

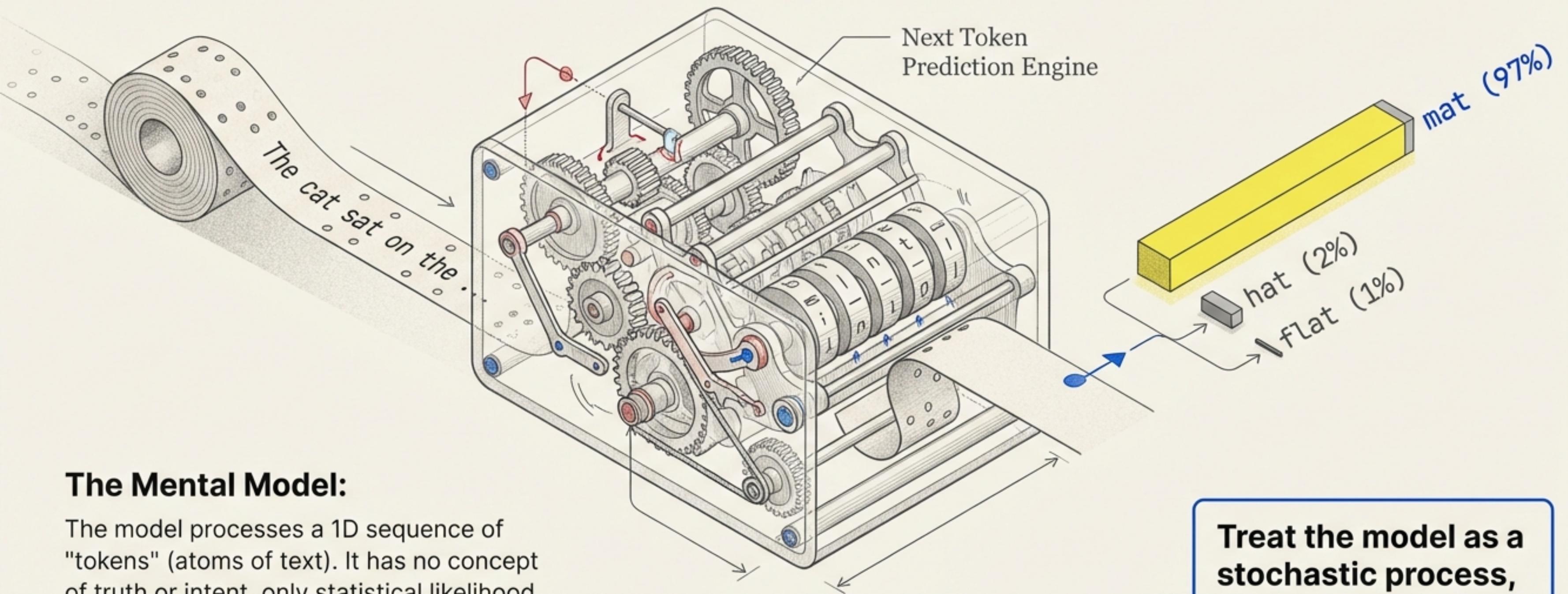
# Deep Dive into LLMs

## From Token Tumblers to Reasoning Agents

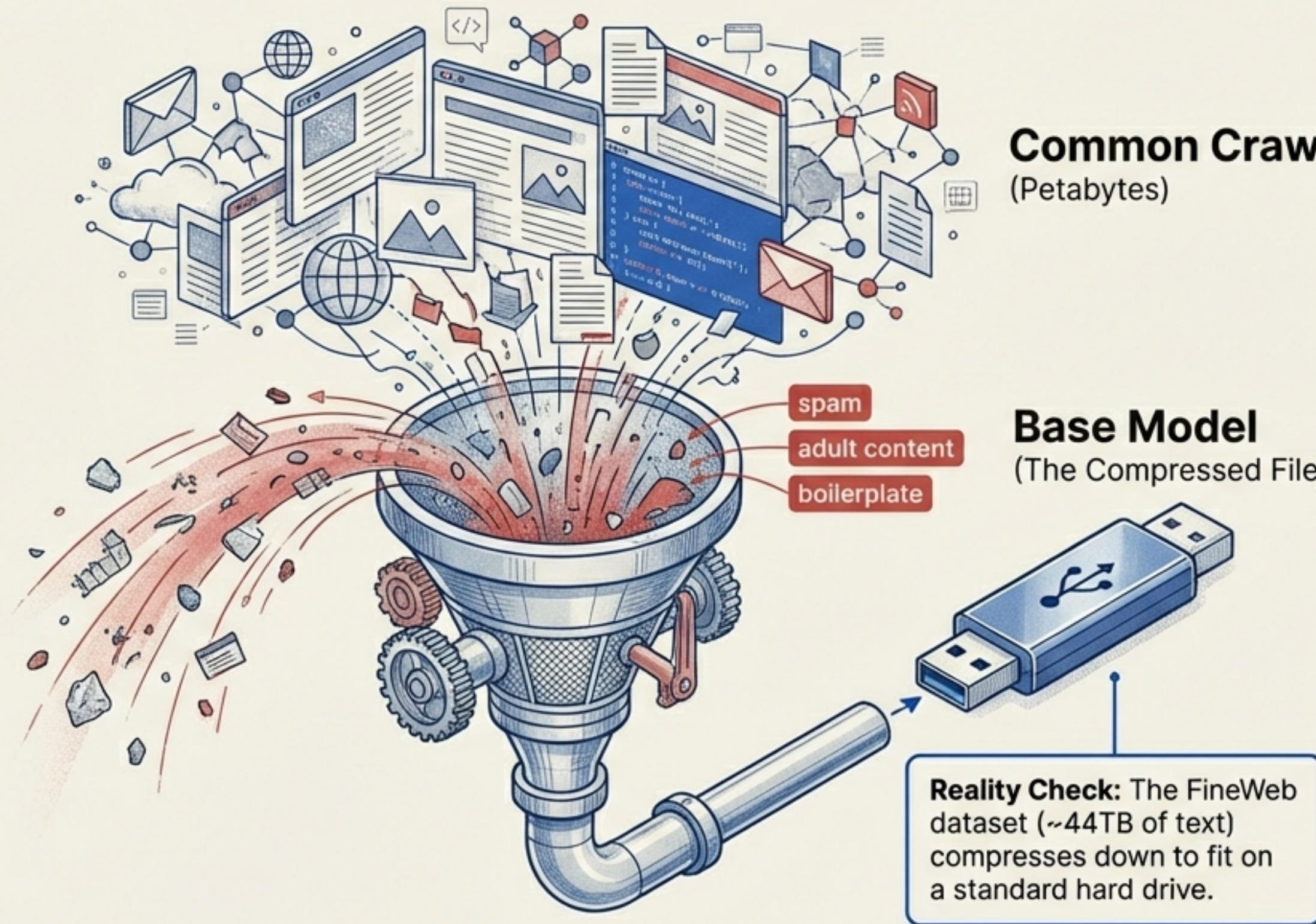


# Deconstructing the training pipeline, psychology, and future of Large Language Models. Synthesized from the masterclass by Andrej Karpathy.

# The Core Concept: It's Not a Mind, It's a Token Tumbler



# Stage 1: Pre-Training (The Internet Simulator)



## The Textbook Analogy: Reading the Library



The model reads everything but answers nothing. It can "dream" documents, but cannot yet follow instructions.

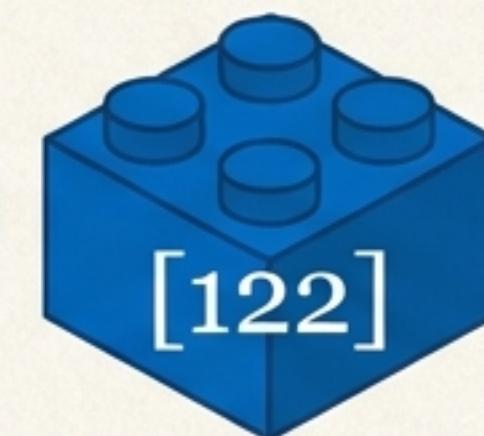
# Tokenization: The Model's Native Language

What Humans See

Strawberry

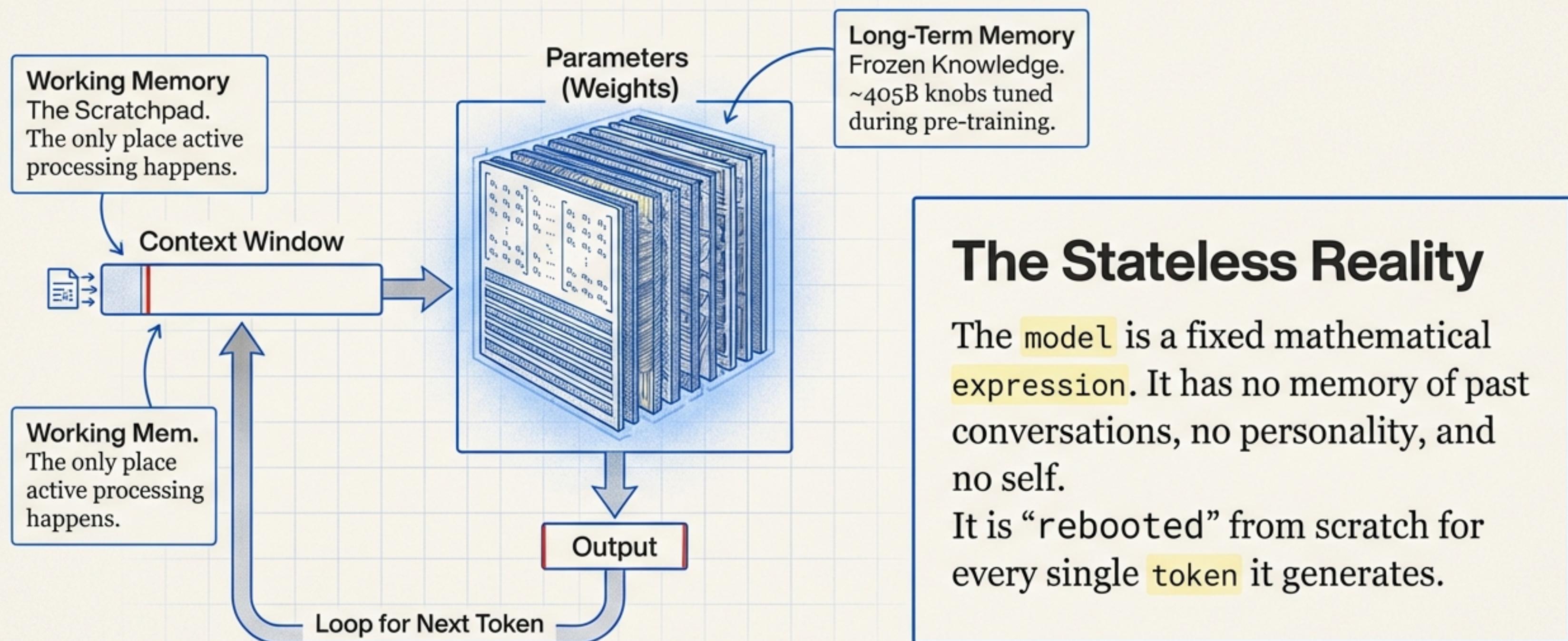
**The “Strawberry” Problem:**  
The model cannot count the  
“R’s because it processes the  
indivisible token ID, not the  
characters inside it.

