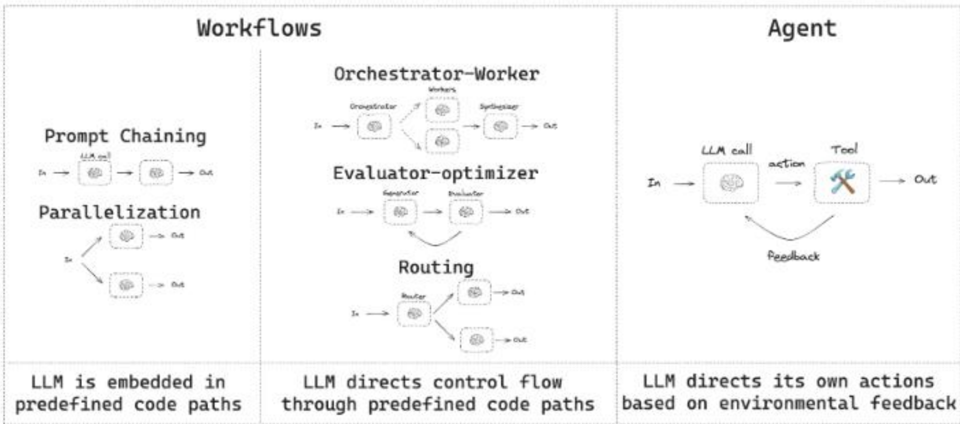
Workflow And Agents

Common Patterns

- AnthropicAI **Building effective agents**

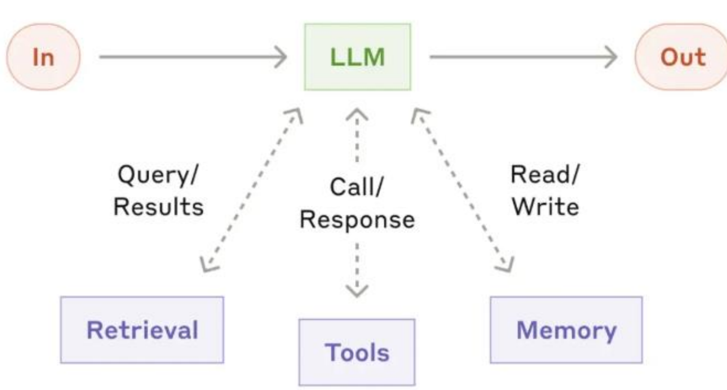
1. **Workflow**:
    a. Create a scaffolding of predefined code paths around LLM calls
    b. LLMs directs control flow through predefined code paths
2. **Agent**: Remove this scaffolding (LLM directs its own **actions**, responds to **feedback**)



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

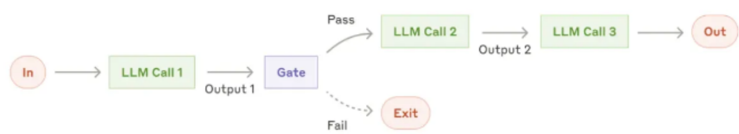
Augmented LLM




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

```python
# Schema for structured output
from pydantic import BaseModel, Field
class SearchQuery(BaseModel):
    search_query: str = Field(None, description="Query that is optimized web search.")
    justification: str = Field(
        None, justification="Why this query is relevant to the user's request."
    )

# Augment the LLM with schema for structured output
structured_llm = llm.with_structured_output(SearchQuery)

# Invoke the augmented LLM
output = structured_llm.invoke("How does Calcium CT score relate to high cholesterol?")
print(output.search_query)
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 triggers the tool call
msg = llm_with_tools.invoke("What is 2 times 3?")

# Get the tool call
msg.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

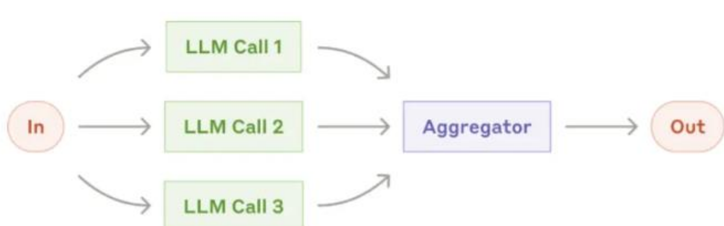
```python
from typing_extensions import TypedDict

# 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"""

    msg = 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.invoke(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 = llm.invoke(f"Add a surprising twist to this joke: {state['improved_joke']}")
    return {"final_joke": msg.content}
```

