

# Understanding LLM Development Through Longitudinal Study: Insights from the Open Ko-LLM Leaderboard

<sup>1</sup>Chanjun Park<sup>†</sup>, <sup>2</sup>Hyeonwoo Kim

<sup>1</sup>Korea University, <sup>2</sup>Upstage AI  
bcj1210@korea.ac.kr  
choco\_9966@upstage.ai

## Abstract

This paper conducts a longitudinal study over eleven months to address the limitations of prior research on the Open Ko-LLM Leaderboard, which have relied on empirical studies with restricted observation periods of only five months. By extending the analysis duration, we aim to provide a more comprehensive understanding of the progression in developing Korean large language models (LLMs). Our study is guided by three primary research questions: (1) What are the specific challenges in improving LLM performance across diverse tasks on the Open Ko-LLM Leaderboard over time? (2) How does model size impact task performance correlations across various benchmarks? (3) How have the patterns in leaderboard rankings shifted over time on the Open Ko-LLM Leaderboard?. By analyzing 1,769 models over this period, our research offers a comprehensive examination of the ongoing advancements in LLMs and the evolving nature of evaluation frameworks.

## 1 Introduction

The rapid advancement of large language models (LLMs) (Zhao et al., 2023) has led to the creation of various leaderboards designed to evaluate their performance across a wide range of tasks (Li et al., 2023b; Lee et al., 2023; Hughes and Bae, 2023; BigCode, 2023; Li et al., 2023a). Among these, the Open LLM Leaderboard (Beeching et al., 2023; Fourrier et al., 2024) developed by Hugging Face (Jain, 2022) has achieved significant global recognition. In the context of Korean language models, the Open Ko-LLM Leaderboard (Park et al., 2024) was established to specifically assess LLM performance within the Korean language environment.

While previous analyses of the Open Ko-LLM Leaderboard (Park et al., 2024) have provided valuable insights into LLM performance, they have

been constrained observation periods of only five months, limiting their ability to capture long-term trends. To better understand the ongoing evolution and inherent challenges in LLM development, a more comprehensive and extended analysis is required. This paper addresses this gap by conducting a detailed longitudinal study of the Open Ko-LLM Leaderboard, guided by three primary research questions:

**First**, we analyze the longitudinal changes in performance across five tasks monitored by the Open Ko-LLM Leaderboard. These tasks are designed to evaluate various capabilities of LLMs, including reasoning, natural language understanding, and common sense knowledge. By examining data collected over an eleven-month period, this study aims to identify which capabilities have presented the greatest challenges for LLM developers, which tasks have reached performance saturation rapidly, and which tasks continue to pose significant difficulties. This analysis will provide quantitative insights into performance trends across different tasks, thereby guiding targeted research efforts and highlighting key areas that require further advancement to push the boundaries of model development.

**Second**, we explore the correlations between different tasks based on model size. This aspect of the study examines how the performance across different tasks varies depending on the scale of the model. Understanding these correlations will provide insights into the interaction between model capacity and task performance, offering a deeper understanding of how scaling influences overall effectiveness across tasks.

**Third**, we examine the evolution of leaderboard dynamics from the initial stages to the present by focusing on three key aspects: the correlations between task performances in the early months compared to the entire eleven-month period, the temporal changes in performance based on model type, and the shifts in performance relative to model size.

<sup>†</sup> Corresponding Author

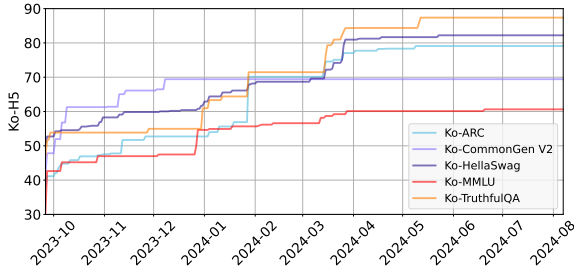


Figure 1: Performance trends of LLMs across different tasks on the Open Ko-LLM Leaderboard over an eleven-month period. The total number of submitted models is 1,769.

