

# Automatic Chain of Thought Prompting in Large Language Models (2022)

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# What is Chain-of-Thought

## 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?

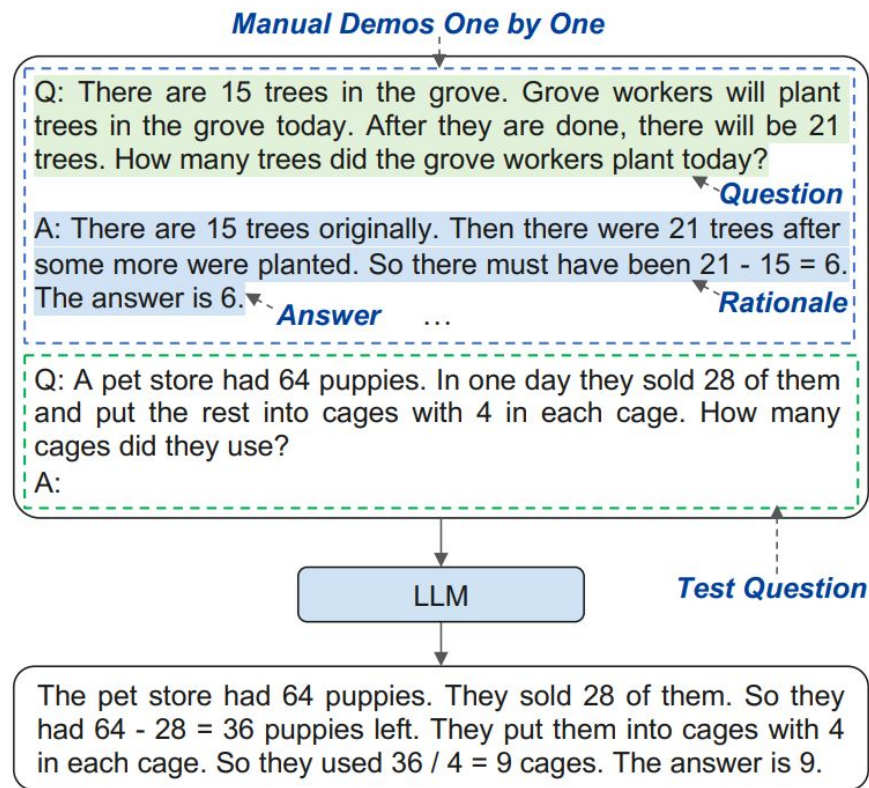
Model Output

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. ✅

Chain of thought prompting elicits reasoning in large language models.

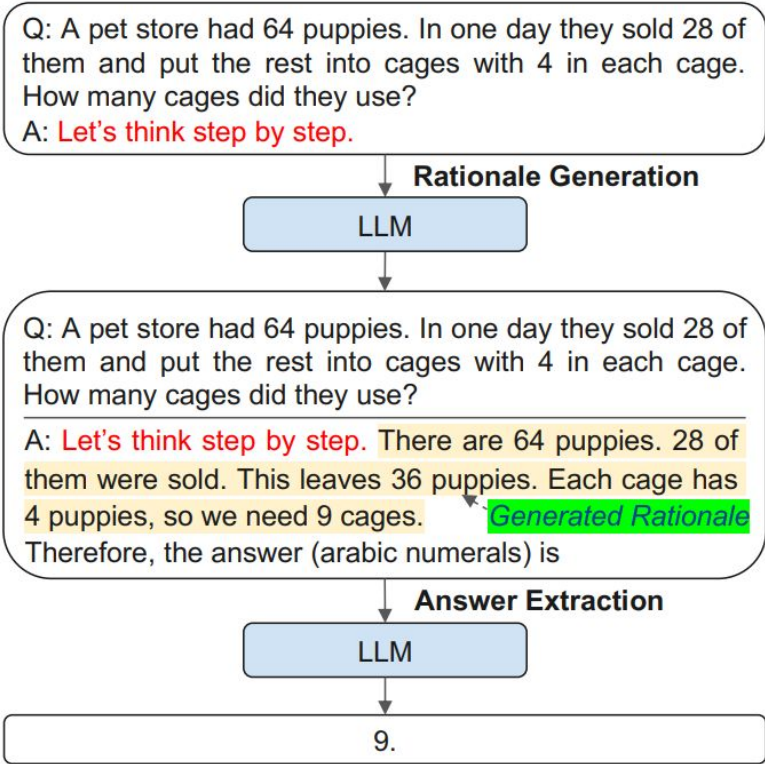
## Simple Methods: Manual CoT

- Few-shot Prompting
- Illustrate the intermediate steps
- In-Context Learning



# Simple Methods: ZeroShot CoT

Magic words:  
Let's think step by step.



