

Procesamiento de Lenguaje Natural Avanzado

Prompt-Based Learning & Reasoning in Large Language Models



iimas

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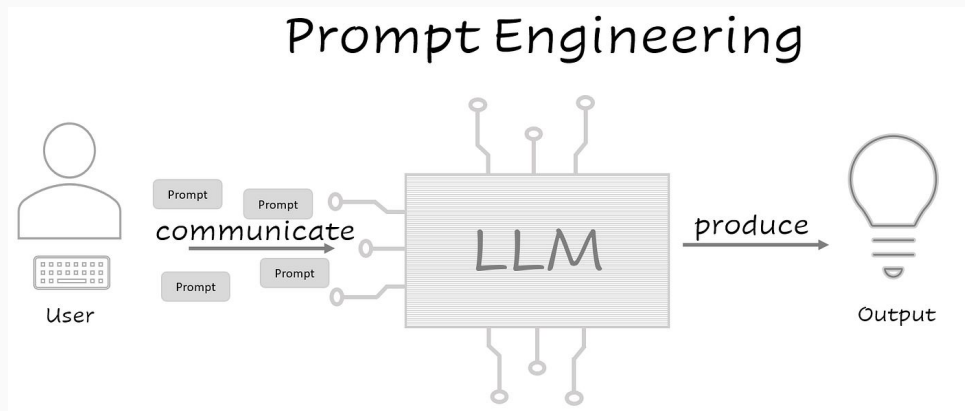
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Why Prompt-Based Learning?

- LLMs are **not retrained for every task**
- Instead, they are **prompted**
- Prompt = **interface to control behavior**

Key Question:

👉 *How do we make LLMs do what we want?*



Prompting

From Fine-tuning to Prompting

Traditional ML

Train model for each task

Feature engineering

Requires labeled data

Model changes

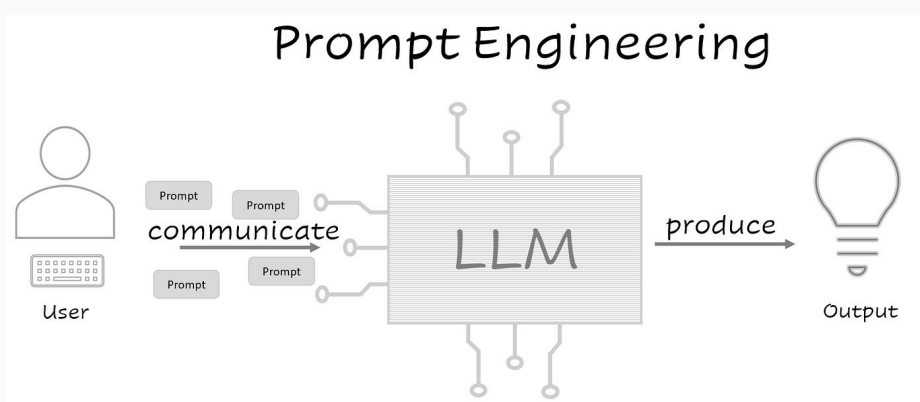
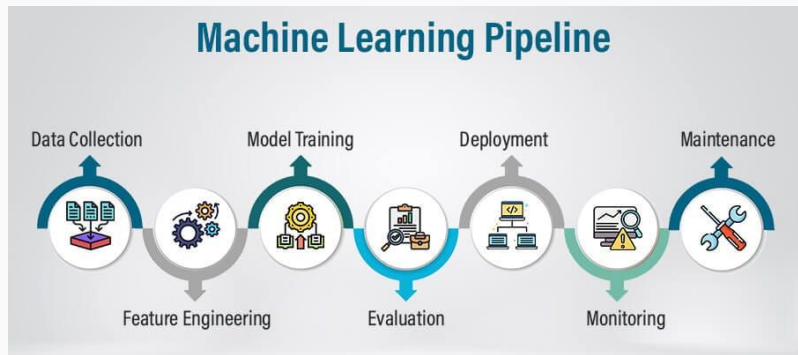
LLMs

