Reference Card: LangChain
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Introduction

Introduction to LangChain

What is LangChain?
LangChain: A comprehensive framework for building LLM-powered applications

- **Core Purpose**: Simplify development of applications using LLMs
- **Key Solutions**:
  - **RAG**: Connect language models to external data sources
  - **Agentic**: Allow language models to interact with their environment
- **Main Features**:
  - Generic interface to various foundation models
  - Advanced prompt management framework
- **Availability**: Python and JavaScript libraries
- **Open Source**: MIT License, created by Harrison Chase
- **Repository**: https://github.com/langchain-ai/langchain

(Ref: Getting Started with LangChain: A Beginner's Guide to Building LLM-Powered Applications)

Why You Need LangChain
- LLMs alone lack context, memory, and retrieval abilities.
- Chatbots need to manage chat history and company knowledge bases.
- Storing, retrieving, and reasoning over data is complex manually.
- LangChain acts as an abstraction layer for building AI agents.
- It integrates LLMs, memory, and tools seamlessly.
- Enables vendor flexibility, easy switch between Open/Close models.
- Reduces code complexity and accelerates AI app development.
- Simplifies connecting models, databases, and APIs into a single framework.

LLMs vs Agentic Software
- LLMs are static, respond from training data without awareness.
- Agents have autonomy, memory, and tool use for dynamic actions.
- Example: Refund query, agent retrieves policy, product, and chat history.
- Agents can access vector databases and retrieve company knowledge.
- LangChain enables memory persistence across user conversations.
- Traditional software follows fixed logic; agents make adaptive decisions.
- Agentic software uses modular components (LLMs, memory, retrievers).
- LangChain provides prebuilt tools for these agentic capabilities.

LangChain Core Components and Labs
- Core modules: LLM connectors, memory, embeddings, vector stores.
- Simplifies LLM API setup, e.g., ChatOpenAI() or ChatGroq()
- Supports databases like Chroma or Pinecone for knowledge retrieval.
- Prompt templates manage dynamic, reusable prompts and chat context.
- LCEL (LangChain Expression Language) composes chains without legacy LLMChain wrappers
- Enables async, streaming, and batch workflows with type safety.

So, Why LangChain?
- **RAG Applications**: Build Retrieval Augmented Generation apps with external data
- **Agent Systems**: Create intelligent agents with tool access
- **Production Ready**: Logging, callbacks, monitoring built-in
- **Model Agnostic**: Switch between LLM providers easily
- **Modular Design**: Compose components as needed

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

LangChain Community & Ecosystem

- **Community Growth**:
  - Over 80,000+ GitHub stars (as of 2024)
  - 2,000+ contributors
  - Millions of monthly downloads
  - Active Discord, Twitter/X presence
- **License**: MIT License - freely modifiable and commercial-friendly
- **Ecosystem Components**:
  - **LangChain Core**: Foundation library
  - **LangGraph**: Stateful, multi-actor applications
  - **LangServe**: Deploy as REST APIs
  - **LangSmith**: Debugging, testing, monitoring

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

Installation & Setup

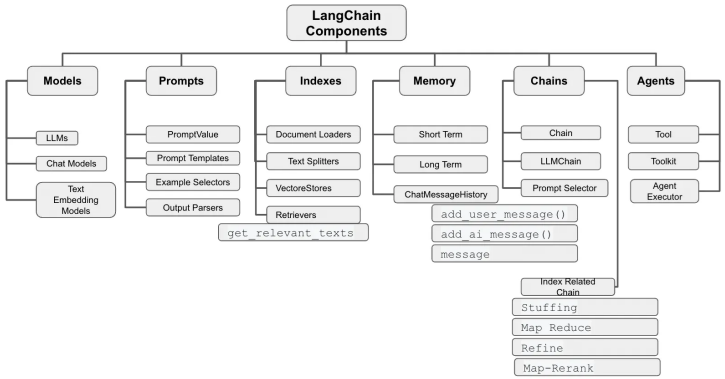
Prerequisites:

- Python version ≥ 3.9 and < 4.0
- Modern Installation (2024)
- (Ref: Official LangChain Documentation 2024)

