# Vector Database Architecture Cheat Sheet

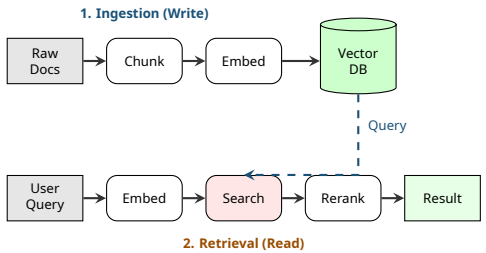
*End-to-End Guide: From Data Ingestion to Query Serving*

## 1. DEFINITION

**Vector Database:** A specialized database optimized for storing and querying high-dimensional vectors (embeddings).

- **Why Used:** Traditional DBs compare exact values (SQL 'WHERE id=5'). Vector DBs compare semantic similarity ('Find closest meaning') using distance metrics like Cosine Similarity. Essential for RAG and Semantic Search.

## 2. HIGH LEVEL ARCHITECTURE FLOW




- **Ingestion:** Raw data → Chunks → Vectors → Indexing.
- **Retrieval:** Query → Vector → ANN Search → Rerank → Response.

## 3. CORE COMPONENTS

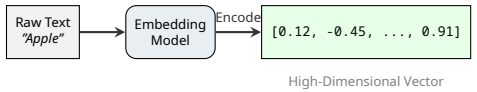
- **Ingestion Layer:** Connectors (S3, SQL, PDF loaders) to fetch data.
- **Chunking/Preprocessing:** Splitting text into manageable windows (e.g., 512 tokens).
- **Embedding Layer:** Model (e.g., OpenAI text-embedding-3) converting text to floats.
- **Indexing Layer:** Organizes vectors for fast retrieval (IVF, HNSW).
- **Storage Layer:** Persists vectors, metadata, and the index structure.
- **Query Layer:** Handles search requests, filtering, and pre/post processing.
- **Reranking Layer:** Refines top-K results using a high-precision Cross-Encoder.

**Chunking Strategy (LangChain):**

```python
from langchain.text_splitter import
      RecursiveCharacterTextSplitter

text_splitter = RecursiveCharacterTextSplitter(
    chunk_size=500,      # Characters per chunk
    chunk_overlap=50,    # Context overlap
    separators=["\n\n", "\n", " ", ""]
)
chunks = text_splitter.split_text(raw_text)
```

## 4. EMBEDDING LAYER IMPLEMENTATION

### Transformation



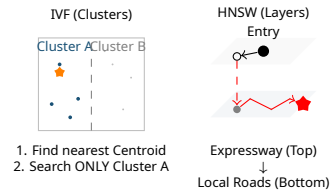

### Providers

- **OpenAI:** Simple API, high quality, usage cost.
- **Sentence Transformers (HF):** Run locally (CPU/GPU), free, privacy-friendly.
- **Custom Fine-Tuned:** Best for domain-specific jargon (Medical/Legal).

```python
from sentence_transformers import SentenceTransformer

# Load a local model
model = SentenceTransformer('all-MiniLM-L6-v2')

# Create embeddings
text = "Vector databases allow semantic search."
vector = model.encode(text)
# Output: [0.034, -0.12, ... 384 dims]
```

## 5. INDEXING AND SEARCH ALGORITHMS

### Algorithm Visuals




**Implementing FAISS (IndexFlatL2):**

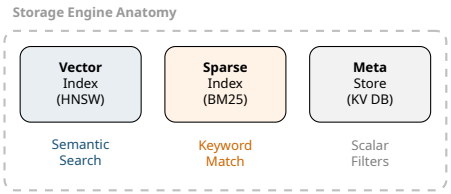
```python
import faiss
import numpy as np

d = 384                              # Dimension
index = faiss.IndexFlatL2(d)         # Brute-force L2
index.add(embeddings_matrix)         # Add vectors

# Search
D, I = index.search(query_vector, k=5)
# D = Distances, I = Indices
```

- **Flat Index:** Brute force. 100% Recall. Slow ($O(N)$).
- **IVF (Inverted File):** partitions space into clusters (Voronoi cells). Search only nearest clusters. Faster ($O(\sqrt{N})$), lower recall.
- **HNSW (Hierarchical Navigable Small World):** Multi-layer graph. Best trade-off for speed/recall. High memory usage.
- **PQ (Product Quantization):** Compresses vectors (lossy compression) to save RAM.

## 6. STORAGE ARCHITECTURE

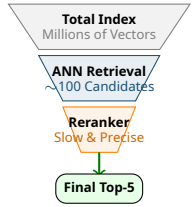
### Types

- **In-Memory (Redis/Milvus):** Ultra-low latency, expensive (RAM constrained).
- **Disk-Based (DiskANN):** Stores vectors on SSD. Slower, but scales to billions.
- **Metadata:** Stored separately (e.g., RocksDB, Postgres) for filtering.
- **Hybrid Search:** Storing both Dense Vectors and Sparse Vectors (Keywords/BM25) to handle exact matches.




