RAG Cheat Sheet

A comprehensive visual guide to Retrieval-Augmented Generation architectures, implementation, and best practices

What is RAG?

Retrieval-Augmented Generation (RAG) is an AI architecture that enhances Large Language Models (LLMs) by combining them with external knowledge retrieval systems. Rather than relying solely on the model's internal parameters, RAG allows LLMs to access, retrieve, and use up-to-date information from external databases before generating responses.

Core Components:

Document Processing

Converting documents into embeddings

Vector Database

Storing embedded documents

Retriever

Finding relevant documents

When to Use RAG

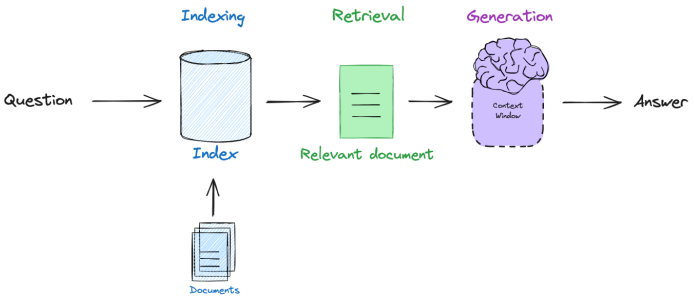
- ✓ When you need factual accuracy beyond the LLM's training data
- ✓ When working with domain-specific or proprietary information
- ✓ When information needs to be up-to-date and verifiable
- ✓ When transparency and citation of sources matters
- ✓ When you need to reduce hallucinations in LLM outputs

Basic RAG Flow:

1. Document Collection → Document Chunking → Embedding Generation → Vector Database Storage
2. User Query → Query Embedding → Similarity Search → Relevant Document Retrieval
3. Retrieved Documents + Original Query → LLM Generation → Response

Generator

Creating accurate responses



10 RAG Architectures Compared

Beginner

1. Standard RAG

```
User Query → Query Processing →
Retrieval → Document Selection →
Context Integration → LLM Response
```

When to Use: For basic question-answering systems needing external knowledge

Real-World Example: Customer support chatbots that access product documentation

> **Implementation Tip:** Start with smaller chunk sizes (512-1024 tokens) and adjust based on performance

Intermediate

2. Corrective RAG

```
User Query → Initial Response →
Error Detection → Retrieval →
Response Correction → Final
Response
```

When to Use: High-precision use cases where accuracy is critical

Real-World Example: Medical information systems, legal documentation assistance

> **Implementation Tip:** Implement a feedback loop with multiple verification passes

Intermediate

3. Speculative RAG

```
User Query → Small Model Draft →
Parallel Retrievals →
Large Model Verification →
Response
```

When to Use: When balancing speed and accuracy is important

Real-World Example: Real-time customer service where response time impacts

Intermediate

4. Fusion RAG

```
User Query → Multiple Retrieval
Methods →
Results Fusion → Aggregated
Context →
LLM Response
```

When to Use: When dealing with multiple data sources of varying formats

satisfaction

> **Implementation Tip:** Use a specialized domain-specific small model for draft generation

Real-World Example: Research assistants accessing articles, patents, and databases

> **Implementation Tip:** Weight different sources based on their reliability and relevance

Advanced

5. Agentic RAG

```
User Query → Intent Analysis →
Agent Selection → Parallel
Retrievals →
Strategy Coordination → Response
```

When to Use: Complex queries requiring multiple types of information

Real-World Example: Financial analysis tools accessing market data, company reports, and news

> **Implementation Tip:** Design specialized agents for different query types and data sources

Intermediate

6. Self RAG

```
User Query → Initial Generation →
Self-Critique → Additional
Retrieval →
Refined Response
```

When to Use: For conversational systems requiring consistency

Real-World Example: Educational tutoring systems that build on previous explanations

> **Implementation Tip:** Store conversation history as retrievable context

Advanced

7. Hierarchical RAG

```
User Query → Top-Level Retrieval →
Sub-document Identification →
Focused Retrieval → Response
```

