Lecture 7

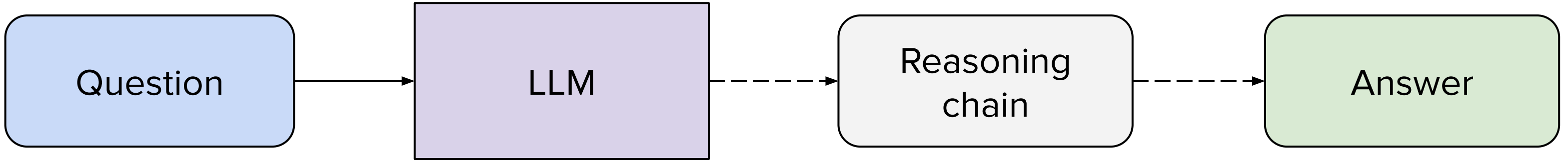
CME 295: Transformers & Large Language Models

 **Afshine Amidi & Shervine Amidi** 

Stanford University

Recap of last episode...

Reasoning models



Recap of last episode...

Reasoning models

GRPO

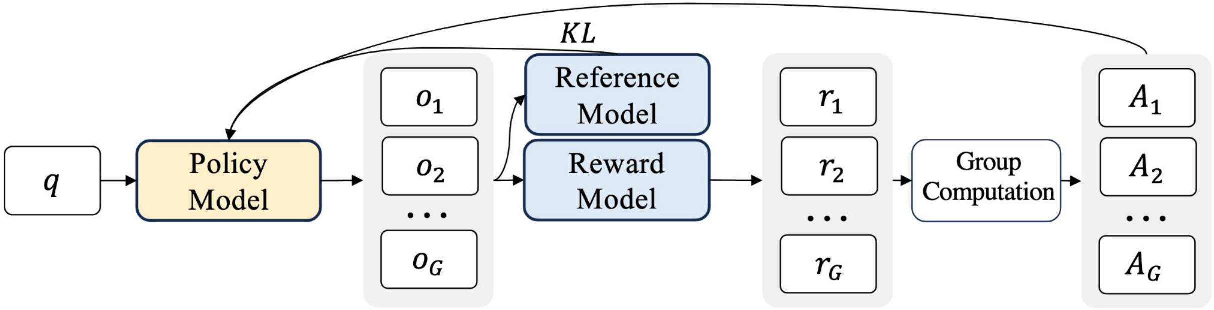
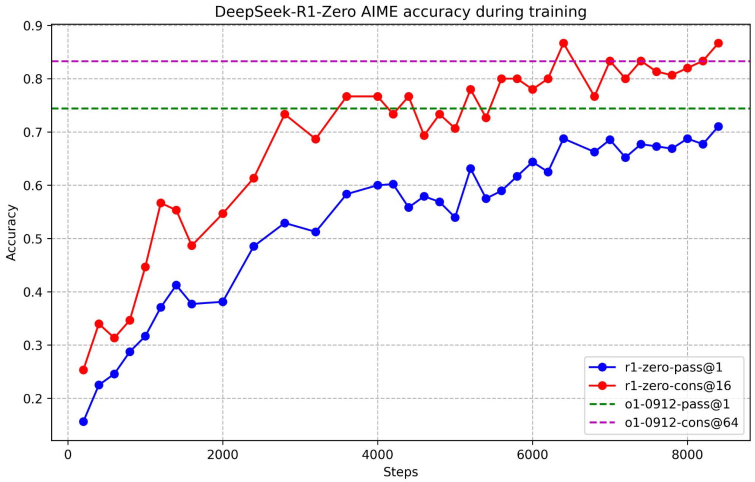
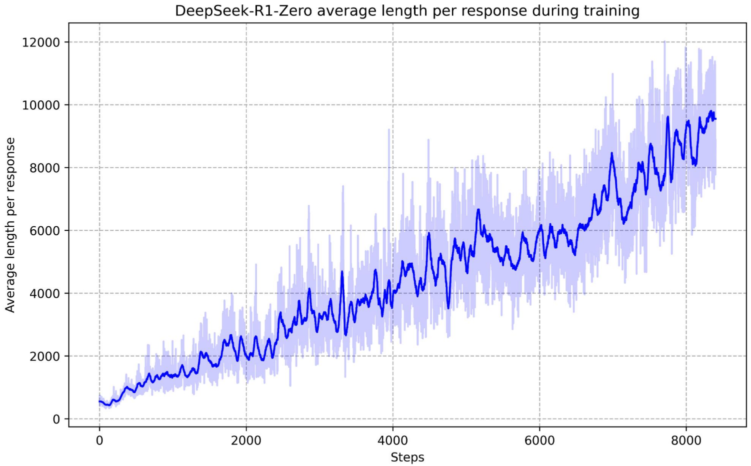


Figure from "DeepSeekMath: Pushing the Limits of Mathematical Reasoning in Open Language Models", Shao et al., 2024.

Recap of last episode...





Recap of last episode...

Original $\frac{1}{G}\sum_{i=1}^{G} \frac{1}{|\mathbf{o}_i|} \sum_{t=1}^{|\mathbf{o}_i|}$

Stanford University

"*DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning*", *DeepSeek-AI, 2025.*

ICME

Recap of last episode...

Original $\frac{1}{G}\sum_{i=1}^{G}\color{red}{\frac{1}{|\mathbf{o}_i|}}\color{black}\sum_{t=1}^{|\mathbf{o}_i|}$

DAPO $\frac{1}{\sum_{i=1}^{G}|o_i|}\sum_{i=1}^{G}\sum_{t=1}^{|o_i|}$

Dr. GRPO $\frac{1}{G}\sum_{i=1}^{G}\sum_{t=1}^{|\mathbf{o}_i|}$

"Understanding R1-Zero-Like Training: A Critical Perspective", Liu et al., 2025.
"DAPO: An Open-Source LLM Reinforcement Learning System at Scale", Yu et al., 2025.

Recap of last episode…

Strengths.

- Great at imitation or idea generation
- Amazing at generating or debugging code

Weaknesses.

- Limited reasoning
- Knowledge is static
- Cannot perform actions
- Hard to evaluate

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Strengths.

- Great at imitation or idea generation
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Weaknesses.

- Limited reasoning
- **Knowledge is static**
- **Cannot perform actions**
- Hard to evaluate

Focus of today

Transformers & Large Language Models

RAG

Tool calling

Agents

Stanford University

ICME

Motivation

- **Knowledge** of LLM **constrained** to pretraining data

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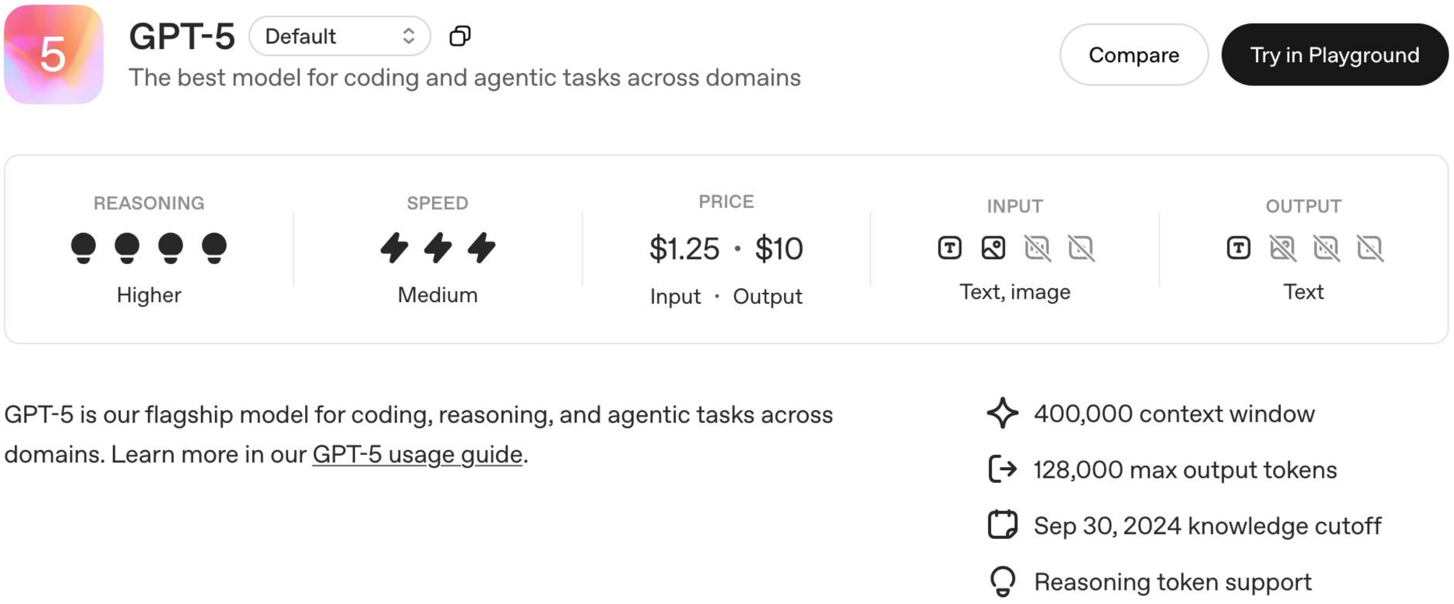

Screenshot of OpenAI's GPT-5 model card, taken on November 9th, 2025.

Motivation

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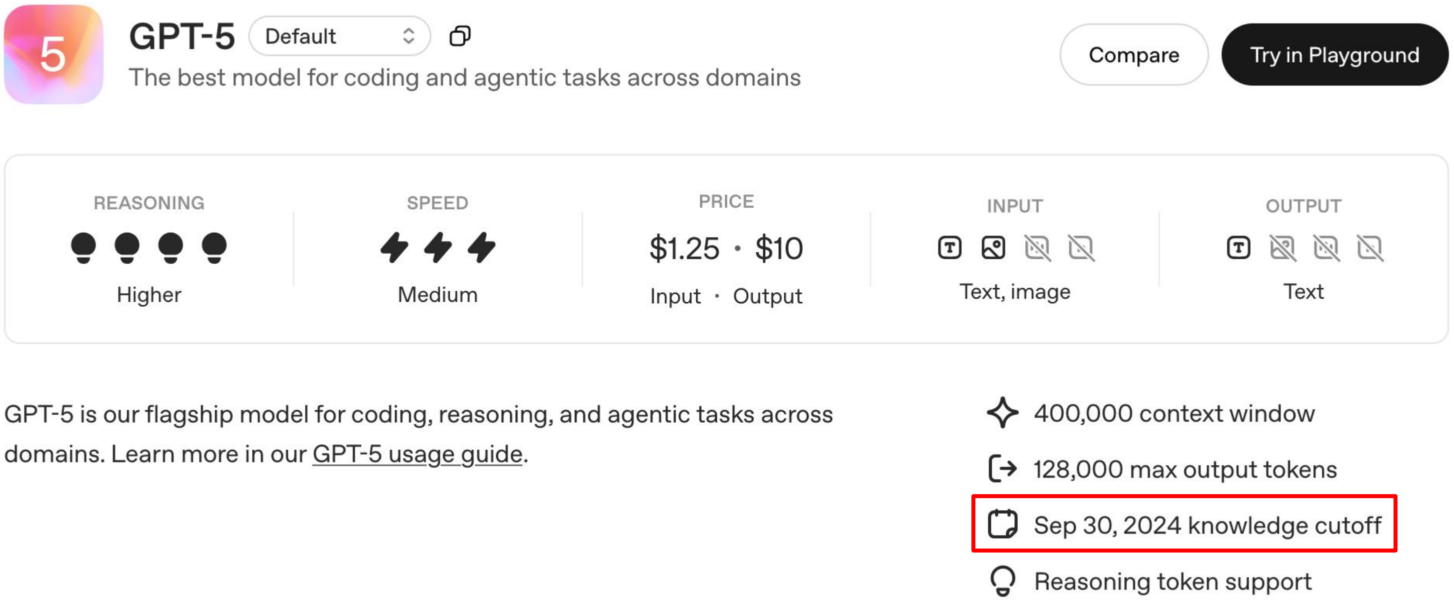

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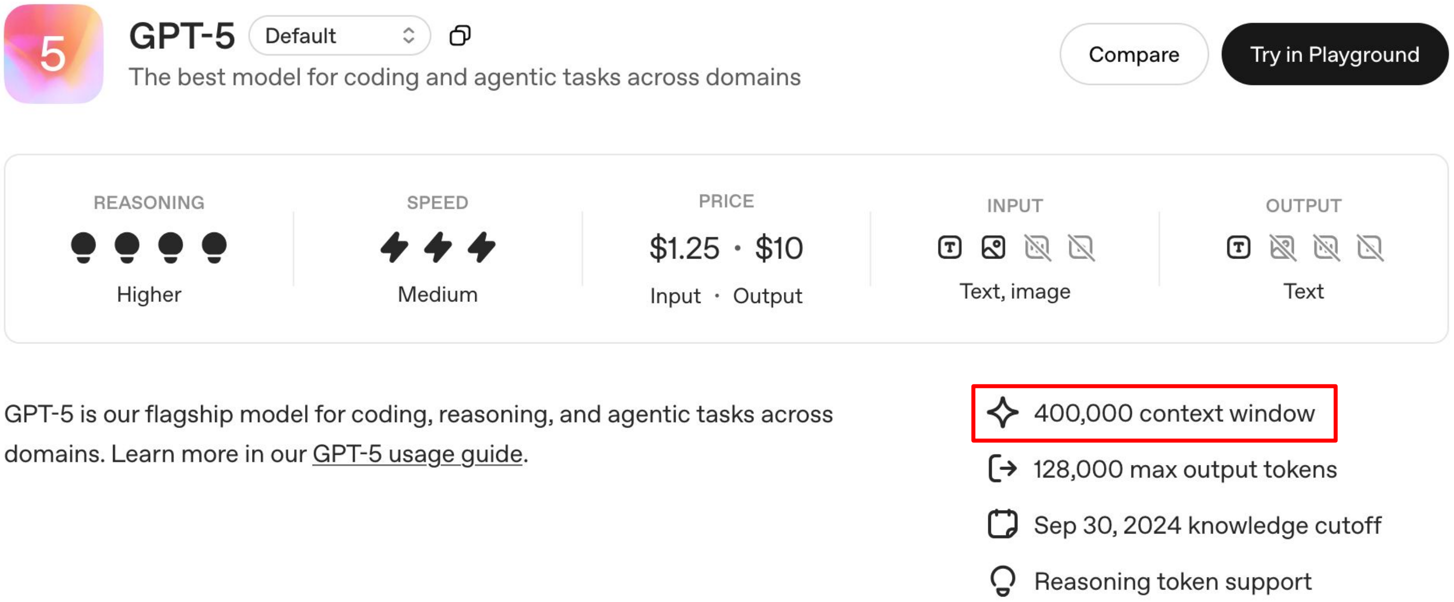

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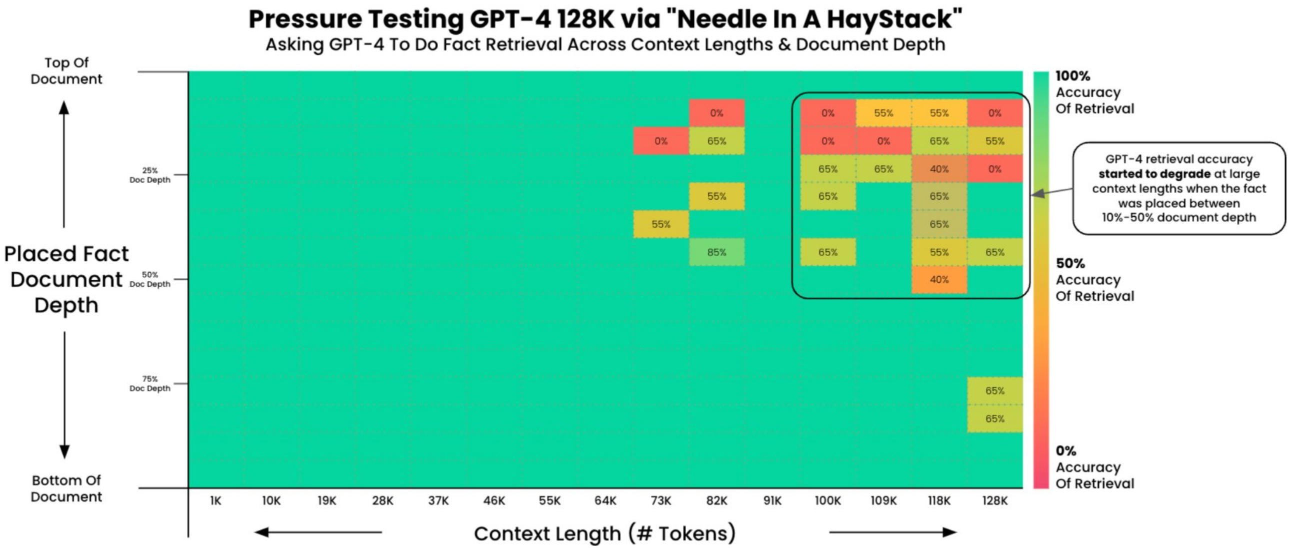

GitHub repo containing "Needle in a Haystack - Pressure Testing LLMs" tests, Kamradt, 2023.

Motivation

- **Knowledge** of LLM **constrained** to pretraining data
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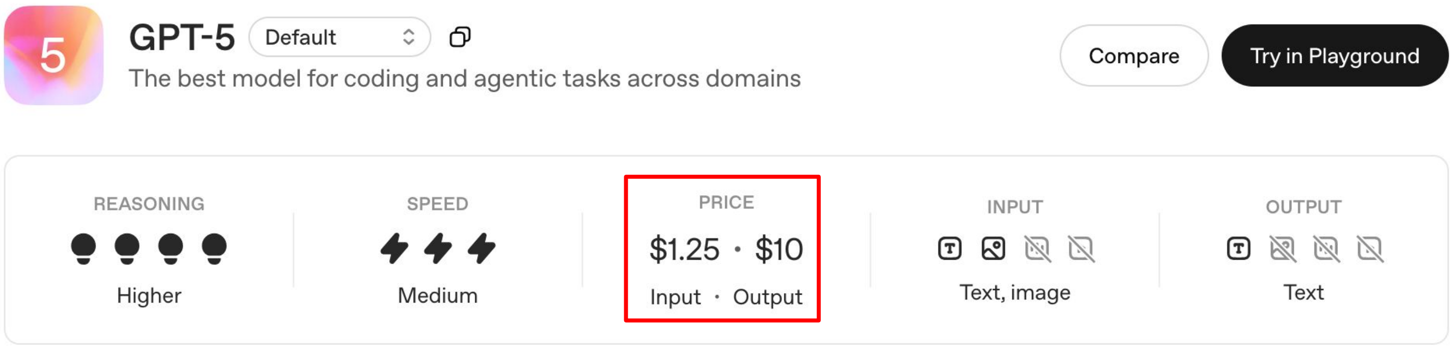

Overview

RAG = **R**etrieval-**A**ugmented **G**eneration

"Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks", Lewis et al., 2020.

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Idea. Augment prompt with **relevant** pieces of information.

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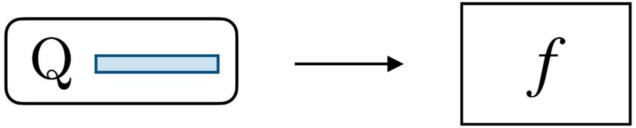

Figure from "Super Study Guide: Transformers & Large Language Models", Amidi et al., 2024.

