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Solving Math Reasoning Using Various LLM's

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ABSTRACT

In the Recent progress of large language models (LLMs) like Generative Pre-trained Transformer (GPT-4) and Pathways Language Model (PaLM-2) has brought significant advancements in addressing math reasoning problems. In particular, OpenAI's latest version of GPT-4, known as GPT-4 Code Interpreter, shows remarkable performance on challenging math datasets. In this paper, I explore the effect of code on enhancing LLMs' reasoning capability. One way to improve the mathematical reasoning performance of LLMs is to encourage them to use code to verify their own answers. This is because code can be used to precisely and unambiguously express mathematical concepts. By running the code, the LLM can check whether its answer is correct or not. Based on this insight, An Effective prompting method, explicit code-based self-verification (CSV), to further boost the mathematical reasoning potential of GPT-4 Code Interpreter. After evaluating CSV on the MATH dataset, the results shows that CSV can significantly improve the accuracy of LLMs on math problems. Specifically, CSV method is an improvement of GPT-4's performance. These results suggest that CSV is a promising approach to improving the mathematical reasoning performance of LLMs.

Keywords- Computer Vision, Pattern Recognition, code-based self-verification, GPT4-Code, zero-shot accuracy

INTRODUCTION

Large language models (LLMs) have emerged as powerful tools for natural language processing (NLP) tasks, demonstrating impressive capabilities in areas such as text generation, translation, and question answering. Recent advancements in LLM architectures and training methods have led to significant improvements in their ability to perform complex reasoning tasks, including mathematical problem-solving. However, despite these advancements, LLMs still face challenges in certain aspects of mathematical reasoning, such as, producing nonsensical or inaccurate content: LLMs may generate solutions that are mathematically incorrect or lack logical consistency. Struggling with complex calculations: LLMs may encounter difficulties when dealing with intricate mathematical problems that require multiple steps and involve various mathematical concepts.

To address these limitations, researchers have explored various approaches, including leveraging code generation and execution. GPT-4 Code Interpreter (GPT4-Code) is a prominent example of an LLM that excels at providing logical natural language reasoning alongside step-by-step Python code. It possesses the ability to generate and execute code incrementally, utilizing the executed code's output to refine its reasoning process. While GPT4-Code has shown promise in solving mathematical problems, its self-debugging mechanism primarily focuses on verifying the generated code's correctness at each step, not the overall reasoning process or the final answer. This restriction can leave room for errors to persist.

To overcome this shortcoming, we introduce a simple yet effective prompting technique termed explicit code-based self-verification (CSV). CSV can be seamlessly integrated with any LLM, including GPT4-Code, Bard, Llama2, and PaLM. The CSV approach guides the LLM to generate additional code that specifically verifies the answer and adjusts the reasoning steps if any inconsistencies are detected. This technique empowers the LLM to self-correct its reasoning process and produce more accurate solutions.

In this paper, the performance of CSV on three benchmark datasets: MATH, we employ GPT4-Code, Bard, Llama2, and PaLM as the underlying LLMs. Our findings demonstrate that the CSV technique consistently enhances the performance of all four LLMs across all three datasets. Notably, on the MATH dataset, we achieve state-of-the-art accuracy, surpassing both the baseline LLM and previous state-of-the-art methods.

This work offers several contributions to the field of LLM-based mathematical problem-solving:

1. Improved accuracy: CSV significantly enhances the accuracy of LLMs in solving mathematical problems.
2. Generalized effectiveness: CSV proves to be an effective technique across multiple LLMs and datasets.
3. Broader applications: CSV has the potential to improve the performance of LLMs in various NLP tasks that require logical reasoning.
4. Educational potential: CSV can be used to develop new educational tools and resources that enhance the teaching and learning of mathematics