Use one pretrained model

Prompt engineering

Uses natural language

Prompt changes

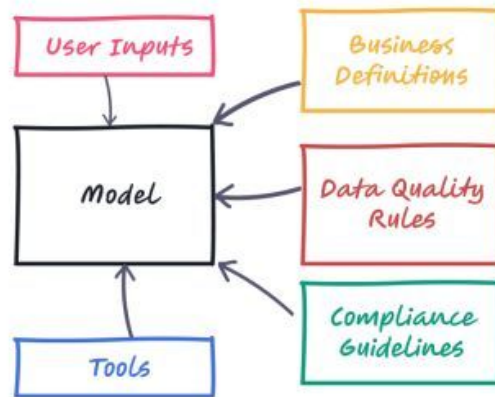


Prompt-Based Learning

- Use **natural language instructions** to guide LLM behavior
- No model retraining required
- Relies on:
 - **Pretrained knowledge**
 - **In-context learning**

👉 The model learns *from the prompt itself*

Context Engineering



Types of Prompting

Zero-shot → No examples

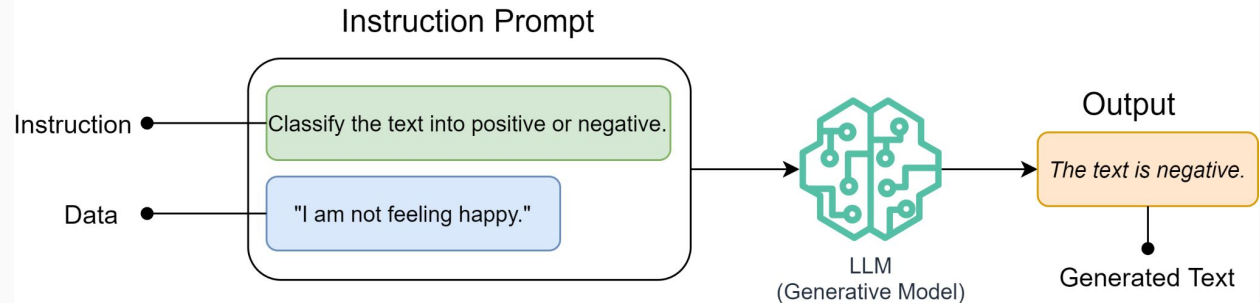
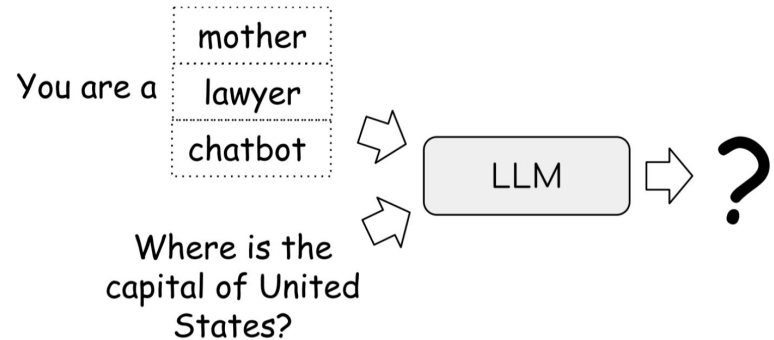
One-shot → One example

