BUILDING ADVANCED AI AGENTS FOR WORKFLOW AUTOMATION WITH LANGGRAPH

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About Me



Yogesh Haribhau Kulkarni

Bio:

- 20+ years in CAD/Engineering software development
- Got Bachelors, Masters and Doctoral degrees in Mechanical Engineering (specialization: Geometric Modeling Algorithms).
- Currently doing Coaching in fields such as Data Science, Artificial Intelligence Machine-Deep Learning (ML/DL) and Natural Language Processing (NLP).
- ▶ Feel free to follow me at:
 - Github (github.com/yogeshhk)
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$Introduction\ to\ Lang Graph$

(Ref: LangGraph Crash Course - Harish Neel)



Background



The Evolution of LLM Applications

- ▶ Early Days: Simple prompt-response patterns with single LLM calls
- Challenge: Real-world problems require multiple steps, decisions, and tool usage
- Question: How do we give LLMs more capability while maintaining control?
- ▶ **Journey**: From deterministic code \rightarrow intelligent chains \rightarrow autonomous agents
- ► Core Tension: Freedom vs Reliability
 - ▶ More autonomy = More capable, but less predictable
 - ► More structure = More reliable, but less flexible
- ▶ Goal: Find the sweet spot between flexibility and control



Levels of Autonomy/Agency/Freedom: Overview

- ▶ Think of autonomy as a spectrum from rigid to flexible
- Each level trades off control for capability
- Understanding these levels helps you choose the right tool
- ► The Spectrum:
 - 1. Code: No autonomy, 100% deterministic
 - 2. LLM Call: Single intelligent decision
 - 3. Chains: Sequential reasoning
 - 4. Routers: Conditional branching
 - 5. State: Workflow modeling with Cycles
 - 6. Agents: Autonomous decision-making with loops
- LangGraph enables 'State' level



Level 1-2: Code and Single LLM Calls

► Level 1: Pure Code:

- ► Example: if temperature > 30: return "It's hot"
- ▶ No autonomy, 100% deterministic, predictable
- ▶ Problem: Must anticipate every scenario
- ► Use case: Simple rule-based logic

► Level 2 - Single LLM Call:

- ightharpoonup Example: "Summarize this article" ightharpoonup LLM ightharpoonup Summary
- One input one output. One atomic task, limited reasoning
- Problem: Trying to do everything in one shot. Cannot break down complex tasks
- Use case: Text generation, classification, extraction
- ▶ Limitation: Both lack multi-step reasoning capability



Level 3: Chains: Sequential Reasoning

- What: Unidirectional sequence of LLM operations, so multiple experts one after another. Breaking down task is possible now.
- ► Example: Customer Support:
 - Step 1: Classify intent (complaint/question/request)
 - Step 2: Extract key information (order ID, issue)
 - ► Step 3: Generate appropriate response
- ▶ **Flow**: $A \rightarrow B \rightarrow C \rightarrow End$ (no branching, no loops)
- ▶ Advantages: Predictable, reliable, easy to debug
- **▶** Limitations:
 - Cannot adapt to different scenarios
 - No conditional logic or branching
 - ► Fixed execution path regardless of context
- ▶ Like an assembly line, efficient but inflexible



Level 4: Routers: Conditional Branching

- What: Chains with decision points, but still unidirectional
- Example: Document Processing:
 - Analyze document type, LLM/ML, decision making (invoice/contract/email)
 - ightharpoonup IF invoice ightharpoonup Extract line items ightharpoonup Calculate total
 - ightharpoonup IF contract ightarrow Extract parties ightarrow Identify key terms
 - ▶ IF email \rightarrow Classify urgency \rightarrow Route to handler
- Flow: Decision node routes to specialized chains
- Advantages: Handles different scenarios, specialized processing
- **▶** Limitations:
 - Still no loops or backward flow
 - Cannot learn from mistake, cannot revisit back
 - One-way path through the system
- Like a train switching tracks more flexible but still one direction

