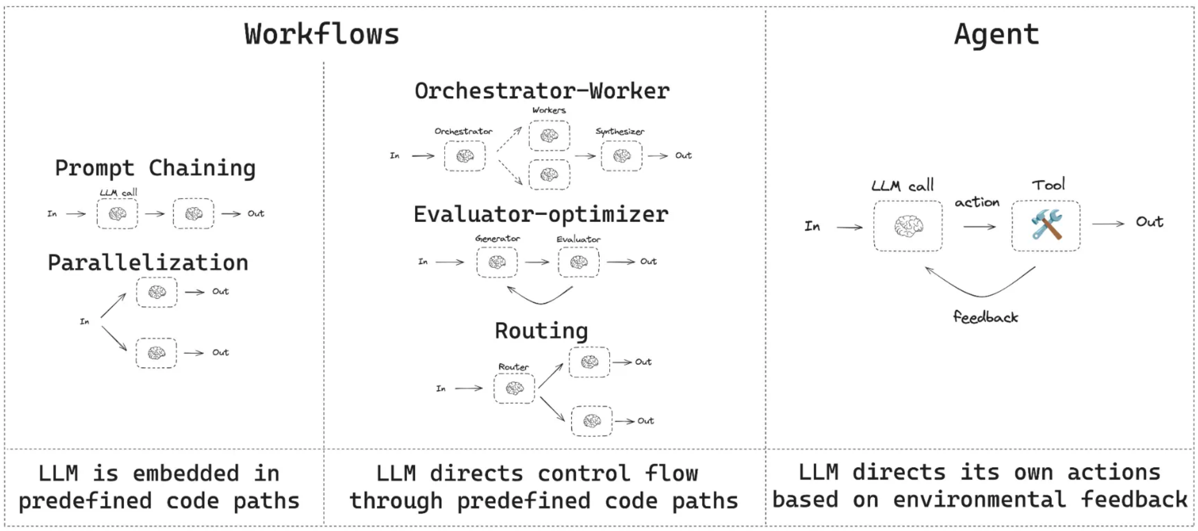
Workflow And Agents

Common Patterns

- AnthropicAI **Building effective agents**

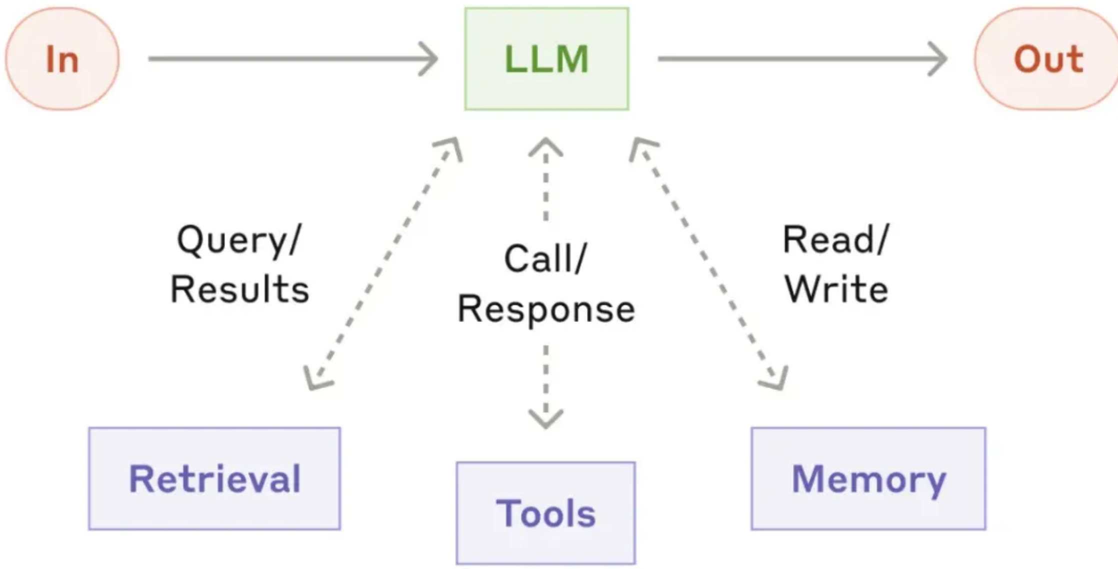
1. **Workflow**:
   a. Create a scaffolding of predefined code paths around LLM calls
   b. LLMs directs control flow through predefined code paths
2. **Agent**: Remove this scaffolding (LLM directs its own **actions**, responds to **feedback**)



Why Frameworks?