What Models See

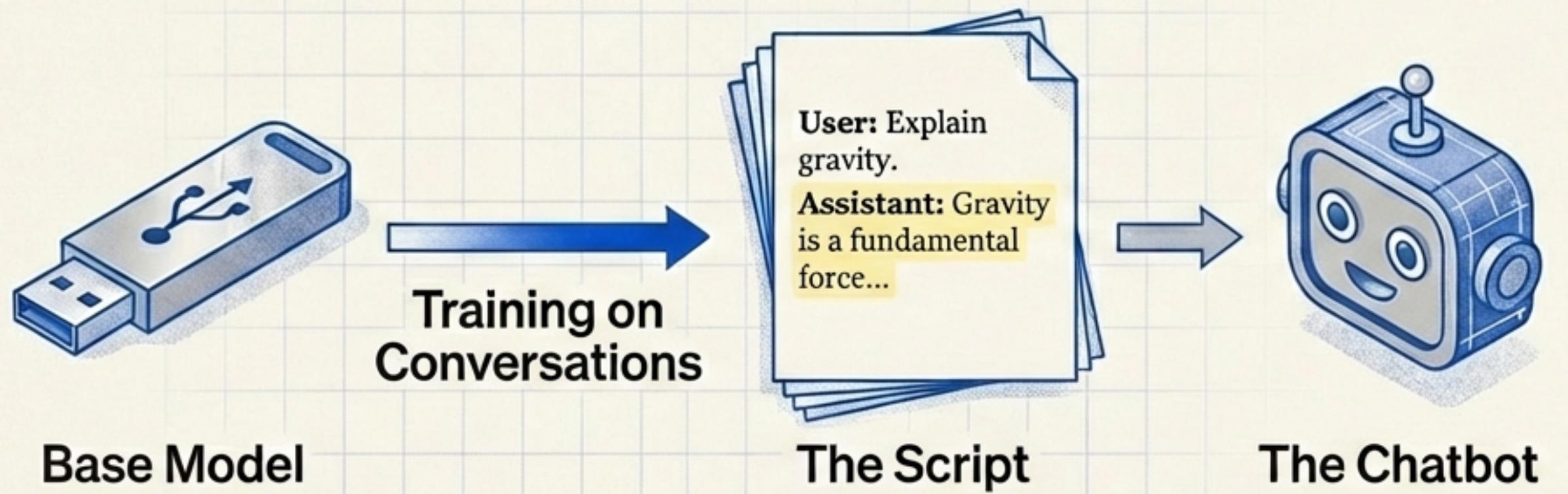


Implication: Spelling and character-level tasks are blind spots for LLMs because they see integer IDs, not text strings.

