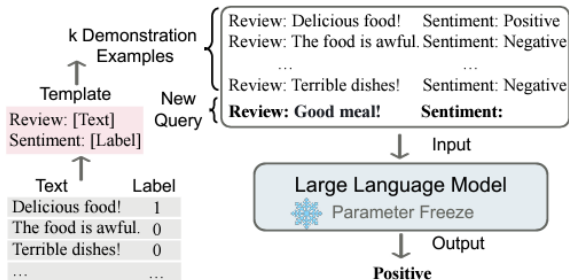


# Plan of the Tutorial

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- 7 Conclusion

# An brief overview on In-Context Learning (ICL)



ICL does not update parameters and instead directly makes predictions using the pretrained language model.

# In-Context Learning Approaches

Now let us explore some popular ICL methods.

- Chain of thought (COT)
- Self-consistency COT

# Chain-of-thought prompting

## 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?

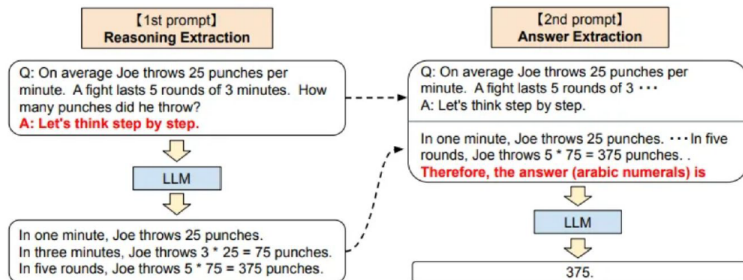
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls.  $5 + 6 = 11$ . The answer is 11.

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. ✅

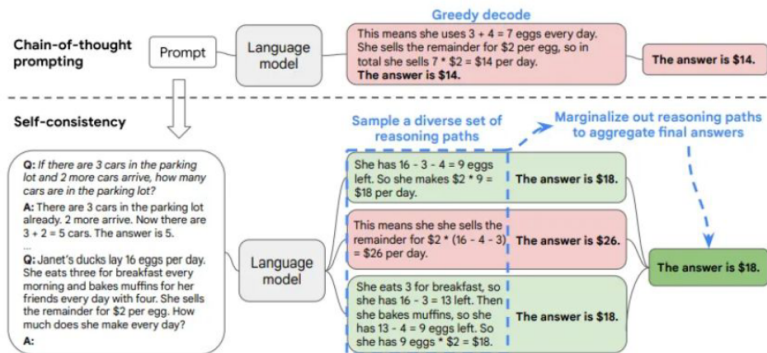
# Dive deep into chain of thought (COT)



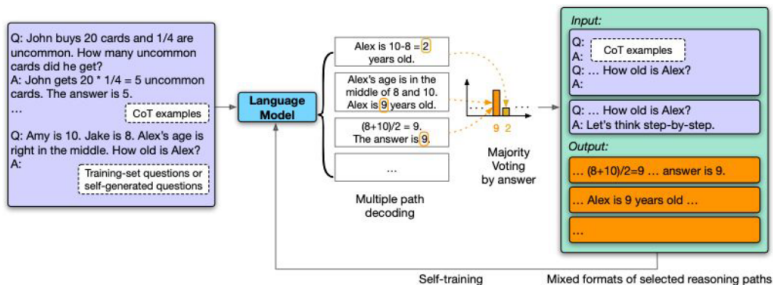
The process involves two steps: first “reasoning prompt extraction” to extract a full reasoning path from a language model, and then use the second “answer prompt extraction” to extract the answer in the correct format from the reasoning text.

# Self-consistency COT

Greedy decoding in COT is replaced by another decoding strategy used in COT prompting named self-consistency COT.



# Self-consistency COT



# Optimal Prompts : Open Problem

No algorithm to  
search for the  
**optimal** prompt!

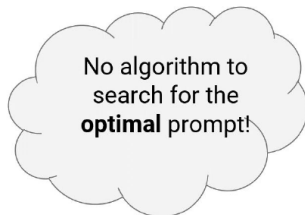
Input: That movie was really great if you are dumb beyond imagination.  
Sentiment expressed in the above sentence is



Input: That movie was really great if you are dumb beyond imagination.  
Sentiment expressed in the above sentence is **on the positive side of the range.**



# Optimal Prompts : Open Problem



Consider the following sentence: "That movie was really great if you are dumb beyond imagination." The author's opinion expressed towards the movie in this sentence is

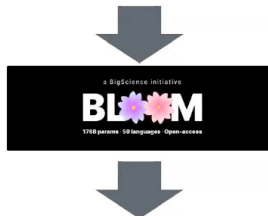


Consider the following sentence: "That movie was really great if you are dumb beyond imagination." The author's opinion expressed towards the movie in this sentence is **neutral**.

# Optimal Prompts : Open Problem

No algorithm to  
search for the  
**optimal** prompt!

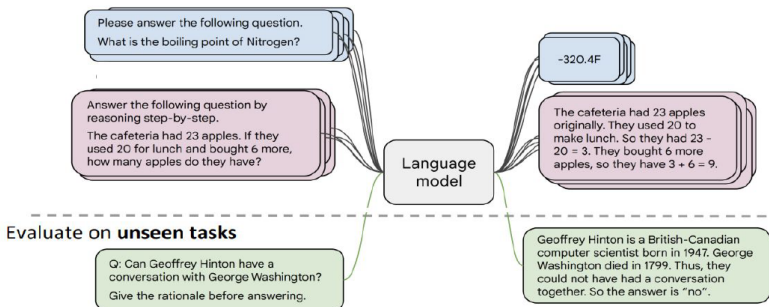
Consider the following sentence: "That movie was really great if you are dumb beyond imagination." In the author's opinion, the movie is



Consider the following sentence: "That movie was really great if you are dumb beyond imagination." In the author's opinion, the movie is **not good**.

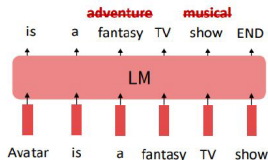
# Instruction Fine Tuning

Collect examples of (instruction, output) pairs across many tasks and finetune an LM



# Limitations of instruction finetuning

- One limitation of instruction fine tuning is obvious: it's expensive to collect ground truth data for tasks.
- Problem 1: tasks like open-ended creative generation have no right answer.
- Problem 2: language modeling penalizes all token-level mistakes equally, but some errors are worse than others.
- Can we explicitly attempt to satisfy human preferences?



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# Conclusion

- The tutorial has provided a comprehensive understanding of the key concepts and principles that form the foundation of large language models.
- From the basics of natural language processing to the inner workings of advanced language models, the audience has gained a solid grounding in the field.
- Hands-on exercises and examples have equipped the audience with practical skills, allowing them to implement and integrate these models into real-world projects.

# Reference I

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# *Thank You!*

**Hands on & Demo:**<https://github.com/payelsantra/FIRE2023tutorial>