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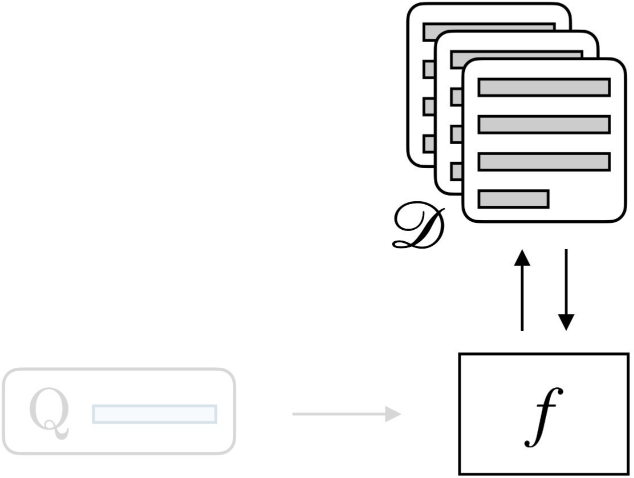

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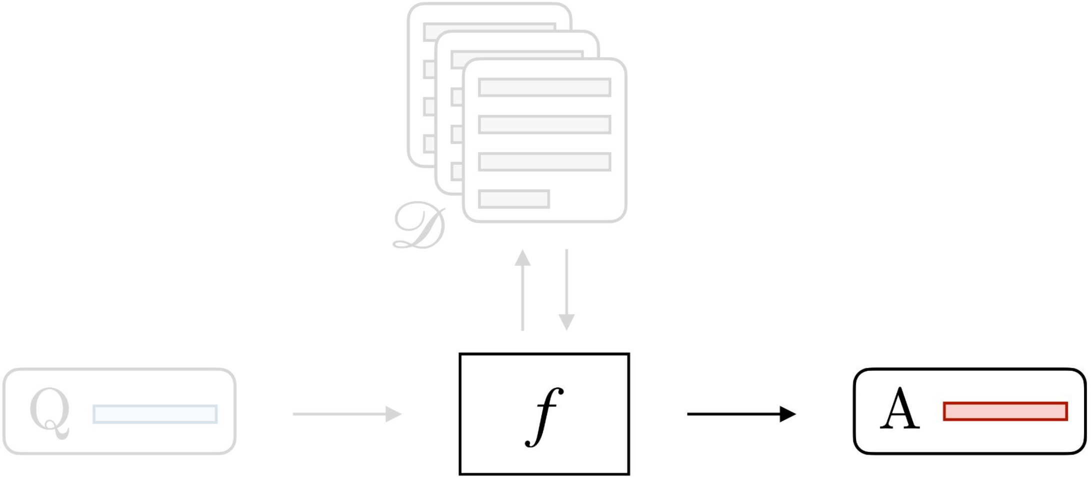

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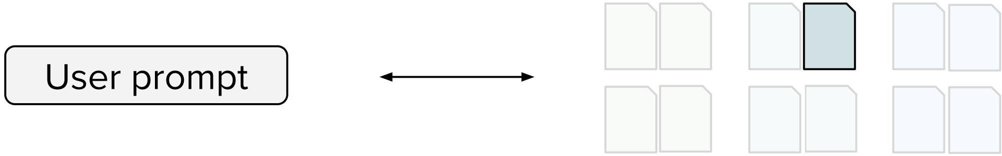
Retrieve, Generate, Augment

1. **Retrieve** relevant document via similarity operation across the knowledge base



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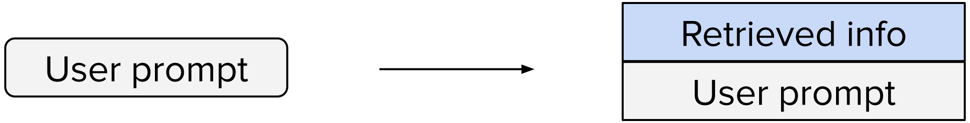

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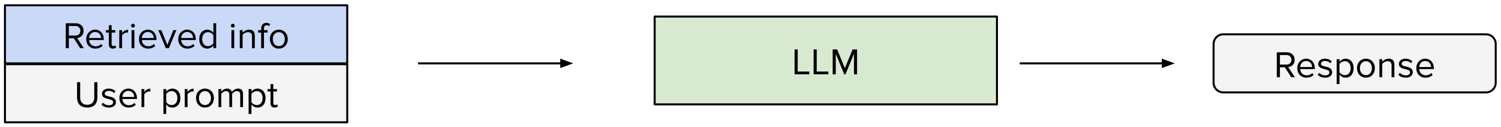


Retrieve, Generate, Augment

1. **Retrieve** relevant document via similarity operation across the knowledge base

User prompt ⟷

2. **Augment** prompt with retrieved information

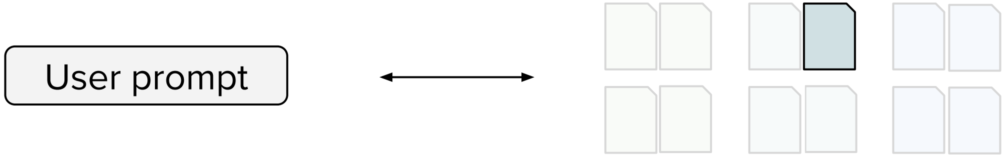
User prompt → Retrieved info / User prompt

3. **Generate** response

Retrieved info / User prompt → LLM → Response

Focus on retrieval stage

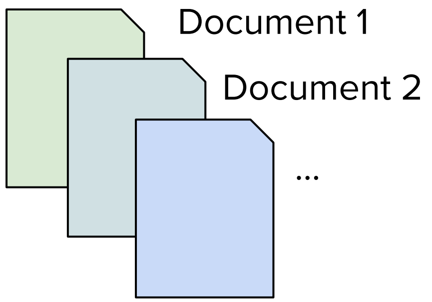
1. **R**etrieve relevant document via similarity operation across the knowledge base



2. **A**ugment prompt with retrieved information

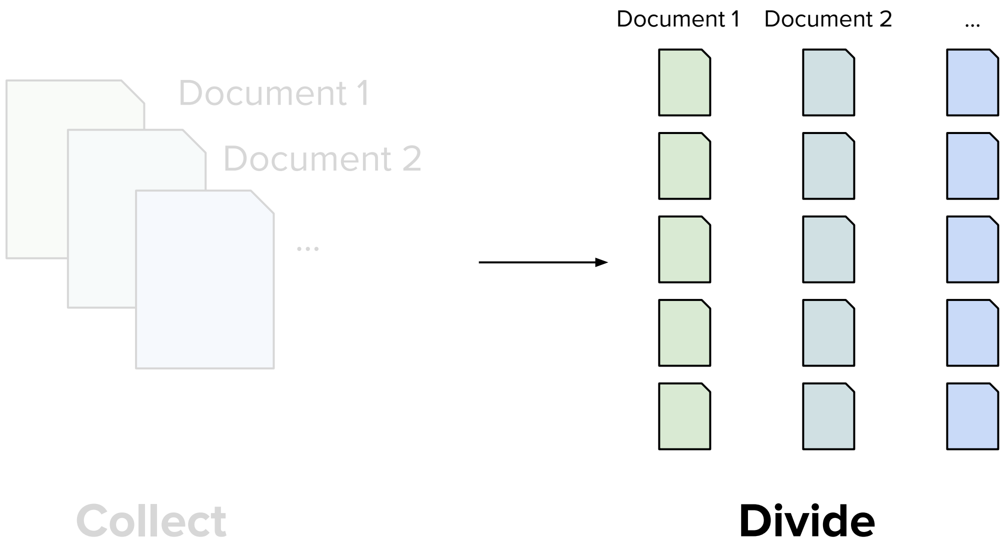
3. **G**enerate response

Prerequisite: Create knowledge base



Collect

Prerequisite: Create knowledge base



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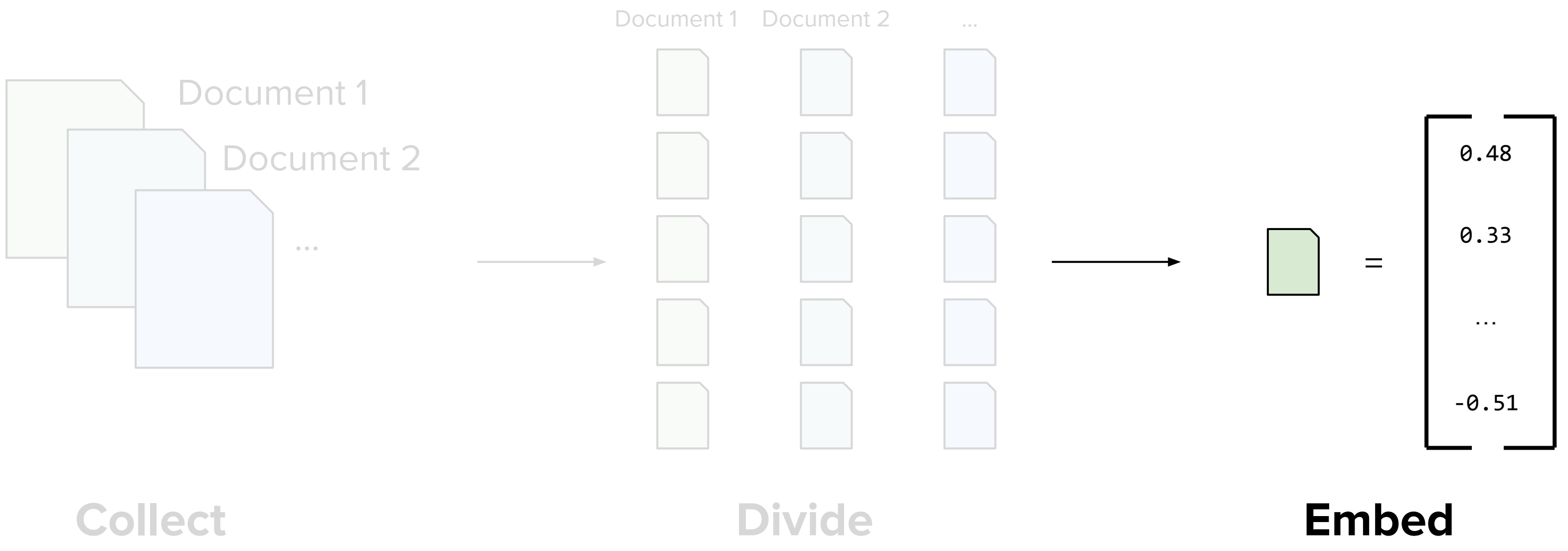

Prerequisite: Create knowledge base

Hyperparameters. Embedding size, chunk size, overlap between chunks

Retrieval overview

Step 1 – Candidate retrieval: Select potentially-relevant candidates

- Maximize recall
- Semantic embeddings and optionally keyword-based methods

Retrieval overview

🎣 **Step 1 – Candidate retrieval**: Select potentially-relevant candidates

- Maximize recall
- Semantic embeddings and optionally keyword-based methods

💯 **Step 2 – Ranking**: Give final relevance score

- Maximize precision
- Re-ranking on smaller set of candidates

Step 1: candidate retrieval

Objective. Select potentially-relevant candidates via search across knowledge base

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Method 1. Semantic search using **embeddings-based similarity**

Step 1: candidate retrieval

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Query

Chunk

Step 1: candidate retrieval

Objective. Select potentially-relevant candidates via search across knowledge base

Method 1. Semantic search using **embeddings-based similarity**

$$\text{Query} = \begin{bmatrix} \texttt{0.48} \\ \cdots \\ \texttt{-0.51} \end{bmatrix}$$

$$\text{Chunk} = \begin{bmatrix} \texttt{-0.82} \\ \cdots \\ \texttt{-0.43} \end{bmatrix}$$

Step 1: candidate retrieval

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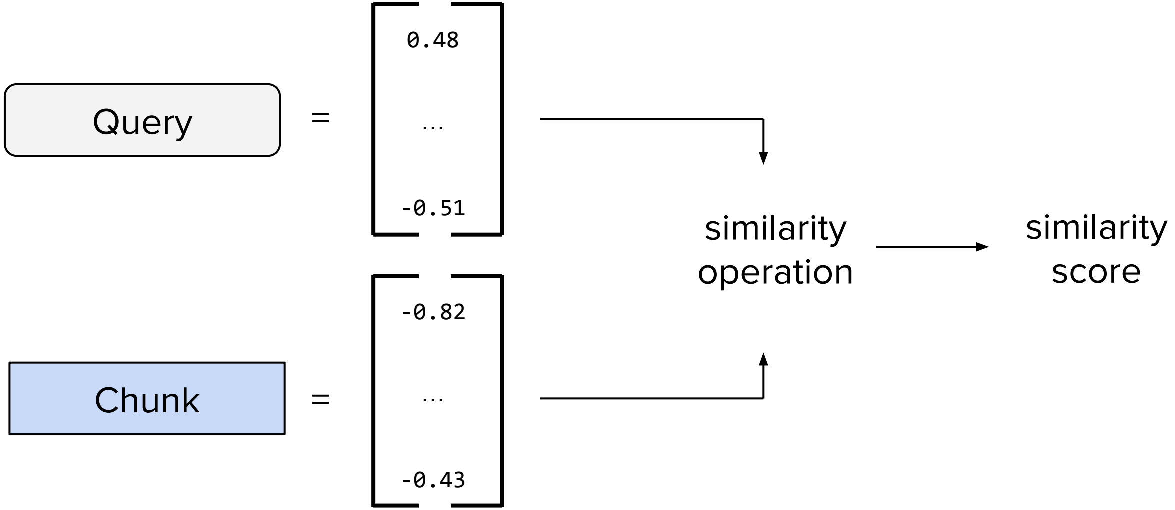
Method 1. Semantic search using **embeddings-based similarity**



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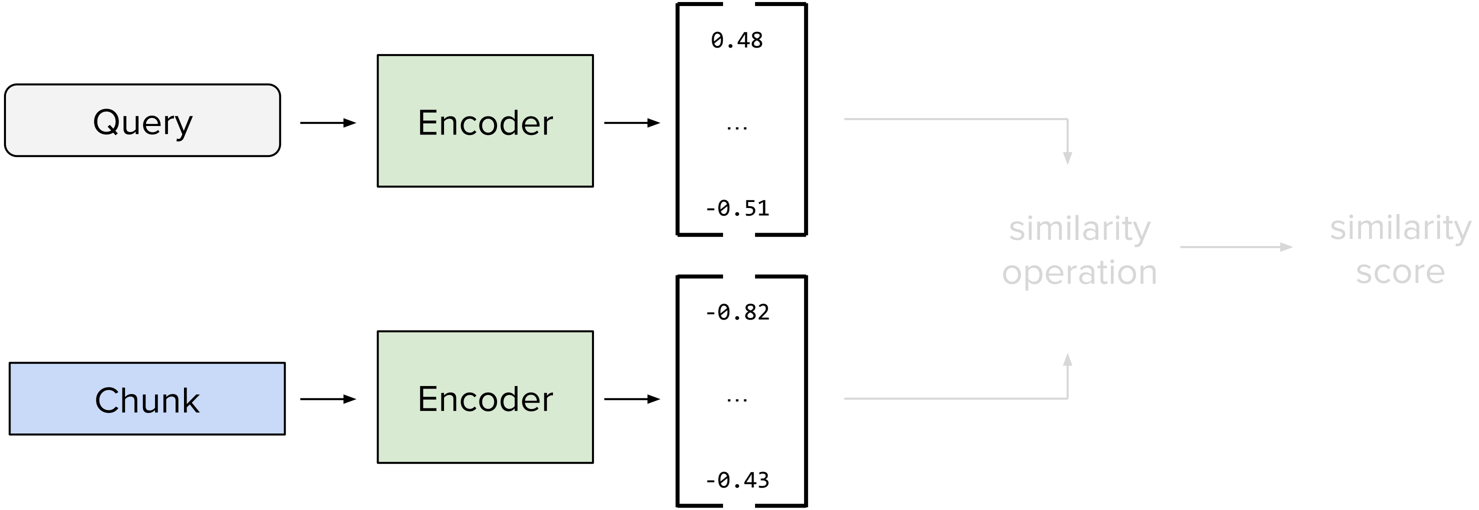

"*Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks*", *Reimers et al., 2019.*

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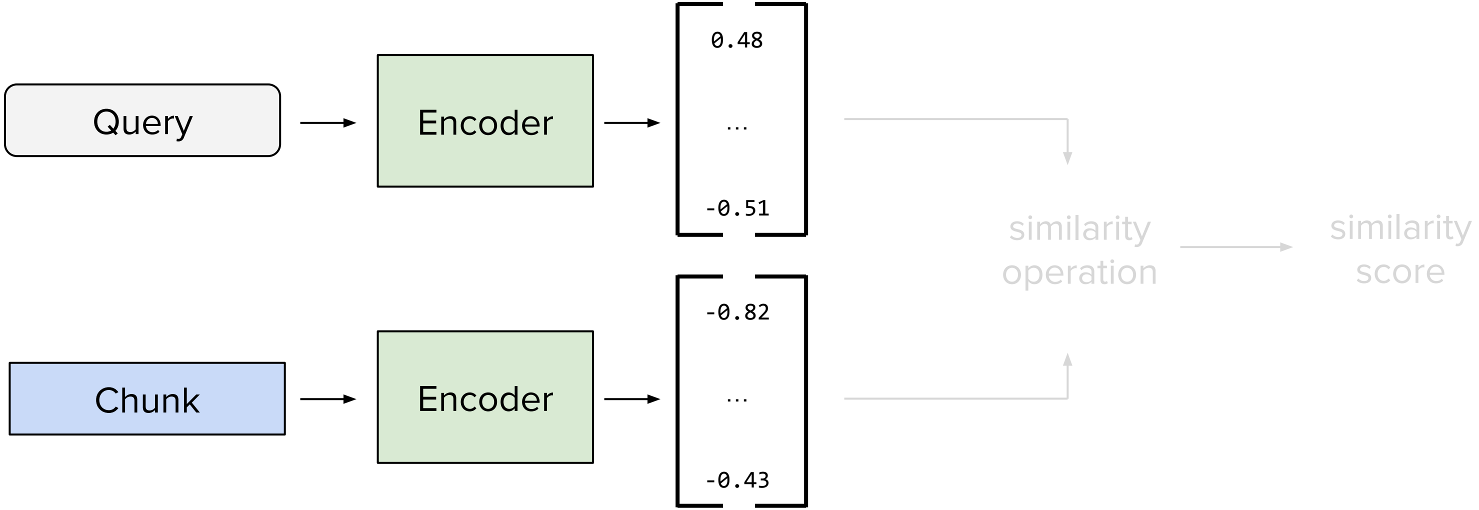
"bi-encoder"



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Where is Cuddly? ⟷

[...] Huggy likes to work downstairs [...]

[...] Where is Paris located? [...]

[...] he was in a cuddly mood [...]

[...] Cuddly spends most days surrounded by books [...]