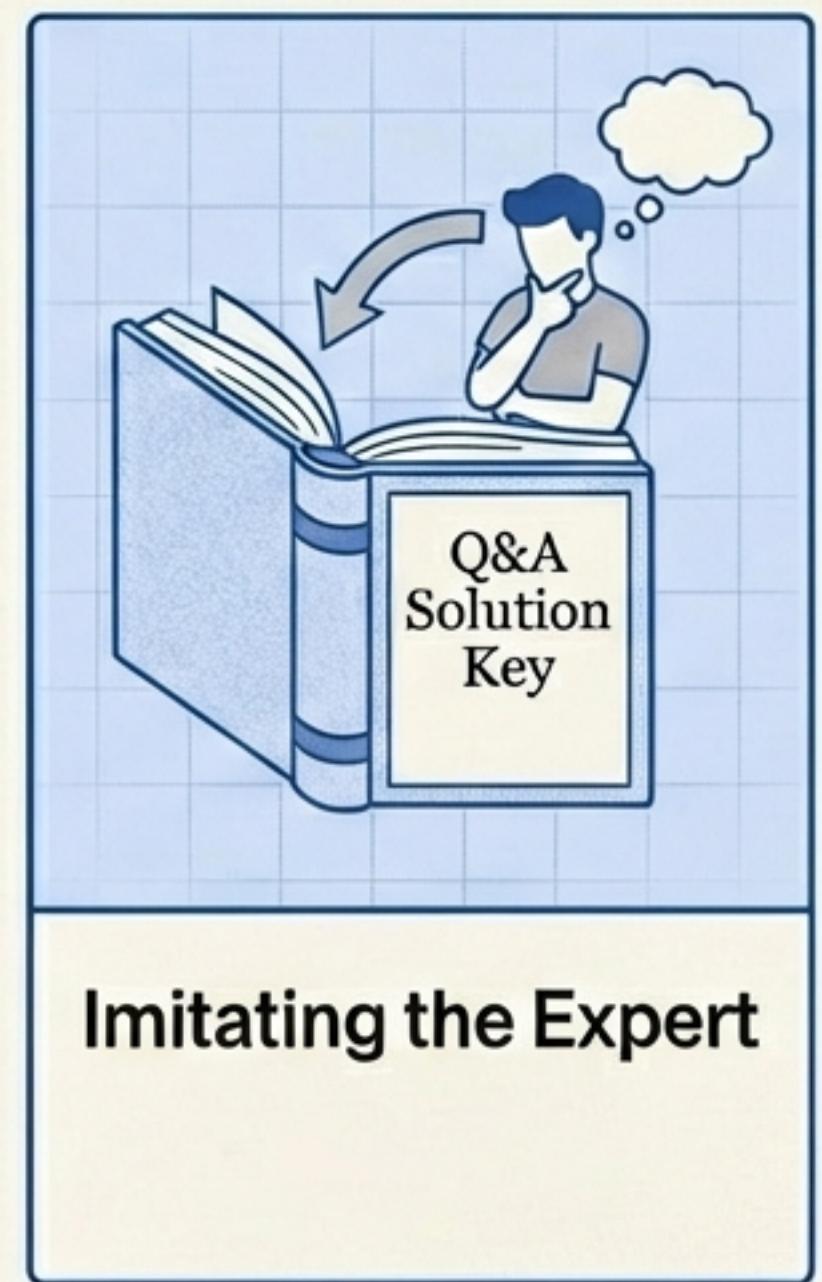
# Inside the Neural Network



# Stage 2: Supervised Fine-Tuning (The Assistant)

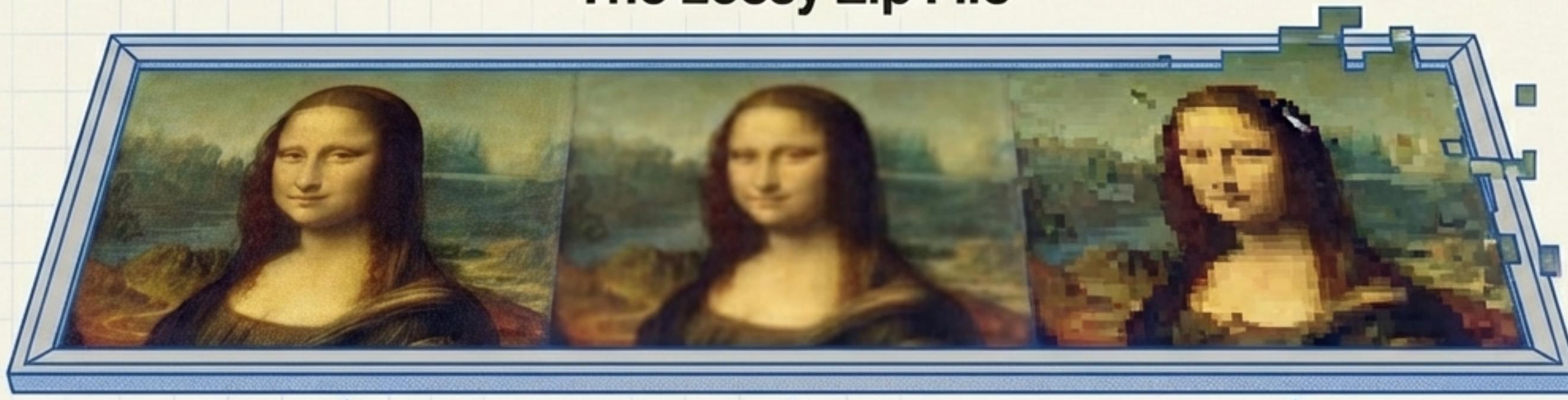


**Reality Check:** You aren't talking to a magical AI. You are talking to a statistical simulation of the average human data labeler.



