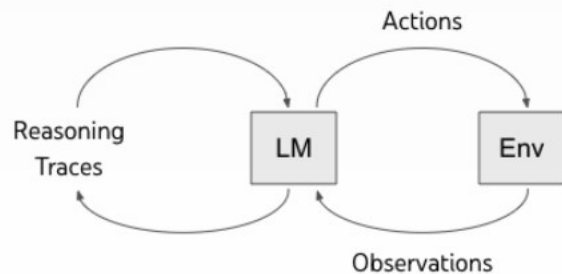




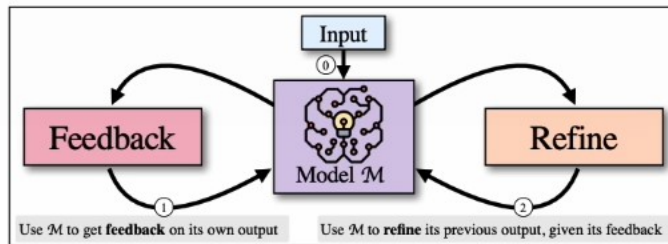
LangGraph supports Cyclic Graphs



ReAct (Reason + Act)

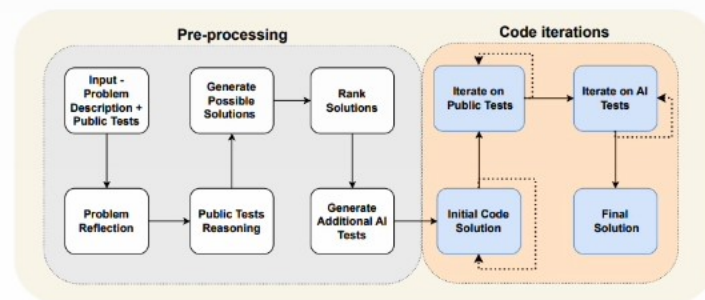
REACT: SYNERGIZING REASONING AND ACTING IN LANGUAGE MODELS

<https://arxiv.org/pdf/2210.03629.pdf>



SELF-REFINE:
Iterative Refinement with Self-Feedback

<https://arxiv.org/pdf/2303.17651.pdf>



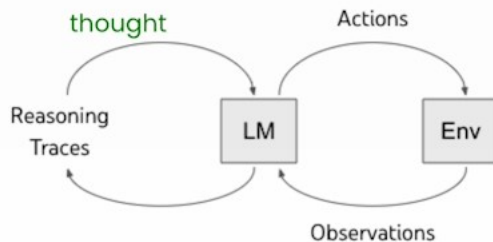
(a) The proposed AlphaCodium flow.

Code Generation with AlphaCodium: From Prompt Engineering to Flow Engineering

<https://arxiv.org/pdf/2401.08500.pdf>



Let's build an agent from scratch

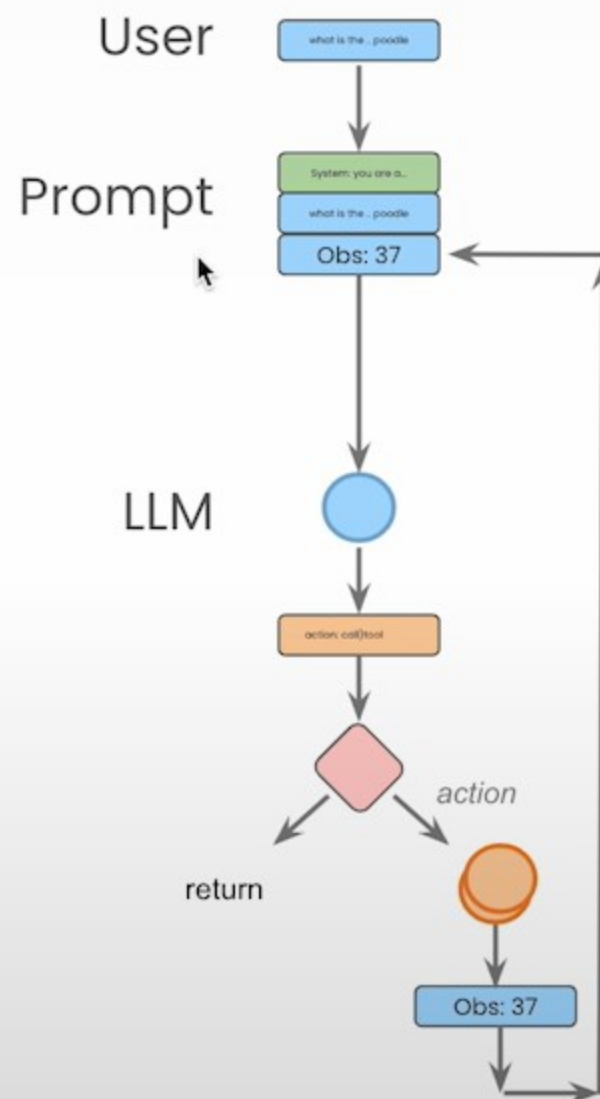


ReAct (Reason + Act)

Published as a conference paper at ICLR 2023

REACT: SYNERGIZING REASONING AND ACTING IN LANGUAGE MODELS

Break Down



System:

You run in a loop of Thought, Action, PAUSE, Observation.

...
Your available actions are:

calculate:
e.g. calculate: 4 * 7 / 3

...
Example session:

User:

... weight of collie...

'Thought: To find the combined weight of a Border Collie and a Scottish Terrier, I need to first find the average weight of each breed and then add those weights together.

Action: average_dog_weight: Border Collie\n PAUSE'

tool

Observation: a Border Collies average weight is 37 lbs

```

def query(question, max_turns=5):
    i = 0
    bot = Agent(prompt)
    next_prompt = question
    while i < max_turns:
        i += 1
        result = bot(next_prompt)
        print(result)
        actions = [action_re.match(a) for a in result.split('\n') if action_re.match(a)]
        if actions:
            # There is an action to run
            action, action_input = actions[0].groups()
            if action not in known_actions:
                raise Exception("Unknown action: {}: {}".format(action, action_input))
            print("-- running {} {}".format(action, action_input))
            observation = known_actions[action](action_input)
            print("Observation:", observation)
            next_prompt = "Observation: {}".format(observation)
        else:
            return
  
