ReAct Agent



ReAct = Reasoning + Acting

- It is a method for building agents where the LLM doesn't just give a direct answer, but:
 - 1. Thinks step by step (Reasoning)
 - 2. Takes actions using tools (Acting)
 - 3. Uses results from tools to continue reasoning
 - 4. Finally answers the user

Why is it needed?

- Normal LLMs can hallucinate (make up wrong answers).
- With **ReAct**, the agent can:
 - Call a tool (like Google, Wikipedia, Calculator, Database, API).
 - Check the tool's result.
 - Use that real information in the answer.

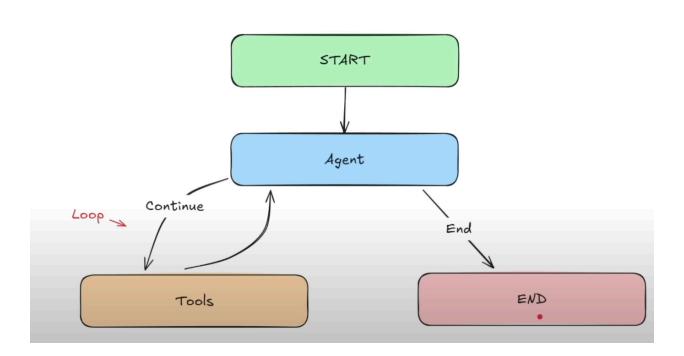
This makes it more reliable.

How does it work internally?

Imagine a conversation:

- 1. User: "What is the population of France divided by 2?"
- 2. **Agent (Reasoning):** I don't know directly. Step 1: I should look up France's population.
- 3. Agent (Action): Calls a tool (Wikipedia API).

- 4. **Tool Result**: "France population = 67 million"
- 5. **Agent (Reasoning)**: Now divide 67 million by 2 = 33.5 million.
- 6. Agent (Final Answer): "It's about 33.5 million."



Code

from typing import Annotated, Sequence, TypedDict

from dotenv import load_dotenv

from langchain_core.messages import BaseMessage # The foundational class for all message types in LangGraph

from langchain_core.messages import ToolMessage # Passes data back to LL

M after it calls a tool such as the content and the tool_call_id

from langchain_core.messages import SystemMessage

from langchain_groq import ChatGroq

from langchain_core.tools import tool

from langgraph.graph.message import add_messages

from langgraph.graph import StateGraph, END

from langgraph.prebuilt import ToolNode

load_dotenv()

Annotated → Allows you to attach extra metadata to a type hint. I

Sequence → It's used to say: "This function accepts any ordered collection, not just a list."

Works with:

- ["a", "b", "c"] (list)
- ("a", "b", "c") (tuple)
- "abc" (string)

★ Why use Sequence instead of List?

- List[str] only accepts lists.
- Sequence[str] is **more flexible**, and works with any indexable iterable (list, tuple, str, etc.).

ToolMessage

- A special message used when a tool has returned a result and you're sending that result back to the LLM.
- Typically follows a tool call that the LLM made.

Purpose:

 Bridges the gap between the LLM asking for a tool and the tool's actual response.

✓ BaseMessage

- BaseMessage is the **abstract base class** for all message types in LangChain.
- Other message types (like HumanMessage, AlMessage, SystemMessage, ToolMessage, etc.) inherit from this.
- BaseMessage is the parent class

SystemMessage

 A message type used to pass instructions, role-setting, or context to the LLM.

add_messages

- This is a reducer function
- LangGraph agents typically maintain a state that contains a list of messages
 (like HumanMessage, AlMessage, etc.). add_messages makes it easier to append new
 messages to that list in a structured and consistent way.

```
from langgraph.graph.message import add_messages
from langchain_core.messages import AlMessage

def some_node(state):
    response = AlMessage(content="Sure, here's the info you asked for.")
    return add_messages(state, [response])
```

ToolMessage →

- A message type specifically used when an LLM calls a tool.
 - It contains the **result of a tool execution**.
 - Also carries the tool_call_id so LangChain knows which request this belongs to.

Example flow:

- 1. LLM says: "Use calculator with input 2+2".
- 2. Tool is executed \rightarrow result = 4.
- 3. This result is wrapped in a ToolMessage and passed back to the LLM.

from langchain_core.tools import tool

@tool → Turns a function into a Tool

• This is a **decorator**. You put otol above a Python function to magically convert it into a tool that the Al can recognize and call.

ToolNode →

A ready-made LangGraph node that handles tool execution.

- Instead of writing your own node to call a tool and process its result, you just use ToolNode.
- It takes care of:
 - Running the tool
 - Wrapping the result in ToolMessage
 - Sending it back to the LLM

A **pre-built node** that handles all the complexity of:

- 1. Receiving a list of tool calls from the Al.
- 2. Finding the correct tool.
- 3. Executing it.
- 4. Packaging the results into objects.

It saves you from writing this logic yourself.

class AgentState(TypedDict):

message: Annotated[Sequence[BaseMessage], add_messages]

Sequence[BaseMessage]

- Sequence = any ordered, indexable collection (like a list or tuple).
- BaseMessage = parent class for HumanMessage , AlMessage , SystemMessage , etc.

So, "message" will hold a list of messages:

```
[
HumanMessage(content="Hello"),
AlMessage(content="Hi, how can I help?")
]
```

Annotated[..., add_messages]

In LangGraph, that metadata (add_messages) tells the framework:

"When this node returns new messages, use the add_messages function to merge them into this field."

