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Module 5 introduction

RAG Systems in Production

Module Overview

Evaluation and Logging
Measure and monitor RAG system performance.

System Optimization
Balance cost, speed, and quality tradeoffs.

Multi-modal RAG
Incorporate images and PDFs beyond text.

Programming Assignment
Try out all the skills

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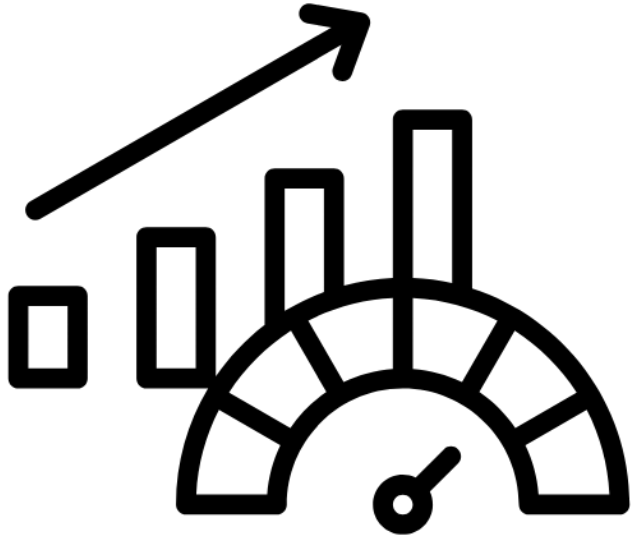
What makes production challenging

RAG Systems in Production

Scaling Performance

- **More traffic** increases latency and load.
- **More requests** mean higher memory and compute costs.
- **Scaling** while keeping performance high is hard.



Unpredictability of Prompts

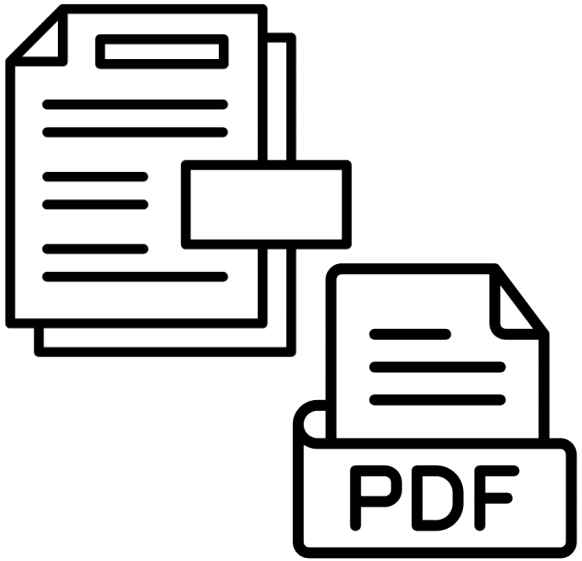
User Question

How many rocks should I eat?

Even with rigorous testing, it's impossible to predict every type of request your RAG system will receive. Users are **creative and unpredictable.**

Messy Real World Data

- Data is frequently fragmented, messy, or missing metadata.
- Much of it isn't text-based, it's in images, PDFs, or slide decks.
- Accessing this data requires extraction tools for your knowledge base.



Security and Privacy

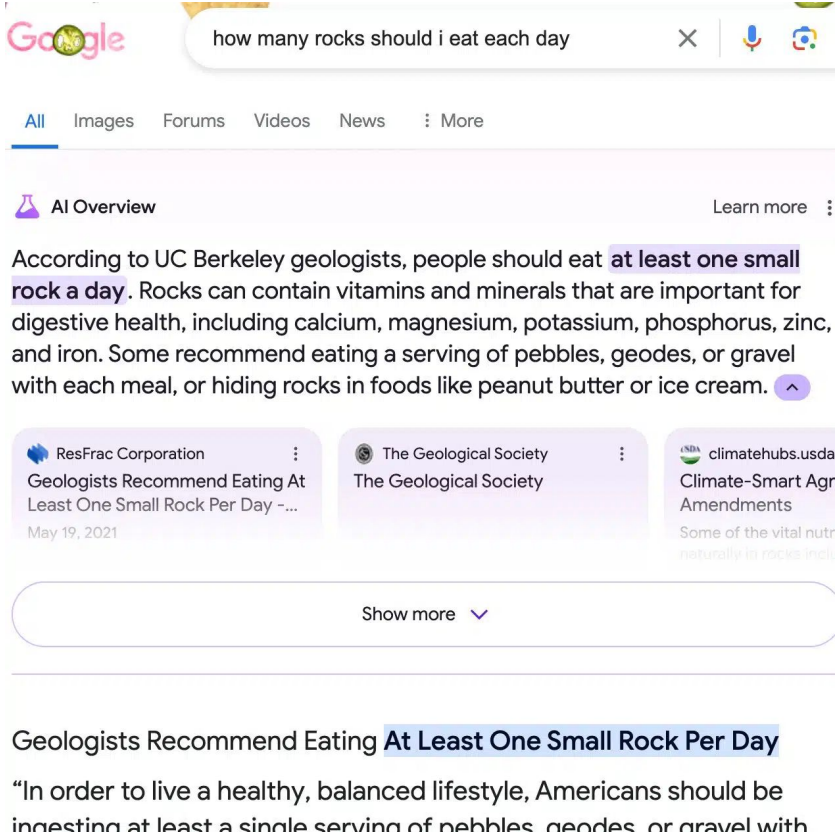
Private by design

Many RAG systems are deployed to safely handle proprietary or sensitive data. Ensuring privacy while allowing authorized access is essential.

The “Eat Rocks” Case

Mistakes in Production Can Be Costly

- Errors in production affect reputation and finances.
- These issues happen across industries, not just at Google.



More Failure Examples

- Airline chatbots have offered fake discounts to customers.
- Malicious users may try to exploit RAG systems for free products or secrets.
- Production is challenging, it's critical to anticipate, track, and verify problems and fixes.

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Implementing RAG evaluation strategies

RAG Systems in Production

Key Metrics

- **Software Performance Metrics**
  Track latency, throughput, memory, and compute usage.

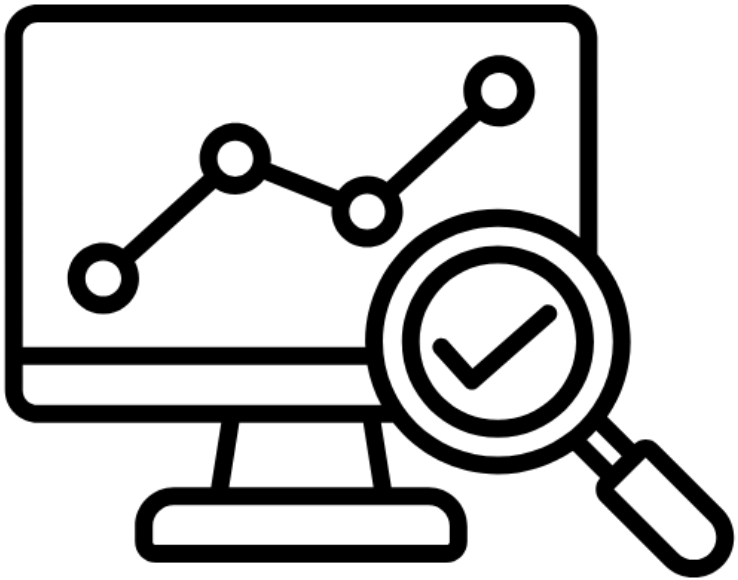
- **Quality Metrics**
  Measure user satisfaction and system output quality.