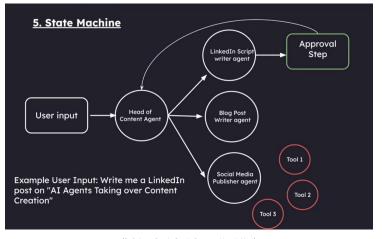


Level 5: State: Flow with Loops

- What: State machines are Routers who can branch and loop.
- Example: Content Creator:
 - Given a theme to write on
 - ► HEAD can sending it for LinkedIn article writing,
 - Once done, we can have Human-approval, if not approved go back to the HEAD. Revise, iterate till approved.
 - Once approved send to other forms such as Blog post, Twitter announcement post etc.
- ► Key Features:
 - Can have human-in-loop for approval
 - ► Multi-Agent systems
 - Advanced Memory Management
 - Can go back in history and explore better/alternate paths
- ▶ **Challenge**: Flow has to be prescribed, not full autonomy.
- ► This is LangGraph



Level 5: State: Flow with Loops



(Ref: LangGraph Crash Course - Harish Neel)

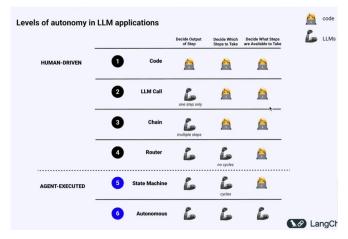


Level 6: Agents: Autonomous with Loops

- ▶ What: State machines with independent thinking, can loop and branch
- Example Research Assistant:
 - User: "Analyze SpaceX's latest launch success rate"
 - ► Agent thinks: "I need current data and historical context"
 - Action 1: Search web for latest SpaceX launches
 - Observation: Found data but it's incomplete
 - ► Action 2: Search for historical launch records
 - ► Observation: Now have full picture
 - ► Final answer: Synthesize findings into analysis
- **Key Features**: Think \rightarrow Act \rightarrow Observe \rightarrow Decide \rightarrow Repeat
- Challenge: Can loop infinitely if not controlled



Levels of Autonomy in LLM Applications



(Ref: LangGraph Crash Course - Harish Neel)

LLM (What AI decides) vs Code (What we prescribe/program)



Human vs Agent Driven

- ▶ 1-4 Human driven vs 5-6 Agent driven
- ▶ Why '5' ie 'State' agent driven? and not '3' or '4' where LLM is playing a part.
- A chain or a router is unidirectional hence it is not an agent
- A state machine can go back in the flow as we have cycles and the flow is controlled by the IIm hence it is called an agent.
- ▶ '3-4'has no self-correction, no training/learning, no refinement. That's intelligence. That's Agent.



 $Introduction\ to\ Lang Graph$



Overview Concl

What is LangGraph?



- LangGraph is an extension of the popular LangChain library.
- Allows you to create AI applications that can perform multiple steps, make decisions, and maintain information across those steps.
- ▶ Think of it like building a flowchart for your AI to follow.



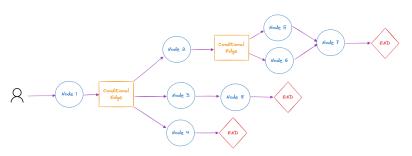
Why LangGraph? - The Comprehensive Pitch

- Problem: Traditional chains are too rigid, pure agents are too unpredictable
- Solution: LangGraph provides controlled flexibility through graph-based state machines
- ► Key Benefits:
 - Explicit control flow with loops, branches, and conditional logic
 - ▶ Built-in state persistence for long-running workflows
 - Human-in-the-loop capabilities at any point
 - ► Streaming support for real-time feedback
 - Production-ready with debugging and observability
- Use Cases: Multi-step reasoning, workflow automation, complex decision trees, collaborative agents
- Result: Reliable autonomous systems that combine flexibility with predictability



How is LangGraph Different?

