Reference Card: LangChain
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Introduction

Introduction to LangChain

What is LangChain?
A Framework for Building LLM Applications

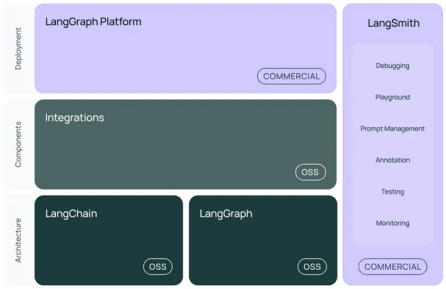
Key Capabilities:

- Connect LLMs to external data (RAG)
- Build intelligent agents
- Manage prompts & memory
- Switch between models easily

Quick Facts:

- Open Source (MIT License)
- Python & JavaScript
- Created by Harrison Chase

From Idea to Production



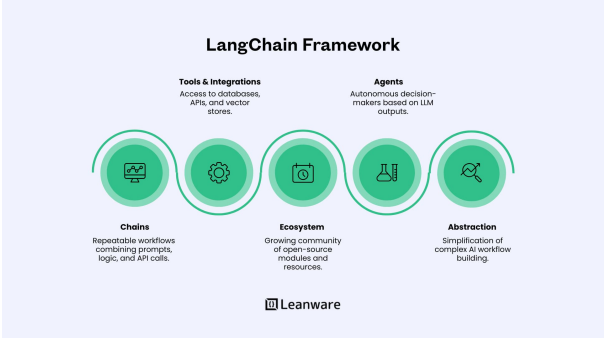
(Ref: Getting Started with LangChain: A Beginner's Guide)

Why You Need LangChain
The Challenge:

- LLMs lack memory
- No access to your data
- Can't use external tools
- Complex integration code

The Solution:

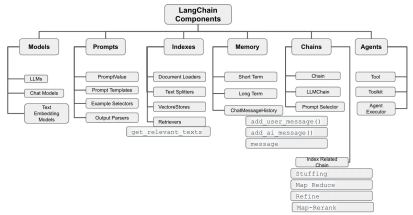
- Memory management built-in
- Easy data integration
- Tool calling framework
- Simple, modular code



(Ref: https://www.leanware.co/insights/langchain-vs-pinecone-which-should-you-choose)

Bottom Line: Build AI apps faster with less code

Core Building Blocks



Foundation:

- **Models**: Connect to any LLM
- **Prompts**: Dynamic templates
- **Memory**: Conversation context

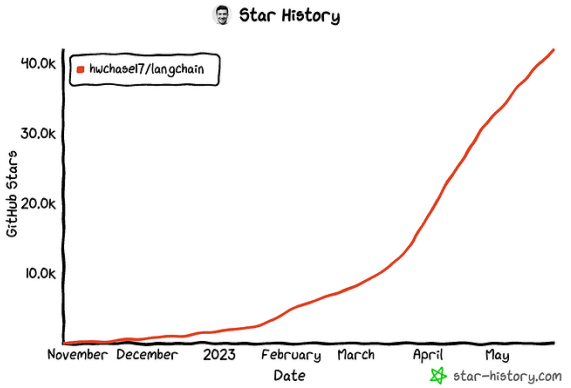
Advanced:

- **Retrievers**: Search your data
- **Agents**: Autonomous reasoning
- **LCEL**: Chain components easily

Mix and match components to build your app

So, Why LangChain?

- **RAG Applications**: Connect LLMs to your data
- **Intelligent Agents**: Autonomous tool usage
- **Production Ready**: Monitoring & logging built-in
- **Model Flexibility**: Switch providers easily
- **Modular Design**: Use only what you need



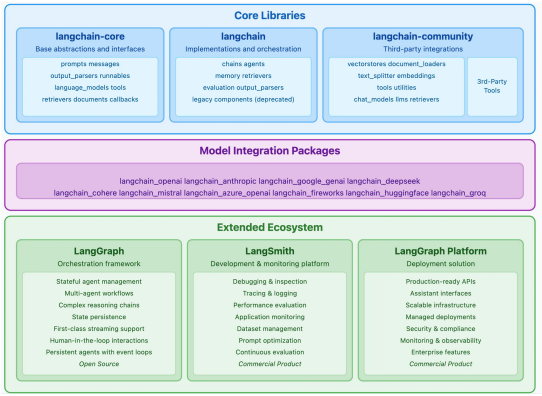
(Ref: LangChain tutorial: Build an LLM-powered app)

The LangChain Community

- 80,000+ GitHub stars
- 2,000+ contributors
- Millions of downloads/month
- Active Discord community
- MIT - Commercial friendly

(Ref: What is Langchain and why should I care as a developer? - Logan Kilpatrick)

The LangChain Ecosystem



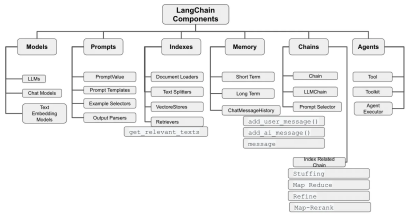
(Ref: Demystifying the LangChain Ecosystem for LLM-Powered Application Development - Wltsankalpa)

Installation & Setup

Python 3.10 or higher

```
# Core packages (LangChain 1.0 focuses on the 'langchain' agent
    framework)
pip install -U langchain langchain-core

# Provider-specific packages (Groq is a first-class integration)
pip install -U langchain-groq

# Document processing (Now separated for better dependency
    management)
pip install -U langchain-community langchain-text-splitters

# Embeddings & Vector Stores
pip install -U langchain-huggingface langchain-chroma

# NEW: Legacy features
# Use this ONLY if you need old chains like LLMChain or RetrievalQA
pip install -U langchain-classic

//API Keys Setup:

import os
os.environ["GROQ_API_KEY"] = "your-groq-api-key-here"
# Or use .env file with python-dotenv

# LangSmith Tracing (Highly recommended for v1.0 Agents)
os.environ["LANGCHAIN_TRACING_V2"] = "true"
os.environ["LANGCHAIN_API_KEY"] = "your-langsmith-key"
os.environ["LANGCHAIN_PROJECT"] = "my-v1-project"
```

Core Components Overview



Component	Purpose	Use Case
Models	Connect to LLMs	Text generation, chat
Prompts	Template management	Dynamic prompts
LCEL	Chain components	Build workflows
Memory	Store conversations	Chatbots
Retrievers	Search data	RAG, Q&A
Agents	Tool selection	Autonomous tasks

(Ref: How LangChain Makes Large Language Models More Powerful)

Key Concepts: Chains vs Agents

- **Chains (LCEL)**:
  - Predetermined sequence of operations
  - Composed with pipe operator: `prompt | llm | parser`
  - Fixed execution path
  - Best for: Structured, predictable workflows
- **Agents**:
  - Dynamic decision-making with LLM reasoning
  - Choose tools based on input
  - Adaptive execution path
  - Best for: Complex, unpredictable scenarios

When to use what?

- Use **Chains/LCEL** when: Steps are known, workflow is fixed
- Use **Agents** when: Need dynamic tool selection, multi-step reasoning

(Ref: Superpower LLMs with Conversational Agents)

What Can You Build?