Step 1: candidate retrieval

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Method 2. Search based on keywords matching via **BM25**

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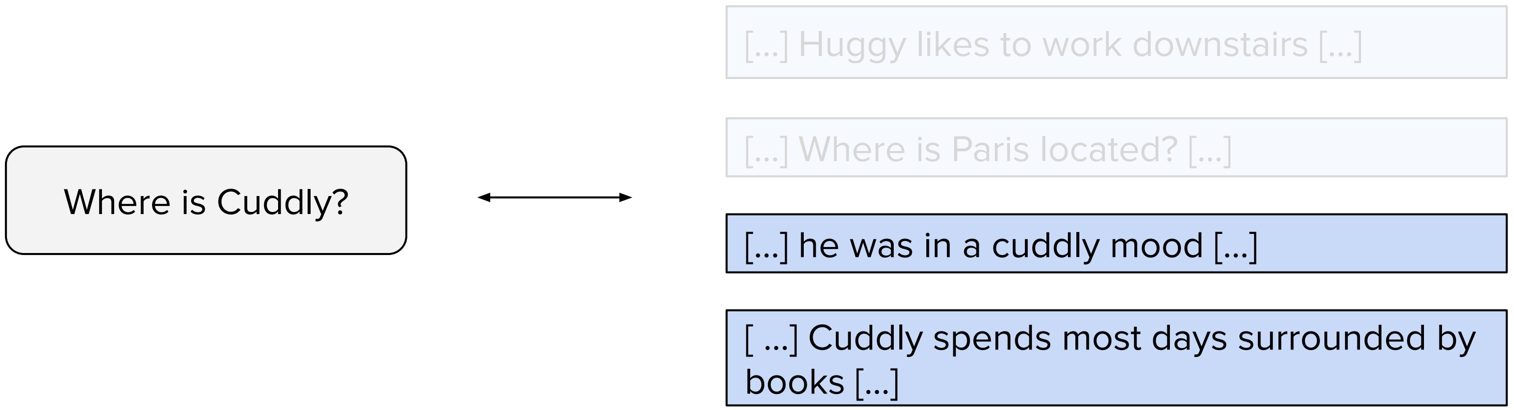

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Method 3. Search based on **hybrid combination** of semantics and BM25

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Extensions that can help with initial retrieval

- Mitigate **discrepancy** in nature of embeddings

"*Precise Zero-Shot Dense Retrieval without Relevance Labels*", *Gao et al., 2022.*

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Prompt

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Extensions that can help with initial retrieval

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Where is Cuddly?

Fake document

Cuddly is in...

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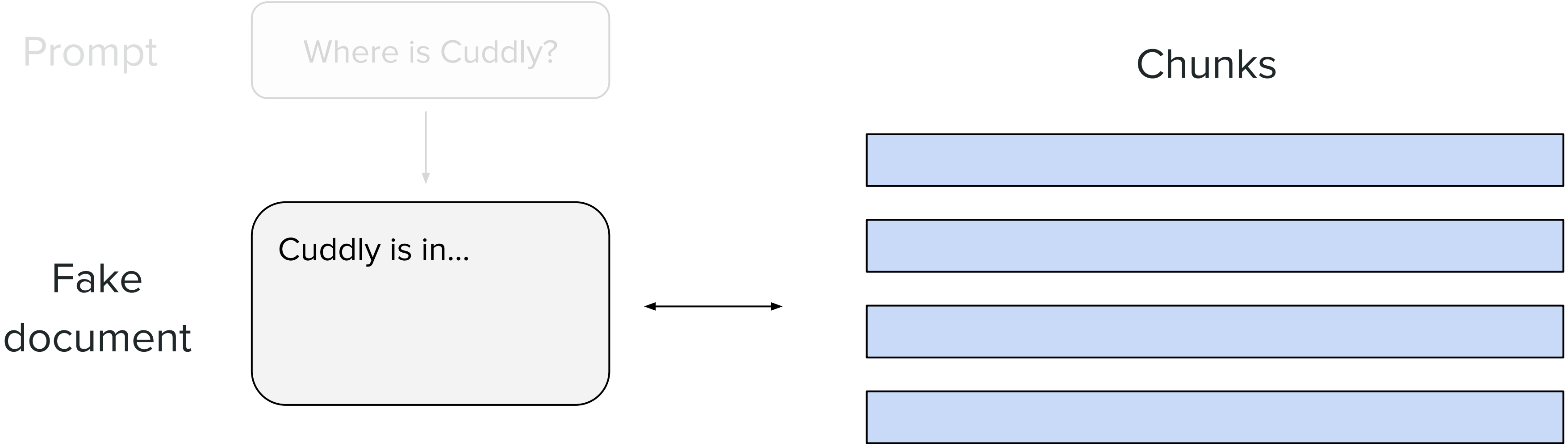

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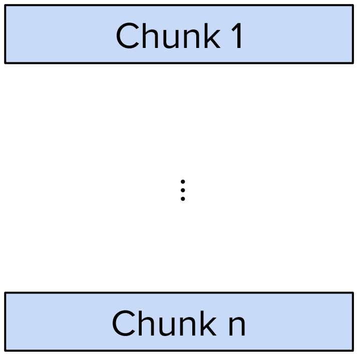

Introducing Contextual Retrieval, Anthropic team, 2024.

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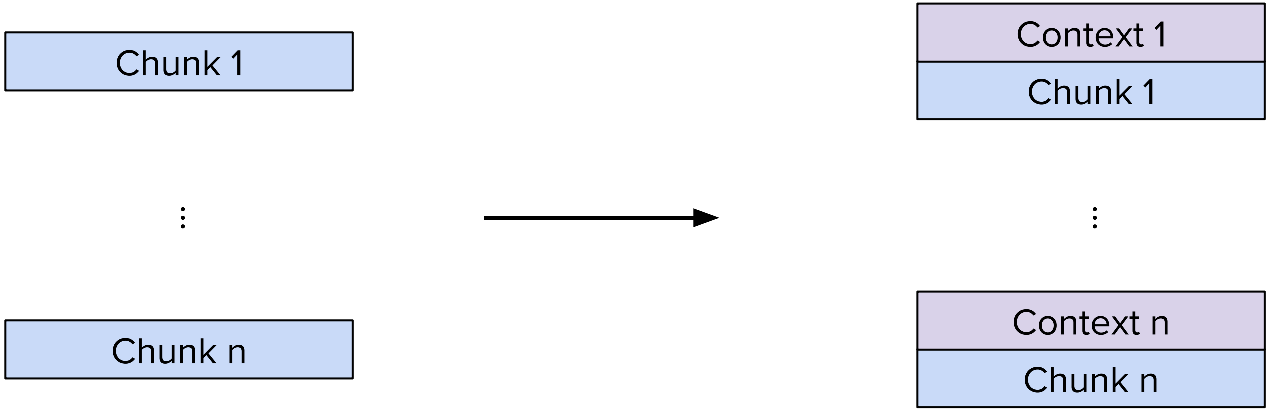

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Prompt caching

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Extensions that can help with initial retrieval

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Pricing

Copy page

Text tokens

Prices per 1M tokens.

Batch | Flex | **Standard** | Priority

MODEL	INPUT	CACHED INPUT	OUTPUT
gpt-5	$1.25	$0.125	$10.00
gpt-5-mini	$0.25	$0.025	$2.00
gpt-5-nano	$0.05	$0.005	$0.40
gpt-5-chat-latest	$1.25	$0.125	$10.00
gpt-5-codex	$1.25	$0.125	$10.00

OpenAI model pricing page, screenshot taken on November 10th, 2025.

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Step 2: ranking

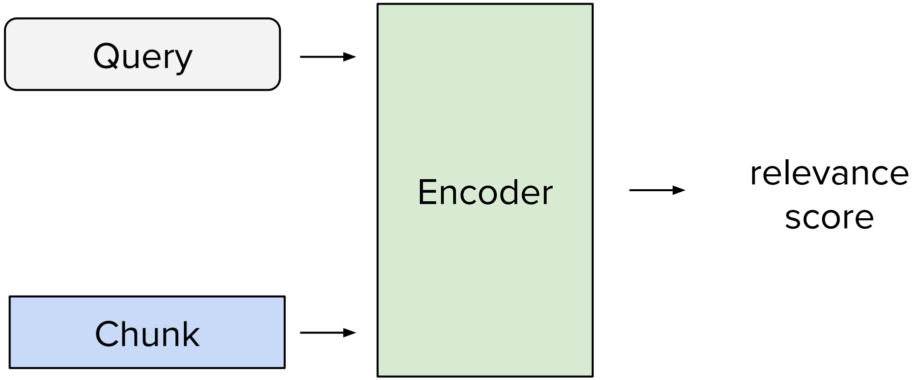
Objective. Provide final relevance score using more sophisticated (re-)ranker

Query

Chunk

Step 2: ranking

Objective. Provide final relevance score using more sophisticated (re-)ranker

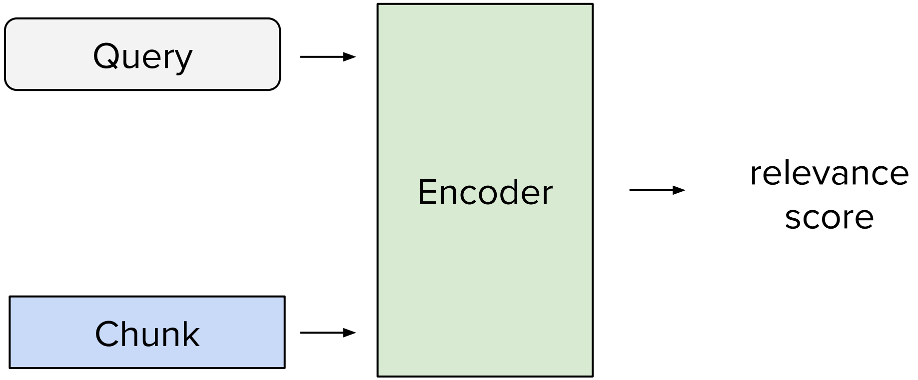


Suggested reading: "Cross-Encoders", SBERT.net

Step 2: ranking

Objective. Provide final relevance score using more sophisticated (re-)ranker

"cross-encoder"



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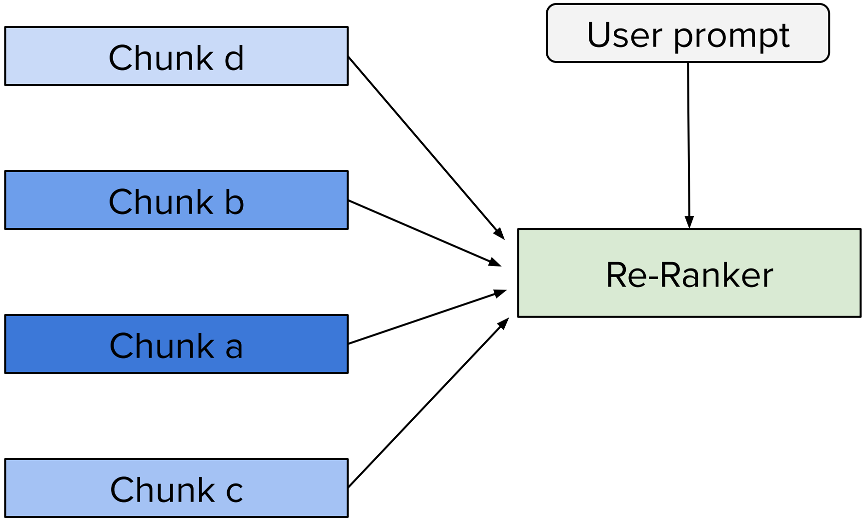

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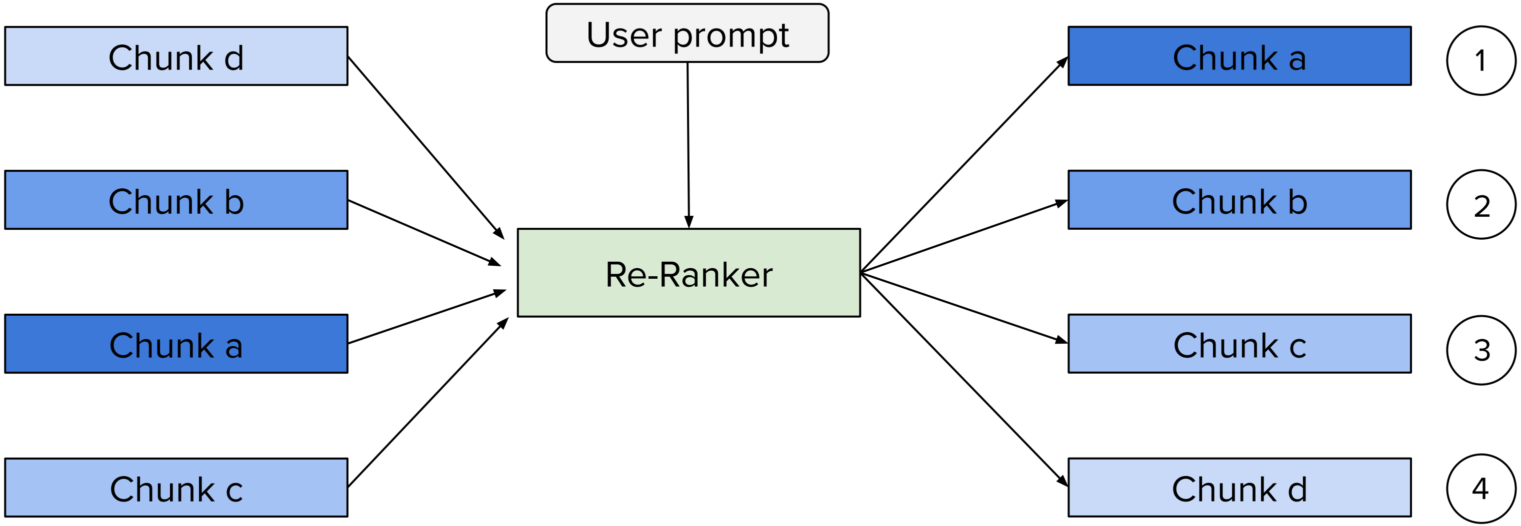

Quantify performance of retrieval

Setup. Evaluate if **retrieved chunks** are **relevant**

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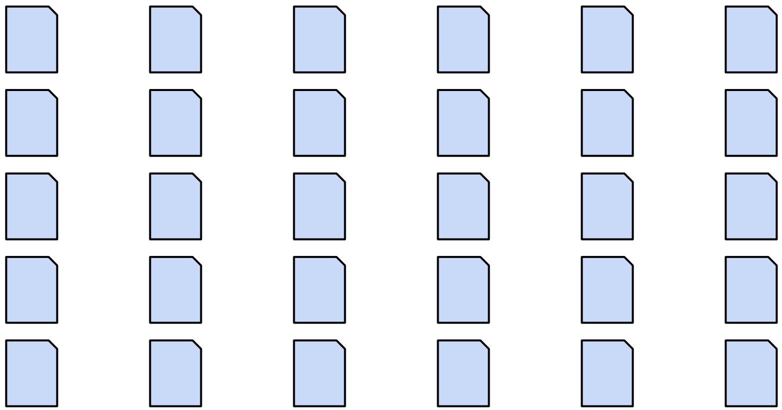

Chunks

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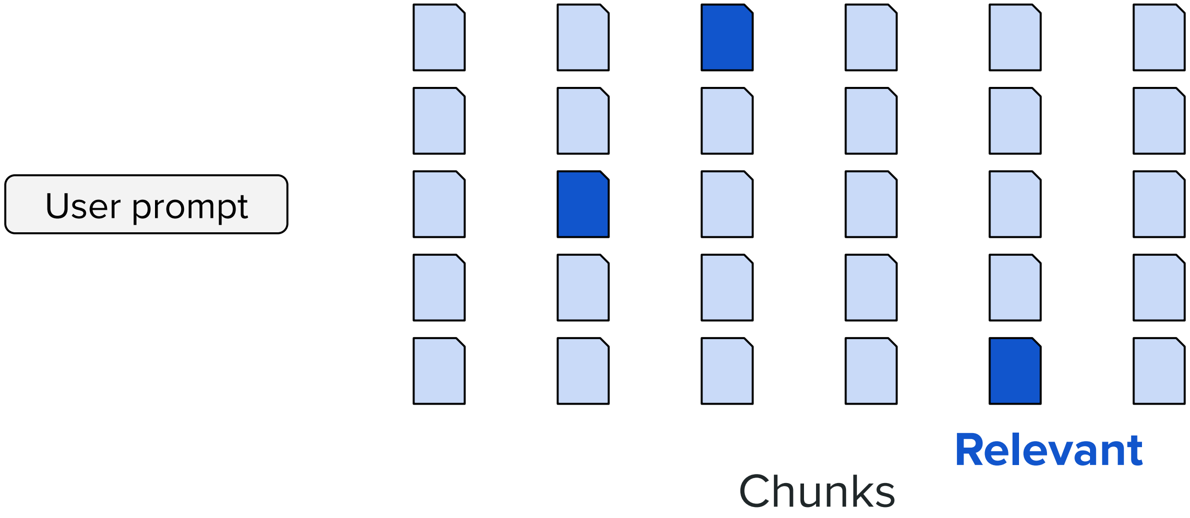

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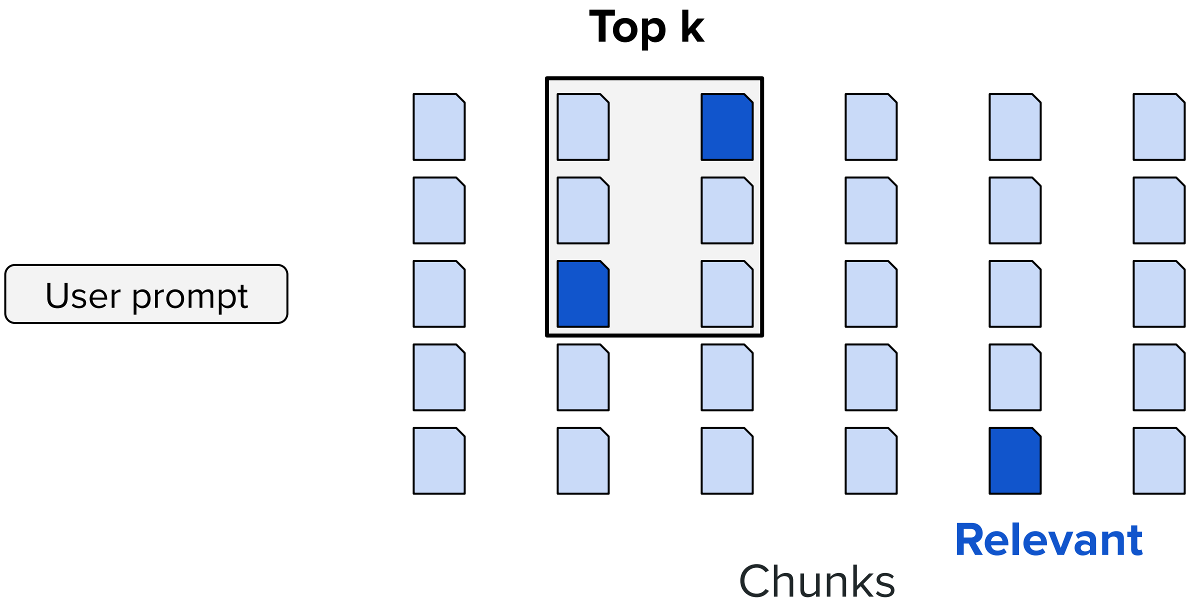

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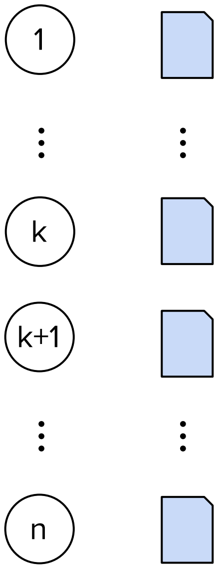
Ranking



