STATFUSIONAI

HOW VECTORS ARE STORED, INDEXED, AND RETRIEVED

INTRODUCTION

How text is converted into vectors, stored in a database, indexed efficiently, and used to retrieve similar information — with code & real-world examples.

"Let's go deep behind the scenes."

TEXT TO VECTOR – EMBEDDING

Code:

```
from sentence_transformers import SentenceTransformer
model = SentenceTransformer('all-MiniLM-L6-v2')
texts = [
    "Apples are sweet and red.",
    "Bananas are yellow and soft.",
    "Kids love mangoes during summer."
]
embeddings = model.encode(texts)
```

Behind the Scenes:

- When model.encode() runs, it:
  1. Tokenizes text → converts to word pieces (subwords like "embed" + "##ding")
  2. Feeds tokens through transformer layers with attention mechanisms
  3. Pools token representations to create a single vector
  4. Outputs a ***vector (384 dimensions)*** representing semantic meaning

Output Example:

```
print(embeddings[0][:5])  # First 5 values of first embedding
# [0.1213, 0.3421, -0.5632, 0.1834, 0.0507]

print(embeddings.shape)
# (3, 384) - 3 texts, each with 384-dimensional vectors
```

HOW EMBEDDINGS ARE STORED IN A VECTOR DATABASE

Conceptual View (For Understanding):

Chunk ID	Text Chunk	Vector (Embedding)	Metadata
text1	"Apples are red."	[0.12, 0.34, -0.22, ...]	page: "1"
text2	"Bananas are yellow."	[0.41, -0.18, 0.65, ...]	page: "2"
text3	"Kids love mangoes."	[0.22, 0.17, -0.34, ...]	page: "3"

Note: This looks like a table, but vector databases use specialized data structures.

Actual Storage Inside Vector DB:

```
# Example using Chroma
import chromadb

client = chromadb.Client()
collection = client.create_collection("fruit_facts")

collection.add(
    ids=["text1", "text2", "text3"],
    embeddings=[
        [0.12, 0.34, -0.22],  # Simplified for demo (really 384-dim)
        [0.41, -0.18, 0.65],
        [0.22, 0.17, -0.34]
    ],
    metadatas=[
        {"text": "Apples are red", "page": 1},
        {"text": "Bananas are yellow", "page": 2},
        {"text": "Kids love mangoes", "page": 3}
    ]
)
```

***What's Happening Under the Hood*:**

```
# Pseudocode for what's happening internally
vector_index["text1"] = [0.12, 0.34, -0.22, ...]  # Goes to optimized vector index
metadata_store["text1"] = {                       # Goes to metadata store
    "text": "Apples are red",
    "page": 1
}
```

- Vectors are stored in **specialized data structures** optimized for similarity search:
  - **HNSW** (Hierarchical Navigable Small World) - graph-based index
  - **IVF** (Inverted File) - clustering-based index
  - **Flat** - brute force comparison (simple but slow)
- Metadata is stored separately in a **key-value store** or document DB
- IDs link the vector index with the metadata store

INDEXING IN VECTOR DATABASES

What is Indexing in VectorDBs?

Indexing is a fundamental technique used to organize vector data for efficient similarity search operations. In the context of vector databases, indexing creates specialized data structures that make nearest neighbor search operations faster and more efficient, especially when dealing with high-dimensional embeddings from text, images, audio, or other data types.