:

```
# Core packages
pip install langchain langchain-core

# Provider-specific packages for Groq
pip install langchain-groq

# Alternative providers
# pip install langchain-anthropic langchain-google-genai

# Community integrations for embeddings
pip install langchain-community langchain-huggingface sentence-transformers

# Optional components
pip install chromadb            # Vector store
pip install langchain-text-splitters  # Document processing

//API Keys Setup:

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

Core Components Overview



- **Models**: LLMs, Chat Models, Embeddings
- **Prompts**: Template management and optimization
- **Chains/LCEL**: Compose components with pipes
- **Memory**: Conversation state management
- **Retrievers**: Access external data
- **Agents**: Dynamic tool selection and execution

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

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 2024)

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"})
```

LCEL: Advanced Features

```
// Streaming Support:

chain = prompt | llm | output_parser

# Stream tokens as they're generated
for chunk in chain.stream({"topic": "AI"}):
    print(chunk, end="", flush=True)

// Async Execution:
# Async invocation
result = await chain.ainvoke({"topic": "AI"})

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

// Batch Processing:
# Process multiple inputs in parallel
results = chain.batch([
    {"topic": "AI"},
    {"topic": "ML"},
    {"topic": "LangChain"}
])
```

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?")

// 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..."})
# Returns: {"summary": "...", "keywords": "..."}
```

Model Integration: Modern Approach

```
Updated Import Structure:

# OpenAI models
from langchain_openai import ChatOpenAI, OpenAIEmbeddings

# Hugging Face models
from langchain_huggingface import HuggingFaceEndpoint

# Google models (Gemini)
from langchain_google_genai import ChatGoogleGenerativeAI

# Anthropic models
from langchain_anthropic import ChatAnthropic

// Example Usage:
from langchain_groq import ChatGroq
from langchain_core.messages import HumanMessage, SystemMessage

# Initialize Groq with Gemma
chat = ChatGroq(model="gemma2-9b-it", temperature=0.7)

messages = [
    SystemMessage(content="You are a helpful assistant"),
    HumanMessage(content="Explain LangChain in 2 sentences")
]

response = chat.invoke(messages)
print(response.content)
```

Complete RAG Application: A Quick Start Example

```
from langchain_groq import ChatGroq
from langchain_community.embeddings import HuggingFaceEmbeddings
from langchain_community.document_loaders import WebBaseLoader
from langchain_text_splitters import RecursiveCharacterTextSplitter
from langchain_community.vectorstores import Chroma
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser
from langchain_core.runnables import RunnablePassthrough

# Load and process documents
loader = WebBaseLoader("https://example.com/doc")
docs = loader.load()
splitter = RecursiveCharacterTextSplitter(chunk_size=1000)
splits = splitter.split_documents(docs)

embeddings = HuggingFaceEmbeddings()
vectorstore = Chroma.from_documents(splits, embeddings)
retriever = vectorstore.as_retriever()

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

model = ChatGroq(model_name="llama3-8b-8192")

# RunnablePassthrough => "context": retriever("What is the main topic?"),
chain = (
    {"context": retriever, "question": RunnablePassthrough()}
    | prompt | model | StrOutputParser())

response = chain.invoke("What is the main topic?")
```

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)

LangChain Use Cases

- **Retrieval Augmented Generation (RAG)**:
  - Document Q&A systems
  - Knowledge base search
  - Semantic search applications
- **Conversational AI**:
  - Chatbots with memory
  - Customer support agents
  - Personal assistants
- **Data Analysis**:
  - SQL query generation
  - Tabular data Q&A
  - Report generation
- **Autonomous Agents**:
  - Web scraping and research
  - Multi-tool workflows
  - API integration

(Ref: LangChain Use Cases Documentation)

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

Model Integration: Modern Syntax

```
from langchain_groq import ChatGroq
from langchain_community.embeddings import HuggingFaceEmbeddings
from langchain_core.messages import HumanMessage, SystemMessage
from langchain_core.output_parsers import StrOutputParser

# Chat Model with Groq
chat = ChatGroq(model_name="llama3-8b-8192", temperature=0.7)

messages = [
    SystemMessage(content="You are a helpful assistant"),
    HumanMessage(content="Explain quantum computing briefly")
]
response = chat.invoke(messages)

# Embedding Model (from Hugging Face)
embeddings = HuggingFaceEmbeddings(model_name="all-MiniLM-L6-v2")
vector = embeddings.embed_query("Machine learning is...")

