Understanding and Building RAG Applications using Langchain

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Outline

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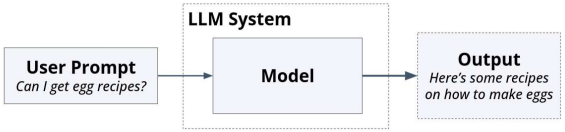
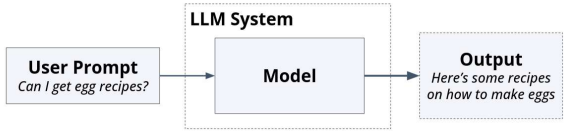
Motivation

LLMs and Domain Knowledge



- **General LLMs lack domain-specific knowledge**
  - Models are trained on broad internet text.
  - Missing specialized vocabulary, rules, and workflows.
- **Improves accuracy in specialized tasks**
  - Finance, healthcare, law, engineering, scientific domains.
  - Reduces wrong assumptions and hallucinations.
- **Aligns model with domain style and terminology**
  - Domain writing patterns, abbreviations, formulas.

LLMs and Domain Knowledge



- **Enhances reliability and safety**
  - Avoids unsafe suggestions in medical/technical domains.
  - Ensures outputs follow domain constraints.
- **Necessary for real-world enterprise use**
  - Internal documents, proprietary workflows.
  - Domain-specific decision support.
- **Reduces cost of over-prompting**
  - Less need to force context through long prompts.

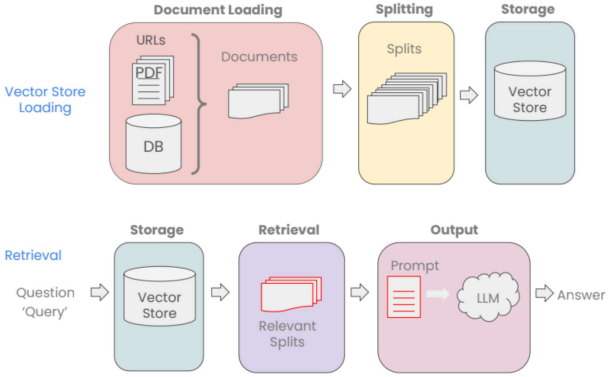
Domain Adaptation Techniques for LLMs

Key Techniques

- **1. Prompt Engineering**
  - Inject domain context via carefully designed prompts.
  - Zero training cost, quick adaptation.
- **2. Pre Traning**
  - Initial stage where an LLM learns general language patterns.
  - Trained on massive text corpora: web pages, books, articles.
- **3. Fine-Tuning**
  - Train the model further on labeled domain datasets.
  - Improves reasoning and domain correctness.
- **4. Retrieval-Augmented Generation (RAG)**
  - Combine LLM with domain documents retrieved at runtime.
  - Avoids hallucinations; supports dynamic updates.

Why RAG and Agentic AI?

- LLMs are powerful but limited: hallucination, context window, stale knowledge.
- RAG (Retrieval-Augmented Generation) grounds generation using retrieved documents.
- Retrieve relevant documents and load into `"working memory"` / context window.



LangChain Fundamentals

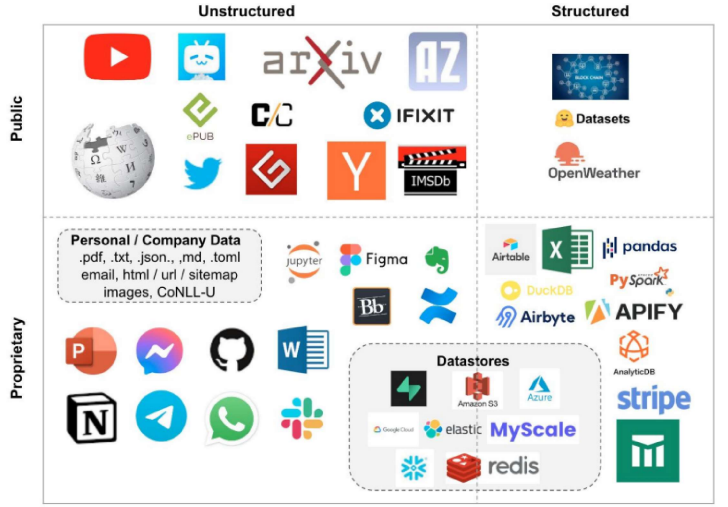
LangChain : Primitives

LangChain provides modular building blocks: **Loaders**, **Splitters**, **Embeddings**, **VectorStores**, **Retrievers**, **Chains**, **Agents**.

Loaders

- **Loaders** deal with the specifics of accessing and converting data
  - **Accessing**
    - Web Sites
    - Data Bases
    - YouTube
    - arXiv
    - ...
  - **Data Types**
    - PDF
    - HTML
    - JSON
    - Word, PowerPoint...
- Returns a list of `Document` objects:

Document Loaders

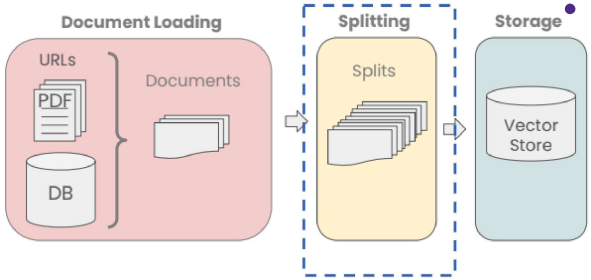


Document Loading (Python)

```python
# Load PDFs -> Document objects
from langchain_community.document_loaders import PyPDFLoader

loader = PyPDFLoader("/content/LoveStories.pdf")
docs = loader.load()
print(len(docs), docs[0].metadata)
```