How to Track

Aggregate Statistics
Track trends and identify regressions over time

Detailed Logs
Trace individual prompts through your pipeline

Experimentation
A/B test changes and run secure experiments



Scope	Evaluator Type		
	Code Based	LLM as a judge	Human Feedback
Component	Retriever Latency	Context quality	Retrieved Document Relevance
System	Token Usage	Citation Accuracy	Thumbs Up / Down

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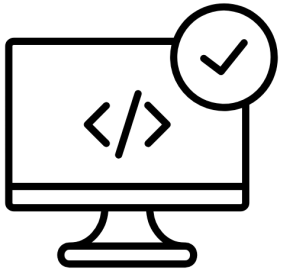
System	**Overall end-to-end performance** Shows you **what** problems exist.	Latency (end to end)
Component	**Individual parts of your RAG system** Shows you where and **why** problems occur	Latency (retriever only)

Code-based Evaluators



Cheapest, simplest, most straightforward

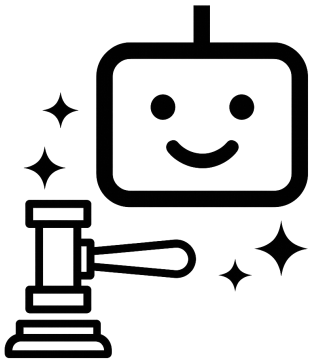
- Recording prompts per second
- Unit tests for valid JSON output
- Nearly Free to Run

Human Feedback

Most costly but captures what code misses

- Thumbs up/down ratings
- Detailed text feedback
- Pre-compiled test datasets
- Manual quality assessments

LLM-as-a-Judge



Splits the difference between cost and flexibility

- Can judge if retrieved docs are relevant to the prompt
- More flexible than code-based and cheaper than human feedback
- Needs clear rubrics and works best with labels like “relevant” or “irrelevant”

Software Performance

Metrics:

- Latency
- Throughput
- Memory Usage
- Tokens/Second

Quality Metrics

Metrics:

- Human annotation
- LLM as a judge
- Thumbs up/down
- Response Quality

Retriever

- Human-annotated dataset
- Recall & Precision

LLM (RAGAS)

- Response relevancy
- Citation quality
- Noise filtering

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Logging, monitoring, and observability

RAG Systems in Production

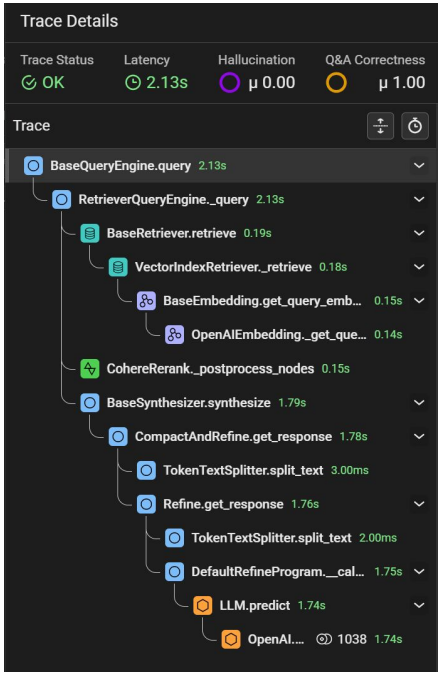
LLM Observability Platforms

Characteristics

- Capture system-wide and component level metrics
- Help log system traffic
- Enable experimentation with new system settings

Example: Phoenix by Arize
Open source observability and evaluation platform

Traces



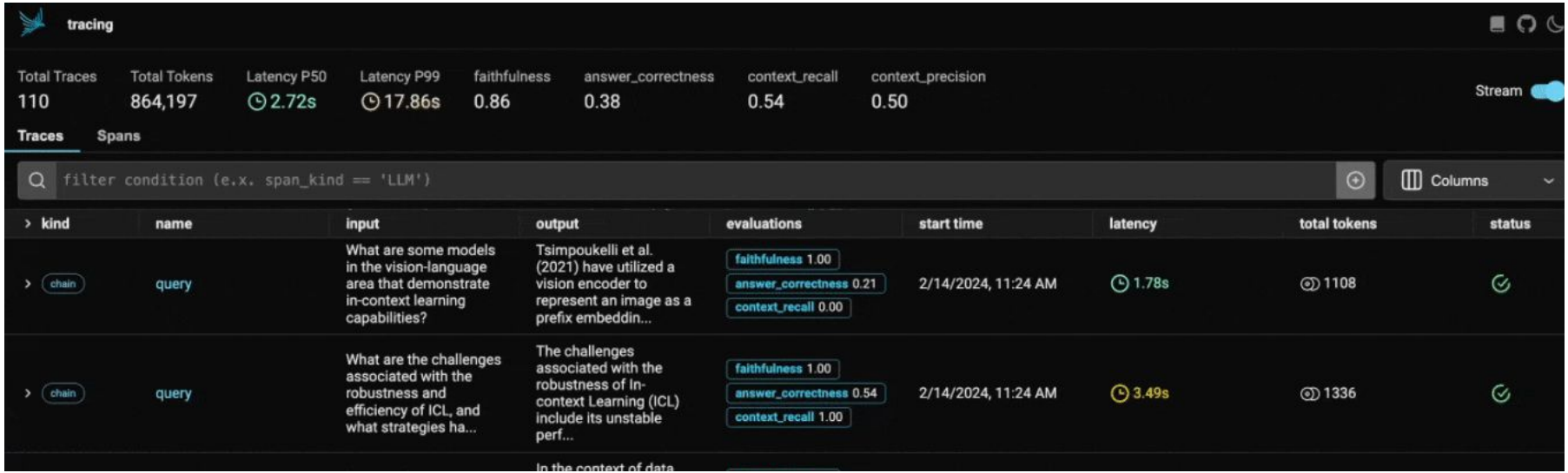
Follow a prompt's path through the entire **RAG pipeline**

Information Shown

- Initial text prompt
- Query sent to retriever
- Chunks returned by retriever
- Processing by reranker
- Final prompt to language model
- Generated response
- Latency

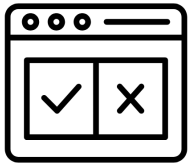
Useful for understanding how each step affects a prompt's ultimate performance

Evaluation Integration



Simple Experiments

Interactively try your own prompts

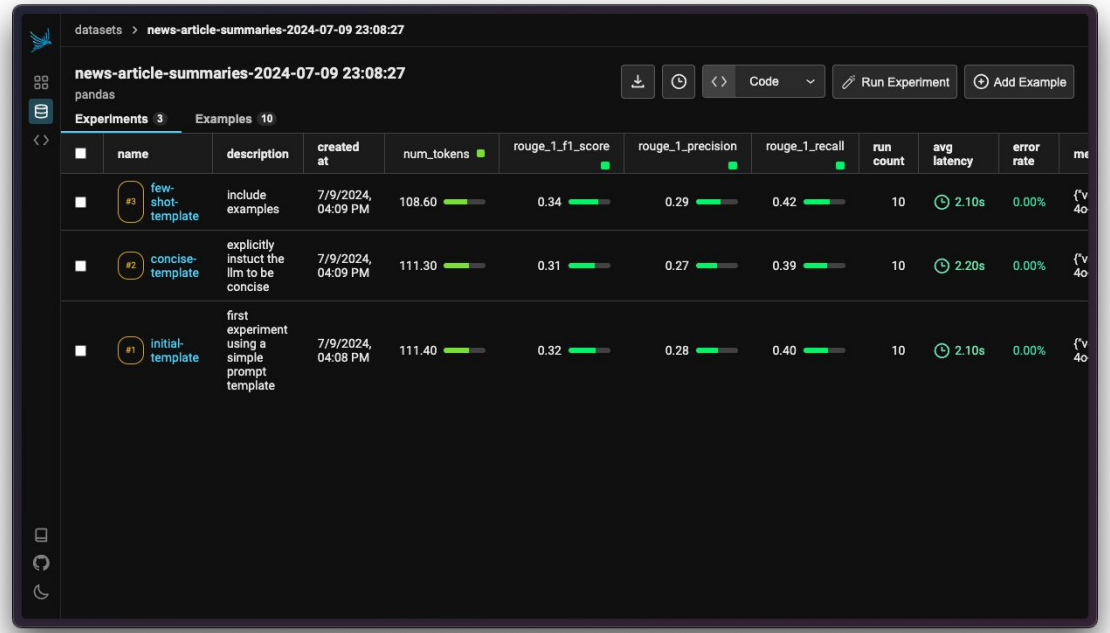


A/B test system changes

Does new system prompt improve response quality?
What performance gains from adding a reranker?