- Implementing these patterns *does not* require a framework like LangGraph.
- LangGraph aims to *minimize* overhead of implementing these patterns.
- LangGraph provides supporting infrastructure underneath *any**workflow / agent:
  - **Persistence**
    - Memory
    - Human-In-The-Loop
  - **Streaming**
    - From any LLM call or step in workflow / agent
  - **Deployment**
    - Testing, debugging, and deploying

Augmented LLM

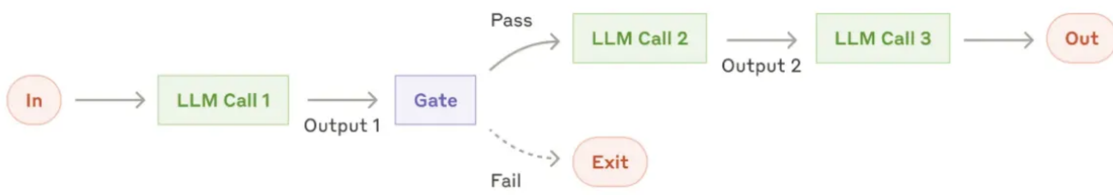



```
# LLM from langchain_anthropic import ChatAnthropic llm = ChatAnthropic(model="claude-3-5
-sonnet-latest")
```

```
# Schema for structured output from pydantic import BaseModel, Field class SearchQuery(Ba
seModel): search_query: str = Field(None, description="Query that is optimized web searc
h.") justification: str = Field( None, justification="Why this query is relevant to the u
ser's request." ) # Augment the LLM with schema for structured output structured_llm = ll
m.with_structured_output(SearchQuery) # Invoke the augmented LLM output = structured_llm.
invoke("How does Calcium CT score relate to high cholesterol?") print(output.search_quer
y) print(output.justification)
```

```
# Define a tool def multiply(a: int, b: int) -> int: return a * b # Augment the LLM with
tools llm_with_tools = llm.bind_tools([multiply]) # Invoke the LLM with input that trigge
rs the tool call msg = llm_with_tools.invoke("What is 2 times 3?") # Get the tool call ms
g.tool_calls
```

Prompt Chaining



Each LLM call processes the output of the previous one:

- E.g., when decomposing a task into multiple LLM calls has benefit.

Example:

- Take a topic, LLM makes a joke, check the joke, improve it twice

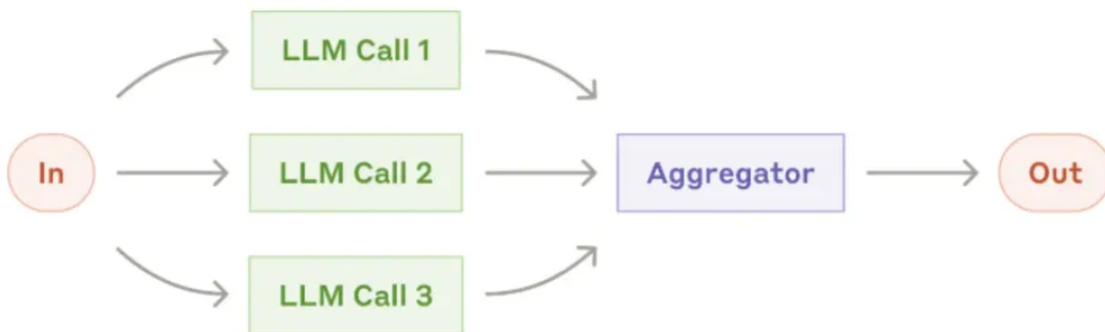
```
from typing_extensions import TypedDict # Graph state class State(TypedDict): topic: str
joke: str improved_joke: str final_joke: str
```

```
# Nodes def generate_joke(state: State): """First LLM call to generate initial joke""" ms
g = llm.invoke(f"Write a short joke about {state['topic']}") return {"joke": msg.content}
def improve_joke(state: State): """Second LLM call to improve the joke""" msg = llm.invok
e(f"Make this joke funnier by adding wordplay: {state['joke']}") return {"improved_joke":
msg.content} def polish_joke(state: State): """Third LLM call for final polish""" msg = l
lm.invoke(f"Add a surprising twist to this joke: {state['improved_joke']}") return {"fina
l_joke": msg.content} # Conditional edge function to check if the joke has a punchline de
f check_punchline(state: State): """Gate function to check if the joke has a punchline"""
# Simple check - does the joke contain "?" or "!" if "?" in state["joke"] or "!" in state
["joke"]: return "Pass" return "Fail"
```

```
from langgraph.graph import StateGraph, START, END from IPython.display import Image, dis
play # Build workflow workflow = StateGraph(State) # Add nodes workflow.add_node("generat
e_joke", generate_joke) workflow.add_node("improve_joke", improve_joke) workflow.add_node
("polish_joke", polish_joke) # Add edges to connect nodes workflow.add_edge(START, "gener
ate_joke") workflow.add_conditional_edges( "generate_joke", check_punchline, {"Pass": "im
prove_joke", "Fail": END} ) workflow.add_edge("improve_joke", "polish_joke") workflow.add
_edge("polish_joke", END) # Compile chain = workflow.compile() # Show workflow display(Im
age(chain.get_graph().draw_mermaid_png()))
```

```
state = chain.invoke({"topic": "cats"}) print("Initial joke:") print(state["joke"]) print
("\n--- --- ---\n") if "improved_joke" in state: print("Improved joke:") print(state["imp
roved_joke"]) print("\n--- --- ---\n") print("Final joke:") print(state["final_joke"]) el
se: print("Joke failed quality gate - no punchline detected!")
```