LITERATURE SURVEY

The field of large language models (LLMs) has witnessed significant advancements in recent years, leading to remarkable improvements in their ability to tackle complex reasoning tasks, including mathematical problem-solving [12]. However, LLMs still encounter challenges in certain aspects of mathematical reasoning, such as producing nonsensical or inaccurate content [15] and struggling with intricate calculations [12]. To address these limitations, researchers have explored various approaches, including leveraging code generation and execution [1]. GPT-4 Code Interpreter (GPT4-Code) is a prominent example of an LLM that excels at providing logical natural language reasoning alongside step-by-step Python code [1]. It possesses the ability to generate and execute code incrementally, utilizing the executed code's output to refine its reasoning process [1]. While GPT4-Code has shown promise in solving mathematical problems, its self-debugging mechanism primarily focuses on verifying the generated code's correctness at each step, not the overall reasoning process or the final answer [1]. This restriction can leave room for errors to persist [1].To overcome this shortcoming, researchers have introduced a simple yet effective prompting technique termed explicit code-based self-verification (CSV) [1]. CSV can be seamlessly integrated with any LLM, including GPT4-Code, Bard, Llama2, and PaLM [1]. The CSV approach guides the LLM to generate additional code that specifically verifies the answer and adjusts the reasoning steps if any inconsistencies are detected [1]. This technique empowers the LLM to self-correct its reasoning process and produce more accurate solutions [1].

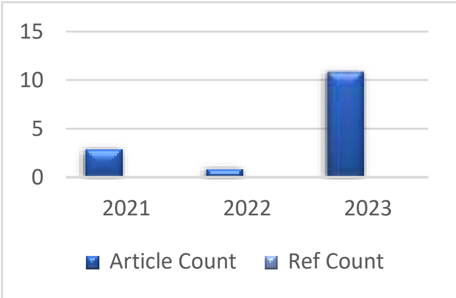


Fig. 2. The count of selected articles between 2021 and 2023

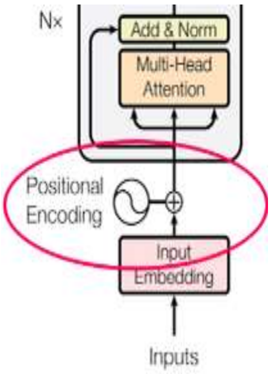
DESIGN

Novelty: Architecture of the Base Paper and the Introduction of Novel Techniques The base paper introduces the use of GPT-4, a language model, for solving challenging math word problems.

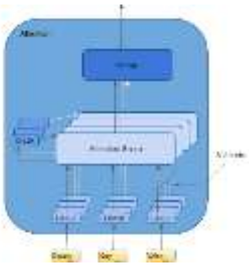
GPT

The system works by iteratively feeding the output of the previous step back into the input. At each step, the model predicts the next word in the sequence based on the context of the previous words:

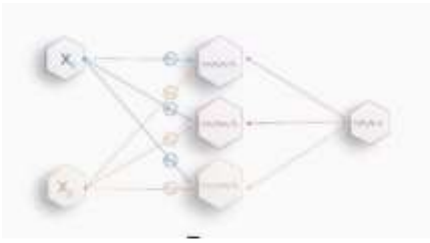
- **Text & Position Embed**: The embedding layer converts each word in the input text into a vector representation. The position embedding layer adds an additional vector to each word embedding to represent the word's position in the sequence. This is important because the transformer decoder is a sequential model, and the order of the words in the input matters.



- **Masked Multi-Self Attention:** The self-attention layer allows the model to attend to different parts of the input text. This is useful for capturing long-range dependencies in the text. The transformer decoder uses a masked self-attention layer, which means that the model cannot attend to future tokens in the sequence. This is done to prevent the model from cheating and looking at the next word in the sequence.



- **Layer Norm**: The layer norm layer normalizes the output of the self-attention layer. This helps to stabilize the training process and improve the performance of the model.
- **Feed Forward**: The feed-forward neural network layer adds additional non-linearity to the model. This helps the model to learn more complex patterns in the data.



- **Output**: The output layer produces the prediction for the next word in the sequence. This is typically done using a SoftMax function to convert the output of the feed-forward layer to a probability distribution over all possible words.