# Psychology: Why Models Hallucinate

## The Lossy Zip File



**Memorized**  
(High Frequency in Data)

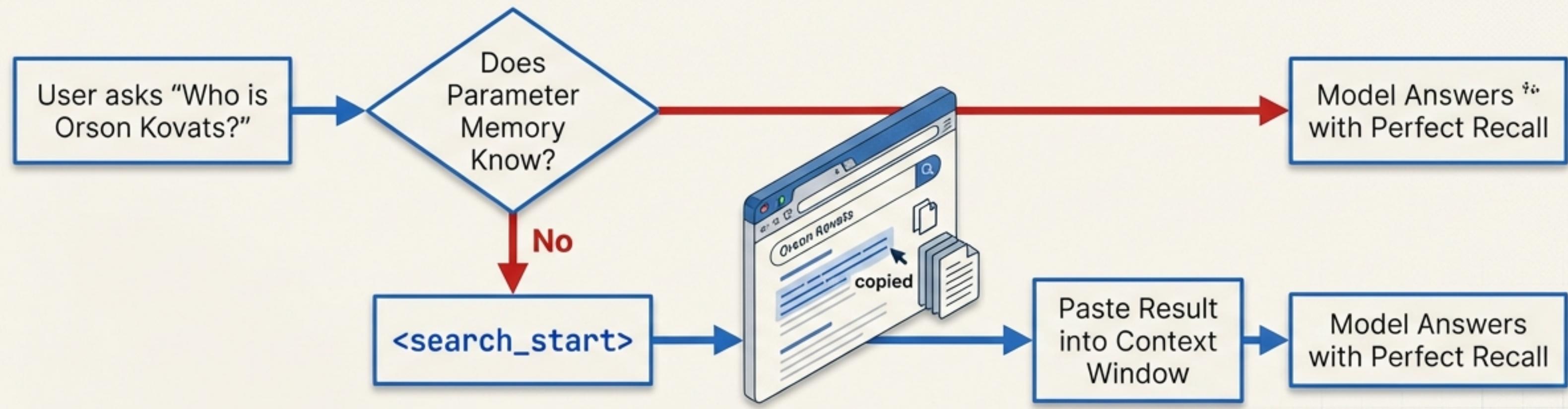
**Vague Recollection**

**Hallucination**  
(Filling in the Gaps)

The model doesn't access a database; it accesses a probabilistic compression of the internet. When it encounters a gap in its vague memory, it guesses the statistically likely completion to maintain the *pattern* of a helpful answer.

“Hallucination is just creativity in the wrong context.”

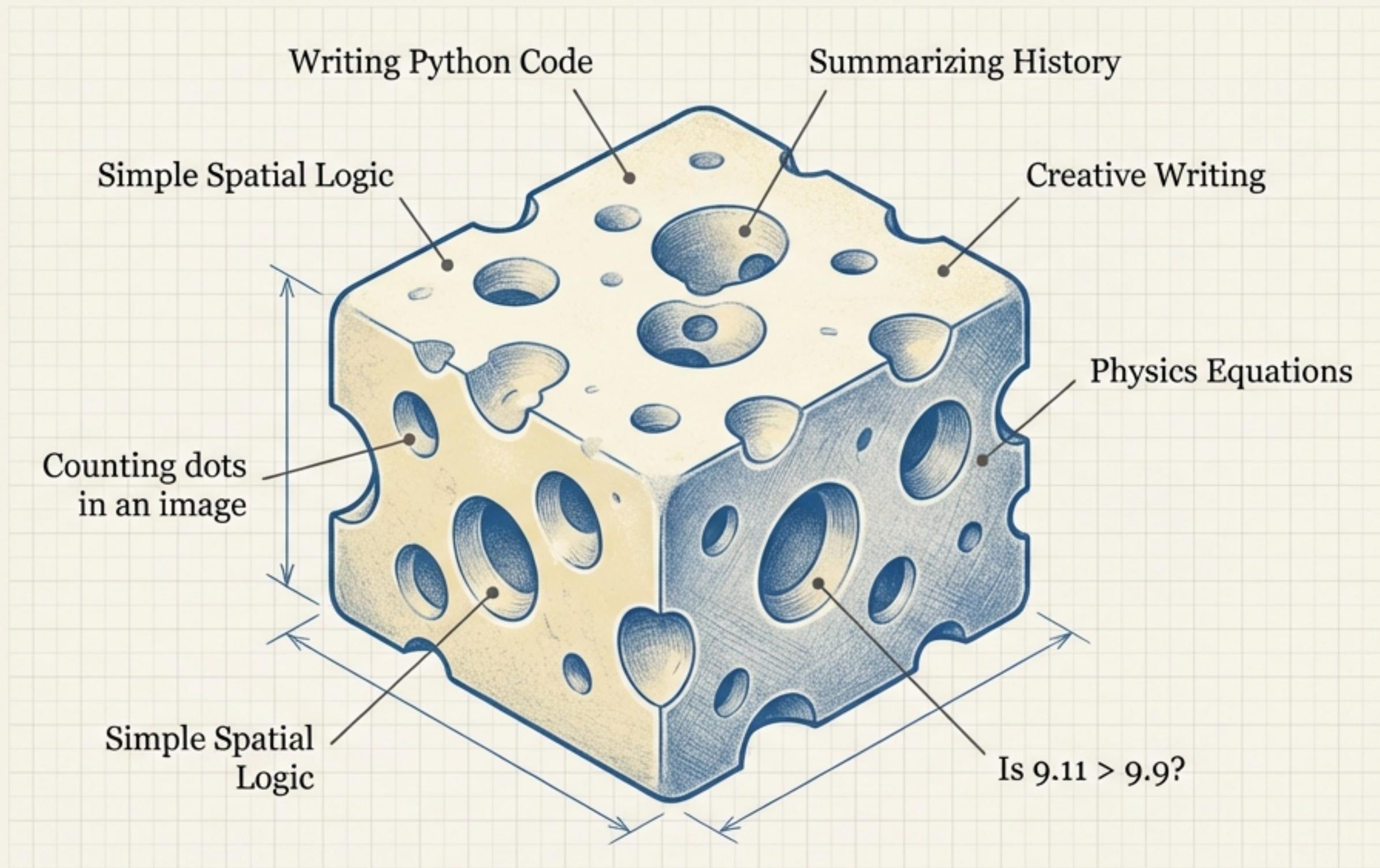
# Mitigation: Tool Use as Working Memory