# Auto CoT: Powered Manual CoT

Manual CoT generally performs better than ZeroShot, but:

1. It hinges on the hand-drafting, involves:
  - a. designing question
  - b. designing reasoning chain
2. Different tasks require different ways of demonstration
  - a. arithmetic
  - b. commonsense reasoning
  - c. ...

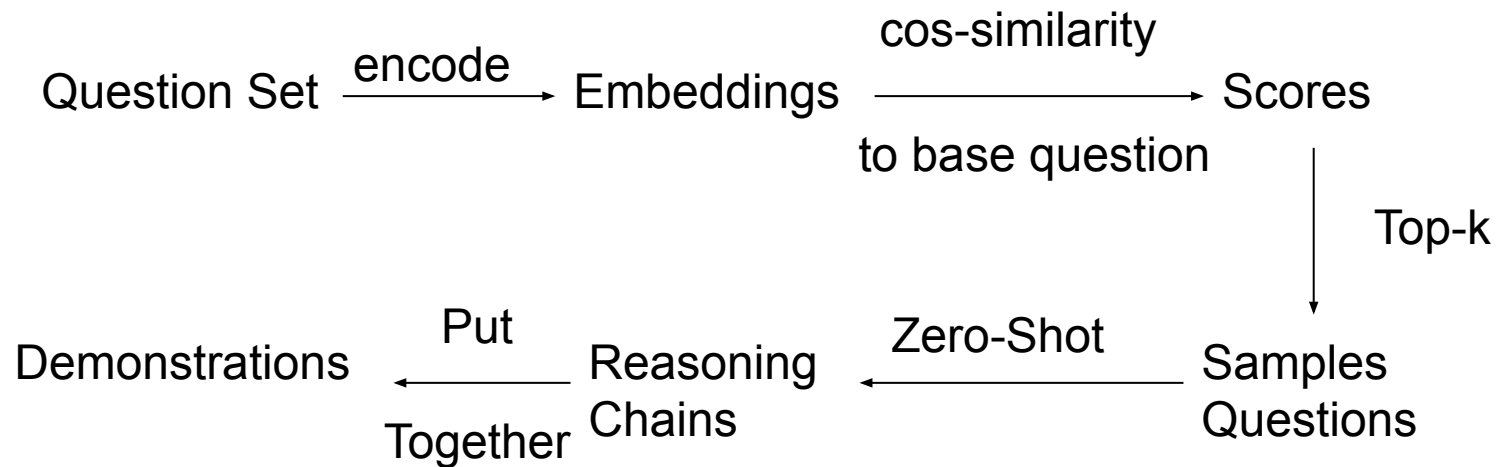
# Key Challenge: Automatically constructing demonstrations

**Fact:** demonstrations written by different annotators brings up 28.2% accuracy disparity

**Two Parts:** Question, Reasoning Chain

## Select Questions: The Trivial Way

### **similarity-based retrieval methods:**



Wrong!

Table 1: Accuracy (%) of different sampling methods. Symbol † indicates using training sets with annotated reasoning chains.

Method	MultiArith	GSM8K	AQuA
Zero-Shot-CoT	78.7	40.7	33.5
Manual-CoT	<b>91.7</b>	46.9	35.8†
Random-Q-CoT	86.2	47.6†	36.2†
Retrieval-Q-CoT	82.8	<b>48.0†</b>	<b>39.7†</b>

with human-annotation it works — but its nontrivial



## Why ? Assumption

### **Fact:**

Zero-Shot CoT may lead to incorrect reasoning chains for difficult problems.

**Assumption:** For challenging problems:

- Similarity-based sampling gathers similar hard problems and produce large number of incorrect reasoning chain.
- Random sampling collects a diverse range of problems, allowing some problems to be solved, which aids further reasoning.

## Why ? Experiment

To put it simply:

They collect all the problems that Zero-Shot cannot solve and test them using these two CoT method.

Random sampling greatly outperforms Retrieval sampling.

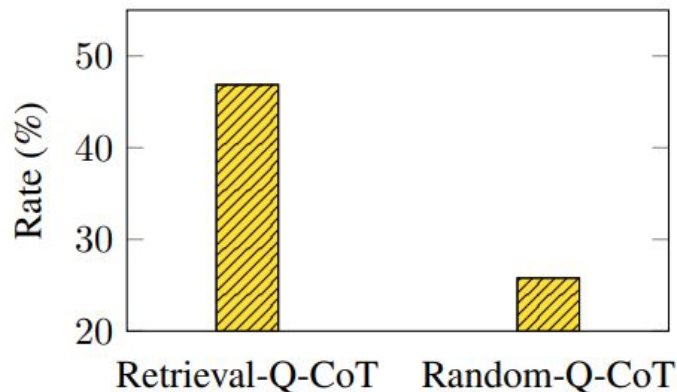


Figure 2: Unresolving Rate.