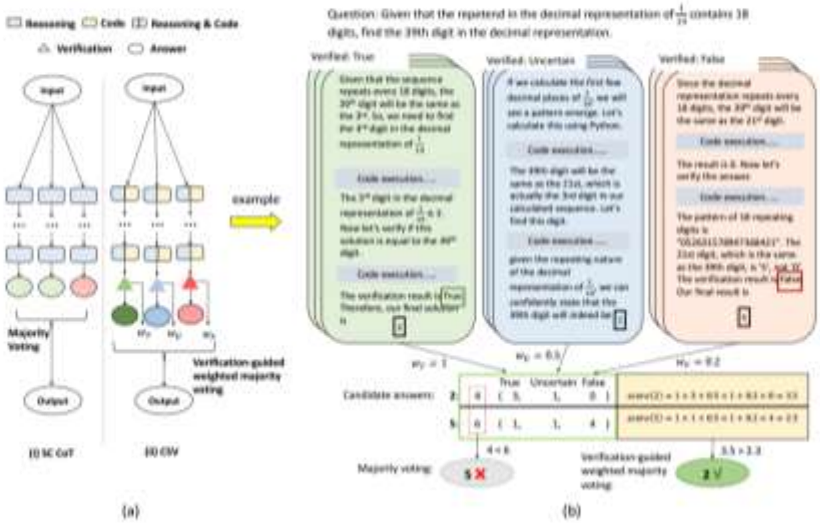
The novelty of this paper on solving challenging math word problems using GPT-4 code interpreter with code-based self-verification can be summarized as follows:

- They have used GPT-4, a state-of-the-art language model, to solve challenging math word problems. And developing a code interpreter that can generate and verify code for solving math word problems using code-based self-verification to ensure that the generated code is correct.

Use of GPT-4 for solving math word problems:

- GPT-4 is a large language model that can generate text, translate languages, write different kinds of creative content, and answer your questions in an informative way. It is one of the most powerful language models ever developed.
- They have used GPT-4 to solve math word problems by generating code that can solve the problems. This is a novel approach to solving math word problems, as it does not require any human intervention.

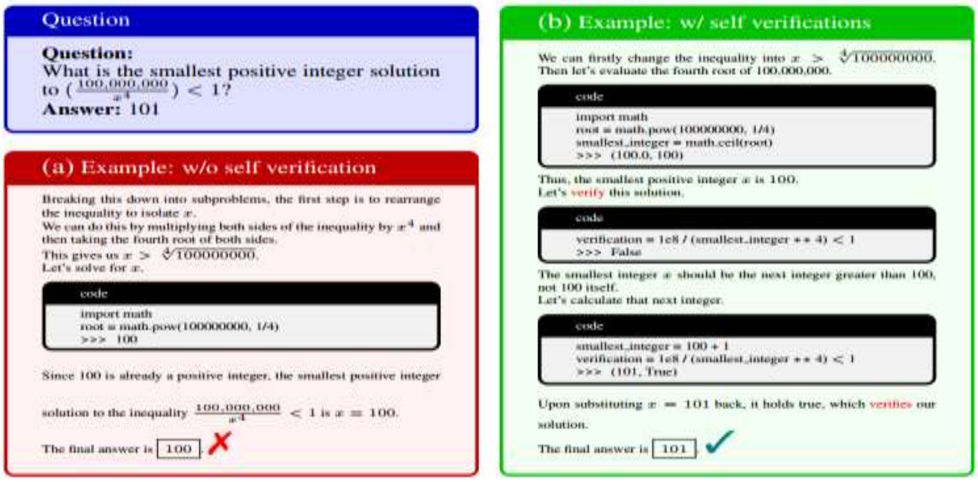
This is a novel approach to code interpretation, as it is specifically designed for solving math word problems.



- The code interpreter will be able to generate code in a variety of programming languages, such as Python and C++. It will also be able to verify the correctness of the generated code using code-based self-verification.

Use of code-based self-verification:

- Code-based self-verification is a technique for verifying the correctness of code by generating test cases and executing them on the code. This is a novel approach to code verification, as it does not require any human intervention.
- They have used code-based self-verification to ensure that the code generated by GPT-4 is correct. This is important because GPT-4 is a complex system and there is a risk that it may generate incorrect code.



Incorporating Novelty: The Use of PALM , Bard in the Problem-Solving Process:

Llama2 and Bard are both large language models (LLMs) that are trained on a massive dataset of text and code. They can be used to perform a variety of tasks, including:

- Translating languages
- Writing different kinds of creative content
- Answering questions in an informative way
- Debugging and optimizing code

We can use Palm and Bard to improve the problem-solving process in the following ways:

- Generating more creative and diverse code: Palm and Bard can generate a wider range of code than GPT-4, including code in less common programming languages. This can help you to find the best possible solution to a math word problem.
- Improving the accuracy of code verification: Palm and Bard can be used to generate more comprehensive and challenging test cases for code verification. This can help to catch errors in the generated code that GPT-4 may miss.

