# COMP 4901B Large Language Models

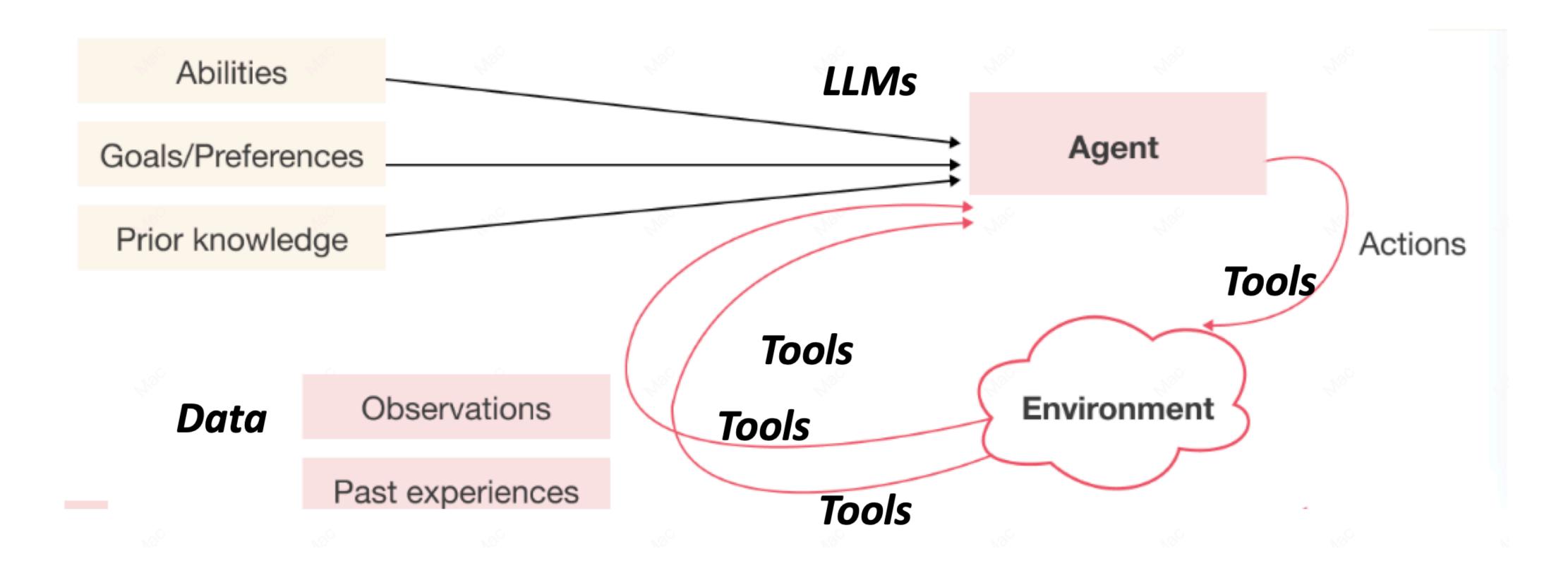
# Language Agents and Tools

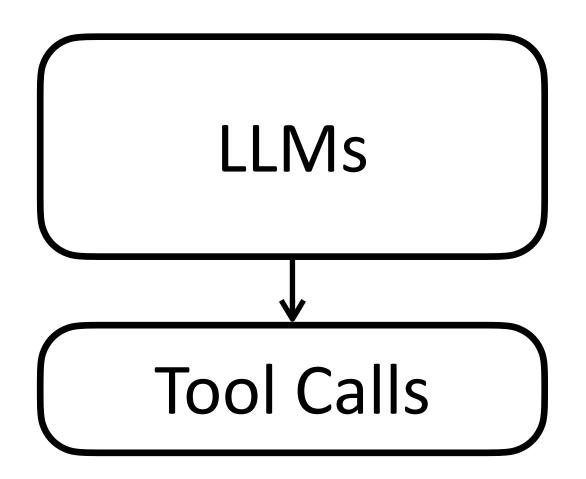
Junxian He

Nov 12, 2025

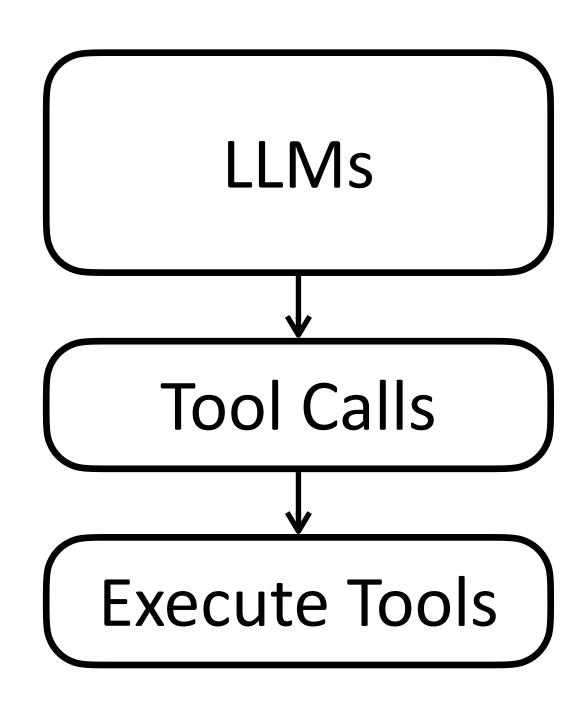
### Recap: What are Agents

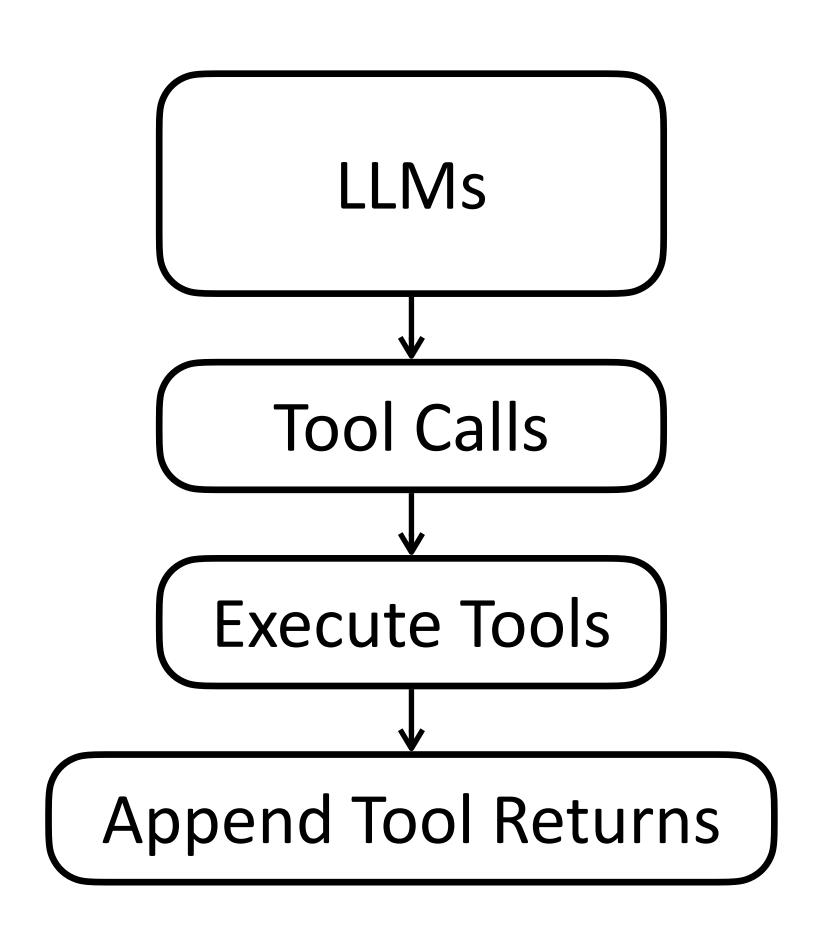
Anything that can be viewed as **perceiving** its environment through sensors and **acting** upon that environment through actuators.