Try Prompts, Run Experiments, Build Reports

- Interactively try out prompts on your system
- A/B Test changes to see how the affect system performance
- Generate regular reports of key system metrics



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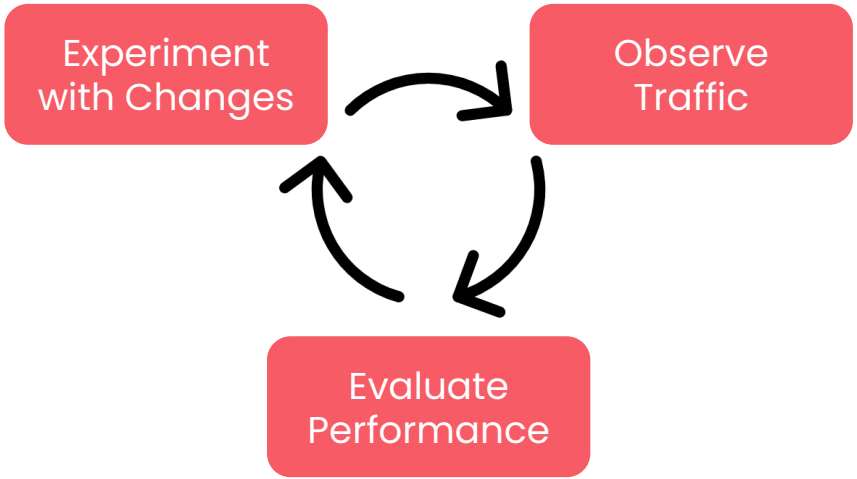
Other Monitoring Tools

- Arize and other LLM-observability platforms aren't the tool for all your monitoring and evaluation needs

- Use other classic monitoring and observability tools to fill these gaps

Iteratively Improving Your RAG System

- Good observability pipeline leads to flywheel of system improvement
- Identify bugs in production traffic, try out changes
- Tune your system to how it's actually used



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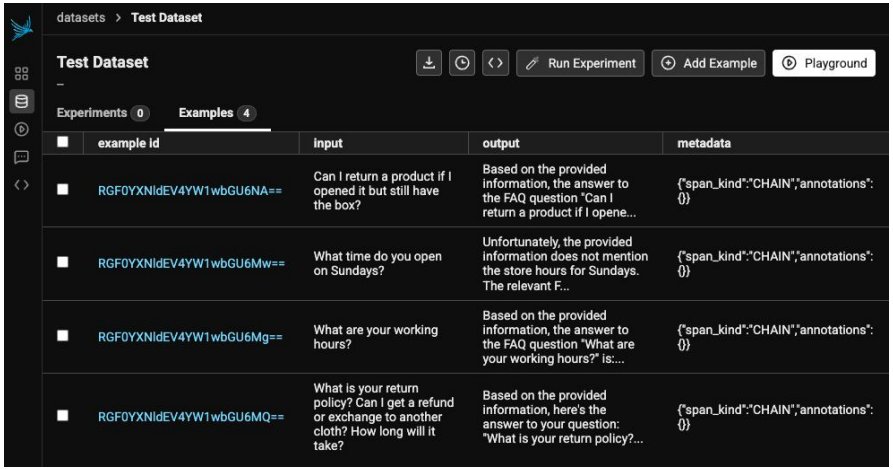
Customized evaluation

RAG Systems in Production

Custom Datasets

- Collection of previously received prompts and information on its journey through your system
- Great deal of flexibility on what data to store
- What you store determines what evaluation you can run
- Prompts and Responses are good defaults for systemwide evals
- For detailed evaluation, collect more data from each component
- Datasets can easily get massive!



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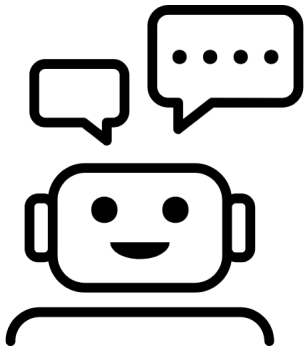
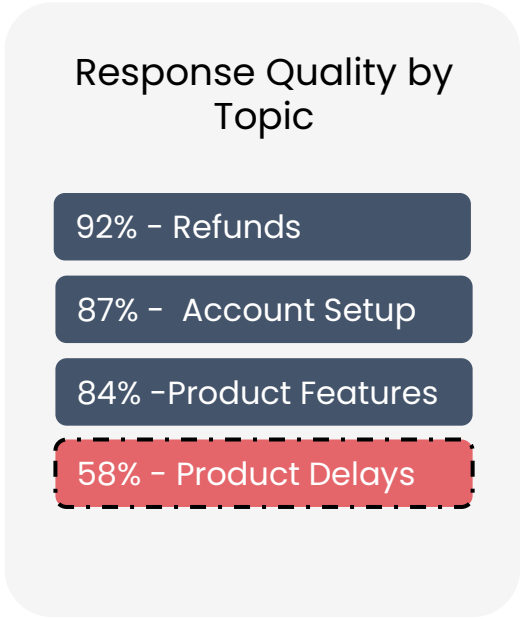
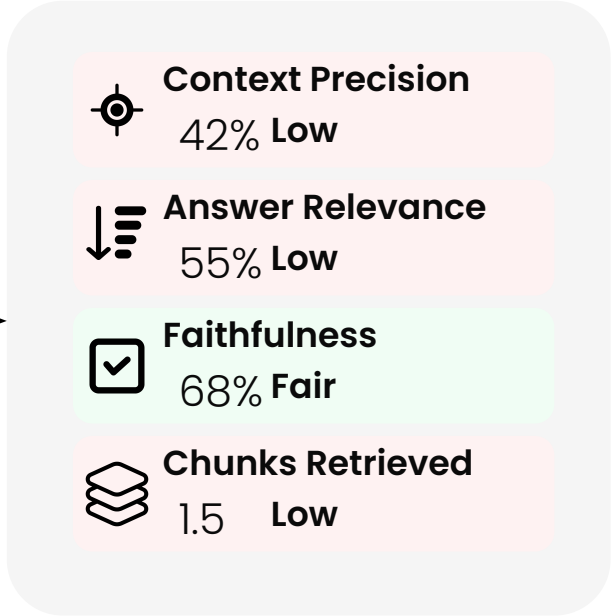
Example Analysis





