Advanced Prompting Techniques

Generative AI

Module 1 – Lesson 4

Today's activities

- Review: Basics of prompt engineering
- Chain-of-thought prompting
- Self-consistency
- Tree-of-thought

Basics of prompt engineering

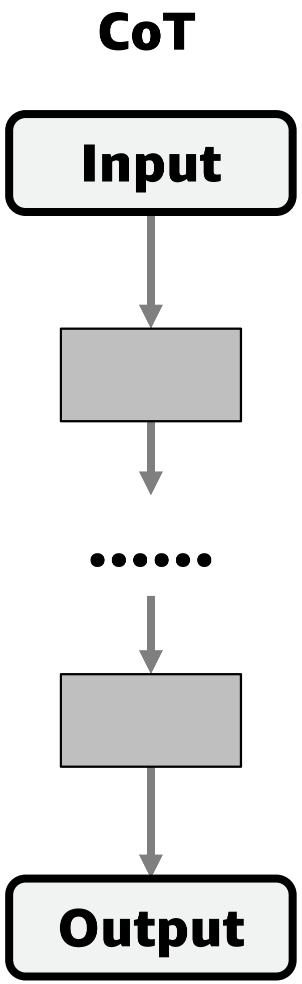
Review: Good prompting practices

- Write **clear** and **specific** instructions (unambiguous and specific)
- Highlight or specify the part of the prompt **that the model should focus** on
- Add relevant **details** or **restrictions** to your prompt
- Separate the instruction, content, question, and output directions
- Prefer using positive instructions
- Try using examples to guide the model's response
  - **In-context learning**
- Finding the optimum prompt is usually an **iterative** process which may take a few attempts

Chain-of-thought prompting

Chain-of-thought (CoT) prompting

- Technique that breaks down complex tasks through **intermediate reasoning steps**
- Encourages model to explain its reasoning process by **decomposing the solution** into a series of steps
  - This behaviour can be facilitated through various strategies (few-shot CoT, zero-shot CoT, …)
  - CoT is the **basis for other prompting techniques** which separate out the task's decomposition and its solving



Zero-shot CoT

- Appending instructions like **"Let's think step by step"** to the prompt elicits the generation of a sequential reasoning chain by the LLM. This derives more precise answers

Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8 ✗

Zero-shot CoT

Q: A juggler can juggle 16 balls. Half of the balls are golf balls and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let's think step by step.***