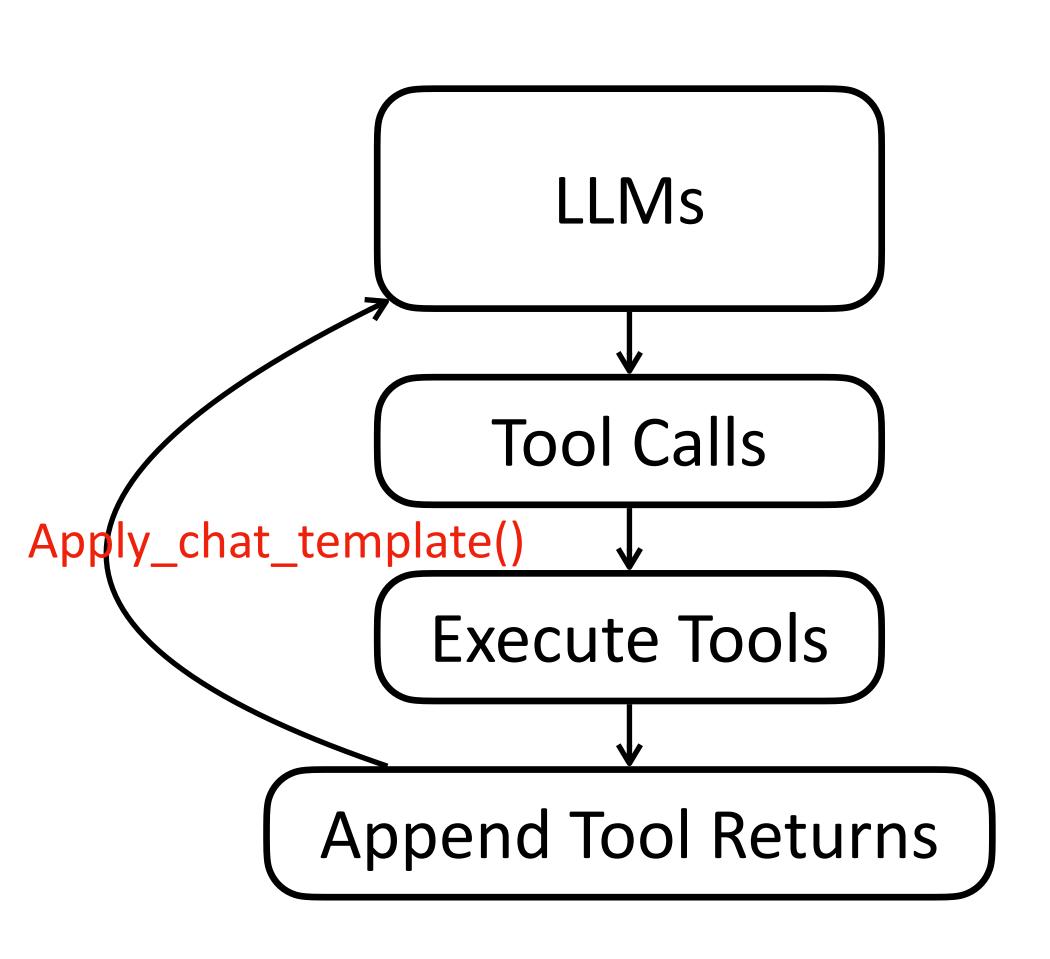


```
"response": "Sure, I'll check the current weather for you.",
 "reasoning": "I need real-time conditions so the user's route
recommendation is accurate.",
 "tool_calls": [
    "name": "get_weather",
    "arguments": {
     "location": "San Jose, CA, US",
     "date": "2025-11-07"
```





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     "location": "San Jose, CA, US",
     "date": "2025-11-07"
 "tool_return": {
   "temperature": 21.5,
   "condition": "clear",
   "humidity": 60,
   "wind_speed": 10,
   "location": "San Jose, CA, US",
  "date": "2025-11-07"
```



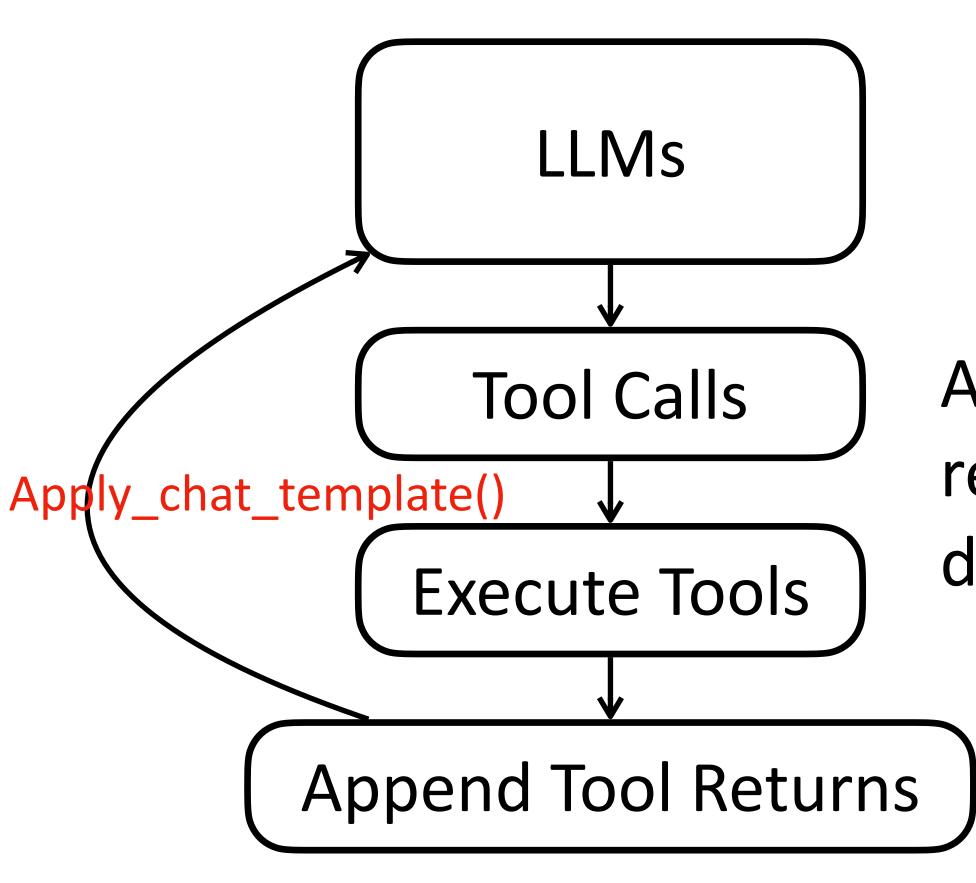
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```

Sure, I'll check the current weather for you.

[thinking] I need real-time conditions so the user's route recommendation is accurate. [/thinking]

```
<tool_call>
{"name": "get_weather", "arguments": {"location": "San Jose, CA, US", "date": "2025-11-07"}}
</tool_call>
<tool_return>
 "temperature": 21.5,
 "condition": "clear",
 "humidity": 60,
 "wind_speed": 10,
 "location": "San Jose, CA, US",
 "date": "2025-11-07"
</tool_return>
```

This is the context fed back to the model to continue generation



Agent Loop

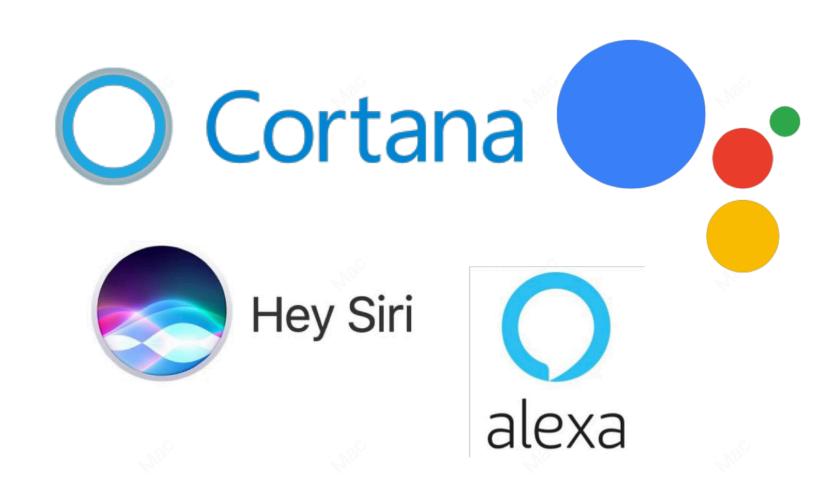
Agent loop ends when the model generates a tex response without tool calling, or sometimes we define a "done" tool for the model to call

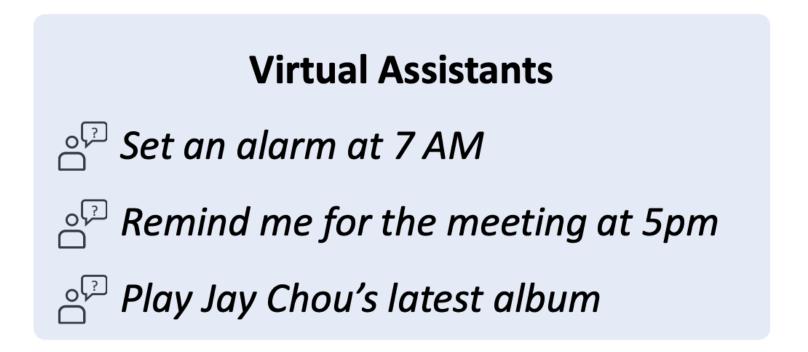
```
def send_messages(messages):
    response = client.chat.completions.create(
       model="deepseek-chat",
        messages=messages,
       tools=tools
    return response.choices[0].message
client = OpenAI(
   api_key="<your api key>",
    base_url="https://api.deepseek.com",
tools = [
        "type": "function",
        "function": {
            "name": "get_weather",
            "description": "Get weather of a location, the user should supply a location first.",
            "parameters": {
                "type": "object",
                "properties": {
                    "location": {
                        "type": "string",
                        "description": "The city and state, e.g. San Francisco, CA",
                "required": ["location"]
            },
messages = [{"role": "user", "content": "How's the weather in Hangzhou, Zhejiang?"}]
message = send_messages(messages)
print(f"User>\t {messages[0]['content']}")
tool = message.tool_calls[0]
messages.append(message)
messages.append({"role": "tool", "tool_call_id": tool.id, "content": "24°("})
message = send_messages(messages)
print(f"Model>\t {message.content}")
```

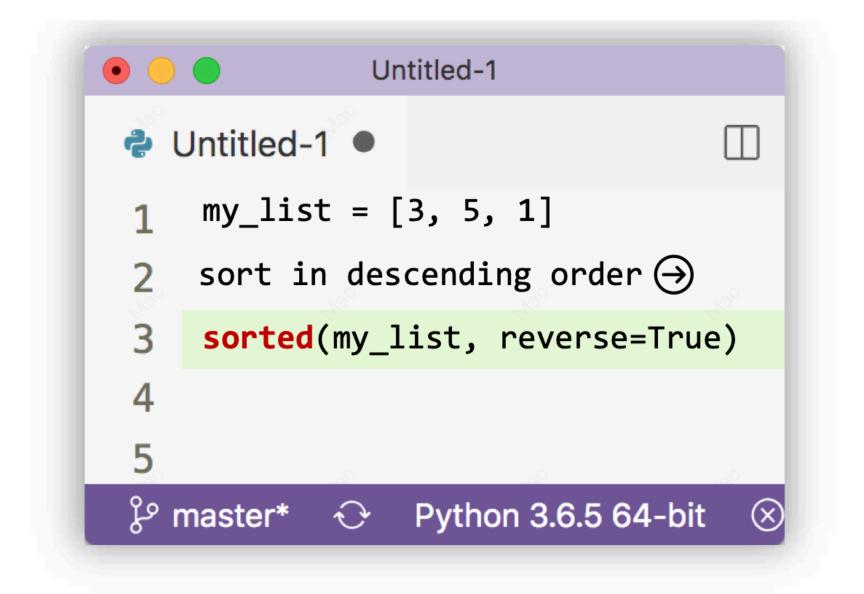