This comprehensive analysis offers insights into the evolving interplay among tasks and the influence of various model characteristics on LLM performance throughout different phases of development.

## 2 Open Ko-LLM Leaderboard

The Open Ko-LLM Leaderboard (Park et al., 2024) is a pioneering platform designed to evaluate large language models (LLMs) specifically in the Korean language, addressing the limitations of predominantly English-focused benchmarks. This leaderboard mirrors the structure of the globally recognized Open LLM Leaderboard by Hugging Face (Beeching et al., 2023), ensuring consistency and comparability across languages. It is built on two key principles: alignment with the English leaderboard and the use of private test sets to avoid data contamination, thereby enhancing evaluation robustness.

The leaderboard employs the Ko-H5 benchmark, comprising five tasks that assess various aspects of language understanding and generation in Korean. These tasks are designed to comprehensively evaluate LLM capabilities. The first task, Ko-Hellaswag (Zellers et al., 2019), tests commonsense reasoning by requiring models to complete sentences contextually and logically. The second task, Ko-ARC (Clark et al., 2018), adapted from the English ARC, evaluates both commonsense and scientific reasoning through multiple-choice questions. Ko-MMLU (Hendrycks et al., 2020), the third task, assesses multitask language understanding and domain knowledge across various subjects, requiring models to respond accurately to questions from different domains. The fourth task, Ko-CommonGen V2 (Seo et al., 2024), focuses on commonsense generation, where models must create coherent sentences from given concepts, testing

their ability to connect common knowledge meaningfully. Lastly, Ko-TruthfulQA (Lin et al., 2021) evaluates a model ability to provide truthful and accurate responses, crucial for assessing the factual integrity of LLMs in real-world scenarios.

Through the Ko-H5 benchmark, the Open Ko-LLM Leaderboard provides a robust framework for evaluating Korean LLMs and promotes linguistic diversity in LLM evaluation. By incorporating tasks that reflect Korean linguistic and cultural nuances, the leaderboard offers valuable insights into LLM performance beyond English, encouraging a more inclusive approach to language model evaluation.

## 3 Empirical Analysis

### 3.1 Challenges in Enhancing Task Performance Over Time

*What are the specific challenges in improving LLM performance across diverse tasks on the Open Ko-LLM Leaderboard over time?* To investigate this question, we conducted a comprehensive analysis of performance trends over an eleven-month period across all tasks on the Open Ko-LLM Leaderboard, including Ko-HellaSwag (commonsense reasoning)(Zellers et al., 2019), Ko-ARC (commonsense and scientific reasoning)(Clark et al., 2018), Ko-MMLU (multitask language understanding and domain knowledge)(Hendrycks et al., 2020), Ko-CommonGEN V2 (commonsense generation)(Seo et al., 2024), and TruthfulQA (truthfulness) (Lin et al., 2021).

Figure 1 and Table 1 show the varying performance patterns of LLMs across these tasks over the eleven-month period. Certain tasks, such as Ko-HellaSwag and Ko-TruthfulQA, exhibit rapid improvements in performance and early saturation. Specifically, Ko-HellaSwag reached a score of 50 almost immediately and achieved 80 by week 26, while Ko-TruthfulQA showed comparable progress, reaching a score of 80 within 25 weeks. These trends indicate that current LLMs are particularly well-suited for tasks requiring straightforward commonsense reasoning and truthfulness, suggesting a relatively lower barrier to achieving performance enhancements in these domains.

Conversely, tasks such as Ko-MMLU and Ko-CommonGEN V2 show slower, more gradual improvements without clear signs of saturation, highlighting their increased complexity and the deeper understanding required from LLMs. Ko-MMLU

Dataset	50	60	70	80
Ko-ARC	~ 6	~ 17	~ 17	-
Ko-HellaSwag	~ 0	~ 10	~ 24	~ 26
Ko-MMLU	~ 13	~ 26	-	-
Ko-TruthfulQA	~ 0	~ 13	~ 17	~ 25
Ko-CommonGen V2	~ 0	~ 1	-	-

Table 1: Number of weeks it took to reach scores of 50, 60, 70, and 80 out of 100 for the individual tasks.

took 13 weeks to reach a score of 50 and then stabilized around 60 after 26 weeks, indicating a limit to the current models capabilities. Similarly, Ko-CommonGEN V2, despite reaching a score of 50 relatively quickly, showed minimal progress beyond 60. These patterns highlight the significant challenges LLMs face in tasks that demand complex reasoning and specialized knowledge, suggesting these are important areas for further research.