Few-shot → Multiple examples

Instruction-based → Explicit task description

Role prompting → Assign a role to the model

Role Prompting



Prompt Engineering Best Practices



Specify an Audience



Be Clear and Specific



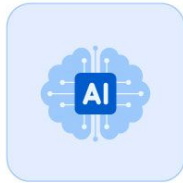
Set a Persona



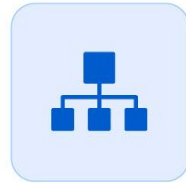
Comprehend the Task at Hand



Remove Ambiguity



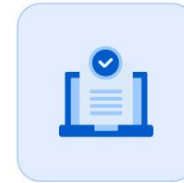
Tell AI What Not to Do



Break Down Complex Tasks



Structure Prompts by Priority



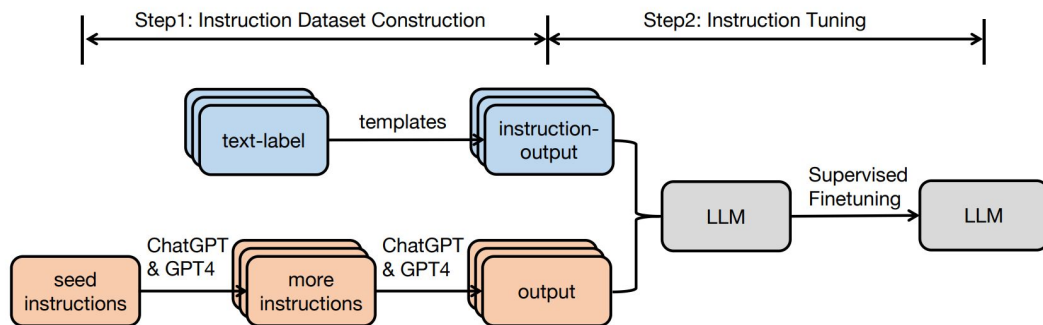
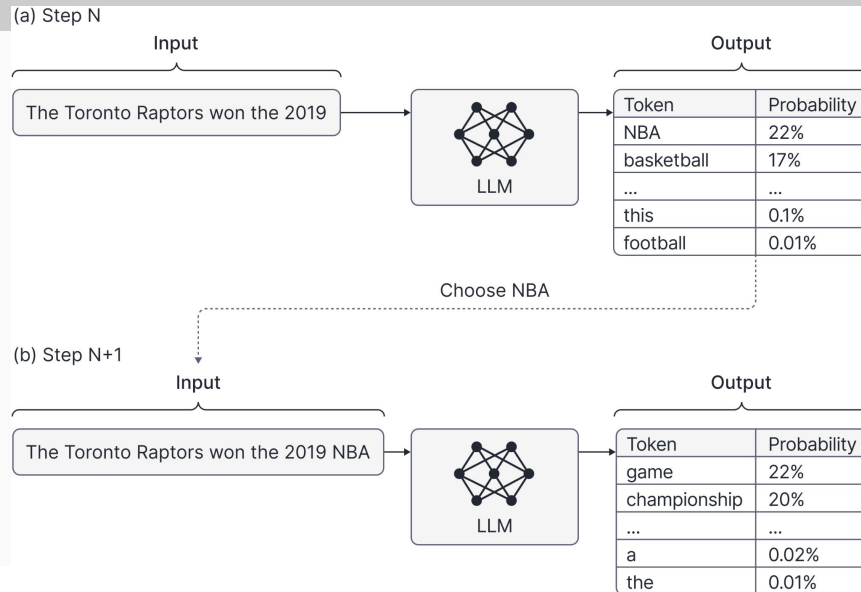
Specify the Output Format

Prompting

Instruction vs Completion

- **Completion style:**
→ “The sentiment is ...”
- **Instruction style:**
→ “Classify the following text into: Positive, Negative, Neutral”

👉 **Instruction-based prompting is more reliable**

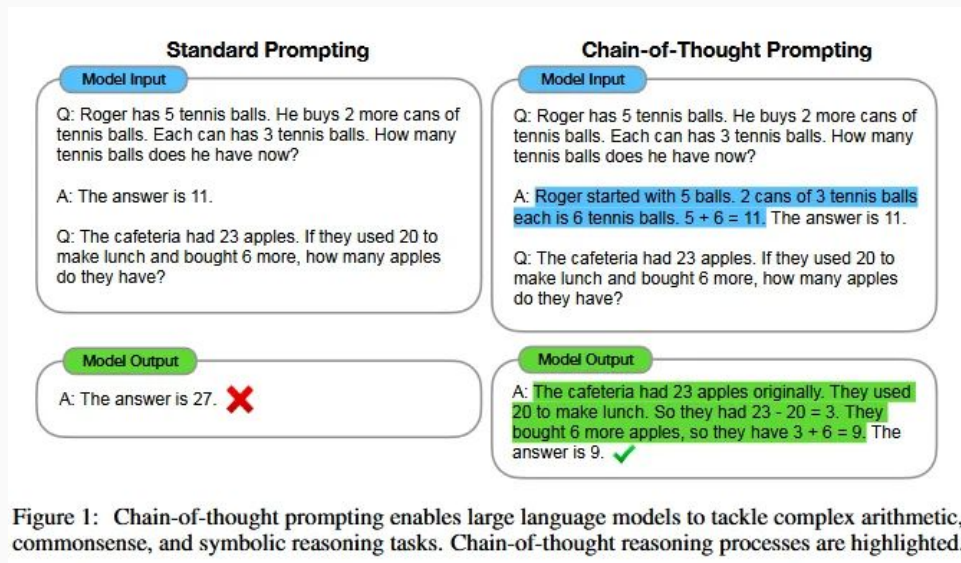


Challenges of LLMs

LLMs struggle with:

- Multi-step reasoning
- Logical problems
- Mathematical tasks

👉 Correct answer \neq correct reasoning



Chain-of-Thought (CoT) Prompting

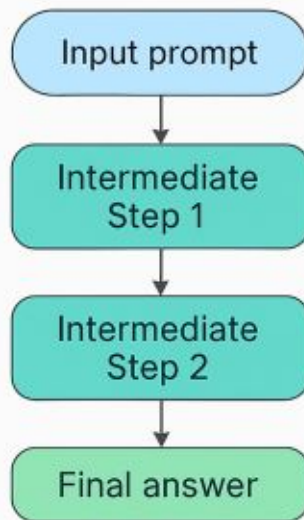
👉 Encourage the model to reason step-by-step

Example trigger:

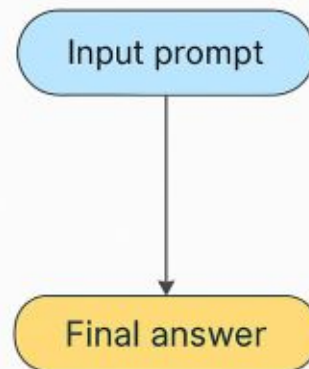
“Let’s think step by step.”

- ✓ *Improves reasoning*
- ✓ *Works for complex tasks*

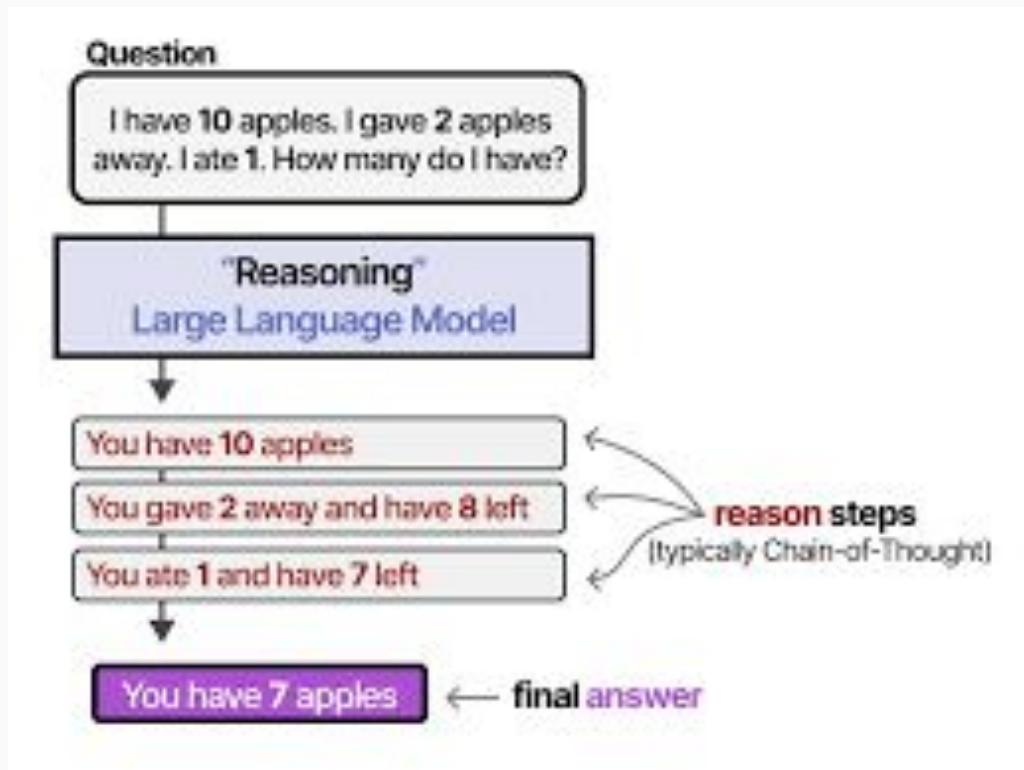
Traditional Reasoning / Chain-of-Thought



