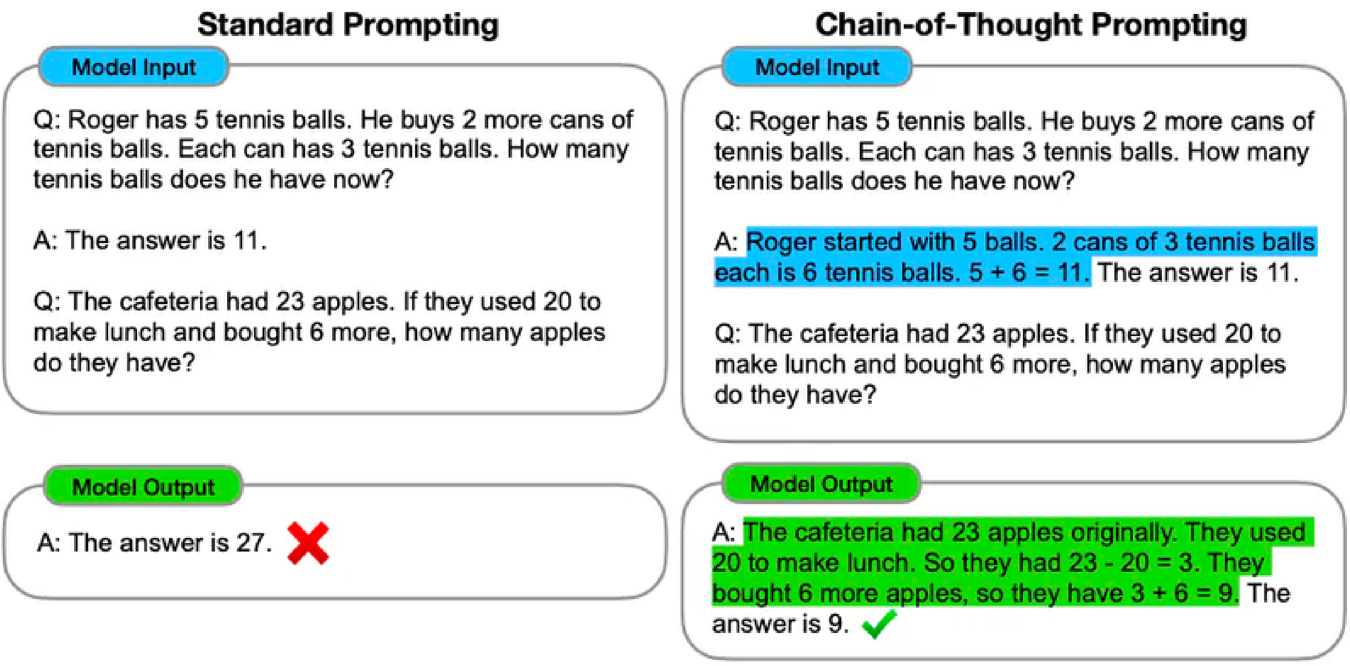
Chain-of-Thought (CoT) Prompting

Introduction of intermediate "reasoning" steps, improves the performance of LLMs in tasks that require complex reasoning like arithmetic, common sense, and symbolic reasoning.

In their paper, "Chain-of-Thought Prompting Elicits Reasoning in Large Language Models", Wei et. al. demonstrated how LLMs naturally start reasoning with a few examples.

In this technique, a few logical reasoning steps are added to the prompt as examples for the LLM to understand how to arrive at the desired outcome.