- Gives you more control over how your AI makes decisions
- Allows your AI to revisit previous steps if needed
- ▶ Makes it easier to add human oversight at specific points
- ▶ Integrates smoothly with other LangChain tools





Overview Conel

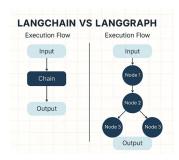
Agents in LangChain vs LangGraph

LangChain Agents (AgentExecutor):

- Black-box execution with limited control
- Fixed ReAct pattern implementation (TAO: Think-Action-Observe loop till we get the final answer)
- Cannot pause, resume, or modify mid-execution
- ► No state persistence across sessions
- ▶ Prone to infinite loops without guardrails

LangGraph Agents:

- White-box with full visibility into execution
- Custom patterns beyond ReAct
- Pause, resume, edit state at any node
- Persistent state with checkpointing
- ► Explicit cycle limits and control flow
- Bottom Line: LangChain agents for simple tasks, LangGraph for production systems





Why Graph Structure Over Chains?

- $\,\blacktriangleright\,$ Chains Limitation: Linear, unidirectional flow A \to B \to C \to End
- ▶ Real-World Problems: Require branching, loops, and conditional paths
- Graph Advantages:
 - ► Conditional branching: "If quality i threshold, loop back"
 - Multiple paths: "Route to specialized nodes based on task type"
 - Cycles: "Iterate until convergence or max iterations"
 - ▶ Parallel execution: "Process multiple sub-tasks simultaneously"
- Research-Backed: Most complex AI problem-solving papers use graph structures
- Natural Fit: Mirrors human problem-solving with think-act-observe-decide cycles
- ▶ Graphs provide flexibility while maintaining explicit control flow



Agentic Patterns: Autonomous vs Workflow Automation

Autonomous Agents:

- ► High-level goals with minimal constraints
- Self-directed exploration and decision-making
- Example: "Research this topic and write a report"
- Higher risk of unpredictability

Workflow Automation Agents:

- Structured processes with defined checkpoints
- Predictable paths with conditional logic
- ightharpoonup Example: "Review email ightharpoonup Classify ightharpoonup Route ightharpoonup Draft response"
- ► Balance between automation and control
- ► LangGraph Sweet Spot: Workflow automation with controlled autonomy
- Graphs enable explicit workflow definition while allowing intelligent decisions at each node

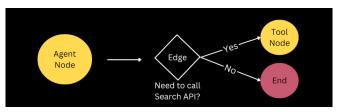


LangGraph Core Concepts



LangGraph Concepts

- Model: Large Language Model that supports Function Calling
- ▶ Tools: Actions taken by app API calls, database operations, etc.
- ▶ State: Information carried throughout the workflow (e.g., Message State)
- ▶ Node: Executable logic container a LangChain runnable or Tool invoker
- ▶ Edge: Control flow of information conditional or normal
- Workflow: The graph with nodes and edges that can be invoked or streamed

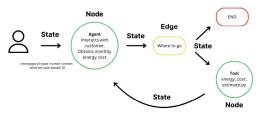


(Ref: Introduction to LangGraph - Building an AI Generated Podcast - Prompt Circle AI)



LangGraph Fundamentals: Nodes, Edges & State

- Nodes (N): Individual processing steps as Python functions that transform state
- Each node encapsulates one sub-task: LLM calls, calculations, tool invocations
- Edges (E): Directed connections determining execution flow between nodes
- Edges can be linear or conditional routes based on current state
- ▶ State (S): Shared data object persisting throughout execution

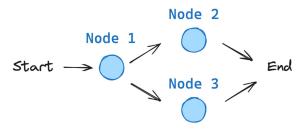


(Ref: The Complete Guide to Building LangChain Agents)



Core Components: Nodes

- Fundamental execution units in the graph
- ► Each node represents a specific operation or LLM call
- Nodes contain the actual logic and processing
- ▶ Can be simple operations or complex LLM interactions
- Examples: Start Node, Generate Content, Evaluate Quality, Tool Invocation, End Node



(Ref: Building Simple LangGraph - Uss Varma)



Is Each Node an Agent or Is the Graph an Agent?