The initial rapid gains in Ko-ARC, followed by minimal progress beyond a score of 60 after 17 weeks, indicate that while LLMs can quickly adapt to certain tasks, their progress is constrained by the need for more complex reasoning skills. This underscores the importance of developing more challenging benchmarks to better evaluate the limitations and capabilities of LLMs, especially in tasks that require more advanced forms of reasoning.

Overall, these findings emphasize the need to include a broad range of complex tasks to comprehensively assess LLM capabilities. While some tasks demonstrate rapid performance saturation, others present ongoing challenges, serving as essential benchmarks for guiding future advancements in LLM development.

### 3.2 The Influence of Model Size on Task Performance Correlations

*How does model size impact task performance correlations across various benchmarks?.* To investigate this question, we analyze how model size affects performance improvements across different tasks, using a framework similar to previous studies (Park et al., 2024). For this analysis, models were divided into three size categories: under 3 billion parameters, 3 to 7 billion parameters, and 7 to 14 billion parameters. This categorization allows for a detailed examination of how scaling impacts task performance.

Figure 2 illustrates distinct patterns in task performance correlations depending on model size. Smaller models (under 3 billion param-

eters) show low or even negative correlations between certain tasks, such as Ko-TruthfulQA and Ko-CommonGen V2, and other tasks. This suggests that smaller models struggle to improve consistently across multiple capabilities, indicating that advancements in one area do not necessarily lead to improvements in others. Consequently, these models tend to have a fragmented skill set, making them less suitable for a comprehensive evaluation of LLM performance.

In contrast, larger models demonstrate higher correlations across most tasks, suggesting that increasing model size results in a more effective integration of various capabilities. For example, models in the 7 to 14 billion parameter category exhibit stronger positive correlations across a majority of tasks, especially those requiring advanced reasoning. This trend indicates that scaling up model size not only enhances performance on individual tasks but also supports a more cohesive development of capabilities, enabling more consistent performance improvements across a wide range of tasks.

These findings highlight the importance of model size in achieving balanced performance across a range of tasks. Smaller models, with their inconsistent performance across tasks, suggest a limitation in their ability to generalize learning effectively. In contrast, the positive correlations observed in larger models imply that increasing model size fosters a more comprehensive understanding and transfer of knowledge across different domains. This insight is crucial for future LLM development, as it underscores the need to consider model size not just for boosting individual task performance, but also for promoting a more integrated and holistic enhancement of capabilities.

### 3.3 Temporal Shifts in Leaderboard Ranking Patterns

*How have the patterns in leaderboard rankings shifted over time on the Open Ko-LLM Leaderboard?.* To investigate this question, we extended our analysis to an eleven-month period to see if the initial trends, defined as those observed during the initial five months in the previous study by Park et al. (2024), remained consistent or if new patterns emerged over time. This longer timeframe allows us to capture shifts in model performance and ranking dynamics.