Parallelization



- Sub-tasks can be parallelized.
    - E.g., when you want multi-perspectives for one task multi-query for RAG).
    - E.g., when independent tasks can be performed w/ different prompts.

Example:

- Take a topic, create a joke, story, and poem

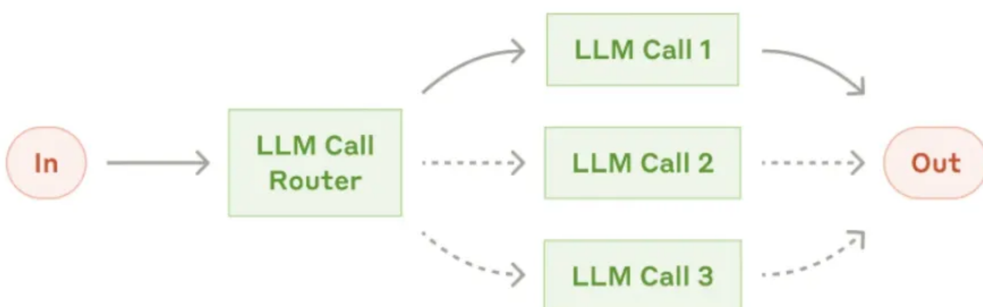
```
# Graph state class State(TypedDict): topic: str joke: str story: str poem: str combined_
output: str
```

```
# Nodes def call_llm_1(state: State): """First LLM call to generate initial joke""" msg =
llm.invoke(f"Write a joke about {state['topic']}") return {"joke": msg.content} def call_
llm_2(state: State): """Second LLM call to generate story""" msg = llm.invoke(f"Write a s
tory about {state['topic']}") return {"story": msg.content} def call_llm_3(state: State):
"""Third LLM call to generate poem""" msg = llm.invoke(f"Write a poem about {state['topi
c']}") return {"poem": msg.content} def aggregator(state: State): """Combine the joke and
story into a single output""" combined = f"Here's a story, joke, and poem about {state['t
opic']}!\n\n" combined += f"STORY:\n{state['story']}\n\n" combined += f"JOKE:\n{state['jo
ke']}\n\n" combined += f"POEM:\n{state['poem']}" return {"combined_output": combined}
```

```
# Build workflow parallel_builder = StateGraph(State) # Add nodes parallel_builder.add_node("call_llm_1", call_llm_1) parallel_builder.add_node("call_llm_2", call_llm_2) parallel_builder.add_node("call_llm_3", call_llm_3) parallel_builder.add_node("aggregator", aggregator) # Add edges to connect nodes parallel_builder.add_edge(START, "call_llm_1") parallel_builder.add_edge(START, "call_llm_2") parallel_builder.add_edge(START, "call_llm_3") parallel_builder.add_edge("call_llm_1", "aggregator") parallel_builder.add_edge("call_llm_2", "aggregator") parallel_builder.add_edge("call_llm_3", "aggregator") parallel_builder.add_edge("aggregator", END) parallel_workflow = parallel_builder.compile() # Show workflow display(Image(parallel_workflow.get_graph().draw_mermaid_png()))
```

```
state = parallel_workflow.invoke({"topic": "cats"}) print(state["combined_output"])
```

Routing



Routing classifies an input and directs it to a specialized followup task.