- ► The Graph is the Agent not individual nodes
- Nodes are: Individual processing units/functions
 - ► Can be simple Python functions
 - Can be LLM calls
 - Can be tool invocations
 - ► Can be sub-agents themselves
- ► The Graph as Agent:
 - ► The complete workflow represents the agent's behavior
 - ► State flows through nodes, creating agent "memory"
 - ► Control flow (edges) represents agent's decision-making
 - Overall graph exhibits autonomous, goal-directed behavior
- ► Analogy: Nodes are like neurons, the graph is the brain
- Individual nodes are stateless functions; the graph maintains state



What Can Nodes Do? - Part 1

- Nodes are Extremely Flexible any Python function
- ▶ 1. Simple LLM Calls:
 - Generate text, classify, extract information
 - Example: 'Ilm.invoke("Summarize this text")'
- ▶ 2. RAG Operations:
 - Retrieve documents from vector database
 - ▶ Rerank results
 - Generate answers with retrieved context
 - ightharpoonup Example: Vector search ightharpoonup Context ightharpoonup LLM generation
- ▶ 3. API Calls:
 - External service calls (weather, database, CRM)
 - ► Example: Fetch customer data from Salesforce API



What Can Nodes Do? - Part 2

► 4. Tool-Calling Agents:

- Node can itself be an agent with tools
- Example: Research node that uses search, calculator, Wikipedia tools
- Inner agent makes tool decisions, outer graph manages workflow

▶ 5. Multi-Agent Nodes:

- ► Node can coordinate multiple sub-agents
- Example: "Code Review" node with architect, tester, security agents

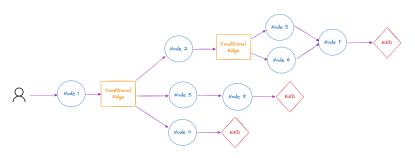
▶ 6. Any Computation:

- Data processing, calculations, file operations
- ► Validation, formatting, business logic
- ▶ **Key Point**: Nodes are building blocks combine them creatively



Core Components: Edges

- ► Connections between nodes in the graph
- ▶ Represent the flow of execution from one node to another
- ▶ Define possible paths through the workflow
- ► Can be simple directional connections
- ► Ensure proper sequence of operations



(Ref: A Comprehensive Guide About Langgraph: Code Included - Shivam Danawale)



Core Components: Conditional Edges

- Decision points in the workflow
- ► Enable branching based on specific conditions
- Example: After generation, route to criticism OR end based on quality
- ▶ Represented by dotted lines in diagrams
- ► Allow for dynamic execution paths
- Essential for implementing loops and conditional branching



Core Components: State

- ▶ A central object updated over time by the nodes in the graph
- ► Maintains context throughout workflow execution
- Preserves information between node executions
- State contains: messages, intermediate results, iteration count, tool outputs
- Enables nodes to access and modify shared information
- Critical for maintaining workflow coherence
- Supports complex, stateful operations



LangGraph Key Features

- ▶ Looping and Branching: Conditional statements and loop structures
- ▶ **State Persistence**: Automatic save/restore, pause and resume
- ▶ Human-in-the-Loop: Insert human review, state editing capabilities
- ▶ **Streaming Processing**: Real-time feedback on execution status
- ▶ LangChain Integration: Reuses existing components, LCEL support
- ▶ Provides controlled flexibility unlike pure React agents
- Production-ready with debugging and observability



Tutorial: Workflow Automation



Tutorial: Email Classification Workflow

- Goal: Automate email triage with classification and routing
- Workflow Steps:
 - 1. Read incoming email
 - 2. Classify as spam/legitimate using LLM
 - 3. Route to spam handler or response drafter
 - 4. Draft response for legitimate emails
 - 5. Send notification
- Demonstrates conditional routing and structured workflow
- Shows how graphs handle if/else logic naturally



