AGENTIC TOOL CALLING IN LLMS

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ABSTRACT

This paper investigates the performance gains achieved by augmenting static Large Language Models(LLM) with external, Agentic tool-calling capabilities. Models with fewer parameters (e.g. 1–8 billion) do not perform well on tasks requiring precise numerical reasoning and complex computation, such as the GSM8K problem-solving benchmark, as they rely exclusively on fixed internal knowledge. The performance of the LLM is monitored on different levels of problems with and without the tool calling system which clearly displays the working nature of an LLM and significant enhancement in accuracy and robustness, illustrating the impact of external tool assistance on the utility of smaller-scale LLMs. The paper exclusively derives inferences on the calculator tool used by the LLMs on multi-step reasoning questions involving complex computation.

Index Terms— Agentic tool-calling, Agentic-AI

1. INTRODUCTION

The rapid evolution of Large Language Models (LLMs) has positioned them as powerful general-purpose reasoners capable of handling diverse cognitive tasks [1] involving multistep reasoning. However, a core limitation remains: their reliance on static, internal knowledge, which makes them prone to factual inconsistencies, known as "hallucinations," and incapable of accessing real-time information [2]. These models are trained on a vast amount of data so they are capable of learning reasoning patterns [1] but the complex computation is external code to them so they tend to hallucinate in these kinds of problems. When the model is asked a question like “I run 7 kilometres everyday, How much do I run in a year?” The proceedings of this paper has shown that although the models are capable of figuring out that the mentioned problem requires the multiplication of two numbers 7 and 365 but it fails to conclude the answer as it hallucinates on the computational part.

The performance gap for static LLMs is most pronounced in two domains: complex arithmetic and knowledge-intensive question answering (QA). For example, on benchmark datasets like GSM8K [3], which requires multi-step mathematical reasoning, LLMs often fail to maintain numerical accuracy throughout the generation process. While methods such as Chain-of-Thought (CoT) prompting [1] have improved the structure of LLM reasoning, they do not overcome the fundamental constraint of the model's closed nature-it cannot execute external code or retrieve up-to-date information. Consequently, a baseline LLM remains susceptible to producing errors when computational resources are needed.

There is a critical need for a dynamic and efficient system that empowers smaller, more accessible open-source LLMs (~1−8B parameters) to autonomously decide when and which external tool to invoke. This paper addresses this gap by proposing and evaluating an Agentic Tool-Calling System. This system leverages the LLM's reasoning capabilities to act as a controller, enabling it to dynamically inject grounded information (from a calculator) into its ongoing reasoning trace. The primary objective of this study is to systematically quantify the performance enhancement provided by this agentic system.

2. RELATED WORKS

The foundation of modern LLM capability lies in their training on vast amounts of text data, which enables them to learn complex linguistic and reasoning patterns [4, 5]. This capability was dramatically unlocked by the discovery of Chain-of-Thought (CoT) prompting, which encourages the model to generate a sequence of explicit, intermediate reasoning steps before arriving at a final answer [1]. However, despite learning these abstract reasoning patterns, LLMs remain fundamentally limited when faced with tasks requiring complex, multi-step numerical computation, such as those found in the GSM8K benchmark [3]. The primary constraint is that the model's "reasoning" is purely a process of autoregressive token prediction, it predicts the next most likely token based on statistical patterns from its training data, rather than executing symbolic, deterministic code [6].

LLMs cannot reliably perform arithmetic beyond basic, single-step operations. When a complex calculation is required, the model must *guess* the numerical result token-by-token. This process is inherently prone to error and statistical noise, leading to frequent and unpredictable numerical inaccuracies that break the reasoning chain [6]. The LLM can *plan* the calculation (e.g., "first multiply X by Y, then add Z"), but it fails at the symbolic execution of the math itself.