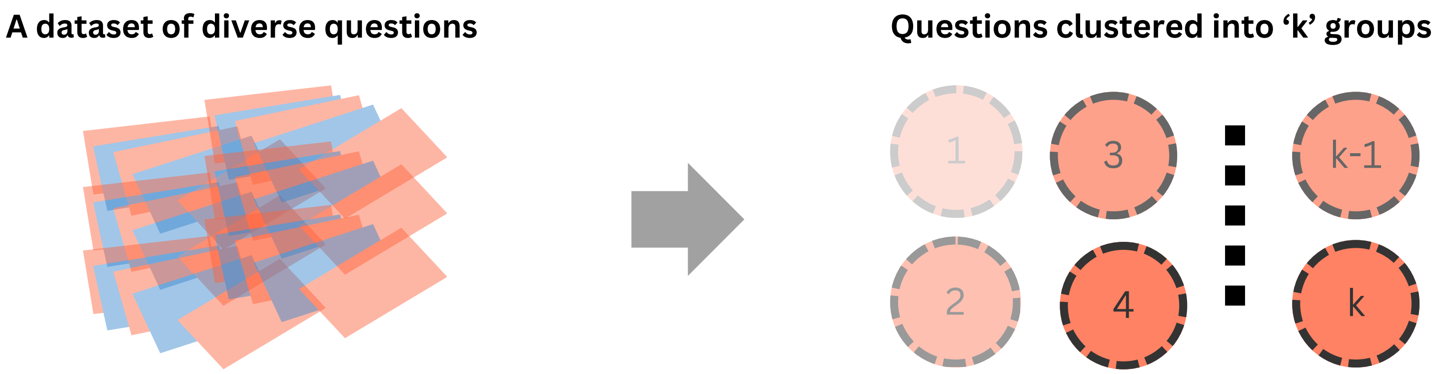
Wei et al. (2022)
Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

Another idea of **"Zero Shot CoT"** was introduced by Kojima et al. 2022 where, instead of adding examples for Few Shot CoT, we just add **"Let's think step by step"** to the prompt.

Automatic Chain-of-Thought (Auto-CoT)

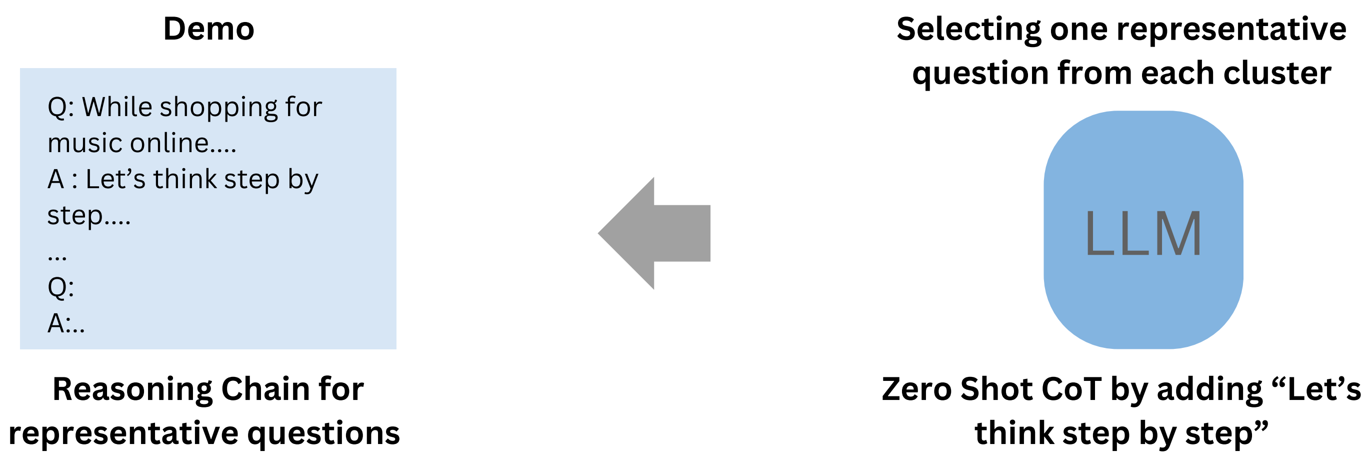
As we saw, CoT prompting involves creating examples for the LLM. This is a manual process and introduces subjectivity. To reduce this subjectivity, Zhang et al. (2022) introduced Auto-COT. There are two stages involved in Auto-CoT

A: Question Clustering



Stage A: Create clusters from a dataset of diverse question

B: Demonstration Sampling



Stage B: Select one question from each cluster and generate its reasoning chain using Zero-Shot-CoT with simple heuristics

The Questions with Reasoning Chain in the Demo are then used as examples for new questions

[Checkout Auto-CoT Code]

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Benefits of Chain of Thought Prompting

Breaks down multi-step problems into simpler components to enable more efficient solving

Provides transparency into models' reasoning for interpretability

Applicable across diverse reasoning tasks like math, commonsense, and symbolic manipulation.