Installation

LangGraph requires Python 3.8 or later.

```
pip install -U langgraph

python -c "import langgraph; print(langgraph.__version__)"

4
```



Step 1: Define State

- ▶ State holds all information passed between nodes
- ► Type hints ensure clarity and validation
- DO NOTE, in the following functions, the incoming state object is not updated with newer values of the field, but a new State object is returned.

```
from typing import List, Dict
  from pydantic import BaseModel
  class EmailState(BaseModel):
      email content: str = ""
      is_spam: bool = False
      category: str = ""
     draft_response: str = ""
     messages: List[Dict[str. str]] = []
9
    def classify_email(state: EmailState) -> EmailState:
        # WRONG - Mutating incoming state
        state.is spam = True # DON'T DO THIS
        state.messages.append(...) # DON'T DO THIS
        return state
```



Overview Concl

Step 2: Create Node Functions

```
import os
2 from langchain groq import ChatGroq
4 llm = ChatGrog(model="llama-3.1-8b-instant")
6 def read email(state: EmailState) -> EmailState:
      return state
8
  def classify_email(state: EmailState) -> EmailState:
10
      prompt = f"Classify this email as spam or
        legitimate:\n{state.email_content}\nRespond with only 'spam' or
        'legitimate'."
      response = 1lm.invoke(prompt)
      is_spam = "spam" in response.content.lower()
      return EmailState(
           email content=state.email content,
14
           is_spam=is_spam,
16
           category=state.category,
          draft_response=state.draft_response,
          messages=state.messages + [{"role": "classifier". "content":
        response.content}])
```

Step 2: Create Node Functions

```
def handle spam(state: EmailState) -> EmailState:
      new messages = state.messages + [{"role": "system", "content": "Email
       marked as spam"}]
      return EmailState(
          email content=state.email content,
5
          is_spam=state.is_spam,
          category=state.category,
          draft_response=state.draft_response,
          messages=new_messages
9
  def draft response(state: EmailState) -> EmailState:
      prompt = f"Draft a professional response to:\n{state.email content}"
      response = llm.invoke(prompt)
      return EmailState(
          email content=state.email content,
          is_spam=state.is_spam,
          category=state.category,
          draft response=response.content,
          messages=state.messages + [{"role": "drafter", "content":
       response.content}]
```



Step 3: Define Routing Logic

- Routing function decides next node based on state
- ▶ Returns the name of the target node
- ► Enables dynamic workflow execution

```
def route_email(state: EmailState) -> str:
    """Conditional routing based on classification"""
    if state.is_spam:
        return "spam_handler"
    else:
        return "response_drafter"
```



Step 4: Build the Graph

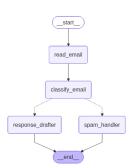
```
from langgraph.graph import StateGraph, START, END
  workflow = StateGraph(EmailState) # Create graph
  workflow.add node("read email", read email)
6 workflow.add_node("classify_email", classify_email)
  workflow.add node("spam handler", handle spam)
8 workflow.add node("response drafter", draft response)
10 workflow.add edge(START, "read email")
  workflow.add_edge("read_email", "classify_email")
  def route email(state: EmailState) -> str:
      if state.is_spam:
14
          return "spam handler" # Exact node name
       else:
16
          return "response drafter" # Exact node name
18
  workflow.add conditional edges("classify email", route email)
  workflow.add_edge("spam_handler", END)
  workflow.add edge("response drafter", END)
22
  app = workflow.compile()
24
```



Step 5: Visualize the Graph

- Visualize the workflow structure in ASCII format
- Shows nodes and their connections clearly

```
# Visualize and save the graph
png_graph = app.get_graph().draw_mermaid_png()
with open("langgraph_email_workflow_graph.png", "wb")
as f:
    f.write(png_graph)
print(f"Graph saved as
    'langgraph_email_workflow_graph.png' in
    {os.getcwd()}")
```