'NoThinking' Prompting

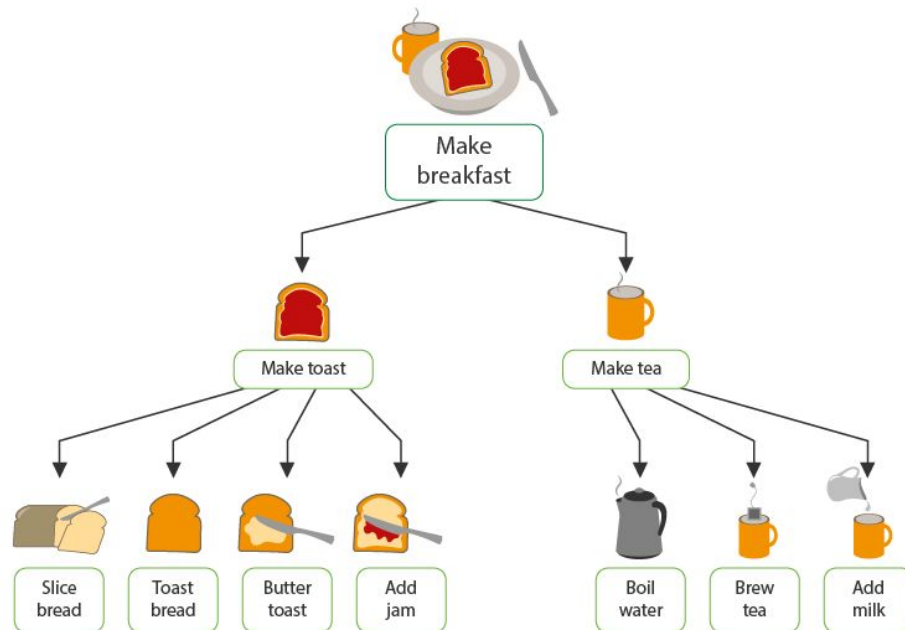


Chain-of-Thought Example



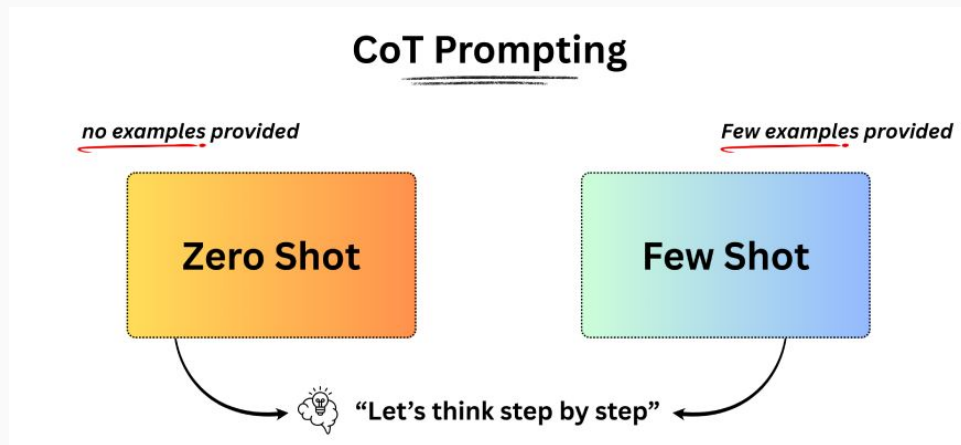
Why Does Chain-of-Thought Work?

- Activates **latent reasoning abilities**
- Breaks problems into **simpler steps**
- Reduces **hallucinations**
- Improves **accuracy on complex tasks**



FS/ZS Chain-of-Thought

- Provide examples with reasoning:
- **Example:**
Q: ...
A: Step 1 → Step 2 → Final Answer
- 👉 Model learns *how to reason*, not just *what to answer*



