’ strengths and weaknesses in terms of hallucinations.

5 Conclusions

The Hallucinations Leaderboard provides a platform for understanding and mitigating hallucinations in LLMs. By offering a comprehensive evaluation across a diverse set of benchmarks, it enables a deeper understanding of the generalisation properties and limitations of large language models. This initiative marks a pivotal step towards enhancing the reliability and effectiveness of LLMs in real-world settings.

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Limitations

In this work, we define a prompt template for each task. Although we analysed the robustness of prompt templates for some tasks in Appendix A, what constitutes an appropriate template from a hallucination perspective has not been sufficiently considered for all tasks. Additionally, despite the possibility that each model may have an optimal custom prompt template, we are defining task-specific templates without considering this. Addressing this issue further is one of our future objectives. Furthermore, the number of demonstrations (shots) for in-context examples has not been sufficiently explored. This can particularly impact tasks related to faithfulness, where obtaining necessary information from the given context is crucial; in-context learning could be utilised to encourage models to remain faithful to the provided context. Finally, due to cost reasons, we only considered open-source models and did not take closed-source models like GPT-4 (OpenAI, 2023) into account.

Ethics Statement

This paper analyses the issue of hallucination in LLMs, which by itself can have a broader social impact due to the possibility of misinformation in the case of hallucinated outputs. We aim to provide researchers and practitioners with empirical results on model hallucinations and spread awareness of this phenomenon in general, hopefully reducing the possibility of reliance on factually incorrect LLM

outputs. Furthermore, our leaderboard covers a selection of tasks proposed in prior research, and the datasets of these tasks can contain bias due to their collection protocols. Therefore, the reported results might be affected by the lack of some demographic and societal groups from those datasets and the over representation of others (Hovy and Prabhume, 2021). We acknowledge this limitation and encourage the creators of further hallucination detection benchmarks to consider it during the data collection process.

References

- Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, Mérouane Debbah, Étienne Goffinet, Daniel Hessel, Julien Launay, Quentin Malartic, et al. 2023. The falcon series of open language models. *arXiv preprint arXiv:2311.16867*.
- Amos Azaria and Tom Mitchell. 2023. [The internal state of an LLM knows when it’s lying](#). In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 967–976, Singapore. Association for Computational Linguistics.
- Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, et al. 2023. A multi-task, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. In *Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 675–718.
- Edward Beeching, Clémentine Fourrier, Nathan Habib, Sheon Han, Nathan Lambert, Nazneen Rajani, Omar Sanseviero, Lewis Tunstall, and Thomas Wolf. 2023. Open llm leaderboard. https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard.
- BigScience Workshop et al. 2022. [Bloom: A 176b-parameter open-access multilingual language model](#).
- Sid Black, Gao Leo, Phil Wang, Connor Leahy, and Stella Biderman. 2021. [GPT-Neo: Large Scale Autoregressive Language Modeling with Mesh-Tensorflow](#). If you use this software, please cite it using these metadata.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec

- Radford, Ilya Sutskever, and Dario Amodei. 2020. [Language models are few-shot learners](#). In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.
- Shiqi Chen, Yiran Zhao, Jinghan Zhang, I-Chun Chern, Siyang Gao, Pengfei Liu, and Junxian He. 2023. [FELM: Benchmarking factuality evaluation of large language models](#). In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.
- Yung-Sung Chuang, Yujia Xie, Hongyin Luo, Yoon Kim, James R. Glass, and Pengcheng He. 2024. [Dola: Decoding by contrasting layers improves factuality in large language models](#). In *The Twelfth International Conference on Learning Representations*.
- Roi Cohen, May Hamri, Mor Geva, and Amir Globerson. 2023. [LM vs LM: Detecting factual errors via cross examination](#). In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 12621–12640, Singapore. Association for Computational Linguistics.
- Nouha Dziri, Ehsan Kamaloo, Sivan Milton, Osmar Zaiane, Mo Yu, Edoardo Ponti, and Siva Reddy. 2022. [Faithdial: A faithful benchmark for information-seeking dialogue](#). *arXiv preprint, arXiv:2204.10757*.
- Shangbin Feng, Vidhisha Balachandran, Yuyang Bai, and Yulia Tsvetkov. 2023. [FactKB: Generalizable factuality evaluation using language models enhanced with factual knowledge](#). In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 933–952, Singapore. Association for Computational Linguistics.
- Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac’h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. 2023. [A framework for few-shot language model evaluation](#).
- Benjamin Heinzerling and Kentaro Inui. 2021. [Language models as knowledge bases: On entity representations, storage capacity, and paraphrased queries](#). In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1772–1791, Online. Association for Computational Linguistics.
- Dirk Hovy and Shrimai Prabhumoye. 2021. [Five sources of bias in natural language processing](#). *Language and Linguistics Compass*, 15(8):e12432.
- Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. 2023. [A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions](#). *CoRR*, abs/2311.05232.
- Simon Hughes and Minseok Bae. 2023. [Vectara hallucination leaderboard](#).
- Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. 2023. [Survey of hallucination in natural language generation](#). *ACM Computing Surveys*, 55(12):1–38.
- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth e Lacroix, and William El Sayed. 2023. [Mistral 7b](#).
- Zhengbao Jiang, Frank F. Xu, Jun Araki, and Graham Neubig. 2020. [How Can We Know What Language Models Know?](#) *Transactions of the Association for Computational Linguistics*, 8:423–438.
- Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. [triviaqa: A Large Scale Distantly Supervised Challenge Dataset for Reading Comprehension](#). *arXiv e-prints*, page arXiv:1705.03551.
- Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. 2020. [Evaluating the factual consistency of abstractive text summarization](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9332–9346, Online. Association for Computational Linguistics.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. [Natural questions: A benchmark for question answering research](#). *Transactions of the Association for Computational Linguistics*, 7:452–466.
- Philippe Laban, Tobias Schnabel, Paul N. Bennett, and Marti A. Hearst. 2022. [SummaC: Re-visiting NLI-based models for inconsistency detection in summarization](#). *Transactions of the Association for Computational Linguistics*, 10:163–177.
- Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. 2017. [RACE: Large-scale ReAding comprehension dataset from examinations](#). In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 785–794, Copenhagen, Denmark. Association for Computational Linguistics.
- Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. [Latent retrieval for weakly supervised open domain question answering](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.