When to Use: With large, structured documents or knowledge bases

Real-World Example: Enterprise search across documentation hierarchies

> **Implementation Tip:** Create multi-level embedding indexes for efficient

Advanced

8. Multi-modal RAG

```
User Query → Cross-modal
Understanding →
Multi-format Retrieval →
Format Integration → Response
```

When to Use: When information spans text, images, audio, or video

Real-World Example: E-commerce search using both product descriptions and images

navigation

Implementation Tip: Use specialized embeddings for each modality and create bridging mechanisms

Advanced

9. Adaptive RAG

```
User Query → Query Analysis →
Retrieval Strategy Selection →
Dynamic Parameter Adjustment →
Response
```

When to Use: For systems facing diverse query types and user needs

Real-World Example: Academic research assistants handling various disciplines

Implementation Tip: Implement real-time feedback to tune retrieval parameters per query

Intermediate

10. Fine-tuned RAG

```
User Query → Domain-Specific
Processing →
Specialized Retrieval →
Context-Aware LLM → Response
```

When to Use: For specialized domains requiring expert-level responses

Real-World Example: Technical support systems for complex products

Implementation Tip: Fine-tune both embeddings and LLM on domain-specific data

Best Practices for RAG Implementation

Document Processing

1. **Chunking Strategy**
   Balance between semantic coherence and retrieval granularity
2. **Chunk Size**
   256-1024 tokens depending on content complexity

Embedding Selection

1. **General Purpose**
   OpenAI ada-002, BERT-based models
2. **Specialized Domains**
   Consider domain-specific embedding models

3 **Overlap**
10-20% chunk overlap to maintain context across chunks

3 **Dimensions**
Higher dimensions (768+) for complex information

Retrieval

1 **Top-k Selection**
Usually 3-5 chunks for typical queries

2 **Re-ranking**
Consider adding a re-ranking step after initial retrieval

3 **Hybrid Search**
Combine semantic and keyword search for better results

Prompt Engineering

1 **Template**
"Based on the following information: {context}, please answer: {query}"

2 **Instruction**
"Use only the provided information. If you don't know, say so."

3 **Source Attribution**
"For each point in your answer, indicate which source it came from."

Common RAG Challenges & Solutions

Challenge	Solution
Hallucination	Implement fact-checking and source validation
Retrieval Latency	Use approximate nearest neighbor algorithms
Context Length Limits	Implement recursive summarization of retrieved chunks
Irrelevant Retrieval	Add filtering and pre-processing of documents

Response Consistency	Implement conversation history as part of the context

Evaluating RAG Systems

Metric	Description	Target
Answer Relevance	How well the response answers the query	>85%
Factual Accuracy	Correctness of facts in the response	>95%
Retrieval Precision	Relevance of retrieved documents	>80%
Response Time	Time from query to response	<2s
Source Coverage	Using multiple relevant sources	≥2 sources

Real-World Use Cases

🏢 **Enterprise Knowledge Base**
Connect employees to internal documentation

🛎️ **Customer Support**
Provide accurate product information and troubleshooting

🔬 **Research Assistant**
Aid in literature review and information synthesis

📋 **Compliance Monitoring**
Ensure responses adhere to regulatory guidelines

🎓 **Educational Tutoring**
Provide accurate explanations with cited sources

Advanced RAG Optimizations

Query Reformulation

Retrieval Augmentation

Rewrite user queries for better retrieval performance

```
// Example Query Reformulation
User: "Tell me about rockets"
Reformulated: "What are rockets, their history, types, and applications in space exploration?"
```

Enhance retrieved context with related information

```
// Retrieved Context Augmentation
1. Original: "SpaceX Falcon 9 specifications"
2. Augmented: + "Rocket propulsion systems"
3. Augmented: + "Comparison with other launch vehicles"
```

Contextual Compression

Condense retrieved information to focus on relevance

```
// Context Compression Pipeline
1. Retrieve k=10 documents
2. Generate summary for each document
3. Rank summaries by relevance
4. Select top n=3 summaries
```