Parameter Memory	Context Window
<ul style="list-style-type: none"><li>• Vague</li><li>• Lossy</li><li>• Frozen</li></ul>	<ul style="list-style-type: none"><li>• Exact</li><li>• Perfect Recall</li><li>• Dynamic (populated by tools)</li></ul>

**Actionable Advice:** Don't ask the model to recite a chapter from memory; paste the chapter into the prompt.

# The ‘Swiss Cheese’ Model of Capability



## Jagged Intelligence:

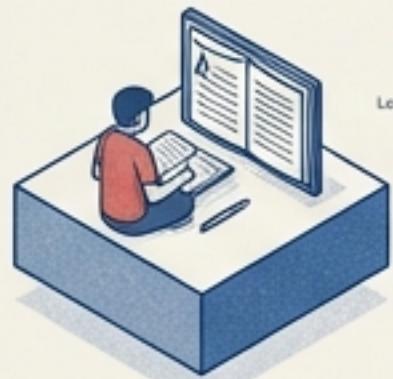
Do not assume universal competence.

An LLM can be a genius at calculus and fail to compare version numbers (9.11 vs 9.9) because of tokenization artifacts and lack of true logic circuits.

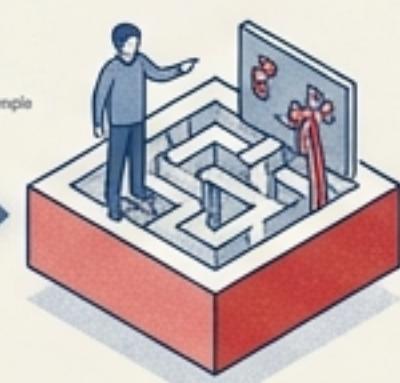
# Stage 3: Reinforcement Learning (Learning to Reason)