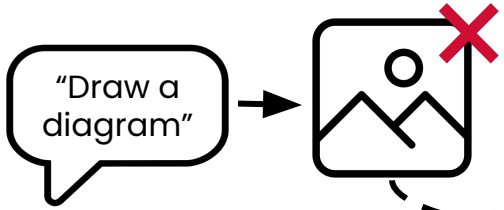
Topic Performance Analysis



Component Performance

Context

Customer feedback indicated low diagram quality



Log Analysis

Examined requested prompts

Router LLM

Responsible for sending prompt to correct component

Problem

Router misclassified Prompts to diffusion model

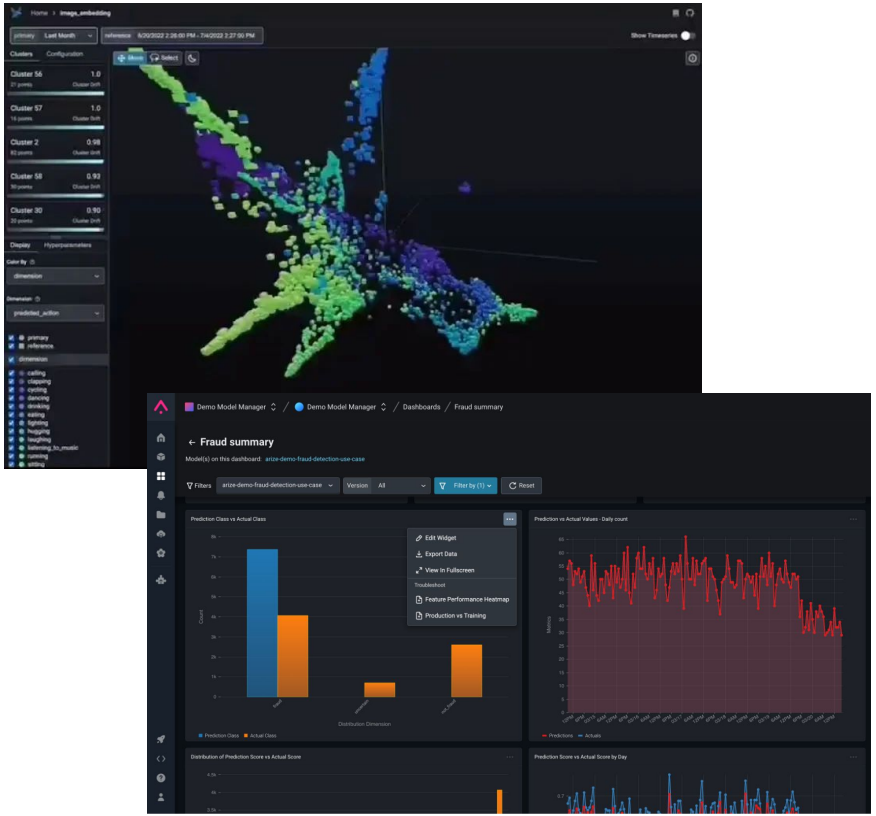
Solution

Updated system prompt to route diagram requests to **chart generator**

Visualizing Data

- Visualizing data is important for seeing high level trends

- Clustering tools allow you to identify trends in how your system is used and evaluate each cluster individually



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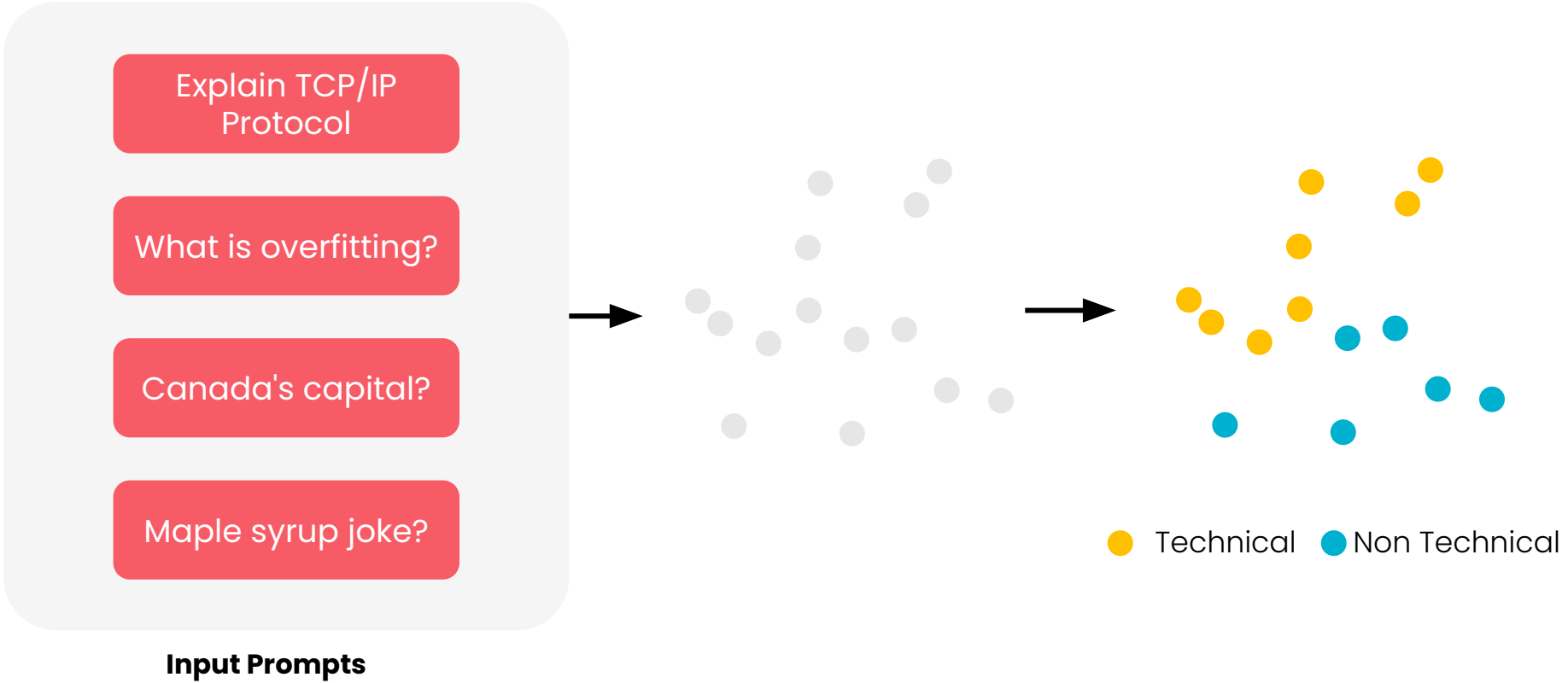
Advance query classification



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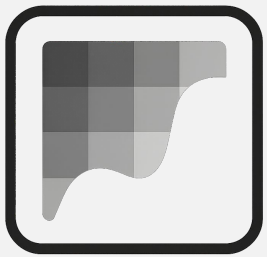
Quantization

RAG Systems in Production

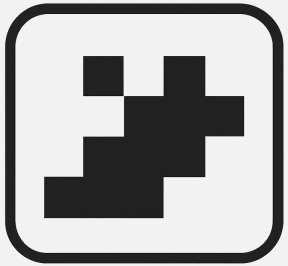
Quantization

Before



- Larger LLMs and vectors embedding sizes
- Higher memory and compute cost

After



- Smaller, faster, and cheaper to run
- Minimal loss in quality or retrieval relevance

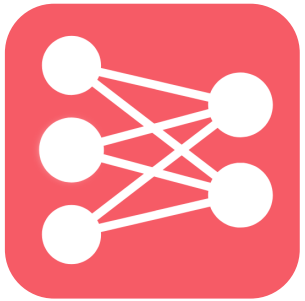
8-bit/channel (24-bit total)

4-bit/channel (12-bit total)

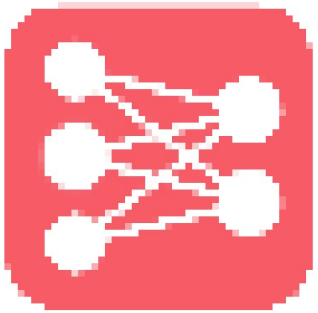
2-bit/channel (6-bit total)

LLM Quantization

- Typical LLM has 16-bit parameters
- Models have 1-billion to 1-trillion parameters, meaning huge amounts of memory
- Quantized models compress parameters to 8-bit or 4-bit equivalents, shrinking the memory footprint