### One-step Example

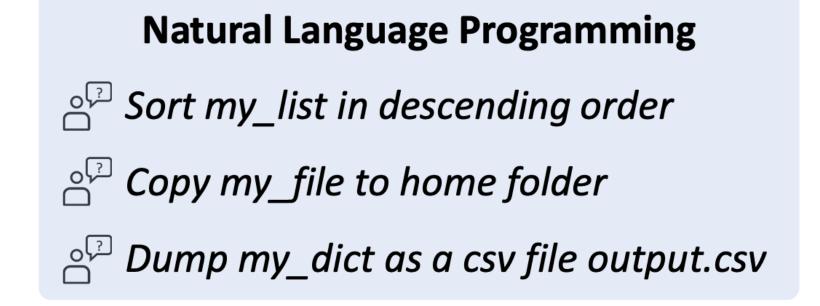
### Why Do We Want Agents

Imagine if things get done by just talking...









# Training-free Methods for Building Agents

### How to Let LLM Become an Agent

Sure, I'll check the current weather for you.

[thinking] I need real-time conditions so the user's route recommendation

```
<tool_call>
{"name": "get_weather", "arguments": {"location": "San Jose, CA, US", "dat
</tool_call>
```

The New England Journal of Medicine is a registered trademark of [QA("Who is the publisher of The New England Journal of Medicine?") → Massachusetts

Medical Society] the MMS.

Out of 1400 participants, 400 (or [Calculator(400 / 1400)]  $\rightarrow$  0.29] 29%) passed the test.

The name derives from "la tortuga", the Spanish word for [MT("tortuga") → turtle] turtle.

The Brown Act is California's law [WikiSearch("Brown Act") → The Ralph M. Brown Act is an act of the California State Legislature that guarantees the public's right to attend and participate in meetings of local legislative bodies.] that requires legislative bodies, like city councils, to hold their meetings open to the public.

We just need the LLMs to output certain formats of tool calls that we can parse

### Just Prompt

Supposing you have the following APIs, answer the given question.

#### Available APIs:

- 1. weather(location): for getting the weather information given a location
- 2. location(): for getting the location of the user.
- 3. bus\_route(start, end): for finding the current bus route from the start position to the end position.
- 4. count\_characters(s): for counting the number of characters in a string s.

Question: Is it okay to go hiking today?

To know the answer, we first need to know the current location of the user.

API call: location() = Seattle.

Next, we need to know the current weather in Seattle.

API call: weather(Seattle) = Cloudy with a chance of rain.

Based on this information, it is not recommended to go hiking today in Seattle.

#### Available APIs:

- 1. weather(location): for getting the weather information given a location
- location(): for getting the location of the user.
- 3. bus\_route(start, end): for finding the current bus route from the start position to the end position.
- 4. count\_characters(s): for counting the number of characters in a string s.

Question: how long does it take to take a bus to Vancouver?

To answer this question, we first need to know the current location of the user.

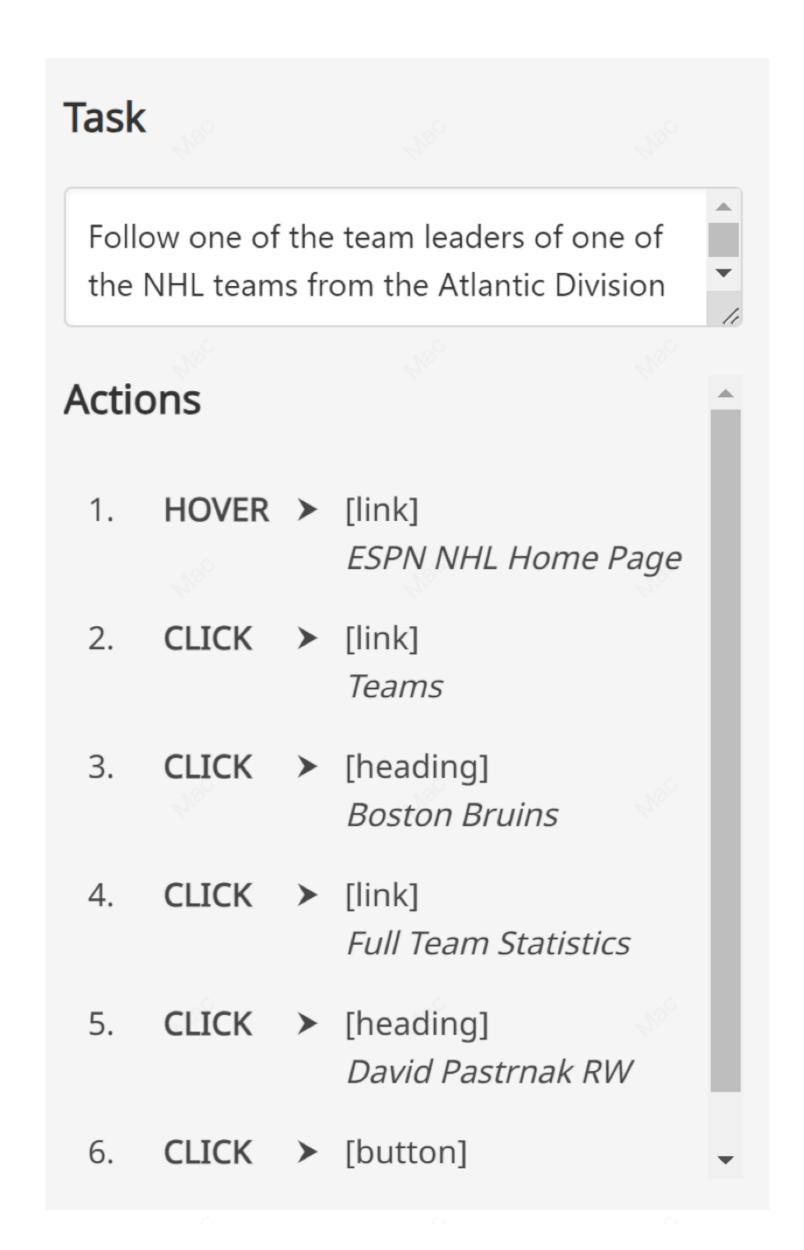
API call: location() = Seattle. Next, we need to find the bus route from Seattle to Vancouver. API call: bus\_route(Seattle, Vancouver) = 4 hours.