Document Splitting

- Splitting retains meaningful relationships within text while producing chunks that fit LLM context windows .i.e splitting documents into smaller chunks

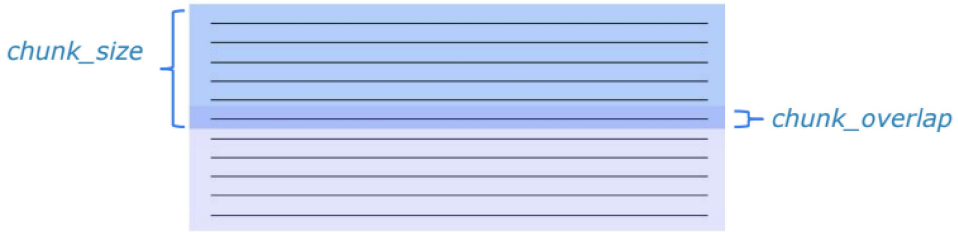


- ...on this model. The Toyota Camry has a head-snapping 80 HP and an eight-speed automatic transmission that will
  - Chunk 1: on this model. The Toyota Camry has a head-snapping
  - Chunk 2: 80 HP and an eight-speed automatic transmission that will

Question: What are the specifications on the Camry?

Splitter Example (Python)

```python
from langchain_text_splitters import RecursiveCharacterTextSplitter

splter = RecursiveCharacterTextSplitter(chunk_size=1000, chunk_overlap=200)
chunks = splter.split_documents(docs)

print("chunks:", len(chunks))
print("first chunk content preview:", chunks[0].page_content[:300])
```



Types of Text Splitters

Classes within `langchain.text_splitter`:

- `CharacterTextSplitter()` - Implementation of splitting text that looks at characters.
- `MarkdownHeaderTextSplitter()`- Implementation of splitting markdown files based on specified headers.
- `TokenTextSplitter()` - Implementation of splitting text that looks at tokens.
- `SentenceTransformersTokenTextSplitter()` - Implementation of splitting text that looks at tokens.
- `RecursiveCharacterTextSplitter()` - Implementation of splitting text that looks at characters. Recursively tries to split by different characters to find one that works.
- `Language()` for CPP, Python, Ruby, Markdown etc
- `NLTKTextSplitter()` - Implementation of splitting text that looks at sentences using NLTK (Natural Language Tool Kit)

Embeddings & Vector Stores

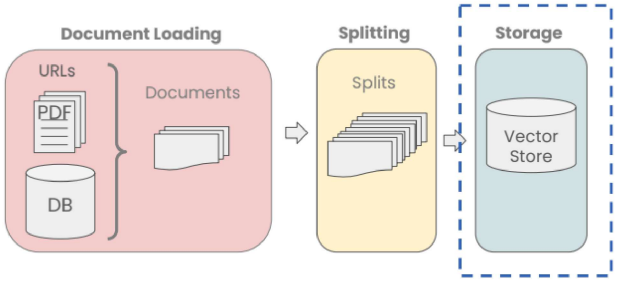
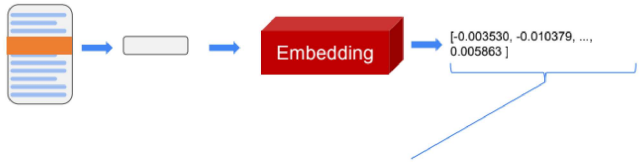


Figure: Vector Stores

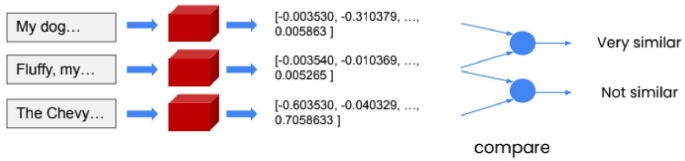
- Convert chunks into embeddings and store in vector DBs (FAISS, Chroma, Pinecone, Weaviate).
- Include metadata for filtering and LLM-aided retrieval.

Embeddings

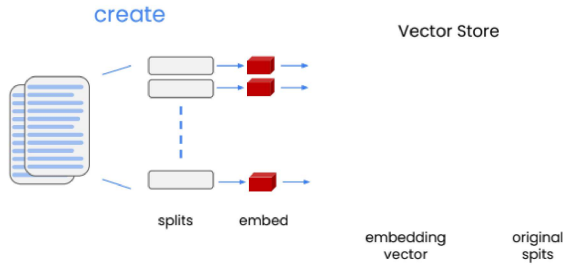


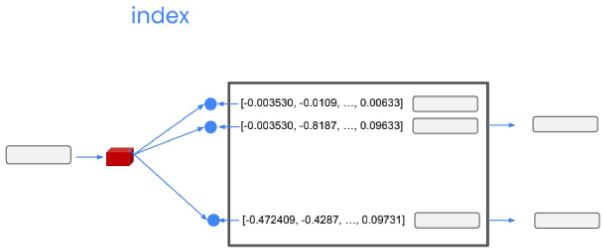
- Embedding vector captures content/meaning
- Text with similar content will have similar vectors

1) My dog Rover likes to chase squirrels.
2) Fluffy, my cat, refuses to eat from a can.
3) The Chevy Bolt accelerates to 60 mph in 6.7 seconds.