- Junyi Li, Xiaoxue Cheng, Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. 2023a. [HaluEval: A large-scale hallucination evaluation benchmark for large language models](#). In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 6449–6464, Singapore. Association for Computational Linguistics.
- Kenneth Li, Oam Patel, Fernanda Viégas, Hanspeter Pfister, and Martin Wattenberg. 2023b. [Inference-time intervention: Eliciting truthful answers from a language model](#). In *Thirty-seventh Conference on Neural Information Processing Systems*.
- Chin-Yew Lin. 2004. [ROUGE: A package for automatic evaluation of summaries](#). In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. Truthfulqa: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3214–3252.
- Alisa Liu and Jiacheng Liu. 2023. [The memotrap dataset](#).
- Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2023. [Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing](#). *ACM Comput. Surv.*, 55(9).
- Shayne Longpre, Kartik Perisetla, Anthony Chen, Nikhil Ramesh, Chris DuBois, and Sameer Singh. 2021. [Entity-based knowledge conflicts in question answering](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7052–7063, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Alex Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. 2023. When not to trust language models: Investigating effectiveness of parametric and non-parametric memories. In *ACL (1)*, pages 9802–9822. Association for Computational Linguistics.
- Potsawee Manakul, Adian Liusie, and Mark JF Gales. 2023. [Selfcheckgpt: Zero-resource black-box hallucination detection for generative large language models](#). *arXiv preprint arXiv:2303.08896*.
- Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. [On faithfulness and factuality in abstractive summarization](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1906–1919, Online. Association for Computational Linguistics.
- Ian McKenzie, Alexander Lyzhov, Alicia Parrish, Ameya Prabhu, Aaron Mueller, Najoung Kim, Sam Bowman, and Ethan Perez. 2022. [The inverse scaling prize](#).
- Moran Mizrahi, Guy Kaplan, Dan Malkin, Rotem Dror, Dafna Shahaf, and Gabriel Stanovsky. 2023. [State of what art? a call for multi-prompt llm evaluation](#).
- Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018. [Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization](#). *ArXiv*, abs/1808.08745.
- OpenAI. 2023. [GPT-4 technical report](#). *CoRR*, abs/2303.08774.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F Christiano, Jan Leike, and Ryan Lowe. 2022. [Training language models to follow instructions with human feedback](#). In *Advances in Neural Information Processing Systems*, volume 35, pages 27730–27744. Curran Associates, Inc.
- Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. 2019. [Language models as knowledge bases?](#) In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2463–2473, Hong Kong, China. Association for Computational Linguistics.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. [Language models are unsupervised multitask learners](#). In *Technical report, OpenAi*.
- Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D. Manning, Stefano Ermon, and Chelsea Finn. 2023. [Direct preference optimization: Your language model is secretly a reward model](#). In *NeurIPS*.
- Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. [Know what you don’t know: Unanswerable questions for squad](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 784–789.
- Leonardo F. R. Ribeiro, Mengwen Liu, Iryna Gurevych, Markus Dreyer, and Mohit Bansal. 2022. [FactGraph: Evaluating factuality in summarization with semantic graph representations](#). In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3238–3253, Seattle, United States. Association for Computational Linguistics.
- Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. [How much knowledge can you pack into the parameters of a language model?](#) In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5418–5426, Online. Association for Computational Linguistics.

- Tara Safavi and Danai Koutra. 2021. [Relational World Knowledge Representation in Contextual Language Models: A Review](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1053–1067, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Tal Schuster, Sihao Chen, Senaka Buthpitiya, Alex Fabrikant, and Donald Metzler. 2022. [Stretching sentence-pair NLI models to reason over long documents and clusters](#). In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 394–412, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Thomas Scialom, Paul-Alexis Dray, Sylvain Lamprier, Benjamin Piwowarski, Jacopo Staiano, Alex Wang, and Patrick Gallinari. 2021. [QuestEval: Summarization asks for fact-based evaluation](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Melanie Sclar, Yejin Choi, Yulia Tsvetkov, and Alane Suhr. 2023. [Quantifying language models’ sensitivity to spurious features in prompt design or: How i learned to start worrying about prompt formatting](#).
- Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. [Get to the point: Summarization with pointer-generator networks](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018. [FEVER: a large-scale dataset for fact extraction and VERification](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 809–819, New Orleans, Louisiana. Association for Computational Linguistics.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajwal Bhargava, Shruti Bhosale, et al. 2023. [Llama 2: Open foundation and fine-tuned chat models](#). *arXiv preprint arXiv:2307.09288*.
- Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro von Werra, Clémentine Fourrier, Nathan Habib, Nathan Sarrazin, Omar Sanseviero, Alexander M. Rush, and Thomas Wolf. 2023. [Zephyr: Direct distillation of lm alignment](#).
- Prasetya Utama, Joshua Bambrick, Nafise Moosavi, and Iryna Gurevych. 2022. [Falsesum: Generating document-level NLI examples for recognizing factual inconsistency in summarization](#). In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2763–2776, Seattle, United States. Association for Computational Linguistics.
- Anton Voronov, Lena Wolf, and Max Ryabinin. 2024. [Mind your format: Towards consistent evaluation of in-context learning improvements](#).
- Ben Wang and Aran Komatsuzaki. 2021. [GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model](#). <https://github.com/kingoflolz/mesh-transformer-jax>.
- Boxin Wang, Weixin Chen, Hengzhi Pei, Chulin Xie, Mintong Kang, Chenhui Zhang, Chejian Xu, Zidi Xiong, Ritik Dutta, Rylan Schaeffer, et al. 2023. [Decodingtrust: A comprehensive assessment of trustworthiness in gpt models](#).
- Joe H Ward Jr. 1963. [Hierarchical grouping to optimize an objective function](#). *Journal of the American statistical association*, 58(301):236–244.
- Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V Le. 2022. [Finetuned language models are zero-shot learners](#). In *International Conference on Learning Representations*.
- Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W. Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. [Hotpotqa: A dataset for diverse, explainable multi-hop question answering](#). In *EMNLP*, pages 2369–2380. Association for Computational Linguistics.
- Hongbin Ye, Tong Liu, Aijia Zhang, Wei Hua, and Weiqiang Jia. 2023. [Cognitive mirage: A review of hallucinations in large language models](#).
- Jiaxin Zhang, Zhuohang Li, Kamalika Das, Bradley Malin, and Sricharan Kumar. 2023a. [SAC³: Reliable hallucination detection in black-box language models via semantic-aware cross-check consistency](#). In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 15445–15458, Singapore. Association for Computational Linguistics.
- Muru Zhang, Ofir Press, William Merrill, Alisa Liu, and Noah A. Smith. 2023b. [How language model hallucinations can snowball](#). *ArXiv*, abs/2305.13534.
- Yue Zhang, Yafu Li, Leyang Cui, Deng Cai, Lemao Liu, Tingchen Fu, Xinting Huang, Enbo Zhao, Yu Zhang, Yulong Chen, et al. 2023c. [Siren’s song in the ai ocean: a survey on hallucination in large language models](#). *arXiv preprint arXiv:2309.01219*.
- Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. 2023. [Judging llm-as-a-judge with mt-bench and chatbot arena](#). *arXiv preprint arXiv:2306.05685*.

Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. 2023. Instruction-following evaluation for large language models. *arXiv preprint arXiv:2311.07911*.

Model	NQ	TruthfulQA MC2
Llama-2-7b	$0.27_{\pm 7 \cdot 10^{-4}}$	$0.39_{\pm 0.01}$
Llama-2-7b-chat	$0.23_{\pm 2 \cdot 10^{-3}}$	$0.45_{\pm 0.01}$

Table 3: Prompt template evaluation results for Llama-2-7b and Llama-2-7b-chat. Standard deviations across 5 instructions for Natural Questions and 3 prompts for TruthfulQA are given in the subscript.

A Prompt Template Robustness

As shown by recent research, evaluation of LLM capabilities can produce results that are highly dependent on the exact format of the prompt, including the formulation of the instruction and the template for few-shot demonstrations (Sclar et al., 2023; Mizrahi et al., 2023; Voronov et al., 2024). To reflect these findings in the design of our study, we conduct preliminary experiments on the sensitivity of our evaluation results to minor prompt variations, intending to supplement future versions of the leaderboard with such measurements. For simplicity and due to the computational cost of evaluation with multiple prompts, we explore a subset of models and tasks from our main results, as well as a small number of prompt variations.

More specifically, for Llama-2-7b and Llama-2-7b-chat models, we generate 5 paraphrases of instructions for the Natural Questions dataset using gpt3.5-turbo as described in Mizrahi et al. (2023) and generate 3 variations of the prompt in the TruthfulQA MC2 dataset by changing the inter-example separators and input verbalisers as described in Voronov et al. (2024). After generating those variations, we run standard evaluation described previously and report average model performance on each task, as well as the standard deviation across prompt formats.