RAG Applications:

- Document Q&A
- Knowledge base search
- Semantic search

Conversational AI:

- Chatbots with memory
- Customer support
- Personal assistants

Data Analysis:

- SQL query generation
- Report generation
- Data insights

Autonomous Agents:

- Web research
- API integration
- Multi-step workflows

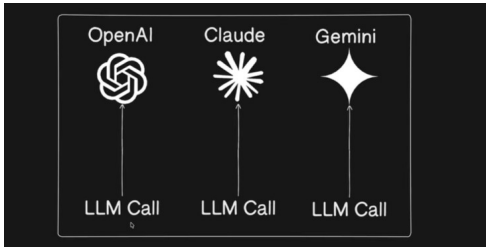
(Ref: LangChain Use Cases Documentation)

Implementation

Implementations

Use as LLM

Diff LLMs, Diff Calls



(Ref: What is LangChain - Yash Jain)

Langchain provides abstraction. No LLM specific API calls, but a generic way. Need to install specific extension though and have to have respective KEYs.

```
pip install -U langchain langchain-openai langchain-anthropic
    langchain-google-genai langchain-groq
```

Common Way of Calling Diff LLMs: V0

```
from langchain_openai import ChatOpenAI
from langchain_groq import ChatGroq
from langchain_anthropic import ChatAnthropic
from langchain_google_genai import ChatGoogleGenerativeAI
from langchain_core.messages import HumanMessage

gpt_model = ChatOpenAI(
    model="gpt-4o",
    temperature=0.7,
    max_tokens=500)

groq_model = ChatGroq(
    model="llama-3.3-70b-versatile",
    temperature=0.2,
    # Groq-specific param example:
    # reasoning_format="raw" )

claude_model = ChatAnthropic(
    model="claude-3-5-sonnet-latest",
    timeout=None,
    stop_sequences=["\n\nHuman:"])

gemini_model = ChatGoogleGenerativeAI(
    model="gemini-1.5-pro",
    convert_system_message_to_human=True # Legacy helper for older
        models)

def run_demo(model, provider_name):
    message = [HumanMessage(content="Explain quantum
        entanglement in one sentence.")]
    response = model.invoke(message)
    print(f"Response: {response.content}\n")

run_demo(gpt_model, "OpenAI")
```

Common Way of Calling Diff LLMs: V1

```
import os
from langchain.chat_models import init_chat_model
from langchain_core.messages import HumanMessage, SystemMessage

# os.environ["OPENAI_API_KEY"] = "sk-..."
# os.environ["ANTHROPIC_API_KEY"] = "sk-ant-..."
# os.environ["GOOGLE_API_KEY"] = "..."
# os.environ["GROQ_API_KEY"] = "gsk_..."

def get_response(provider_string, user_query):
    """
    Initializes a model based on the provider string: 'openai',
        'anthropic', 'google', or 'groq'.
    """
    llm = init_chat_model(provider_string, temperature=0)

    messages = [
        SystemMessage(content="You are a helpful research assistant."),
        HumanMessage(content=user_query)     ]
    return llm.invoke(messages)

gpt_response = get_response("openai:gpt-4o", "What is LangChain
        v1?")
print(f"GPT-4o: {gpt_response.content[:100]}...")

claude_response =
        get_response("anthropic:claude-3-5-sonnet-latest", "What is
        LangChain v1?")
print(f"Claude: {claude_response.content[:100]}...")

gemini_response = get_response("google_genai:gemini-1.5-pro",
        "What is LangChain v1?")
print(f"Gemini: {gemini_response.content[:100]}...")

groq_response = get_response("groq:llama-3.3-70b-versatile", "What
        is LangChain v1?")
print(f"Groq: {groq_response.content[:100]}...")
```

Sentiment Analysis: Zero Shot

```
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser

# 1. Define the LLM
model = ChatGroq(model_name="llama-3.3-70b-versatile",
        temperature=0)

# 2. Create a prompt template
prompt = ChatPromptTemplate.from_template(
    "Analyze the sentiment of the following text. "
    "Respond with only one word: Positive, Negative, or Neutral.\n"
    "Text: {input_text}"
)

# 3. Create a simple output parser
parser = StrOutputParser()

# 4. Build the LCEL chain
chain = prompt | model | parser

# Define input text
input_text = "I love LangChain! It's the best NLP library I've ever
        used."

# 5. Invoke the chain
sentiment = chain.invoke({"input_text": input_text})

# Print the sentiment
print(sentiment)
```

Named Entity Recognition (NER): Zero Shot

```
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser

# 1. Setup Model
model = ChatGroq(model="llama-3.3-70b-versatile")

# 2. Create Prompt for NER extraction
template = """
Identify the named entities (Person, Organization, Amount) in the text.
Format the output as a bulleted list.

Text: {text}
"""
prompt = ChatPromptTemplate.from_template(template)

# 3. Build Chain
chain = prompt | model | StrOutputParser()

# 4. Invoke
input_text = "Microsoft is acquiring Nuance Communications for $19.7
        billion."
entities = chain.invoke({"text": input_text})
print(entities)
```

Use as Chains

LCEL: Basic Example

```
#  Old Pattern (Deprecated):
from langchain.llms import OpenAI
from langchain.chains import LLMChain

llm = OpenAI()
chain = LLMChain(llm=llm, prompt=prompt)
result = chain.run("input")

# Modern LCEL Pattern with Groq:
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser

# Set up Groq model, e.g., Gemma or Llama 3
llm = ChatGroq(model_name="gemma-7b-it")
prompt = ChatPromptTemplate.from_template("Tell me about
        {topic}")
output_parser = StrOutputParser()

# Build chain with pipe operator
chain = prompt | llm | output_parser

# Invoke the chain
result = chain.invoke({"topic": "LangChain"})
print(result)
```

LCEL: Advanced Features

Streaming Support:

```
import asyncio

async def main():
    # Stream tokens as they're generated (Works in standard functions)
    for chunk in chain.stream({"topic": "AI"}):
        print(chunk, end="", flush=True)
    print("\n")

    # Async invocation (Must be inside async function)
    result = await chain.ainvoke({"topic": "AI"})
    print(f"Result: {result}\n")

    # Async streaming
    async for chunk in chain.astream({"topic": "AI"}):
        print(chunk, end="", flush=True)
    print("\n")

    # Process multiple inputs in parallel (Sync version)
    results = chain.batch([
        {"topic": "AI"},
        {"topic": "ML"},
        {"topic": "LangChain"}
    ])
    print(f"Batch Results: {results}")

if __name__ == "__main__":
    asyncio.run(main())
```

LCEL: Complex Chains

Multi-step Chain with RunnablePassthrough:

```
from langchain_core.runnables import RunnablePassthrough

chain = (
    {"context": retriever, "question": RunnablePassthrough()}
    | prompt
    | llm
    | output_parser
)

result = chain.invoke("What is LangChain?")
print(result)

# Parallel Execution with RunnableParallel:
from langchain_core.runnables import RunnableParallel

chain = RunnableParallel(
    summary=prompt1 | llm | output_parser,
    keywords=prompt2 | llm | output_parser
)

result = chain.invoke({"text": "Long document..."})
print(result)
# Returns: {"summary": "...", "keywords": "..."}
```