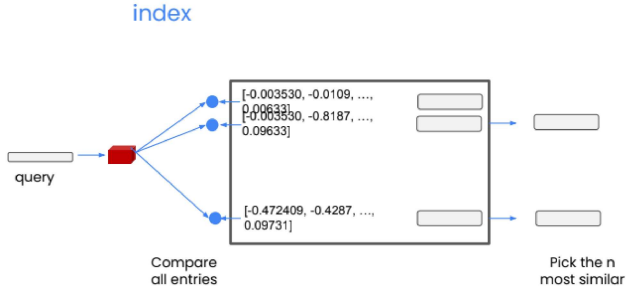


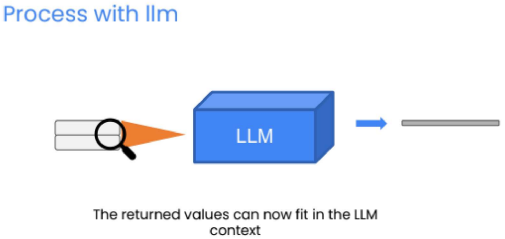
Vector Stores





Vector Stores/Databases



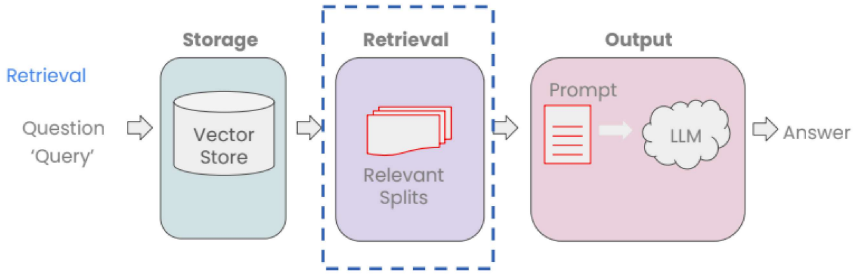


Create & Query Vector Store

```
from langchain_community.embeddings import HuggingFaceEmbeddings
from langchain_community.vectorstores import FAISS

# Choose any HuggingFace embedding model
emb = HuggingFaceEmbeddings(model_name="sentence-transformers/all-MiniLM-L6
    -v2")

# Create FAISS index from your chunks
index = FAISS.from_documents(chunks, emb)

retriever = index.as_retriever(search_kwargs={"k": 5})
results_with_scores = index.similarity_search_with_score("A STRANGE TWIST
    OF FATE ", k=5)
for doc, score in results_with_scores:
   print(doc.metadata.get("source"), score)
```


Retrieval Strategies

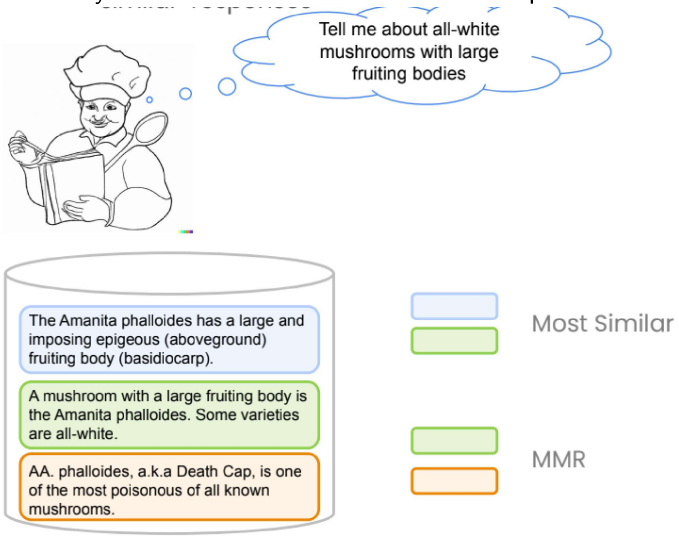
Retrieval modes



- Accessing/indexing the data in the vector store
- Modes:
  - Semantic similarity (embedding cosine)
  - Maximum Marginal Relevance (MMR) for diversity
  - LLM-aided retrieval / Self-query for structured filters
  - Compression LLM to condense retrieved splits for LLM context

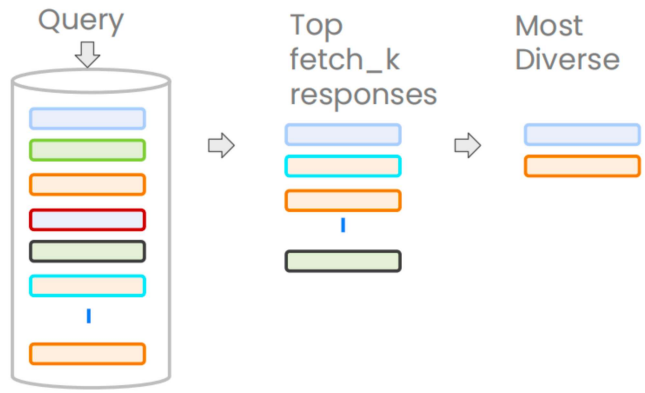
Maximum marginal relevance (MMR)

- You may not always want to choose the most similar responses



Maximum marginal relevance (MMR)

- Query the Vector Store
- Choose the fetch k most similar responses
- Within those responses choose the k most diverse