Why Indexing Matters

- **Raw vector comparison** (brute force) becomes prohibitively slow as datasets grow
- **Dimensionality curse** makes searching in high-dimensional spaces challenging
- Properly indexed data can deliver results orders of magnitude faster
- Enables practical applications of vector search in production environments

Two Major Categories of Indexing

1. **Exact Indexing**
   - Guarantees 100% accurate results
   - Generally slower but provides perfect recall
   - Example: Flat (brute-force) index
2. **Approximate Indexing (ANN - Approximate Nearest Neighbors)**
   - Trades a small amount of accuracy for significant speed gains
   - Uses various techniques to efficiently narrow down the search space
   - Examples: IVF, HNSW, PQ, ANNOY

Distance Metrics in Vector Search

The choice of distance metric is critical in vector search:

- **Euclidean Distance (L2):** Measures straight-line distance between vectors
- **Cosine Similarity:** Measures the cosine of the angle between vectors (similarity of orientation)
- **Dot Product:** Inner product between vectors (works well with normalized vectors)
- **Manhattan Distance (L1):** Sum of absolute differences between vectors
- **Hamming Distance:** For binary vectors, counts positions where bits differ

FLAT (BRUTE-FORCE) INDEX

What is the Flat Index?

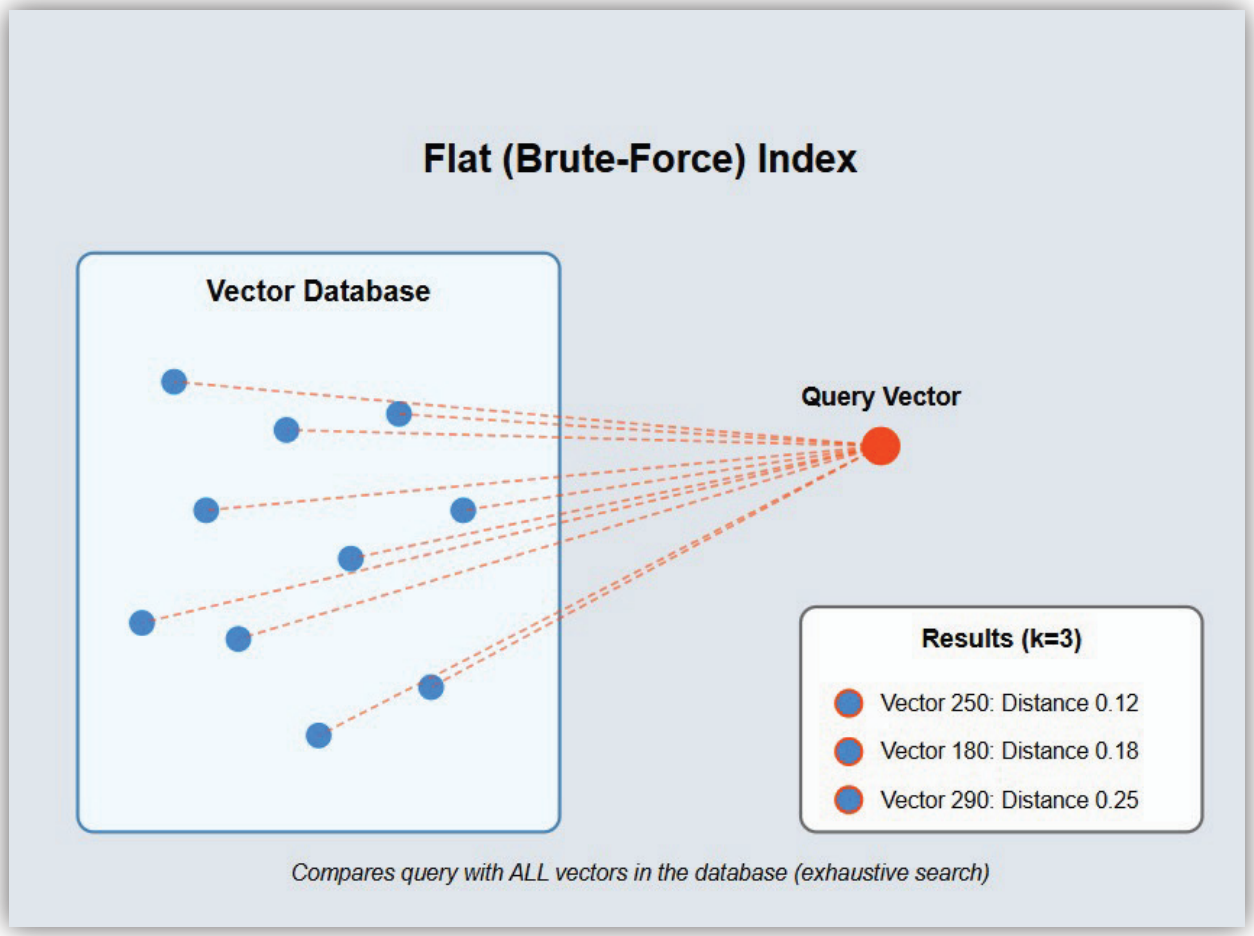
A flat index is the simplest indexing method that performs an exhaustive search by comparing the query vector with every vector in the database.

