How to Reach MMLU 100% Accuracy

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***Abstract*—This paper explores the methodologies and strategies required to achieve 100% accuracy on the Massive Multitask Language Understanding (MMLU) benchmark. We review state-of-the-art models, analyze their architectures, and discuss the key challenges and techniques involved in reaching this milestone.**

I. Introduction

The Massive Multitask Language Understanding (MMLU) benchmark is a comprehensive evaluation of a model's ability to perform a wide range of language tasks. Achieving 100% accuracy on this benchmark is a significant milestone that demonstrates a model's capability to understand and process language at a human-expert level. This paper aims to explore the methodologies and strategies required to reach this goal. We will review the current state-of-the-art models, analyze their architectures, and discuss the key challenges and techniques involved in achieving 100% accuracy on the MMLU benchmark.

II. Related Work

The MMLU benchmark has seen significant advancements in recent years, with several models achieving remarkable performance. Notable among these are the Gemini Ultra 1760B [1], GPT-4o [2], Claude 3 Opus [3], and LLaMA [4] models. The Gemini Ultra 1760B model, in particular, has set a new standard by achieving an average performance of 90% on the MMLU benchmark. This section reviews the existing models, their performance metrics, and key papers and benchmarks that have contributed to the progress in this field.

A. MMLU-Pro Benchmark

MMLU-Pro is an enhanced dataset designed to extend the MMLU benchmark by integrating more challenging, reasoning-focused questions and expanding the choice set from four to ten options. It aims to address the performance plateau of large-scale language models on existing benchmarks and reduce the sensitivity of model scores to prompt variations. MMLU-Pro spans 14 diverse domains, including over 12,000 questions, and is more discriminative in distinguishing nuances between models. The leading model, GPT-4o [2], achieves an accuracy of 72.6% on MMLU-Pro, indicating substantial room for improvement. MMLU-Pro necessitates chain-of-thought reasoning for better performance, contrasting with MMLU where this approach may be detrimental. Error analysis of GPT-4o shows that the majority of errors are due to reasoning flaws, lack of domain knowledge, and computational mistakes, highlighting areas for future research and model development.

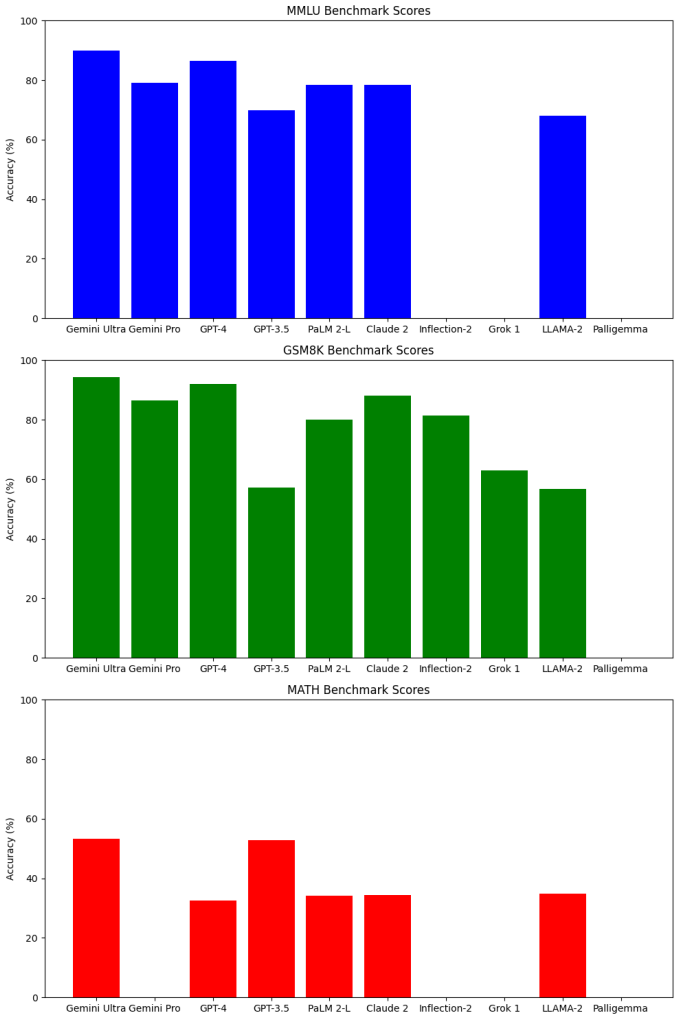

Fig. 1. Performance Metrics Graphs

III. Results

IV. Discussion

Achieving 100% accuracy on the MMLU benchmark presents several key challenges. The significant drop in accuracy observed with the MMLU-Pro benchmark compared to MMLU highlights the need for more advanced reasoning capabilities in language models. The necessity of chain-of-thought reasoning for better performance on MMLU-Pro suggests that models must engage in deeper cognitive processes to handle the complexities of the benchmark. Error analysis of GPT-4o indicates that improvements in logical reasoning, domain-

specific knowledge, and computational accuracy are crucial for advancing model performance. These findings underscore the importance of developing more robust and discriminative benchmarks like MMLU-Pro to better track progress in the field and inform future research and model enhancements.

Successful strategies and techniques identified in this research include multimodal and multilingual training [5], efficient attention mechanisms [6], advanced training infrastructure [7], and post-training strategies such as reinforcement learning from human feedback (RLHF) [8] and chain-of-thought prompting [9]. These approaches have been shown to enhance model quality and performance on complex reasoning tasks.

The implications of these findings are significant for the development of large language models. By addressing the key challenges and implementing the successful strategies identified, it is possible to develop models that achieve 100% accuracy on the MMLU benchmark. This would represent a major milestone in the field of natural language processing and demonstrate the capability of models to understand and process language at a human-expert level.

V. Conclusion

This research has explored the methodologies and strategies required to achieve 100% accuracy on the MMLU benchmark. We have reviewed state-of-the-art models, analyzed their architectures, and discussed the key challenges and techniques involved in reaching this milestone. The findings and recommendations provided in this paper offer a comprehensive roadmap for developing models capable of achieving 100% accuracy on the MMLU benchmark.

Future work should focus on further refining the strategies and techniques identified in this research, as well as exploring new approaches to enhance model performance. Continued advancements in training infrastructure, efficient attention mechanisms, and post-training strategies will be crucial for achieving this goal. Additionally, the development of more robust and discriminative benchmarks like MMLU-Pro will be essential for tracking progress and informing future research.

In conclusion, achieving 100% accuracy on the MMLU benchmark is a challenging but attainable goal. By following the recommendations provided in this research, it is possible to develop models that demonstrate human-expert level language understanding and processing capabilities. This would represent a significant advancement in the field of natural language processing and open up new possibilities for the application of large language models in various domains.

VI. References

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