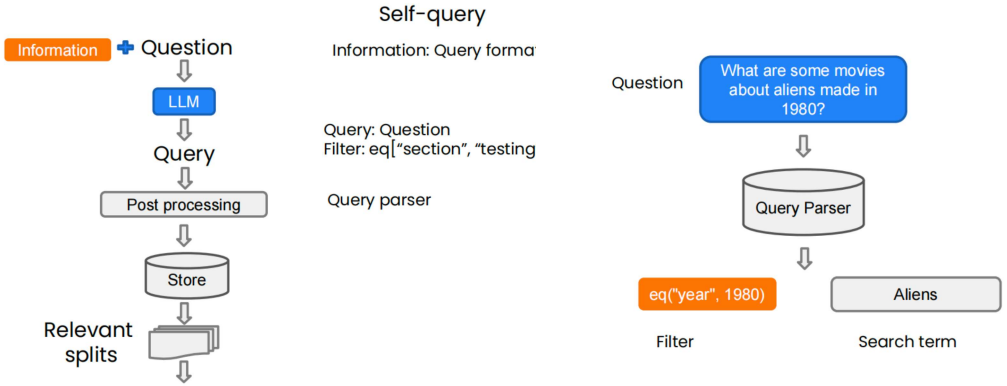


MMR Sketch (Python-style pseudocode)

```
# Pseudo-code: select k items that maximize relevance and diversity
def mmr_select(query_vec, candidates, k, lambda_param=0.5):
    selected = []
    while len(selected) < k:
        best = None
        best_score = -1e9
        for c in candidates:
            relevance = cosine_sim(query_vec, c.vec)
            diversity_penalty = max(cosine_sim(c.vec, s.vec) for s in
                selected) if selected else 0
            score = relevance - lambda_param * diversity_penalty
            if score > best_score:
                best_score, best = score, c
        selected.append(best)
    return selected
```


LLM-aided Retrieval (Self-query)

- Use an LLM to transform a free-form question into a query spec (filters + keywords) to apply to a vector store with metadata support

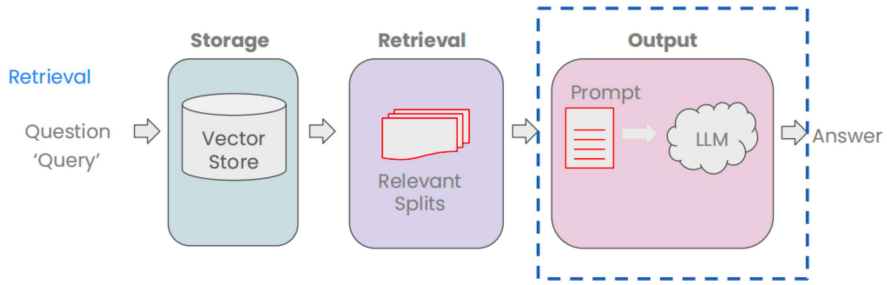


Self-query Example

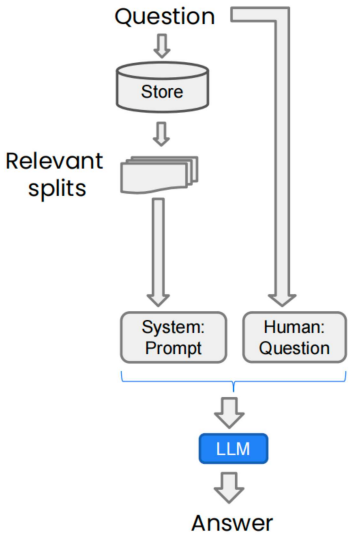
```
from langchain_google_genai import ChatGoogleGenerativeAI
import os

os.environ["GOOGLE_API_KEY"] = "YOUR_GOOGLE_API_KEY"

llm = ChatGoogleGenerativeAI(model="gemini-2.0-flash",temperature=0,)
prompt = "Create a JSON query for: 'movies about aliens in 1980'"
response = llm.invoke(prompt)
if isinstance(response.content, str) and response.content.strip():
    query_spec = response.content
else:
    query_spec = response.response_metadata["candidate_texts"][0]
print(query_spec)
```

RAG: Retrieval Augumented Generation

Question Answering



RetrievalQA Chain



Question is applied to the Vector Store as a query

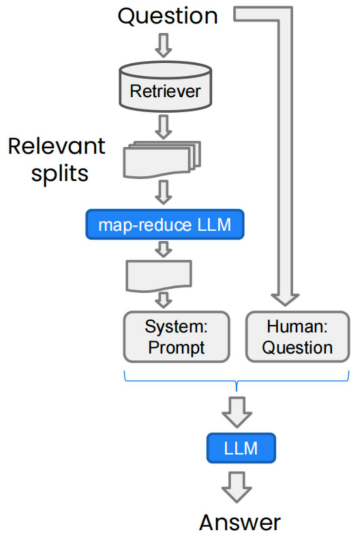
Vector store provides k relevant documents

Docs and original question are sent to an LLM

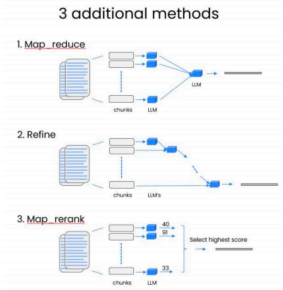
RetrievalQA chain patterns

```python
from langchain_classic.chains import RetrievalQA
from langchain_google_genai import ChatGoogleGenerativeAI
# Gemini LLM
llm = ChatGoogleGenerativeAI(
    model="gemini-2.0-flash", # or gemini-1.5-pro
    temperature=0
)
# Create QA chains
qa_stuff = RetrievalQA.from_chain_type(
    llm=llm,
    chain_type='stuff',
    retriever=retriever
)
# Query
print(qa_stuff.run('Title of the chapters'))
```