Use as RAG

Complete RAG Application: A Quick Start Example

```
# imports

loader = PyPDFLoader("data/ag-studio.pdf")
docs = loader.load()

splitter = RecursiveCharacterTextSplitter(chunk_size=1000,
        chunk_overlap=100)
splits = splitter.split_documents(docs)

embeddings =
        HuggingFaceEmbeddings(model_name="all-MiniLM-L6-v2")
vectorstore = Chroma.from_documents(documents=splits,
        embedding=embeddings,collection_name="local-pdf-rag")
retriever = vectorstore.as_retriever(search_kwargs={"k": 3})

prompt = ChatPromptTemplate.from_template("""Answer the
        question based ONLY on the following context:
{context} Question: {question}""")

model = init_chat_model("llama-3.3-70b-versatile",
        model_provider="groq",temperature=0)

# Note: retriever | format_docs ensures the model gets text, not
        Document objects
def format_docs(docs):
    return "\n\n".join(doc.page_content for doc in docs)

chain = ({"context": retriever | format_docs, "question":
        RunnablePassthrough()}
    | prompt | model | StrOutputParser())

response = chain.invoke("What is the main topic of this document?")
print(response)
```

Use as Agent

Example: Modern Agent in LangChain v1

```
from langchain.agents import create_agent
from langchain.chat_models import init_chat_model
from langchain_core.tools import tool

@tool
def get_weather(city: str) -> str:
    """Get weather for a given city."""
    # Add a print here so you can see when the function actually runs!
    print(f"--- Executing get_weather for {city} ---")
    return f"It's always sunny in {city}!"

llm = init_chat_model("llama-3.3-70b-versatile",
        model_provider="groq")

# In v1.0, create_agent creates a compiled graph.
# We need to make sure the agent is permitted to call tools.
agent = create_agent(
    model=llm,
    tools=[get_weather],
    system_prompt="You are a helpful assistant. If you need weather
        info, use the tool."
)

# Use the invoke method
inputs = {"messages": [("user", "What is the weather in Pune?")]}
response = agent.invoke(inputs)

# In v1.0, the response contains the full message history of the turn.
# The last message should now be the assistant's final answer AFTER
        the tool result.
for msg in response["messages"]:
    msg.pretty_print()
```

Framework

LangChain Framework Components

Framework Architecture

Chains: The core of Lang*Chain*. Components (and even other chains) can be stringed together to create *chains*.
Prompt templates: Prompt templates are templates for different types of prompts. Like "chatbot" style templates, ELI5 question-answering, etc
LLMs: Large language models like GPT-3, BLOOM, etc
Indexing Utils: Ways to interact with specific data (embeddings, vectorstores, document loaders)
Tools: Ways to interact with the outside world (search, calculators, etc)
Agents: Agents use LLMs to decide what actions should be taken. Tools like web search or calculators can be used, and all are packaged into a logical loop of operations.
Memory: Short-term memory, long-term memory.

Core Building Blocks:

- **Models**: LLMs, Chat Models, Embeddings
- **Prompts**: Dynamic template management
- **Output Parsers**: Structured output extraction
- **Retrievers**: Document and data access
- **Memory**: Conversation state persistence
- **Agents & Tools**: Dynamic reasoning and actions

(Ref: Building the Future with LLMs, LangChain, & Pinecone)

Models

Models in LangChain
Three Types of Models:

- **LLMs (Large Language Models)**:
  - Input: String (prompt)
  - Output: String (completion)
  - Examples: GPT-4, Claude, Gemma, Llama 3, Mixtral.
  - Use case: Text generation, completion
- **Chat Models**:
  - Input: List of messages
  - Output: Chat message
  - Examples: ChatGPT, Claude Chat, ChatGroq
  - Use case: Conversational AI
- **Embedding Models**:
  - Input: Text
  - Output: Vector (list of floats)
  - Examples: OpenAI Embeddings, HuggingFace, Sentence Transformers
  - Use case: Semantic search, similarity

Models Functionality

- Tool calling: calling external tools (like databases queries or API calls) and use results in their responses.
- Structured output: where the model's response is constrained to follow a defined format.
- Multimodality: process and return data other than text, such as images, audio, and video.
- Reasoning: models perform multi-step reasoning to arrive at a conclusion.

Models Usage

- With agents: Models can be dynamically specified when creating an agent.
- Standalone: Models can be called directly (outside of the agent loop) for tasks like text generation, classification, or extraction without the need for an agent framework.

Model Integration: Modern Syntax
For standalone model `init_chat_model`

```
from langchain.chat_models import init_chat_model  # Still valid in v1
# OR use provider-specific import (recommended)
from langchain_groq import ChatGroq
from langchain.messages import HumanMessage, AIMessage,
        SystemMessage


# Initialize Groq LLM (ensure GROQ_API_KEY is set in your
        environment)
model = ChatGroq(model="llama-3.3-70b-versatile")  #
        https://console.groq.com/docs/models

# # or assuming os.environ["ANTHROPIC_API_KEY"] = "sk-..."
# model = init_chat_model(
#     "claude-sonnet-4-5-20250929",
#     # Kwargs passed to the model:
#     temperature=0.7,
#     timeout=30,
#     max_tokens=1000,
# )

conversation = [
    SystemMessage("You are a helpful assistant that translates English
        to French."),
    HumanMessage("Translate: I love programming."),
    AIMessage("J'adore la programmation."),
    HumanMessage("Translate: I love building applications.")
]

response = model.invoke(conversation)
print(response)  # AIMessage("J'adore creer des applications.")
```

Multimodal

Certain models can process and return non-textual data such as images, audio, and video. You can pass non-textual data to a model by providing content blocks.

```
response = model.invoke("Create a picture of a cat")
print(response.content_blocks)
# [
#     {"type": "text", "text": "Here's a picture of a cat"},
#     {"type": "image", "base64": "...", "mime_type": "image/jpeg"},
# ]
```

Reasoning

Many models are capable of performing multi-step reasoning to arrive at a conclusion.

```
## Streaming
for chunk in model.stream("Why do parrots have colorful feathers?"):
    reasoning_steps = [r for r in chunk.content_blocks if r["type"] ==
        "reasoning"]
    print(reasoning_steps if reasoning_steps else chunk.text)

## Complete Output
response = model.invoke("Why do parrots have colorful feathers?")
reasoning_steps = [b for b in response.content_blocks if b["type"] ==
    "reasoning"]
print(" ".join(step["reasoning"] for step in reasoning_steps))
```

Prompts

Prompts in LangChain

Prompt Management Strategies:

- **Prompt Templates**:
  - Parameterized templates with variables
  - Dynamic input insertion
  - Reusable prompt structures
- **Chat Prompt Templates**:
  - Multi-message conversations
  - System, human, AI message roles
  - Better for chat models
- **Few-Shot Prompts**:
  - Include example inputs/outputs
  - Guide model response style
  - Improve accuracy