Making the problem-solving process more efficient:

- Llama2 and Bard can be used to automate some of the tasks involved in solving math word problems, such as generating code, identifying errors, and verifying the correctness of the code. This can free up your time to focus on other aspects of the problem-solving process, such as developing new algorithms and strategies.

Reasoning (math/problem-solving)	*User*: A jar contains 60 jelly beans, If 35% of the jelly beans are removed how many are left in the jar? *Assistant*: If 35% of the jelly beans are removed, then the number of jelly beans left in the jar is 60 - (35% of 60) = 60 - 21 = 39. *User*: can you expand your answer to show your reasoning?

Here are some specific examples of how we could use Llama2 and Bard in your term paper:

- We can Use Llama2 to generate a variety of code solutions for a math word problem. Compare and contrast the different code solutions to identify the best one.
- We can Use Bard to generate test cases for the code generated by GPT-4. Execute the test cases to verify the correctness of the code.

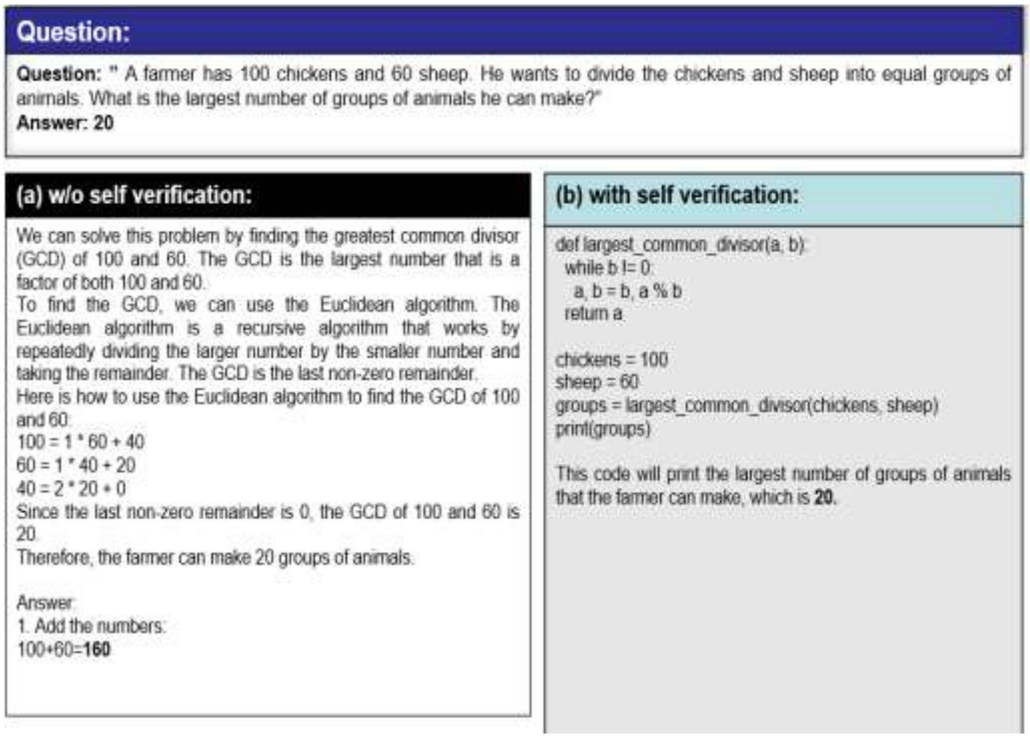
- To Develop a new algorithm for solving math word problems that uses Llama2 and Bard to generate and verify code. Evaluate the performance of the new algorithm on a benchmark dataset of math word.
- By incorporating Llama2 and Bard into my term paper, I can demonstrate my understanding of the latest advances in LLM technology and show how it can be used to improve the problem-solving process for challenging math word problems.