(Output) *There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.* ✓

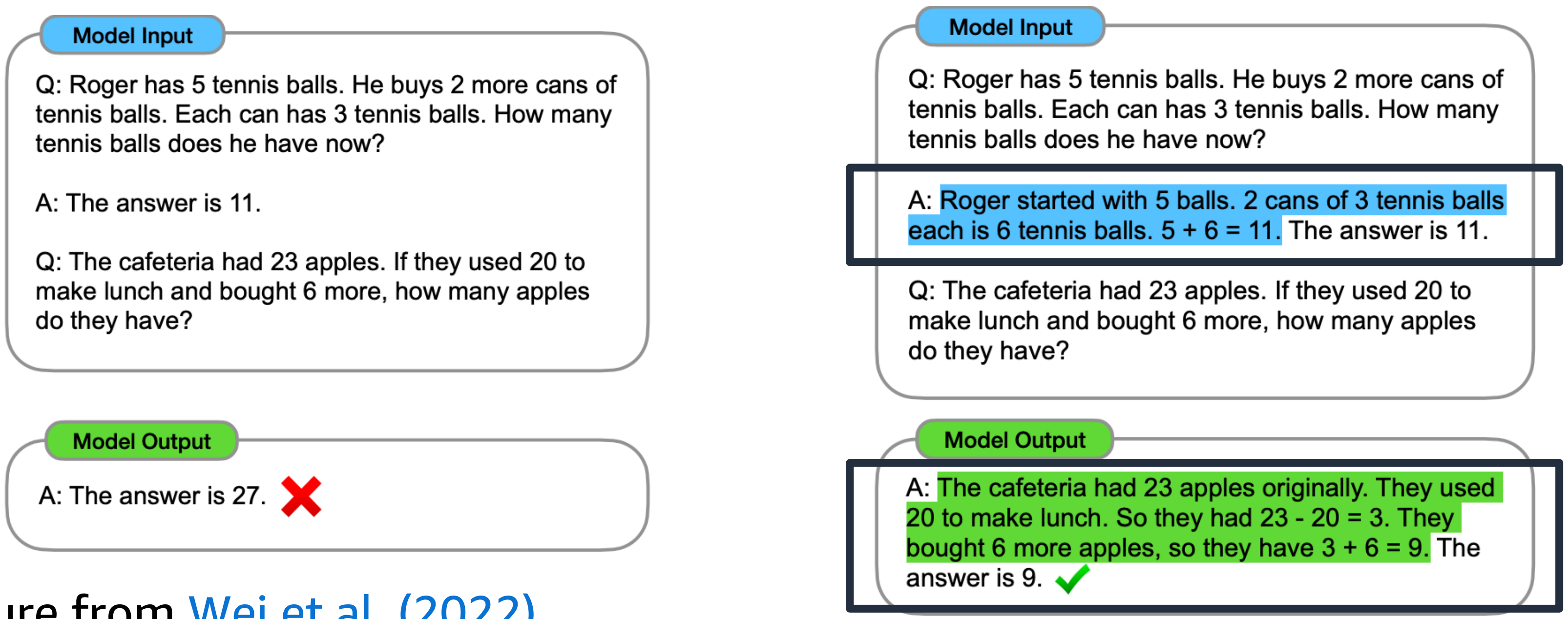
CoT query augmentation

Figure from Kojima et al. (2022)

Few-shot CoT

- Show LLM examples with reasoning so that the LLM will also produce a reasoned answer. This **explanation of reasoning often leads to more accurate results**

Few-shot **Few-shot CoT**



CoT example(s)

Step-by-step answer

Figure from [Wei et al. (2022)]

Benefits of CoT

- LLMs can benefit from **detailed and logical steps** to process the prompt
- Such chains of thought can be facilitated by:
  - Addition of **smaller logical steps** in the prompt to break down the question or task
  - A series of **demonstrations**, composed of question and reasoning chain leading to an answer
  - Prompt augmentations like **“Let’s think step by step”**
- CoT can **enhance performance** of LLMs on tasks requiring arithmetic, common-sense, and symbolic reasoning
- Performance **gains in models of ~100B** parameters [Wei et al. 2022]

Limitations of CoT

- CoT prompts (especially few-shot examples) are **specific to a problem type**
- Smaller models might produce fluent but **illogical CoT**, with lower performance
- Increased cost of generation

Overview of prompting techniques

Method	Use case
Zero-shot prompting	Tasks that the LLM is capable of performing simply **leveraging the information** from the large amounts of data it has been pre-trained on.
One-shot prompting	Output needs to follow a certain structure that can be demonstrated via **one example**.
Few-shot prompting	Output needs to follow a certain structure that can be demonstrated via **various examples**.
Chain of thought	Complex tasks that require **reasoning** before a response can be generated.

Review: Standard prompting strategies

- Standard prompt engineering techniques helps get **improved results** from LLMs for different tasks. Best practices:
  - Write clear, concise, positive, and precise instructions
  - Supplement with examples (one/few-shot prompting)
  - Ask the model to decompose a task into reasoning steps (CoT prompting)