```python
# Conditional edge function to check if the joke has a punchline
def 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"
```

```python
from langgraph.graph import StateGraph, START, END
from IPython.display import Image, display

# Build workflow
workflow = StateGraph(State)

# Add nodes
workflow.add_node("generate_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, "generate_joke")
workflow.add_conditional_edges(
    "generate_joke", check_punchline, {"Pass": "improve_joke", "Fail": END}
)
workflow.add_edge("improve_joke", "polish_joke")
workflow.add_edge("polish_joke", END)

# Compile
chain = workflow.compile()

# Show workflow
display(Image(chain.get_graph().draw_mermaid_png()))
```

```python
state = chain.invoke({"topic": "cats"})
print("Initial joke:")
print(state["joke"])
print("\n--- --- ---\n")
if "improved_joke" in state:
    print("Improved joke:")
    print(state["improved_joke"])
    print("\n--- --- ---\n")

    print("Final joke:")
    print(state["final_joke"])
else:
    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

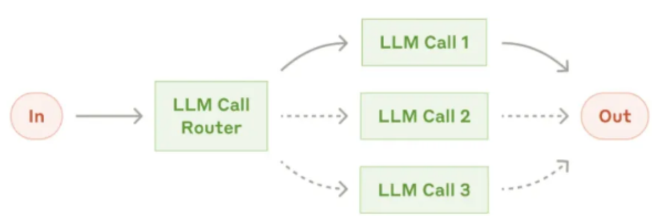
```python
# Graph state
class State(TypedDict):
    topic: str
    joke: str
    story: str
    poem: str
    combined_output: str
```

```python
# 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 story 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['topic']}")
    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['topic']}!\n\n"
    combined += f"STORY:\n{state['story']}\n\n"
    combined += f"JOKE:\n{state['joke']}\n\n"
    combined += f"POEM:\n{state['poem']}"
    return {"combined_output": combined}
```

```python
# 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()))
```

```python
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

```python
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)
```

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

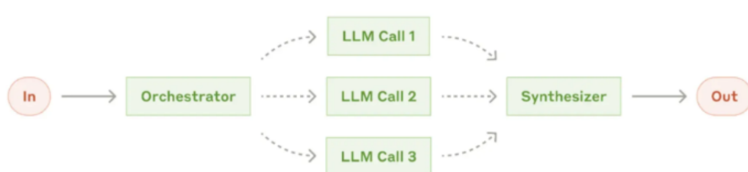
```python
from langchain_core.messages import HumanMessage, SystemMessage

# 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}
```

```python
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 requ
est."
            ),
            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"
```

```python
# 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()))
```

```python
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

```python
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 section of the report.",
    )
    description: str = Field(
        description="Brief overview of the main topics and concepts to be covered in thi
s section.",
    )
```

```python
class Sections(BaseModel):
    sections: List[Section] = Field(
        description="Sections of the report.",
    )

# Augment the LLM with schema for structured output
planner = llm.with_structured_output(Sections)
```

```python
# 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 WorkerState(TypedDict):
    section: Section
    completed_sections: Annotated[list, operator.add]
```

```python
# Nodes
def orchestrator(state: State):
    """Orchestrator that generates a plan for the report"""

    # Generate queries
    report_sections = planner.invoke(
        [
            SystemMessage(content="Generate a plan for the report."),
            HumanMessage(content=f"Here is the report topic: {state['topic']}"),
        ]
    )

    return {"sections": report_sections.sections}


def llm_call(state: WorkerState):
    """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 descripti
on: {state['section'].description}"
            ),
        ]
    )

    # Write the updated section to completed sections
    return {"completed_sections": [section.content]}


def synthesizer(state: State):
    """Synthesize full report from sections"""

    # List of completed sections
    completed_sections = state["completed_sections"]

    # Format completed 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 r
eport
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"]]
```

```python
from langgraph.constants import Send

# Build workflow
orchestrator_worker_builder = StateGraph(State)

# Add the nodes
orchestrator_worker_builder.add_node("orchestrator", orchestrator)
orchestrator_worker_builder.add_node("llm_call", llm_call)
orchestrator_worker_builder.add_node("synthesizer", synthesizer)

# Add edges to connect nodes
orchestrator_worker_builder.add_edge(START, "orchestrator")
orchestrator_worker_builder.add_conditional_edges(
    "orchestrator", assign_workers, ["llm_call"]
)
orchestrator_worker_builder.add_edge("llm_call", "synthesizer")
orchestrator_worker_builder.add_edge("synthesizer", END)

# Compile the workflow
orchestrator_worker = orchestrator_worker_builder.compile()

# Show the workflow
display(Image(orchestrator_worker.get_graph().draw_mermaid_png()))
```

```python
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).