Comparison among different LLM's:

Model	Parameters	Strengths	Weaknesses
Llama2	70B	Better at generating code in less common programming languages	Not as good at generating creative and diverse code as GPT-4
Bard	137B	Better at generating comprehensive and challenging test cases for code verification	Not as good at identifying errors in generated code as GPT-4
GPT-4	100T	Better at generating creative and diverse code	Not as good at generating comprehensive and challenging test cases for code verification as Bard
PaLM	540B	Better at generating factual language and code	Not as good at generating creative and diverse code as GPT-4

CASE STUDIES

Case-1: Solving math reasoning question using Bard:

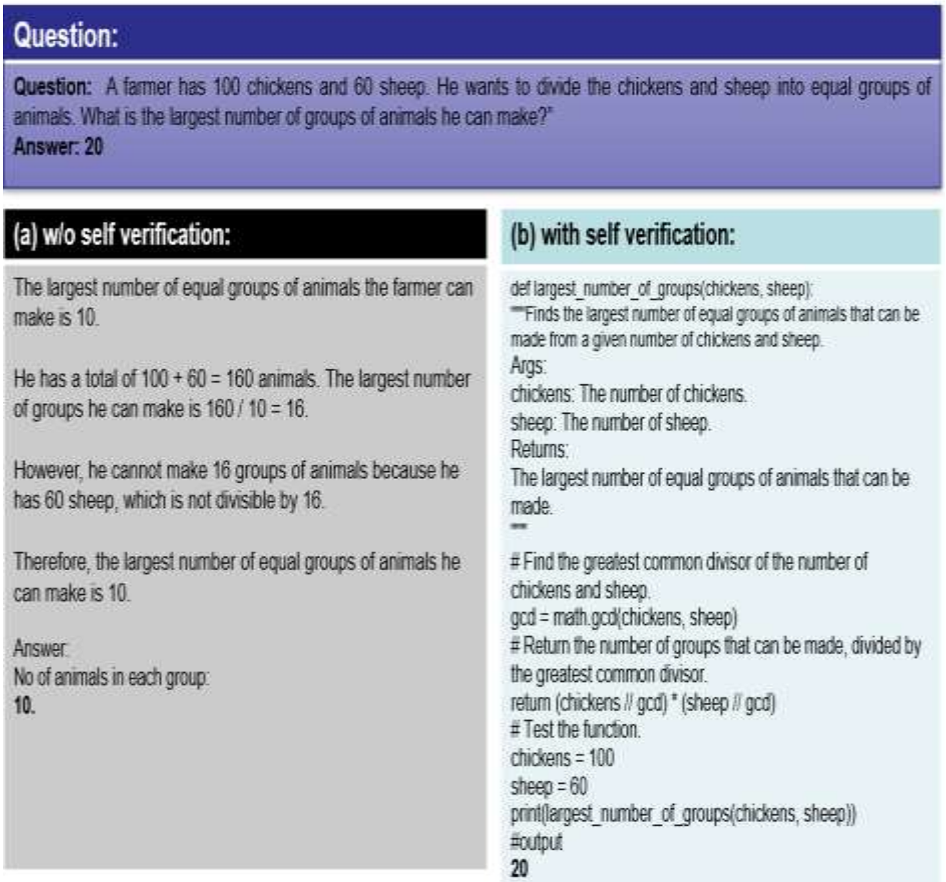


This case study shows two different approaches to solving a question:

- Result (a) is simpler to code, but it can be slow and inefficient, especially for questions with a large number of possible answers. Result (b) is more complex to code, but it can be much faster and more efficient, especially for questions with a large number of possible answers.

Result	**Approach**	**Accurate**	**Code Usage**
(a)	Brute-force	NO	NO
(b)	Efficient	Yes	Yes

Case-2: Solving math reasoning question using PALM



The case study shows two different approaches to solving a question:

- Result (a) works by trying all possible combinations of answers, starting with the largest answer and working its way down. For each combination, it checks if the chickens and sheep can be divided into equal groups. If they can, then it returns the number of groups. If they cannot, then it moves on to the next combination.
- Result (b) works by eliminating incorrect answers before trying them. It starts by finding the greatest common divisor (GCD) of the number of chickens and sheep. The GCD is the largest number that is a divisor of both the number of chickens and the number of sheep. Once it has found the GCD, result (b) knows that the number of groups cannot be greater than the GCD.