Step 6: Run the Workflow

- Workflow executes automatically with proper routing
- State carries results through entire execution

```
1 # Test with legitimate email
  state = EmailState(
      email_content="Hello, I'd like to schedule a meeting to discuss the
        project timeline."
5 result = app.invoke(state)
  print(f"Is Spam: {result['is_spam']}")
7 print(f"Draft Response: {result['draft_response']}")
9 # Test with spam email
  spam_state = EmailState(
      email_content="URGENT! You've won $1M! Click here now!!!"
11
spam_result = app.invoke(spam_state)
  print(f"Is Spam: {spam_result['is_spam']}")
```



Tutorial Takeaways

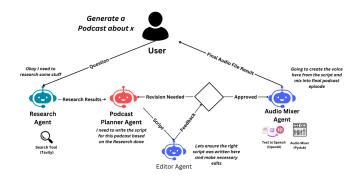
- ▶ Clear Structure: Graph makes workflow explicit and understandable
- ► Conditional Logic: Natural if/else through routing functions
- ▶ State Management: Single state object tracks entire process
- ► Extensibility: Easy to add new nodes (e.g., "urgent" category)
- ▶ **Debugging**: Can inspect state at each node
- Production-Ready: Add checkpointing, error handling, retries
- ▶ This pattern scales to complex multi-step workflows



Real-World Applications



Example: Podcast Generator

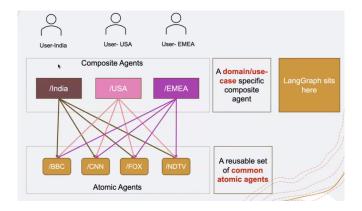


(Ref: Introduction to LangGraph - Building an Al Generated Podcast - Prompt Circle Al)

Code at https://github.com/hollaugo/langgraph-framework-tutorial



Example: News Aggregator



Code:

https://github.com/rajib76/multi_agent/01_how_to_langgraph_example_01.py

(Ref: Langgraph: The Agent Orchestrator - Rajib Deb)



Best Practices

- State Design: Keep simple and clear, use type hints, only necessary information
- Node Functions: Single responsibility, handle exceptions, return new state objects
- Edge Design: Clear conditional logic, avoid complex cycles, consider all paths
- Error Handling: Add at critical nodes, provide fallback mechanisms, log errors
- ► Testing: Test individual nodes, test routing logic, test complete workflows
- Observability: Use tracing tools (Langfuse, LangSmith) for production monitoring



Advanced Concepts in LangGraph



Human-in-the-Loop: Overview

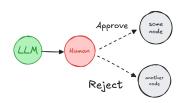
What: Ability to pause execution and request human input/approval

Why Needed:

- Critical decisions require human judgment
- Verify agent actions before execution
- ► Edit/correct agent outputs
- Ensure safety and compliance

▶ Use Cases:

- Approve before sending emails or making purchases
- Review generated code before deployment
- Validate data modifications
- Content moderation and quality control
- ► LangGraph Implementation: Interrupts and checkpointing



Human-in-the-Loop: Implementation Patterns

- ► Pattern 1: Breakpoints:
 - Pause execution at specific nodes
 - Example: Stop before "send_email" node
- ► Pattern 2: Approval Gates:
 - ▶ Node requests approval, waits for response
 - ► Conditional edge based on approval status
- ► Pattern 3: State Editing:
 - Pause. allow human to modify state
 - ▶ Resume with corrected state
- ► Pattern 4: Continuous Monitoring:
 - ► Human can interrupt at any time
 - Useful for long-running agents



Human-in-the-Loop: Code Example

```
from langgraph.graph import StateGraph

# Create graph with checkpointing (required for interrupts)
memory = MemorySaver()
workflow = StateGraph(State)

workflow.add_node("draft_email", draft_email_node)
workflow.add_node("send_email", send_email_node)
workflow.add_edge("draft_email", "send_email")

# Compile with interrupt BEFORE send_email node
app = workflow.compile(
checkpointer=memory,
interrupt_before=["send_email"]) # Pause here for human approval
```