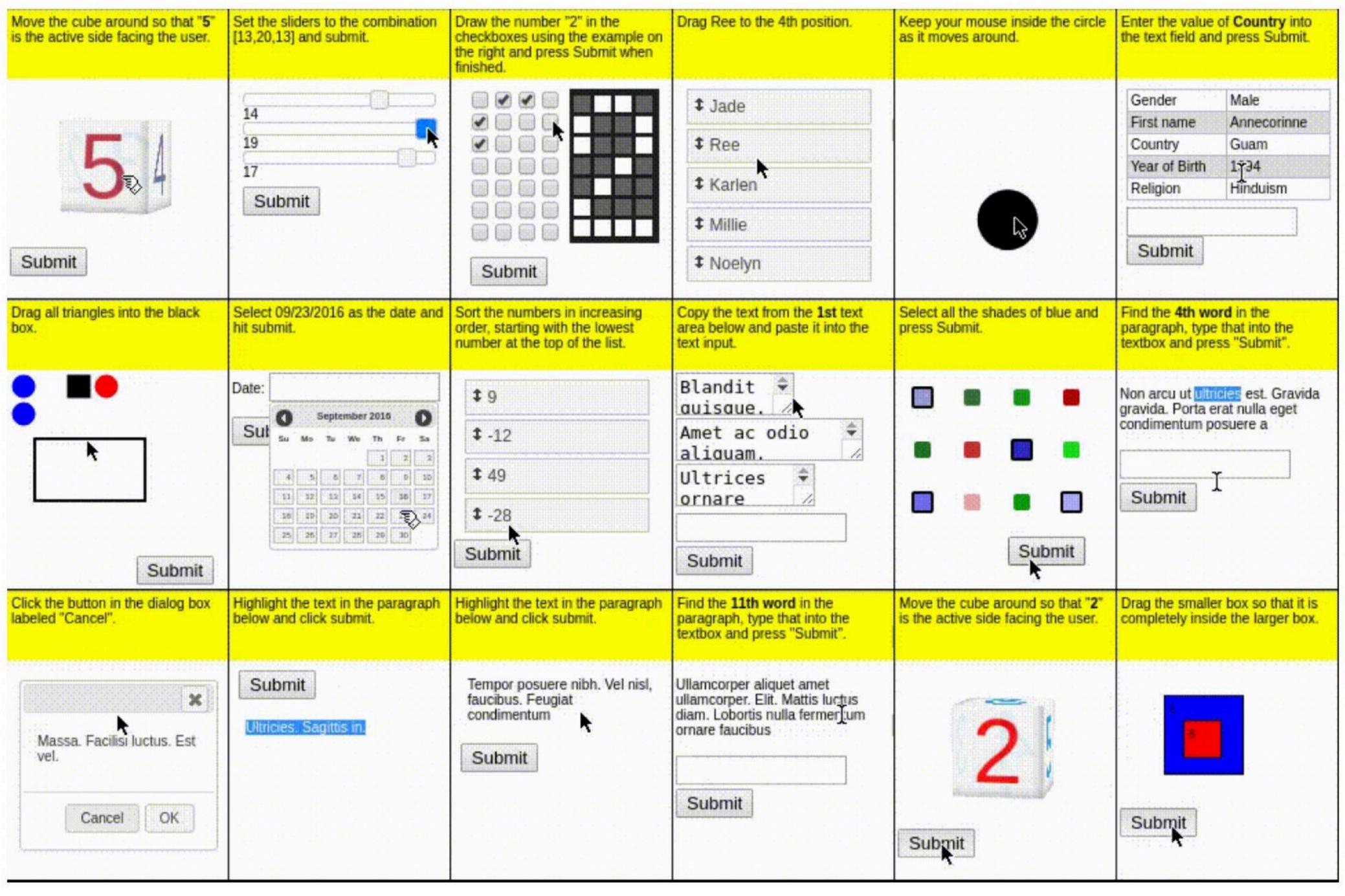
We just need the LLMs to output certain formats of tool calls that we can parse

# Evaluating Language Agents

## Evaluation of LLM Agents

- Simplified environments and basic tasks
- Performance is saturating.
  - 1.Stateless, non interactive environment, e.g. Mind2Web (Deng et al. 2023) has only dumped pages.
  - 2. Checking action sequence accuracy (step-wise, surface form only)
  - 3.Simple interactive environment, short horizon, e.g. WebShop (Yao et al. 2023), MiniWoB++ (Humphreys et al. 2022)





Instruction: i am looking for x-large, red color women faux fur lined winter warm jacket coat, and price lower than 70.00 dollars

Current Query: women fur jacket coat

#### Results

Page 1 (1-10) of 50 total results

Back to Search

Next >







Current Action: click [Fjackets Real Lambskin...]



### Key to Agent Benchmarks

#### **Environment:**

- Diverse functionality.
- Rich and realistic content.
- Interactive
- Easily Extendable
- Reproducible

#### Tasks:

- Long horizon tasks
- Enough difficulty
- Involves multiple websites

#### **Evaluation:**

- Reliable metrics
- Encourage final goal rather than partial satisfaction.

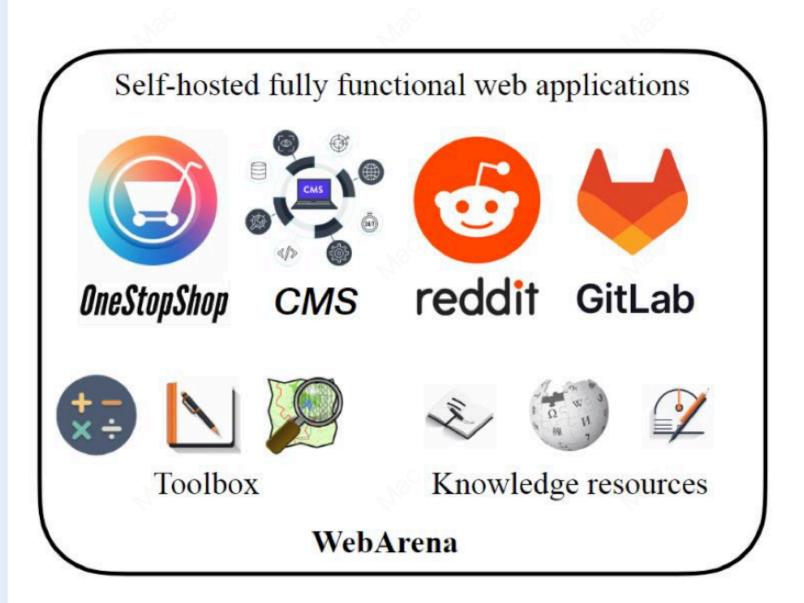
### WebArena

#### **Environment:**

- Diverse functionality.
- Rich and realistic content.
- Interactive
- Easily Extendable
- Reproducible

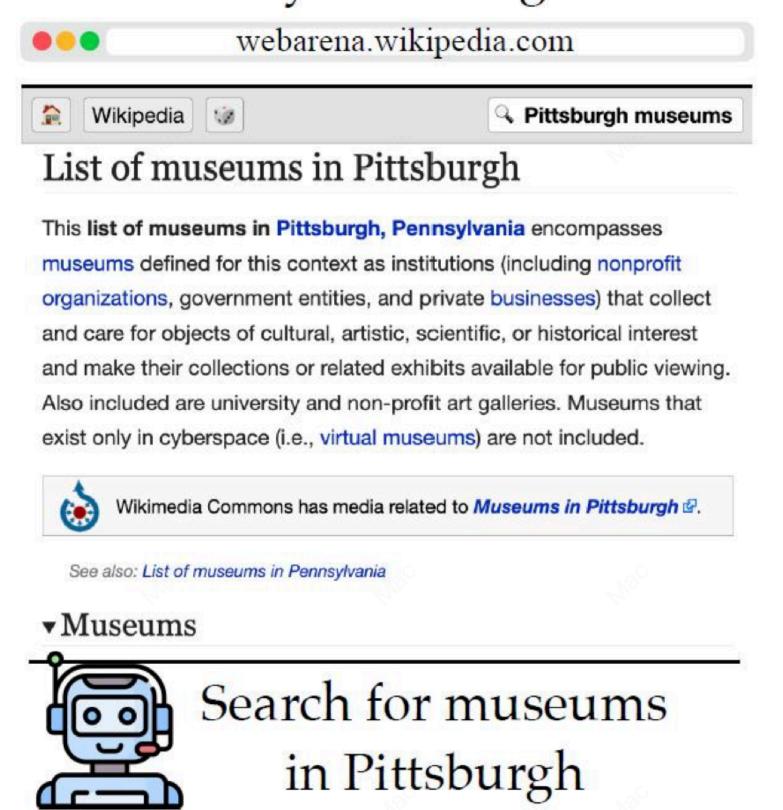
#### A sandbox Internet:

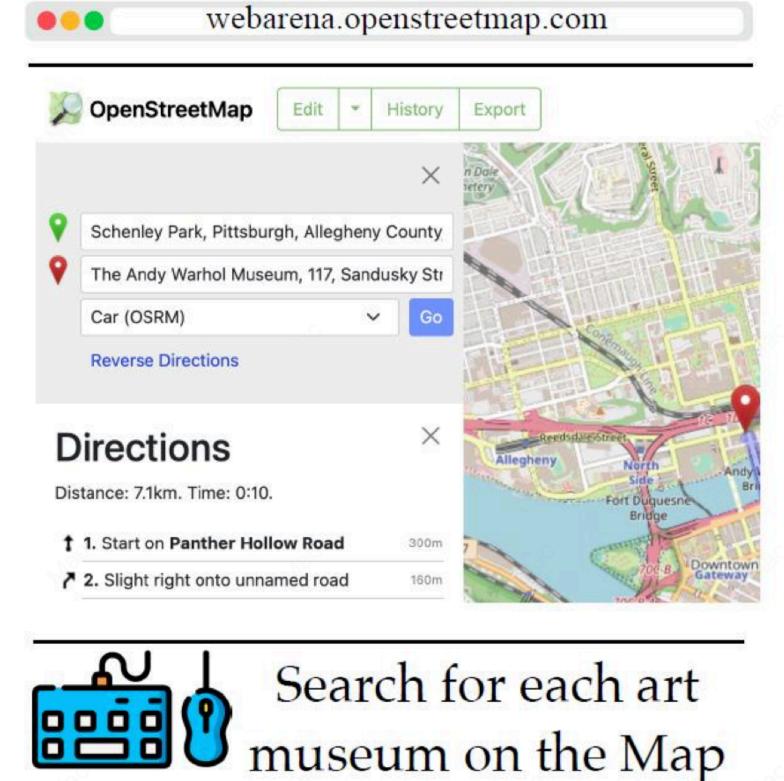
- Open source, production-ready implementation of the websites
- Data populated from real-world websites
- Easily distributable Dockers,
   AWS images, etc.