Prompt Templates: Modern Examples

```
from langchain_core.prompts import PromptTemplate

# Use in chain with Groq
from langchain_groq import ChatGroq
from langchain_core.output_parsers import StrOutputParser

template = """You are a {role} assistant.
Task: {task}
Context: {context}
Provide a {format} response."""

prompt = PromptTemplate(
    template=template,
    input_variables=["role", "task", "context", "format"]
)

formatted = prompt.format(
    role="helpful",
    task="explain quantum computing",
    context="for beginners",
    format="simple"
)

chain = prompt | ChatGroq(model="llama-3.3-70b-versatile") |
        StrOutputParser()
result = chain.invoke({
    "role": "helpful",
    "task": "explain quantum computing",
    "context": "for beginners",
    "format": "simple"
})

print(result)
```

Chat Prompting

```
# Chat Prompt Template:
from langchain_core.prompts import ChatPromptTemplate

prompt = ChatPromptTemplate.from_messages([
    ("system", "You are a {role}"),
    ("human", "{input}"),
    ("ai", "I understand. Let me help with that."),
    ("human", "{follow_up}")
])

chain = prompt | ChatGroq(model="llama-3.3-70b-versatile") |
        StrOutputParser()
result = chain.invoke({
    "role": "helpful",
    "input": "Explain quantum computing",
    "follow_up": "Make it simpler"
})
print(result)
```

Document Loaders & Retrievers

Document Loading

Wide Range of Loaders:

- **Files**: PDF, Word, PowerPoint, CSV, Markdown
- **Web**: HTML, URLs, sitemaps, web scraping
- **Cloud**: S3, GCS, Google Drive, Notion
- **Databases**: SQL, MongoDB, Elasticsearch
- **Communication**: Email, Slack, Discord
- **Code**: GitHub, GitLab, Jupyter notebooks

Modern Document Processing:

```
from langchain_community.document_loaders import (
    PyPDFLoader,
    WebBaseLoader,
    TextLoader)
from langchain_text_splitters import RecursiveCharacterTextSplitter

loader = PyPDFLoader("document.pdf")
documents = loader.load()

splitter = RecursiveCharacterTextSplitter(
    chunk_size=1000,
    chunk_overlap=200)

chunks = splitter.split_documents(documents)
```

Vector Stores & Retrievers

Popular Vector Stores:

- **Chroma**: Open-source, local-first, easy setup
- **Pinecone**: Managed service, production-ready
- **Weaviate**: GraphQL API, hybrid search
- **Qdrant**: High performance, filtering support
- **LanceDB**: Serverless, embedded option

Complete Example with Chroma & HuggingFace Embeddings:

```
# from langchain_community.embeddings import
      HuggingFaceEmbeddings
from langchain_huggingface import HuggingFaceEmbeddings
from langchain_community.vectorstores import Chroma
from langchain_text_splitters import RecursiveCharacterTextSplitter
from langchain_community.document_loaders import WebBaseLoader

loader = WebBaseLoader("https://example.com/article")
docs = loader.load()

splitter = RecursiveCharacterTextSplitter(chunk_size=1000,
      chunk_overlap=200)
splits = splitter.split_documents(docs)

vectorstore = Chroma.from_documents(
    documents=splits,

        embedding=HuggingFaceEmbeddings(model_name="all-MiniLM-L6-v2"))

retriever = vectorstore.as_retriever(search_kwargs={"k": 3})
```

Retrieval Strategies

Different Retrieval Methods:

```
# Returns the most semantically similar documents to the user
# query based purely on vector distance (top-k closest matches).
retriever = vectorstore.as_retriever(search_type="similarity",
      search_kwargs={"k": 4})

# MMR (Maximum Marginal Relevance)Balances relevance and
      diversity,
# ensuring the retrieved documents aren't repetitive by reducing
      semantic redundancy among the top-k results.
retriever = vectorstore.as_retriever(search_type="mmr",
      search_kwargs={"k": 4, "fetch_k": 20})

# Filters out documents that fall below a minimum similarity score,
# ensuring only high-confidence matches are returned (still limited
      by k)
retriever = vectorstore.as_retriever(search_type =
      "similarity_score_threshold",
    search_kwargs={"score_threshold": 0.8, "k": 4})
```

```
# Manual search: Directly retrieves the top-k most similar documents
# without using a retriever wrapper same as search_type "similarity"
        but explicitly called.
results = vectorstore.similarity_search("What is machine learning?",
        k=3)

# With scores: Same as above but also returns the similarity
# score for each document, helping you inspect retrieval quality
results_with_scores = vectorstore.similarity_search_with_score(
    "What is machine learning?", k=3)
```

Chains with LCEL

Modern LangChain: LCEL (LangChain Expression Language)

What is LCEL?

- Modern, declarative way to build chains (introduced 2023)
- Uses pipe operator `|` to chain components
- Replaces old `LLMChain` pattern
- Built-in streaming, async, and batch support

Key Benefits:

- **Simplicity**: More readable and concise
- **Streaming**: Built-in streaming by default
- **Async**: Native async/await support
- **Observability**: Better tracing and debugging
- **Fallbacks**: Easy error handling and retries

(Ref: LangChain LCEL Documentation)

Modern Chains: LCEL Overview

What Changed?

- **Old**: `LLMChain`, `SimpleSequentialChain` (Deprecated)
- **New**: LCEL with pipe operator `|`

Core Runnables:

- `RunnablePassthrough`: Pass data through
- `RunnableParallel`: Execute in parallel
- `RunnableLambda`: Custom functions
- `RunnableBranch`: Conditional execution

LCEL: Basic Chain Patterns

```
// Simple Chain:
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser

prompt = ChatPromptTemplate.from_template("Tell me a joke about
        {topic}")
model = ChatGroq(model_name="gemma-7b-it")
output_parser = StrOutputParser()

chain = prompt | model | output_parser
result = chain.invoke({"topic": "programming"})

// Chain with Multiple Steps:
# Step 1: Generate topic
topic_chain = (
    ChatPromptTemplate.from_template("Suggest a {genre} topic")
    | ChatGroq(model_name="gemma-7b-it")
    | StrOutputParser()
)

# Step 2: Write content
content_chain = (
    ChatPromptTemplate.from_template("Write a story about:
        {topic}")
    | ChatGroq(model_name="llama3-8b-8192")
    | StrOutputParser()
)

# Combine: topic generates input for content
full_chain = {"topic": topic_chain} | content_chain
result = full_chain.invoke({"genre": "science fiction"})
```

LCEL: RAG Chain Pattern

Retrieval Augmented Generation:

```
from langchain_core.runnables import RunnablePassthrough
from langchain_groq import ChatGroq
# Assume 'retriever' from previous slide is defined

# Format documents
def format_docs(docs):
    return "\n\n".join(doc.page_content for doc in docs)

# RAG chain
rag_chain = (
    {
        "context": retriever | format_docs,
        "question": RunnablePassthrough()
    }
    | ChatPromptTemplate.from_template("""
        Answer the question based on the context:

        Context: {context}

        Question: {question}
    """)
    | ChatGroq(model_name="llama3-8b-8192")
    | StrOutputParser()
)

# Use it
answer = rag_chain.invoke("What is LangChain?")
```