When to Use Flat Index

- Small to medium datasets (typically ≤100K vectors)
- When 100% accuracy is critical (e.g., security applications, financial matching)
- During development and testing to establish baseline performance
- When the dimensionality of vectors is relatively low

How Flat Index Works

- No preprocessing or clustering is performed
- All vectors are stored in their original form
- Each query requires direct distance computation with every stored vector
- Typically uses Euclidean (L2) distance or cosine similarity



Implementation Example (FAISS)

```
import faiss
import numpy as np

# Create sample data
dimension = 128
num_vectors = 10000
vectors = np.random.random((num_vectors,
dimension)).astype('float32')

# Create a flat index with L2 distance
index_flat_l2 = faiss.IndexFlatL2(dimension)
# For cosine similarity, normalize vectors and use dot product
index_flat_ip = faiss.IndexFlatIP(dimension)  # IP = Inner Product

# Add vectors to the index
index_flat_l2.add(vectors)

# Search
k = 5  # Number of nearest neighbors to retrieve
query = np.random.random((1, dimension)).astype('float32')
distances, indices = index_flat_l2.search(query, k)
```

Advantages

- Simple implementation requiring no training phase
- 100% accurate results (exact nearest neighbors)
- Works with any distance metric
- No hyperparameters to tune

Disadvantages

- Search time grows linearly with dataset size (O(n) complexity)
- Memory intensive as all vectors must be stored in full precision
- Becomes impractical for large datasets

INVERTED FILE INDEX (IVF)

What is IVF?

IVF organizes vectors into clusters (using algorithms like k-means) and narrows search to only the most relevant clusters, dramatically speeding up search on large datasets.

When to Use IVF

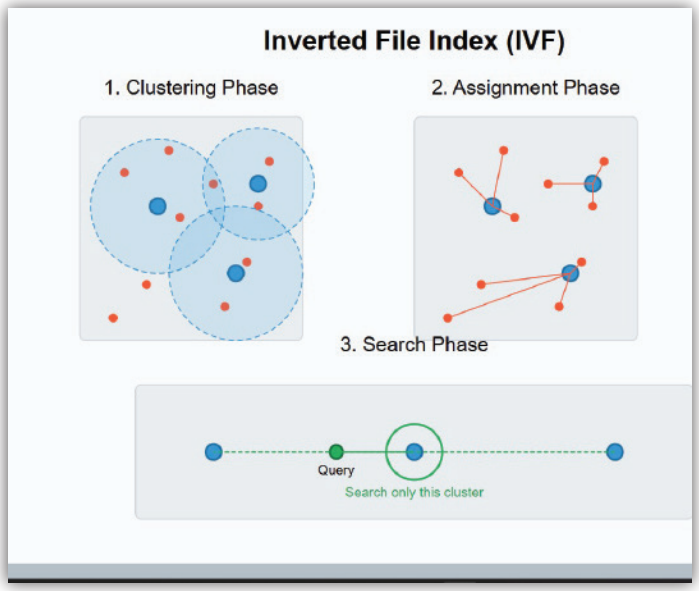
- Medium to large datasets (1M+ vectors)
- When you need a balance between speed and accuracy
- When you can accept approximate results (small accuracy trade-off)
- When you have a representative sample for training

