

# **Cheat Sheet: Build a Comprehensive RAG Application**

**Estimated Reading Time: 15 minutes** 

## **FAISS** vs Chroma DB Comparison

### FAISS (Facebook AI Similarity Search)

FAISS is a library developed by Meta for fast vector search that runs on a single machine using either CPU or GPU.

#### **Key Characteristics:**

- Type: Library for vector search operations
- Deployment: Single-node operation, no native distributed scaling
- Usage: Code-based integration, no server component
- Control: Full control over indexing and performance
- · Metadata: No native metadata support
- Integration: Works with LangChain and LlamaIndex

#### Chroma DB

Chroma DB is a vector database built for AI use cases that stores both vectors and metadata like tags or descriptions. It can be run locally or as a server.

#### **Key Characteristics:**

- Type: Full vector database
- Deployment: Supports both single-node and distributed deployments
- Scaling: Clear path to scale for larger workloads
- · Metadata: Native support for storing and filtering metadata
- Indexing: Only supports HNSW (Hierarchical Navigable Small World)
- Integration: Works well with tools like LangChain, easy to integrate

## **Technology Comparison Summary**

- FAISS: Library vs. Chroma DB: Full database
- FAISS: Single-node only vs. Chroma DB: Single-node and distributed
- FAISS: Many indexing options vs. Chroma DB: HNSW only
- FAISS: No native metadata support vs. Chroma DB: Metadata support and filtering
- · Both: Work with LangChain and LlamaIndex

## **FAISS Index Types**

### Flat Index

A flat index compares the distance (using either Euclidean distance or dot product) between the query embedding and every vector in the vector store using brute force search.

#### Characteristics:

- Method: Brute force comparison with all vectors
- Accuracy: Very accurate approach
- Performance: Very slow for large datasets
- · Use Case: Small datasets where accuracy is critical

## **Inverted File Index (IVF)**

An IVF index speeds up vector search by clustering vectors using methods like k-means, forming Voronoi cells around centroids. Each cell contains vectors closest to its centroid.

#### **Technical Process:**

- Clustering: Vectors grouped using k-means into Voronoi cells
- Search Strategy: Query searches only nearest cells, reducing computations
- Trade-off: Faster than flat index but may slightly reduce accuracy
- Limitation: Some nearby vectors might be in other cells

## Locality-Sensitive Hashing (LSH)

LSH uses hash functions to map similar vectors to the same bucket, allowing for fast and memory-efficient search.

#### Characteristics:

- Method: Hash functions group similar vectors into buckets
- Performance: Fast and memory-efficient
- Best Use: High-dimensional sparse data such as text embeddings
- Trade-off: Neither the fastest nor the most accurate method
- Search Process: Searches vectors in closest matching groups

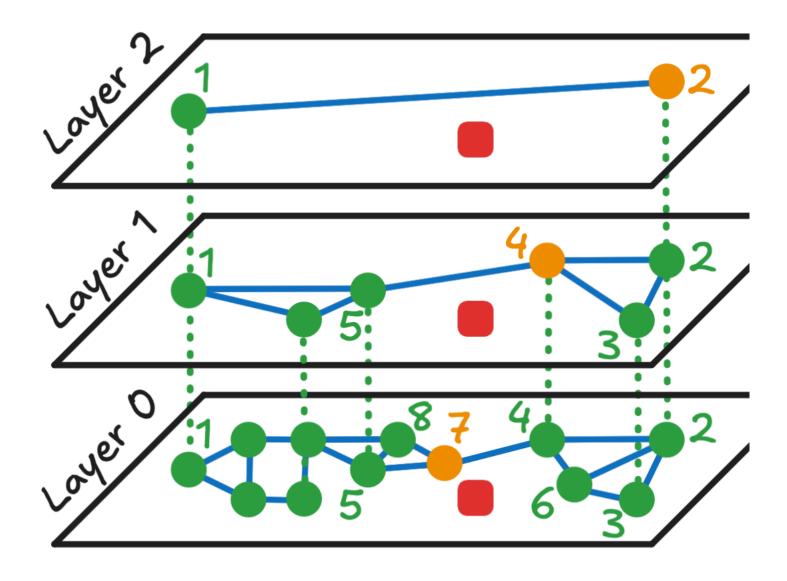
## Hierarchical Navigable Small World (HNSW)

HNSW organizes vectors into a hierarchy of layers where top layers are sparse with few vectors acting like express highways, helping the search algorithm quickly approach the target region.