LCEL: Parallel Execution

Benefits:

- Faster execution
- Clean code structure
- Easy to add/remove tasks

Run Multiple Chains in Parallel:

```
from langchain_core.runnables import RunnableParallel
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser

# Define parallel tasks
parallel_chain = RunnableParallel(
    summary=ChatPromptTemplate.from_template("Summarize:
        {text}")
    | ChatGroq(model_name="llama3-8b-8192")
    | StrOutputParser(),

    keywords=ChatPromptTemplate.from_template("Extract keywords:
        {text}")
    | ChatGroq(model_name="gemma-7b-it")
    | StrOutputParser(),

    sentiment=ChatPromptTemplate.from_template("Analyze
        sentiment: {text}")
    | ChatGroq(model_name="gemma-7b-it")
    | StrOutputParser()
)

# Execute all in parallel
results = parallel_chain.invoke({"text": "Long document content..."})
```

LCEL: Error Handling & Fallbacks

```
// Fallback to Alternative Model:
from langchain_groq import ChatGroq
from langchain_anthropic import ChatAnthropic

primary = ChatGroq(model_name="llama3-70b-8192")
fallback = ChatAnthropic(model="claude-3-opus-20240229")

chain = prompt | primary.with_fallbacks([fallback]) | output_parser

// Retry Logic: If Groq fails, automatically retries
from langchain_core.runnables import RunnableRetry

chain_with_retry = (
    prompt
    | RunnableRetry(max_attempts=3, wait_exponential_jitter=True)
    | ChatGroq(model_name="gemma-7b-it")
    | output_parser
)

// Custom Error Handling:
from langchain_core.runnables import RunnableLambda

def handle_errors(x):
    try:
        return x
    except Exception as e:
        return {"error": str(e)}

chain = prompt | model | RunnableLambda(handle_errors)
```

LCEL: Streaming

```
// Stream Tokens as Generated:
from langchain_groq import ChatGroq
# Assume prompt and output_parser are defined
chain = prompt | ChatGroq(model_name="gemma-7b-it") |
        StrOutputParser()

# Stream output
for chunk in chain.stream({"topic": "AI"}):
    print(chunk, end="", flush=True)

// Async Streaming:
import asyncio

async def stream_response():
    async for chunk in chain.astream({"topic": "AI"}):
        print(chunk, end="", flush=True)

asyncio.run(stream_response())
```

```
// Streaming with Events:
# Get detailed streaming events
async for event in chain.astream_events({"topic": "AI"},
        version="v1"):
    kind = event["event"]
    if kind == "on_chat_model_stream":
        content = event["data"]["chunk"].content
        print(content, end="", flush=True)
```

Memory

Memory in LangChain

Why Memory?

- LLMs are stateless by default
- Chatbots need conversation context
- Memory stores and retrieves conversation history

Memory Types (Consolidated):

- **ConversationBufferMemory**:
  - Stores entire conversation history
  - Simple but can exceed token limits
  - Best for: Short conversations
- **ConversationBufferWindowMemory**:
  - Keeps only last K interactions
  - Prevents token overflow
  - Best for: Longer conversations with recent context
- **ConversationSummaryMemory**:
  - Summarizes old messages
  - Reduces token usage
  - Best for: Very long conversations

Memory: Implementation Examples

Important Note

In LangChain v1, memory classes have moved to `langchain-classic`. To use `pip install langchain-classic`

```
from langchain_classic.memory import ConversationBufferMemory
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate,
        MessagesPlaceholder
from langchain_core.runnables import RunnablePassthrough

memory = ConversationBufferMemory(
    return_messages=True,
    memory_key="history")

prompt = ChatPromptTemplate.from_messages([
    ("system", "You are a helpful assistant"),
    MessagesPlaceholder(variable_name="history"),
    ("human", "{input}")])

chain = (
    RunnablePassthrough.assign(history=lambda x:
        memory.load_memory_variables({})["history"]    )
    | prompt
    | ChatGroq(model_name="gemma2-9b-it"))

# Use the chain
response = chain.invoke({"input": "Hi, I'm Alice"})
memory.save_context({"input": "Hi, I'm Alice"}, {"output":
        response.content})
```

Memory: Window Memory

Benefits:

- Fixed memory footprint
- Maintains recent context
- Prevents token limit issues

Buffer Window Memory (Keeps Last K):

```
from langchain.memory import ConversationBufferWindowMemory

memory = ConversationBufferWindowMemory(
    k=3, # Only keeps last 3 interactions
    return_messages=True,
    memory_key="history"
)

conversations = [ # Add conversations
    ("Tell me about Python", "Python is a versatile language..."),
    ("What makes it popular?", "Its simplicity and libraries..."),
    ("Give an example", "Like NumPy for computing..."),
    ("What about AI?", "Python excels in AI with TensorFlow...")
]

for input_text, output_text in conversations:
    memory.save_context({"input": input_text}, {"output":
        output_text})

# Retrieves only last 3 interactions
history = memory.load_memory_variables({})
print(f"Stored messages: {len(history['history'])}")  # Will be 6 (3
        pairs)
```

Agents & Tools

Modern Agents Overview

What Are Agents?

- Use LLMs as reasoning engines
- Dynamically choose which tools to use
- Iterative: observe, think, act, repeat
- Best for complex, multi-step tasks

Modern Agent Types (LangChain v1):

- **create_agent**: Primary method, uses ReAct pattern
- **create_deep_agent**: For complex, long-running tasks

When to Use:

- **create_agent**: Simple chatbots, Q&A, tool calling
- **create_deep_agent**: Research, multi-step planning, file-system access
- **LangGraph**: Custom workflows requiring fine-grained control

(Ref: LangChain Agents Documentation)

Creating Tools: Modern Approach

Tool Requirements:

- Must have a docstring (used by LLM to understand tool purpose)
- Type hints are required for parameters
- Return type should be string or JSON-serializable

```
// Method 1: Using @tool Decorator:
from langchain_core.tools import tool

@tool
def search_wikipedia(query: str) -> str:
    """Search Wikipedia for information about a topic."""
    from wikipedia import summary
    try:
        return summary(query, sentences=3)
    except:
        return "Could not find information."

@tool
def calculate(expression: str) -> str:
    """Evaluate a mathematical expression."""
    try:
        return str(eval(expression))
    except:
        return "Invalid expression"
```

Creating Tools: Modern Approach

// Method 2: From Function:

```
from langchain_core.tools import Tool

def get_weather(location: str) -> str:
    """Get weather for a location."""
    return f"Weather in {location}: Sunny, 72F"

weather_tool = Tool.from_function(
    func=get_weather,
    name="weather",
    description="Get current weather for a location")
```

Modern Agent: create_agent()