**Task Correlations Over Time.** Figure 3 shows the correlation analysis between tasks during the

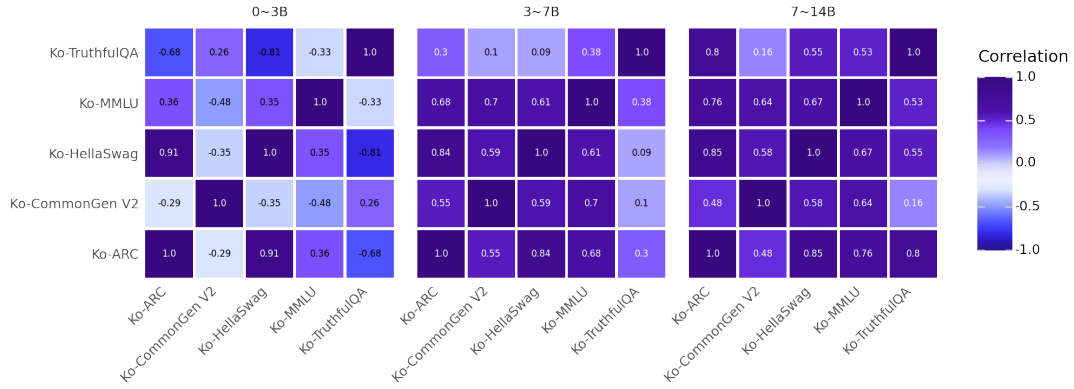


Figure 2: Correlation between task performances across different model size categories, illustrating how task correlations change with increasing model size.

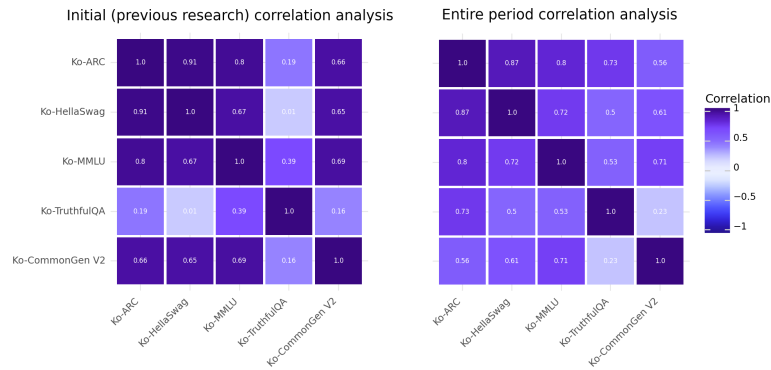


Figure 3: Analysis of Task Correlations Over Time.

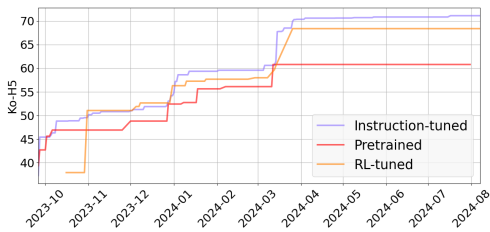


Figure 4: Performance Trends Over Time for Different Model Types.

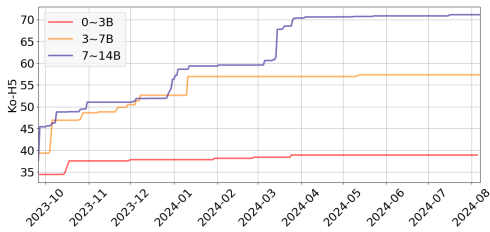


Figure 5: Performance Trends by Model Size.

served in the correlation between Ko-Truthful QA and other tasks, especially Ko-Hellaswag. This correlation, initially very low at 0.01, rose significantly to 0.5 over time. This change suggests that as higher-performing models, particularly those with 7 billion parameters or more, were introduced, the alignment between tasks became stronger. For most other tasks, correlations remained relatively stable, reflecting their initial patterns.

**Performance Trends by Model Type.** Figure 4 presents the performance trends over time for different model types. As noted in previous research (Park et al., 2024), improvements in instruction-tuned models typically lagged behind those of pretrained models by about one week. When a pretrained model showed a significant performance boost, instruction-tuned models followed with a similar increase roughly one week later. This pattern persisted throughout the entire period analyzed, indicating a reliance of instruction-tuned

initial phases of the leaderboard and over the full eleven-month period. A notable increase was ob-