# Using with LCEL
from langchain_core.prompts import ChatPromptTemplate

prompt = ChatPromptTemplate.from_template("Explain {topic}")
chain = prompt | chat | StrOutputParser()
result = chain.invoke({"topic": "blockchain"})
```

Alternative Model Providers

```
// Groq (Recommended for Fast Inference):
from langchain_groq import ChatGroq

# Gemma 2 - Very fast, efficient
llm = ChatGroq(model_name="gemma2-9b-it", temperature=0.7)
response = llm.invoke("What is the Groq LPU?")

# Llama 3 - Balanced performance
llm = ChatGroq(model_name="llama3-70b-8192", temperature=0.7)

// Hugging Face (Self-hosted):
from langchain_huggingface import HuggingFaceEndpoint
llm = HuggingFaceEndpoint(
    repo_id="mistralai/Mistral-7B-Instruct-v0.2",
    temperature=0.7
)

// Google Gemini (Multimodal):
from langchain_google_genai import ChatGoogleGenerativeAI
llm = ChatGoogleGenerativeAI(model="gemini-pro", temperature=0.7)

// Anthropic Claude (Reasoning):
from langchain_anthropic import ChatAnthropic
llm = ChatAnthropic(model="claude-3-5-sonnet-20241022")
```

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

Basic Prompt Template:

```
from langchain_core.prompts import PromptTemplate

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"
)

// 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}")
])
```

Few-Shot Prompting

```
from langchain_core.prompts import FewShotPromptTemplate, PromptTemplate

# Define examples
examples = [
    {"input": "happy", "output": "joyful, cheerful, delighted"},
    {"input": "sad", "output": "unhappy, sorrowful, dejected"},
]

# Example template
example_prompt = PromptTemplate(
    input_variables=["input", "output"],
    template="Input: {input}\nSynonyms: {output}"
)

# Few-shot template
few_shot_prompt = FewShotPromptTemplate(
    examples=examples,
    example_prompt=example_prompt,
    prefix="Provide synonyms for the following word:",
    suffix="Input: {word}\nSynonyms:",
    input_variables=["word"]
)

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

chain = few_shot_prompt | ChatGroq(model_name="gemma-7b-it") | StrOutputParser()
result = chain.invoke({"word": "angry"})
```

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

Buffer Memory (Stores Everything):

```
from langchain.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)
```

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 (2024):

- **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 Chains: LCEL Overview

What Changed?

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

LCEL Advantages:

- **Composability**: Chain components naturally
- **Streaming**: Built-in streaming support
- **Async**: Native async/await
- **Batch**: Process multiple inputs
- **Fallbacks**: Error handling built-in
- **Parallelization**: Run steps in parallel
- **Observability**: Better tracing

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)
```

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 (2024):

- **Tool Calling Agent**: Uses function calling (recommended)
- **JSON Chat Agent**: Output formatting based on Json
- **Structured Chat Agent**: For multi-input tools
- **ReAct Agent**: Reasoning and acting pattern

Deprecated (Don't Use):

- zero-shot-react-description
- conversational-react-description
- self-ask-with-search

(Ref: LangChain Agents Documentation 2024)

Creating Tools: Modern Approach

```
// 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"

// Method 2: From Function:
\begin{lstlisting}[language=python, basicstyle=\tiny]
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")
```

Tool Calling Agent Example

```
from langchain_groq import ChatGroq
from langchain.agents import create_tool_calling_agent, AgentExecutor
from langchain_core.prompts import ChatPromptTemplate, MessagesPlaceholder
from langchain_core.tools import tool

@tool
def search_wikipedia(query: str) -> str:
    """Search Wikipedia for a topic."""
    # Dummy implementation
    return f"Results for {query} from Wikipedia."

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

tools = [search_wikipedia, calculate]

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

llm = ChatGroq(model_name="llama3-70b-8192", temperature=0)
agent = create_tool_calling_agent(llm, tools, prompt)

agent_executor = AgentExecutor(agent=agent, tools=tools, verbose=True)

result = agent_executor.invoke({"input": "What is the capital of France?"})
```