Easily integrated into existing models via prompting. Does not require any architectural change

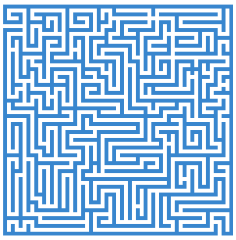
Makes models' thought processes relatable to facilitate human-AI collaboration

Adapts complexity of reasoning chain to task difficulty for broad applicability

Enables error identification by exposing models' step-by-step reasoning logic

Teaches generalizable structured problem-solving strategies transferable across tasks.

Limitations of CoT



Task Complexity

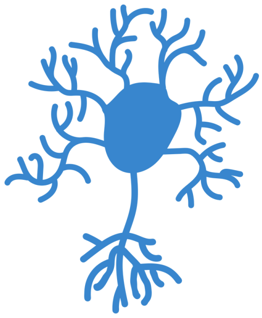
Chain of Thought Prompting offers minimal additional value over standard prompting for tasks that lack multi-step reasoning requirements or cannot be easily decomposed. Its benefits are best achieved for problems requiring sequential logic or intermediate explanatory steps

Prompt Quality

The technique depends heavily on prompt quality to steer models through reasoning chains. Crafting prompts that provide effective stepwise guidance demands care and can prove difficult for complex domains necessitating expert knowledge.

Scalability

While Auto CoT tries to automate the process of creating the reasoning chains, it still remains a complex and labor intensive process to create them. As the tasks increase, the manual effort in creating or verifying the reasoning chains keeps on increasing.



Model Size

Chain of Thought reasoning works well only on very large models with more than 100 Billion parameters. On smaller models the efficiency reduces. On the other hand, the efficacy of CoT remains to be seen as the model size increases further.

Some Advanced Prompting Techniques

Self Consistency

While CoT uses a single Reasoning Chain in Chain of Thought prompting, Self Consistency aims to sample multiple diverse reasoning paths and use their respective generations to arrive at the most consistent answer

Generated Knowledge Prompting

This technique explores the idea of prompt-based knowledge generation by dynamically constructing relevant knowledge chains, leveraging models' latent knowledge to strengthen reasoning.

Tree of Thoughts Prompting

This technique maintains an explorable tree structure of coherent intermediate thought steps aimed at solving problems.

Automatic Reasoning and Tool-use (ART)

ART framework automatically interleaves model generations with tool use for complex reasoning tasks. ART leverages demonstrations to decompose problems and integrate tools without task-specific scripting.

Automatic Prompt Engineer (APE)

The APE framework automatically generates and selects optimal instructions to guide models. It leverages a large language model to synthesize candidate prompt solutions for a task based on output demonstrations.

Some Advanced Prompting Techniques

Active Prompt

Active-Prompt improves Chain-of-thought methods by dynamically adapting Language Models to task-specific prompts through a process involving query, uncertainty analysis, human annotation, and enhanced inference.

ReAct Prompting

ReAct integrates LLMs for concurrent reasoning traces and task-specific actions, improving performance by interacting with external tools for information retrieval. When combined with CoT, it optimally utilizes internal knowledge and external information, enhancing interpretability and trustworthiness of LLMs.

Recursive Prompting

Recursive prompting breaks down complex problems into sub-problems, solving them sequentially using prompts. This method aids compositional generalization in tasks like math problems or question answering, with the model building on solutions from previous steps.

Hi! I'm Abhinav

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