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

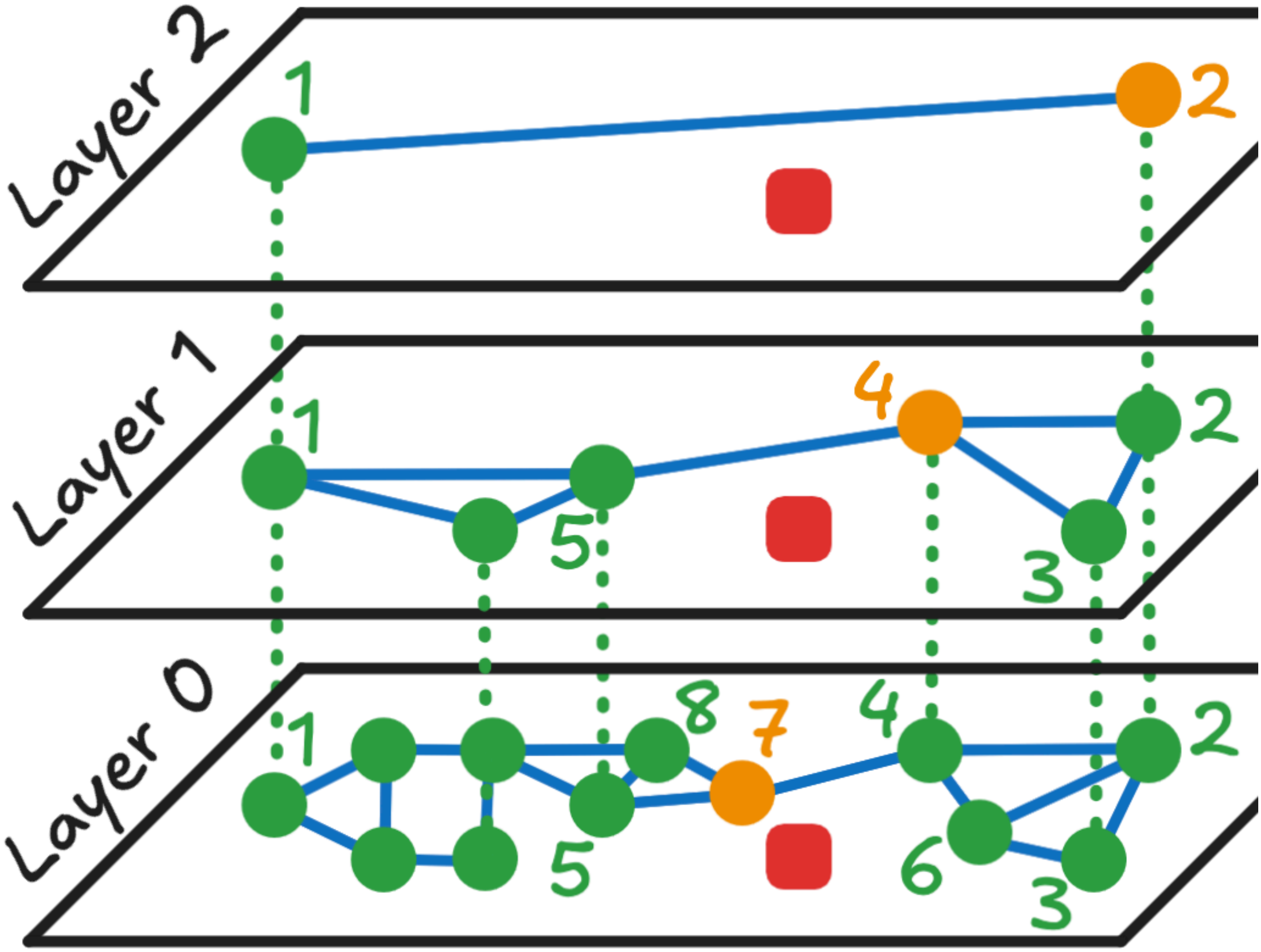
Hierarchical Navigable Small World (HNSW)

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
- 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)

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