How IVF Works

1. **Training phase:** Vectors are clustered into nlist clusters (centroids)
2. **Assignment phase:** Each vector is assigned to its nearest centroid
3. **Search phase:**
    - Query vector is compared to all centroids
    - Only vectors in the nprobe nearest clusters are examined
    - nprobe is a tunable parameter that balances speed vs. accuracy

Distance Metrics

- Uses the same distance metrics as flat indexes (typically L2 or cosine)
- The choice affects both clustering and search phases



Implementation Example (FAISS)

```
import faiss
import numpy as np

dimension = 128
num_vectors = 1000000
vectors = np.random.random((num_vectors,
dimension)).astype('float32')

# Create quantizer (the index for centroids)
quantizer = faiss.IndexFlatL2(dimension)

# Create the IVF index
nlist = 100  # Number of clusters
index_ivf = faiss.IndexIVFFlat(quantizer, dimension, nlist,
faiss.METRIC_L2)

# Must train the index with representative data
index_ivf.train(vectors[:100000])  # Can use subset for training
index_ivf.add(vectors)

# Set search parameters
index_ivf.nprobe = 10  # Number of clusters to visit during search
```

Tuning IVF Parameters

- nlist (number of clusters): Higher values = faster search but lower accuracy
  - Rule of thumb: nlist = sqrt(N) where N is dataset size
- nprobe (clusters to search): Higher values = higher accuracy but slower search
  - Typical values: 1-10% of nlist

Advantages

- Much faster than flat index for large datasets
- Scalable to millions of vectors
- Adaptable trade-off between speed and accuracy via nprobe

Disadvantages

- Requires a training phase with representative data
- Not 100% accurate (may miss some relevant vectors)
- Performance depends on data distribution and clustering quality

PRODUCT QUANTIZATION (PQ)

What is Product Quantization?

PQ is a compression technique that reduces the memory footprint of vectors by encoding them into compact codes, making it possible to store and search billions of vectors efficiently.

When to Use PQ

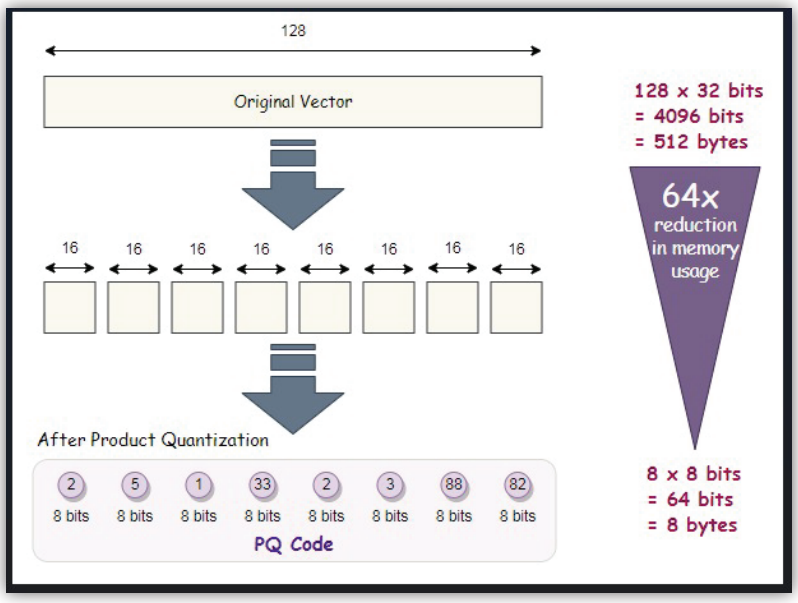
- Very large datasets (10M+ vectors)
- Memory-constrained environments
- When speed and memory efficiency are more important than perfect accuracy
- Often combined with IVF for better performance (IVF-PQ)