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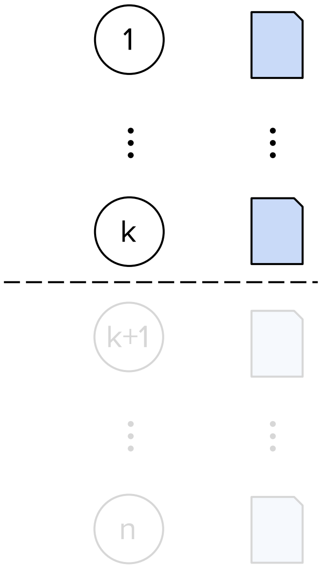

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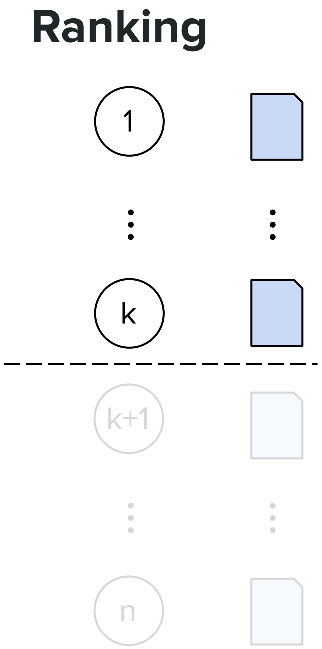

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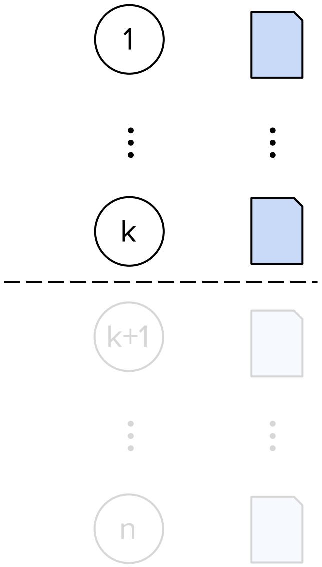

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$$\boxed{\mathrm{DCG@}k = \sum_{i=1}^{k} \frac{\mathrm{rel}_i}{\log_2(i+1)}} \qquad \text{with} \quad \mathrm{rel}_i \in \{0, 1\}$$

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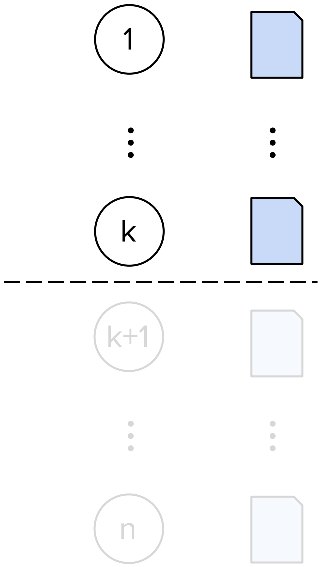

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with $\mathrm{rel}_i \in \{0, 1\}$

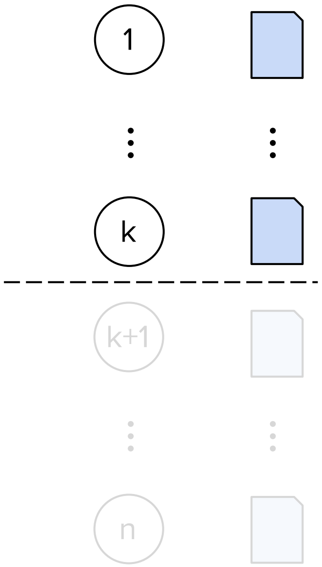
$$\mathrm{NDCG@}k = \frac{\mathrm{DCG@}k}{\mathrm{IDCG@}k}$$

$\mathrm{DCG@}k$ if ranking was perfect

Quantify performance of retrieval

Setup. Evaluate if **retrieved chunks** are **relevant**

Ranking



- **N**ormalized **D**iscounted **C**umulative **G**ain at **k** (**NDCG@k**)
- **R**eciprocal **R**ank at **k** (**RR@k**)

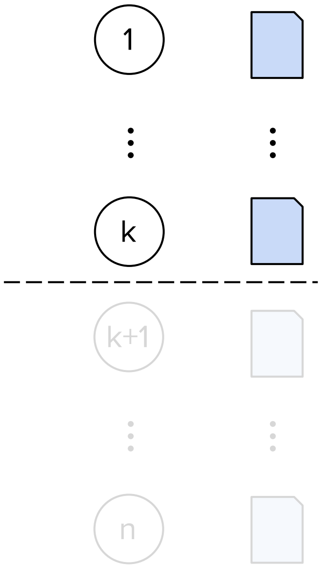
$$\mathrm{RR} = \frac{1}{\mathrm{rank}}$$

rank of the first relevant chunk

Quantify performance of retrieval

Setup. Evaluate if **retrieved chunks** are **relevant**

Ranking



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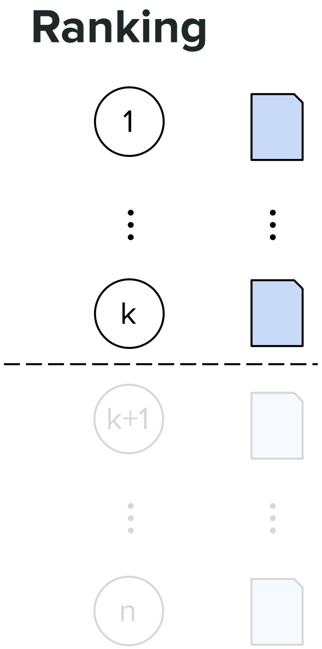

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$$\boxed{\text{Recall@}k = \frac{|\text{relevant in top } k|}{|\text{relevant}|}}$$

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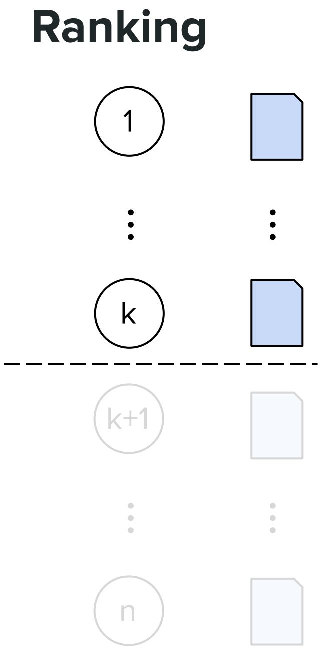

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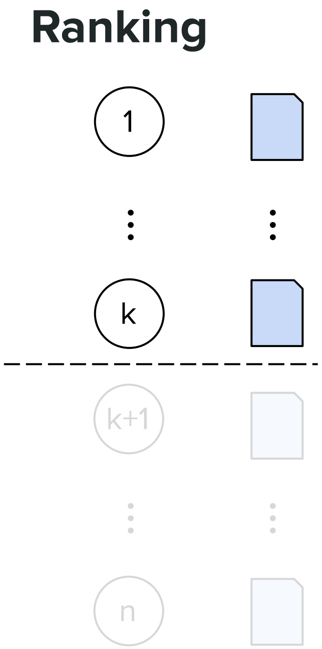

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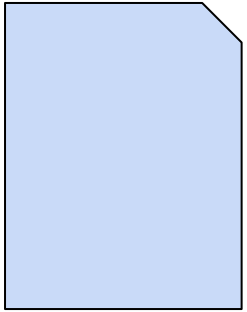
Transformers & Large Language Models

RAG

Tool calling

Agents

Motivation



Unstructured

RAG

Motivation

Unstructured

RAG

ID	Field	…
123	Obs	…
…	…	…

Structured

Idea

ID	Field	…
123	Obs	…
…	…	…

→

Function

```python
def get_data(
  id, field, ...
):
    # Logic.
    …
    return result
```

Definition

"**Tool calling** [...] allows autonomous systems to complete complex tasks by dynamically accessing and [may act] upon external resources."

"Tool calling overview", IBM.

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"**Tool calling** [...] allows autonomous systems to **complete** complex **tasks** by dynamically accessing and [may act] upon **external resources**."

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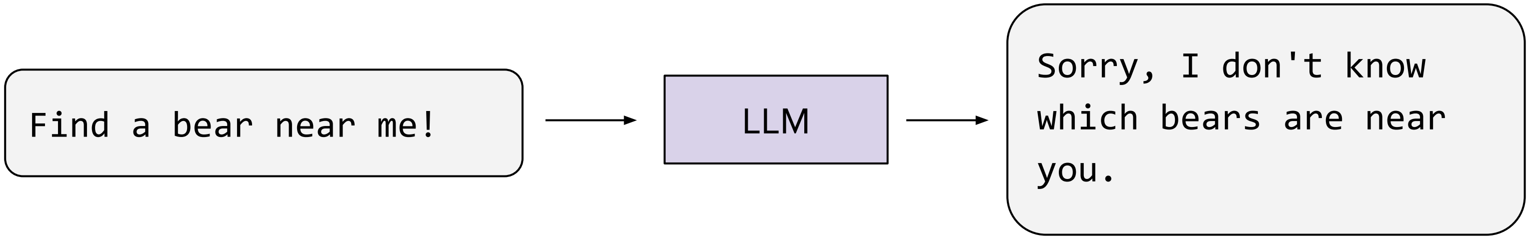
Real-life example

LLM as we've known it so far



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LLM as we've known it so far

Find a bear near me! → LLM → Sorry, I don't know which bears are near you.

LLM with tools

<function API>

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find_teddy_bear.py

```python
from dataclasses import dataclass
from geopy.distance import geodesic
import requests

@dataclass
class TeddyBearInfo:
    name: str
    distance_meters: float
    mood: str
    message: str

def find_teddy_bear(location: tuple[float, float]) -> TeddyBearInfo:
    """
    Finds the nearest teddy bear to the given GPS coordinates.

    Parameters:
        location: A (latitude, longitude) pair representing the user's current
            location.

    Returns:
        TeddyBearInfo: Information about the nearest teddy bear found.
    """
    # Call API to get the closest teddy bear
    user_lat, user_lon = location
    api_url = "https://api.to.teddy.bears.com/v1/closest"
    try:
        response = requests.get(
            api_url,
            params={"latitude": user_lat, "longitude": user_lon},
            timeout=5
        )
        response.raise_for_status()
        closest_teddy_bear = response.json()
    except requests.RequestException as e:
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```

```python
    # Extract coordinates from API response
    bear_lat, bear_lon = closest_teddy_bear["coords"]

    # Compute distance to the bear using geopy (returns distance in meters)
    distance = geodesic((user_lat, user_lon), (bear_lat, bear_lon)).meters

    return TeddyBearInfo(
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has a descriptive, well-documented API

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(optional) has some backend call

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```

returns some info

How it works

How it works

1. Let **LLM** find **argument** for **relevant function** call

```
<function API>

Find a bear near me!
```

→ LLM →

```
location = (37.42,-122.17)
with find_teddy_bear()
```

How it works

1. Let **LLM** find **argument** for **relevant function** call

`<function API>`

`Find a bear near me!`

→ LLM →

`location = (37.42,-122.17)`

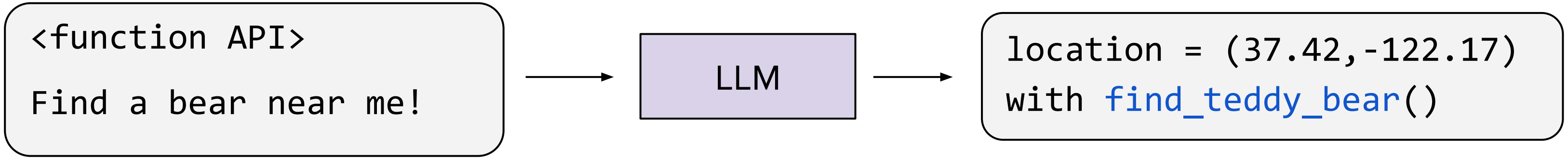
`with find_teddy_bear()`

2. Make **function call**

`find_teddy_bear(location)` → Backend → `{"name": "Teddy", ...}`

How it works

1. Let **LLM** find **argument** for **relevant function** call



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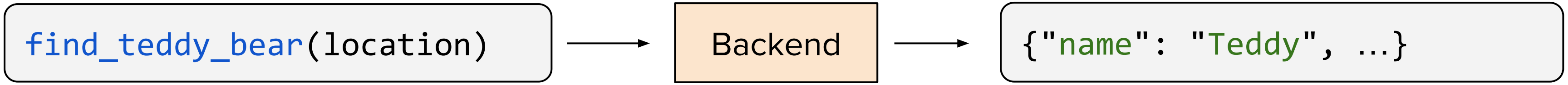
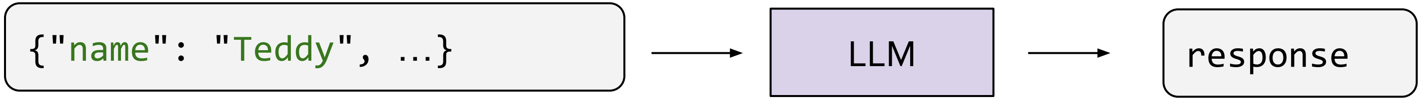


3. Let **LLM deduce** conclusion **based on results**



Teach a model to use a tool

Method 1: via training

Teach a model to use a tool

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Find a bear near me!
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Tool prediction

Teach a model to use a tool

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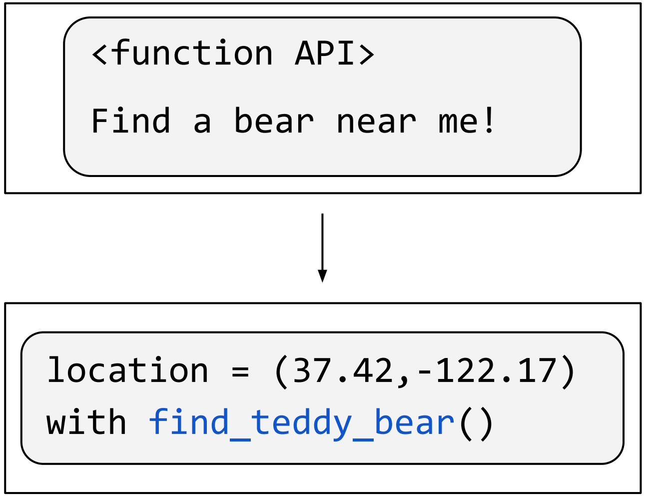
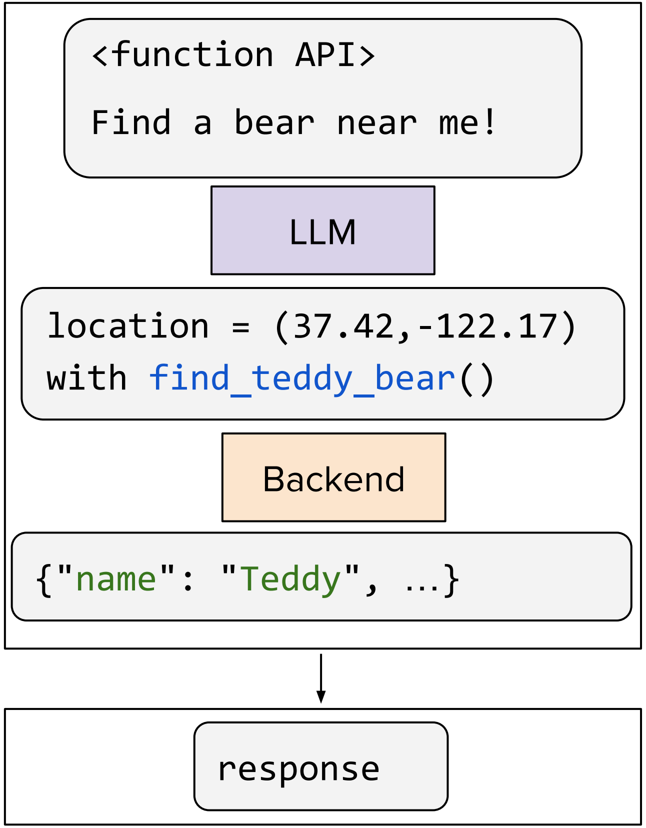


Tool prediction



Response generation

Teach a model to use a tool

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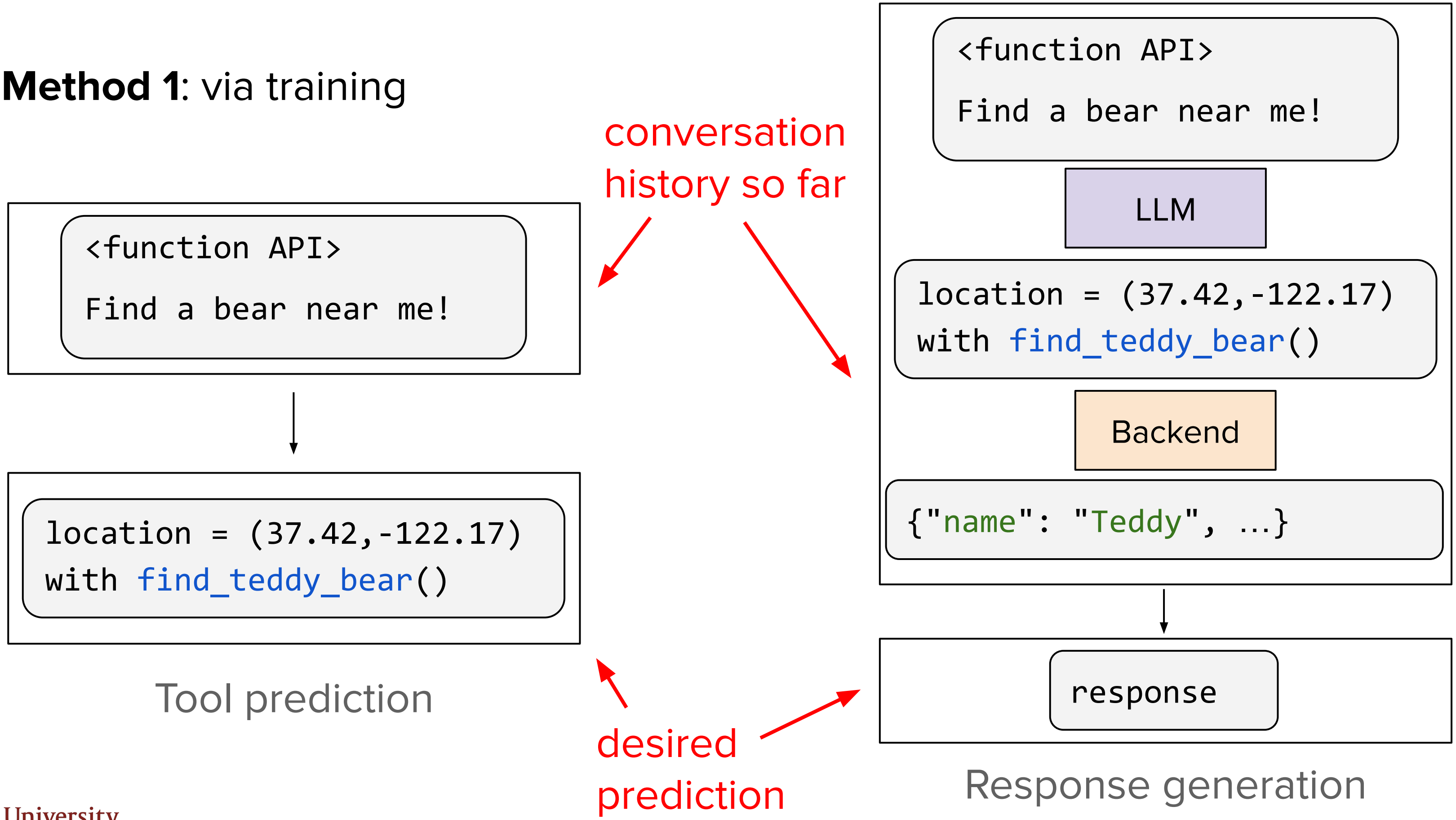