- E.g., when routing a question to different retrieval systems.

Example:

- Route an input between joke, story, and poem

```
from typing_extensions import Literal # Schema for structured output to use as routing logic class Route(BaseModel): step: Literal["poem", "story", "joke"] = Field( None, description="The next step in the routing process" ) # Augment the LLM with schema for structured output router = llm.with_structured_output(Route)
```

```
# State class State(TypedDict): input: str decision: str output: str
```

```
from langchain_core.messages import HumanMessage, SystemMessage # Nodes def llm_call_1(state: State): """Write a story""" print("Write a story") result = llm.invoke(state["input"]) return {"output": result.content} def llm_call_2(state: State): """Write a joke""" print("Write a joke") result = llm.invoke(state["input"]) return {"output": result.content} def llm_call_3(state: State): """Write a poem""" print("Write a poem") result = llm.invoke(state["input"]) return {"output": result.content} def llm_call_router(state: State): """Route the input to the appropriate node""" # Run the augmented LLM with structured output to serve as routing logic decision = router.invoke( [ SystemMessage( content="Route the input to story, joke, or poem based on the user's request." ), HumanMessage(content=state["input"]), ] ) return {"decision": decision.step} # Conditional edge function to route to the appropriate node def route_decision(state: State): # Return the node name you want to visit next if state["decision"] == "story": return "llm_call_1" elif state["decision"] == "joke": return "llm_call_2" elif state["decision"] == "poem": return "llm_call_3"
```

```
# Build workflow router_builder = StateGraph(State) # Add nodes router_builder.add_node("llm_call_1", llm_call_1) router_builder.add_node("llm_call_2", llm_call_2) router_builder.add_node("llm_call_3", llm_call_3) router_builder.add_node("llm_call_router", llm_call_router) # Add edges to connect nodes router_builder.add_edge(START, "llm_call_router") router_builder.add_conditional_edges( "llm_call_router", route_decision, { # Name returned by route_decision : Name of next node to visit "llm_call_1": "llm_call_1", "llm_call_2": "llm_call_2", "llm_call_3": "llm_call_3", }, ) router_builder.add_edge("llm_call_1", END) router_builder.add_edge("llm_call_2", END) router_builder.add_edge("llm_call_3", END) # Compile workflow router_workflow = router_builder.compile() # Show the workflow display(Image(router_workflow.get_graph().draw_mermaid_png()))
```

```
state = router_workflow.invoke({"input": "Write me a joke about cats"}) print(state["output"])
```

Orchestrator-Worker

Orchestrator breaks down a task and delegates each sub-task to workers.

- E.g., planning a report where LLM can determine the number of sections.

Example

- Take a topic, plan a report of section, have each worker write a section

```
from typing import Annotated, List import operator # Schema for structured output to use
in planning class Section(BaseModel): name: str = Field( description="Name for this secti
on of the report.", ) description: str = Field( description="Brief overview of the main t
opics and concepts to be covered in this section.", ) class Sections(BaseModel): section
s: List[Section] = Field( description="Sections of the report.", ) # Augment the LLM with
schema for structured output planner = llm.with_structured_output(Sections)
```