How PQ Works

1. **Vector splitting:** Each vector is divided into M equal sub-vectors
2. **Codebook generation:** For each sub-vector space, k-means clustering creates a codebook
3. **Quantization:** Each sub-vector is replaced by its nearest centroid's index
4. **Storage:** Instead of storing the full vector, only centroid indices are stored
5. **Distance approximation:** Distances are computed using pre-computed lookup tables

Distance Considerations with PQ

- PQ works best with Euclidean (L2) distance
- For cosine similarity, vectors should be normalized before quantization
- Distance computations are approximated, affecting accuracy



Implementation Example (FAISS)

```
import faiss
import numpy as np

dimension = 128
num_vectors = 10000000
vectors = np.random.random((num_vectors,
dimension)).astype('float32')

# Create quantizer
quantizer = faiss.IndexFlatL2(dimension)

# Create an IVF-PQ index
nlist = 1000  # Number of clusters
m = 8         # Number of subquantizers
nbits = 8     # Bits per subquantizer (256 centroids per subquantizer)
index_ivfpq = faiss.IndexIVFPQ(quantizer, dimension, nlist, m, nbits)

# Train and add vectors
index_ivfpq.train(vectors[:100000])
index_ivfpq.add(vectors)

# Set search parameters
index_ivfpq.nprobe = 20  # Number of clusters to search
```

Tuning PQ Parameters

- **m** (number of subquantizers): Higher values = better accuracy but larger codes
- **nbits** (bits per subquantizer): Usually 8 (256 centroids per subquantizer)
- **nlist** and **nprobe**: Same as in IVF

Advantages

- Extremely memory efficient (can reduce memory by 10-100x)
- Enables searching billions of vectors on standard hardware
- Fast distance computations using lookup tables

Disadvantages

- Lower accuracy compared to flat or IVF indexes
- Complex setup with multiple hyperparameters
- Performance highly dependent on data characteristics

GRAPH-BASED INDEXING (HNSW)

What is HNSW?

Hierarchical Navigable Small World (HNSW) is a graph-based indexing method that creates a multi-layered graph structure for efficient navigation to nearest neighbors.

When to Use HNSW

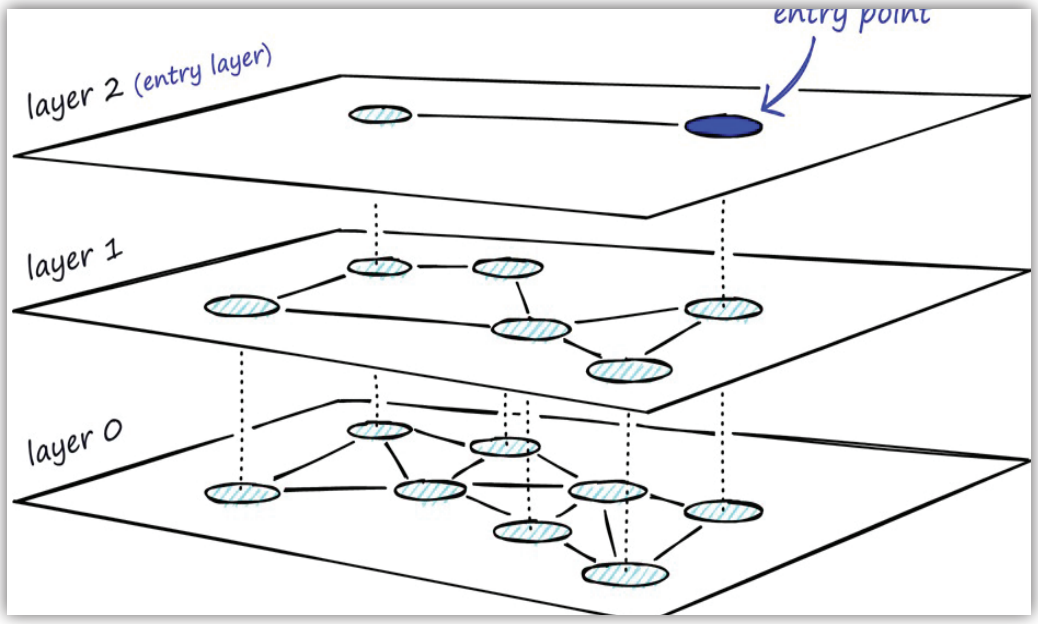
- Medium to large datasets where search speed is critical
- Real-time applications requiring low latency
- When high accuracy is important, but you can't use flat index
- When you have sufficient memory to store the graph structure