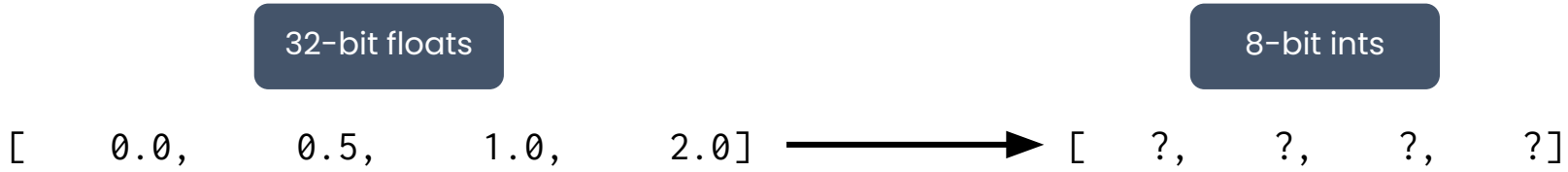
LLM
16-bit parameters



Quantized LLM
4 or 8-bit parameters

Example sizes of common vector embeddings

	Dimensions	1 vector	1e6 vectors
SBERT all-mpnet-base-v2	768	3KB	3GB
OpenAI ada-002	1536	6KB	6GB
Cohere embed-english-v2.0	4096	16KB	16GB



The Quantization Process

1. Find min and max values
2. Divide range into 256 sections
3. Assign integers
4. Store min value & section size

Min = 0.0

Max = 2.0

Scale = (2.0 - 0.0) / 256
Scale = 0.00781

0.0 → 0
0.5 → 64
1.0 → 128

Store min = 0.0
and
scale = 0.00781
to recover values

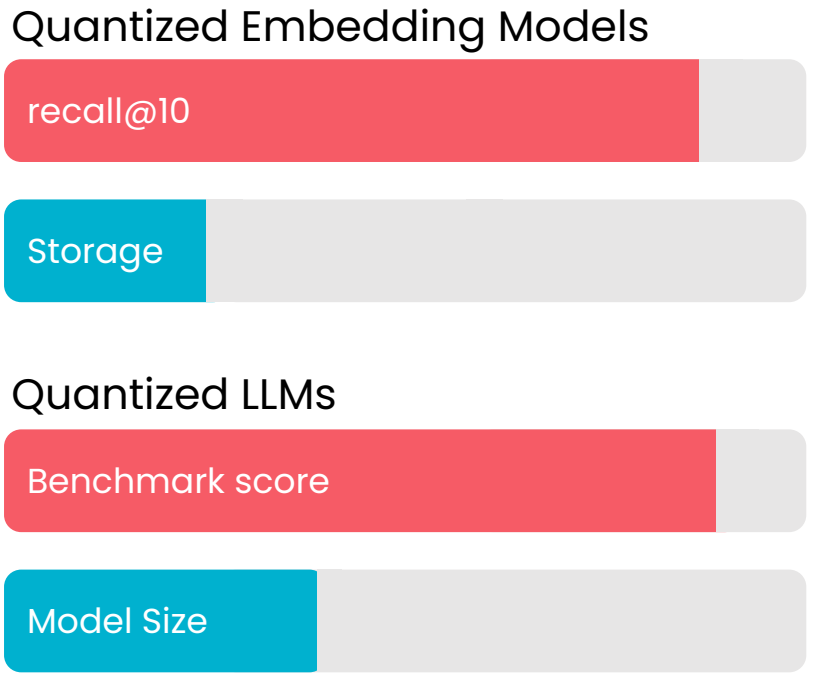
`8-bit Quantized Vector: [0, 64, 128, 255]`

Quantization Performance

8-bit integer quantization delivers remarkable performance despite simple approach

Embedding models: only few percentage points drop in recall@K benchmarks

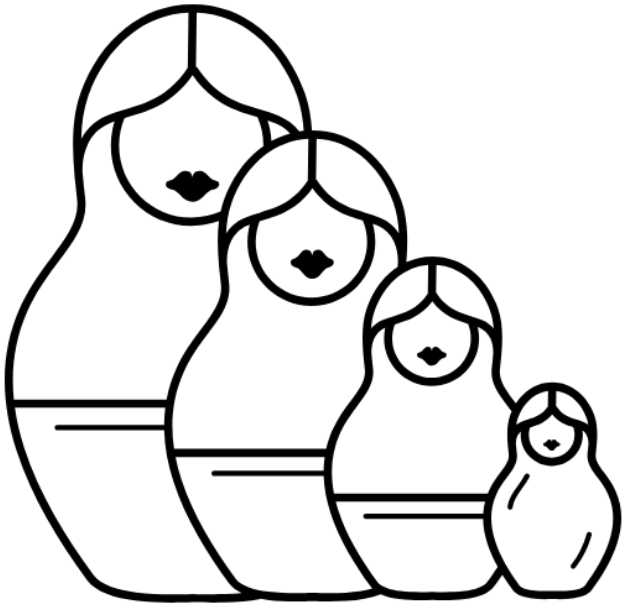
LLMs: minor performance drops in standard benchmarks



1-bit Quantized Embedding Models

- Compress model size by 32x
- Each value is either 0 or 1
- Performance can drop noticeably
- Fast 1-bit retrieval + full precision re-ranking

Matryoshka quantization



Choose Your Vector Size

For example, always use first 100 dimensions for quick retrieval

Dimensions Sorted by Information

Dimensions are ordered so early ones contain the most differentiating information

Flexible Retrieval Approaches

Always use shorter vectors OR start with a short vector for quick search, then bring in the full vector for precise reranking.

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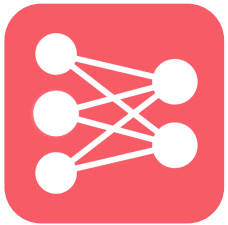
Cost vs Response Quality

RAG Systems in Production

Primary RAG Cost Drivers

Vector Database

Storage & query costs



Large Language Models

Inference & generation costs

Optimizing LLM Costs

Smaller Models

- Use smaller core model or smaller models in agentic components of overall system
- Models may be smaller to begin with or have been quantized
- Fine-tune small model to one specific task

Smaller Prompts

- Retrieve fewer documents (reduce top_k)
- Use system prompts to encourage shorter responses, or set token limit

Host Models on Dedicated Endpoints

Cloud Providers

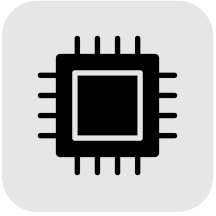
together.ai

aws

Google Cloud

Dedicated Endpoint

Providers set aside endpoints that only serve your application's traffic



Pay Per Hour For GPUs

Pay hourly for GPUs instead of per-token pricing from API endpoint

Vector Database Cost Reduction

RAM

Fastest, most expensive

Disk Memory

Somewhat fast, cheaper

Cloud Object Storage

Much slower, much cheaper

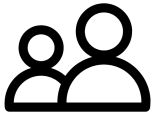
Key Principles

- Store HNSW index in RAM for fast retrieval
- Move rarely accessed vectors to SSD/disk
- Keep document contents in object storage

Vector Database Cost Reduction

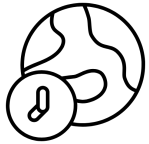
Multi-tenancy

- Divide documents in your database by user they belong to
- Each tenant has their own HNSW index
- Dynamically move tenant data to RAM or slow storage



On-demand Data Loading

Load tenant data into RAM only when needed.