- Built on LangGraph (durable execution)
- Automatic tool calling loop
- Simple, unified API

```
from langchain.agents import create_agent
from langchain_core.tools import tool
from langchain_groq import ChatGroq

@tool
def get_weather(city: str) -> str:
    """Get weather for a given city."""
    return f"It's sunny in {city}!"

@tool
def search_wikipedia(query: str) -> str:
```

```
    """Search Wikipedia for information."""
    return f"Wikipedia results for: {query}"

# Create agent with tools
agent = create_agent(
    model="llama-3.3-70b-versatile",  # Can use model string or
        ChatGroq object
    tools=[get_weather, search_wikipedia],
    system_prompt="You are a helpful assistant that can check weather
        and search Wikipedia.")

# Run the agent
response = agent.invoke({"messages": [{"role": "user", "content":
        "What's the weather in Paris?"}]})

print(response["messages"][-1].content)
```

Modern Approach with bind_tools

```
from langchain_groq import ChatGroq
from langchain_core.tools import tool

@tool
def multiply(a: int, b: int) -> int:
    """Multiply two numbers."""
    return a * b

@tool
def add(a: int, b: int) -> int:
    """Add two numbers."""
    return a + b

# Bind tools to model
llm = ChatGroq(model_name="llama3-8b-8192")
llm_with_tools = llm.bind_tools([multiply, add])

# Invoke
response = llm_with_tools.invoke("What is 3 times 4 plus 5?")

# Check if tool was called
if response.tool_calls:
    tool_call = response.tool_calls[0]
    print(f"Tool: {tool_call['name']}")
    print(f"Args: {tool_call['args']}")
```

Agent Middleware

Extend Agent Behavior Without Modifying Core Logic:

- **Human-in-the-loop**: Approve tool calls before execution
- **Conversation compression**: Summarize long conversations
- **PII redaction**: Remove sensitive data
- **Rate limiting**: Control API usage
- **Error handling**: Retry failed operations

```
from langchain.agents import create_agent
from langchain.agents.middleware import AgentMiddleware

# Example: Logging middleware
class LoggingMiddleware(AgentMiddleware):
    async def on_agent_start(self, state, context):
        print(f"Agent started with input:
        {state['messages'][-1].content}")

    async def on_agent_end(self, state, context):
        print(f"Agent completed with output:
        {state['messages'][-1].content}")

# Create agent with middleware
agent = create_agent(
    model="llama-3.3-70b-versatile",
    tools=[get_weather],
    middleware=[LoggingMiddleware()]
)
```

Output Parsers

Output Parsers Overview

Why Output Parsers?

- LLMs return unstructured text
- Applications need structured data
- Parsers extract and validate output

Common Parser Types:

- **StrOutputParser**: Basic string extraction
- **JsonOutputParser**: Parse JSON responses
- **PydanticOutputParser**: Structured data with validation
- **StructuredOutputParser**: Multiple fields
- **CommaSeparatedListOutputParser**: Lists

Modern Best Practice:

- Use OpenAI's `with_structured_output()` when possible
- More reliable than prompt-based parsing
- Leverages function calling internally

Structured Output: Modern Approach

Benefits:

- Type-safe responses
- Automatic validation
- More reliable than prompt-based parsing

```
from langchain_groq import ChatGroq
from pydantic import BaseModel, Field

# Define output schema
class Person(BaseModel):
    name: str = Field(description="Person's name")
    age: int = Field(description="Person's age")
    occupation: str = Field(description="Person's job")

# Create model with structured output (relies on tool-calling)
llm = ChatGroq(model_name="llama3-70b-8192")
structured_llm = llm.with_structured_output(Person)

# Use in chain
response = structured_llm.invoke(
    "Tell me about a software engineer named Alice who is 28"
)

# Response is a Pydantic object
print(response.name)
print(response.age)
print(response.occupation)
```

Pydantic Output Parser (Alternative)

```
from langchain.output_parsers import PydanticOutputParser
from langchain_groq import ChatGroq
from pydantic import BaseModel, Field, validator
from typing import List

class MovieReview(BaseModel):
    title: str = Field(description="Movie title")
    rating: int = Field(description="Rating from 1-10")

parser = PydanticOutputParser(pydantic_object=MovieReview)

# Add to prompt
prompt = ChatPromptTemplate.from_template("""
Review the movie: {movie}

{format_instructions}""")

chain =
        (prompt.partial(format_instructions=parser.get_format_instructions())
    | ChatGroq(model_name="gemma-7b-it") | parser)

result = chain.invoke({"movie": "Inception"})
```

Output Parser Error Handling

```
from langchain_groq import ChatGroq
# Assume 'parser' is a defined PydanticOutputParser

// OutputFixingParser (Auto-fix Errors):
from langchain.output_parsers import OutputFixingParser

# If parsing fails, use LLM to fix
fixing_parser = OutputFixingParser.from_llm(
    parser=parser,
    llm=ChatGroq(model_name="gemma-7b-it")
)

// Automatically fixes malformed output
# result = fixing_parser.parse(malformed_output)

// RetryOutputParser (Retry with Context):
from langchain.output_parsers import RetryWithErrorOutputParser

retry_parser = RetryWithErrorOutputParser.from_llm(
    parser=parser,
    llm=ChatGroq(model_name="llama3-8b-8192")
)

# Retries with both output and original prompt
# result = retry_parser.parse_with_prompt(...)
```

LangChain Ecosystem

LangChain Ecosystem Components

- **LangChain Core**:
  - Base abstractions and LCEL
  - Foundation for all other packages
- **LangChain Community**:
  - Third-party integrations
  - Vector stores, document loaders
  - Community-maintained tools
- **LangGraph**:
  - Build stateful, multi-actor applications
  - Complex agent workflows with cycles
  - State management for agents
- **LangServe**:
  - Deploy chains as REST APIs
  - Automatic FastAPI generation
  - Production deployment
- **LangSmith**:
  - Debugging and monitoring
  - Tracing and evaluation
  - Dataset management

LangGraph: Stateful Agents

- Build complex, stateful agent workflows
- Support for cycles and conditional logic
- Persist state across interactions
- Multiple agents working together

```
from langgraph.graph import StateGraph
from typing import TypedDict, Annotated
import operator

class AgentState(TypedDict):
    messages: Annotated[list, operator.add]
    next: str

def call_model(state):
    response = llm.invoke(state["messages"])
    return {"messages": [response]}

def should_continue(state):
    if len(state["messages"]) > 5:
        return "end"
    return "continue"

workflow = StateGraph(AgentState)
workflow.add_node("agent", call_model)
workflow.add_conditional_edges("agent", should_continue)
workflow.set_entry_point("agent")

app = workflow.compile()
```

LangServe: Deploy as API

Automatic Features:

- Interactive playground at `/chat/playground`
- OpenAPI docs at `/docs`
- Streaming support
- Batch processing

Deploy Any Chain as REST API:

```
from fastapi import FastAPI
from langserve import add_routes
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate

# Create chain
prompt = ChatPromptTemplate.from_template("Tell me about
        {topic}")
chain = prompt | ChatGroq(model_name="gemma-7b-it")

# Create FastAPI app
app = FastAPI(
    title="LangChain API", version="1.0",
    description="API for my LangChain application")

# Add chain as route
add_routes(app, chain, path="/chat")

# Run: uvicorn app:app --reload
# API available at: http://localhost:8000/chat
```

LangSmith: Monitoring & Debugging

What is LangSmith?