Human-in-the-Loop: Code Example

```
# Run workflow
config = {"configurable": {"thread_id": "1"}}
result = app.invoke(initial_state, config)

# At this point, execution is paused
# Human reviews the drafted email in result.draft

# To resume after approval:

app.invoke(None, config) # Continues from where it stopped

# To modify state and resume:
updated_state = result.copy()
updated_state.draft = "Modified email content"
app.invoke(updated_state, config)

# Run workflow
config = {"thread_id": "1"}}

# At this point, execution is paused
# Human reviews the drafted email in result.draft
# To resume after approval:

updated_state and resume:
updated_state = result.copy()
updated_state.draft = "Modified email content"
app.invoke(updated_state, config)
```



Advanced Concept: State Persistence and Checkpointing

- What: Automatically save state at each node execution
- Benefits:
 - Resume after failures or interruptions
 - Time-travel debugging (replay from any checkpoint)
 - Support long-running workflows across sessions
 - ► Enable human-in-the-loop patterns
- ► Checkpoint Storage Options:
 - In-memory (development/testing)
 - ► SQLite (local persistence)
 - PostgreSQL (production)
 - Redis (distributed systems)
- Key Feature: Each checkpoint is immutable and versioned
- Can fork from any checkpoint to explore alternative paths



Advanced Concept: Streaming and Real-Time Updates

- ▶ What: Stream intermediate results as graph executes
- Why Important:
 - Provide real-time feedback to users
 - Show progress in long-running workflows
 - Better user experience (vs waiting for completion)
- ► Streaming Modes:
 - values: Stream complete state after each node
 - updates: Stream only state changes
 - messages: Stream LLM token by token
- ▶ Use Case: Chatbot showing "thinking..." \rightarrow "searching..." \rightarrow "responding..."



Streaming Example

- Streaming provides transparency into agent execution
- Critical for production applications with users waiting

```
# Instead of invoke(), use stream()
for chunk in app.stream(initial_state, config):
    # chunk contains state updates after each node
    print(f"Node: {chunk['node']}")
    print(f"State: {chunk['state']}")

# For token-by-token LLM streaming
saync for event in app.astream_events(initial_state, config):
    if event["event"] == "on_chat_model_stream":
        # Stream each token as LLM generates
        print(event["data"]["chunk"], end="", flush=True)
```



Advanced Concept: Subgraphs and Modularity

- What: Embed complete graphs as nodes within parent graphs
- Benefits:
 - Modular, reusable workflow components
 - Hierarchical organization of complex systems
 - Encapsulation and separation of concerns
- ► Example Hierarchy:
 - Parent: Customer service orchestrator
 - Subgraph 1: Email classification workflow
 - Subgraph 2: Ticket routing workflow
 - Subgraph 3: Response generation workflow
- Each subgraph is self-contained with own state and logic
- Parent graph coordinates between subgraphs
- Enables building complex systems from simple components



Advanced Concept: Parallel Execution

- ▶ What: Execute multiple nodes simultaneously
- ▶ Use Cases:
 - ► Call multiple APIs concurrently
 - Search multiple data sources in parallel
 - Generate multiple variations simultaneously
- ▶ Implementation: Send edges from one node to multiple nodes

```
# Parallel node execution
workflow.add_node("search_web", search_node)
workflow.add_node("search_db", database_node)
workflow.add_node("search_docs", documents_node)
workflow.add_node("aggregate", aggregate_results)
# Fan-out: one node to many
workflow.add_edge("start", "search_web")
workflow.add_edge("start", "search_db")
workflow.add_edge("start", "search_docs")
# Fan-in: many nodes to one
workflow.add_edge("search_web", "aggregate")
workflow.add_edge("search_db", "aggregate")
workflow.add_edge("search_db", "aggregate")
workflow.add_edge("search_docs", "aggregate")
```