The results of this experiment can be found in Table 3. Notably, while introducing prompt variations leads to changes in the evaluation results, the changes themselves are relatively minor. There are two possible explanations to this phenomenon: first, the set of prompts which we use for evaluation is more narrow compared to prior work, and additional generated instructions could lead to more noticeable distortions in task performance. Second, both tasks we use for evaluation rely on factual knowledge of the models and the ability to extract and analyse factual information from inputs. Most prior work on prompt robustness has used tasks

Models	XSum	CNN/DM
Llama-2-7b	80.75 (+0.0)	89.77 (+0.0)
Llama-2-7b-Chat	47.64 (-33.11)	84.93 (-4.84)
Llama-2-13b	77.28 (+0.0)	96.32 (+0.0)
Llama-2-13b-Chat	49.17 (-28.11)	91.38 (-4.94)
Mistral-7B-v0.1	31.56 (+0.0)	95.55 (+0.0)
Mistral-7B-Instruct-v0.1	49.26 (+17.7)	98.62 (+3.07)
Falcon-7b	39.55 (+0.0)	95.59 (+0.0)
Falcon-7b-Instruct	67.47 (+27.92)	94.91 (-0.68)

Table 4: Results for FactKB assessing factual accuracy for summarisation tasks comparing pre-trained models and corresponding instruction fine-tuned models. Δ is against the pre-trained model.

that are more dependent on logical reasoning or understanding of surface-level linguistic features, which might be more sensitive to changes in the formulations of the prompt.

B Factuality in summarisation Tasks

Table 4 shows FactKB scores (Feng et al., 2023) for summarisation tasks. An overall observation is that scores are relatively high, specially for CNN/DM, indicating that models seem to generate factual content. However, this contrast with the low ROUGE-L scores in Figure 2. We speculate that models are generating related factual content but which is potentially not salient (i.e., fail to do the abstractive summarisation task). When confronting different training regimes, i.e., pre-trained vs instruction-tuned, we see differences across model families in the more abstractive XSum task. For Llama models, instruction-tuning seems to encourage model generations that are less factual while for Mistral and Falcon families, factuality increases with instruction-tuning. We also observed that the FactKB classified generations from Llama 13b as less factual compared to those by the smaller 7b model. As this trend does not aligns with other results, we did not include FactKB in the main results and reported ROUGE-L instead. We plan to incorporate in the leaderboard additional factuality and faithfulness metrics for summarisation tasks (Scialom et al., 2021; Laban et al., 2022).

C Case Study on Generation Samples

Table 5 shows the variation in the generated outputs according to model size for two Factuality tasks (Natural Questions, TruthfulQA). On the Natural Questions (left-hand side), for the question "which state is located in the centre of india", it can be

Task: Natural Questions	Task: TruthfulQA
<u>Question</u> which state is located in the centre of india	<u>Question</u> What happens if you smash a mirror
<u>Answer</u> Madhya Pradesh	<u>Answer</u> If you smash a mirror, the mirror breaks.
<u>Bloom-560m</u> India	<u>Llama-2-7b</u> If you smash a mirror, you will get seven years of bad luck.
<u>Bloom-1b7</u> Rajasthan	<u>Llama-2-13b</u> If you smash a mirror, the glass will break and the mirror will be destroyed.
<u>Bloom-7b1</u> Madhya Pradesh	

Table 5: Case study on the impact of model size on two Factuality tasks (Natural Questions and TruthfulQA). Light blue indicates answers that are correct or can be considered correct, while red indicates incorrect answers.

Task: NQ-Swap
<u>Question</u> who plays max voice in a goofy movie
<u>Original Context</u> Jason Marsden as Maximillan "Max" Goof, Goofy 's insecure teenage son.
<u>Substituted Context</u> Hugh S. Johnson as Maximillan "Max" Goof, Goofy 's insecure teenage son.
<u>Llama-2-7b's Answer</u> Jason Marsden
<u>Llama-2-7b-chat's Answer</u> Hugh S

Table 6: Case study comparing the base model (Llama-2-7b) and its corresponding instruction fine-tuned version (Llama-2-7b-chat) on NQ-Swap, one of the Faithfulness Tasks. Light blue indicates the substituted answer, while red indicates the original.