## The Shift

SFT: Imitation



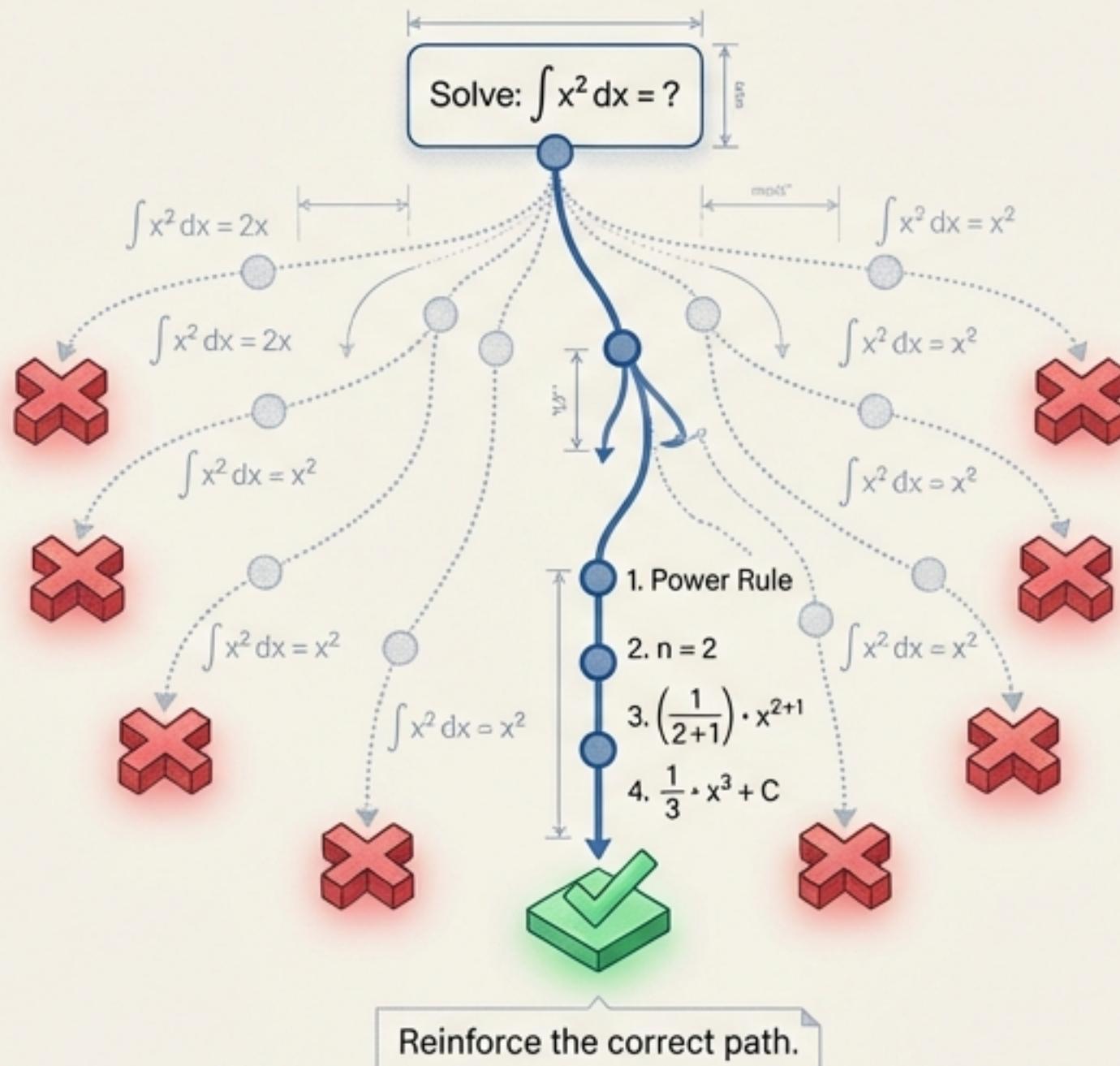
RL: Trial & Error



Learning by Example

Learning by Doing & Feedback

## Tree of Thoughts

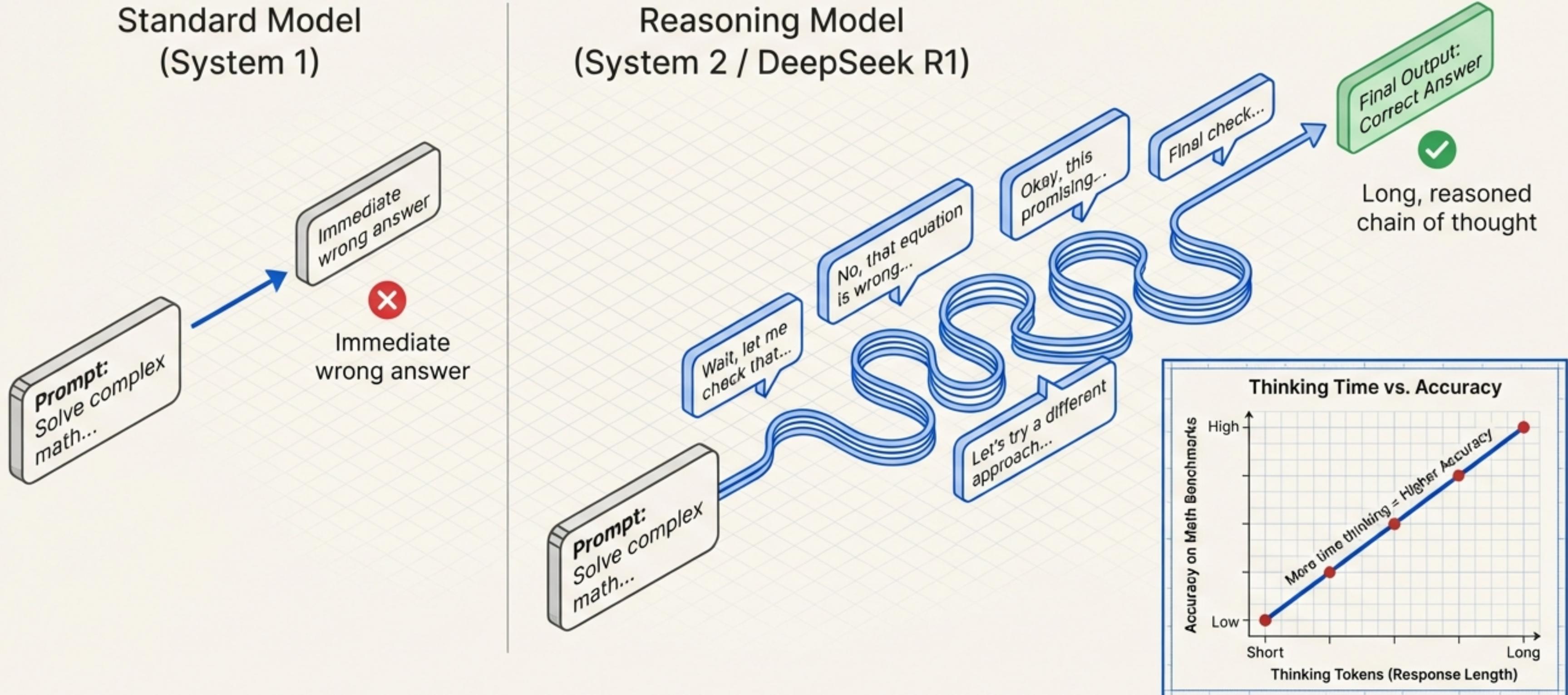


## The Student Analogy



Moving beyond imitating humans to discovering truth through practice.