```

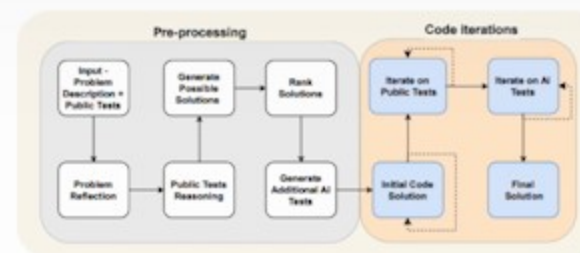
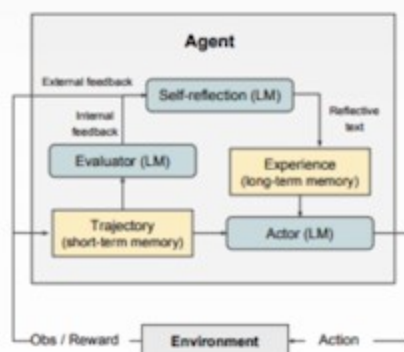
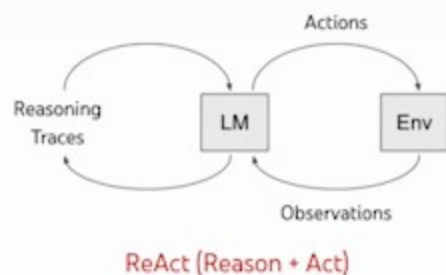
```

def calculate(what):
    return eval(what)
  
```

```

def average_dog_weight(name):
    if name in "Scottish Terrier":
        return("Scottish Terriers average 20 lbs")
    elif name in "Border Collie":
        return("a Border Collies average weight is 37 lbs")
    elif name in "Toy Poodle":
        return("a toy poodles average weight is 7 lbs")
    else:
        return("An average dog weights 50 lbs")
  
```

Graphs



(a) The proposed AlphaCodium flow.

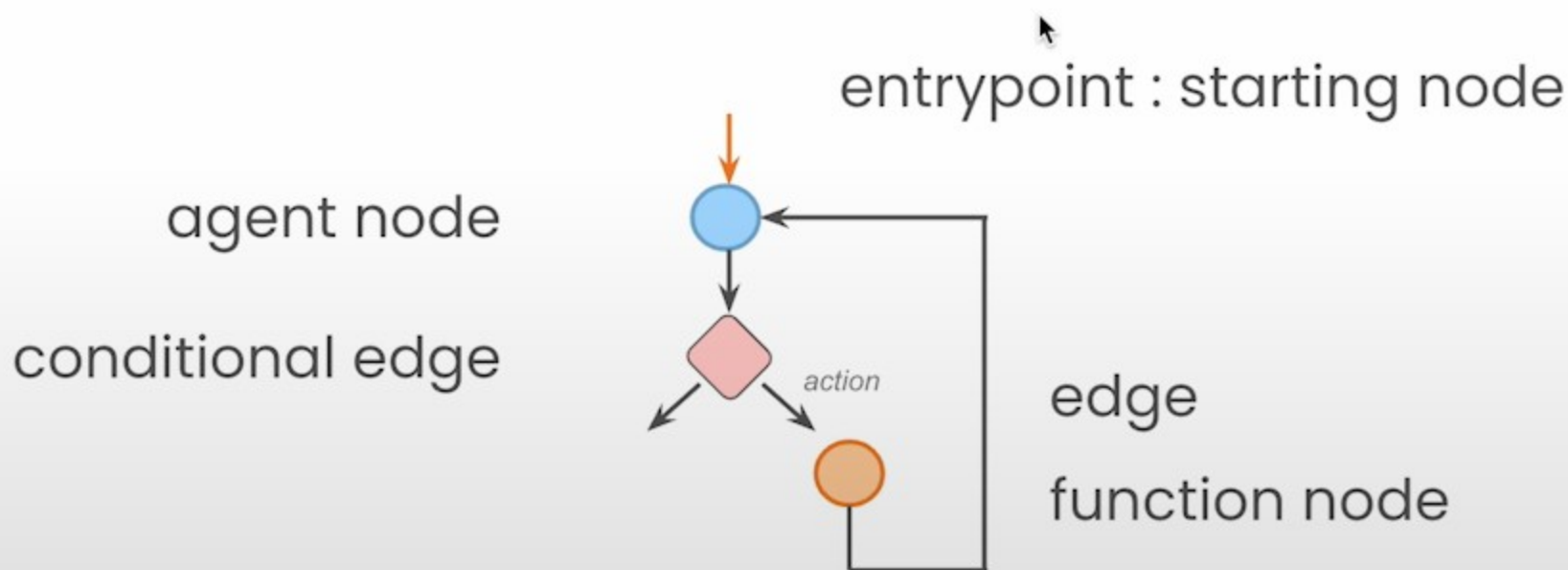
- LangGraph is an extension of LangChain that supports graphs.
- Single and Multi-agent flows are described and represented as graphs.
- Allows for extremely controlled “flows”
- Built-in persistence allows for human-in-the-loop workflows

Graphs

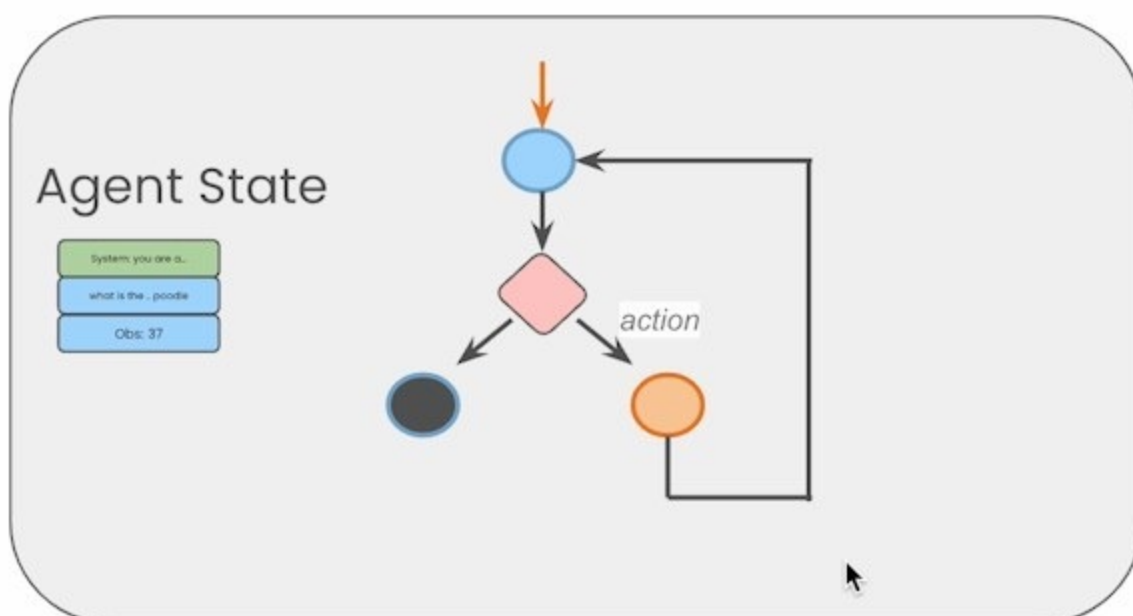
  **Nodes:** Agents or functions

 **Edges:** connect nodes

 **Conditional edges:** decisions



Data/State



- Agent State is accessible to all parts of the graph
- It is local to the graph
- Can be stored in a persistence layer

