# Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

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### **Executive Summary**

- **Objective**: Explore how generating a *chain of thought* (a series of intermediate reasoning steps) improves complex reasoning in LLMs.
- **Method**: Chain-of-thought prompting provides few-shot exemplars with intermediate reasoning steps.
- **Results**: Significant performance improvements on arithmetic, commonsense, and symbolic reasoning tasks.
- **Key Findings**: Emergence of reasoning abilities at model scales 100B parameters and above.

#### Introduction

- Language models have transformed NLP, with improved performance and sample efficiency as size increases.
- However, scaling size alone is insufficient for tasks like arithmetic, commonsense, and symbolic reasoning.
- This work combines natural language generation and prompting to improve reasoning in LLMs.
- Chain-of-thought prompting provides models with intermediate reasoning steps.

#### Standard Prompting Chain-of-Thought Prompting **Model Input Model Input** Q: Roger has 5 tennis balls. He buys 2 more cans of Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls. Each can has 3 tennis balls. How many tennis halls does he have now? tennis balls does he have now? A: The answer is 11 A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls, 5 + 6 = 11. The answer is 11. Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples Q: The cafeteria had 23 apples. If they used 20 to do they have? make lunch and bought 6 more, how many apples do they have? Model Output **Model Output** A: The cafeteria had 23 apples originally. They used A: The answer is 27. 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

Figure: Chain-of-thought prompting enables large language models to tackle complex arithmetic, commonsense, and symbolic reasoning tasks.

### Key Innovations in Chain-of-Thought Prompting

- Natural Language Rationales: Models generate intermediate natural language rationales leading to final answers.
- Few-Shot Prompting: Exemplars in prompting provide input, chain of thought, and output triples.
- **Decomposition**: Allows models to decompose problems into intermediate steps, allocating computation as needed.
- Interpretability: Chains of thought provide insight into model behavior, aiding debugging and understanding.

### Experimental Setup: Arithmetic Reasoning

- Benchmarks: GSM8K, SVAMP, ASDiv, AQuA, MAWPS
- Prompting Methods:
  - Standard prompting (input-output pairs)
  - Chain-of-thought prompting (input, chain of thought, output triples)
- Language Models Evaluated: GPT-3, LaMDA, PaLM, UL2, Codex

### Results: Arithmetic Reasoning

- Chain-of-thought prompting yields substantial performance improvements.
- Examples:
  - GSM8K: PaLM 540B achieved state-of-the-art performance with a significant margin.
  - MAWPS: Performance gains for difficult subsets.
- Emergent abilities observed: Major improvements for models above 100B parameters.

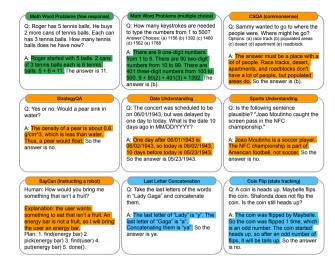


Figure: Examples of chain-of-thought prompting for arithmetic, commonsense, and symbolic reasoning benchmarks.

## Ablation Study: Arithmetic Reasoning

#### ■ Baseline Comparison:

- Standard prompting
- Equation-only
- Variable compute-only
- Reasoning after the answer

#### Results:

- Chain-of-thought prompting provides the highest gains.
- Equation-only and variable-compute-only approaches performed worse than chain-of-thought prompting.

### Experimental Setup: Commonsense Reasoning

- Benchmarks: CSQA, StrategyQA, BIGBench Date and Sports, SayCan
- Prompting Methods:
  - Standard prompting
  - Chain-of-thought prompting
- Language Models Evaluated: GPT-3, LaMDA, PaLM

### Results: Commonsense Reasoning

- Chain-of-thought prompting improves performance across all tasks.
- Examples:
  - StrategyQA: PaLM 540B achieved 75.6% (vs. 69.4% prior SOTA)
  - Sports Understanding: PaLM 540B achieved 95.4% (vs. 84% unaided sports enthusiast)

## Types of errors made by a 62B language model:

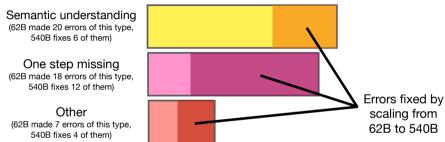


Figure: Error analysis showing the effect of chain-of-thought prompting on commonsense reasoning tasks.

### Experimental Setup: Symbolic Reasoning

#### ■ Tasks:

- Last letter concatenation
- Coin flip

#### Prompting Methods:

- Standard prompting
- Chain-of-thought prompting

#### In-Domain vs. Out-of-Domain:

- In-domain: Examples with the same number of steps as exemplars.
- Out-of-domain: Examples with more steps than exemplars.

### Results: Symbolic Reasoning

- Chain-of-thought prompting enables models to perform symbolic reasoning tasks effectively.
- In-domain performance:
  - PaLM 540B achieved 100% solve rates for both tasks.
- OOD performance:
  - Standard prompting fails; chain-of-thought prompting shows successful length generalization.



Figure: Chains-of-thought prompt facilitates length generalization to longer sequence lengths.

#### Conclusion

- Chain-of-thought prompting is a versatile method for eliciting reasoning in LLMs.
- It significantly improves performance on arithmetic, commonsense, and symbolic reasoning tasks.
- The method is especially effective at large model scales ( 100B params and above).
- Future directions:
  - Explore other prompting methods to further expand the capabilities of LLMs.
  - Investigate ways to induce reasoning in smaller models.