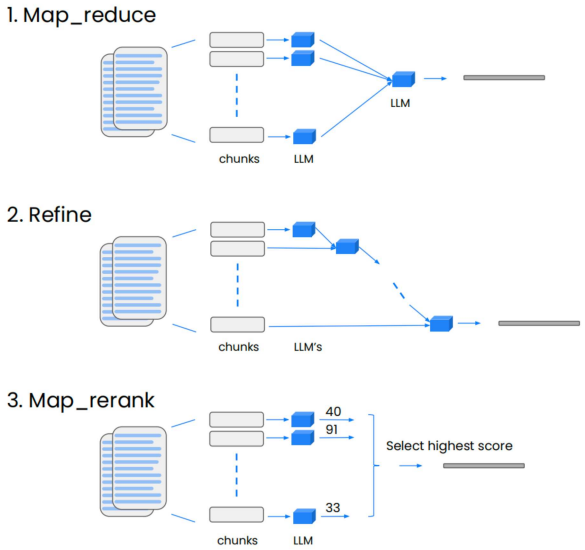
RetrievalQA Chain



You many have too many docs to fit into an LLM context. The solution is to use an LLM to select the 'most relevant' information



RetrievalQA Chain



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# Gemini LLM
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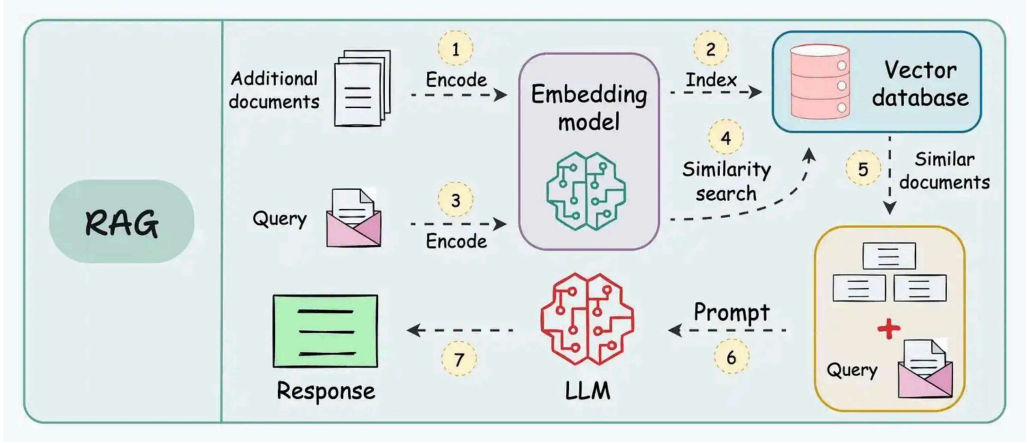
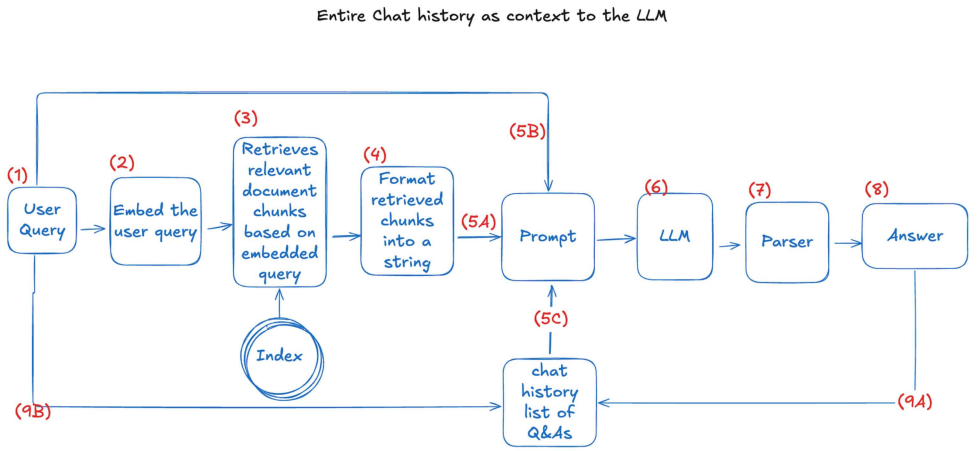
    model="gemini-2.0-flash", # or gemini-1.5-pro
    temperature=0
)
# Create QA chains
qa_stuff = RetrievalQA.from_chain_type(
    llm=llm,
    chain_type='map_reduce',
    retriever=retriever
)
# Query
print(qa_stuff.run('Title of the chapters'))
```


Retrieval Augmented Generation

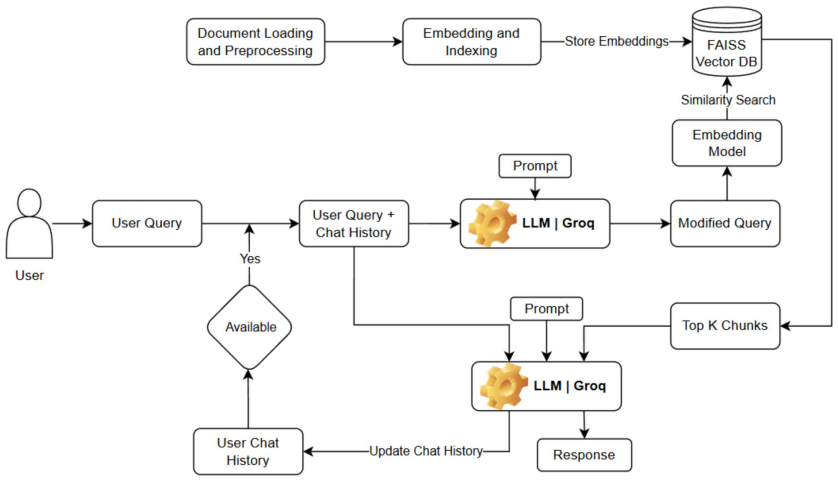


Types of RAG

Conversational RAG



Conversational RAG



Memory Types in LangChain

- **ConversationBufferMemory**
  - Stores full conversation history verbatim.
  - Injects entire chat history into every LLM prompt.
  - Useful for short or simple conversations.
  - Ideal for quick development and prototyping.
  - Can lead to large context windows and higher cost.
- **ConversationSummaryMemory / SummaryBufferMemory**
  - Summarizes older conversation turns using the LLM.
  - Keeps recent messages verbatim for short-term context.
  - Maintains a rolling summary to control token usage.
  - Scales efficiently for long-running dialog systems.
  - Produces concise state representations.

Memory Types in LangChain

- **ConversationBufferWindowMemory**
  - Retains only the last k conversation turns.
  - Ensures fixed-size, predictable memory usage.
  - Suitable for systems relying only on recent context.
  - Avoids summarization overhead.
- **Entity Memory / Key–Value Memory**
  - Stores structured facts such as:
    - User names and identities.
    - Preferences and personal details.
    - Task-specific variables and states.
  - Supports personalization in agents and chatbots.
  - Easily retrieved and injected into prompts.

Memory Types in LangChain

- **Vector-Based Memory (RAG-Style Memory)**
  - Stores embeddings of conversation chunks or summaries.
  - Uses vector databases: Chroma, FAISS, Pinecone, Weaviate.
  - Enables semantic retrieval of past interactions.
  - Scales to very long-term or multi-session memory.
  - Ideal for: Conversational RAG, Domain-specific chat applications.

Hybrid Memory Architectures

- Combine multiple memory types:
  - Buffer memory (recent context)
  - Summary memory (long-term compressed context)
  - Vector memory (semantic retrieval)
- Common in production conversational agents.

RetrievalQA chain patterns