Simple

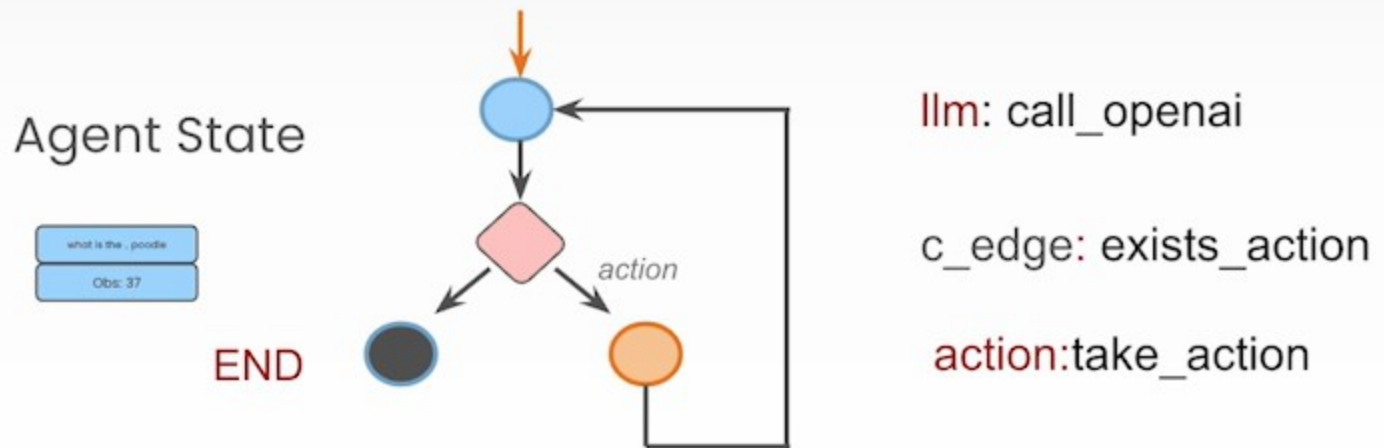
1. BaseMessage is a langchain type. It's annotated with `operator.add`.
2. Whenever there are new messages it would instead of overwriting.
3. Intermediate steps are tracked

```
class AgentState(TypedDict):
    messages: Annotated[Sequence[BaseMessage], operator.add]
```

Complex

```
class AgentState(TypedDict):
    input: str
    chat_history: list[BaseMessage]
    agent_outcome: Union[AgentAction, AgentFinish, None]
    intermediate_steps: Annotated[list[tuple[AgentAction, str]], operator.add]
```

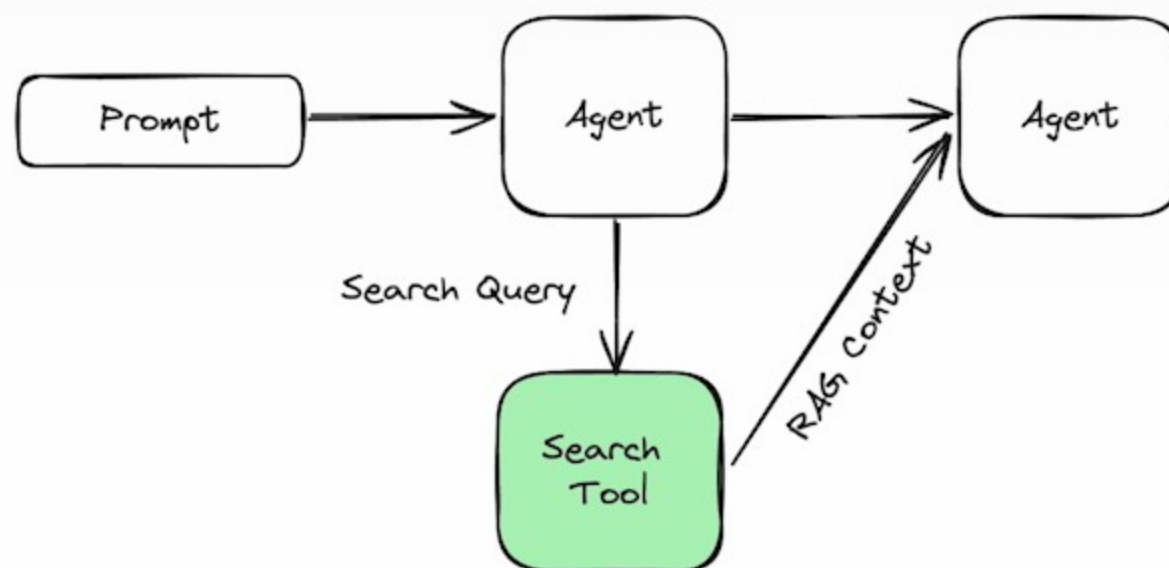
CODE



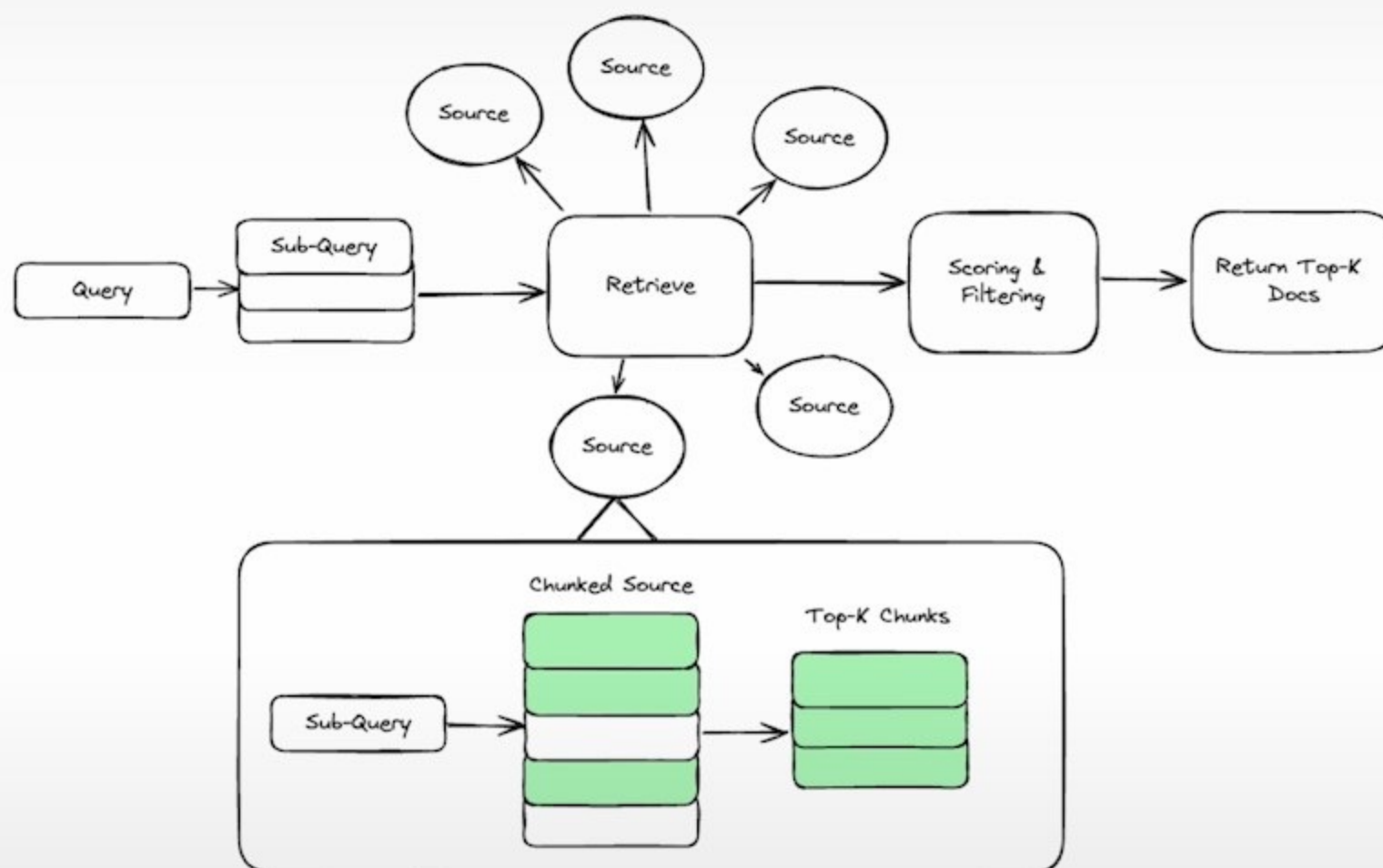
State

```
class AgentState(TypedDict):  
    messages: Annotated[list[AnyMessage], operator.add]
```