## Inspiration: Errors Frequently Fall into the Same Cluster

- k-means to partition all test questions into 8 clusters
- cluster 2 is extremely difficult to solve

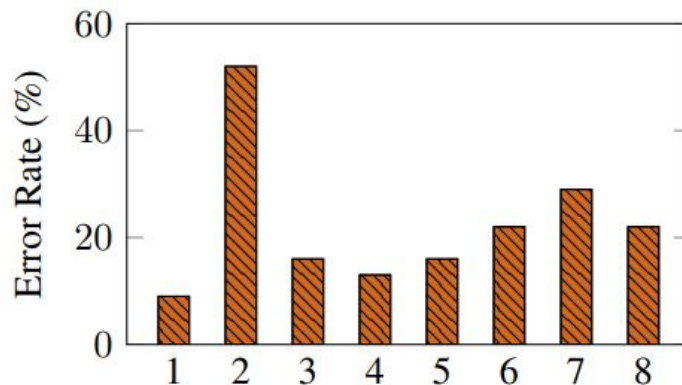
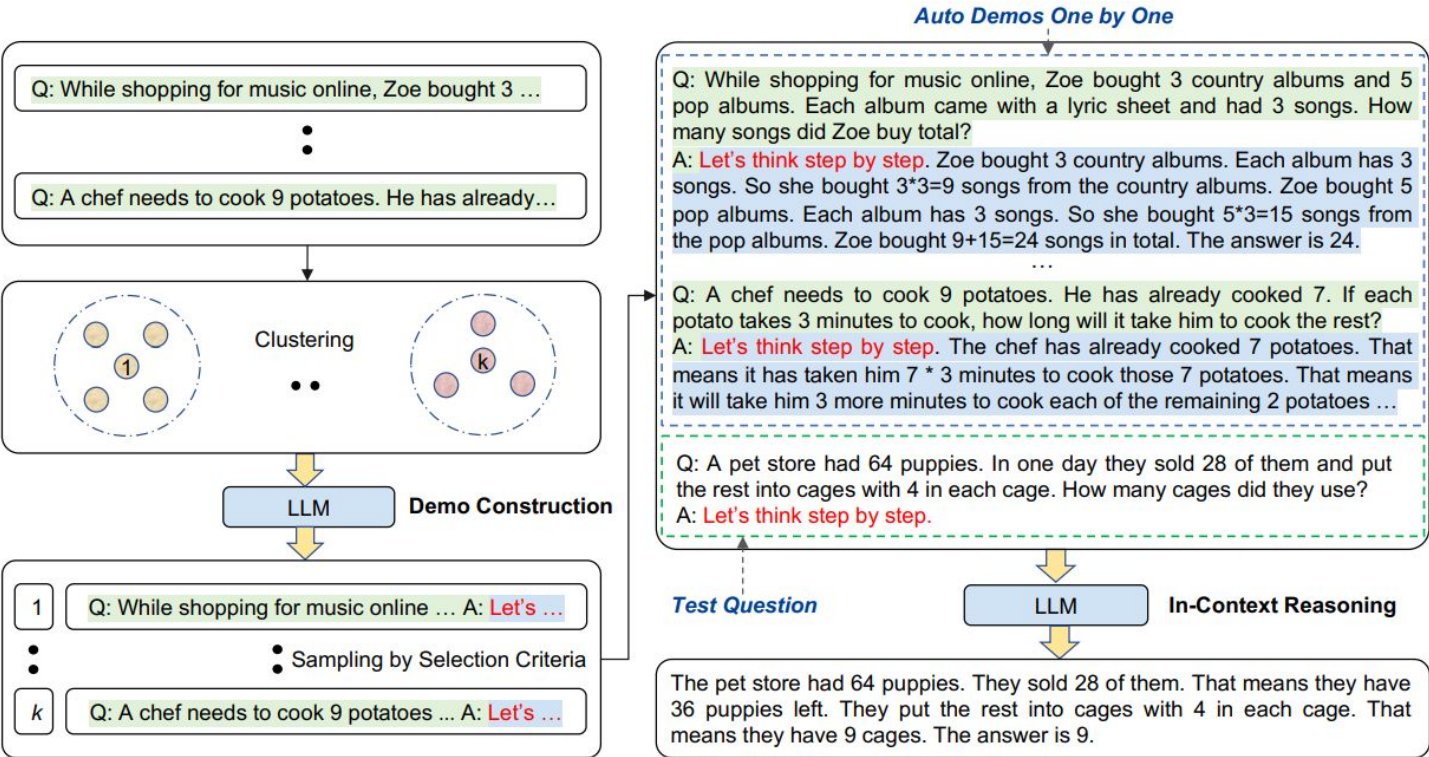


Figure 3: Clusters of similar questions.

# Inspiration: Diversity May Mitigate Misleading by Similarity

- a small portion of mistakes would not harm the overall reasoning performance
- different clusters reflect diverse semantics of the questions
- diverse demonstrations seem to cover more alternative skills for solving target questions

# Inspiration: Diversity May Mitigate Misleading by Similarity



Thank you