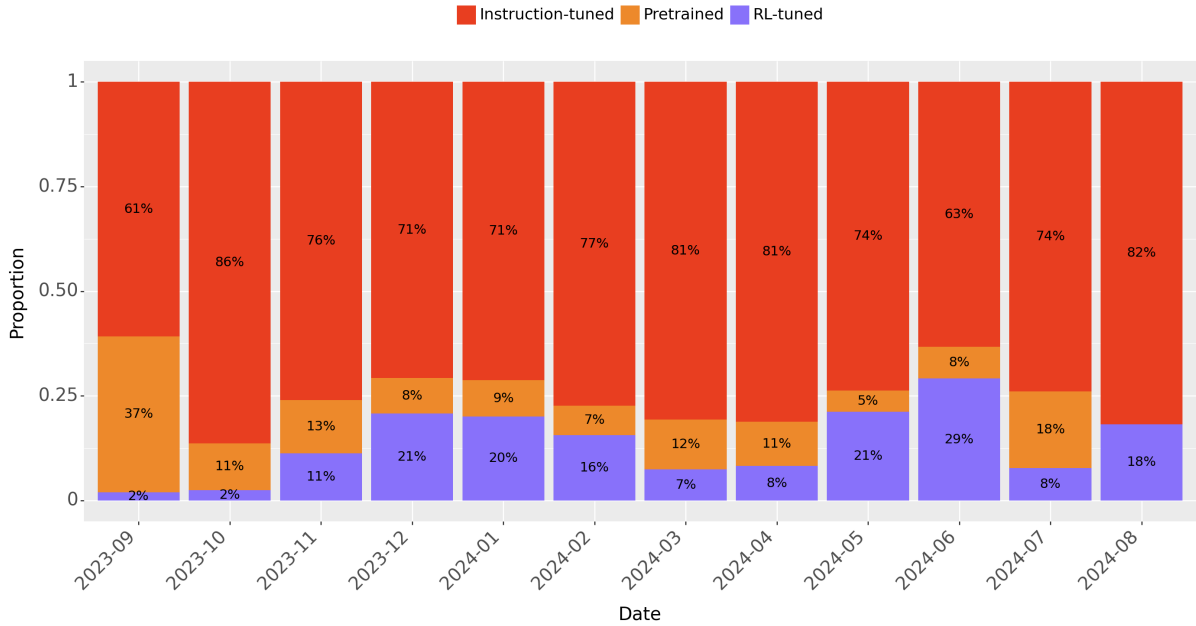


Figure 6: Monthly distribution of submissions by model type on the Open Ko-LLM leaderboard.

Date	Model Submissions Count	Model Evaluation Count
2023-09	51	40
2023-10	322	255
2023-11	337	280
2023-12	260	225
2024-01	289	234
2024-02	115	99
2024-03	176	153
2024-04	170	122
2024-05	156	134
2024-06	79	72
2024-07	142	129
2024-08	33	26
<b>Total</b>	<b>2230</b>	<b>1769</b>

Table 2: Monthly distribution of model submissions and evaluation on the Open Ko-LLM leaderboard.

models on the advancements made by pretrained models. After April 2024, the performance of pretrained models stabilized, leading to a corresponding lack of progress in both instruction-tuned and RL-tuned models. This trend indicates the fundamental role of pretrained models in driving overall performance gains in LLMs and suggests that further improvements in pretrained models are necessary for advancing model capabilities.

**Performance Trends Across Model Sizes.** Figure 5 shows performance variations by model size. Models in the 0-3B range exhibited minimal improvement throughout the leaderboard period, indicating inherent scalability limitations. Similarly,

models in the 3-7B range initially demonstrated gains, but their progress stabilized around five months in (April 2024 to August 2024), revealing similar scalability constraints.

Larger models in the 7-14B range showed steady performance improvements during the early phase of the leaderboard, continuing throughout the entire analysis period. However, after April 2024, their performance also reached a saturation point. This stagnation is likely due to the absence of new, high-performing Korean pretrained models, a trend also evident in the analysis of different model types in Figure 4.

These findings emphasize that improving LLM

performance largely depends on advancements in pretrained models. The leaderboard analysis indicates that, without new breakthroughs in pretrained models, further improvements are limited. This highlights the essential role of continuous innovation in pretrained models for advancing LLM performance.

### 3.4 Evaluation Patterns and Submission Insights

Figure 6 presents the monthly distribution of submissions across different model types on the Open Ko-LLM leaderboard. Initially, pretrained models constituted 37% of all submissions, but this proportion declined sharply over time, with no pretrained models submitted by August 2024. This trend signals a diminishing focus on pretrained models within the community, which is concerning given their foundational importance discussed in Section 3.3. Therefore, a renewed emphasis on fostering interest and engagement with pretrained models could help address this emerging gap.