Why Search Tool

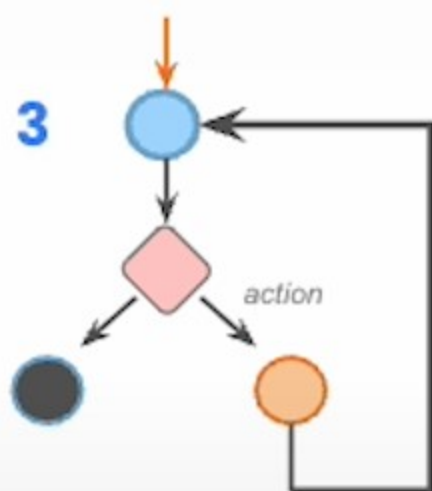


Inside a Search Tool

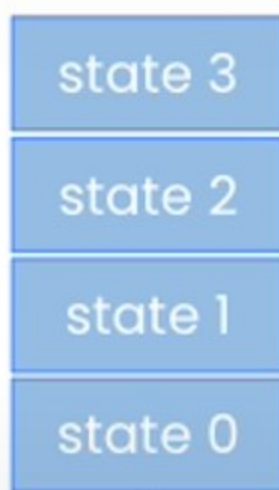


1. It would understand the questions and divide into sub questions.
2. Find the best source choosing from multiple integrations.
3. Should extract the relevant information from the search tool.
 - a. Chunking the search results
 - b. Vector search -> retrieve top k
 - c. Score the results from various sources.
 - d. Filter out less relevant

State Memory



Memory

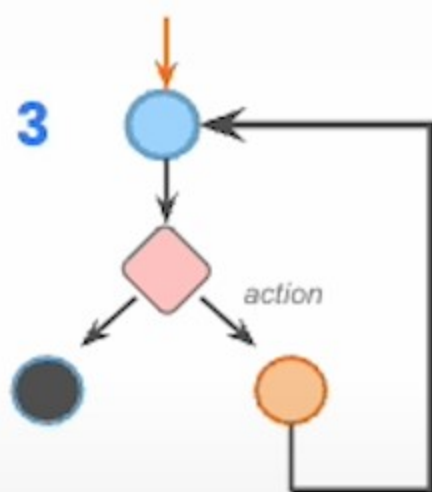


StateSnapshot: { AgentState, useful_things }

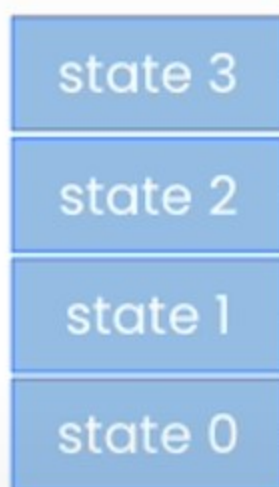
{ .., thread, thread_ts.. }

config={ 'configurable': { 'thread_id': '1',
 'thread_ts': '1ef17b36-ed06-6185-8001-15cf75dea535' } }