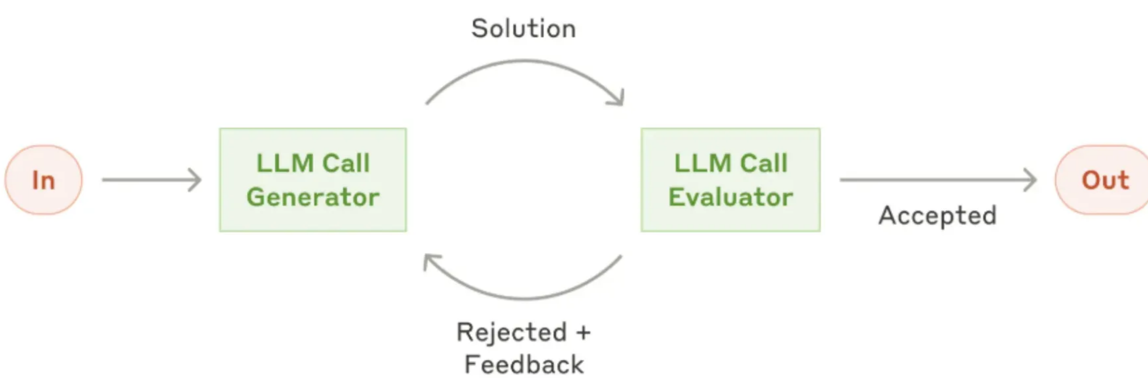
```
# Graph state class State(TypedDict): topic: str # Report topic sections: list[Section] #
List of report sections completed_sections: Annotated[ list, operator.add ] # All workers
write to this key in parallel final_report: str # Final report # Worker state class Worke
rState(TypedDict): section: Section completed_sections: Annotated[list, operator.add]
```

```
# Nodes def orchestrator(state: State): """Orchestrator that generates a plan for the rep
ort""" # Generate queries report_sections = planner.invoke( [ SystemMessage(content="Gene
rate a plan for the report."), HumanMessage(content=f"Here is the report topic: {state['t
opic']}"), ] ) return {"sections": report_sections.sections} def llm_call(state: WorkerSt
ate): """Worker writes a section of the report""" # Generate section section = llm.invoke
( [ SystemMessage(content="Write a report section."), HumanMessage( content=f"Here is the
section name: {state['section'].name} and description: {state['section'].description}" ),
] ) # Write the updated section to completed sections return {"completed_sections": [sect
ion.content]} def synthesizer(state: State): """Synthesize full report from sections""" #
List of completed sections completed_sections = state["completed_sections"] # Format comp
leted section to str to use as context for final sections completed_report_sections = "\n
\n---\n\n".join(completed_sections) return {"final_report": completed_report_sections} #
Conditional edge function to create llm_call workers that each write a section of the rep
ort def assign_workers(state: State): """Assign a worker to each section in the plan""" #
Kick off section writing in parallel via Send() API return [Send("llm_call", {"section":
s}) for s in state["sections"]]
```

```
from langgraph.constants import Send # Build workflow orchestrator_worker_builder = State
Graph(State) # Add the nodes orchestrator_worker_builder.add_node("orchestrator", orchest
rator) orchestrator_worker_builder.add_node("llm_call", llm_call) orchestrator_worker_bui
lder.add_node("synthesizer", synthesizer) # Add edges to connect nodes orchestrator_worke
r_builder.add_edge(START, "orchestrator") orchestrator_worker_builder.add_conditional_edg
es( "orchestrator", assign_workers, ["llm_call"] ) orchestrator_worker_builder.add_edge
("llm_call", "synthesizer") orchestrator_worker_builder.add_edge("synthesizer", END) # Co
mpile the workflow orchestrator_worker = orchestrator_worker_builder.compile() # Show the
workflow display(Image(orchestrator_worker.get_graph().draw_mermaid_png()))
```

```
state = orchestrator_worker.invoke({"topic": "Create a report on LLM scaling laws"}) from
IPython.display import Markdown Markdown(state["final_report"])
```

Evaluator-optimizer



One LLM call generates a response while another provides evaluation and feedback in a loop.

- E.g., when grading the quality of responses from a RAG system (for hallucinations).

```
# Schema for structured output to use in evaluation class Feedback(BaseModel): grade: Lit
eral["funny", "not funny"] = Field( description="Decide if the joke is funny or not.", )
feedback: str = Field( description="If the joke is not funny, provide feedback on how to
improve it.", ) # Augment the LLM with schema for structured output evaluator = llm.with_
structured_output(Feedback)
```