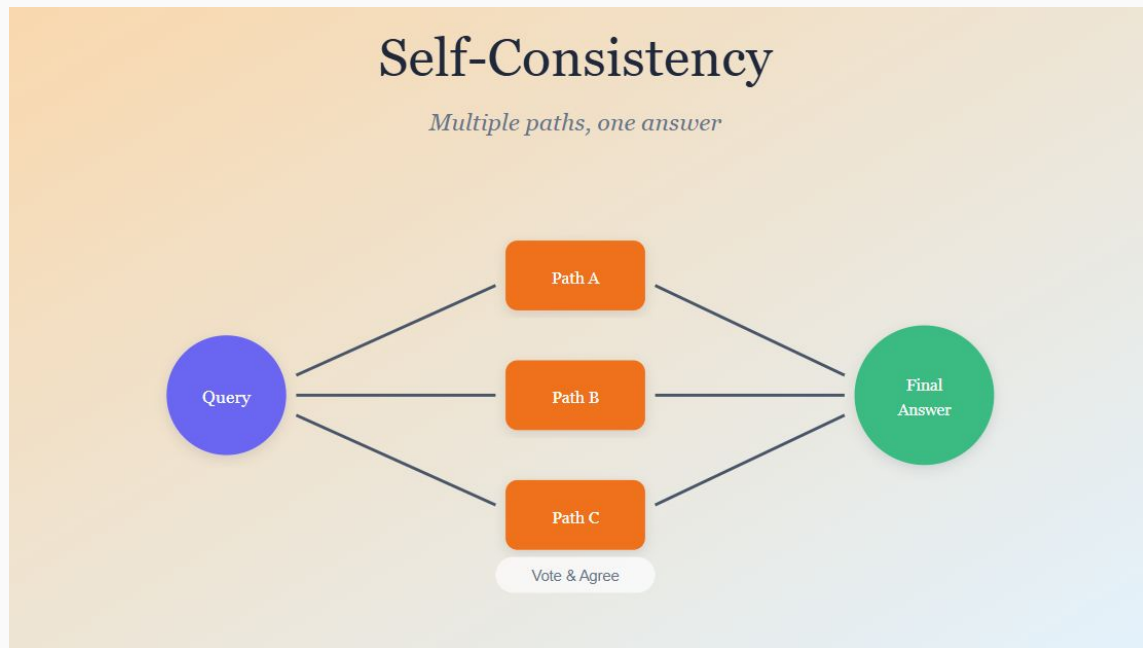
Self-Consistency

👉 Instead of one reasoning path:

- Generate **multiple outputs**
- Use **majority voting**

✓ More robust

✓ Reduces randomness



Tree-of-Thought (ToT)

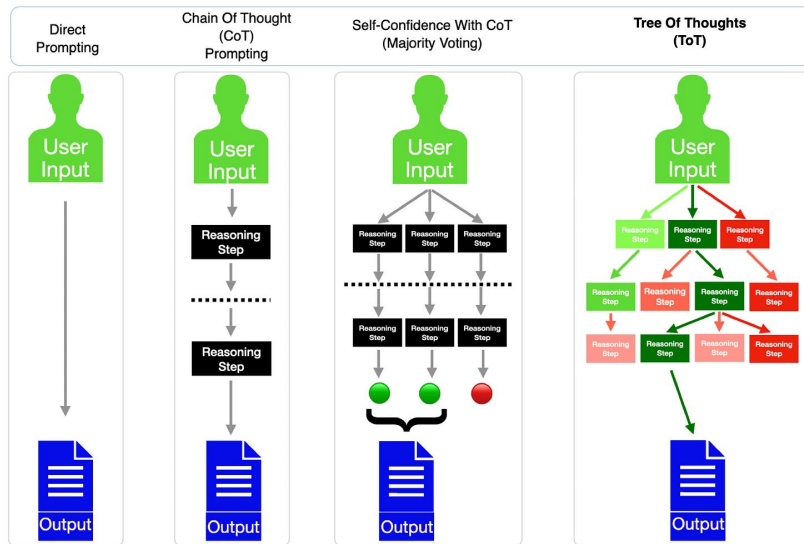
👉 Explore multiple reasoning paths

- Branching reasoning
- Search over solutions
- Evaluate intermediate steps

✓ Better for complex problems

Tree Of Thoughts Prompting (ToT)


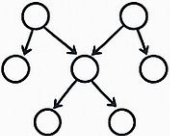
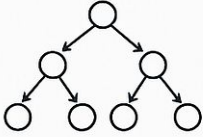
With Implementation from  LangChain



Adapted From: <https://arxiv.org/pdf/2305.10601>

www.cobusgreyling.com

Chain-of-Thought vs Tree-of-Thought vs Self-Consistency: Prompting Method Performance