Adaptive RAG

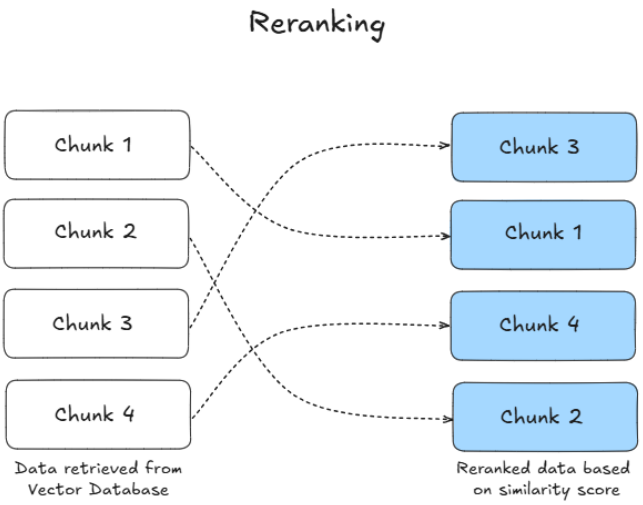
Dynamically adjust retrieval parameters based on query type

```
// Adaptive Parameter Selection
if query_is_factual():
    k = 3  # fewer, precise documents
    similarity_threshold = 0.8
elif query_is_exploratory():
    k = 7  # more, diverse documents
    similarity_threshold = 0.6
```

Continuous Learning

Update vector stores and embeddings as new information arrives

```
// Incremental Updating
1. Monitor for new documents
2. Process and embed new content
3. Merge into existing vector store
4. Periodically re-index for optimization
```



Practical RAG Implementation Guide

1 Setting Up Your Document Processing Pipeline

```
import os
from langchain.document_loaders import DirectoryLoader
from langchain.text_splitter import RecursiveCharacterTextSplitter

# Load documents
loader = DirectoryLoader('./documents/', glob="**/*.pdf")
documents = loader.load()

# Split into chunks
text_splitter = RecursiveCharacterTextSplitter(
    chunk_size=1000,
    chunk_overlap=200,
    length_function=len,
)
chunks = text_splitter.split_documents(documents)
```

2 Creating and Storing Embeddings

```
from langchain.embeddings import OpenAIEmbeddings
from langchain.vectorstores import Chroma

# Initialize embeddings
embeddings = OpenAIEmbeddings()

# Create vector store
vectorstore = Chroma.from_documents(
    documents=chunks,
    embedding=embeddings,
    persist_directory="./chroma_db"
)

# Persist to disk
vectorstore.persist()
```

3 Building the Retrieval System

```
from langchain.retrievers import ContextualCompressionRetriever
from langchain.retrievers.document_compressors import LLMChainExtractor

# Create base retriever
retriever = vectorstore.as_retriever(
    search_type="similarity",
    search_kwargs={"k": 4}
)

# Add compression for better context
llm = ChatOpenAI(temperature=0)
compressor = LLMChainExtractor.from_llm(llm)
compression_retriever = ContextualCompressionRetriever(
    base_compressor=compressor,
    base_retriever=retriever
)
```

4 Implementing the RAG Chain

```
from langchain.chat_models import ChatOpenAI
from langchain.chains import RetrievalQA

# Initialize LLM
llm = ChatOpenAI(temperature=0, model="gpt-4")

# Create RAG chain
qa_chain = RetrievalQA.from_chain_type(
    llm=llm,
    chain_type="stuff",
    retriever=compression_retriever,
    return_source_documents=True,
    chain_type_kwargs={
        "prompt": CUSTOM_PROMPT_TEMPLATE
    }
)

# Query the system
```

```
result = qa_chain({"query": "How do rockets work?"})
print(result["result"])
```

Popular Vector Database Comparison

Pinecone

- Fully managed service
- Low latency queries
- Scales to billions of vectors
- High availability

Weaviate

- Open-source
- GraphQL API
- Classification support
- Multi-tenancy support

Chroma

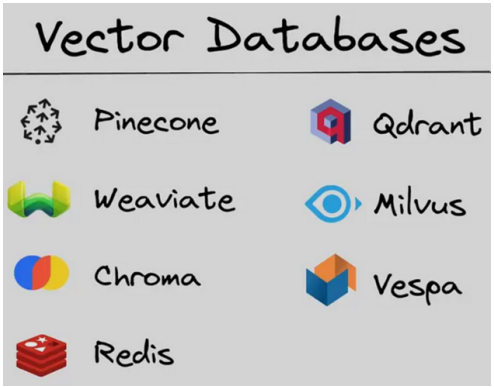
- Open-source
- Easy Python integration
- Simple deployment
- Good for prototyping