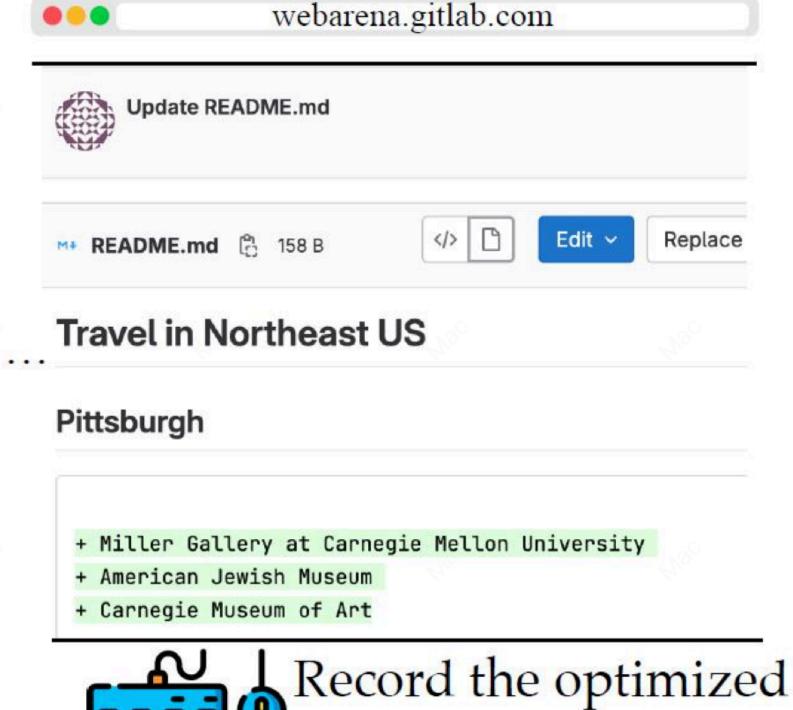


### Example Tasks in WebArena

"Create a plan to visit Pittsburgh's art museums with minimal driving distance starting from Schenley Park. Log the order in my "awesome-northeast-us-travel" repository







results to the repo

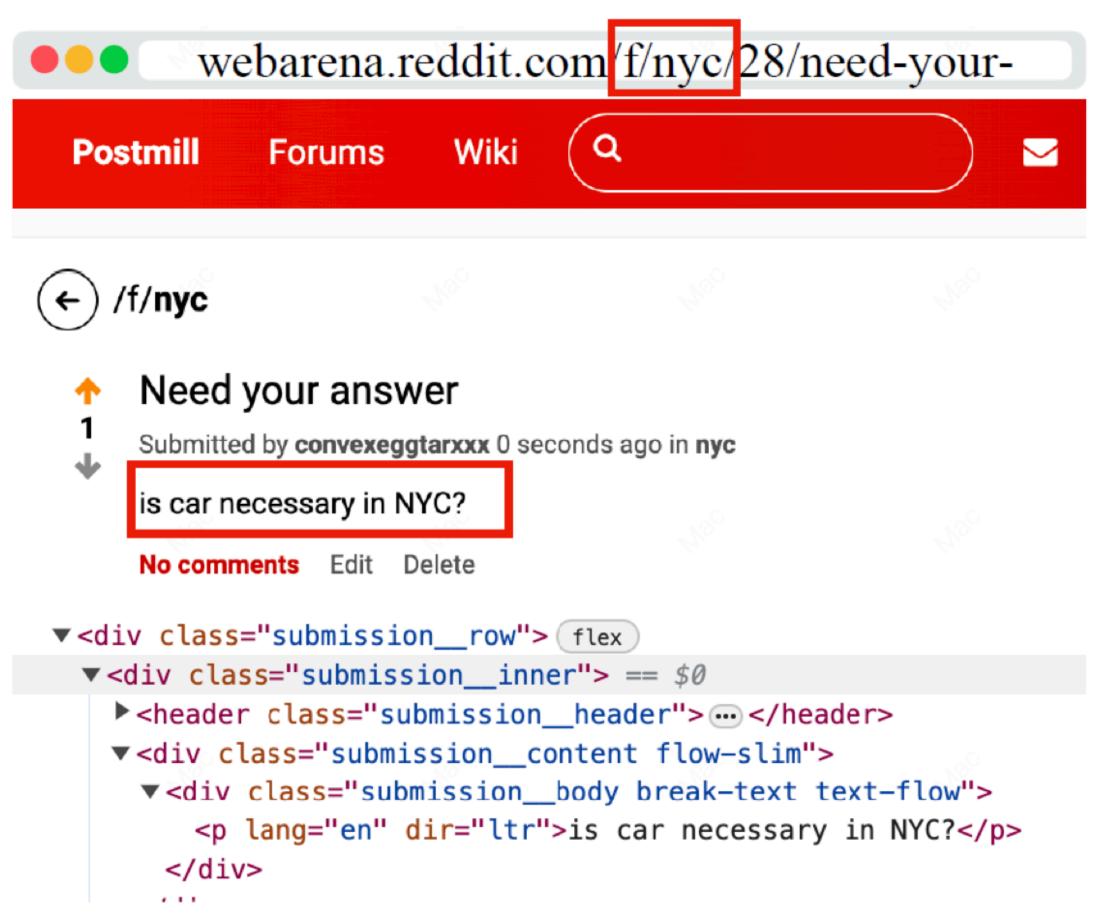
### Outcome/Execution-based Evaluation

Goal: directly validate the correctness of the execution

- "When was the last time I bought shampoo?"