Advanced Concept: Dynamic Graph Modification

- What: Modify graph structure during execution
- Use Cases:
 - Add nodes based on runtime conditions
 - Dynamically adjust workflow based on results
 - Create adaptive systems that evolve
- ► Example Scenario:
 - Research agent discovers new sub-topics
 - Dynamically creates specialized research nodes
 - ► Each node investigates a different aspect
- ▶ Limitation: Advanced feature, use with caution
- Most use cases handled by conditional edges
- True dynamic modification for special scenarios only



Advanced Patterns: Map-Reduce

- Pattern: Split work, process in parallel, combine results
- Example Document Summarization:
 - 1. Split large document into chunks (map)
 - 2. Summarize each chunk in parallel (parallel processing)
 - 3. Combine summaries into final summary (reduce)
- ► Implementation:
 - ► Split node: Divides input into subtasks
 - Multiple processing nodes: Execute in parallel
 - Aggregation node: Combines results
- ▶ Benefits: Scalability, speed, handles large inputs
- Common in RAG systems for processing multiple documents



Best Practices for Advanced Features

- Start Simple: Add complexity only when needed
- ► Checkpointing: Always use for production systems
- ▶ Error Handling: Add try-except in nodes, fallback paths in graph
- ▶ **Observability**: Use LangSmith/Langfuse to trace execution
- ▶ **Testing**: Test nodes individually, then integration test graphs
- ▶ State Size: Keep state minimal only essential data
- ▶ Cycle Limits: Set maximum iterations to prevent infinite loops
- ► Human Approval: For high-stakes actions (financial, emails, deletions)
- ▶ **Documentation**: Graph visualization helps team understanding



Summary

- LangGraph enables controlled, flexible AI workflows through graph structures
- Solves limitations of rigid chains and unpredictable pure agents
- ▶ Key components: Nodes (logic), Edges (flow), State (context)
- ▶ Ideal for workflow automation with intelligent decision-making
- ▶ Production-ready with state persistence, human-in-loop, streaming
- ▶ Start with simple workflows, expand to complex multi-agent systems
- ► The future of reliable, autonomous AI applications



Conclusions



Best Practices and Considerations

- Keep state models simple and clear with necessary information only
- Maintain single responsibility in node functions
- Handle exceptions and return new state objects
- Use clear conditional logic in edge design
- Avoid complex cyclic dependencies in workflow
- ▶ Add error handling at critical nodes with fallback mechanisms
- ► Consider performance impacts of checkpoint mechanism
- ▶ Choose appropriate data processing methods for use cases



Future Developments and Limitations

- Current streaming has long waiting times for LLM nodes
- ▶ Ideal: Node-level streaming within graph streaming
- Market agents provide better step-by-step streaming
- ► LangGraph rapidly evolving with frequent updates
- Pre-built components may change in future versions
- Monitor documentation for latest features and changes
- ► Core design philosophy remains valuable for learning
- Expected improvements in streaming processing capabilities



Conclusion

- ► LangGraph addresses LCEL and AgentExecutor limitations effectively
- Graph-based approach provides intuitive workflow representation
- Advanced features support complex AI application development
- ▶ State management and persistence enable long-running conversations
- Human-in-the-loop capabilities enhance decision quality
- Modular subgraph architecture improves maintainability
- ▶ Streaming responses provide real-time user feedback
- ► Continuous evolution promises enhanced capabilities for AI development



References

Many publicly available resources have been refereed for making this presentation. Some of the notable ones are:

- LangGraph Crash Course Harish Neel
- LangGraph Advanced Tutorial James Li
- ► Learn LangGraph The Easy Way, very nice explanation
- ► LangGraph Crash Course with code examples Sam Witteveen
- Official Site: https://python.langchain.com/docs/langgraph https://github.com/langchain-ai/langgraph/tree/main
- LangGraph (Python) Series
- Introduction to LangGraph Building an AI Generated Podcast
- Langgraph: The Agent Orchestrator Rajib Deb
- ► LangGraph Deep Dive: Build Better Agents James Briggs



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Thanks ...

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