

# 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

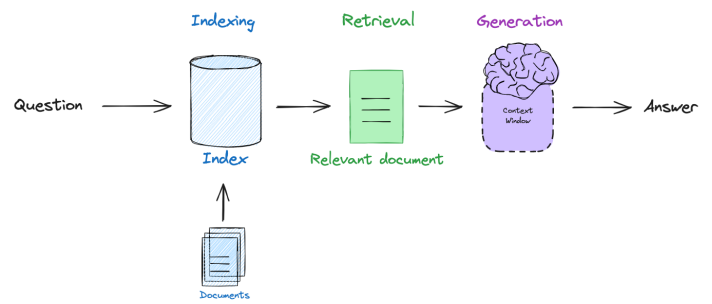
3

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

## 5. Agentic RAG

Advanced

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

## 6. Self RAG

Intermediate

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

## 7. Hierarchical RAG

Advanced

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

## 8. Multi-modal RAG

Advanced

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

## 9. Adaptive RAG

Advanced

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

## 10. Fine-tuned RAG

Intermediate

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

### Chunking Strategy

- 1 Balance between semantic coherence and retrieval granularity

### Chunk Size

- 2 256-1024 tokens depending on content complexity

## Embedding Selection

### General Purpose

- 1 OpenAI ada-002, BERT-based models

### Specialized Domains

- 2 Consider domain-specific embedding models

### Overlap

3

10-20% chunk overlap to maintain context across chunks

### Dimensions

3

Higher dimensions (768+) for complex information

## Retrieval

### Top-k Selection

1

Usually 3-5 chunks for typical queries

### Re-ranking

2

Consider adding a re-ranking step after initial retrieval

### Hybrid Search

3

Combine semantic and keyword search for better results

## Prompt Engineering

### Template

1

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

### Instruction

2

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

### Source Attribution

3

"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

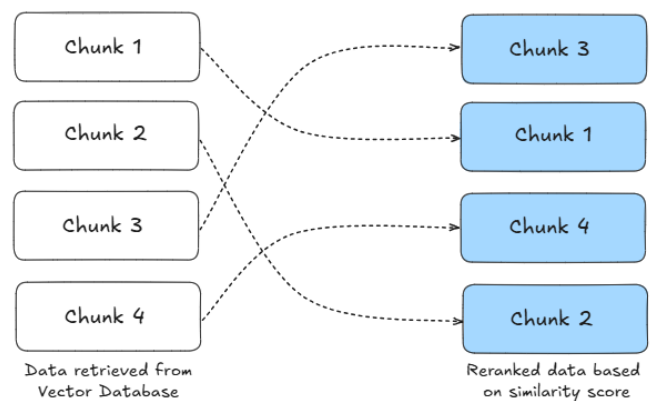
```
// Adaptive Parameter Selection
if query_is_factual():
    k = 3 # fewer, precise
    documents
    similarity_threshold = 0.8
elif query_is_exploratory():
    k = 7 # more, diverse
    documents
    similarity_threshold = 0.6
```

## 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
```

### Reranking



# Practical RAG Implementation Guide

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## 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

### Vector Databases

 Pinecone

 Qdrant

 Weaviate

 Milvus

 Chroma

 Vespa

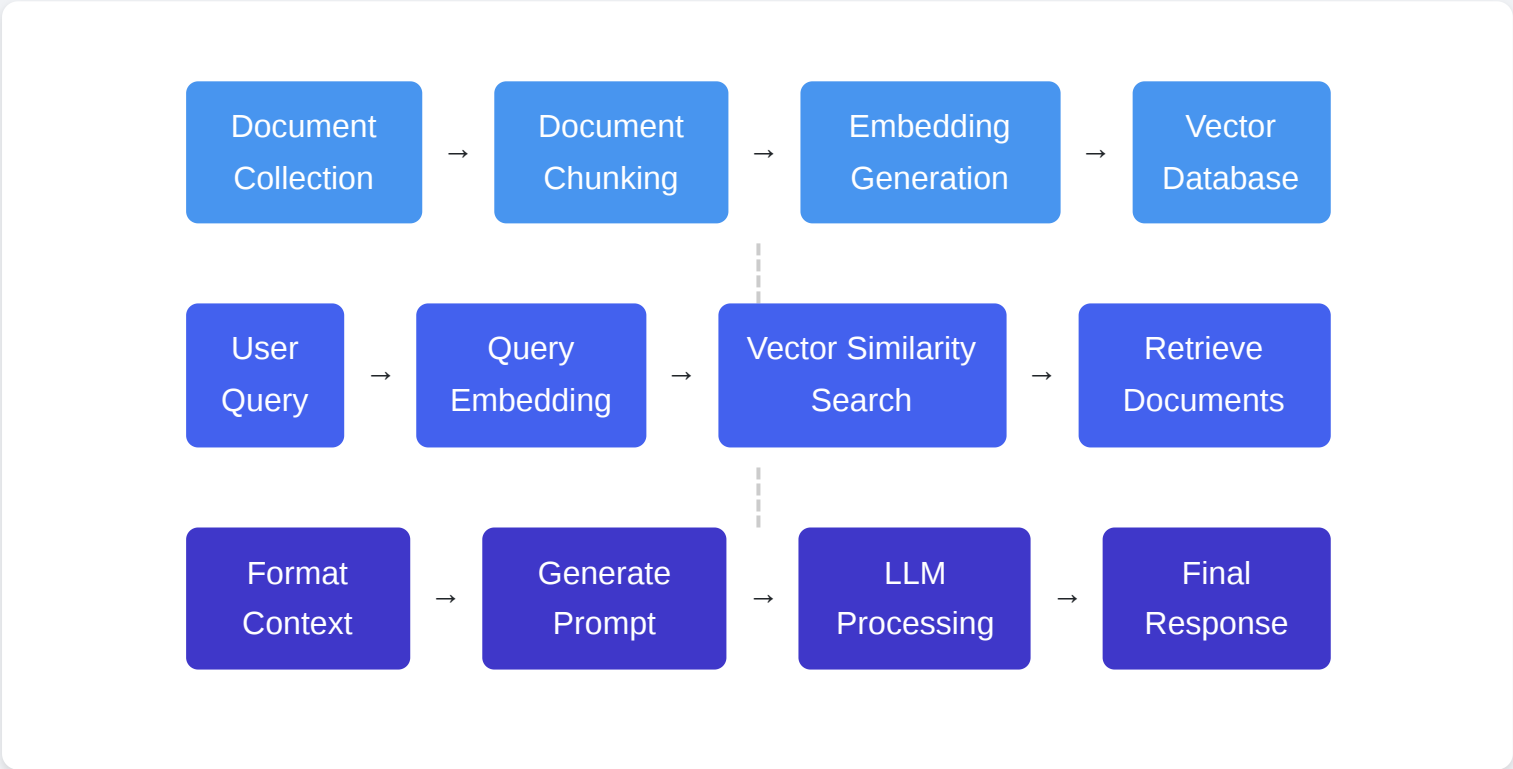
 Redis

# 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