Milvus

- Open-source
- Distributed architecture
- Hybrid search
- High scalability

Qdrant

- Open-source
- Filtering capabilities
- On-prem deployment
- REST and gRPC APIs

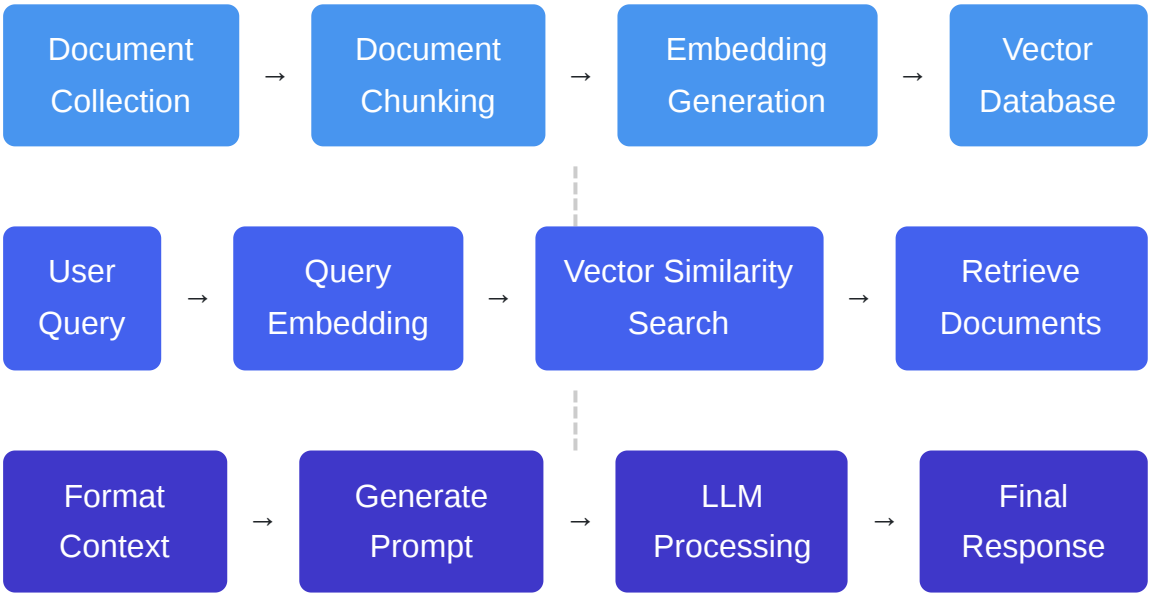


Comparing RAG Performance Metrics

Architecture	Response Time	Accuracy	Memory Usage	Implementation Complexity
Standard RAG	⭐⭐⭐⭐	⭐⭐⭐	⭐⭐⭐	⭐

Corrective RAG	⭐⭐	⭐⭐⭐⭐⭐	⭐⭐⭐	⭐⭐⭐
Speculative RAG	⭐⭐⭐⭐⭐	⭐⭐⭐⭐	⭐⭐	⭐⭐⭐⭐
Fusion RAG	⭐⭐	⭐⭐⭐⭐	⭐⭐	⭐⭐⭐⭐
Agentic RAG	⭐⭐	⭐⭐⭐⭐⭐	⭐	⭐⭐⭐⭐⭐

Standard RAG Implementation Flowchart



Popular RAG Tools and Frameworks

LangChain

Framework for connecting LLMs with external data sources

⭐⭐⭐⭐⭐

LlamaIndex

Data framework for augmenting LLMs with private data

⭐⭐⭐⭐

Haystack

End-to-end framework for building NLP pipelines

⭐⭐⭐⭐

Semantic Kernel

Microsoft's SDK for integrating LLMs with code

⭐⭐⭐

txtai

All-in-one embeddings database with search capabilities

⭐⭐⭐