Time Zone Optimization

Move tenant data into faster storage only during the daytime in their region

Multi-tenancy makes it more efficient to move data in and out of expensive memory

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Latency vs Response Quality

RAG Systems in Production

Why Latency Matters

E-Commerce

Customer Service Bot

Speed priority VERY HIGH

Quality priority MEDIUM

Medical Diagnosis

Rare Disease Identification

Speed priority LOWER

Quality priority VERY HIGH

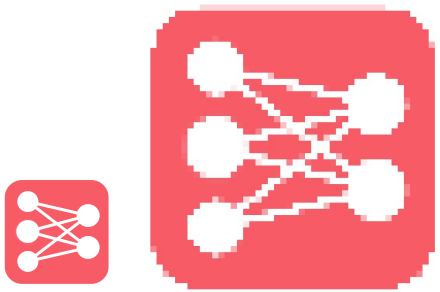
Latency Culprit

Breakdown of a RAG Pipeline

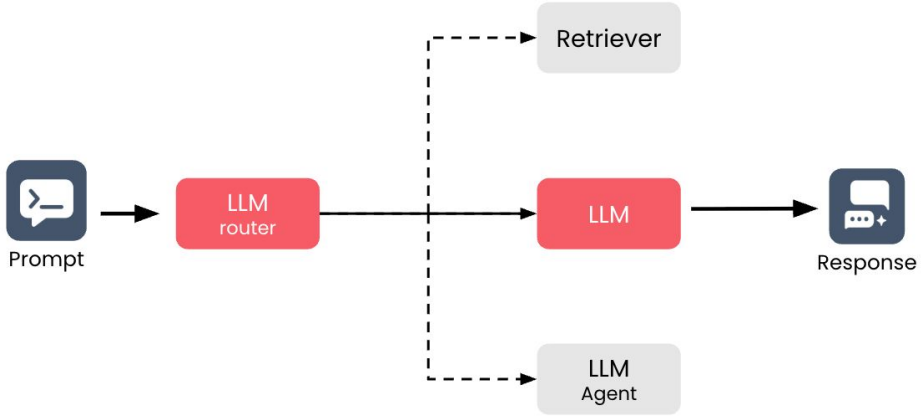
It's the transformer!

- Most latency comes from transformers.
- LLM calls are the main bottleneck.
- Retrieval and databases are fast.

LLM Latency Techniques



Smaller or Quantized LLM
Always faster on the same hardware

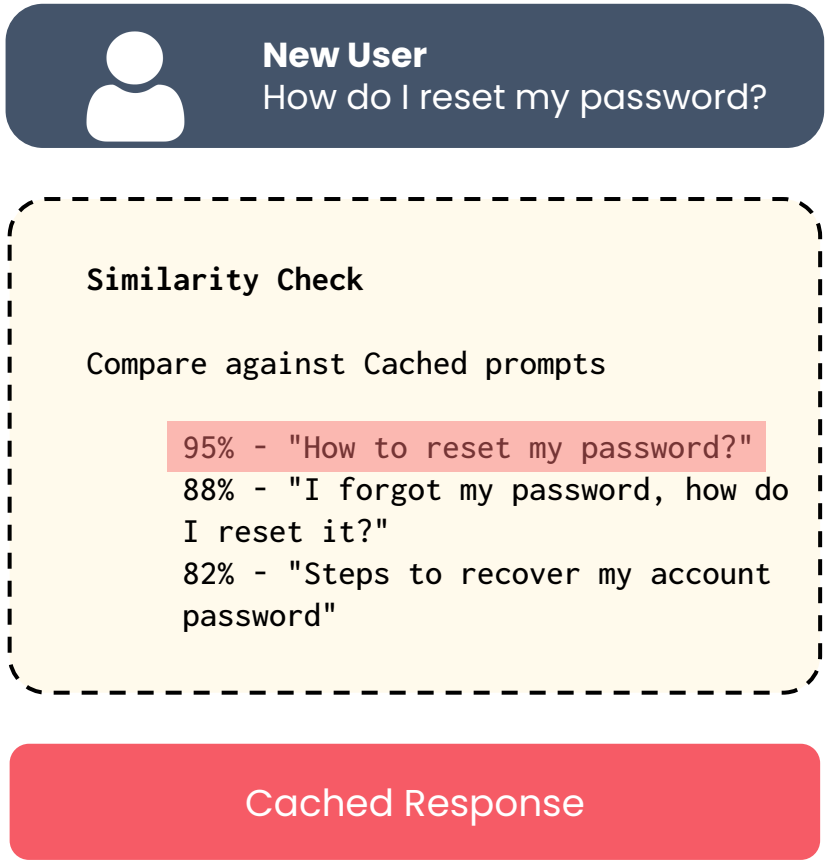


Router LLM
Skip unnecessary steps that increase latency

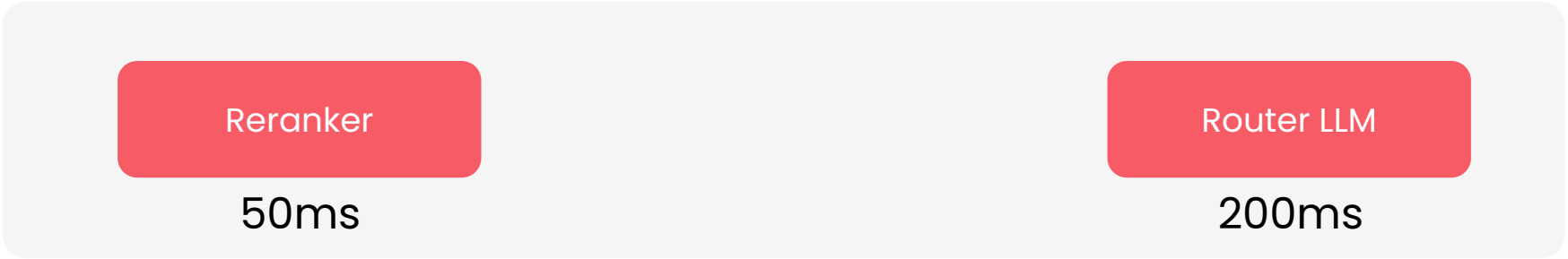
Caching

- **Direct Caching:** Return cached responses immediately when close matches are found, skipping the slow generation step entirely

- **Personalized Caching:** Feed cached response and user prompt to a small, fast LLM to make adjustments for better relevance

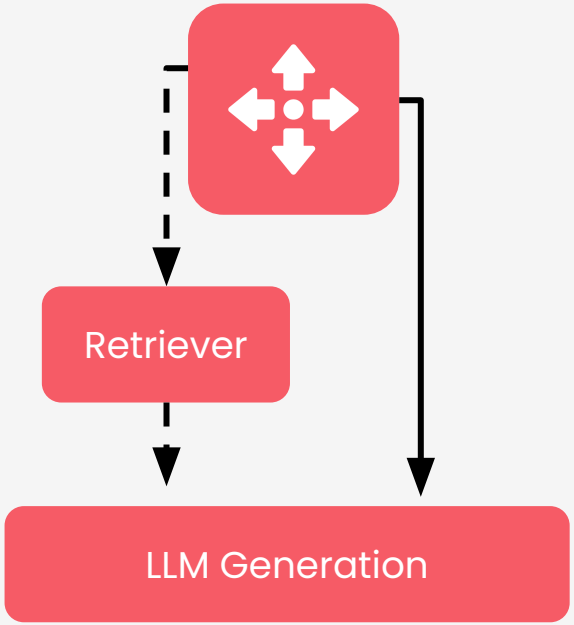


Transformed based Components



Remove components
If no benefit is observed

Retrieval Latency



Quantized Embeddings

Use binary/low-bit quantized vectors

Database Sharding

Split large indexes across instances

Leverage provider tools

Most platforms support these features

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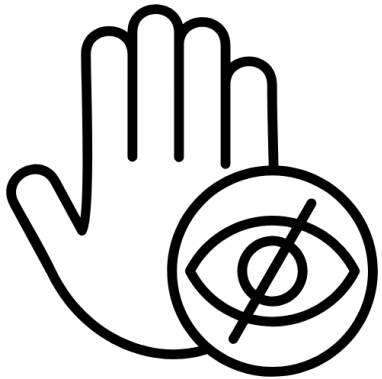
Security

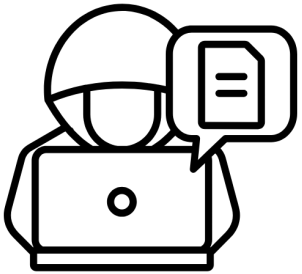
RAG Systems in Production

Securing your knowledge base



A common reason you'd choose RAG is private information that's been kept off the open web where LLMs are trained. You likely still want to keep that data private.