State Memory



Memory

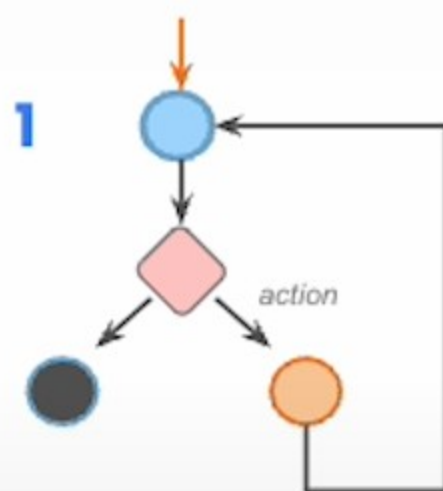


`g.get_state_history(thread)`

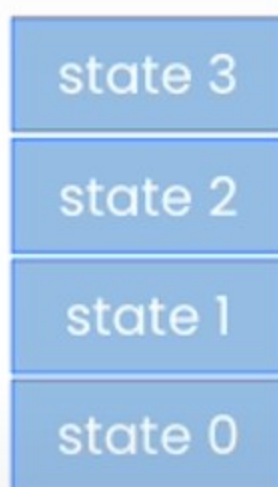


Returns iterator over all
StateSnapshots

State Memory



Memory

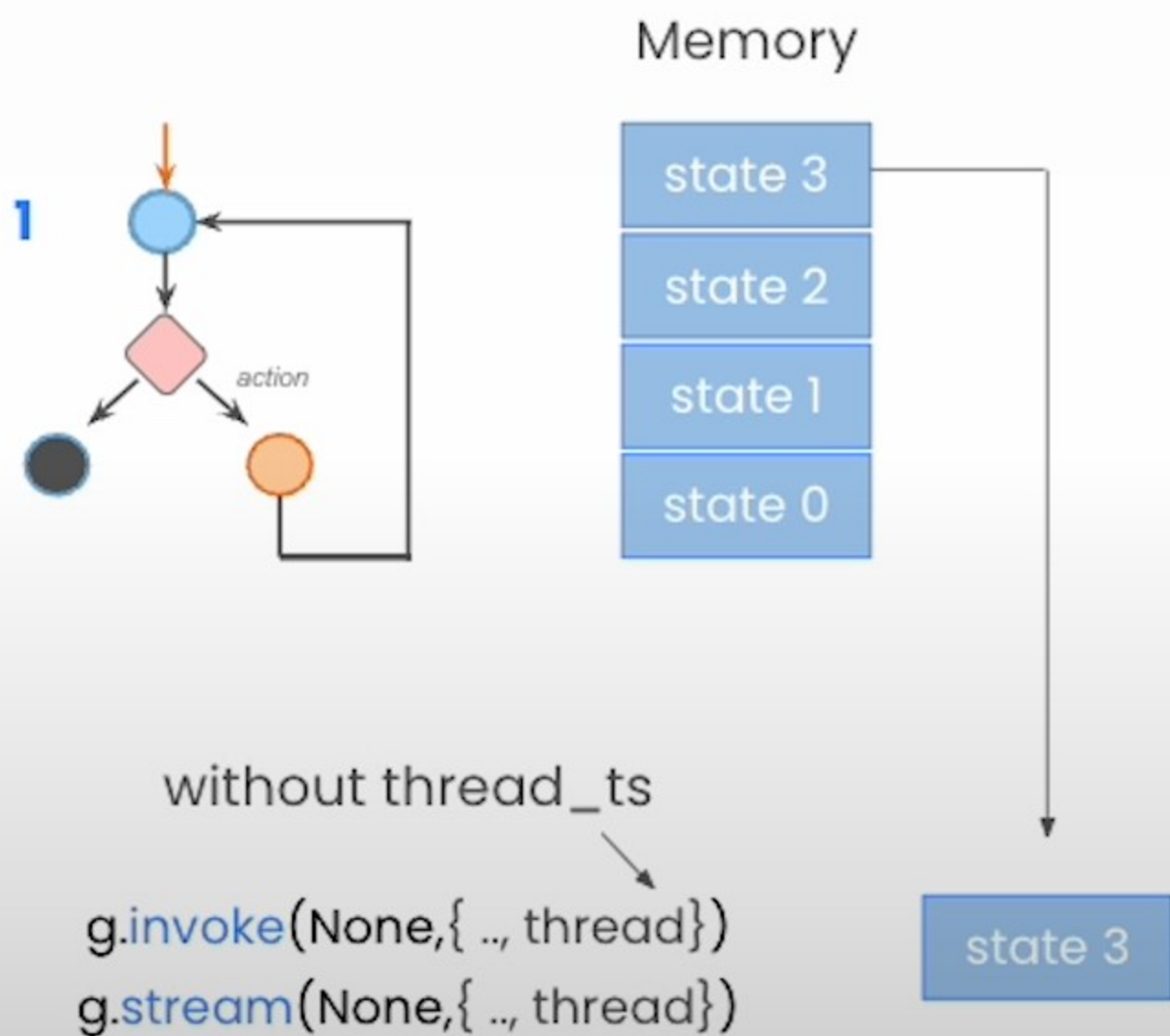


```
g.invoke(None, { .., thread, thread_ts.. })  
g.stream(None, { .., thread, thread_ts.. })
```

state 1

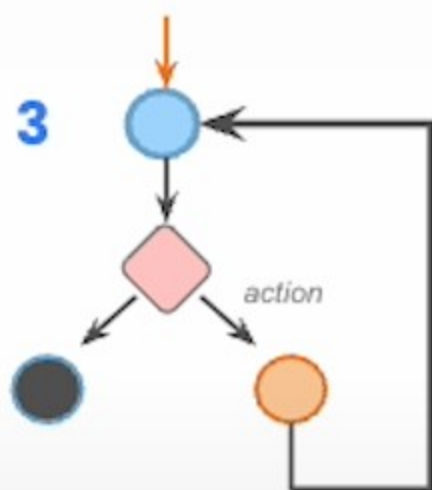
runs with state 1 as starting point
Time Travel