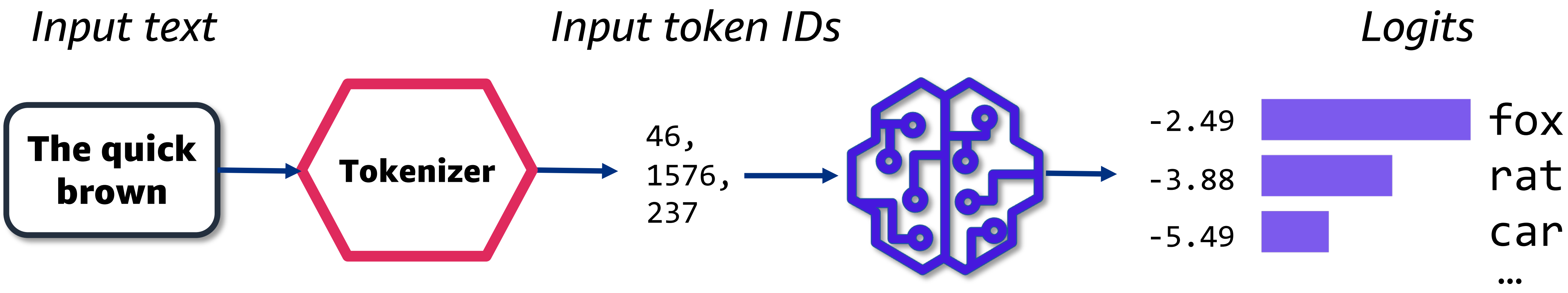
Towards advanced prompting

- Difficult questions might require the LLM to follow complex instructions and perform multi-step reasoning. **Standard prompting techniques are often not enough.**
  - Few-shot learning requires the **limited context window** of most LLMs to be occupied with exemplars
  - CoT does **not guarantee correct reasoning paths** and can give rise to both correct and incorrect answers
  - LLMs can be **tricked** into providing harmful output if safeguards aren’t put in place

Self-consistency

Decoding for text generation

- Decoder-only models generate text **word by word**
- LLMs calculate logits: **scores** assigned to every possible token in their vocabulary via a probability distribution
- **Decoding** is the process of turning the logits coming from the probability distributions generated by the model into actual text

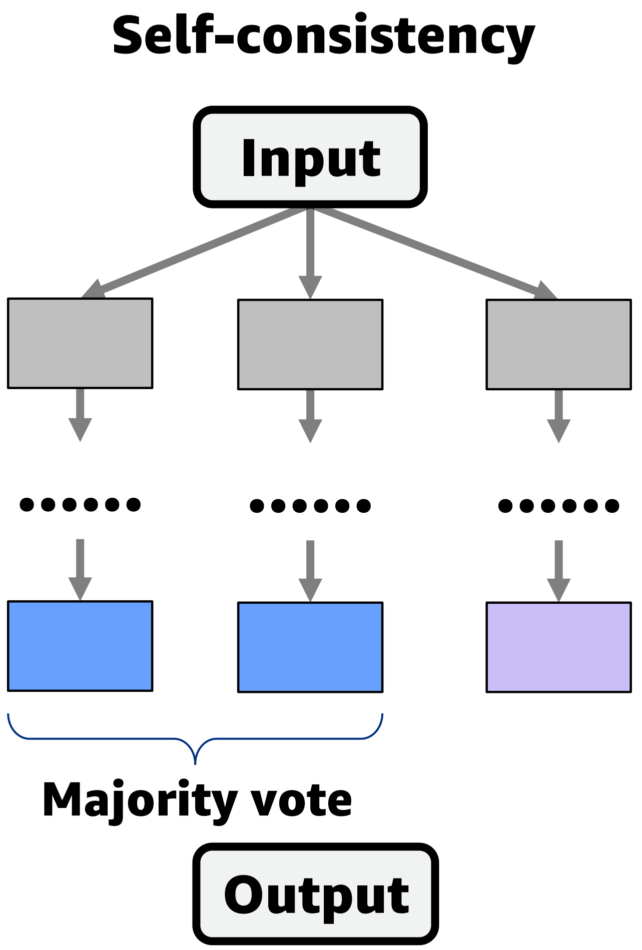


Greedy vs stochastic decoding

Greedy	Stochastic
Deterministic decoding method	**Non-deterministic** decoding method
At each step: select the token with the **highest probability**	At each step: select next token based on the **probability distribution**
Fast and efficient, as it doesn't keep track of multiple sequences	Sampled token is **not guaranteed** to have the highest individual probability.
Can get stuck in repetitive loops; generated output is **not "creative"**	Allows for **greater diversity** in the generated output
Equivalent to sampling with **T = 0**	Sampling controlled by **several params**

Self-consistency

- Technique that builds on chain-of-thought prompting
- Idea: generate **multiple, diverse reasoning paths** through few-shot CoT, and use them to verify the **consistency** of the responses
- Model gains the ability to explore multiple possibilities for the elicited reasoning chain and helps boost performance on arithmetic and common-sense reasoning tasks



Self-consistency improves performance

- Usual baseline for comparison: Chain-of-thought
- Self-consistency generates **multiple chains of thought** and takes the **majority vote** of these multiple outputs as the final answer
  - This improves reliability and accuracy
  - The idea reminds of “model ensembling” in machine learning
- Self-consistency improves CoT when used in a range of **common arithmetic and common-sense reasoning benchmarks**
  - Use to improve on tasks that admit a unique correct answer, such as quantitative business questions