The **special instruction** add_messages , LangGraph knows:

"Whenever I add new messages, I should not overwrite old ones, but append them to the list."

Create Tool

```
@tool
def add(a: int, b:int):
    """This is an addition function that adds 2 numbers together"""
    return a + b

@tool
def subtract(a: int, b: int):
    """Subtraction function"""
    return a - b

@tool
def multiply(a: int, b: int):
    """Multiplication function"""
    return a * b
```



!!If the doc string is removed, the function will not work.

Create a list of tools

```
#Create a list of tools
tools = [add, subtract, multiply]
```

Model + Tools:

```
#Model
```

model = ChatGroq(model="llama-3.3-70b-versatile").bind_tools(tools)

• In this way, model has access to the tools

Model Call Node:

```
def model_call(state:AgentState) → AgentState:
    system_prompt = SystemMessage(content="You are my AI assistant, pleas
e answer my query to the best of your ability.")
    response = model.invoke([system_prompt] + state["messages"])
    return {"messages": [response]}
```

Output:

AlMessage(content="I'll do my best to provide a helpful and accurate response. What's your question?", additional_kwargs={}, response_metadata= {'token_usage': {'completion_tokens': 19, 'prompt_tokens': 47, 'total_token s': 66, 'completion_time': 0.046528529, 'prompt_time': 0.017985182, 'queu e_time': 0.047918769, 'total_time': 0.064513711}, 'model_name': 'llama-3.3-70b-versatile', 'system_fingerprint': 'fp_2ddfbb0da0', 'finish_reason': 'sto

```
p', 'logprobs': None}, id='run--3883e593-2eb1-4480-b079-6ea4c53ca20 3-0', usage_metadata={'input_tokens': 47, 'output_tokens': 19, 'total_token s': 66})
```

return {"messages": [response]} → Compact way to update the state.



We are not returning a string because (response.content) → "messages" field must hold a list of BaseMessage objects, not plain strings.



We just write "messages": [response] because the add_messages function handles the appending of messages.

Conditional Edge

```
def should_continue(state:AgentState) → AgentState:

messages = state["messages"]

last_message = messages[-1]

if not last_message.tool_calls:
    return "end"

else:
    return "continue"
```

messages[-1] gets the most recent message (last one in the list)

What is .tool_calls?

Some messages (usually from the assistant) may contain tool calls.

- Example: the assistant might decide: "I need to use the Wikipedia API tool".
- In that case, the message will have something like:

```
{
    "role": "assistant",
    "tool_calls": [{"id": "1", "name": "WikipediaAPIWrapper", "argument
s": {"query": "cats"}}]
}
```

If tool_calls is **empty**, it means the assistant is not calling any tool and is just giving a final response.

- If the last message has no tool calls → that means the assistant is done → return "end".
- If the last message contains tool calls → that means the assistant wants to run tools (like search, calculator, DB query) → return "continue".

Graph

```
graph = StateGraph(AgentState)

graph.add_node("our_agent", model_call)

#Tool Node

tool_node = ToolNode(tools=tools)
graph.add_node("tools", tool_node) #Contains multiple tools

graph.set_entry_point("our_agent")

graph.add_conditional_edges(
   "our_agent",
   should_continue,
   {
      "continue": "tools",
```

```
"end": END
}

#Edge that goes back to our tool
graph.add_edge("tools", "our_agent")

app = graph.compile()
```

graph.add_edge("tools", "our_agent"): Edge that goes back to our tool.

But we also wanted tools → our_agent

Stream

```
def print_stream(stream):
    for s in stream:
        message = s["messages"][-1]
    if isinstance(message, tuple):
        print(message)
    else:
        message.pretty_print()
```

for s in stream:

- This means: go through each **item** (s) inside stream.
- If stream is a list (or an iterable object), this loop will pick one item at a time.

Think of stream like a **queue of updates/messages** coming from an Al pipeline — you're checking them one by one.

message = s["messages"][-1]

- s is expected to be a dictionary (key-value pairs).
- Inside s, there is a key "messages".
- s["messages"] is a list of messages.

[-1] means "last item in the list".

if isinstance(message, tuple):

- isinstance(x, tuple) checks if message is a **tuple** (a fixed group of values like (a, b) in Python).
- Why? Because sometimes the last message might be stored as a tuple instead
 of a custom object.
- If message is not a tuple, it must be some kind of **object** (likely a ChatMessage or AIMessage from LangChain).
- That object has a built-in method .pretty_print() which formats it nicely for display.

```
inputs = {"messages": [("user", "Add 40 + 12")]}
print_stream(app.stream(inputs, stream_mode="values"))
```

• .stream(inputs, stream_mode="values") runs the pipeline but instead of giving you the
final result all at once, it yields outputs step by step as a stream (like a

generator).

• Each yielded value (s) is a dictionary containing intermediate + final messages.

```
inputs = {"messages": [("user", "Add 40 + 12. add 5+7")]}
print_stream(app.stream(inputs, stream_mode="values"))
```

```
Add 40 + 12. add 5+7
Tool Calls:
add (asx4mnnn7)
Call ID: asx4mnnn7
Args:
 a: 40
 b: 12
add (fkhb2dq20)
Call ID: fkhb2dq20
Args:
 a: 5
Name: add
12
       The results of the additions are 52 and 12.
```

Visualize

from IPython.display import Image, display display(Image(app.get_graph().draw_mermaid_png()))

