LLM Foundations for Agents

Week 2: Prompting, Reasoning, and Context

PhD Course in Agentic Artificial Intelligence

Learning Objectives

Bloom's Taxonomy Levels

- **Remember**: Define CoT (Chain-of-Thought), ToT (Tree-of-Thoughts), Self-Consistency
- **Understand**: Explain how reasoning emerges from prompting strategies
- **Apply**: Implement various prompting techniques for complex reasoning
- **Analyze**: Compare effectiveness of different prompting strategies
- **Evaluate**: Assess trade-offs between reasoning depth and cost
- **Create**: Design custom prompting strategies for specific domains

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These prompting techniques are the foundation of agent reasoning.

Why Prompting Matters for Agents

The Reasoning Gap

- LLMs can reason, but not always reliably
- Prompting is "programming in natural language"
- The right prompt can unlock latent capabilities

Agent Applications

- **Planning**: Decompose complex tasks into steps
- **Decision-making**: Weigh alternatives systematically
- **Error recovery**: Self-diagnose and correct mistakes
- **Tool selection**: Choose appropriate actions

Effective prompting is essential for building reliable agents.

Chain-of-Thought Prompting

Key Insight (Wei et al., 2022)

- Elicit intermediate reasoning steps before final answer
- “Let’s think step by step” unlocks reasoning

Example

Without CoT

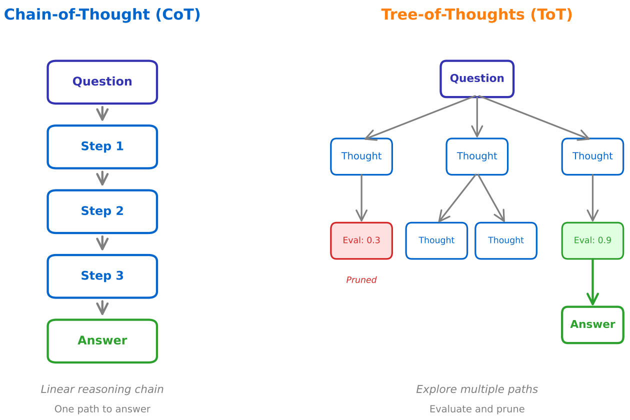
Q: Roger has 5 tennis balls. He buys 2 cans of 3 balls each. How many balls?
A: 11

With CoT

Q: [same question] Let’s think step by step.
A: Roger starts with 5 balls. 2 cans of $3 = 6$ balls. Total: $5 + 6 = 11$.

CoT significantly improves math and multi-step reasoning tasks.

Chain-of-Thought vs Tree-of-Thoughts



ToT (Yao et al., 2023) enables exploration and backtracking.

Tree-of-Thoughts: Deliberate Problem Solving

Key Innovation (Yao et al., 2023)

- Explore multiple reasoning paths simultaneously
- Evaluate intermediate states with value function
- Backtrack when paths look unpromising

Algorithm

1. Generate multiple candidate thoughts
2. Evaluate each thought (LLM as evaluator)
3. Select best paths for expansion
4. Repeat until solution or budget exhausted

Complexity: $O(b^d)$ where $b =$ branching factor, $d =$ depth

ToT excels at creative and planning tasks where exploration helps.

Self-Consistency Decoding

Key Idea (Wang et al., 2023)

- Sample multiple reasoning paths at temperature (randomness) > 0
- Take majority vote on final answers
- Robust answers emerge from diverse reasoning

Formula

$$\hat{a} = \arg\max_{a} \sum_{i=1}^{k} \nVdash [a_i = a]$$

When to Use

- Math problems, logical reasoning
- When single path may hallucinate
- Trade-off: More tokens, more cost, better accuracy

Self-consistency is simple but effective for improving reliability.

Zero-Shot Chain-of-Thought

"Let's think step by step" (Kojima et al., 2022)

- No few-shot (example-based) prompts needed
- Simple prompt addition unlocks reasoning
- Works across many task types

Effective Phrases

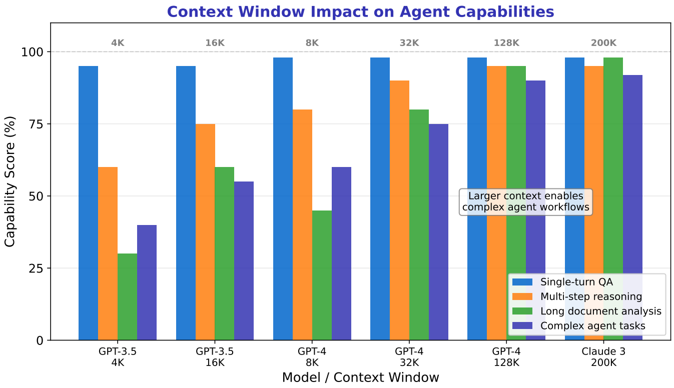
- "Let's think step by step"
- "Let's work this out in a step by step way"
- "First, ... Then, ... Finally, ..."
- "Let me break this down"

Agent Application

- Use in ReAct "Thought" steps
- Combine with tool-use for grounded reasoning

Zero-shot CoT is the simplest way to improve LLM reasoning.