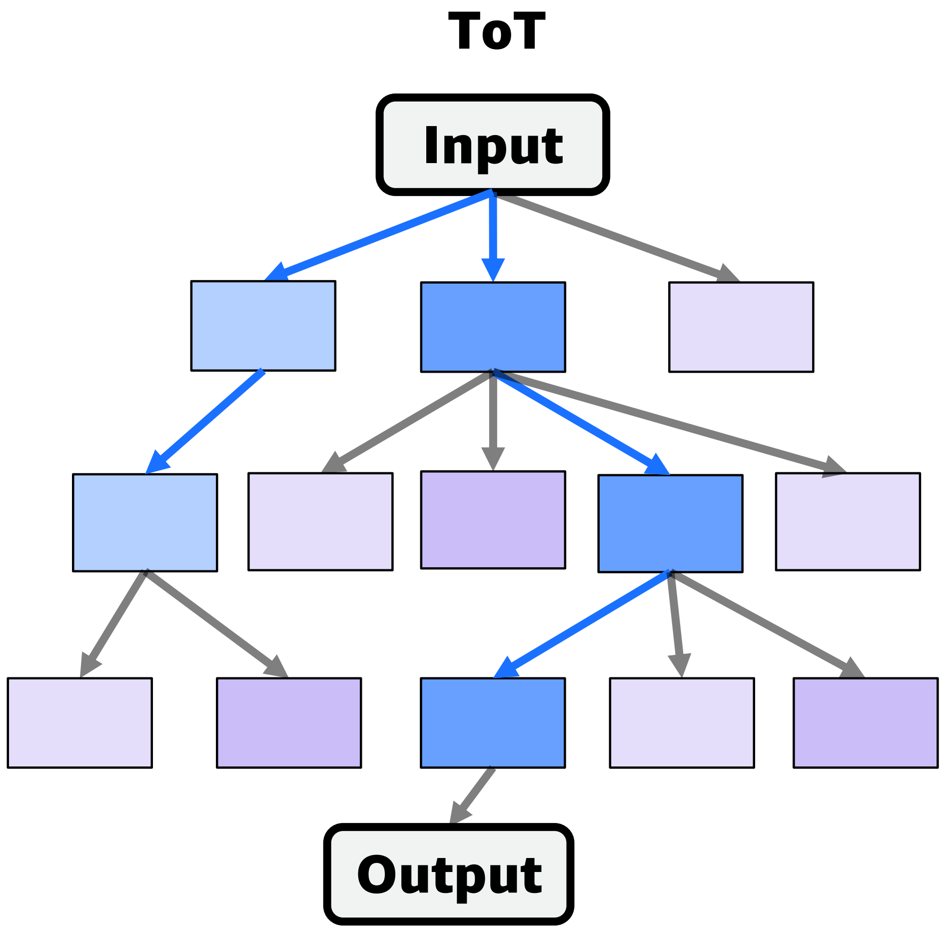
Limitations of self-consistency

- Self-consistency incurs **more computational cost** than CoT
  - In practice, generate a small number of paths (e.g. 5-10); in most cases the performance saturates quickly
  - Potential solution: use self-consistency to generate better supervised data to fine-tune the model, and use the fine-tuned model to get improved accuracy in a single inference run
- LLMs can often generate **incorrect or non-sensical** reasoning
  - If most CoT paths are erroneous, self-consistency marginalization will fail
  - Further work needed to understand what elicits proper reasoning

Tree-of-thought

Tree-of-thoughts prompting

- Strategy that guides LLMs to generate, evaluate, expand on, and decide among **multiple solutions**
- Similar to problem-solving by humans: evaluate potential solutions before deciding on the most promising one
- ToT builds a tree where ***thoughts*** represent coherent language sequences that serve as intermediate steps toward solving a problem
  - Creative writing tasks such as ad copy generation
  - Mathematical reasoning tasks, crosswords, …



ToT helps decision-making

- Tree-of-thoughts prompting generalizes over chain of thought
- ToT encourages exploration over ***"thoughts"*** that serve as intermediate steps for general problem solving with LLMs
  - LLM generates thoughts (via CoT prompting)
  - Add tree-branching technique (breadth-first and depth-first search)
  - This enables **systematic exploration** with look-ahead and back-tracking