```python
# Schema for structured output to use in evaluation
class Feedback(BaseModel):
    grade: Literal["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)
```

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

```python
# Nodes
def llm_call_generator(state: State):
    """LLM generates a joke"""

    if state.get("feedback"):
        msg = llm.invoke(
            f"Write a joke about {state['topic']} but take into account the feedback: {st
ate['feedback']}"
        )
    else:
        msg = llm.invoke(f"Write a joke about {state['topic']}")
    return {"joke": msg.content}


def llm_call_evaluator(state: State):
    """LLM evaluates the joke"""

    grade = evaluator.invoke(f"Grade the joke {state['joke']}")
    return {"funny_or_not": grade.grade, "feedback": grade.feedback}
```

```python
# Conditional edge function to route back to joke generator or end based upon feedback fr
om the evaluator
def route_joke(state: State):
    """Route back to joke generator or end based upon feedback from the evaluator"""

    if state["funny_or_not"] == "funny":
        return "Accepted"
    elif state["funny_or_not"] == "not funny":
        return "Rejected + Feedback"
```

```python
# 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_evaluator", llm_call_evaluator)

# Add edges to connect nodes
optimizer_builder.add_edge(START, "llm_call_generator")
optimizer_builder.add_edge("llm_call_generator", "llm_call_evaluator")
optimizer_builder.add_conditional_edges(
    "llm_call_evaluator",
    route_joke,
    {  # Name returned by route_joke : Name of next node to visit
        "Accepted": END,
        "Rejected + Feedback": "llm_call_generator",
    },
)

# Compile the workflow
optimizer_workflow = optimizer_builder.compile()

# Show the workflow
display(Image(optimizer_workflow.get_graph().draw_mermaid_png()))
```

```python
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

```python
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 add(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: second int
    """
    return a / b


# Augment the LLM with tools
tools = [add, multiply, divide]
tools_by_name = {tool.name: tool for tool in tools}
llm_with_tools = llm.bind_tools(tools)
```

```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 not"""

    return {
        "messages": [
            llm_with_tools.invoke(
                [
                    SystemMessage(
                        content="You are a helpful assistant tasked with performing arith
metic on a set of inputs."
                    )
                ]
                + state["messages"]
            )
        ]
    }


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"]]
        observation = tool.invoke(tool_call["args"])
        result.append(ToolMessage(content=observation, tool_call_id=tool_call["id"]))
    return {"messages": result}
```

```python
# Conditional edge function to route to the tool node or end based upon whether the LLM m
ade a tool call
def should_continue(state: MessagesState) -> Literal["environment", END]:
    """Decide if we should continue the loop or stop based upon whether the LLM made a to
ol call"""

    messages = state["messages"]
    last_message = messages[-1]
    # If the LLM makes a tool call, then perform an action
    if last_message.tool_calls:
        return "Action"
    # Otherwise, we stop (reply to the user)
    return END
```

```python
# Build workflow
agent_builder = StateGraph(MessagesState)

# Add nodes
agent_builder.add_node("llm_call", llm_call)
agent_builder.add_node("environment", tool_node)

# Add edges to connect nodes
agent_builder.add_edge(START, "llm_call")
agent_builder.add_conditional_edges(
    "llm_call",
    should_continue,
    {
        # Name returned by should_continue : Name of next node to visit
        "Action": "environment",
        END: END,
    },
)
agent_builder.add_edge("environment", "llm_call")
```


```python
# Add edges to connect nodes
agent_builder.add_edge(START, "llm_call")
agent_builder.add_conditional_edges(
    "llm_call",
    should_continue,
    {
        # Name returned by should_continue : Name of next node to visit
        "Action": "environment",
        END: END,
    },
)
agent_builder.add_edge("environment", "llm_call")
```


```python
# Compile the agent
agent = agent_builder.compile()

# Show the agent
display(Image(agent.get_graph(xray=True).draw_mermaid_png()))
```

```python
messages = [HumanMessage(content="Add 3 and 4. Then, take the output and multiple by
4.")]
messages = agent.invoke({"messages": messages})
for m in messages["messages"]:
    m.pretty_print()
```