How HNSW Works

1. Graph construction: Each vector becomes a node connected to its neighbors
2. Hierarchical structure: Multiple layers with varying connection densities
3. Search process:
   - Start at entry point in the top layer
   - Greedily move to closer neighbors
   - Descend through layers, refining the search
   - Stop at the bottom layer with the best candidates

Distance Metrics in HNSW

- Works with any distance metric (L2, cosine, etc.)
- Distance calculations are exact, but search path is approximate
- The choice of metric affects both graph construction and search



Implementation Example (FAISS)

```
import faiss
import numpy as np

dimension = 128
num_vectors = 1000000
vectors = np.random.random((num_vectors,
dimension)).astype('float32')

# Create HNSW index
M = 16    # Number of connections per layer
efC = 100  # Construction-time exploration factor
index_hnsw = faiss.IndexHNSWFlat(dimension, M)
index_hnsw.hnsw.efConstruction = efC
index_hnsw.hnsw.efSearch = 64  # Search-time exploration factor

# Add vectors (no separate training needed)
index_hnsw.add(vectors)
```

Tuning HNSW Parameters

- M (connections per node): Higher values = better accuracy but more memory
  - Typical values: 16-64
- efConstruction (build-time accuracy): Higher values = better index quality but slower build
  - Typical values: 100-500
- efSearch (search-time accuracy): Higher values = better search accuracy but slower search
  - Can be adjusted at query time

Advantages

- Excellent balance of speed and accuracy
- No training phase required
- Dynamic updates possible (can add vectors after construction)
- Works well with filtered queries

Disadvantages

- Memory intensive (stores both vectors and graph links)
- Index construction can be slow
- More complex implementation than other methods

SCALAR QUANTIZATION (SQ)

What is Scalar Quantization?

Scalar Quantization reduces the precision of vector components (e.g., from 32-bit float to 8-bit integer) to decrease memory usage while maintaining reasonable accuracy.

When to Use SQ

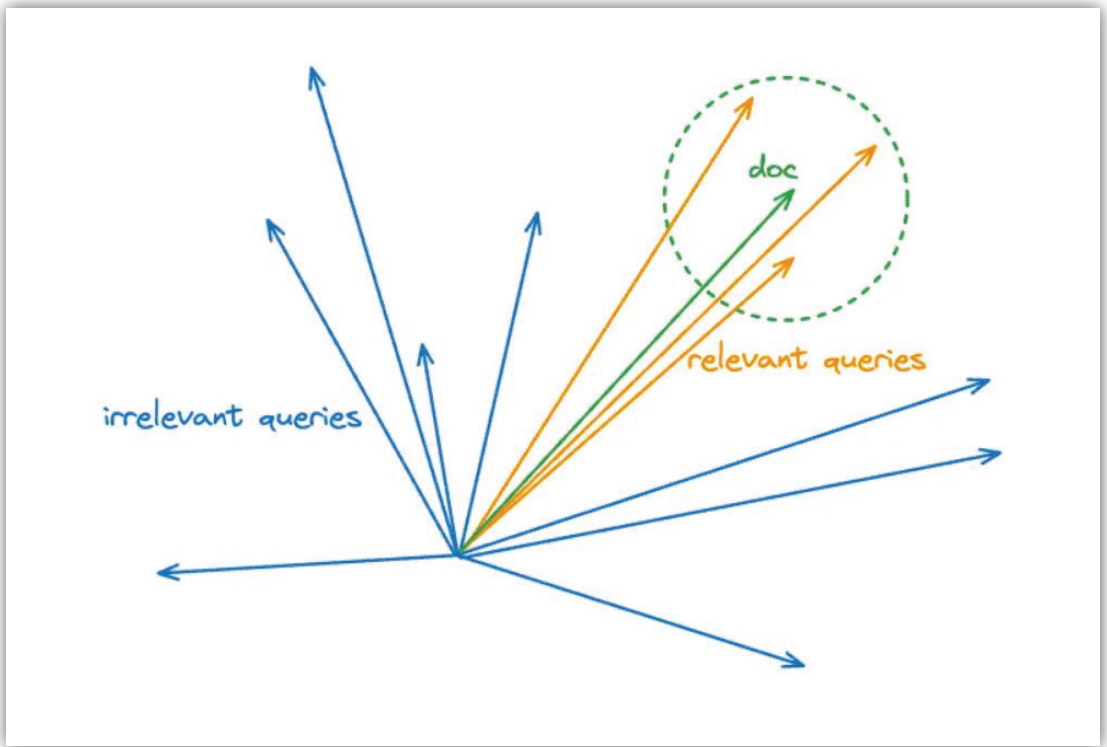
- When you need moderate memory savings with minimal accuracy loss
- As a simpler alternative to PQ when extreme compression isn't needed
- Can be combined with other index types (Flat-SQ, IVF-SQ, etc.)

