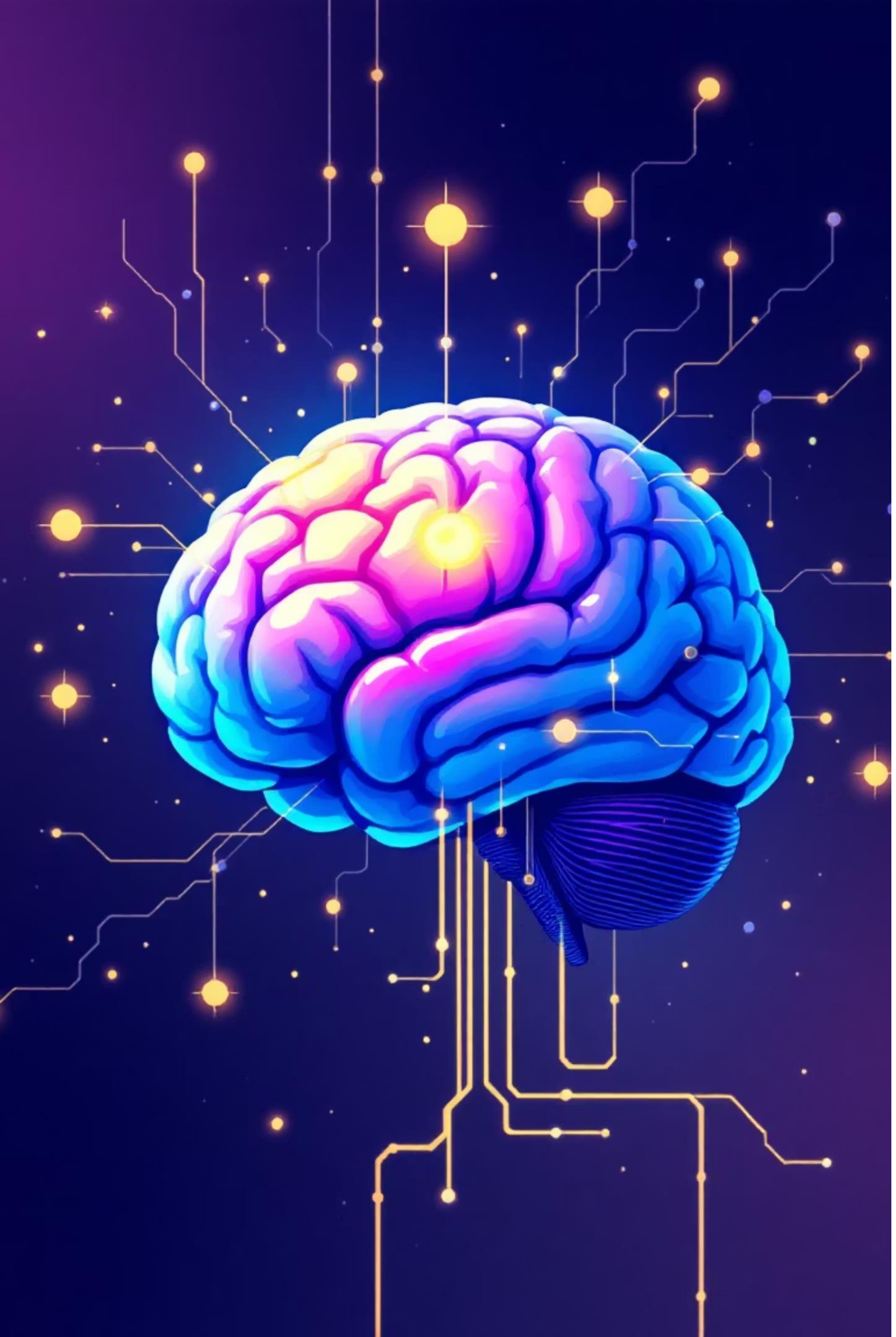
Day - 3

Chain of thoughts and Self-Consistency



Why LLMs Need Reasoning

Large Language Models (LLMs) excel at pattern recognition, but they don't "think" in the human sense. Their core function is to predict the next token based on vast amounts of data.