Context Window and Agent Performance



Context length determines how much history and context an agent can use.

Context Window Management

The Challenge

- Agents need: system prompt + history + tools + current task
- Context fills up quickly in multi-turn interactions

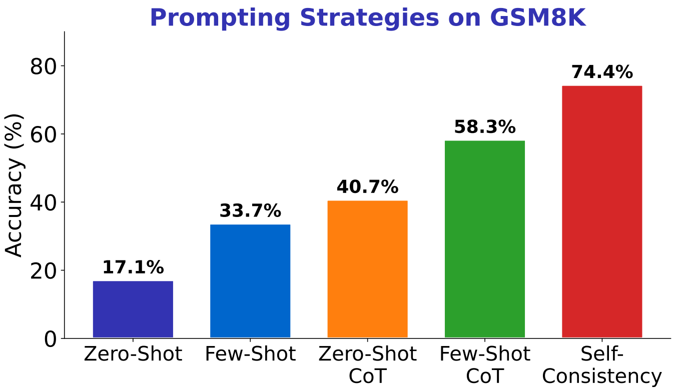
Strategies

- **Sliding window**: Keep recent N turns
- **Summarization**: Compress old history
- **RAG** (Retrieval-Augmented): Fetch relevant context on demand
- **Hierarchical**: Use different models for different tasks

Token Budget Planning

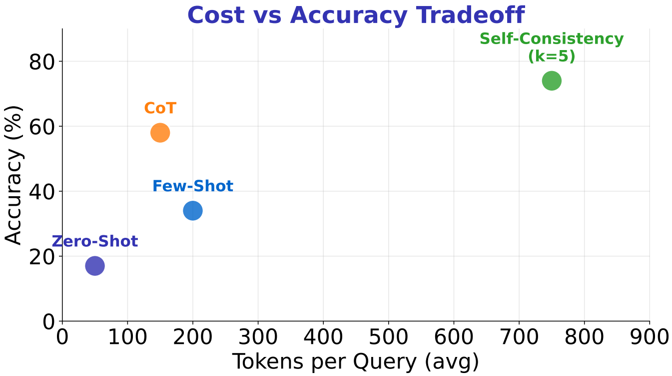
- Reserve space for: System (500-2K), Tools (1-5K), Response (1-4K)
- Remaining: Available for history and context

Context management is crucial for long-running agent tasks.



Self-consistency achieves 74.4% accuracy vs 17.1% zero-shot (GSM8K benchmark).

Cost vs Accuracy Tradeoff



Better accuracy requires more tokens – choose based on task criticality.

Comparison of Prompting Strategies

Strategy	Tokens	Best For	Trade-off
Zero-shot	Low	Simple tasks	May miss nuance
Few-shot (examples)	Medium	Task demonstration	Example selection
Chain-of-Thought	Medium	Math, logic	Linear only
Tree-of-Thoughts	High	Creative, planning	Cost, latency
Self-Consistency	Very High	Reliability	Many samples

For Agents

- Use Zero-shot CoT for simple reasoning
- ToT for planning and task decomposition
- Self-Consistency for critical decisions

Choose prompting strategy based on task complexity and cost constraints.

Temperature and Sampling for Agents

Temperature Effects

- $T = 0$: Deterministic, best for factual tasks
- $T = 0.3 - 0.7$: Balanced creativity and coherence
- $T > 1.0$: High creativity, risk of incoherence

Agent Guidelines

- **Tool selection**: $T = 0$ (deterministic)
- **Planning**: $T = 0.2 - 0.5$ (some exploration)
- **Self-Consistency**: $T = 0.7+$ (diversity)
- **Creative writing**: $T = 0.8 - 1.0$

Temperature is a key hyperparameter for agent behavior.

Practical Implementation Tips

Prompt Structure for Agents

1. System context and role
2. Available tools and their descriptions
3. Output format specification
4. Few-shot examples (if applicable)
5. Current task and context

Common Pitfalls

- Overloading system prompt (keep focused)
- Inconsistent formatting (LLM gets confused)
- Missing error handling instructions
- Vague tool descriptions

Clear, consistent prompts lead to reliable agent behavior.

Required Readings

This Week

- Wei et al. (2022). "Chain-of-Thought Prompting Elicits Reasoning." *NeurIPS 2022*. arXiv:2201.11903

Supplementary

- Yao et al. (2023). "Tree of Thoughts." arXiv:2305.10601
- Wang et al. (2023). "Self-Consistency." arXiv:2203.11171
- Kojima et al. (2022). "Zero-Shot Reasoners." arXiv:2205.11916

Chain-of-Thought is required; others are recommended.

Summary and Key Takeaways

Key Concepts

- **Chain-of-Thought**: Linear reasoning traces
- **Tree-of-Thoughts**: Branching exploration
- **Self-Consistency**: Majority vote over samples
- **Context Window**: Limits agent memory and complexity

Key Equation

$$\hat{a} = \arg\max_a \sum_{i=1}^{k} \mathbb{1}[a_i = a] \quad \text{(Self-Consistency)}$$

Next Week

- Tool Use and Function Calling
- Model Context Protocol (MCP)

Prompting strategies form the reasoning backbone of LLM agents.