



# Research Update Presentation

**Teaching Algorithmic Reasoning via In-context Learning**

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# Problem Statement

## Teaching Algorithmic Reasoning

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LLMs struggle with algorithmic reasoning due to a lack of understanding of the approach to a problem statement if it differs from their training. They are sensitive to prompting and formatting and fall behind in multi-step logical and algorithmic problem-solving.

# Research Approach

Below is the approach I followed over the past week to gain a better understanding of the problem statement.

## Paper Shortlisting

Shortlisted papers which are relevant to the problem statement on Microsoft Whiteboard to focus on main topic.

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## Presentation

Created a presentation to explain the key findings and future work that can be done to solve the problem.

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## Summarizing papers

Read and summarized the shortlisted papers to create a better understanding of the current research and looking for potential solutions.

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# Key Findings

After reading the papers, a common approach that I came across in a few of them was:

## Improving the Prompting

LLMs are sensitive to prompting, so to help them better understand the task, we can refine the prompts. Several approaches were mentioned, including Algorithmic Structuring in Reasoning, Algorithmic Prompting, Chain of Thought, Tree/Graph of Thoughts, and Decomposed Prompting.

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## Improving the Transformer Architecture

The current architecture lacks certain properties, such as iteration. It can be improved by designing better architectures, like the Looped Transformer Architecture, which incorporates an iterative approach.

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## Improving the Training Data

Conventional data formats are inefficient for teaching arithmetic to transformers. Training on chain-of-thought-style data enhances accuracy and learning speed.

# Next Steps and Future Work

## Understanding Transformers in LLMs

Researching the current transformer architecture in LLMs and exploring ways to improve it in the context of algorithmic reasoning.

## Experimenting with Prompting

Experimenting with various prompting methods to determine which yields better results, while comparing factors like computational costs and processing time.

## Enhancing Training Data for LLMs

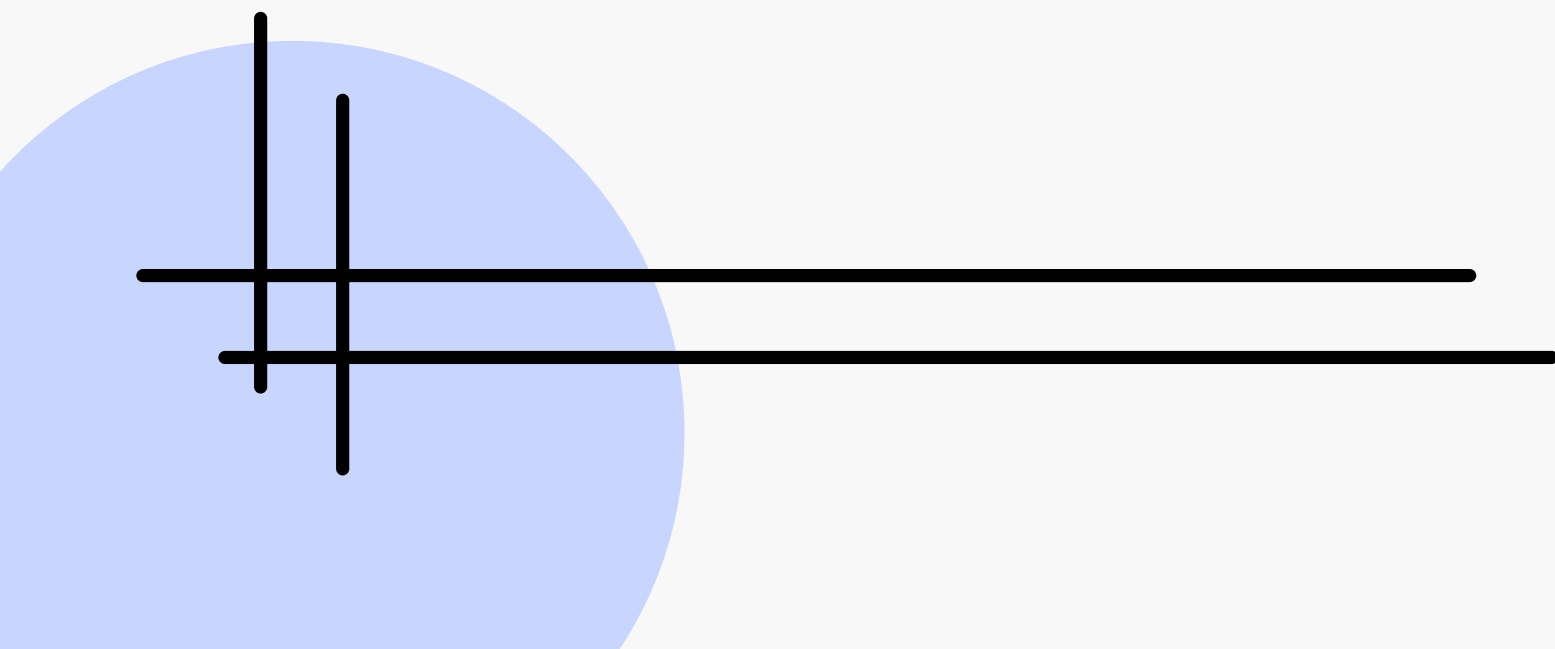
Investigating how training data can be improved for a solid foundation and to create accurate response.

# Conclusion

Algorithmic reasoning in LLMs remains a challenging problem due to their limitations in understanding structured problem-solving, multi-step reasoning, and algorithm execution. Through my research, I identified three key approaches to address these challenges:

- Improving Prompting
- Enhancing Transformer Architecture
- Refining Training Data

Moving forward, further research is needed to optimize these approaches.



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# Thank You

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