When tasks demand logical deduction or multiple sequential steps, simple prediction falls short. This is where the concept of reasoning becomes critical for LLMs.

The Gap: Prediction vs. Reasoning

Pattern Completion

LLMs operate on sophisticated pattern matching, completing sequences rather than understanding underlying logic.

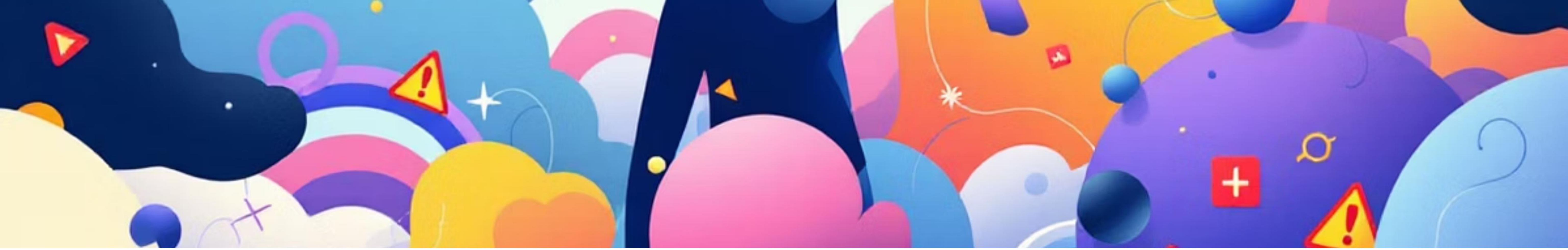
Need for Structured Thought

Complex, multi-step tasks require a structured, methodical approach that prediction alone cannot provide.

Bridging the Gap

Without guided reasoning, LLMs can struggle with coherence, consistency, and factual accuracy.

This fundamental difference leads to common LLM pitfalls that reasoning techniques aim to address.



The Challenges of Unguided LLMs

Logical Jumps

Models may skip necessary intermediate steps, leading to incomplete or flawed conclusions.

Hallucinations

Without a clear reasoning path, LLMs can confidently generate factually incorrect information.

Skipped Steps

Crucial parts of a problem-solving sequence might be omitted, undermining the final answer's validity.

These issues highlight the critical need for explicit reasoning mechanisms to guide LLM behavior.

Introducing Chain-of-Thought (CoT)

> CoT is a prompting technique that makes the model “show its work.”

Chain-of-Thought (CoT) transforms how LLMs approach complex problems by instructing them to vocalize their reasoning process. This makes the invisible steps visible, leading to more robust and verifiable outputs.

It's akin to a student showing all their calculations in a math problem—the final answer is important, but the process reveals understanding.

How CoT Works: Key Principles

Forces Step-by-Step

CoT explicitly guides the LLM to break down problems into sequential, manageable steps.

Exposes Logic

The intermediate reasoning becomes transparent, allowing users to understand the model's path to a solution.

Mimics Human Problem Solving

Inspired by how humans tackle complex tasks, CoT encourages a more deliberate and structured approach.

Enhances Specific Tasks

It is particularly effective for reasoning, mathematics, planning, and multi-step decision-making.

CoT shifts the LLM from simply "guessing an answer" to "walking through the solution" systematically.