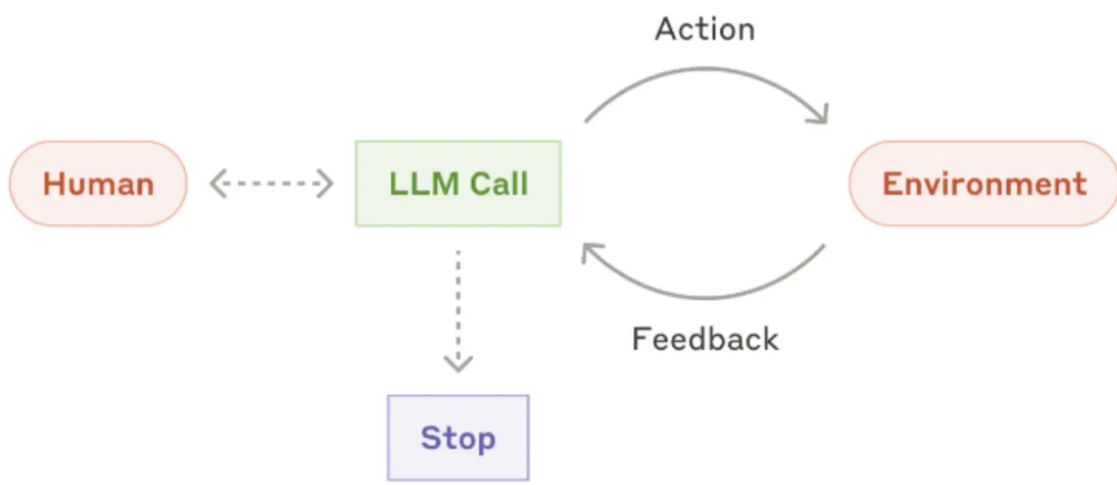
```
# Graph state class State(TypedDict): joke: str topic: str feedback: str funny_or_not: st
r
```

```
# Nodes def llm_call_generator(state: State): """LLM generates a joke""" if state.get("fe
edback"): msg = llm.invoke( f"Write a joke about {state['topic']} but take into account t
he feedback: {state['feedback']}" ) else: msg = llm.invoke(f"Write a joke about {state['t
opic']}") return {"joke": msg.content} def llm_call_evaluator(state: State): """LLM evalu
ates the joke""" grade = evaluator.invoke(f"Grade the joke {state['joke']}") return {"fun
ny_or_not": grade.grade, "feedback": grade.feedback} # Conditional edge function to route
back to joke generator or end based upon feedback from the evaluator def route_joke(stat
e: State): """Route back to joke generator or end based upon feedback from the evaluato
r""" if state["funny_or_not"] == "funny": return "Accepted" elif state["funny_or_not"] ==
"not funny": return "Rejected + Feedback"
```

```
# Build workflow optimizer_builder = StateGraph(State) # Add the nodes optimizer_builder.
add_node("llm_call_generator", llm_call_generator) optimizer_builder.add_node("llm_call_e
valuator", llm_call_evaluator) # Add edges to connect nodes optimizer_builder.add_edge(ST
ART, "llm_call_generator") optimizer_builder.add_edge("llm_call_generator", "llm_call_eva
luator") optimizer_builder.add_conditional_edges( "llm_call_evaluator", route_joke, { # N
ame returned by route_joke : Name of next node to visit "Accepted": END, "Rejected + Feed
back": "llm_call_generator", }, ) # Compile the workflow optimizer_workflow = optimizer_b
uilder.compile() # Show the workflow display(Image(optimizer_workflow.get_graph().draw_me
rmaid_png()))
```

```
state = optimizer_workflow.invoke({"topic": "Cats"}) print(state["joke"])
```

Agent



Agents plan, take actions (via tool-calling), and respond to feedback (in a loop).

- E.g., when solving open-ended problems that you cannot lay out as a workflow

```
from langchain_core.tools import tool # Define tools @tool def multiply(a: int, b: int) -
> int: """Multiply a and b. Args: a: first int b: second int """ return a * b @tool def a
dd(a: int, b: int) -> int: """Adds a and b. Args: a: first int b: second int """ return a
+ b @tool def divide(a: int, b: int) -> float: """Divide a and b. Args: a: first int b: s
econd int """ return a / b # Augment the LLM with tools tools = [add, multiply, divide] t
ools_by_name = {tool.name: tool for tool in tools} llm_with_tools = llm.bind_tools(tools)
```

Python

Copy

```python
from langgraph.graph import MessagesState from langchain_core.messages import ToolMessage
# Nodes def llm_call(state: MessagesState): """LLM decides whether to call a tool or no
t""" return { "messages": [ llm_with_tools.invoke( [ SystemMessage( content="You are a he
lpful assistant tasked with performing arithmetic on a set of inputs." ) ] + state["messa
ges"] ) ] } def tool_node(state: dict): """Performs the tool call""" result = [] for tool
_call in state["messages"][-1].tool_calls: tool = tools_by_name[tool_call["name"]] observ
ation = tool.invoke(tool_call["args"]) result.append(ToolMessage(content=observation, too
l_call_id=tool_call["id"])) return {"messages": result} # Conditional edge function to ro
```