## 7. QUERY PROCESSING

### Query Pipeline (The Funnel)




**Reranking (Cross-Encoder):**

```python
from sentence_transformers import CrossEncoder

reranker = CrossEncoder('cross-encoder/ms-marco-MiniLM-L-6-
      v2')
# (Query, Document) pairs
pairs = [('query', 'doc1_text'), ('query', 'doc2_text')]
scores = reranker.predict(pairs)

# Sort by score descending
ranked_results = sorted(zip(scores, docs), reverse=True)
```

- **1. Query Embed:** Convert user question to vector using same model as ingestion.
- **2. ANN Search:** Find approximate nearest neighbors (Top-K candidates).
- **3. Filtering:** Pre-filter (restrict search space) or Post-filter (remove results). Pre-filtering is faster but harder to implement with HNSW.
- **4. Reranking:** Re-score Top-K using a slower, precise model (Cross-Encoder).

## 8. VECTOR DATABASE IMPLEMENTATIONS

- **FAISS (Meta):** Library, not a DB. Good for local scripts. Fast.
- **Milvus/Zilliz:** Scalable, cloud-native DB. Good for massive datasets.
- **Weaviate:** Native hybrid search, modular (GraphQL).
- **Pinecone:** Fully managed SaaS. Easy to start, closed source.
- **Qdrant:** Rust-based, high performance, good filtering support.

- **Chroma:** Lightweight, developer-friendly, often local.

## 9. END TO END EXAMPLE FLOW

**Scenario:** User searches "Legal limitation for contracts."

1. **Query:** User input string.
2. **Embed:** OpenAI API converts string to 1536-dim vector.
3. **Search:** Vector DB scans HNSW index for nearest 100 neighbors.
4. **Filter:** Apply Metadata filter `doc_type == "legal"`.
5. **Rerank:** Cohere Rerank API re-sorts the 20 results by semantic relevance.
6. **Return:** Top 5 chunks returned to LLM context.

## 10. PERFORMANCE METRICS

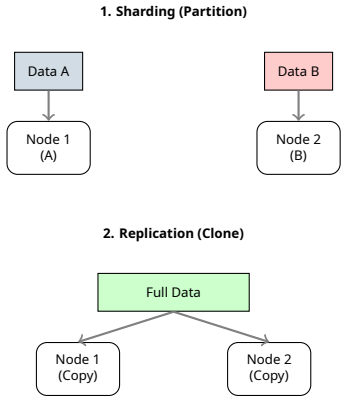
- **Recall@K:** % of true nearest neighbors found in the top K results. (Quality).
- **Precision@K:** How many retrieved items are actually relevant.
- **Latency (p99):** Time taken for search. (Speed).
- **Throughput:** QPS (Queries Per Second). (Scale).
- **Index Build Time:** Time to index new data.
- **Memory Footprint:** RAM usage per million vectors.

**Recall Calculation:**

```python
def recall_at_k(actual_ids, predicted_ids, k):
    # Set intersection
    relevant_retrieved = set(actual_ids) & set(
       predicted_ids[:k])
    return len(relevant_retrieved) / len(actual_ids)
```

## 11. SCALING & OPTIMIZATION

### Sharding vs Replication



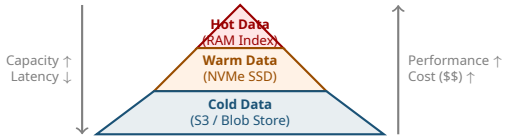

- **Sharding:** Split vectors across nodes to fit in memory (Horizontal Scaling).
- **Replication:** Copy index to multiple nodes to increase QPS (Throughput).
- **Async Updates:** Updates are eventually consistent to avoid blocking reads.

## 12. RELIABILITY & CONSISTENCY

- **Replication:** Ensures high availability if a node fails.
- **Backups:** Snapshotting the index to S3/Blob storage.
- **Consistency:** Most Vector DBs are *Eventually Consistent* (newly added vectors might not appear in search immediately) to favor speed.

## 13. COST OPTIMIZATION

### Tiered Storage Hierarchy




- **Tiered Storage:** Keep hot data (recent) in RAM, cold data (old) on Disk/SSD.
- **Index Compression:** Use PQ (Product Quantization) or Binary Quantization to reduce RAM usage by 10x-30x.
- **Separation:** Separate Compute nodes (search) from Storage nodes.

## 14. SECURITY & GOVERNANCE

- **RBAC:** Role-Based Access Control to restrict who can query collections.
- **Data Isolation:** Multi-tenancy (Metadata filtering vs Separate Indexes) for different users.
- **PII:** Redacting sensitive info before embedding (embeddings can theoretically be inverted).

## 15. COMMON FAILURE POINTS

- **Index Corruption:** Index file gets corrupted during write.
- **Embedding Drift:** Query model version doesn't match Ingestion model version (Silent failure).
- **Recall Degradation:** As index size grows or deletes happen, ANN accuracy drops (requires re-indexing).
- **Metadata Mismatch:** Filtering removes all relevant vector results.

## 16. SUMMARY

**Goal:** Efficiently store and retrieve knowledge based on meaning.

- **Architecture:** Embed $\rightarrow$ Index $\rightarrow$ Query.
- **Tradeoff:** Recall vs Latency vs Cost.
- **Key Tech:** HNSW (Graph Index), Quantization (Compression), Hybrid Search (Keyword + Vector).