- Platform for debugging LLM applications
- Trace every step of chain execution
- Evaluate model performance
- Manage test datasets
- Monitor production applications

Setup:

```
import os
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser

os.environ["LANGCHAIN_TRACING_V2"] = "true"
os.environ["LANGCHAIN_API_KEY"] = "your-langsmith-api-key"
os.environ["LANGCHAIN_PROJECT"] = "my-groq-project"

# Now all chain executions are automatically traced
prompt = ChatPromptTemplate.from_template("Tell me about
        {topic}")
llm = ChatGroq(model_name="gemma-7b-it")
output_parser = StrOutputParser()
chain = prompt | llm | output_parser
result = chain.invoke({"topic": "Large Language Models"})

# View traces at: https://smith.langchain.com
```

Best Practices

Best Practices: Error Handling

```
// 1. Use Fallbacks:
from langchain_groq import ChatGroq
from langchain_anthropic import ChatAnthropic

primary = ChatGroq(model_name="llama3-70b-8192")
fallback = ChatAnthropic(model="claude-3-opus-20240229")

chain = prompt | primary.with_fallbacks([fallback]) | parser

// 2. Implement Retries:
from langchain_core.runnables import RunnableRetry

chain_with_retry = (
    prompt
    | RunnableRetry(
        max_attempts=3,
        wait_exponential_jitter=True
    )
    | ChatGroq(model_name="gemma-7b-it")
    | parser
)

// 3. Graceful Degradation:
try:
    result = chain.invoke(input_data)
except Exception as e:
    # logger.error(f"Chain failed: {e}")
    # result = fallback_response()
    pass
```

Best Practices: Token Management with Groq

Groq Models - Fast and Free Tier:

- gemma2-9b-it: Ultra-fast, 8K context, great for chat
- llama3-8b-8192: Balanced, 8K context, general purpose
- llama3-70b-8192: Most capable, 8K context, complex tasks
- llama-3.1-8b-instant: Fastest, optimized for low latency
- Groq billed by requests/day on free tier, not tokens

```
from langchain_groq import ChatGroq

# Choose model based on needs
llm_fast = ChatGroq(
    model_name="gemma2-9b-it",
    max_tokens=500,
    temperature=0.7,
    max_retries=2
)

# Monitor context length manually
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("google/gemma-2-9b-it")
token_count = len(tokenizer.encode(text))

# Groq's speed allows batch processing without latency concerns
```

Best Practices: Security & Privacy

- Be aware of the data usage policies of your LLM provider.
- Groq has a zero-retention policy for API data.
- Consider self-hosted models for maximum data control.
- Implement PII detection and redaction before sending data.

```
// 1. API Key Management:
import os
from dotenv import load_dotenv

load_dotenv()  # Load from .env file
api_key = os.getenv("GROQ_API_KEY")

// 2. Timeouts and Retries:
from langchain_groq import ChatGroq

llm = ChatGroq(model_name="llama3-8b-8192",
    temperature=0,
    max_retries=2,
    request_timeout=30) # seconds

// 3. Input Validation:
def validate_input(user_input: str) -> str:
    if len(user_input) > 8000:      # Sanitize input
        raise ValueError("Input too long for the model context.")
    # Remove potential injection attempts
    return user_input.strip()
```

Best Practices: Choosing the Right Model

Groq Model Selection Guide:

Use Case	Model	Why
Chatbots	gemma2-9b-it	Fast, efficient, good reasoning
Summarization	llama3-8b-8192	Balanced speed/quality
Complex reasoning	llama3-70b-8192	Most capable
Ultra-low latency	llama-3.1-8b-instant	Optimized for speed
Code generation	llama3-70b-8192	Better instruction following

```
# Pattern: Start with fast model, fallback to capable model
from langchain_groq import ChatGroq

primary = ChatGroq(model_name="gemma2-9b-it",
        temperature=0.7)
fallback = ChatGroq(model_name="llama3-70b-8192",
        temperature=0.7)

chain = prompt | primary.with_fallbacks([fallback]) | parser
```

Best Practices: Async Patterns

Benefits:

- Faster parallel processing
- Better resource utilization
- Improved user experience with streaming

```
// Use Async for Better Performance:
import asyncio

async def process_multiple_queries(queries):
    # Process queries concurrently
    tasks = [chain.ainvoke({"input": q}) for q in queries]
    results = await asyncio.gather(*tasks)
    return results

# Run
queries = ["Query 1", "Query 2", "Query 3"]
results = asyncio.run(process_multiple_queries(queries))
// Async Streaming:
async def stream_response(input_text):
    async for chunk in chain.astream({"input": input_text}):
        print(chunk, end="", flush=True)

asyncio.run(stream_response("Tell me about AI"))
```

What's New

What's New in LangChain Ecosystem

(Oct 2025, Release of 1.0 version)

Major Additions in LangChain/Graph 1.0

- LangChain is now on top of LangGraph (not the other way round, as before)
- LangChain agent `create_agent` (ReACT) is one specialized case of many types in LangGraph. You can even visualize it as a workflow of nodes.
- Middle-ware to control the data before going to LLM. Curation, sumamrization, context engineering, etc.
- Standard content blocks to cater to different output formats by different LLMs.

Code Reorganization in LangChain/Graph 1.0

This is in line with principle of 'Simplified Name-spaces'.

- LangChain legacy chains, hub, vector stores, retrievers etc are now part of `langchain_classic` module.
- All agents are in `langchain.agents`
- All Models are in `langchain.chat_models`
- All Tools are in `langchain.tools`
- All Messages are in `langchain.messages`
- All Embeddings are in `langchain.embeddings`

LangChain v1: What's New

Major Changes in v1.0 (October 2025):

- **Simplified Package Structure**:
  - Core functionality in `langchain`
  - Legacy features moved to `langchain-classic`
  - Requires Python 3.10+ (Python 3.9 EOL October 2025)
- **Agent-First Design**:
  - New `create_agent()` function
  - Built on LangGraph runtime
  - Durable execution and persistence
- **Content Blocks**:
  - Standardized message format across providers
  - Support for text, images, reasoning, tool calls
  - Better multimodal support
- **Middleware System**:
  - Inject custom logic at any point
  - Human-in-the-loop support
  - Error handling and retries

(Ref: LangChain v1.0 Release Notes)

How LangChain 1.0 Simplifies Agents to Just 10 Lines of Code

- LangChain 1.0 Alpha released; full 1.0 expected by late October.
- Rewritten as a simplified agent runtime built on LangGraph.
- Agents can now be created in roughly 10/few lines of code.
- Legacy LangChain moved to "LangChain Classic."
- Functionally similar to OpenAI or Pedantic SDK agents.
- Unified "create_agent" abstraction across languages.
- Integrates easily with external SDKs like Google's 80k.

Why LangGraph 1.0 is Nearly Non-Breaking and Production-Ready

- LangGraph 1.0 introduces minimal breaking changes from prior releases.
- Existing LangGraph implementations continue to work as-is.
- Core runtime stable across Python and TypeScript.
- Supports durable execution with checkpoints and rollback.
- State can persist via Postgres or SQLite for reliability.
- Human-in-the-loop and interrupt handling built-in.
- Ready for production-grade use; used by Uber, LinkedIn, Klarna, JPMorgan, Cloudflare.