When to Leverage Chain-of-Thought

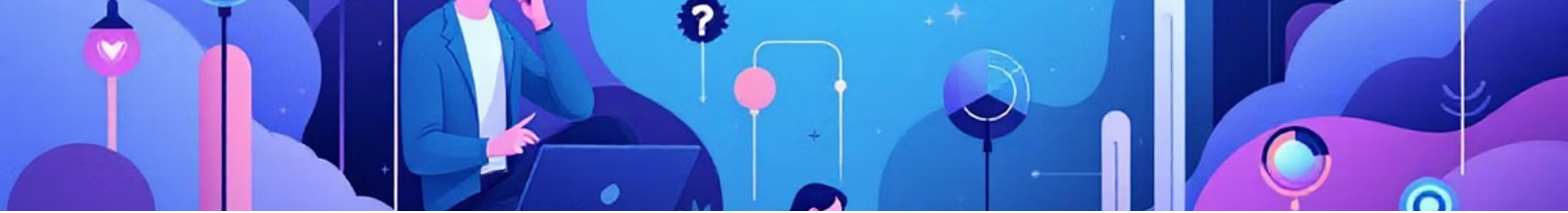
Best Use Cases:

- Math & arithmetic problems
- Logical deduction & puzzles
- Multi-step decision making
- Multi-hop questions (requiring multiple information retrievals)
- Complex planning tasks
- Classification with detailed explanation

Avoid CoT for:

- Simple Q&A (e.g., "What is the capital of France?")
- Short creative tasks (e.g., "Write a haiku")
- Direct fact retrieval

A good rule of thumb: If a question requires more than a single step or direct recall, CoT can significantly improve the LLM's performance.



Why CoT Enhances Performance

Breaks Down Problems

CoT deconstructs complex challenges into a series of manageable, logical steps.

Reduces Hallucinations

By articulating each step, the model is less likely to invent facts or make unsupported claims.

Fosters Self-Correction

The visible reasoning path allows the LLM to evaluate its own logic and potentially correct errors.

Mimics Human Cognition

This structured approach mirrors effective human problem-solving, leading to more reliable outcomes.

Ultimately, CoT prompts encourage "slow thinking," resulting in more accurate, consistent, and explainable answers from LLMs.

Mastering CoT Prompt Patterns

General Reasoning

"Let’s think step by step."

"Explain your reasoning before answering."

Mathematical Tasks

"Solve it step-by-step and show the calculations."

Logical Deduction

"Think through each condition one-by-one."

Planning & Execution

"List the steps needed to reach the final solution."