- Directly compare with the annotated answer: Answer is "Dec 15th, 2022"

### Outcome/Execution-based Evaluation

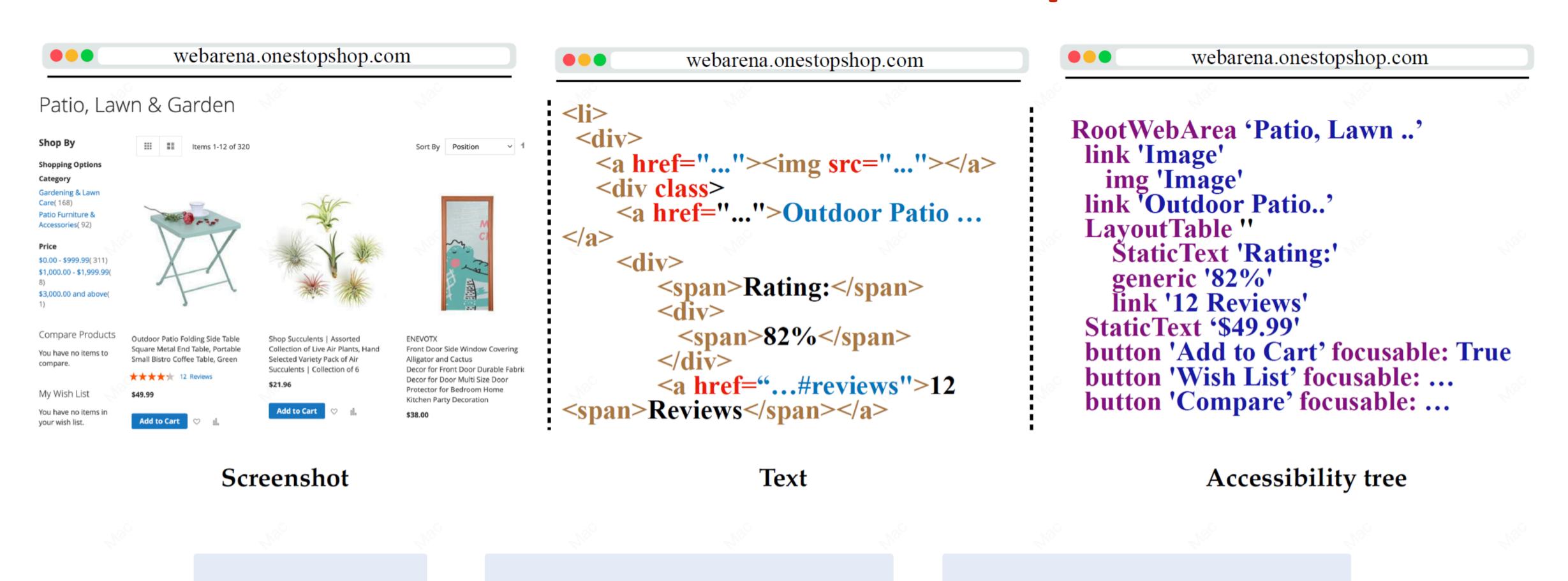
Post my question, "is car necessary in NYC", in a subreddit where I'm likely to get an answer



"f/nyc" in page.url

"Is car necessary in NYC?" in document.querySelector(".su bmission\_\_inner").outText

### Observation & Action Space



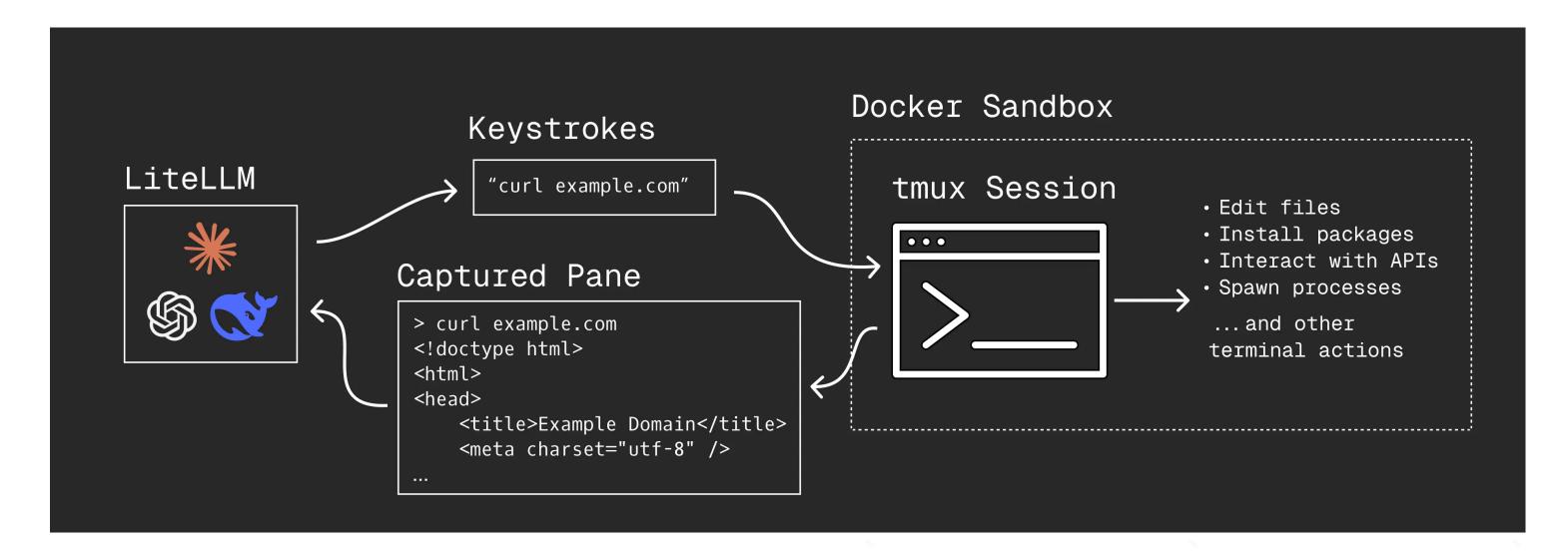
Keyboard: type

Mouse: click, hover, scroll

Browser: New tab, go back

Another type of web agents, GUI agents, directly takes image as input observations

### TerminalBench



#### **Terminal-Bench: Possible Agent Actions**

- Run shell commands (ls, cd, make, python, etc.)
- Manage tmux sessions/panes (new-session, split-window, select-pane)
- Edit files ( vim , nano , echo > file , etc.)
- Install/build software (apt install, gcc, make)
- Read & analyze outputs/logs (cat, less, grep)
- Navigate directories and view help ( cd , ls , --help )
- Verify or fix results (re-run scripts, check outputs)

## Training Methods for Improving Agents

### Learning of LLM Agents

In-Context Learning – Learning from few-shot exemplars

Supervised Finetuning – Learning From Experts

Reinforcement Learning – Learning from Environment

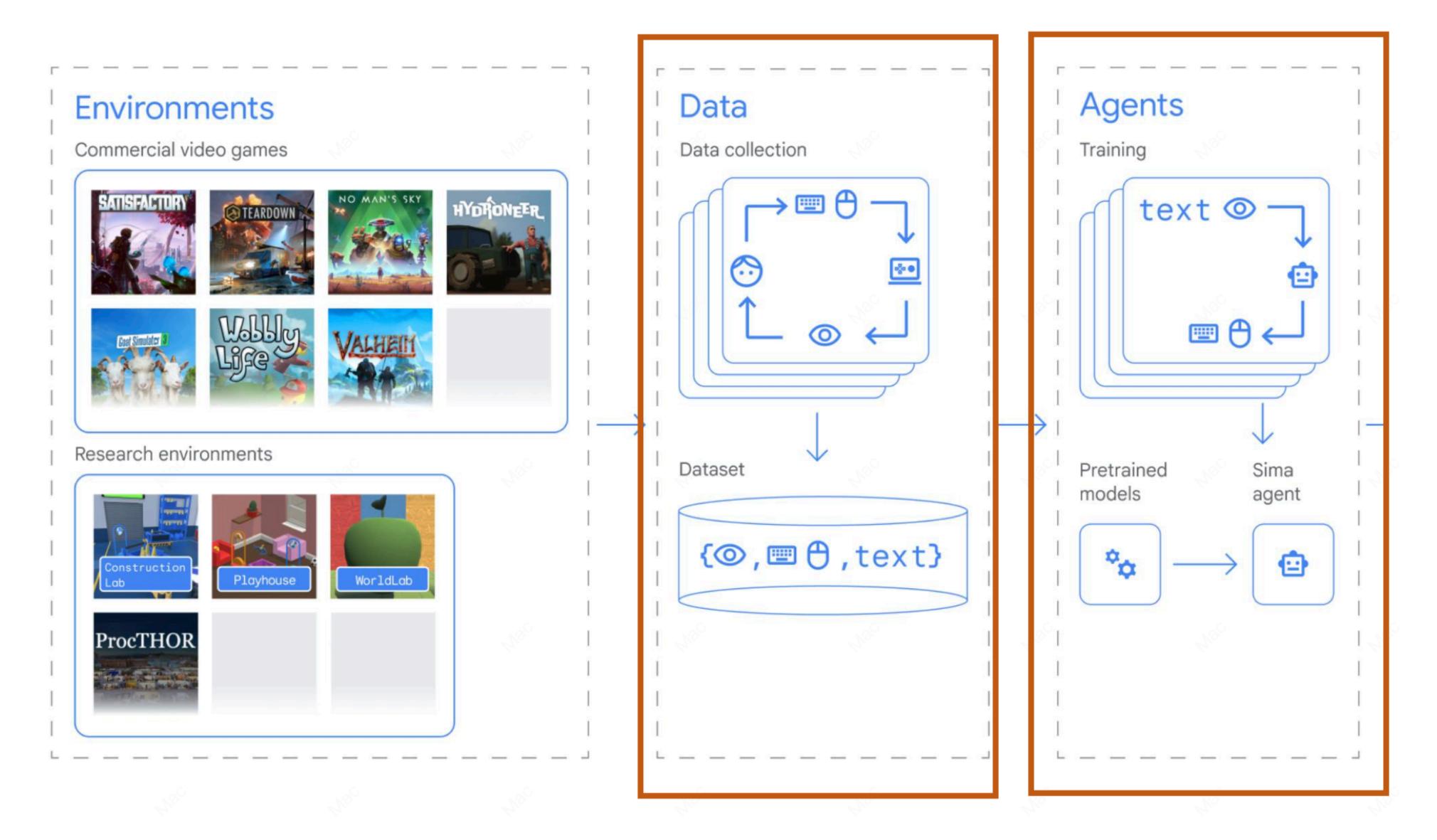
### Supervised Finetuning

Collect large amount of expert trajectories (e.g. from human annotation)

```
task_intent, [(obs_1, action_1), ...,(obs_N, action_N)]
```

• Finetune the LLM with standard cross-entropy loss.