How SQ Works

1. Determine the range of values in each dimension
2. Map these ranges to fixed-bit representations (typically 8-bit)
3. Convert each floating-point value to its quantized form

Distance Considerations

- Works with both L2 distance and inner product (cosine similarity)
- Slightly reduced accuracy due to quantization error
- Computations may be faster due to integer arithmetic



Implementation Example (FAISS)

```
import faiss
import numpy as np

dimension = 128
num_vectors = 1000000
vectors = np.random.random((num_vectors,
dimension)).astype('float32')

# Create Scalar Quantized index
index_sq = faiss.IndexScalarQuantizer(dimension,
faiss.ScalarQuantizer.QT_8bit, faiss.METRIC_L2)
# Alternative: combine with IVF
quantizer = faiss.IndexFlatL2(dimension)
index_ivfsq = faiss.IndexIVFScalarQuantizer(quantizer, dimension, 1000,
                                            faiss.ScalarQuantizer.QT_8bit, faiss.METRIC_L2)

# Train and add vectors
index_ivfsq.train(vectors[:100000])
index_ivfsq.add(vectors)
```

Advantages

- Simple implementation and concept
- Moderate memory savings (4x compared to 32-bit floats)
- Minimal accuracy impact

Disadvantages

- Less compression than PQ
- Still requires significant memory for large datasets

VECTORDB SPECIFIC INDEXING FEATURES

Major Vector Database Comparison

Vector Database	Supported Index Types	Distance Metrics	Auto-Indexing?	Key Features
FAISS	Flat, IVF, PQ, HNSW, SQ, LSH, combinations	L2, Cosine, Dot Product	❌	Highly customizable, GPU support
Pinecone	Proprietary (HNSW-based)	Cosine, Dot Product, Euclidean	✅	Fully managed, serverless, auto-scaling
Weaviate	HNSW, Flat	Cosine	✅	Schema-based, multi-modal, GraphQL API
Qdrant	HNSW, Scalar Quantization	Cosine, Dot Product, Euclidean	✅	Strong filtering, payload storage
Milvus	IVF, HNSW, PQ, ANNOY, combinations	Euclidean, IP, Jaccard, others	✅	Hybrid search, cloud/self-hosted
Chroma	HNSW	Cosine, L2, IP	✅	Simple API, embedding function integration
Elasticsearch	HNSW	Cosine, Dot Product, L2	✅	Text+vector search, mature ecosystem
pgvector	IVF, HNSW	Cosine, L2, IP	✅	Postgres extension, familiar SQL interface