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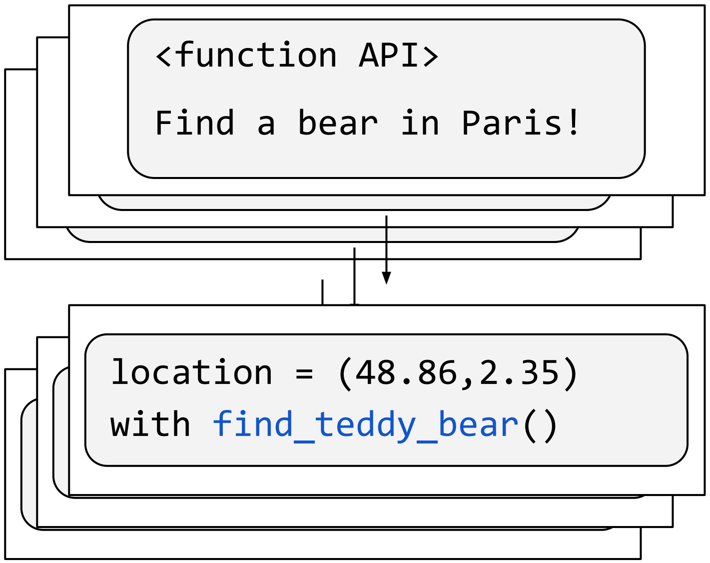
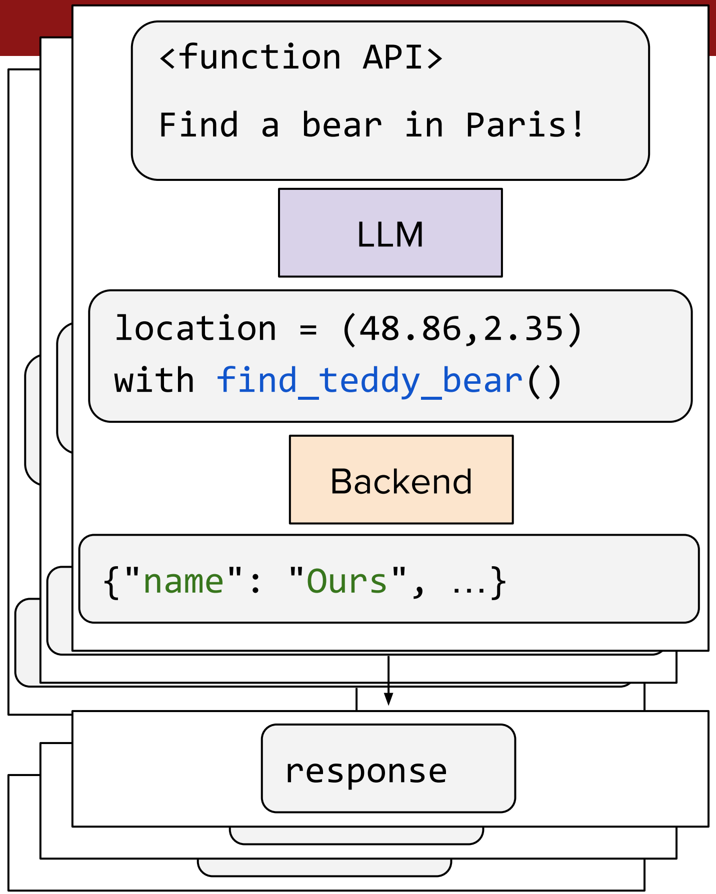


Tool prediction



Response generation

Teach a model to use a tool

Method 1: via training

Method 2: via prompting

```
<function API> + <detailed explanation on how to use it>

Find a bear near me!
```

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Method 2: via prompting

how to write such a description?

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Teach a model to use a tool

Method 1: via training

Method 2: via prompting

how to write such a description?

```
<function API> + <detailed explanation on how to use it>

Find a bear near me!
```

One way: Use SFT pairs as evaluation + use a powerful reasoning model to write it for you!

Examples of common use cases

Information

- Web/database search
- Weather, stocks, and any other tracker
- Codebase

Computation

- Calculator
- Code execution (often in Python)

...and many more!

Action

- Send emails/messages and other in-computer action
- anything else within the domain of an assistant

In practice: many tools

```python
def find_teddy_bear(
 location: tuple[float,
                 float]
) -> TeddyBearInfo:
   # ...
```

```python
def hug_teddy_bear(
 recipient: TeddyBear,
 intensity: str = "warm"
) -> HugResponse:
   # ...
```

```python
def check_teddy_mood(
 name: TeddyBear
) -> TeddyMood:
   # ...
```

```python
def send_teddy_gift(
 recipient: TeddyBear,
 gift: str = "poetry book"
) -> GiftResponse:
   # ...
```

```python
def schedule_playdate(
 host: TeddyBear,
 guest: TeddyBear,
 time: datetime
) -> Confirmation:
   # ...
```

```python
def send_message(
 recipient: TeddyBear,
 message: str
) -> MessageResponse:
   # ...
```

In practice: many tools

~~<function API>~~
~~Find a bear near me!~~
~~→ LLM →~~
~~location = (37.42,-122.17)~~
~~with find_teddy_bear()~~

<**list of** function API**s**>
Find a bear near me!
→ LLM →
location = (37.42,-122.17)
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Tools summary

Benefits.

- LLMs just became way more useful!
- They can also interact with the real world
- Overcomes "knowledge cutoff" limitation

Tools summary

Benefits.

- LLMs just became way more useful!
- They can also interact with the real world
- Overcomes "knowledge cutoff" limitation

Challenges.

- More tools = decrease performance
- Finite context length: not scalable
- Many tools to define. Lots of work.

"Automatic Tool Selection to Reduce Large Language Model Latency", Robert et al., 2024.

Tool selection

Goal. Both reduce latency and improve performance

"*Automatic Tool Selection to Reduce Large Language Model Latency*", *Robert et al., 2024.*

Tool selection

Goal. Both reduce latency and improve performance

1 `Find a bear near me!` → Router → List of **selected** tools

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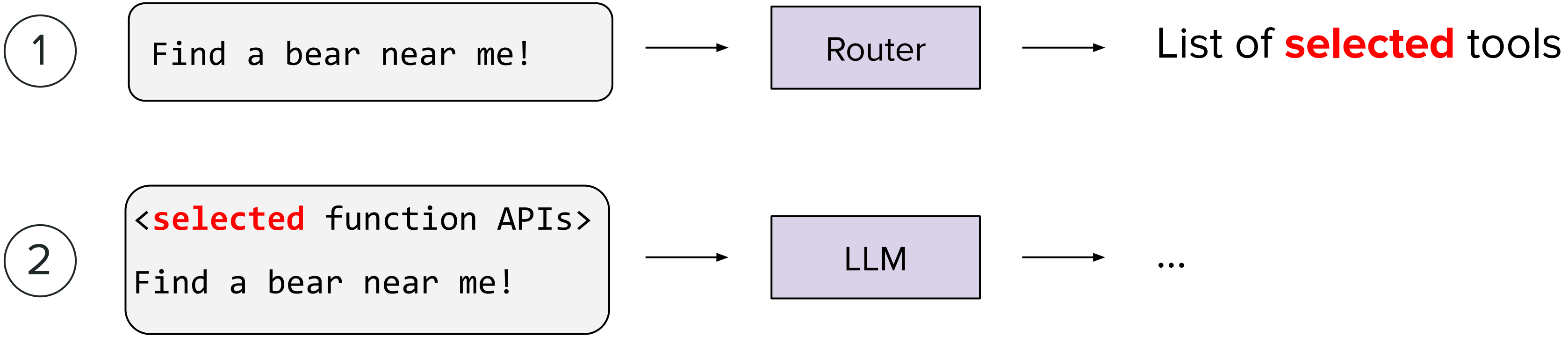

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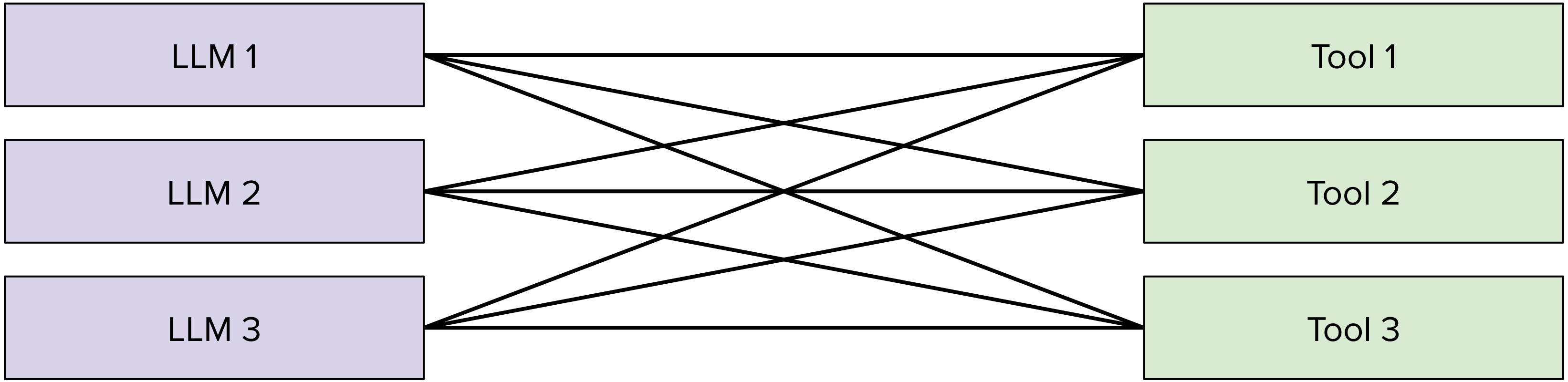
Motivation for standardized protocol

Goal. Avoid duplication of tool implementations



Standardization: MCP

MCP = **M**odel **C**ontext **P**rotocol

Idea. Connect tools/data to LLMs in a standard way

"*Introducing the Model Context Protocol*", *Anthropic, 2024.*

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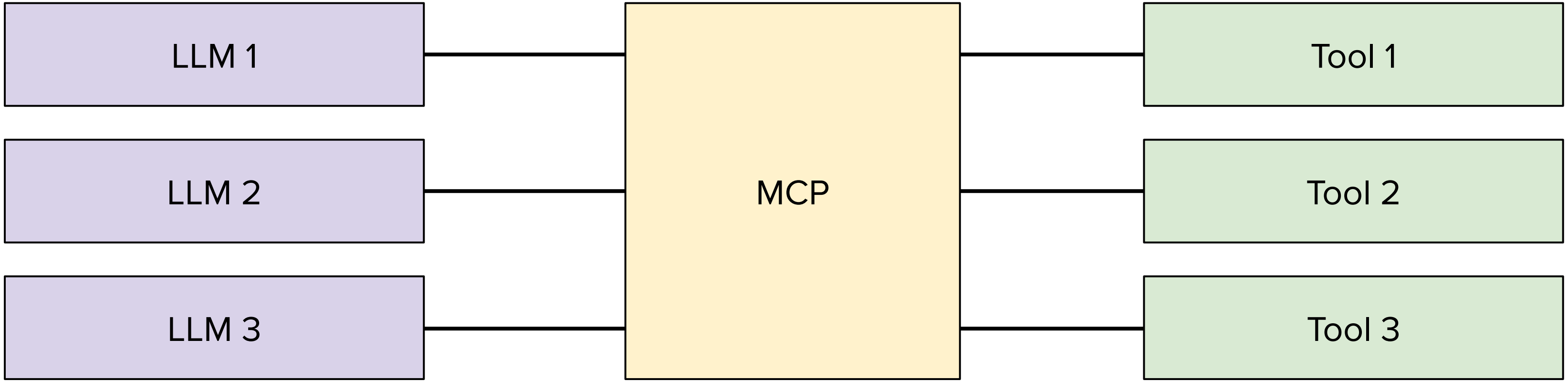

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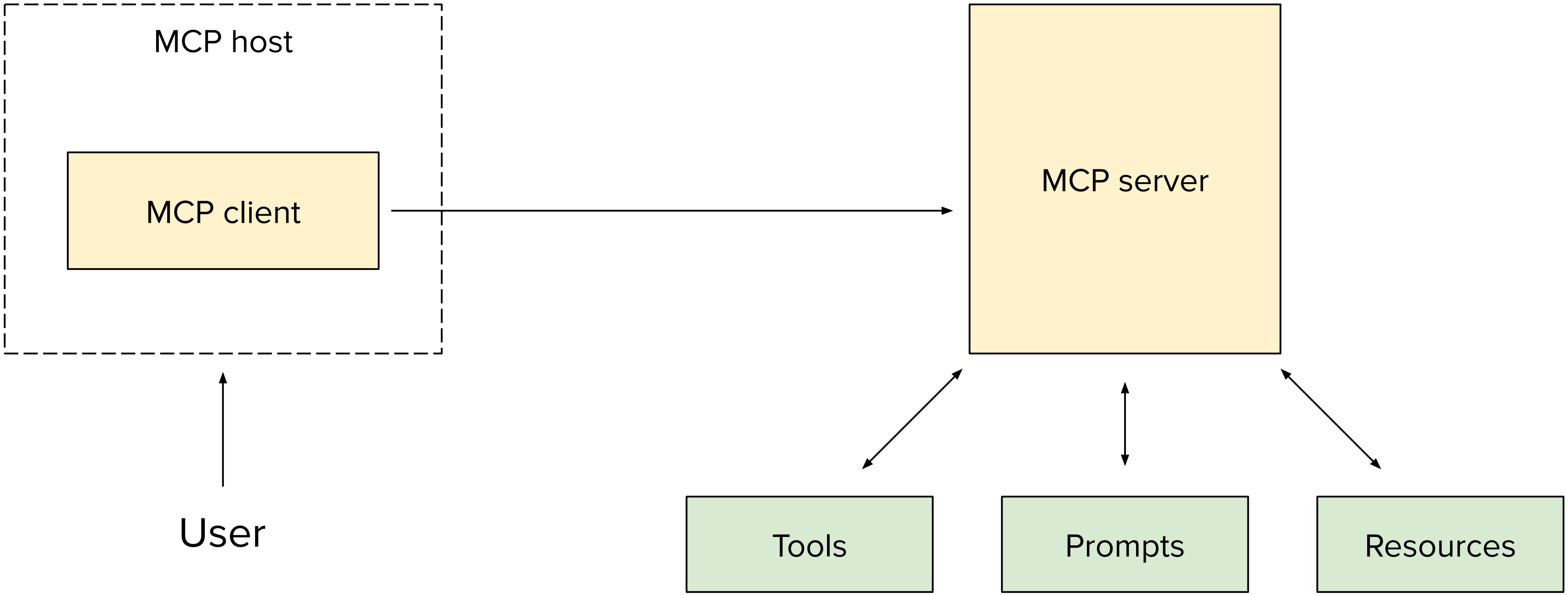

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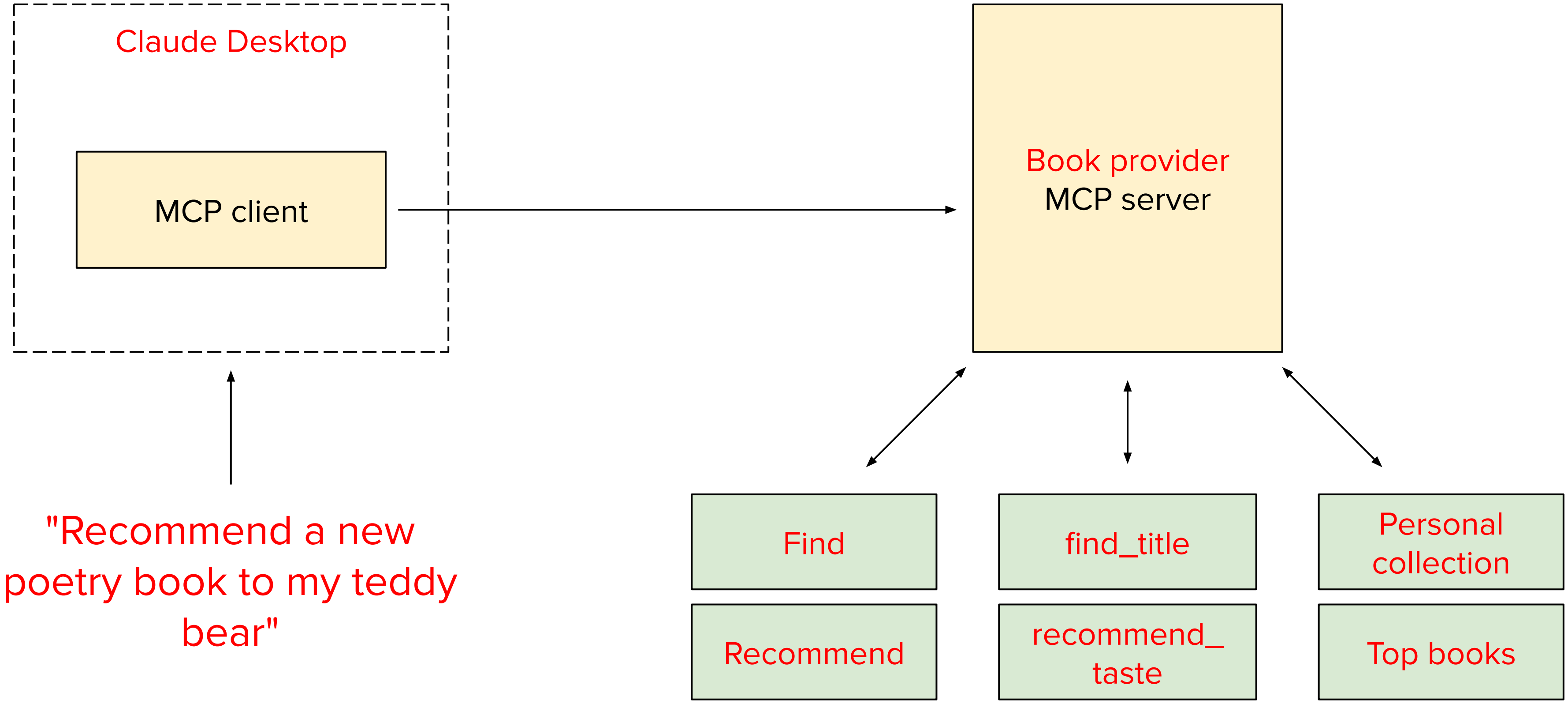