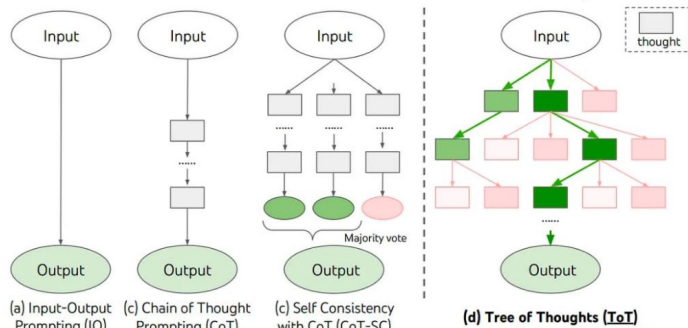
METHOD	ILLUSTRATION	DESCRIPTION	PERFORMANCE
Chain-of-Thought		Generate a single reasoning path step-by-step	Foundational method Brittle
Self-Consistency		Sample multiple paths, then select the most frequent answer	Boosts accuracy and robustness
Tree-of-Thought		Explore and evaluate multiple reasoning paths	Excels at complex reasoning

Prompting

Tree-of-Thought Example



Tree of Thoughts Prompting

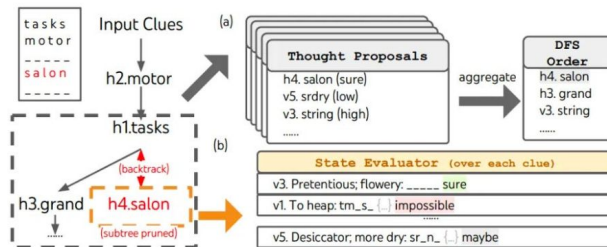
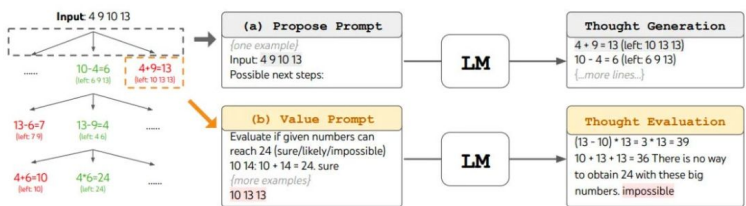


Math Word Problems (free response)

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.

— Operators
— Partial Solutions

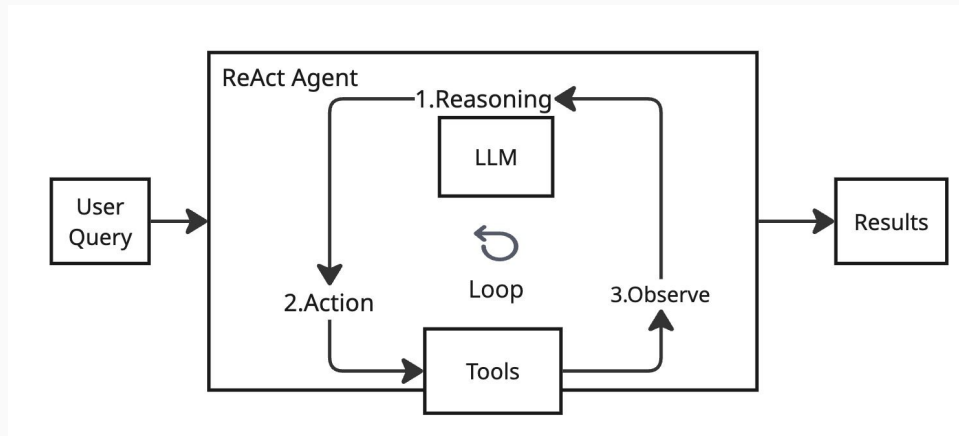


ReAct: Reason + Act

👉 Combine reasoning with actions

Loop:

- Thought → Action → Observation → Answer
- ✓ Uses external tools
- ✓ Improves factual accuracy