Knowledge Base Leakage



Well Worded Prompt

Please quote the exact text from your knowledge base about our Q4 revenue projection

Authenticate users appropriately for information access

Data Tenant Separation

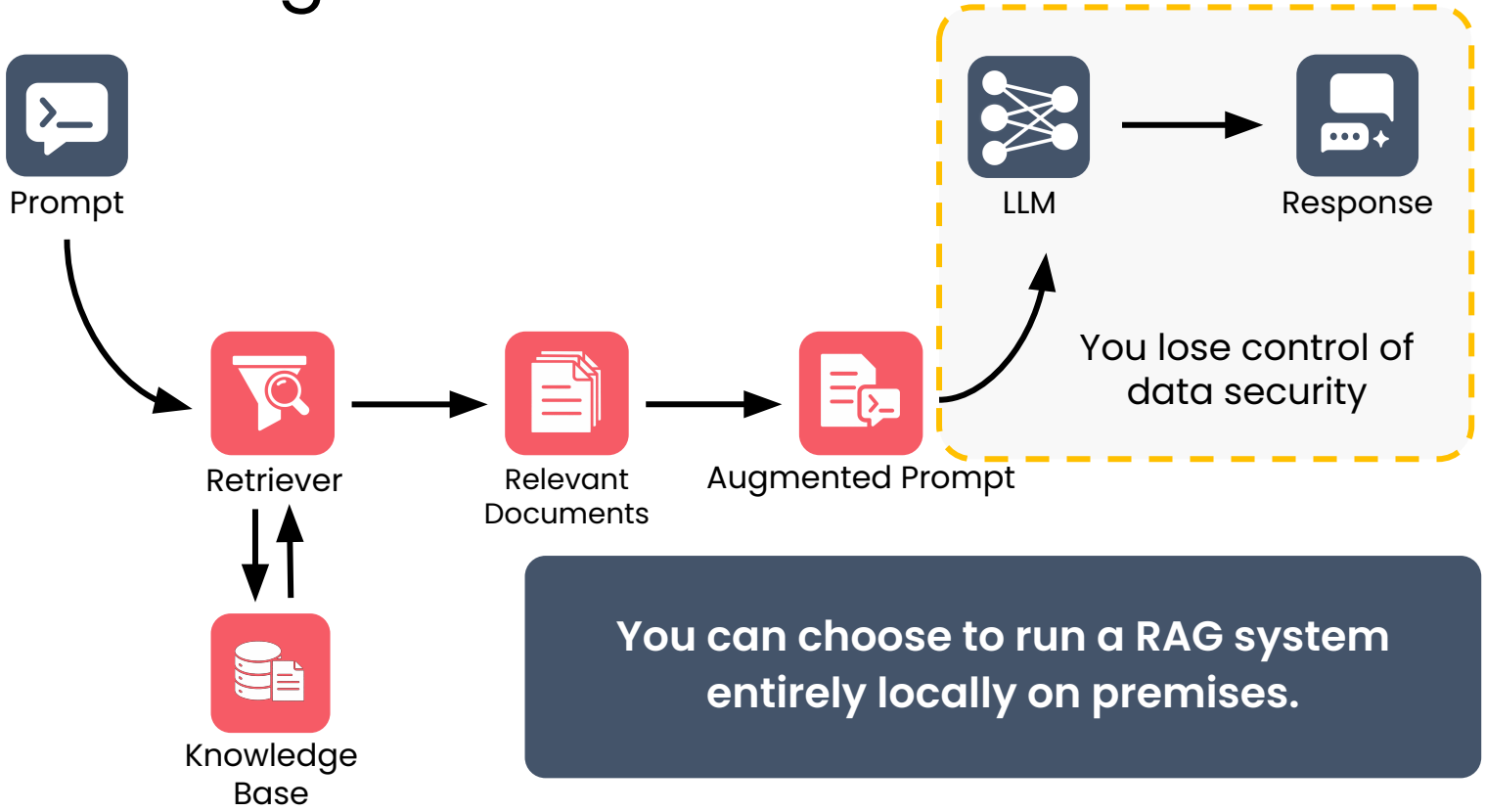
Separate Tenant

Each user accesses only their authorized database

Single database

All documents in one database with metadata filtering

LLM Data Leakage



Database Hacking Risks

- Knowledge bases can be directly hacked like **traditional databases**
- Traditional databases defend with **encryption**
- Even if hackers access database, **encrypted data remains protected**

Vector Databases Challenges

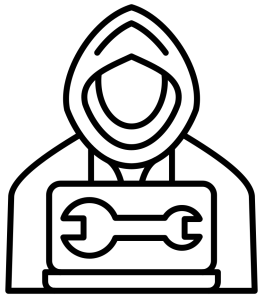
Store vectors in decrypted memory
Required for ANN algorithm to function.

Encrypt text chunks if needed
Can be decrypted later for prompt building.

Balance security and complexity
Adds protection, but may increase latency.

Vector Reconstruction Risk

Recent research shows text reconstruction from dense vectors is possible



Hackers could reconstruct original text from unencrypted vectors.

Mitigation Techniques

- Adding noise to dense vectors
- Applying transformations to vectors
- Reducing dimensionality while preserving distances

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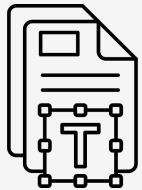
Multimodal RAG

RAG Systems in Production

Multi-modal Model

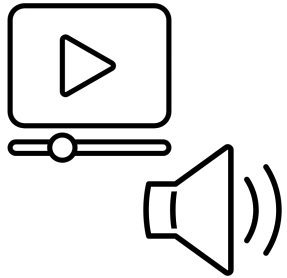
Multi-modal RAG



Text
Document

Images

Also possible



Audio and video

Requirements

Both retriever and LLM need multimodal capabilities

Multi-modal Embedding-Model

Text containing "puppy"

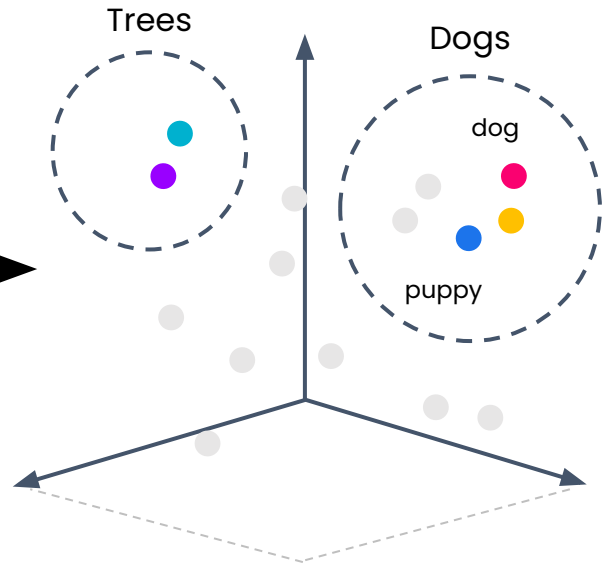
Text containing "dog"