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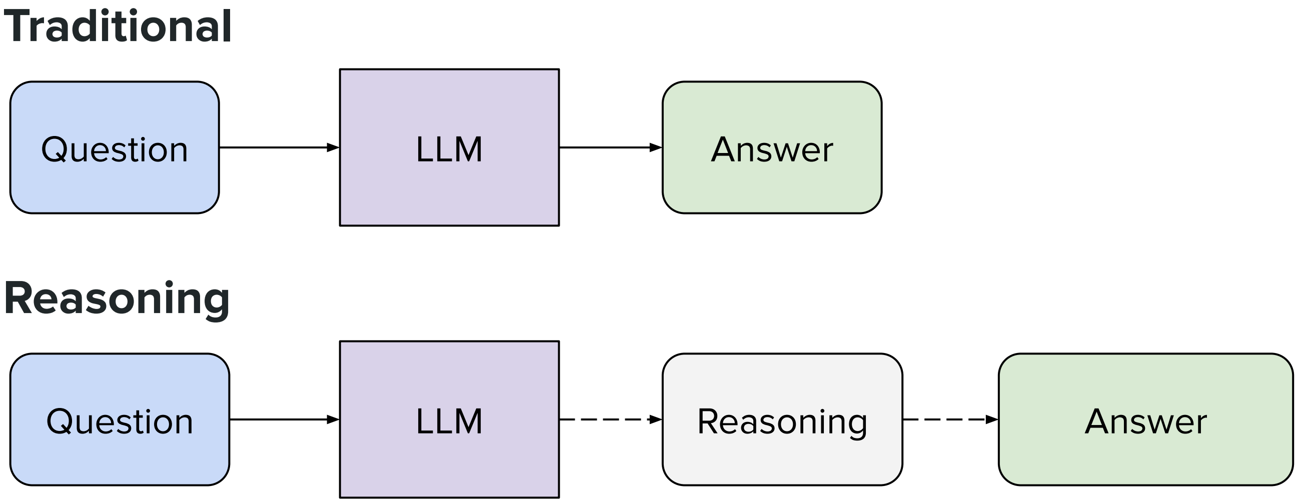
High-level idea



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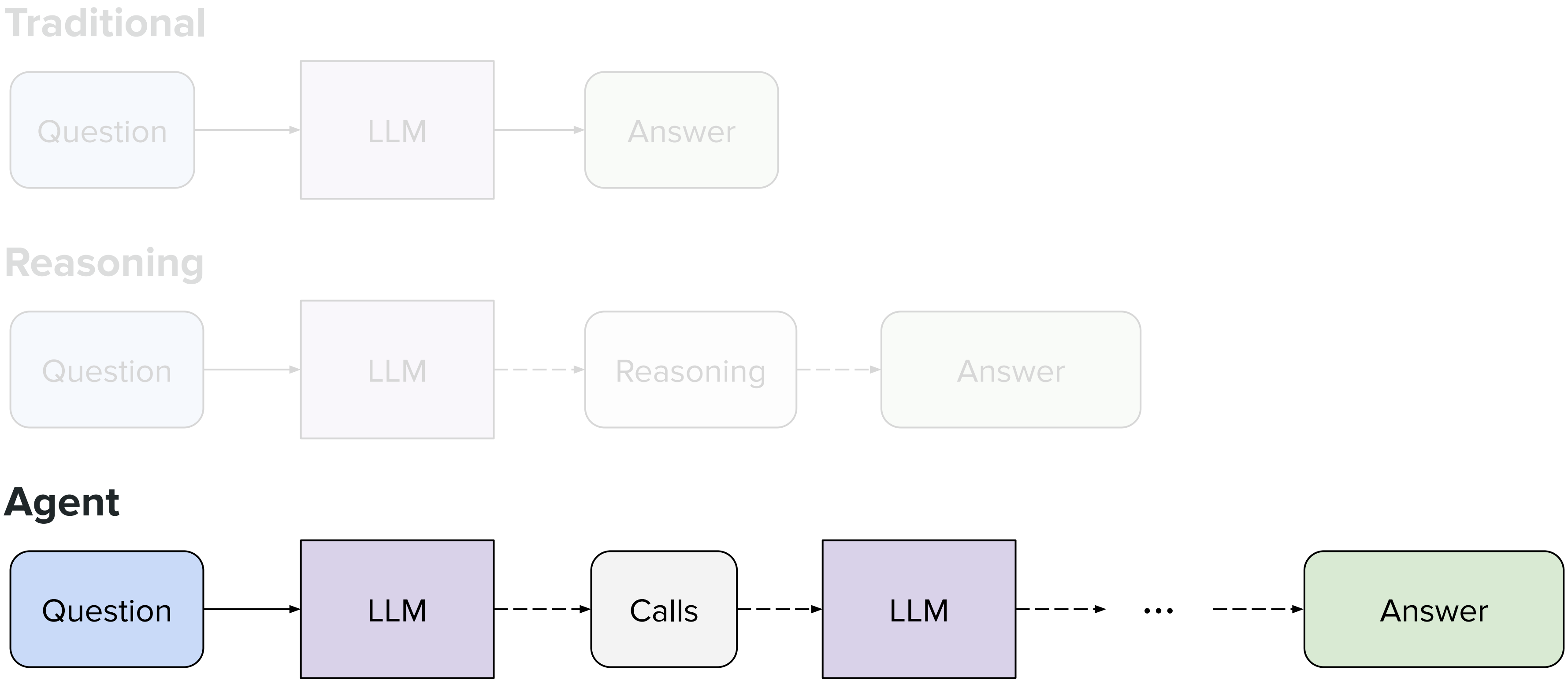
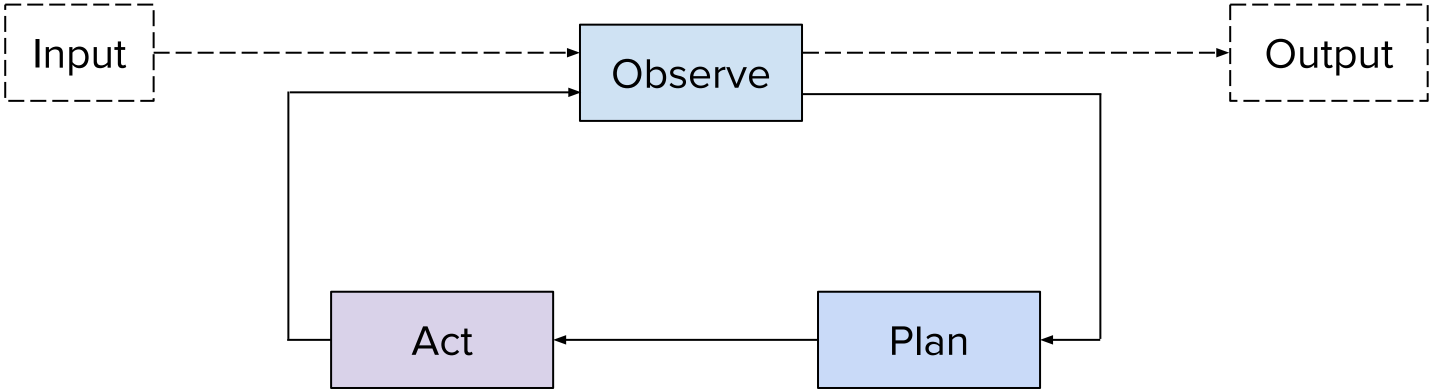


Overview

ReAct = **Re**ason + **Act**



"ReAct: Synergizing Reasoning and Acting in Language Models", Yao et al., 2022.

ReAct in action

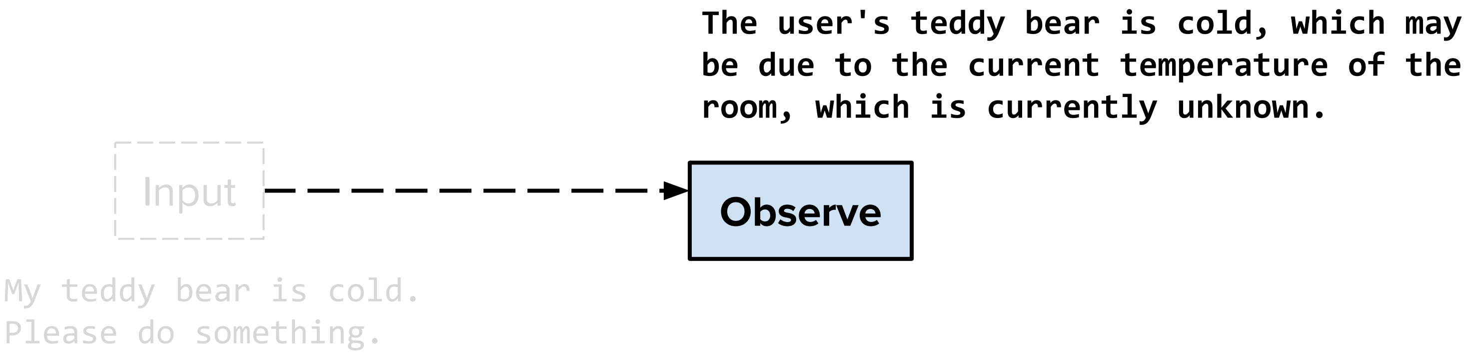
Input

```
My teddy bear is cold.
Please do something.
```

Examples:

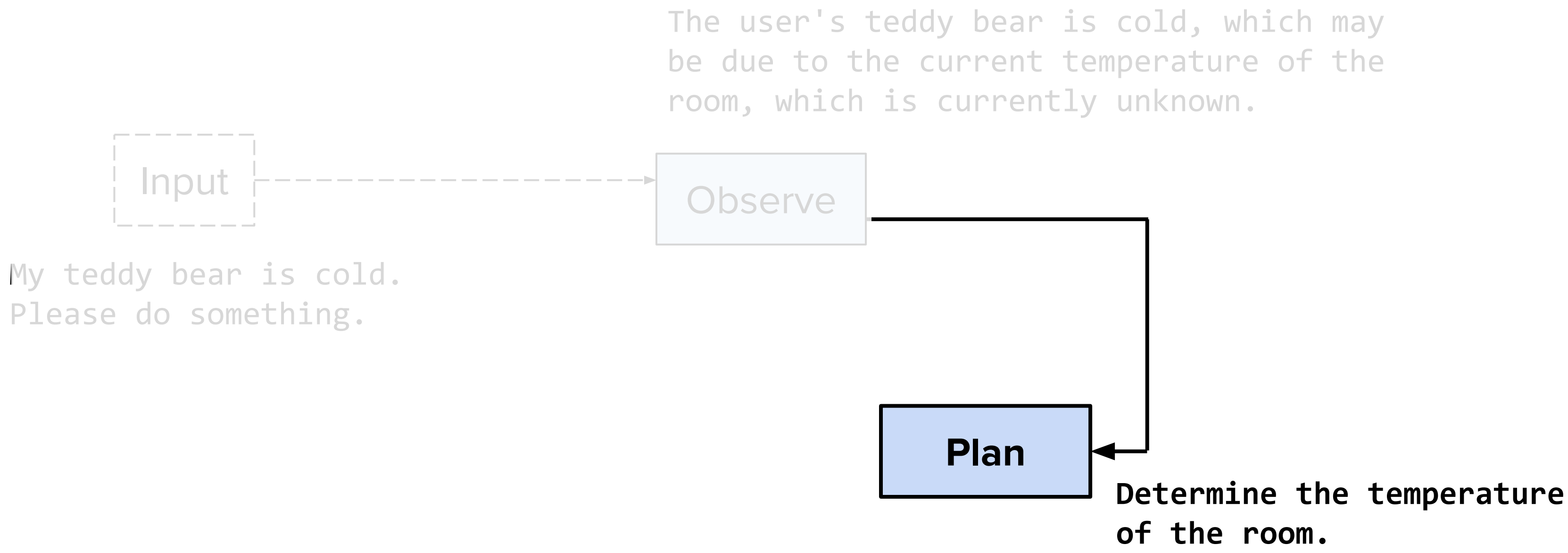
- Manually entered (e.g. user question)
- External event (e.g. metric going beyond a threshold)

ReAct in action



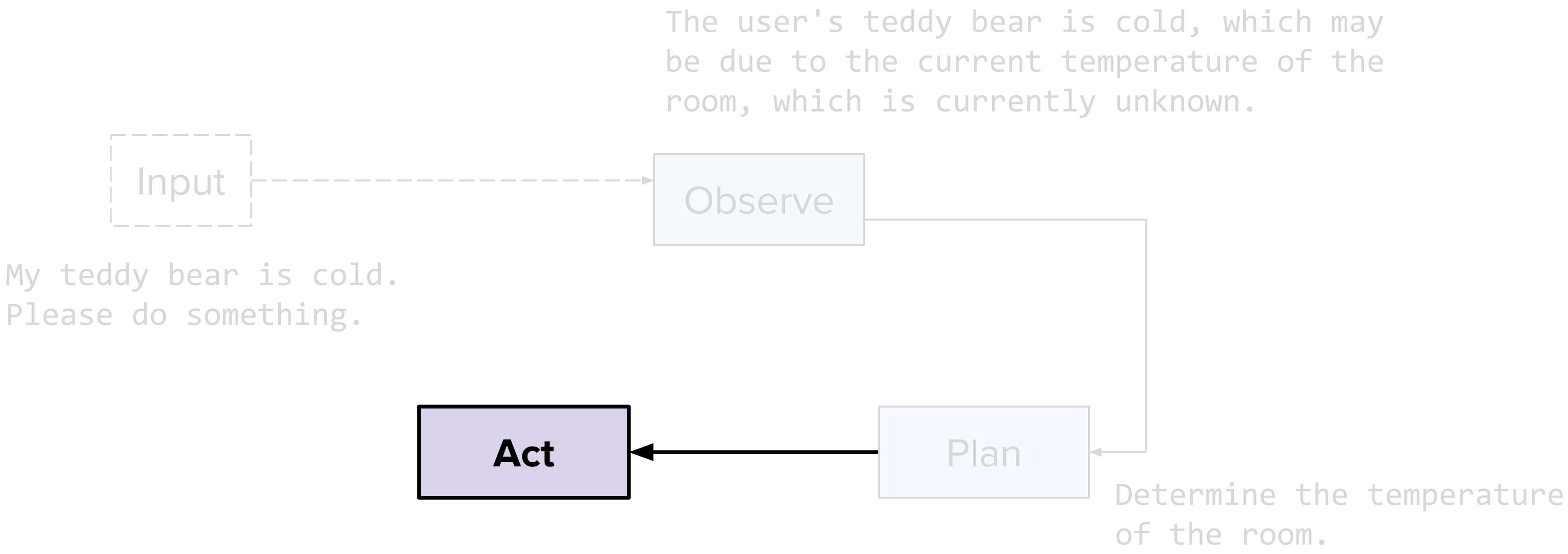
- **Synthesize** previous actions + explicitly **state** what is **currently known** including own knowledge
- **Reasoning**-heavy step to figure out **what is needed**

ReAct in action



Detail **what tasks** need to be accomplished and **what tools** to call

ReAct in action



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- **Look** for info in a **database** of documents

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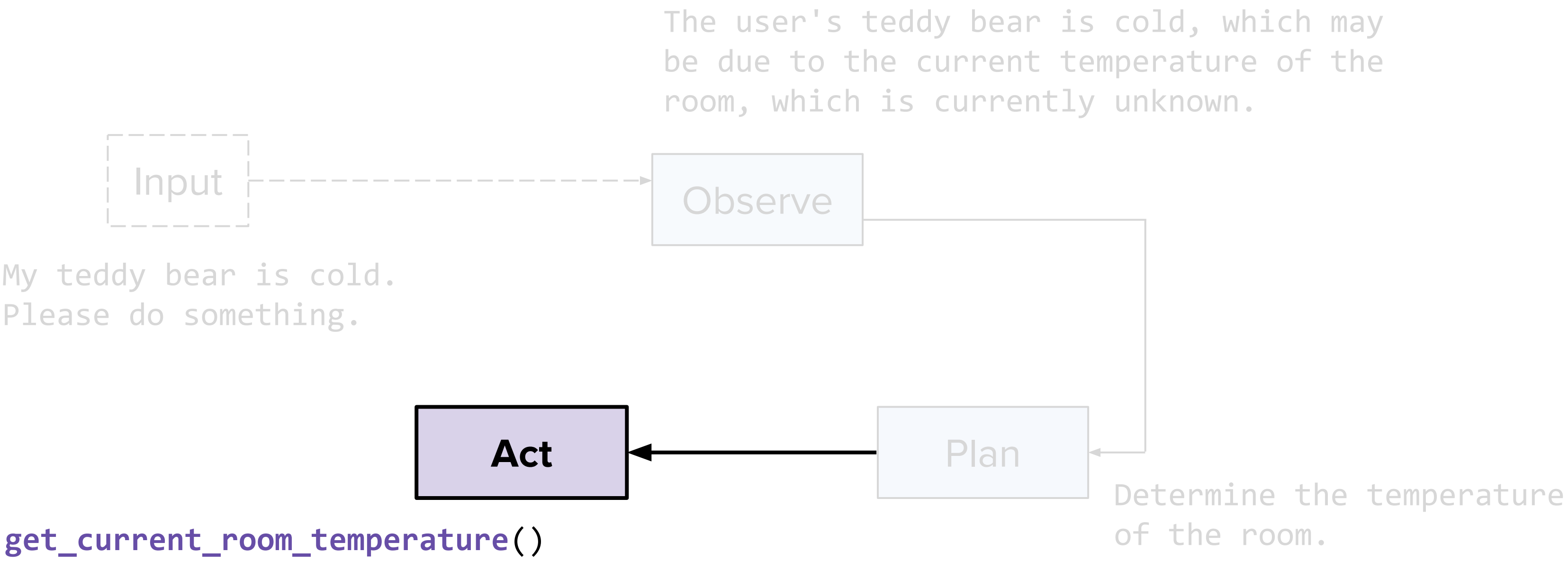

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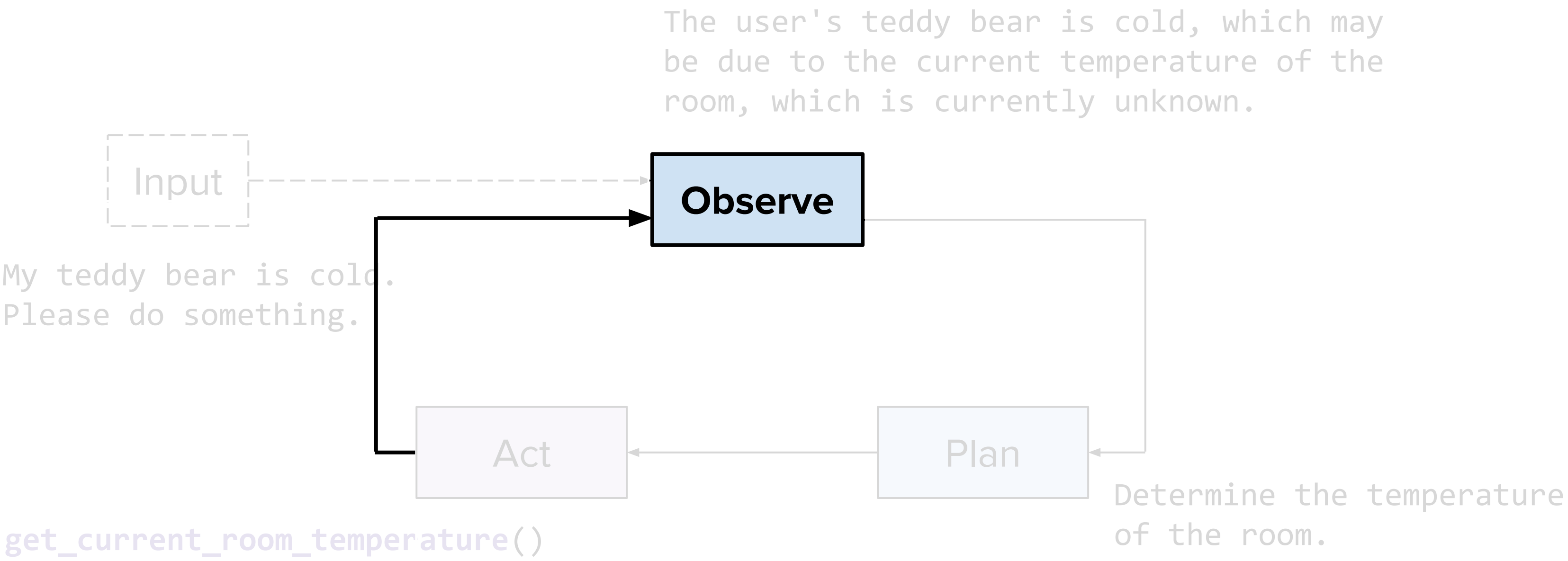