```
from langchain_google_genai import ChatGoogleGenerativeAI
from langchain_classic.chains import ConversationChain
from langchain_classic.memory import ConversationBufferMemory

llm = ChatGoogleGenerativeAI(model="gemini-2.0-flash", temperature=0)
mem = ConversationBufferMemory(memory_key="history", return_messages=True)
chat = ConversationChain(llm=llm, memory=mem, verbose=False)

print("Me : Hi, my name is Shailesh.")
print("Bot : ",chat.predict(input="Hi, my name is Shailesh."))
print("Me : Remember that I like sci-fi movies.")
print("Bot : "+chat.predict(input="Remember that I like sci-fi movies."))
print("Me : What is my name and what do I like?")
answer = chat.predict(input="What is my name and what do I like?")
print("Bot : "+answer)
```


Tool Calling in LangChain

What is Tool Calling?

- A method that allows an LLM to call external functions (“tools”).
- Tools are Python functions wrapped using LangChains `tool` decorator.
- The model decides when to call the tool and with which arguments.

Why Use Tools?

- Add real capabilities: calculations, API calls, DB queries.
- Keep the LLM grounded and reliable.
- Build Agentic AI workflows.

Basic Structure in LangChain

1. Define a Python function.
2. Wrap it using `@tool`.
3. Pass the tool list into the LLM.
4. LLM responds with either: a normal text answer, or a `tool_call` block with arguments.

Example: Tool Calling using Gemini

Step 1: Define a Tool

```
from langchain.tools import tool
@tool
def add(a: int, b: int):
    "Return a + b."
    return a + b
```

Step 2: Use Gemini with Tools

