

Chain-of-thought Prompting

Large Language Models (LLMs)

Learning goals

- illustrate chain-of-thought and point out the benefits it brings to LLMs
- illustrate tree-of-thought and point out the benefits it brings to LLMs

CHAIN-OF-THOUGH MOTIVATION

How to boost the reasoning capabilities of LLMs? ► Wei et al., 2021

- Training or tuning with formal languages works well
 - Still, templates & labeled data are costly to create
- Few-shot learning via prompting works for most tasks
 - Still, it works poorly on tasks that require reasoning
- Chain of thought (COT) prompting
 - Prompts in the form <input, *chain of thought*, output>
 - COT: series of intermediate steps that lead to a final output

CHAIN-OF-THOUGHT PROMPTING PARADIGM

CoT enables LLMs to tackle complex arithmetic, commonsense, and symbolic reasoning tasks.

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ❌

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

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 do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 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. ✅

► Source: Wei et al., 2022

BENEFITS OF CHAIN-OF-THOUGHT

- Decompose multi-step problems and thus allocate more compute to problems requiring more reasoning steps
- By describing the reasoning, interpretability is increased. It provides the possibility to observe where reasoning went wrong
- It is closer to how humans solve tasks using language
- By designing a prompt, existing large language models are able to perform chain-of-thought reasoning.

EXAMPLES (1)

Examples of ⟨input, chain of thought, output⟩ triples for arithmetic, commonsense, and symbolic reasoning

StrategyQA

Q: Yes or no: Would a pear sink in water?

A: The density of a pear is about 0.6 g/cm³, which is less than water. Thus, a pear would float. So the answer is no.

Date Understanding

Q: The concert was scheduled to be on 06/01/1943, but was delayed by one day to today. What is the date 10 days ago in MM/DD/YYYY?

A: One day after 06/01/1943 is 06/02/1943, so today is 06/02/1943. 10 days before today is 05/23/1943. So the answer is 05/23/1943.

Sports Understanding

Q: Is the following sentence plausible? "Joao Moutinho caught the screen pass in the NFC championship."

A: Joao Moutinho is a soccer player. The NFC championship is part of American football, not soccer. So the answer is no.

► Source: Wei et al., 2022

EXAMPLES (2)

Examples of ⟨input, chain of thought, output⟩ triples for arithmetic, commonsense, and symbolic reasoning

SayCan (Instructing a robot)

Human: How would you bring me something that isn't a fruit?

Explanation: the user wants something to eat that isn't a fruit. An energy bar is not a fruit, so I will bring the user an energy bar.

Plan: 1. find(energy bar) 2. pick(energy bar) 3. find(user) 4. put(energy bar) 5. done().

Last Letter Concatenation

Q: Take the last letters of the words in "Lady Gaga" and concatenate them.

A: The last letter of "Lady" is "y". The last letter of "Gaga" is "a". Concatenating them is "ya". So the answer is ya.

Coin Flip (state tracking)

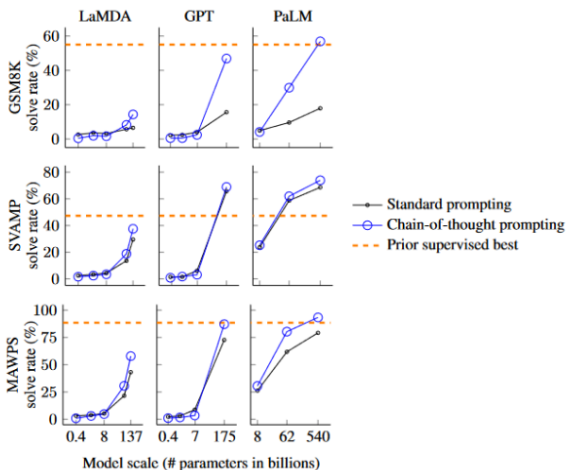
Q: A coin is heads up. Maybelle flips the coin. Shalonda does not flip the coin. Is the coin still heads up?

A: The coin was flipped by Maybelle. So the coin was flipped 1 time, which is an odd number. The coin started heads up, so after an odd number of flips, it will be tails up. So the answer is no.

► Source: Wei et al., 2022

PERFORMANCE (1)

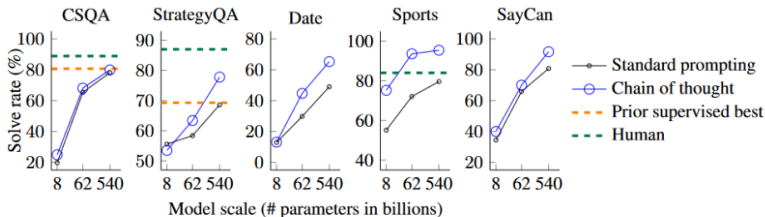
CoT prompting enables LLMs to solve challenging arithmetics.



► Source: Wei et al., 2022

PERFORMANCE (2)

CoT prompting improves commonsense reasoning abilities of LLMs.



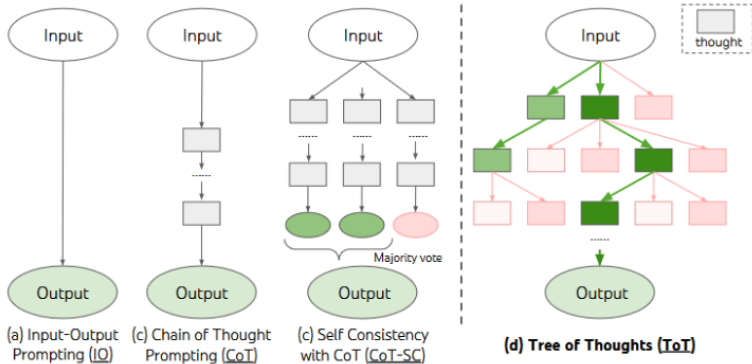
► Source: Wei et al., 2022

TREE-OF-THOUGHT: MOTIVATION

- The token-level and left-to-right decisions of the autoregressive mechanism pose a limitation for:
 - Tasks where initial decisions play a pivotal role
 - Tasks requiring exploration or strategic lookahead
- Potential strategy to solve those:
 - Maintain and explore diverse alternatives instead of just picking one
 - Evaluates current status and looks ahead or backtrack to make global decisions

TREE-OF-THOUGHT: PROMPTING PARADIGM

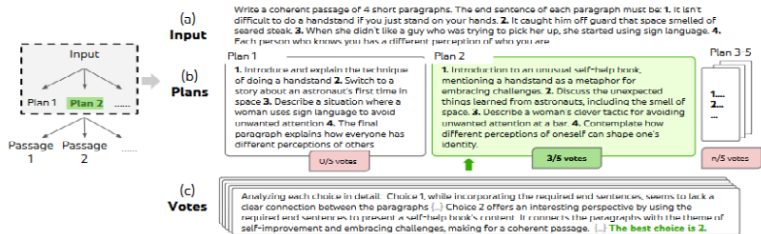
Schematic illustrating various approaches to problem solving with LLMs. Each rectangle box represents a *thought*, a coherent language sequence serving as an intermediate step toward problem solving.



► Yao et al., 2023

TREE-OF-THOUGHT FOR CREATIVE WRITING

A step of deliberate search in a randomly picked Creative Writing task. Given the input, the LM samples five different plans, and then votes five times to decide which plan is best.



► Yao et al., 2023