On the other hand, instruction-tuned models, which started at 61%, consistently dominated the submissions, maintaining a steady presence of 70-80% each month. This trend suggests that the community perceives instruction-tuned models as highly effective or suitable for the tasks evaluated. Additionally, RL-tuned models, though initially making up only 2% of submissions, gradually increased to a peak of 29%, reflecting a growing interest in exploring reinforcement learning approaches within the leaderboard context. This variety indicates a healthy exploration of diverse model types, but also highlights areas where community focus could be broadened or rebalanced.

In addition, Table 2 presents the monthly statistics for both the number of model submissions and the number of completed model evaluations. The *Model Submissions Count* refers to the total number of models submitted to the leaderboard each month. In contrast, the *Model Evaluation Count* represents the number of these submitted models that successfully completed the evaluation process.

The discrepancy between the *Model Submissions Count* and the *Model Evaluation Count* is due to instances where some models fail to complete the evaluation phase on the leaderboard. This failure can occur for several reasons, such as models being too large to be processed within the available computational resources or issues related to library support and compatibility. As a result, not all submit-

ted models are evaluated successfully, highlighting potential challenges and areas for improvement in handling diverse model architectures on the leaderboard.

## 4 Conclusion

This study provides a longitudinal analysis of the Open Ko-LLM Leaderboard, uncovering significant performance trends and underlying challenges in LLM development. It was observed that smaller models consistently face scalability limitations, preventing substantial performance advancements. In contrast, larger models initially show promising improvements but eventually reach a saturation point, highlighting a critical dependency on advancements in pretrained models. These findings underscore the need for continuous innovation and enhancement in the development of pretrained models to push the boundaries of LLM capabilities further. Additionally, the analysis demonstrates the utility of leaderboard data in tracking the evolving dynamics of LLM performance. By examining a broader range of model submissions and evaluation patterns over an extended period, this study provides valuable insights into how model size, type, and tuning methods influence overall effectiveness. Such insights can inform targeted research efforts and encourage the development of strategies aimed at overcoming existing limitations, ultimately supporting more robust and adaptable LLMs.

## Acknowledgments

We sincerely thank the National Information Society Agency (NIA), Korea Telecom (KT), and Flitto for their support. We also extend our gratitude to the Korea University NLP & AI Lab, particularly Professor Heuseok Lim and Jaehyung Seo, for their valuable data contributions, which have greatly enhanced the robustness of the leaderboard. Our appreciation goes to the Hugging Face teams, especially Clémentine Fourier, Lewis Tunstall, Omar Sanseviero, and Philipp Schmid, for their assistance. We would like to thank SeongHwan Cho for his contributions to the leaderboard development, and Sanghoon Kim for his contributions to the leaderboard infrastructure. Special thanks to Hyunbyung Park for his initial contributions to Ko-H5.

We are also grateful to Professor Harksoo Kim from Konkuk University, Professor Hwanjo Yu from Pohang University of Science and Technol-

ogy, Professor Sangkeun Jung from Chungnam National University, and Professor Alice Oh from KAIST for their insightful advice on the Open Ko-LLM Leaderboard. Finally, we deeply appreciate the open-source community for their invaluable feedback and contributions.

This work was supported by Institute of Information & Communications Technology Planning & Evaluation(IITP) grant funded by the Korea government(MSIT) (No. RS-2024-00338140, Development of learning and utilization technology to reflect sustainability of generative language models and up-to-dateness over time).

## Limitations

While this study provides valuable insights into the evaluation of LLMs, several limitations should be acknowledged. First, our analysis is primarily based on data from the Open Ko-LLM Leaderboard. Although this leaderboard offers extensive coverage of various tasks, it may not fully represent the complete spectrum of challenges and scenarios relevant to LLM performance, particularly in specialized or emerging domains.

Additionally, the focus on Korean language models may restrict the generalizability of our findings to other languages and cultural contexts. The linguistic and cultural nuances specific to Korean may not entirely translate to other languages, potentially limiting the applicability of our conclusions.