```
from langchain_google_genai import ChatGoogleGenerativeAI
llm = ChatGoogleGenerativeAI(
    model="gemini-2.0-flash",temperature=0,
    tools=[add] # attach tool
)
response = llm.invoke("What is 12 + 9?")
print(response)
```


GraphRAG: Retrieval-Augmented Generation using Graphs

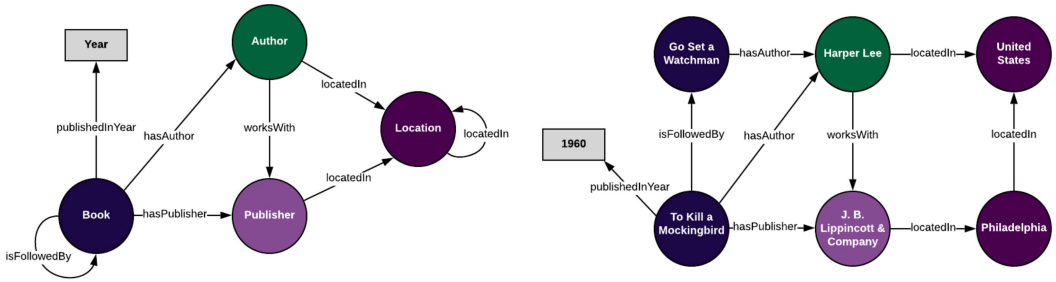
What is GraphRAG?

- A RAG approach where knowledge is stored as a **graph** instead of independent text chunks.
- Nodes represent entities (people, topics, products).
- Edges represent relationships (uses, cites, belongs-to).
- Retrieval is performed over relevant **subgraphs**, not just keyword or vector similarity.

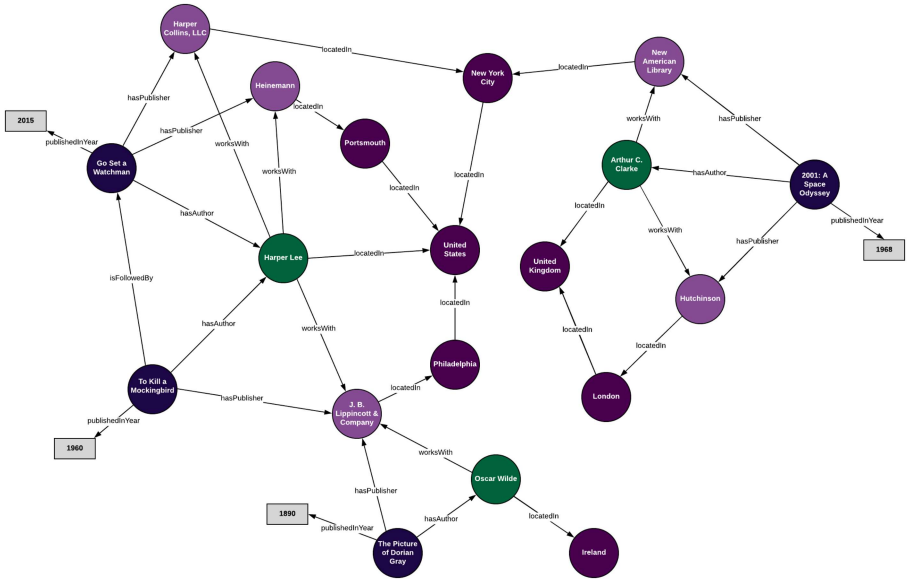
Why GraphRAG?

- Captures structure, relationships, and multi-hop reasoning.
- Better for queries like:
  - "How is X related to Y ?"
  - "Explain the chain of events connecting A and B."
- Improves context precision by retrieving connected graph neighborhoods.

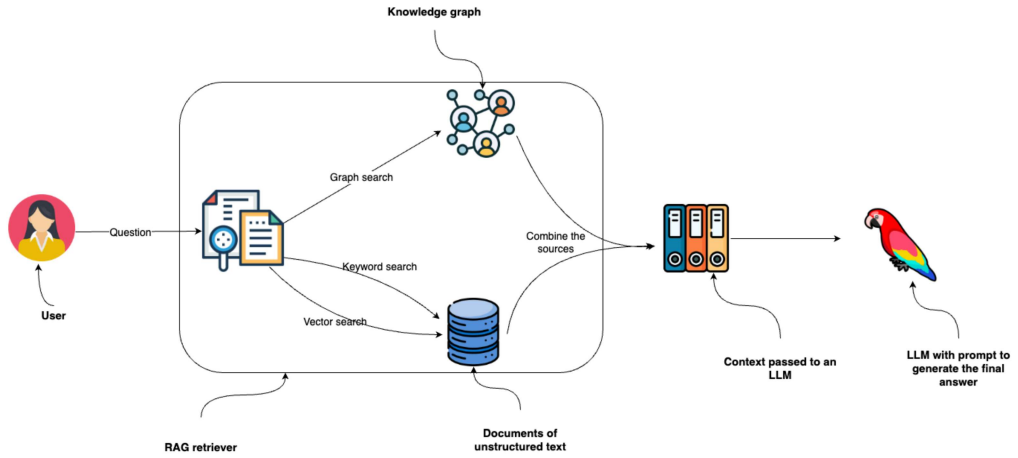
Ontology



Knowledge Graph



Graph RAG



How GraphRAG Works

Pipeline

1. **Ingest Data**
   - Extract entities and relations using NER / IE.
   - Build a Knowledge Graph (KG) or property graph.
2. **Graph Indexing**
   - Create embeddings for nodes / edges.
   - Store in a graph database (Neo4j, Memgraph, ArangoDB).
3. **Graph Retrieval**
   - Expand subgraph around query entity.
   - Retrieve neighbors, paths, or community clusters.
4. **LLM Reasoning**
   - Feed the subgraph context to the LLM.
   - Produce multi-hop, relationship-aware answers.

More RAG Architectures

More RAG Architectures

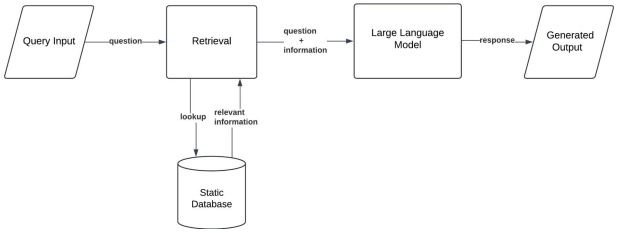


Figure: Simple RAG

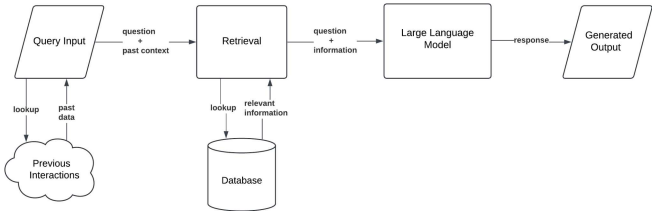


Figure: Simple RAG with Memory

More RAG Architectures

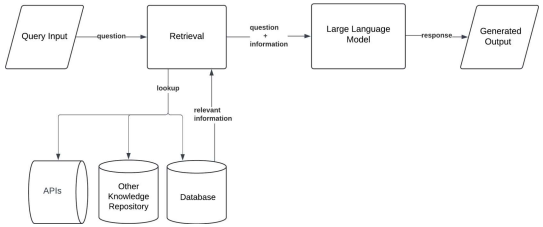


Figure: Branched RAG

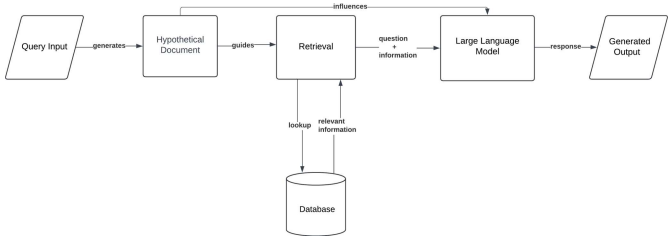


Figure: HyDe (Hypothetical Document Embedding)

More RAG Architectures

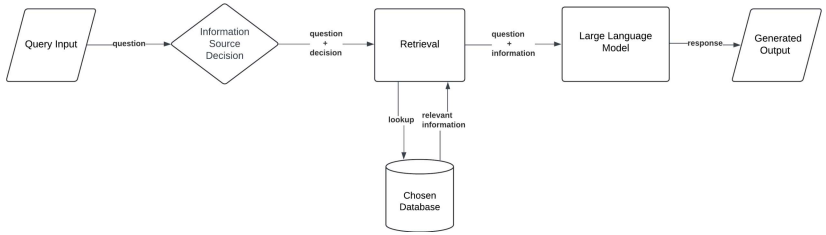


Figure: Adaptive RAG

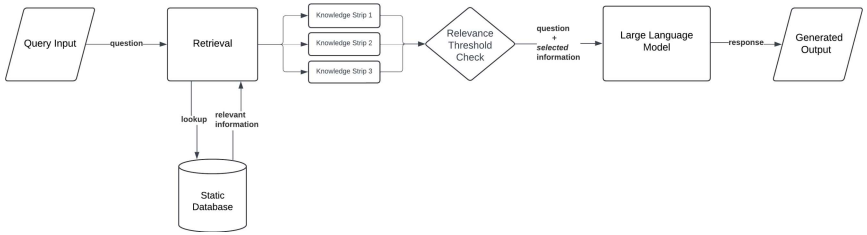


Figure: Corrective RAG (CRAG)

More RAG Architectures

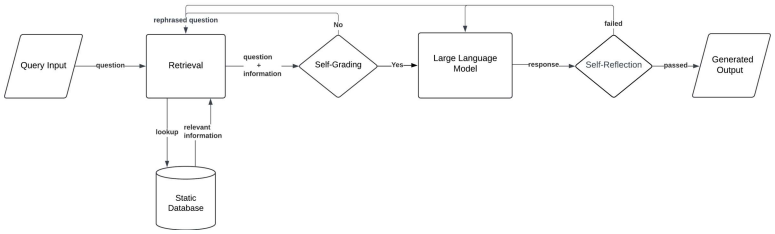


Figure: Self RAG

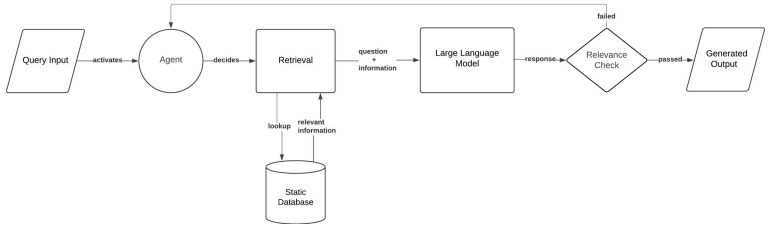


Figure: Agentic RAG

RAG Evaluation

RAG Evaluation: What Do We Measure?

Retrieval-Augmented Generation (RAG) must be evaluated at:

1. **Retrieval Quality**
2. **Context Quality**
3. **Answer (Generation) Quality**
4. **End-to-End System Quality**

Why evaluate RAG?

- Detect retrieval failures
- Reduce hallucinations
- Improve grounding and completeness