State Memory

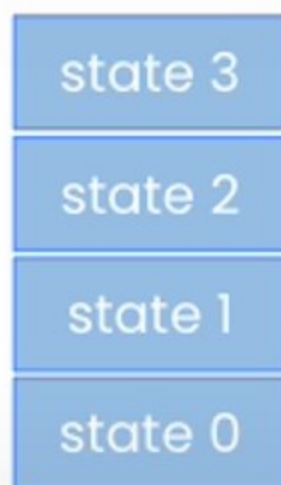


Uses current state as starting point

State Memory



Memory

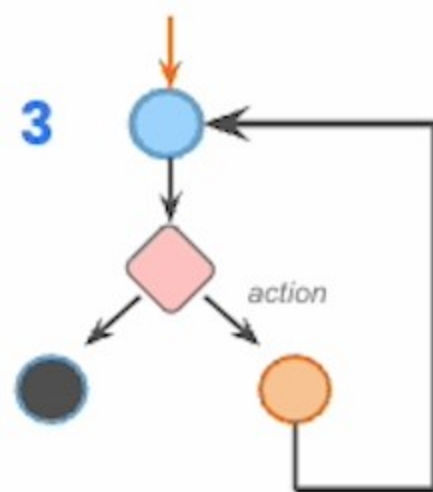


`g.get_state({thread, thread_ts})`

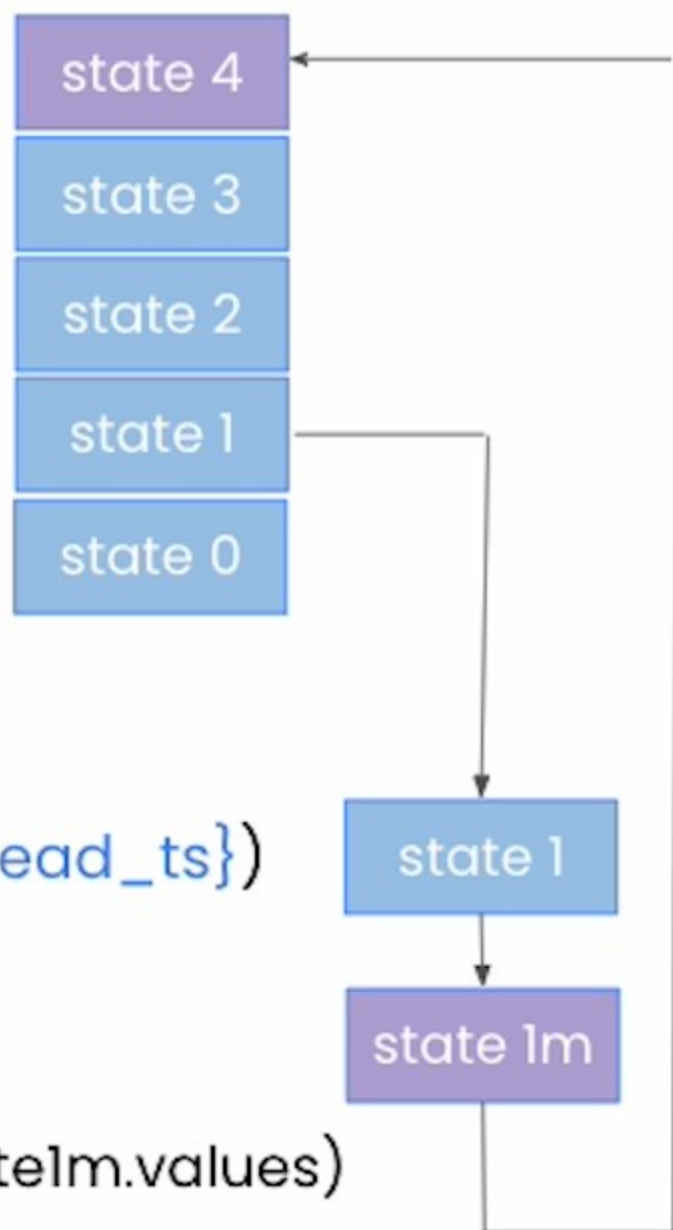
state 1

Returns 'thread_ts
state-snapshot'

State Memory



Memory



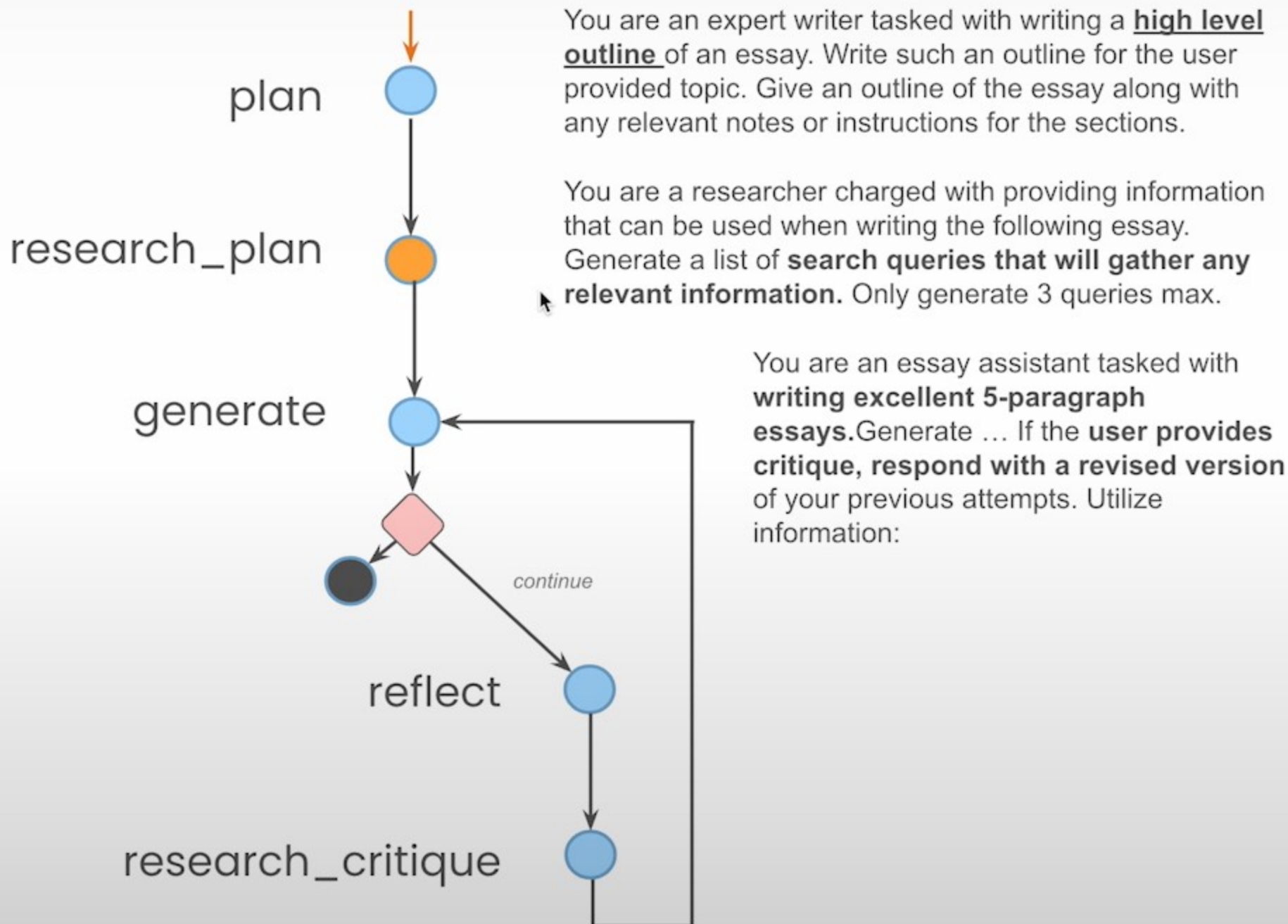
```
g.get_state({thread, thread_ts})
```