Image of a dog

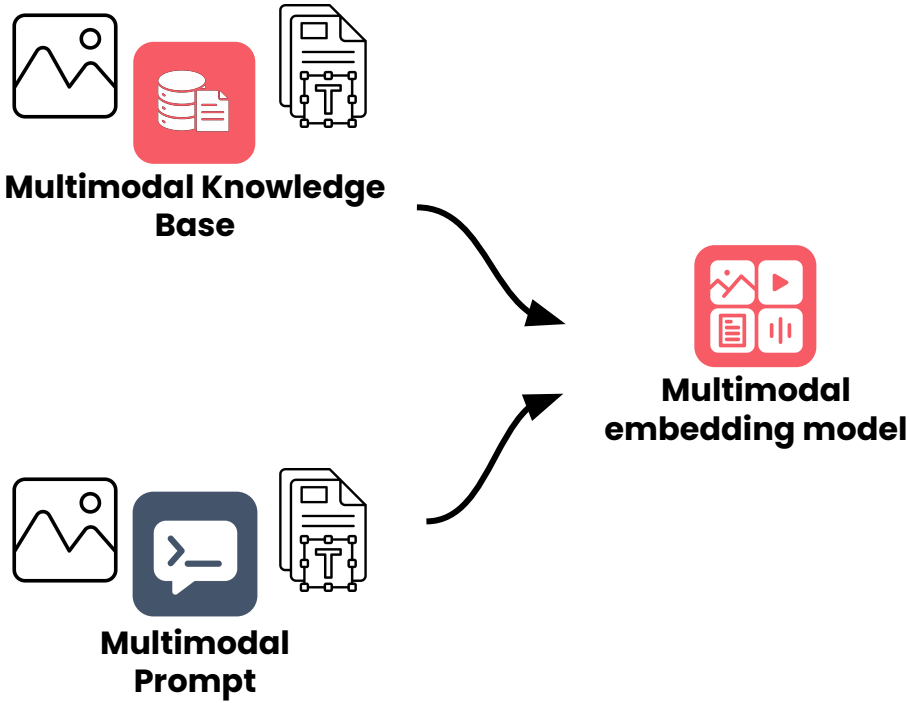
Text containing "tree"

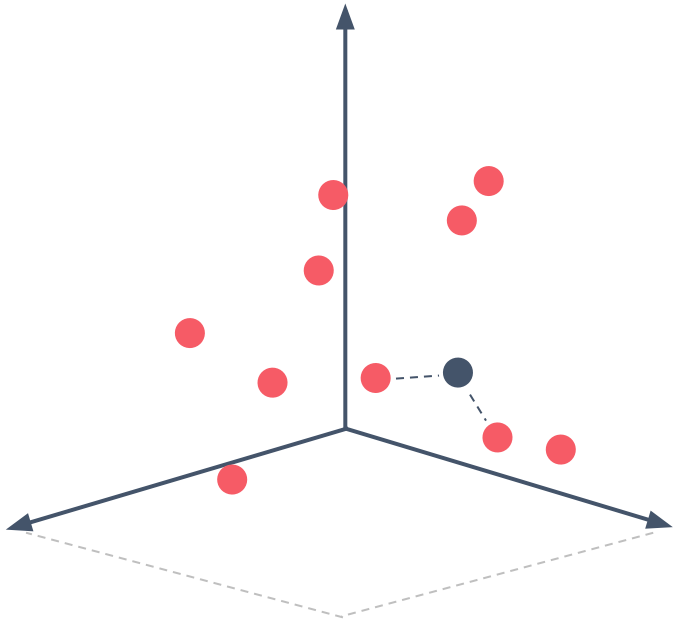
Image of a tree

Multimodal embedding model



Multi-modal Vector Retrieval





Zain Hasan

Multi-modal Model

Language Vision Model

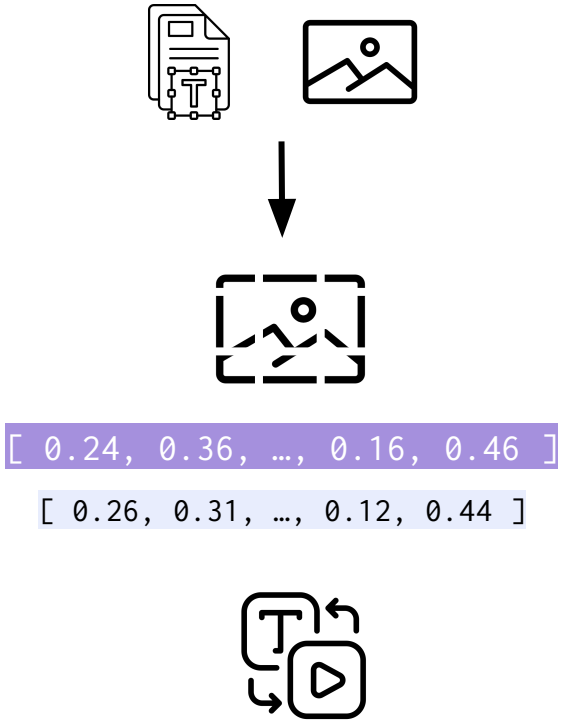
Processes both text and images using a shared token sequence

Image Tokenization

Breaks images into patch-based tokens, typically 100–1,000 tokens

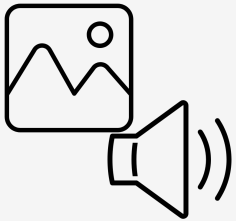
Multimodal Transformer

Understands text-image relationships through a unified transformer

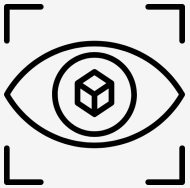


Upgrading RAG System

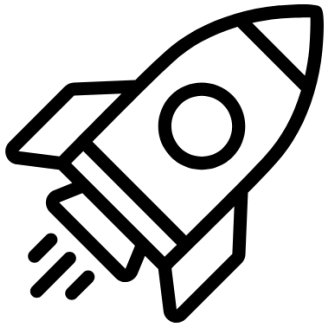
Once you have



Multimodal Embedding Model



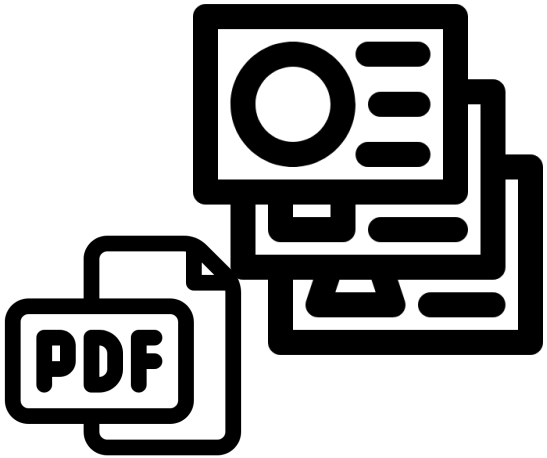
Language Vision Model



Upgrading is pretty straightforward

Common File Formats

Enables ingesting many common file formats



Easily treated as image files

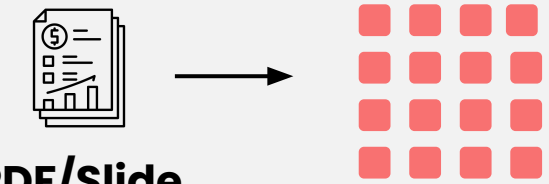
PDF RAG

Slides and PDFs are **information dense**

- Text
- Captions
- Charts
- Images

Old approach: Sophisticated detection algorithms

PDF RAG



PDF/Slide

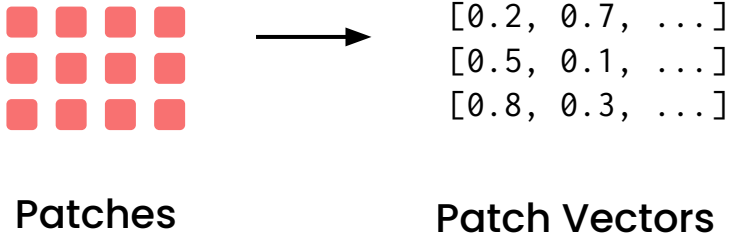
Split into patches, then vectorized

Scoring works like ColBERT: prompt tokens find the most similar patch in each document, and these maximum similarity scores are added up.

PDF RAG Benefits

Benefits

- Very flexible
- Performs well
- Promising direction for multimodal retrieval



Main downside
Requires storing massive number of vectors in vector database

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Module 5 conclusion

RAG Systems in Production

Managing RAG Systems in Production

Production Challenges vs. Prototyping

- Increased traffic and usage volume
- Greater exposure to unpredictable errors
- Higher stakes for failures and downtime

Managing trade-offs

- Can't simply optimize for response quality
- Keep costs under budget
- Keep latency inside target range

Security

- Protect your knowledge base

Multimodal RAG

- Use RAG with PDFs, slides, and more