Furthermore, our study predominantly examines the relationship between model size and performance but does not explore other factors, such as training data diversity or the impact of different fine-tuning techniques, which could also significantly influence model outcomes. Future research should aim to address these gaps by incorporating a broader range of tasks, languages, and evaluation metrics. Expanding the scope of analysis to include models trained in different linguistic and cultural settings, as well as exploring the impact of varied training methodologies, would enhance the robustness and applicability of the findings.

## Ethics Statement

In conducting this research, we adhered to the highest ethical standards, ensuring that all data used in the evaluation was sourced responsibly and in compliance with relevant regulations. We are committed to transparency and integrity in our research practices, and we have made our methods and find-

ings available to the community for further scrutiny and development. We also acknowledge the importance of considering the societal impacts of LLMs, particularly in ensuring that their development and deployment are aligned with ethical principles that promote fairness, inclusivity, and accountability.

## References

- Edward Beeching, Clémentine Fourier, Nathan Habib, Sheon Han, Nathan Lambert, Nazneen Rajani, Omar Sanseviero, Lewis Tunstall, and Thomas Wolf. 2023. Open llm leaderboard (2023-2024). [https://huggingface.co/spaces/open-llm-leaderboard-old/open\\_llm\\_leaderboard](https://huggingface.co/spaces/open-llm-leaderboard-old/open_llm_leaderboard).
- BigCode. 2023. Big code models leaderboard. <https://huggingface.co/spaces/bigcode/bigcode-models-leaderboard>.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*.
- Clémentine Fourier, Nathan Habib, Alina Lozovskaya, Konrad Szafer, and Thomas Wolf. 2024. Open llm leaderboard v2. [https://huggingface.co/spaces/open-llm-leaderboard/open\\_llm\\_leaderboard](https://huggingface.co/spaces/open-llm-leaderboard/open_llm_leaderboard).
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*.
- Simon Hughes and Minseok Bae. 2023. [Vectara hallucination leaderboard](#).
- Shashank Mohan Jain. 2022. Hugging face. In *Introduction to Transformers for NLP: With the Hugging Face Library and Models to Solve Problems*, pages 51–67. Springer.
- Tony Lee, Michihiro Yasunaga, Chenlin Meng, Yifan Mai, Joon Sung Park, Agrim Gupta, Yunzhi Zhang, Deepak Narayanan, Hannah Benita Teufel, Marco Bellagente, et al. 2023. Holistic evaluation of text-to-image models. *arXiv preprint arXiv:2311.04287*.
- Junyi Li, Xiaoxue Cheng, Wayne 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.
- Xuechen Li, Tianyi Zhang, Yann Dubois, Rohan Taori, Ishaan Gulrajani, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023b. AlpacaEval: An automatic evaluator of instruction-following models. [https://github.com/tatsu-lab/alpaca\\_eval](https://github.com/tatsu-lab/alpaca_eval).

Stephanie Lin, Jacob Hilton, and Owain Evans. 2021. Truthfulqa: Measuring how models mimic human falsehoods. *arXiv preprint arXiv:2109.07958*.

Chanjun Park, Hyeonwoo Kim, Dahyun Kim, SeongHwan Cho, Sanghoon Kim, Sukyung Lee, Yungi Kim, and Hwalsuk Lee. 2024. [Open Ko-LLM leaderboard: Evaluating large language models in Korean with Ko-h5 benchmark](#). In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3220–3234, Bangkok, Thailand. Association for Computational Linguistics.

Jaehyung Seo, Jaewook Lee, Chanjun Park, SeongTae Hong, Seungjun Lee, and Heui-Seok Lim. 2024. Kocomongen v2: A benchmark for navigating korean commonsense reasoning challenges in large language models. In *Findings of the Association for Computational Linguistics ACL 2024*, pages 2390–2415.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. Hellaswag: Can a machine really finish your sentence? *arXiv preprint arXiv:1905.07830*.

Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023. A survey of large language models. *arXiv preprint arXiv:2303.18223*.