modify it

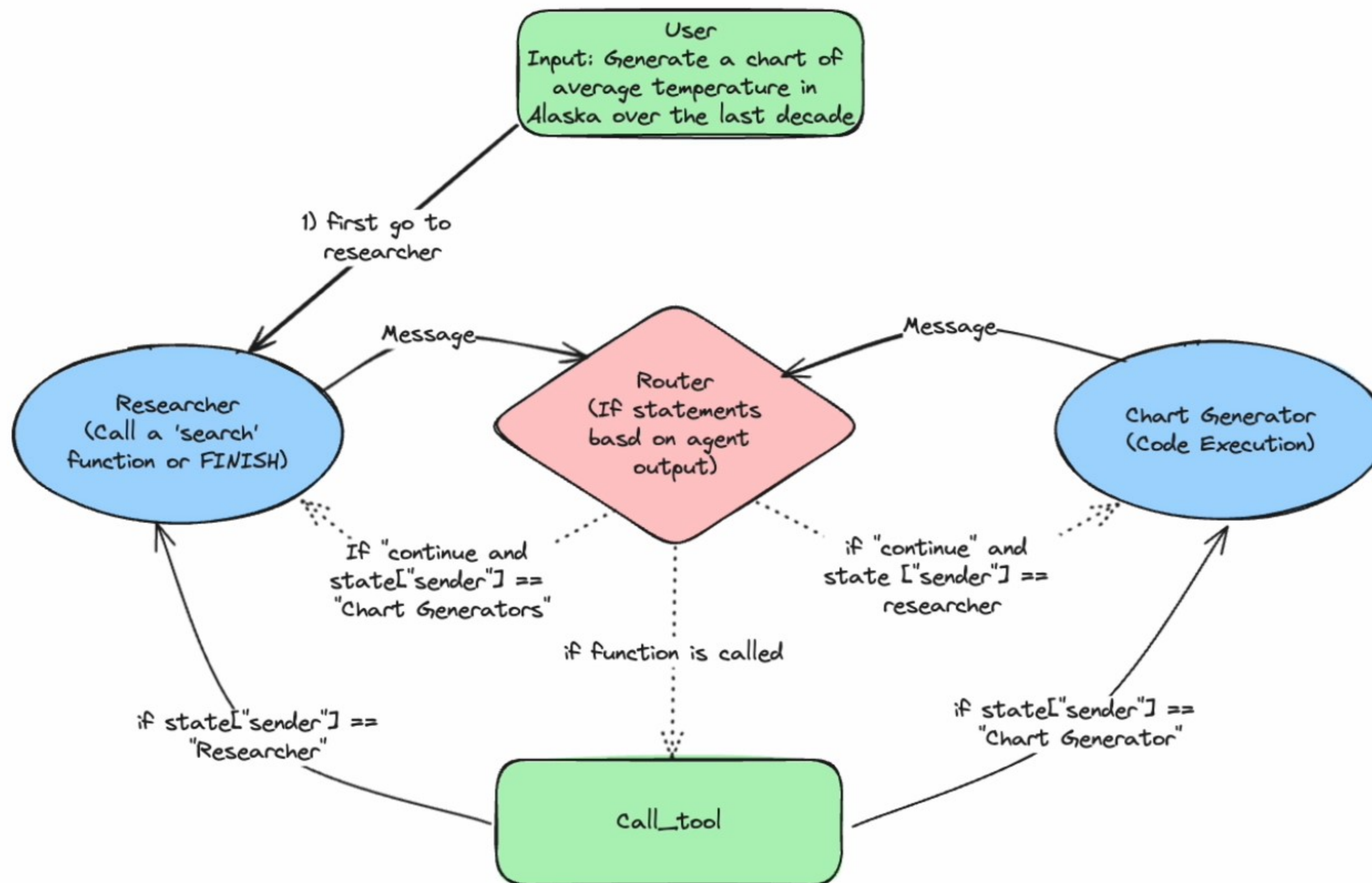
```
g.update_state(thread, state1m.values)
```