The New Standardized Content Blocks for Easier Model Switching

- LangChain Core now uses standardized content/message blocks.
- Abstracts input/output across providers like OpenAI and Anthropic.
- Simplifies switching models without rewriting logic.
- Unifies multimodal inputs, reasoning traces, and tool calls.
- Middleware layer ensures consistent formatting and metadata.
- Supports normalized logging across different model providers.
- Key enabler for multi-model experimentation and portability.

Durable Execution, Streaming, Human-in-the-Loop, and Time Travel

- Agents persist state with rollback and checkpointing.
- Supports human approval and manual intervention mid-run.
- Time travel enables returning to earlier workflow states.
- Four streaming modes: messages, updates, values, custom.
- Update streaming ideal for dashboards and UX refresh.
- State persistence possible locally or via Postgres.
- Enables retry and branch execution for debugging and auditing.

Summary: What's New in LangChain Ecosystem

(Oct 2025, Release of 1.0 version)

1. LangChain Agents: The Standard Loop

- **High-Level Abstraction:** Simplest and fastest way to build an agent.
- **Primary Pattern:** Implements the standard **ReAct-style loop** (Reasoning + Acting).
- **Key Feature**: The `create_agent` function (introduced in v1.0) is the simplest and fastest way to build a production-ready agent. It abstracts away the complexity.
- **Process:** The LLM decides at each step whether to use a tool or provide a final answer.
- **Underlying Technology:** LangChain's agents since v1.0 are built **on top of the LangGraph runtime**.
- **Use Case:** Quick start, simple linear tasks, default agent behavior.

2. LangGraph: Workflow Automation & Control

- **Role:** Low-level **orchestration framework** and runtime.
- **Core Feature:** Defines explicit workflow automation and agent orchestration. Complex, stateful, and cyclic workflows as directed graphs.
- **Structure:** You define:
  1. **Nodes:** Steps (LLM call, tool execution, custom function).
  2. **Edges:** Conditional logic for transitions (e.g., if tool succeeds, go to Node B; if it fails, go to Node C).
- **Multi-Agent Systems:** Provides the explicit control needed for building supervised multi-agent systems and defining handoffs.
- **Relationship to LangChain:** Used when the standard LangChain agent loop is insufficient, requiring **fine-grained control** over the flow.

3. Deep Agents: Concept for Complex Tasks

- **Concept/Library:** Not a separate module, but an architectural pattern built on LangGraph for solving highly complex, long-running tasks.
- **Focus:** Advanced context management and planning.
- **Key Techniques:**
  1. **Planning/Decomposition:** Breaking down the goal (e.g., using a "Todo List" tool).
  2. **Sub-agents:** Delegating specialized tasks to other agents for parallel or sequential execution.
  3. **Long-Term Memory:** Utilizing external memory or file systems for persistent context.
- **Underlying Runtime**: Deep Agents are also built on LangGraph, leveraging its capabilities to manage the complex state and flow of the agent's multi-step plan.

Summary: Agent Framework Comparison

Key Takeaway: LangGraph provides the underlying runtime and control flow for both simple and complex agent applications.

Conclusions

Conclusions

Key Takeaways

What We Learned:

- LCEL makes chains simple
- Agents enable autonomy
- RAG connects to your data
- Memory maintains context
- Modular design = flexibility

You're ready to build intelligent LLM applications!

LangChain at a Glance

- **Models**: LLMs, Chat, Embeddings
- **Prompts**: Dynamic templates
- **Chains**: Compose with LCEL
- **Memory**: Conversation state
- **Retrievers**: Document access
- **Agents**: Autonomous tools

(Ref: Building Generative AI applications - Anand Iyer, Rajesh Thallam)

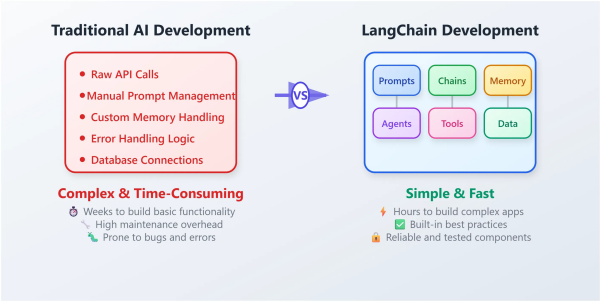
Best Practices to Remember

Development:

- Use LCEL for chains
- Start with simple models
- Add complexity gradually
- Test with small datasets

Production:

- Enable LangSmith tracing
- Implement error handling
- Monitor token usage
- Use async for scale



(Ref: What is LangChain and Why Should You Care? - Saif Ali)

Golden Rule: Keep it simple, make it work, then optimize

Resources & Next Steps

Official Documentation:

- LangChain Docs: https://python.langchain.com
- LangChain Blog: https://blog.langchain.dev
- LangChain Academy: https://academy.langchain.com
- API Reference: https://api.python.langchain.com

GitHub Repositories:

- Core: https://github.com/langchain-ai/langchain
- Templates: https://github.com/langchain-ai/langchain/tree/master/templates
- LangGraph: https://github.com/langchain-ai/langgraph

Community:

- Discord: https://discord.gg/langchain
- Twitter: @LangChainAI
- YouTube: LangChain official channel

Practice:

- Start with simple LCEL chains
- Build a RAG application
- Create custom tools and agents
- Deploy with LangServe

Final Thoughts

LangChain

LangChain makes building with LLMs accessible

- Start experimenting today
- Join the community
- Share your projects
- Keep learning and building

Thank you! Questions? Let's discuss.

(Ref: What is Langchain and why should I care as a developer? - Logan Kilpatrick)

References

References

Many publicly available resources:

- Intro to LangChain for Beginners - A code-based walkthrough- Menlo Park Lab
- LangChain Crash Course (10 minutes): Easy-to-Follow Walkthrough of the Most Important Concepts - Menlo Park Lab
- Official doc: https://docs.langchain.com/docs/
- Git Repo: https://github.com/hwchase17/langchain
- LangChain 101: The Complete Beginner's Guide Edrick https://www.youtube.com/watch?v=P3MAbZ2eMUI A wonderful overview, don't miss
- Cookbook by Gregory Kamradt(Easy way to get started): https://github.com/gkamradt/langchain-tutorials/blob/main/LangChain%20Cookbook.ipynb
- Youtube Tutorials: https://www.youtube.com/watch?v=_v_fg
- LangChain 101 Course (updated with LCEL) - Ivan Reznikov
- https://github.com/IvanReznikov/DataVerse/tree/main/Cou
- A Complete LangChain Guide https://nanonets.com/blog/lan
- 7 Ways to Use LangSmith's Superpowers to Turbo-boost Your LLM Apps - Menlo Park Lab
- LangChain official blog: https://blog.langchain.dev
- LangChain Academy: https://academy.langchain.com
- LangChain templates repo: https://github.com/langchain-ai/langchain/tree/master/templates
- Groq Documentation: https://console.groq.com/docs
- Groq Model Playground: https://groq.com/
- LangChain Groq Integration: https://python.langchain.com/d
- Groq GitHub Examples: https://github.com/groq/groq-python