#### **Architecture:**

- Top Layers: Sparse, contain only a few vectors (express highways)
- Lower Layers: Denser graphs with detailed local connections
- Search Process: Begins at topmost layer, moves downward using best candidate from each layer
- Performance: Both fast and accurate, especially for large datasets

## **HNSW Deep Dive**



## **How HNSW Works - Technical Process**

The algorithm constructs a multi-layer graph where each layer contains progressively more data points with shorter-range connections:

- 1. Top Layer Entry: Search begins at the highest layer with sparse, long-range connections
- 2. Greedy Search: At each layer, move to the neighbor closest to the target query
- 3. Layer Descent: When no closer neighbors exist, descend to the next layer
- 4. Progressive Refinement: Graph becomes denser as search descends to lower layers
- 5. Bottom Layer: Layer 0 contains all data points for final precise search
- 6. Result: Returns approximate nearest neighbors with high accuracy

Navigation Analogy: Like finding a restaurant in a city - start with highways for long jumps, then use local streets for precise location. The algorithm "zooms in" progressively from major connections to fine-grained local connections.

#### **Key Parameters**

#### M (Max Connections)

- Purpose: Controls how many neighbors each point connects to
- **Trade-off**: Higher M = better accuracy, more memory usage
- Impact: Lower M = faster build, less memory, lower accuracy

#### efConstruction (Search Breadth During Build)

- Purpose: Controls how many candidates are considered when finding neighbors during insertion
- Trade-off: Higher efConstruction = better graph quality, slower build
- Impact: Lower efConstruction = faster build, but possibly lower search quality later

#### efSearch (Search Breadth During Querying)

- Purpose: Controls how many candidate nodes are explored during a query
- **Trade-off**: Higher efSearch = better accuracy, slower search
- Impact: Main method to tune speed vs. accuracy at query time

#### ml (Level Multiplier)

- Purpose: Affects how likely a point is to appear in higher layers
- · Impact: Controls the shape of the hierarchy

#### **HNSW Limitations**

#### **Approximate Results**

- Accuracy: HNSW delivers fast results with typical recall rates of 90% to 99%
- Trade-off: May occasionally miss the exact nearest neighbor
- Benefit: For most applications, this trade-off is worthwhile

### **HNSW** and **Dynamic** Updates

- HNSW is best suited for: Mostly-static datasets
- Challenges: Frequent insertions and deletions can degrade the HNSW index's performance over time
- Solution: Periodic reconstruction may be needed for optimal performance

#### **Distance Metric Limitations**

- Works best with: Euclidean distance (L2) and Cosine similarity
- Other metrics: May require modifications or perform suboptimally

## **Extending FAISS with Milvus**

#### **FAISS Limitations**

FAISS is effective for local, high-performance vector search, but it lacks features like metadata support and distributed scaling.

#### Milvus Integration

Milvus, a vector database, uses FAISS as one of its core indexing engines while adding missing capabilities:

- Metadata Support: Storing and filtering metadata alongside vectors
- Hybrid Queries: Enables queries such as "Find similar items under \$50"
- Distributed Deployments: Suitable for large-scale production environments
- Scalability: Addresses FAISS's single-node limitation

## When to Use Each Technology

## **Use FAISS When:**

- · You want full control and performance on a single machine
- · You need access to multiple indexing algorithms
- · You're building custom, high-performance applications
- Metadata support is not required or can be handled externally

### **Use Chroma DB When:**

- You need quick AI development and prototyping
- · Metadata-rich queries are important
- You want easy integration with AI tools

about:blank 3/4

• You need both single-node and distributed deployment options

#### **Use Milvus When:**

- You need a scalable, production-ready vector database
- Hybrid search capabilities are desired
- Distributed capabilities are essential
- You want FAISS-level performance with database features

## **Key Concepts Summary**

## **Index Selection Strategy**

Each FAISS index type balances speed, memory, and accuracy differently:

- Flat: Most accurate, slowest (suitable only for small datasets)
- IVF: Balanced speed/accuracy (effective for medium to large datasets, but may be outperformed by HNSW in many cases)
- LSH: Memory-efficient (best for high-dimensional sparse data, though less commonly used)
- HNSW: Fast and accurate (preferred for medium to large datasets due to strong performance and scalability)

## **HNSW Algorithm Benefits**

- Hierarchical Structure: Multi-layer approach enables O(log n) search complexity
- Performance: 90-99% recall rates with fast search times
- Scalability: Especially effective for large datasets
- Flexibility: Tunable parameters for different speed/accuracy requirements

## **Technology Integration**

- Both FAISS and Chroma DB: Work with LangChain and LlamaIndex for RAG pipelines
- Make a choice based on: Project size, complexity, and infrastructure requirements
- Extension options: Milvus uses FAISS under the hood, but provides additional capabilities

## Author(s)

Wojciech "Victor" Fulmyk



about:blank 4/4