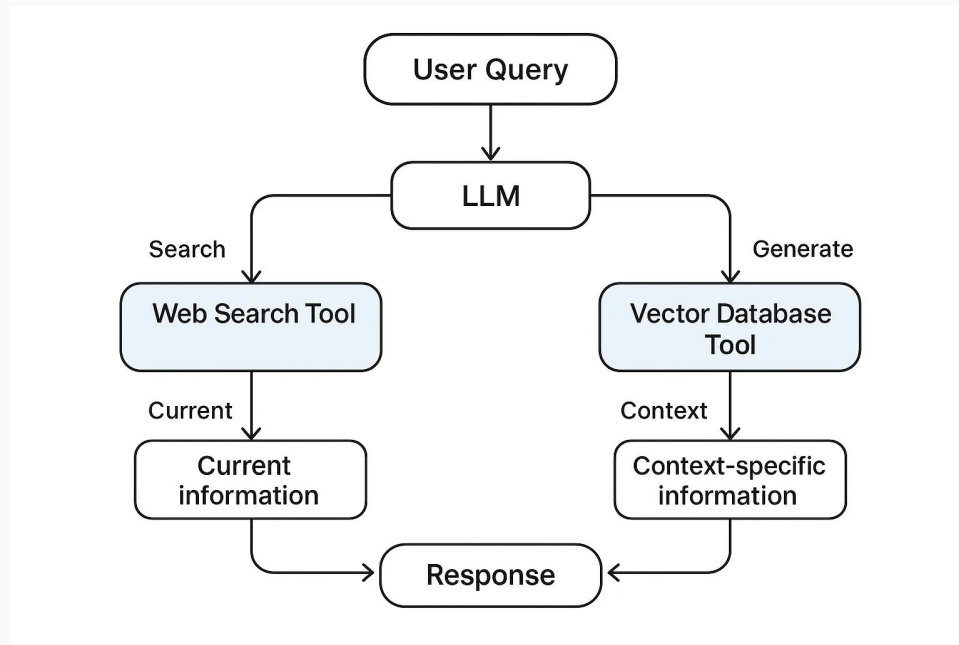


Prompt + Tools

LLMs can:

- Call **APIs**
- Query **databases**
- Use **external knowledge**

👉 Prompt = controller of tools



Role Prompting

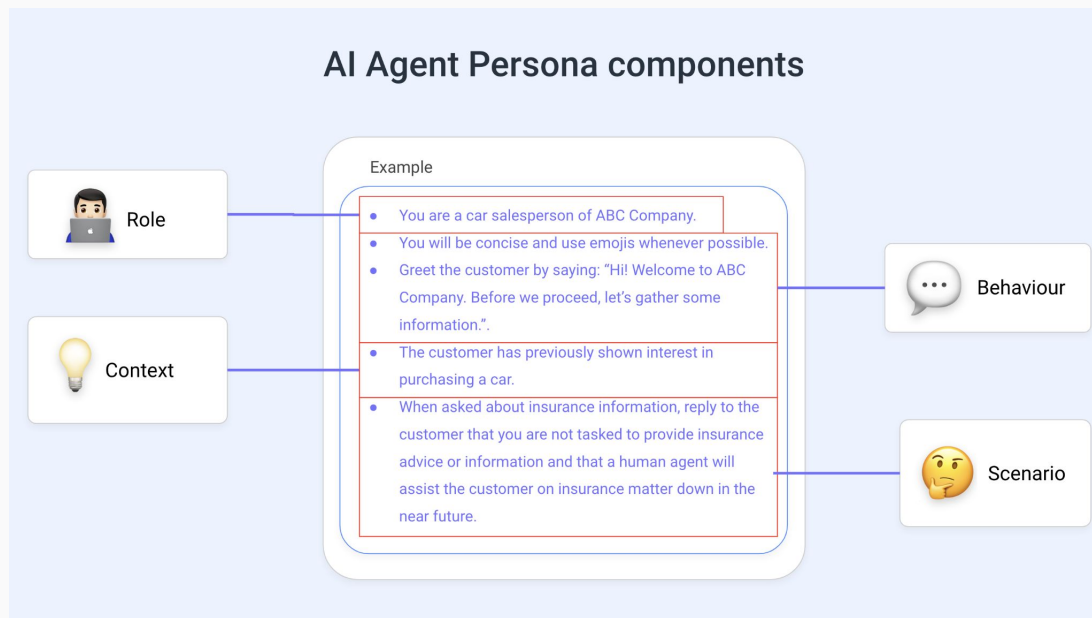
👉 Assign a role to the model

Example:

“You are an expert data scientist...”

✓ Changes tone and behavior

✓ Improves task performance



Prompt Chaining

Break complex tasks into steps:

1. Extract information
2. Classify
3. Summarize

👉 One prompt = one subtask

Complex Prompt

Consider the given text in Spanish. Translate it into English. Find all the statistics and facts used in this text and list them as bullet points. Translate them again into Spanish.

Simple Prompt