## Supervised Finetuning



### Supervised Finetuning

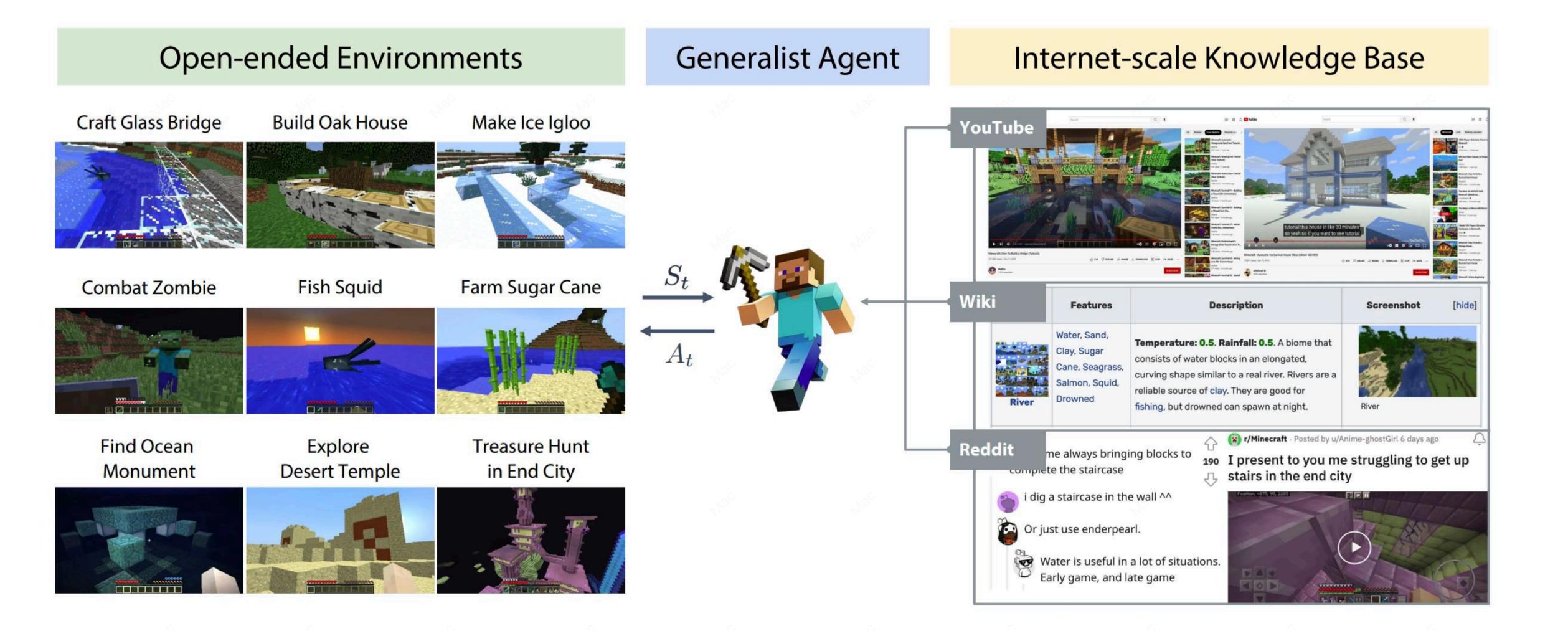
Data hungry

Cannot learn much from failed trajectories

```
a_1, a_2, a_3, ..., a_10 - Success
a_1, a_2, a_3, ..., a_10 - Fail (Wasted)
```

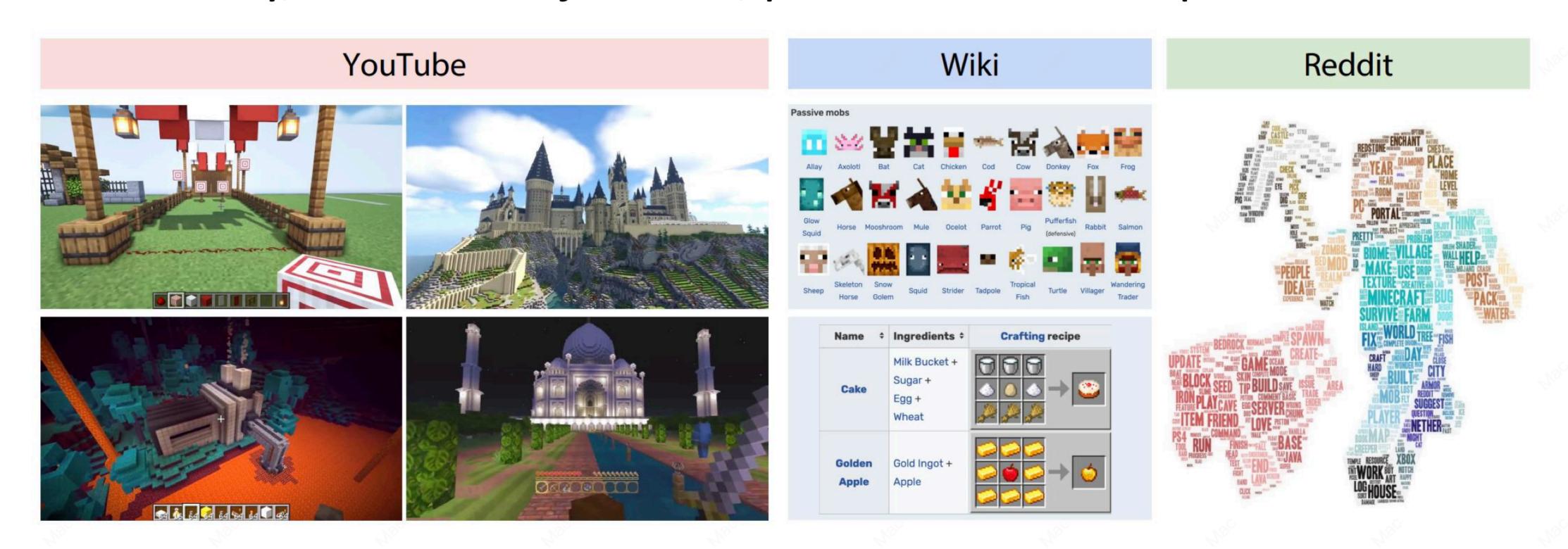
- Need human trajectory?
  - Data augmentation techniques

### **Create More Training Data**



### Data Augmentation

- Continue pre-train on large amount of data automatically mined
- Even noisy, not clear trajectories, provide domain adaptation.

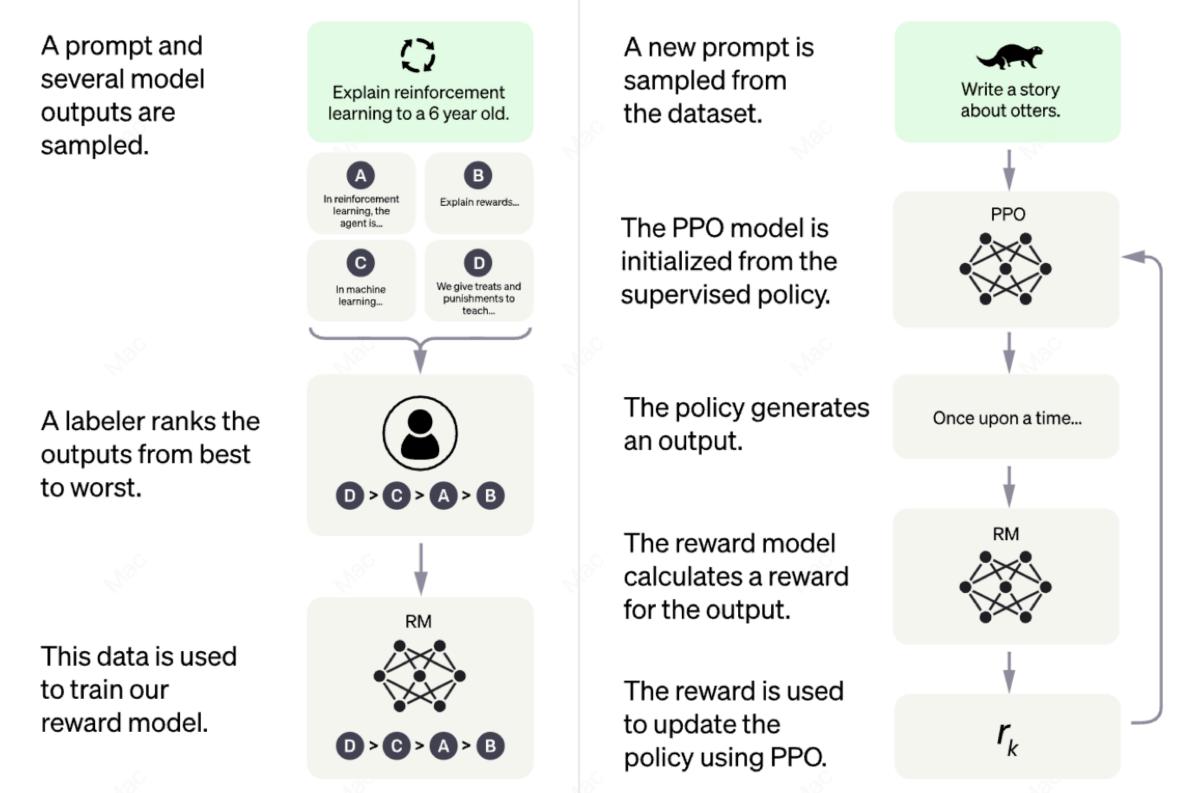


MineDojo, Fan et al. 22' Don't Stop Pretraining, Gururangan et al., 20'

# Reinforcement Learning

Lots of on-going research in this area!