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']}")
```

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, Relase of 1.0 version)

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.

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 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.

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.

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.

Real-World Use Cases

- Meeting notes enrichment and summarization pipelines.
- Financial EDI approval flows with human-in-loop steps.
- Real-time dashboards using streaming "update" mode.
- Persistent agent state across cloud or local environments.
- Dynamic model selection for efficiency (e.g., switching from Claude to Llama3).
- Internal RAG/Graph-RAG systems leveraging PGVector.
- Used at scale in production by enterprises and startups alike.

Example: Defining a Simple Agent in LangChain 1.0

```
from langchain.agents import create_agent

agent = create_agent(
    tools=[search, summarize],
    model="gpt-4-turbo"
)

result = agent("Summarize today's meeting notes")
print(result)
```

Anti-Patterns to Avoid

- Token-only streaming without structured updates.
- Relying on ephemeral in-memory state, persist externally.
- Single-function "flat" agents instead of structured graphs.
- Provider lock-in design for model and SDK portability.
- Neglecting checkpointing and recovery strategies.
- Ignoring observability, use LangSmith, LangFuse, or OpenTelemetry.
- Skipping standardized content blocks creates fragility.

Conclusions

Conclusions

What is LangChain?

LangChain: A Comprehensive Framework for Building LLM-Powered Applications

- **Core Purpose**: Simplify development of complex applications using Large Language Models
- **Key Components**:
  - Unified interface for multiple language models
  - Advanced prompt management
  - Flexible data integration
  - Intelligent agent and tool systems
- **Founding**: Created by Harrison Chase as an open-source project
- **Availability**: Python and JavaScript libraries

Feature	Description
Data Awareness	Connect LLMs to external data sources
Agentic Capability	Enable dynamic interaction with environment
Model Flexibility	Support for multiple LLM providers

(Ref: LangChain Framework Overview)

Why LangChain?

Addressing Challenges in LLM Application Development

- **Limitations in Current LLM Tooling**:
  - Fragmented model interfaces
  - Complex prompt management
  - Limited external data integration
  - Lack of flexible reasoning mechanisms
- **LangChain Solutions**:
  - Model-agnostic framework
  - Standardized prompt engineering
  - Seamless external data augmentation
  - Intelligent agent orchestration
- **Key Advantages**:
  - Rapid prototyping of AI applications
  - Simplified model and tool integration
  - Scalable architecture for complex use cases

Enabling Developers to Build Sophisticated AI Systems with Ease

(Ref: LangChain Development Principles)

One pager

- **Models:** Building blocks supporting different AI model types - LLMs, Chat, Text Embeddings.
- **Prompts:** Inputs constructed from various components. LangChain offers easy interfaces - Prompt Templates, Example Selectors, Output Parsers.
- **Memory:** Stores/retrieves messages, short or long term, in conversations.
- **Indexes:** Assist LLMs with documents - Document Loaders, Text Splitters, Vector Stores, Retrievers.
- **Chains:** Combine components or chains in order to accomplish tasks.
- **Agents:** Empower LLMs to interact with external systems, make decisions, and complete tasks using Tools.

(Ref: Building Generative AI applications made easy with Vertex AI PaLM API and LangChain - Anand Iyer, Rajesh Thallam)

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

Closing Thoughts

- Langchain's usefulness in solving problems today
- Possibility of LLM APIs expanding capabilities over time
- Potential for Langchain to become an interface to LLMs
- Acknowledgment of Langchain's valuable contributions and community efforts
- Appreciation for the work done by Harrison and the Langchain team

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

References

References

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

- 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=P3M A wonderful overview, don't miss
- Cookbook by Gregory Kamradt(Easy way to get started): https://github.com/gkamradt/langchai tutorials/blob/main/LangChain%20Cookbook.ipynb
- Youtube Tutorials: https://www.youtube.com/watch?v=_v_fgW2SkkQ
- LangChain 101 Course (updated 2024 with LCEL) - Ivan Reznikov
- https://github.com/IvanReznikov/DataVerse/tree/main/Courses/LangChain
- A Complete LangChain Guide https://nanonets.com/blog/langchain/
- 7 Ways to Use LangSmith's Superpowers to Turboboost 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/docs/integrations/chat/groq
- Groq GitHub Examples: https://github.com/groq/groq-python