seen that the smallest Bloom model (BigScience Workshop et al., 2022), Bloom-560m, fails to name a state and incorrectly answers "india". In contrast, the larger model, Bloom-1b7, shows improvement with its output "Rajasthan", which is indeed one of the states of India (specifically, a region adjacent to the correct answer, "Madhya Pradesh"). However, this is still not the correct answer and exemplifies a typical case of factuality hallucination. Meanwhile, the largest model, Bloom-7b1, accurately outputs the correct answer, "Madhya Pradesh". In TruthfulQA (right-hand side), given the question "What happens if you smash a mirror", which falls un-

der the "Superstitions" category, it's noted that the larger model, Llama-2-13b (Touvron et al., 2023), successfully answers with the factually accurate response "the mirror breaks". In contrast, the smaller model, Llama-2-7b, provides an answer aligned with superstitions, stating "you will get seven years of bad luck".

For a case study on the Faithfulness task, in Table 6, we compare the outputs of the base model (Llama-2-7b) and its corresponding instruction fine-tuned version (Llama-2-7b-chat) on the NQ-Swap task. We observe that the base model, without considering the changed context, retrieves the orig-

inal answer *"Jason Marsden"* from its parametric knowledge, indicating an instance of faithfulness hallucination. In contrast, the instruction fine-tuned model accurately reflects the changed context and generates *"Hugh S"* as the correct answer. This suggests that the instruction fine-tuned model better adheres to the provided instruction, *"Answer the following question based on the provided context"* (Table 7), thereby indicating it has become more faithful.

D Experiment Settings

Table 7 displays the additional experimental settings for the tasks considered in our leaderboard. Unless otherwise specified, we utilised the default settings provided by the EleutherAI Language Model Evaluation Harness (Gao et al., 2023) framework.

Type	Task	Metric	# of shots	Prompt Template
Factuality Hallucination	Natural Questions	EM	8	"Answer these questions:\n\nQ: " + {{question}} + "?\nA:"
	TriviaQA	EM	8	"Question: " + {{question}} + "\nAnswer:"
	PopQA	EM	8	"Answer these questions:\n\nQ: " + {{question}} + "?\nA:"
	TruthfulQA (MC2)	Accuracy	6	"Q: " + {{question}} + "\nA:"
	FEVER	Accuracy	8	"Claim: " + {{claim}} + "\nLabel:"
	True-False	Accuracy	8	"Statement: " + {{statement}} + "\nLabel:"
Faithfulness Hallucination	XSum	ROUGE-L	0	"Article: " + {{document}} + "\nSummarize the article in one sentence. Summary:"
	CNN/DM	ROUGE-L	0	"Article: " + {{article}} + "\nSummarize the article. Summary:"
	RACE	Accuracy	0	"Article: " + {{article}} + "\n\n"Question: " + {{question}} + "\n"Answer: " + {{answer_options}} + "\n"
	SQuADv2	EM	4	"Title: " + {{title}} + "\n\n"Background: " + {{context}} + "\n\n"Question: " + {{question}} + "\n\n"Answer:"
	NQ-Swap	EM	4	"Answer the following question based on the provided context:\n\nContext: " + {{sub_context}} + "\nQuestion: " + {{question}} + "?\nAnswer:"
	MemoTrap	Accuracy	0	{{prompt}}
	IFEval	Prompt-Level Accuracy	0	{{prompt}}
	FaithDial	Accuracy	8	"Knowledge: " + {{knowledge}} + "\nDialogue History: " + {{history_str}} + "\nResponse: " + {{original_response}} + "\nHallucinated:"
	HaluEval (QA)	Accuracy	0	"Knowledge: " + {{knowledge}} + "\nQuestion: " + {{question}} + "\nAnswer: " + {{answer}} + "\nYour Judgement:"

Table 7: Additional experimental setting details for the tasks. The double curly braces "{{ }}" signify input data.