SYMBOL-LLM: BRIDGING LANGUAGES AND SYMBOLS

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BUILDING A DUAL-COMPETENT MODEL

Our **objective** is to create a model that understands both natural and symbolic languages effectively. This balance is vital for diverse applications.

Data collection consists of three distinct datasets, ensuring comprehensive training. Each dataset addresses unique aspects of symbolic representation for better performance.

By introducing random noise during training, we enhance model robustness, preventing overfitting and ensuring consistent understanding across various symbolic tasks.

LAYING THE SYMBOLIC FOUNDATION

To build a robust model, it is essential to establish **fundamental symbolic comprehension** through diverse datasets that encompass various symbolic operations.

Training on these datasets will ensure the model accurately recognizes and interprets **mathematical and logical symbols**, enhancing its overall performance in symbolic reasoning.

Maintaining a balance between **symbolic accuracy** and natural language proficiency is crucial for the model to perform effectively across different domains.

MERGING SYMBOLIC AND LANGUAGE

The goal is to develop a model that can **fluidly transition** between symbolic and natural language tasks for diverse applications.

By blending symbolic tasks with language tasks, we enhance cross-domain understanding, allowing users to interact naturally with symbols.

Utilizing symbol-to-language mappings during training ensures that **symbolic comprehension** becomes an integral part of the model's capabilities.

EXPERIMENTS & RESULTS

Symbol-LLM was assessed on various **symbol-heavy tasks**, including mathematical reasoning and programming, achieving superior accuracy compared to standard LLMs.

In language tasks, it was evaluated using GLUE and SQuAD benchmarks, displaying competitive capabilities with minimal trade-offs in performance.

Overall, the findings indicate that Symbol-LLM maintains a **balanced performance** across both symbolic and language domains, highlighting its effectiveness in diverse applications.

WHAT WORKED

The **2-phase training strategy** significantly improved performance metrics, showing a marked increase in accuracy over traditional one-stage models.

Models that focused exclusively on **symbolic training** outperformed general LLMs in tasks requiring deep symbolic reasoning and understanding.

Ensuring **alignment and uniformity** in symbolic formats helped maintain consistency, leading to better interpretation and relationships among related symbols.

FUTURE DIRECTIONS

Scaling Symbol-LLM will enable it to tackle **complex tasks** more effectively in various domains.

Introducing self-correction capabilities is vital for improving **symbolic reasoning** accuracy and reliability in practical applications.

Refining the integration of natural and symbolic language understanding is essential for enhancing **overall model performance** and versatility.