chain-of-thought prompting

Large Language Models (LLMs)

Learning goals

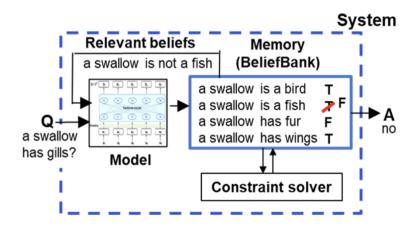
- illustrate chain-of-thought prompting and point out the benefits it brings to LLMs
- illustrate tree-of-thought and point out the benefits it brings to LLMs

chain-of-thought prompting MOTIVATION

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

- Use formal approaches, e.g., logic, symbolic reasoning
 - Example: ► BeliefBank
 - Difficult to train and deploy, not widely used
- Standard few-shot learning via prompting works for many tasks
 - Still, it works poorly for many tasks that require reasoning
- COT-P
 - A new form of few-shot prompting
 - Each "training example" has the form <input, chain of thought, output>
 - chain of thought:
 series of reasoning steps that lead to the final answer
 - applications: complex, commonsense, symbolic reasoning tasks etc

NEUROSYMBOLIC APPROACH (CURRENTLY INFREQUENTLY USED)



LLMS NOT GOOD AT REASONING TASKS



Question: What is the problem here?

chain-of-thought prompting PARADIGM

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

chain-of-thought prompting PARADIGM

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.

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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.

BENEFITS OF chain-of-thought prompting

- 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
- Language models, if given a well designed chain-of-thought prompt, can solve problems they otherwise would not be able to solve.

EXAMPLES OF chain-of-thought prompting

Examples of <input, chain of thought, output> triples for commonsense and symbolic reasoning

► Source: Wei et al., 2022

StrategyQA

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

A: The density of a pear is about 0.6 g/cm^3, 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.

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".

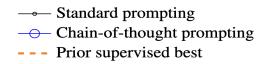
Concatenating them is "ya". So the answer is ya.

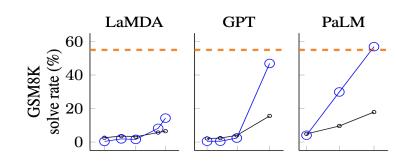
Coin Flip (state tracking)

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.

COT-P IMPROVES ARITHMETIC

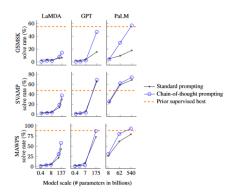




COT-P IMPROVES ARITHMETIC

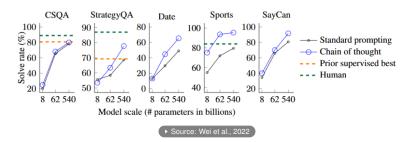
SVAMP: math word problems with varying structures; MAWPS: repository unifying math problems from different sources;

➤ Source: Wei et al., 2022



COT-P IMPROVES COMMONSENSE

CSQA: Contains around 200K dialogs with a total of 1.6M turns. Further, unlike existing large scale QA datasets which contain simple questions that can be answered from a single tuple, the questions in the dialogs require a larger subgraph of the KG.

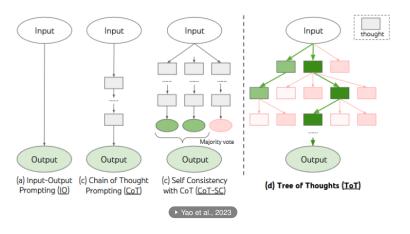


TREE-OF-THOUGHT: MOTIVATION

- 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
- Strategy to solve those:
 - Maintain and explore diverse alternatives instead of just picking one
 - Evaluate current status and look ahead or backtrack to make global decisions

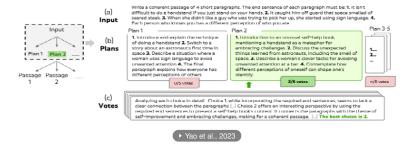
TREE-OF-THOUGHT: PROMPTING PARADIGM

Schematic illustrating three approaches to problem solving with LLMs. Rectangle box = *thought* = a coherent language sequence serving as an intermediate step in problem solving.



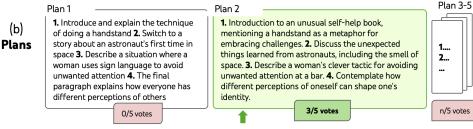
TREE-OF-THOUGHT FOR CREATIVE WRITING

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.



TREE-OF-THOUGHT FOR CREATIVE WRITING (2)

(a) Input Write a coherent passage of 4 short paragraphs. The end sentence of each paragraph must be: 1. It isn't difficult to do a handstand if you just stand on your hands. 2. It caught him off guard that space smelled of seared steak. 3. When she didn't like a guy who was trying to pick her up, she started using sign language. 4. Each person who knows you has a different perception of who you are.



(c) **Votes**

Analyzing each choice in detail: Choice 1, while incorporating the required end sentences, seems to lack a clear connection between the paragraphs (...) Choice 2 offers an interesting perspective by using the required end sentences to present a self-help book's content. It connects the paragraphs with the theme of self-improvement and embracing challenges, making for a coherent passage. {...} The best choice is 2.

chain-of-thought prompting: ERROR BREAKDOWN

- 8% calculator error
- 16% symbol mapping error
- 22% one missing step error
- rest: semantic issues, incoherent COT-P
- Source: Stanford CS25: Beyond LLMs: Agents, Emergent Abilities, Intermediate-Guided Reasoning

chain-of-thought prompting: WHAT COULD GO WRONG?

- Decompose complex problems into a sequence of 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
- Language models, if given a well designed chain-of-thought prompt, can solve problems they otherwise would not be able to solve.
- Question: What could go wrong?

chain-of-thought prompting: WHY DOES IT WORK?

• Question: Why does it work?

chain-of-thought prompting: WHY DOES IT WORK?

 Question: Do top-of-the-line LLMs use chain-of-thought prompting?

CHAIN-OF-THOUGHT: TERMINOLOGY

- Shot = "training example"
- few-shot prompting = few-shot learning
- The prompt "think step by step" by itself (without shots) is not chain-of-thought prompting.
- chain-of-thought prompting is defined as including shots.
- Chain-of-Thought is currently used as a general term to refer to the idea of LLMs using explicit reasoning steps to arrive at an answer.
- So the current usage of Chain-of-Thought is more general than chain-of-thought prompting.

CHAIN-OF-THOUGHT IN OPENAI'S O1

- We are introducing OpenAl o1, a new large language model trained with reinforcement learning to perform complex reasoning.
 o1 thinks before it answers – it can produce a long internal chain of thought before responding to the user.
- internal!

GENERATOR-VERIFIER GAP (NOAM BROWN)

- For many important problems, it is much easier to verify a solution than generating one.
- Chain-of-thought is expected to help for such problems with a generator-verifier gap.
- Problems with generator-verifier gap: Sudoku, doing math, programming
- Problems with less of a generator-verifier gap: knowledge questions (what is the capital of bhutan?), simple pattern matching (which language is this?)

SLIDO

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