Recall RLHF: Reinforcement Learning from Human Feedback:

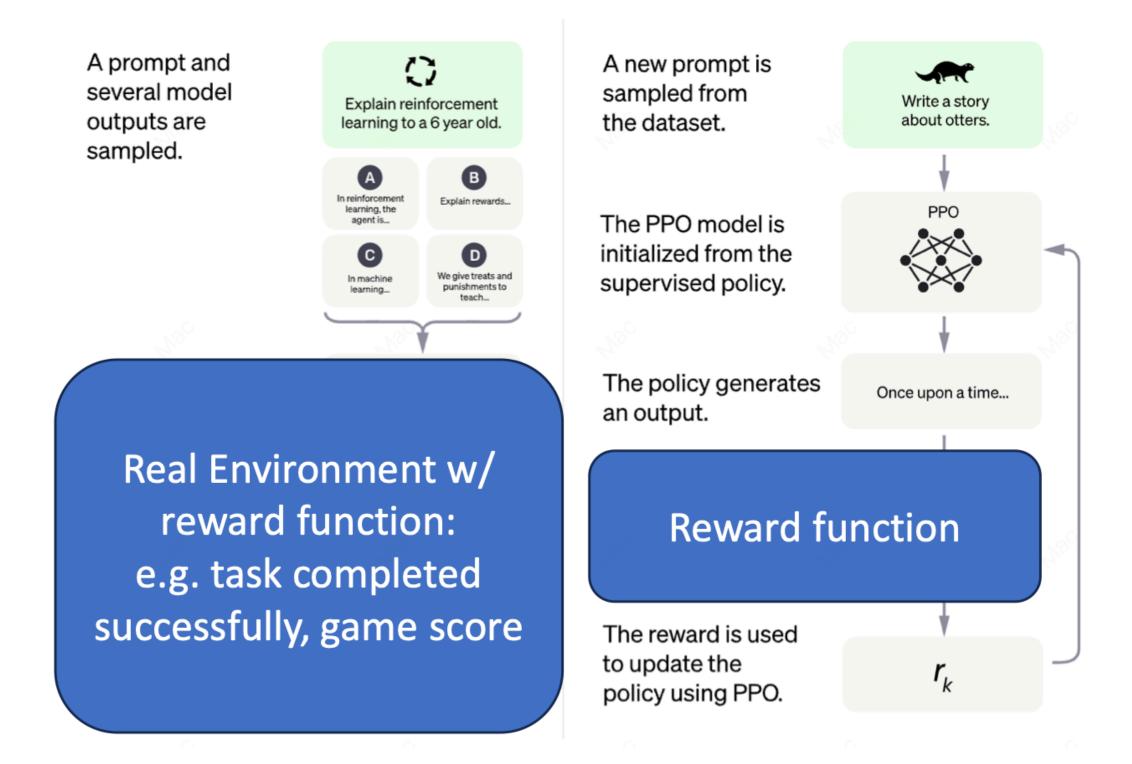


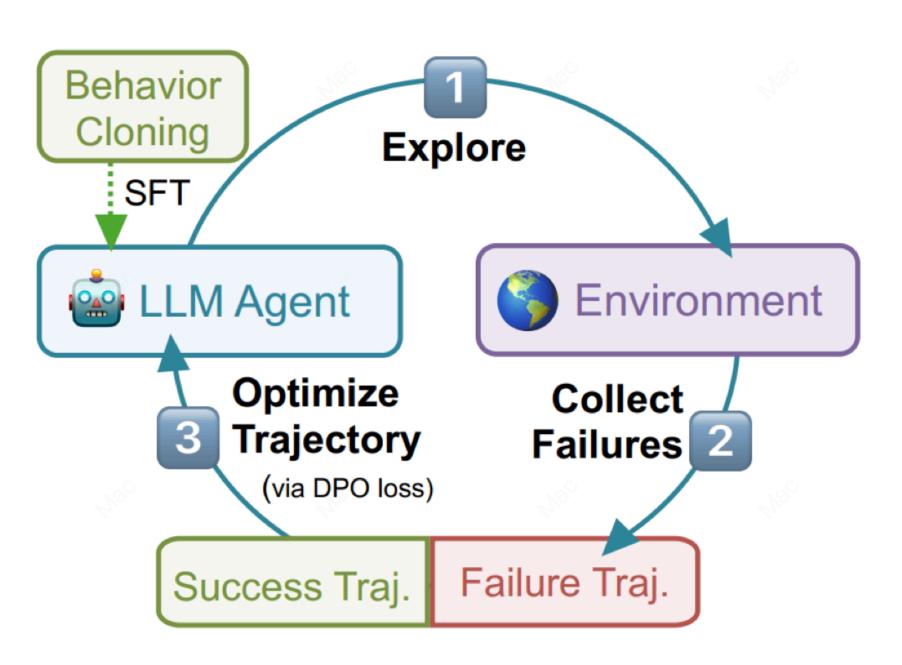
RLHF, Ouyang, et al. 22'

### Reinforcement Learning

### Compared to RLHF:

Given environment, reward function (trajectory, reward) pairs without human





Trial and Error (Song et al. 24')

## Reinforcement Learning

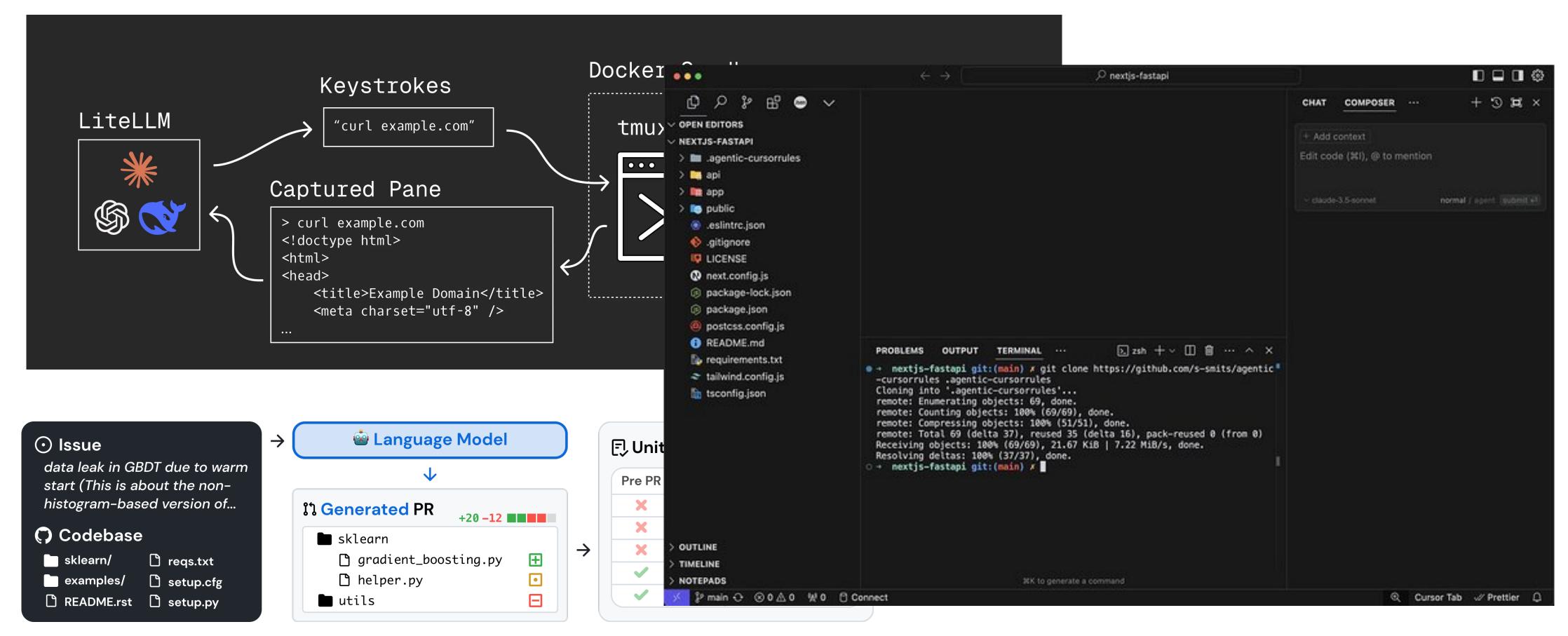
Closed loop, interactive environment

- Need good reward functions
  - O What if the task success/fail is not easy to automatically assess?

- Need good initial models
  - Has decent basic knowledge ability, sparse rewards
- Scalability
  - The environment takes 10 seconds to env.step()
  - The reward function takes 100 seconds to get a scalar reward

### **RL Environments**

Environments and benchmarks typically come together



Research and Products are really close nowadays, and we can directly RL in real, product-level environments

### Thank You!