run it `g.stream(None, thread)`

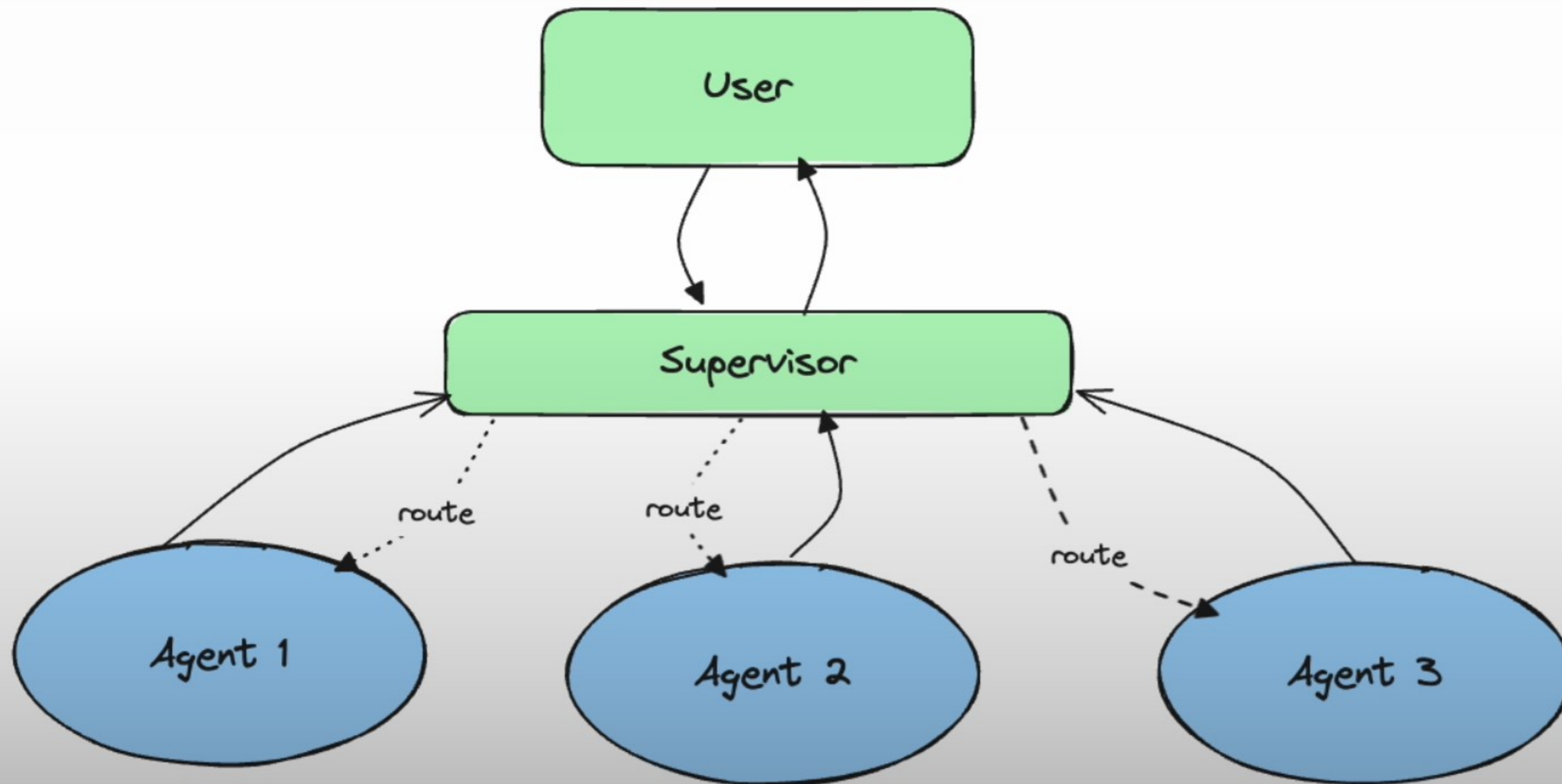
Essay Writer



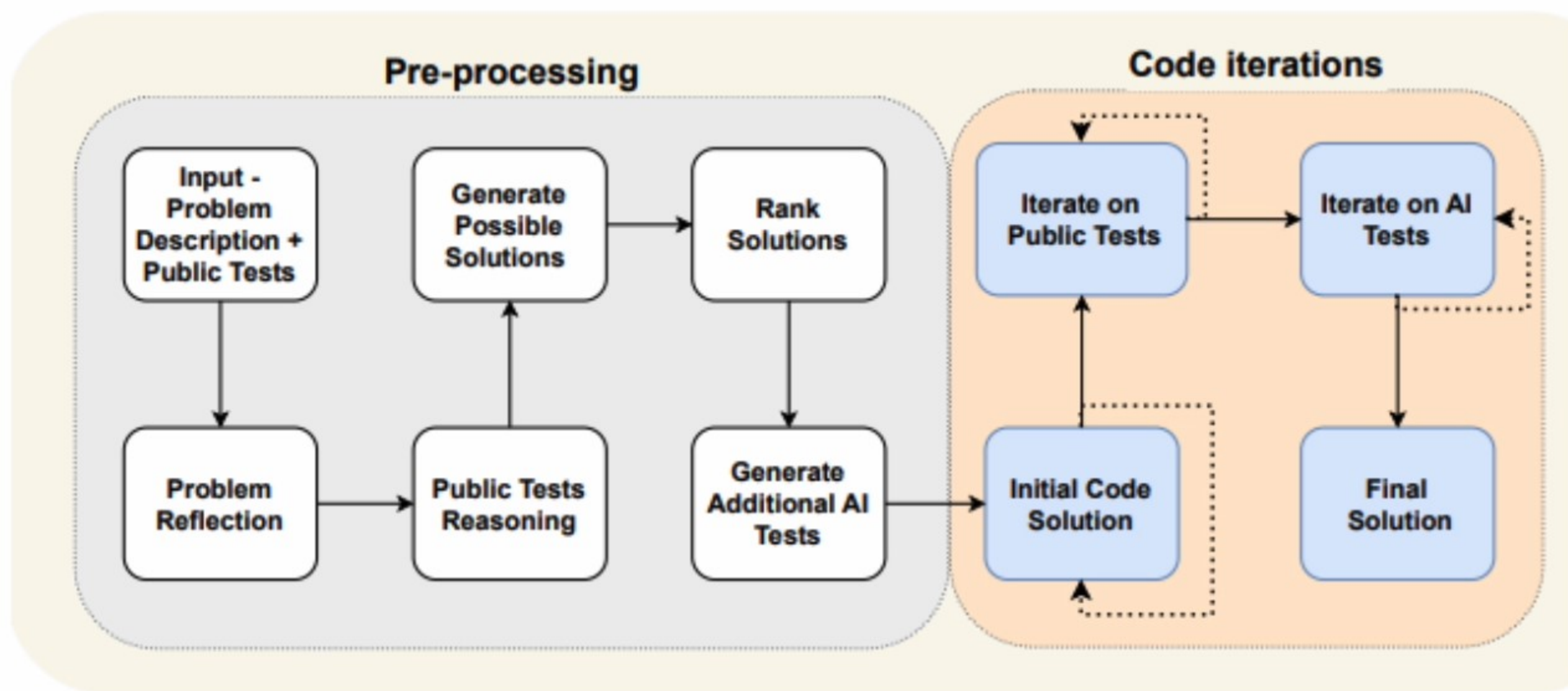
Multi-Agent



Supervisor



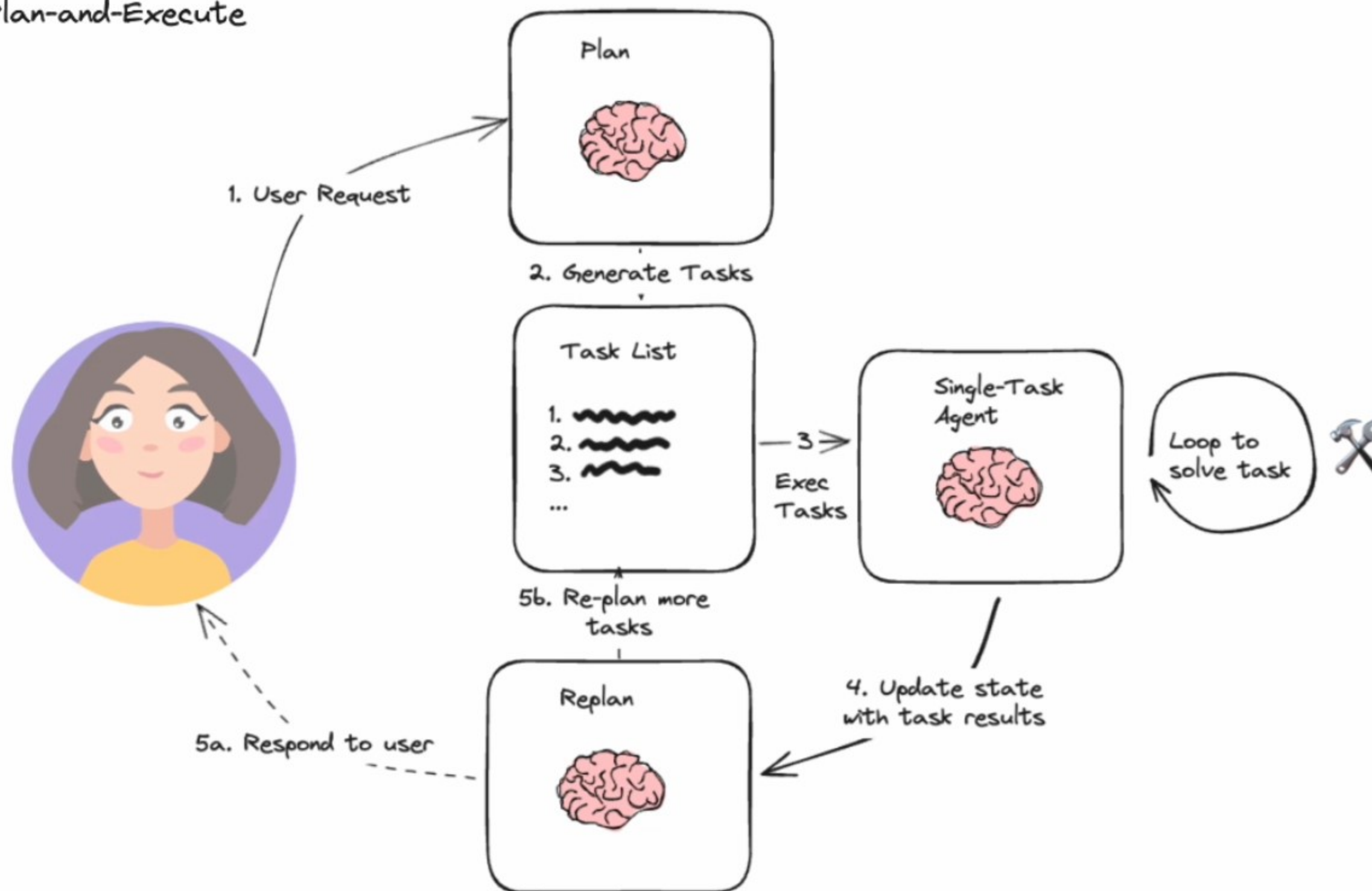
Flow Engineering



(a) The proposed AlphaCodium flow.

Plan and Execute

Plan-and-Execute



Language Agent Tree Search