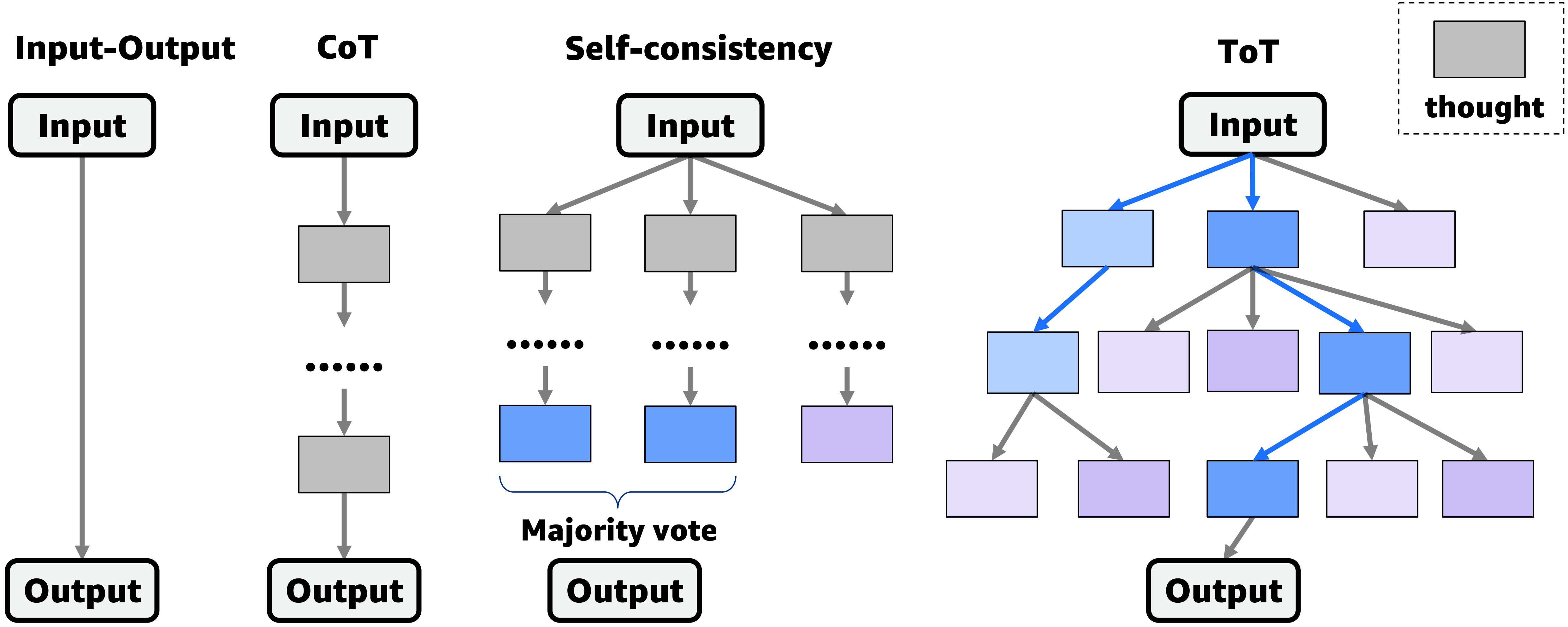
Benefits and limitations of ToT

- ToT is **especially effective** for tasks that involve important initial decisions, strategies for the future, and exploration of multiple solutions

- Deliberate search **might not be necessary** for tasks for which powerful models already excel at

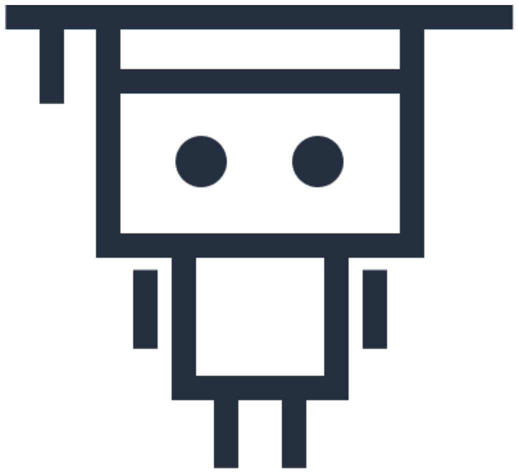
- ToT requires **more resources** than sampling methods
  - Flexibility in tree construction allows users to customize cost-performance trade-offs

From standard to ToT prompting



Next lesson

- This lesson covered some advanced prompt engineering techniques
- In the next lesson, you will explore multimodal solutions using foundation models



Thank you!