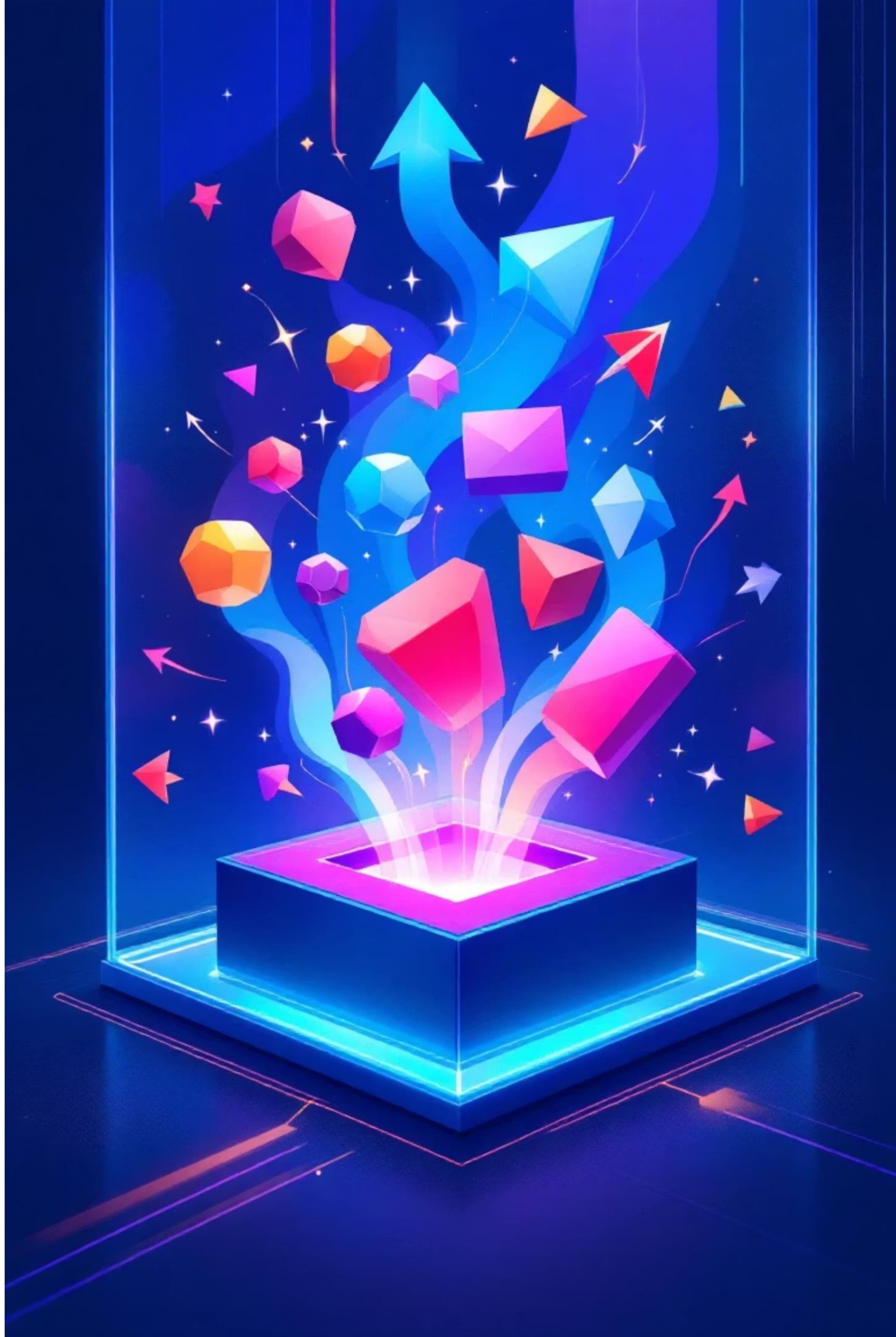
Employing these specific phrases can significantly guide the LLM toward generating clear, step-by-step reasoning sequences.

Introducing Self-Consistency

> Self-consistency: Ask the model to solve the same problem multiple times → pick the most common answer.

While CoT makes the reasoning path visible, self-consistency takes it a step further by leveraging the LLM's capacity to explore multiple reasoning avenues.

By sampling several "thoughts" from the model and identifying the most frequent outcome, we can drastically improve the reliability of the final answer. It's essentially implementing a "majority vote" among the LLM's own internal reasoning processes.



Why Self-Consistency Boosts Accuracy

Diverse Paths

LLMs can generate various reasoning sequences, some correct, others flawed.

Correctness Amplification

The correct answers tend to appear more frequently across multiple samples.

Noise Reduction

Majority voting effectively filters out erroneous or outlier reasoning paths.

Enhanced Stability

This technique makes the LLM's reasoning more robust, especially for challenging questions.

By generating and comparing multiple reasoning trajectories, self-consistency reduces hallucinations and leads to a more stable and accurate final answer.

Hands on tasks

Task 1 — CoT vs No-CoT

- Solve any math word problem
- Compare accuracy with and without CoT

Task 2 — Write a CoT Prompt

- Convert a normal prompt → CoT-enhanced reasoning prompt

Task 3 — Self-Consistency Experiment

- Ask the same question 5 times using CoT
- Count the answers
- Report the majority result

Summary

- **CoT** → Improves LLM reasoning by forcing step-by-step logic
- **Self-consistency** → Improves stability by sampling multiple reasoning paths
- Best for **math, logic, multi-step reasoning, planning**
- Avoid CoT for simple answer tasks
- These techniques reduce hallucination and improve accuracy

CoT + Self-consistency → Stronger, more reliable LLM reasoning.