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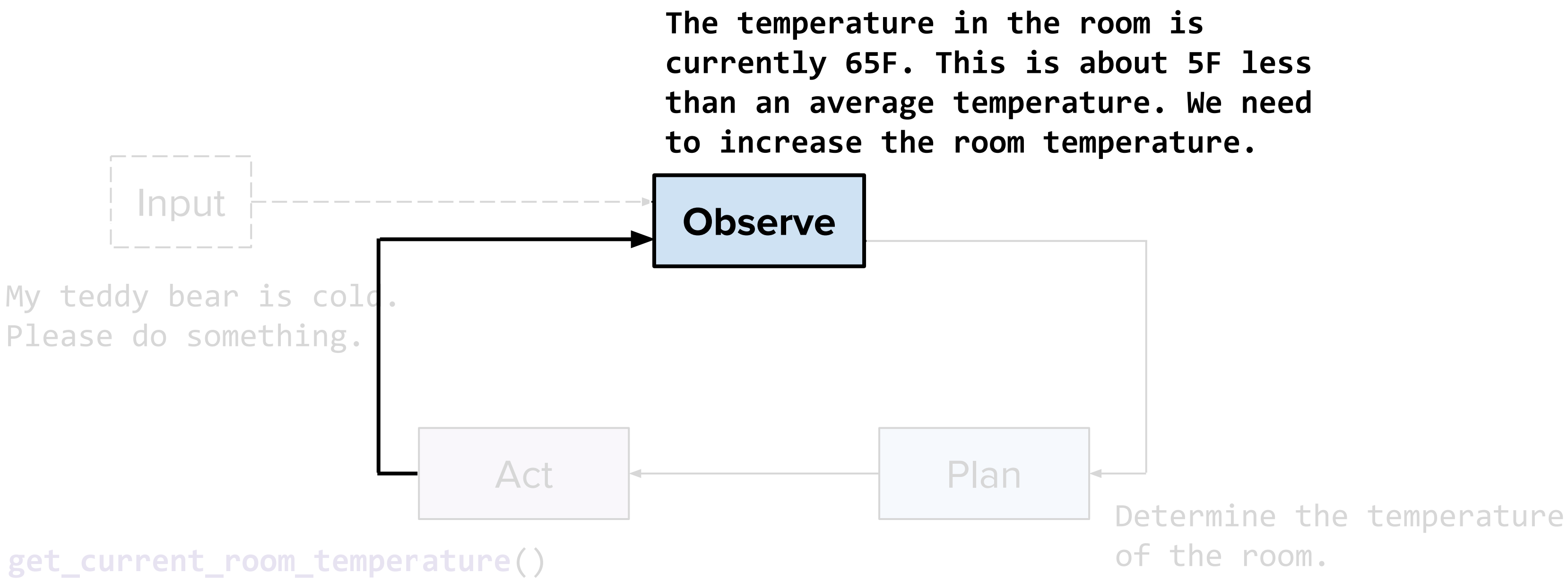

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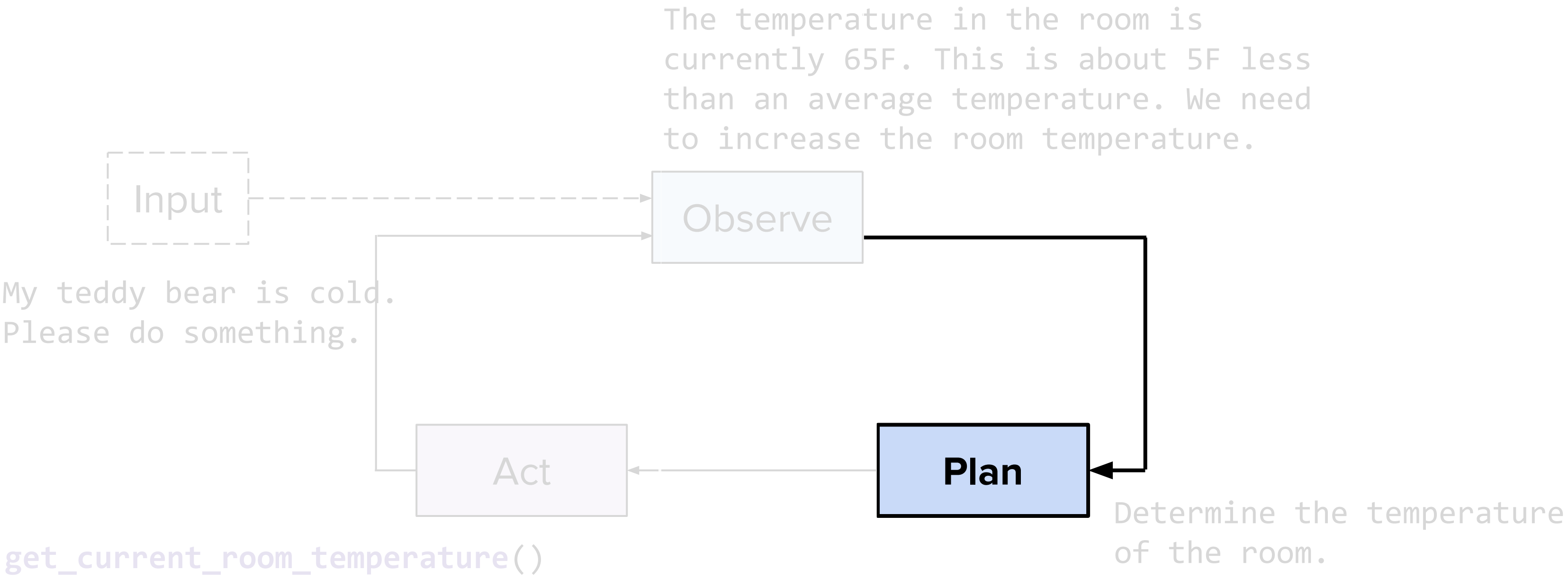
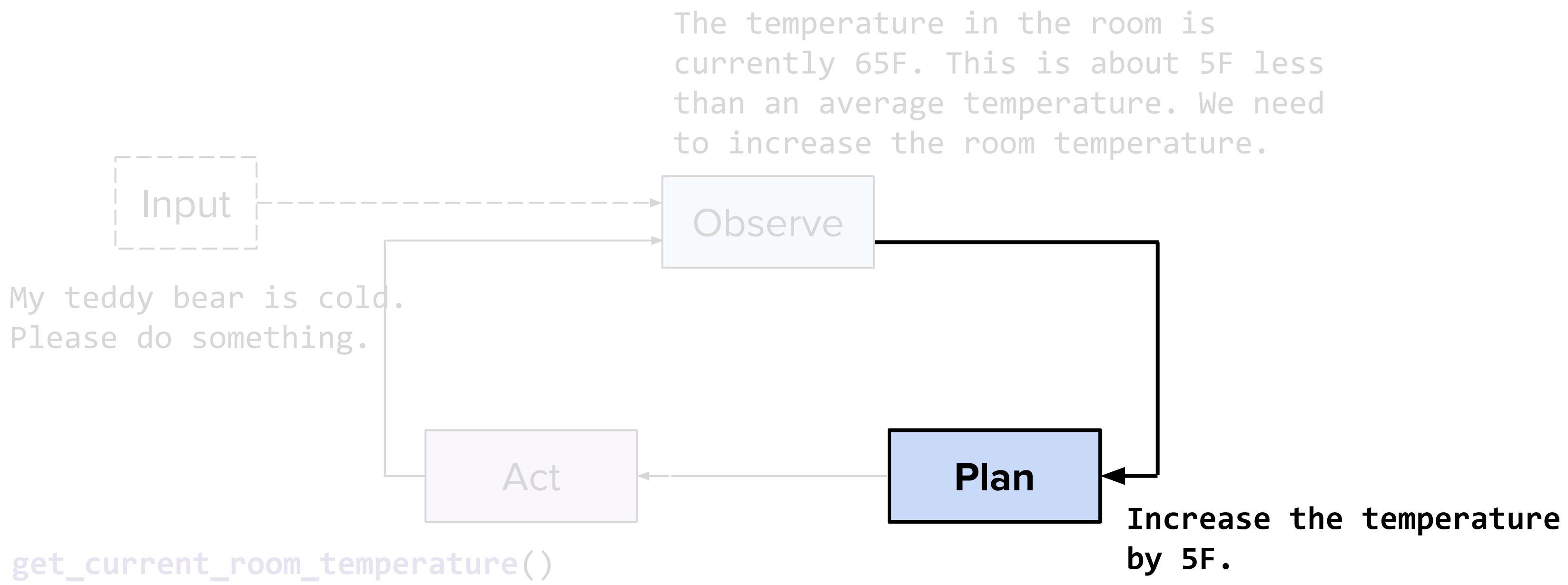


ReAct in action



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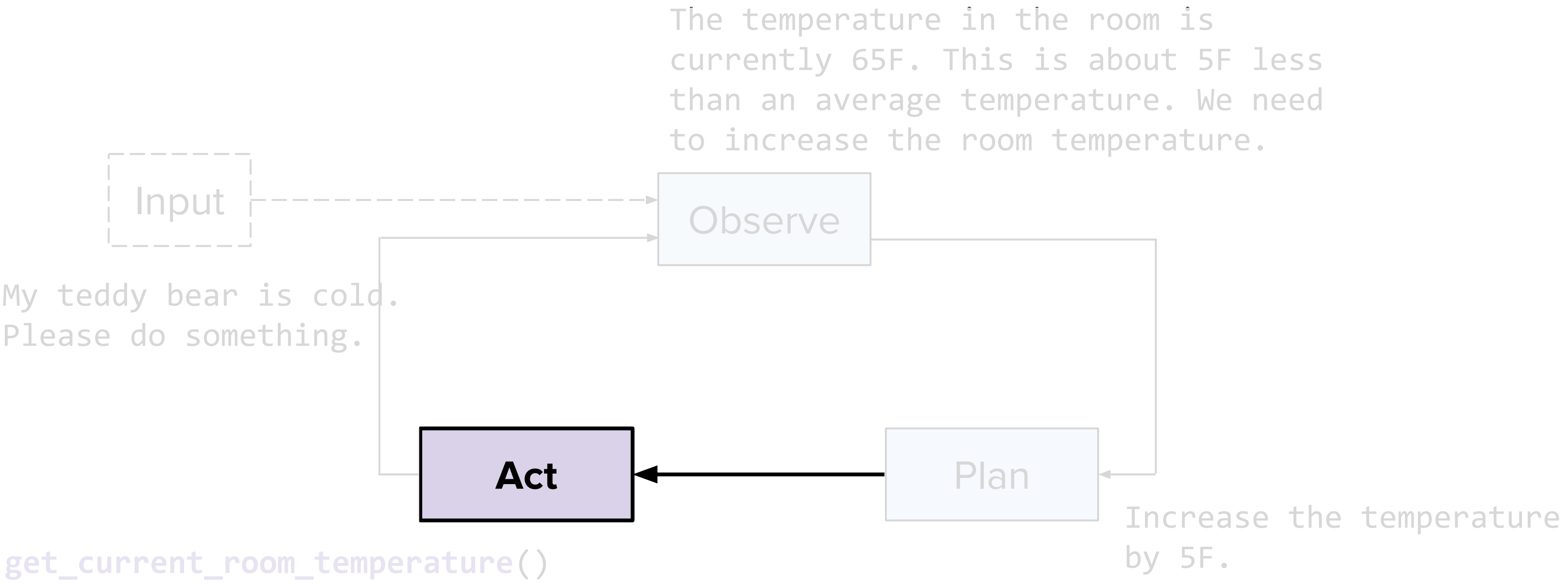

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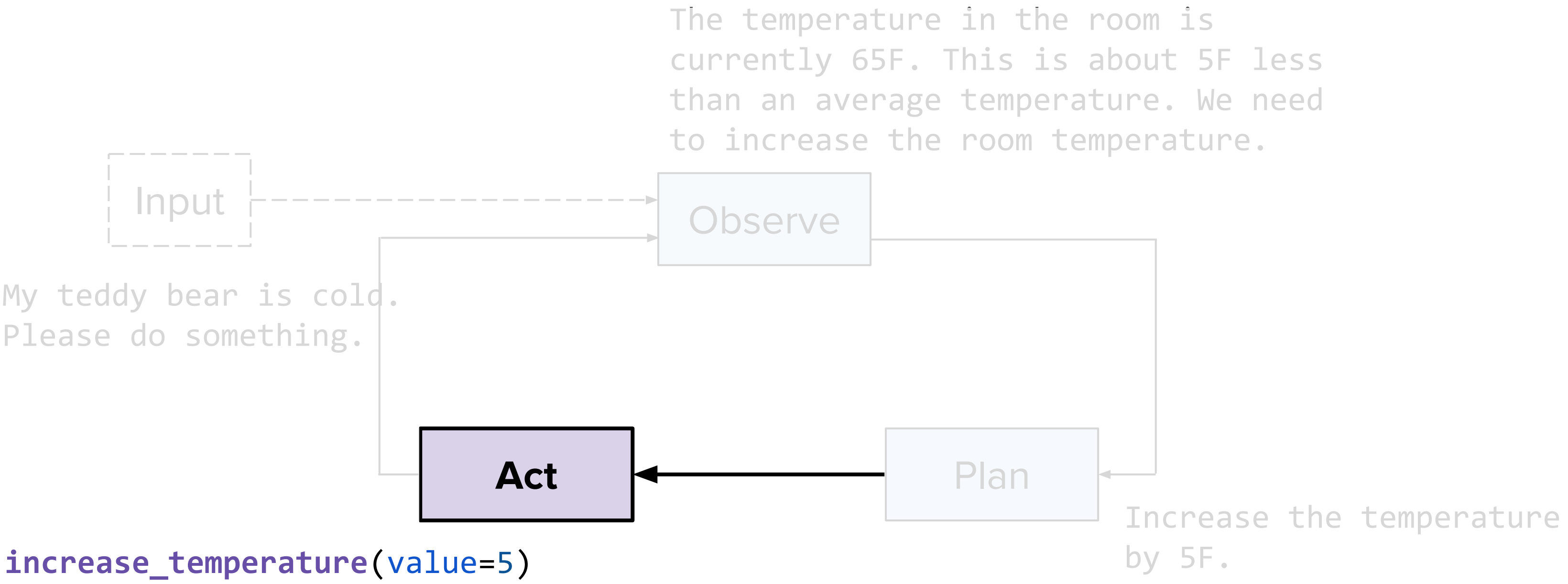

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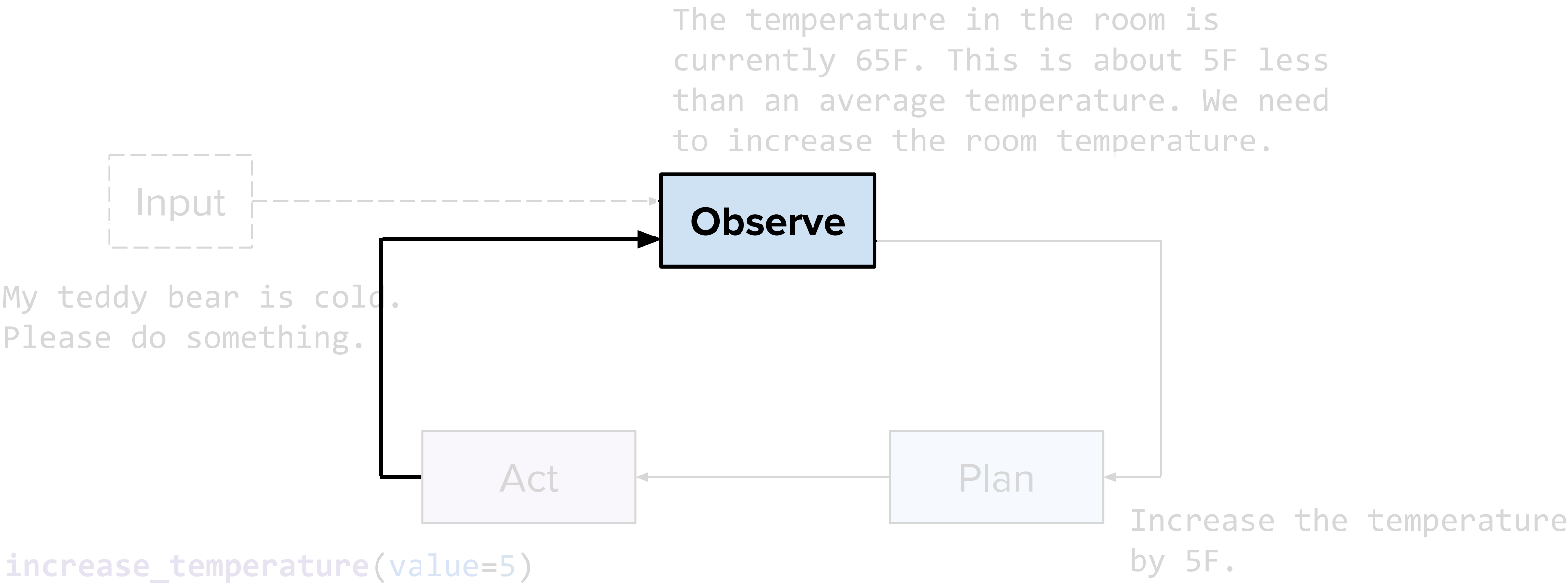