- Compare retrievers / LLMs / pipelines

Retrieval Evaluation Metrics

1. **Recall@k**
   - Fraction of relevant documents retrieved in top-k.
2. **Precision@k**
   - Fraction of retrieved documents that are relevant.
3. **MRR (Mean Reciprocal Rank)**

$$MRR = \frac{1}{N} \sum \frac{1}{rank}$$

4. **mAP (Mean Average Precision)**
   - Averages precision across relevant retrieval positions.
5. **nDCG (Normalized Discounted Cumulative Gain)**
   - Discounts relevant results that appear deeper in ranking.

Context Quality Metrics

Why Context Matters?

- LLM answers are only as good as retrieved context.

1. **Context Relevance**
   - Is the context truly related to the query?
2. **Context Coverage**
   - Does the context contain all key facts needed?
3. **Context Precision**
   - How much of the context is useful vs. noise?

Answer Quality Metrics

1. **Faithfulness (Hallucination Rate)**
   - Does the answer stay grounded in retrieved context?
2. **Answer Relevance**
   - Does the answer address the query?
3. **Answer Correctness**
   - Semantic correctness (LLM-as-a-judge or human).
4. **Answer Completeness**
   - Are all important points included?

System-Level RAG Metrics

1. **RAGAS Score**
   - Combines faithfulness, relevance, context recall, and precision.
2. **Latency**
   - Total time per query (retriever + LLM).
3. **Cost per Query**
   - Token cost + retrieval cost.
4. **End-to-End Accuracy**
   - Does the system produce usable and correct answers?

Advanced RAG Evaluation Metrics

1. **Source Attribution Accuracy**
   - Are claims correctly linked to a document?
2. **Citation Quality**
   - Are the cited passages accurate and relevant?
3. **Multi-hop Reasoning Score**
   - Performance on questions requiring multiple steps.
4. **Drift Detection**
   - Detect degradation in retrieval quality over time.

Conclusion

- Conversational AI becomes significantly more powerful when enriched with context and memory.
- LangChain provides multiple memory mechanisms suited for different use-cases: buffer-based, summary-based, windowed, entity-level, and vector-backed.
- Integrating Google Gemini with LangChain enables fast, multimodal, and highly context-aware conversational systems.
- Combining Memory + Retrieval (RAG) gives a scalable architecture for personalized, knowledge-grounded assistants.
- The right memory choice depends on requirements such as token budget, conversation length, personalization depth, and system latency.

Thank You!

For your attention and participation !!!

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