The limitations of static, text-only reasoning encouraged the development of LLM Agents, which integrate the language model (the planner) with an external environment (the executor). An LLM agent is defined by its ability to autonomously perceive, reason, and act by invoking external tools (e.g., calculators, web search APIs, code interpreters). The ReAct (Reasoning and Acting) framework is a seminal example of this paradigm, demonstrating how interleaving explicit Thoughts with Actions (tool calls) and Observations (tool output) dramatically improves performance on complex tasks [7].

3. METHODOLOGY

This paper focuses on enhancing the mathematical reasoning capabilities of open-source, resource-efficient Large Language Models (LLMs) through a novel Agentic Tool-Calling framework. The core LLM employed is the Meta LLaMa 3.1 8B model [8]. The overall architecture is built upon a standard control loop where the LLM serves as the central planner, interacting with an external environment (the calculator tool) via a structured communication layer. The three primary components are:

i. Core Language Model: The LLaMa 3.1 8B Base Model provides the foundational reasoning and natural language processing capabilities.
ii. The Tool: An external, deterministic Calculator Tool (the expression evaluator of Python with safe expression evaluation and filtering).
iii. Communication Protocol: A rigid protocol defines the structure for tool calls and result integration, leveraging special tokens (e.g., `<CAL>...<CAL>`) to maintain a clean interface between the probabilistic LLM and the deterministic tool.

The agent's decision-making process: determining *when* a calculation is required, is governed by a Prompt-Based Heuristic Policy and structured in two distinct methods:

1. Single-Pass Reasoning (Direct Call): The model is prompted with strict instructions and few-shot examples that guide it to output the required calculation within specific markers (e.g., `<CAL>(200 + 50)/25<CAL>`.
    - Tool Integration: The system intercepts the <CAL>...<CAL> marker, executes the expression, and then appends the deterministic output (e.g., 10) to the model's history, alongside a prompt to continue reasoning. This method provides immediate feedback within a single conversational turn.
    - E.g. "Q: What is 7 squared plus 5? A: <CAL> 7**2<CAL>" Tool is called and tool response is returned with tool call history "Q: What is 7 squared plus 5? H: 7**2 = 49 A: <CAL>49+5<CAL>" again the tool is called.
2. Multi-Step ReAct Planning (Strategic Call): This advanced policy integrates the ReAct (Reasoning and Acting) framework [7] to manage multi-step problems. The LLM first generates a verbose Reasoning Trace (Thought), which includes planned tool calls (Action) and their expected outputs (Observation).
    - Process: The model is first instructed to write a full step-by-step plan. The system then executes the calculator tool calls required by the plan and feeds the verified results back into the model's subsequent reasoning steps, thereby grounding the entire solution in accurate data.
    - E.g. "Q: What is 7 squared plus 5? A: <PLAN> 1. Calculate the square of 7 (7**2). 2. Add 5 to the result of step 1. </ PLAN>." Now the tool is called step by step.

To quantify the necessity of tool augmentation, a series of comparative experiments across different reasoning modalities and datasets was conducted. The description of the datasets:

1. GSM8K [3] : A well-established benchmark of Grade School Math word problems requiring complex, multi-step arithmetic and natural language understanding. To evaluate performance on challenging, multi-step arithmetic reasoning typical of real-world constraints.
2. Custom Math Dataset: A prepared set of math word problems relatively easier than GSM8K. To isolate and test the LLM's raw mathematical execution ability.

4. EXPERIMENTS

The Instruct model of the LLaMa 3.1 8B is a fine tuned model which uses optimal tool calling [9]. The following table summarises the performance of the LLaMa 3.1 8B model variants across the key experiments:

The following inferences can be made from the results of the various experiments listed below.