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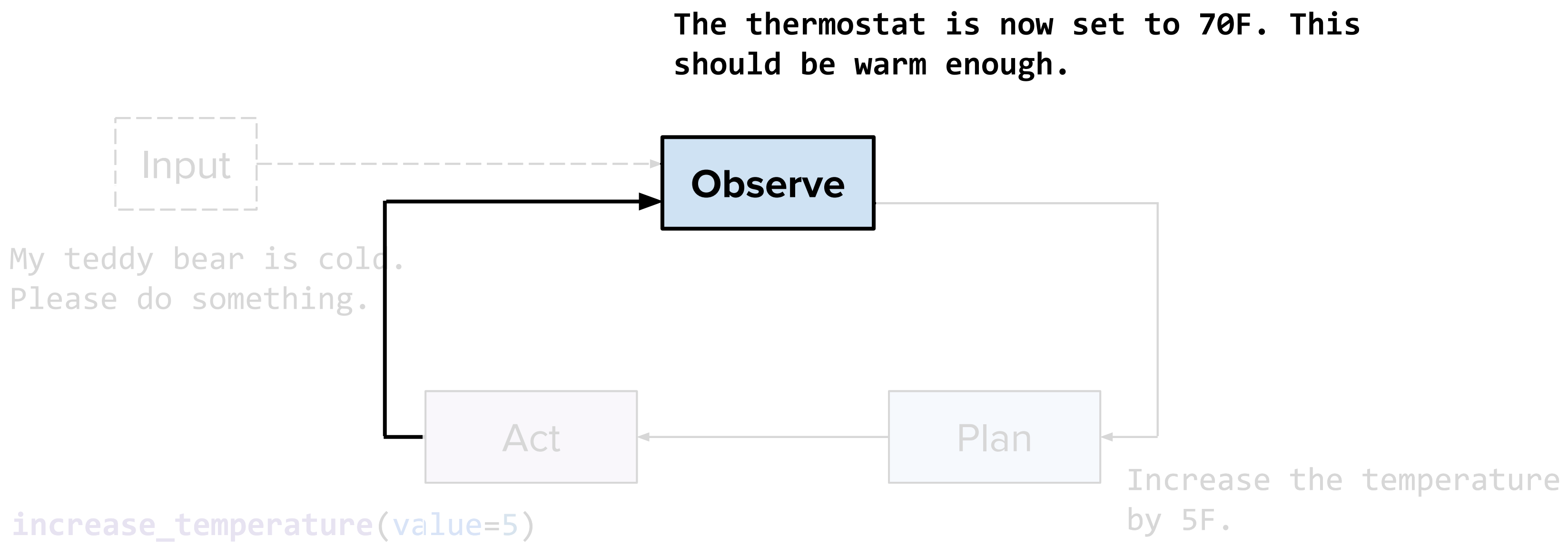

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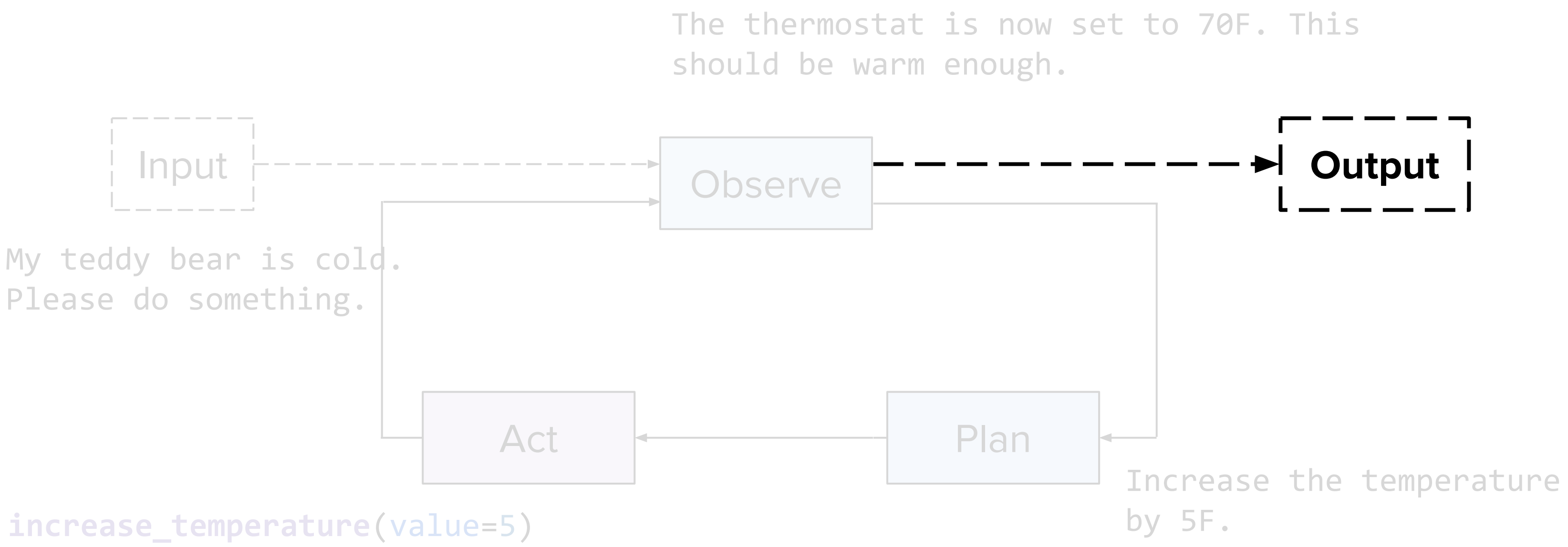

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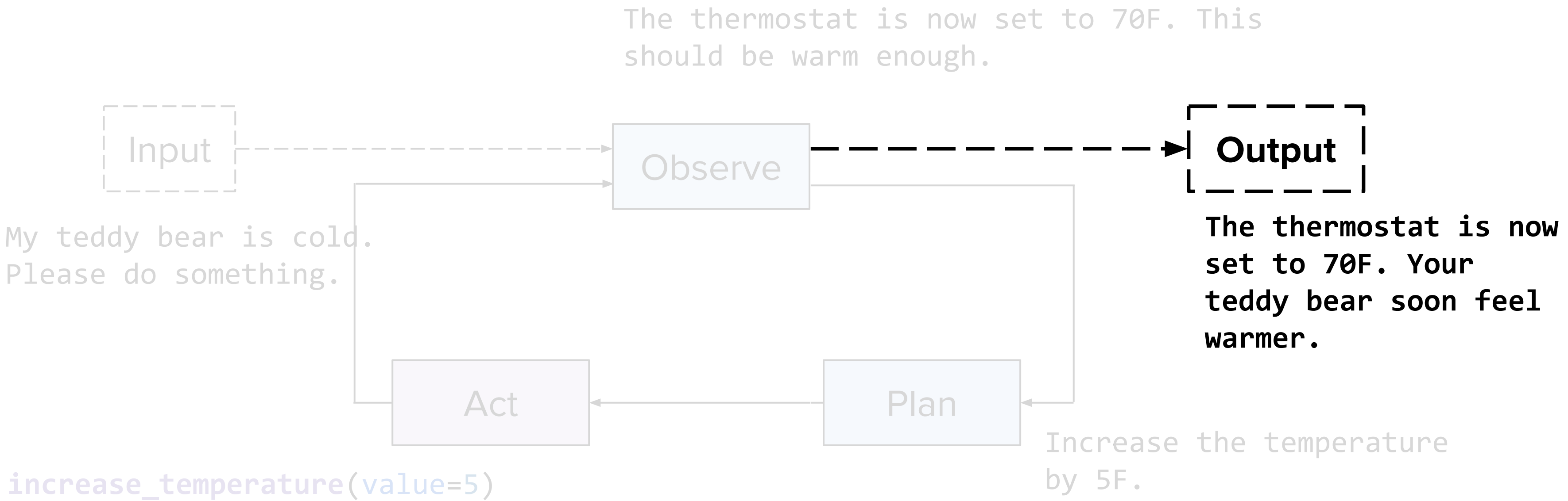


"Agentic" view

`My teddy bear is cold. Please do something.`

`The thermostat is now set to 70F. Your teddy bear soon feel warmer.`

There can be agents for many things

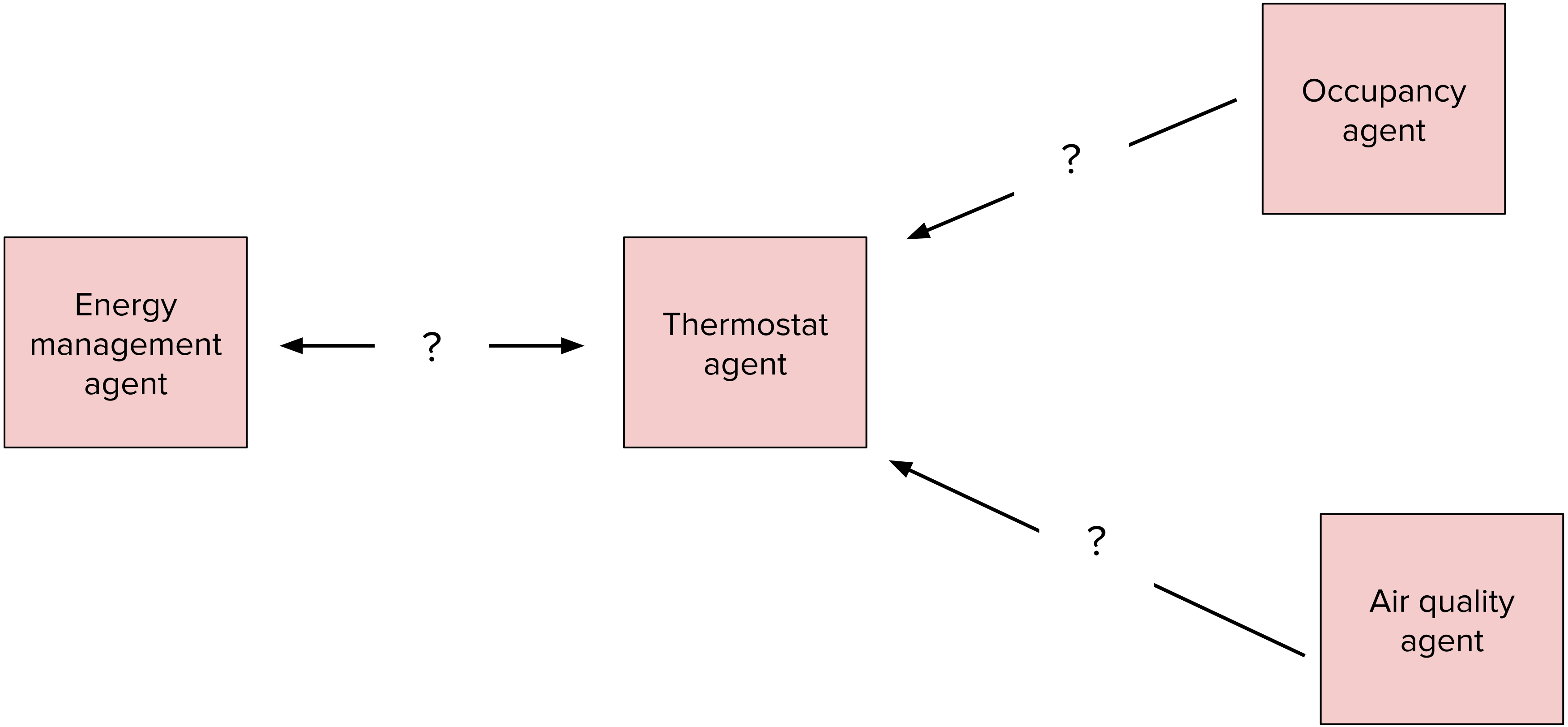
Occupancy agent

Energy management agent

Thermostat agent

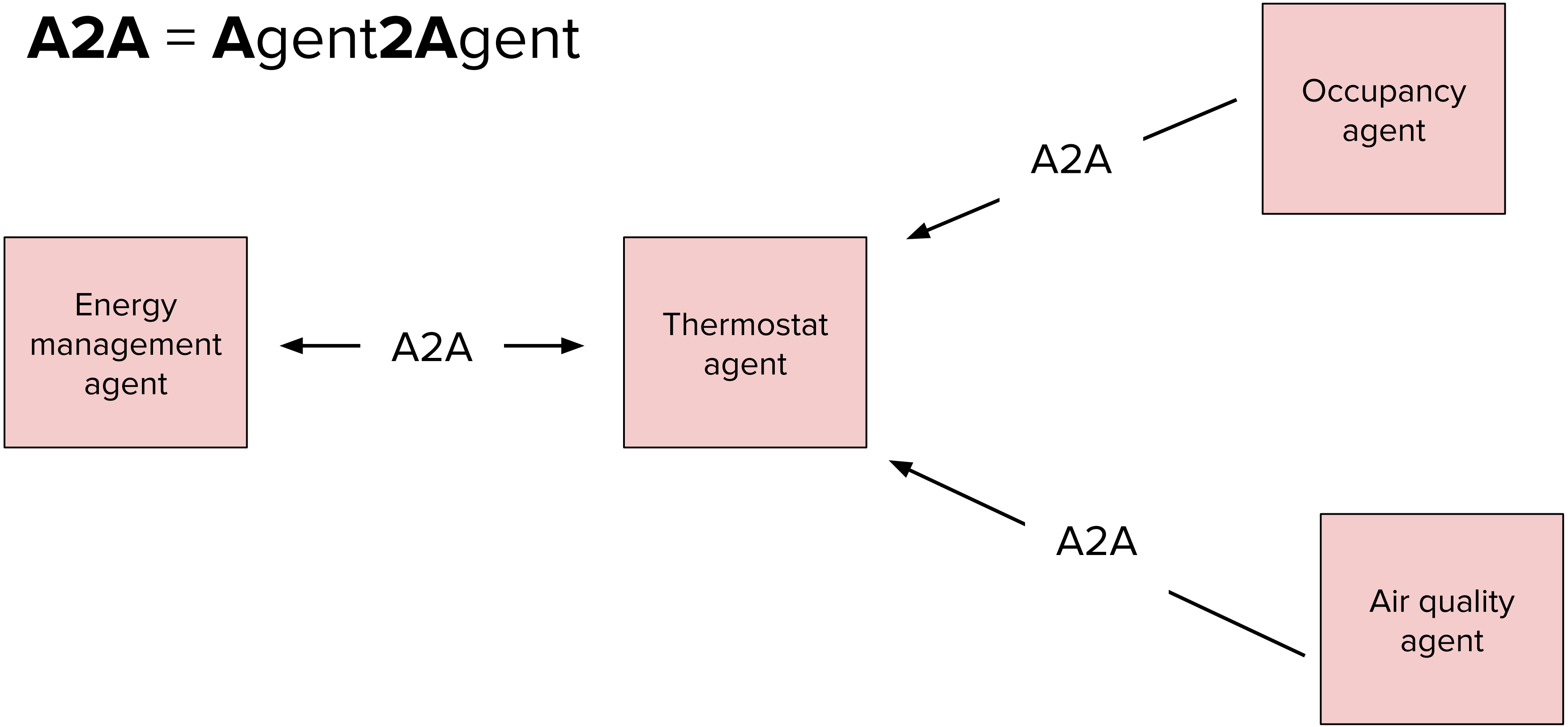
Air quality agent

How can agents communicate with each other?



Standardization: A2A

A2A = **A**gent**2A**gent



"Announcing the Agent2Agent Protocol (A2A)", Google, 2025.

Standardization: A2A

Thermostat agent

=

AgentSkill

```
id='optimize_energy'
description='Reduces energy consumption'
examples=['Save energy overnight']
```

AgentCard

```
name='thermostat agent'
url='http://path.to.agent'
version='1.0.0'
skills=[
 optimize_energy,
 prepare_home,
]
```

AgentExecutor

```
async def execute(self, ...):
  # Logic.

async def cancel(self, ...):
  # Logic.
```


"*Agent2Agent (A2A) Protocol Official Specification*", *Google, 2025.*

Safety

Risks.

- Potential for harm in the real world
- Example: data exfiltration

"*ToolSword: Unveiling Safety Issues of Large Language Models in Tool Learning Across Three Stages*", *Ye et al., 2024.*

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- Inference safeguards
- Benchmarks, e.g. Agent-SafetyBench

"*Towards Tool Use Alignment of Large Language Models*", *Chen et al., 2024.*

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...very important topic!

Just yesterday in the news

Policy

Disrupting the first reported AI-orchestrated cyber espionage campaign

Nov 13, 2025 • 7 min read

Read the report

"Disrupting the first reported AI-orchestrated cyber espionage campaign", *Anthropic, 2025.*

Closing thoughts

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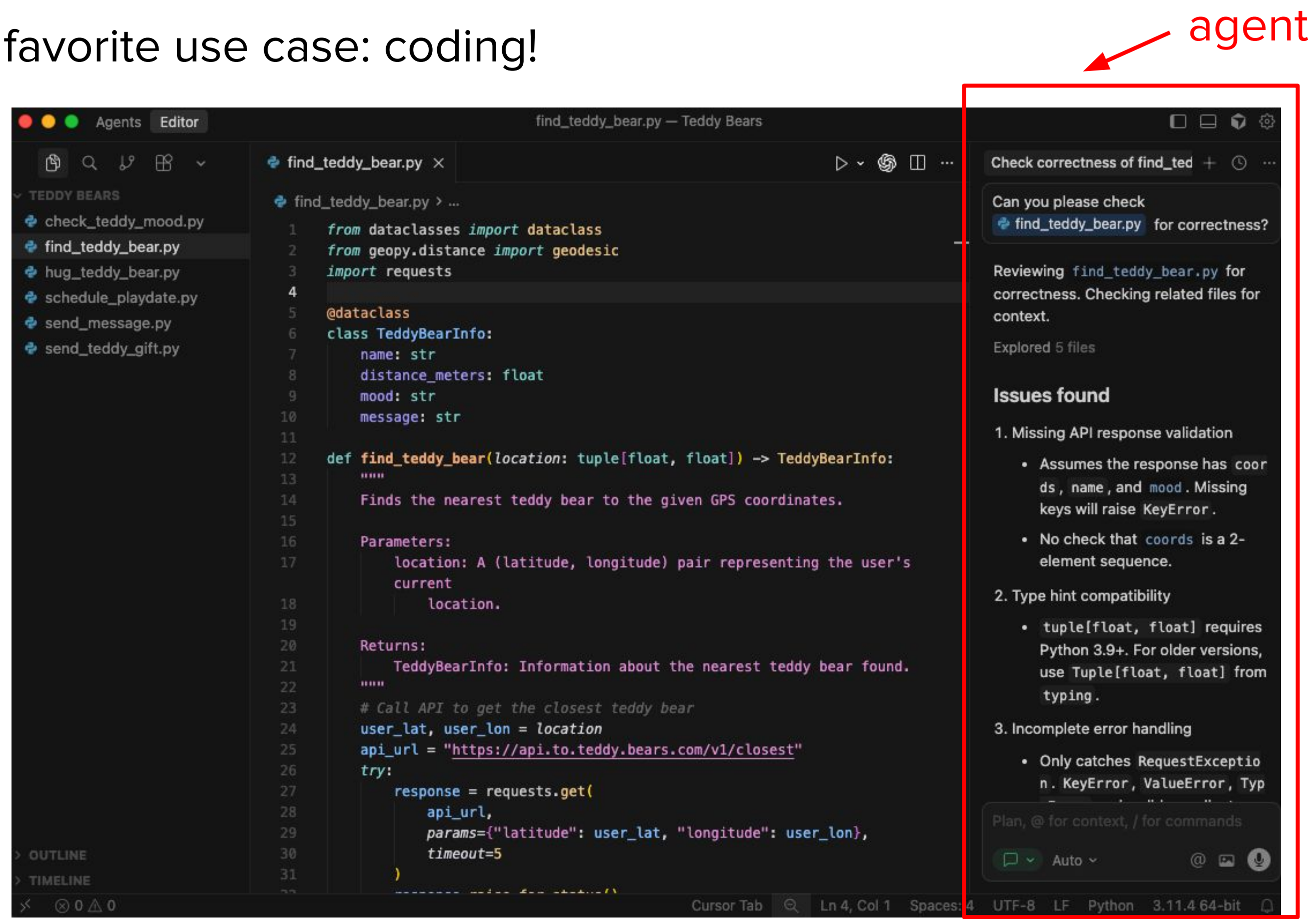
- **Transparency** / **observability** helps with user trust and debuggability

Bonus: AI agents in your daily life

Personal favorite use case: coding!



Thank you for your attention!