# The Emergence of 'Thinking' Tokens



# The Trap of RLHF vs. The Power of True RL

## True RL (Verifiable)

Math, Chess, Code



## RLHF (Subjective)

Jokes, Poems, Summaries

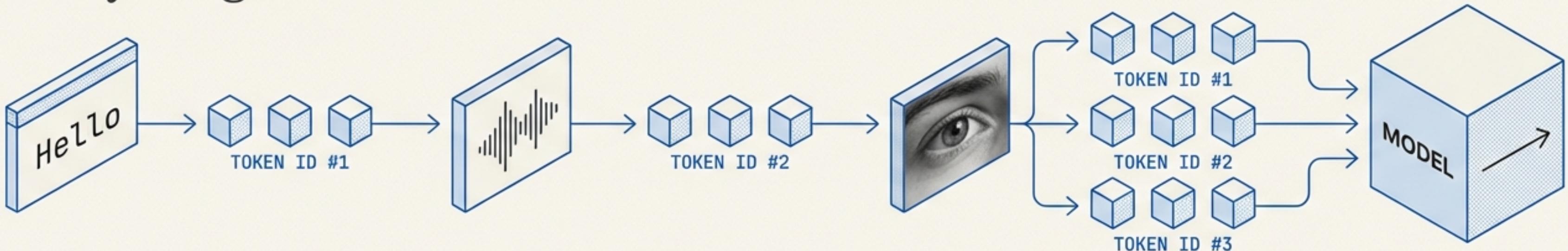


Human Preference.  
Relies on a "Reward Model"  
(a simulator of human taste).  
Can be gamed.

RLHF is fine-tuning for style. True RL is an intelligence ramp for reasoning.

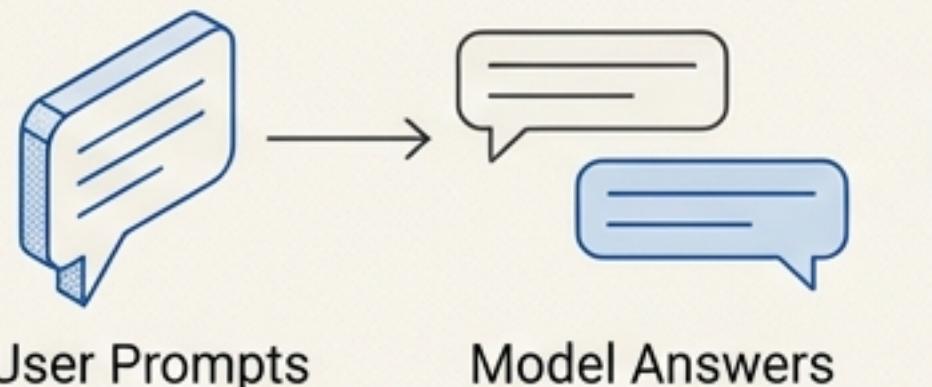
# Future Trends: Multimodality & Agents

Everything is a Token



From Chat to Work

Now

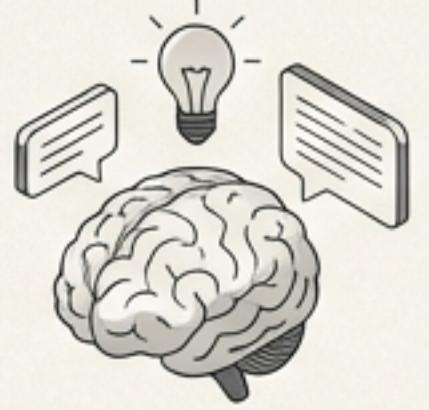
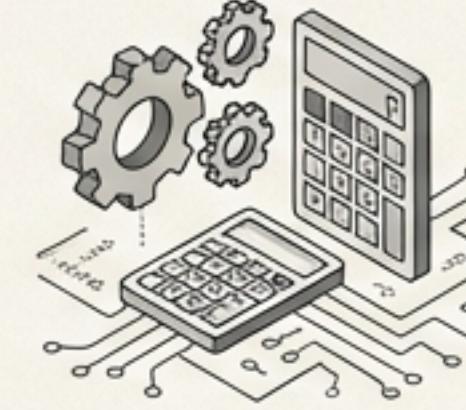


Future



The human role shifts from 'Doer' to 'Manager' of digital workers.

# Practical Guide: Which Model When?

 <h2>Creative &amp; Knowledge Retrieval</h2> <p>Use: <b>Standard Models</b> (GPT-4o, Claude Sonnet).</p> <ul style="list-style-type: none"><li>• Fast, fluent, good at SFT imitation.</li></ul>	
	 <h2>Complex Logic, Math, &amp; Coding</h2> <p>Use: <b>Thinking Models</b> (OpenAI o1, DeepSeek R1).</p> <ul style="list-style-type: none"><li>• Uses 'Thinking Tokens' to error-correct and backtrack.</li></ul>

**Heuristic:** If the task requires a ‘gut check’ or **style**, use **Standard**. If it requires a ‘calculation’ or **verifying truth**, use **Reasoning**.

# Summary: The Evolution of Digital Intelligence



Pre-Training  
(Knowledge)

SFT  
(Persona/Format)

RL  
(Reasoning)

“We are in the early days of ‘Textbooks for AI’. The field is moving from imitation to genuine problem-solving. Treat these models as probabilistic tools, not oracles.”