4.1. Analysing the Reasoning Deficit

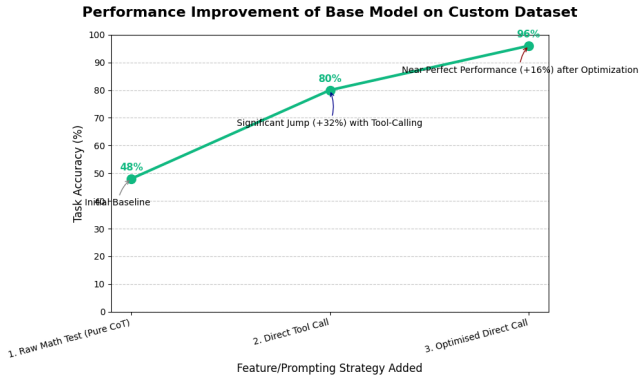
The results unequivocally demonstrate a profound deficiency in the LLaMa 3.1 8B Base Model's native numerical ability, achieving only 15% accuracy on GSM8K (ii). Even on the simpler Custom Math Dataset, the Base Model only reached 48% accuracy (iii), confirming the widely reported observation that LLMs struggle with

	Experimental Setup	Model Type	Dataset	Tool Use	Task Accuracy
i	Fine Tuned Model with optimal tool calling	Instruct Model	GSM8K	Inherently Enabled	84%
ii	Baseline	Base Model	GSM8K	Disabled (Pure CoT)	15%
iii	Raw Math Test	Base Model	Custom	Disabled (Pure CoT)	48%
iv	Direct Tool Call	Base Model	Custom	Tool-calling via special markers	80%
v	Optimised Direct Call	Base Model	Custom	Few Shot+ Strict Prompting	96%
vi	ReAct Agent	Base Model	GSM8K	ReAct Framework	50%

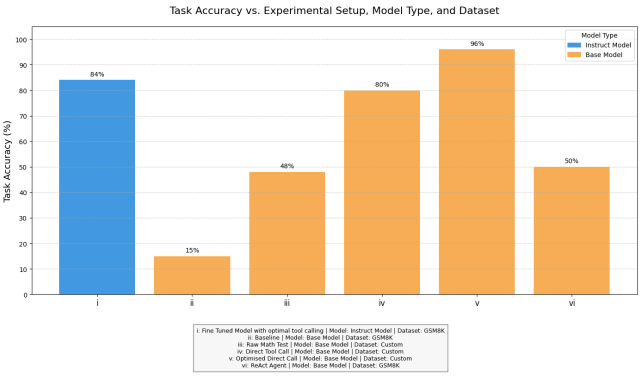
deterministic execution due to the nature of token prediction [6]. This validates our core hypothesis: The model can learn the pattern of reasoning from its vast data [1], but it cannot implement the math reliably by itself.

4.2. Quantifying the Agentic Value

The most significant finding is the contrast between the Base Model and the Tool-Augmented Agent. The simple Direct Tool Call (iv) immediately boosted the Custom Dataset accuracy from 48% to 80%, simply by offloading computation. The final ReAct Agent (vi), built upon the 15%-accurate Base Model, achieved a significant accuracy jump to 50% on the challenging GSM8K benchmark. This 35% absolute increase clearly proves that the Base Model possesses the underlying abstract reasoning intelligence needed to solve these problems; it only required the deterministic execution engine provided by the calculator tool to realise that intelligence.



agentic framework around the Meta LLaMa 3.1 8B Base Model, we systematically demonstrated that while the model's native arithmetic ability is poor (15% on GSM8K), its capacity for abstract reasoning is robust. Augmenting the model with a deterministic Calculator Tool via a ReAct-style policy resulted in a substantial increase to 50% accuracy on the GSM8K benchmark. This performance leap confirms that LLM reasoning failures on mathematical tasks are predominantly failures of execution, not failures of conceptual thought. Future work will focus on optimising the agent's decision policy, potentially through reinforcement learning, to minimise the token overhead while maintaining high accuracy, thereby maximising the practical utility of tool-augmented, open-source LLMs.



5. CONCLUSION

This paper investigated the critical role of external tool augmentation in unlocking the mathematical reasoning potential of resource-efficient LLMs. By designing an

6. REFERENCES

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