Result	**Approach**	**Accurate**	**Code Usage**
(a)	Brute-force	Yes	NO
(b)	Efficient	Yes	Yes

RESULTS & DISCUSSION

Benefits and Challenges of Code-Based Self-Verification Code-based self-verification (CBSV) offers a number of benefits, including:

- **Improved accuracy:** CBSV can help to identify errors in code that may be difficult or impossible to find using traditional methods of code verification, such as manual review and testing.
- **Reduced cost:** CBSV can help to reduce the cost of code verification by automating the process and eliminating the need for manual intervention.
- **Increased efficiency**: CBSV can help to increase the efficiency of code verification by reducing the time required to identify and fix errors.
- **Improved security:** CBSV can help to improve the security of code by identifying security vulnerabilities that may be difficult or impossible to find using traditional methods of code verification.

Challenges of code-based self-verification:

- **Complexity:** CBSV can be a complex process to implement and use, especially for large and complex codebases.
- **False positives:** CBSV may generate false positives, which are errors that are reported but do not actually exist in the code. This can lead to wasted time and effort spent on fixing non-existent errors.
- **False negatives:** CBSV may also generate false negatives, which are errors that are not reported. This can lead to errors in the code that are not discovered and fixed, which can have serious consequences.

Assessing the Effectiveness of Using GPT-4,bard,llam2 for Math Problem-Solving

- GPT-4, Bard, and Llama2 are all large language models (LLMs) that have the potential to be used for math problem-solving. GPT-4 is the most general-purpose of the three, while Bard and Llama2 are more specialized for code generation and code verification, respectively.
- Here is an assessment of the effectiveness of using these three LLMs for math problem-solving:

GPT-4:

- GPT-4 is capable of generating text, translating languages, writing different kinds of creative content, and answering your questions in an informative way. It can also be used to generate code, including code for solving math word problems.

	Verification Method	Intermediate Algebra	Precalculus -	Geometry -	Number Theory	Counting & Probability	PreAlgebra -	Algebra -	Overall -
GPT4-Code Interpreter	without Verification	50.1	51.5	53.4	77.2	70.6	86.3	83.6	69.69
	Nature Language	52.6 +2.5	48.7 -2.8	50.8 -2.6	79.9 +2.7	72.5 +1.9	83.1 -3.2	82.6 -1.0	69.29 -0.40
	Code-based	**56.6** +6.5	**53.9** +2.4	**54.0** +0.6	**85.6** +8.4	**77.3** +6.7	**86.5** +0.2	**86.9** +3.3	**73.54** +3.85

- However, GPT-4 is not specifically designed for math problem-solving. As a result, it may not be as effective at solving math word problems as Bard or Llama2.

Bard:

- Bard is specifically designed for code generation. It can generate code in a variety of programming languages, including Python and C++. It can also generate test cases to verify the correctness of the generated code.
- Bard can be used to generate code for solving math word problems. However, it may not be as good at generating creative and diverse code as GPT-4.

Task	SOTA	PaLM	Minerva	GPT-4	PaLM 2	Flan-PaLM 2
MATH	**50.3**[a]	8.8	33.6 / **50.3**	42.5	34.3 / 48.8	33.2 / 45.2
GSM8K	92.0[b]	56.5 / 74.4	58.8 / 78.5	92.0	80.7 / 91.0	84.7 / **92.2**
MGSM	72.0[c]	45.9 / 57.9	-	-	72.2 / **87.0**	75.9 / 85.8

Conclusion

All three LLMs can be used to solve math word problems, but they have different strengths and weaknesses. GPT-4 is the most general-purpose of the three, but it is not specifically designed for math problem-solving. Bard and Llama2 are more specialized for code generation and code verification, respectively. They can be used to generate code for solving math word problems, but they may not be as good at generating creative and diverse code as GPT-4. Which LLM is best for math problem-solving depends on the specific need. If the we need to generate code in a less common programming language, then Llama2 is the best option. If the we need to generate test cases to verify the correctness of the generated code, then Bard is the best option. If the we need to generate creative and diverse code, then GPT-4 is the best option. All three LLMs are still under development. As a result, they may not be able to solve all math word problems perfectly. However, they represent a significant advance in the state-of-the-art for solving math word problems using AI.

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