Special Features by Database

FAISS

- Supports GPU acceleration for both indexing and search
- Provides multi-GPU and distributed search capabilities
- Allows custom combination of index types (e.g., IVF + PQ + SQ)

Pinecone

1. Automatic index selection and optimization
2. Namespace support for logical data separation
3. Handles pod-based scaling for high throughput

Weaviate

- Modular architecture with multi-modal search
- Contextionization for dynamic vector generation
- BM25/TF-IDF hybrid search with vector search

Qdrant

- Advanced payload filtering with vector search
- Payload-based negative filtering for search results
- Optimized disk storage with memory-mapped files

Milvus

- Dynamic schema changes without reindexing
- Scalar, vector, and hybrid search capabilities
- Time travel queries (historical data access)

CHOOSING THE RIGHT INDEX

Decision Framework

Question	Use Case Example	Recommended Index	Distance Metric
Do you need 100% accuracy?	Financial transaction matching	Flat Index	Typically L2 or cosine
Do you have millions of vectors?	Large-scale semantic search	IVF or HNSW	Cosine for text, L2 for images
Is speed more important than accuracy?	Real-time product recommendations	HNSW	Cosine similarity
Are you on low memory hardware?	Mobile or embedded search	IVF-PQ or SQ	L2 often preferred
Do you need incremental updates?	Dynamic document database	HNSW	Any, depending on data
Is your data high-dimensional (500+)?	Large language model embeddings	PQ + IVF	Cosine similarity

Guidance by Data Size

Dataset Size	First Choice	Alternative	Notes
< 100K vectors	Flat	HNSW	Flat for simplicity, HNSW if query speed critical
100K - 1M vectors	HNSW	IVF	HNSW for better accuracy-speed tradeoff
1M - 10M vectors	IVF-HNSW	IVF	Combined approach for balanced performance
10M - 100M vectors	IVF-PQ	IVF-SQ	Compression becomes necessary
> 100M vectors	IVF-PQ	Distributed HNSW	Must consider distribution or extreme compression

HOW INDEXING WORKS – FAISS EXAMPLE

Code:

```
import faiss
import numpy as np

# Convert embeddings to numpy array (float32 required by FAISS)
embeddings_np = np.array(embeddings).astype('float32')

# Get dimensionality of vectors
d = embeddings_np.shape[1]  # 384 dimensions

# Create a flat index (brute force search)
index = faiss.IndexFlatL2(d)  # L2 = Euclidean distance

# Add vectors to the index
index.add(embeddings_np)
```

Behind the Scenes:

- FAISS creates a **data structure** to efficiently find similar vectors
- For a **Flat index:**
  - Vectors are stored contiguously in memory for cache efficiency
  - Uses SIMD (Single Instruction Multiple Data) for parallel computation
  - Calculates distances between ALL vectors during search (brute force)
- For more advanced indices like **HNSW:**
  - Builds a navigable graph structure with multiple layers
  - Vectors become nodes connected to similar vectors
  - Search follows connections to quickly find similar vectors

Output Example:

```
print(f"FAISS index contains {index.ntotal} vectors of dimension {d}")
# FAISS index contains 3 vectors of dimension 384
```

CREATING ADVANCED INDICES FOR FASTER RETRIEVAL

Code:

```
# Create an HNSW index (much faster for large datasets)
nlist = 1    # Number of clusters (use higher for millions of vectors)
M = 16       # Number of connections per layer (higher = more
accurate, slower)
ef_construction = 200  # Controls index quality

index_hnsw = faiss.IndexHNSWFlat(d, M)
index_hnsw.hnsw.efConstruction = ef_construction
index_hnsw.add(embeddings_np)
```

Behind the Scenes:

- Hierarchical Navigable Small World creates a multi-layer graph
- Each vector connects to M most similar vectors
- Creates "shortcuts" through vector space
- During construction:
  1. Insert vector at top layer
  2. Navigate down through layers using greedy search
  3. Connect to nearest neighbors at each layer
  4. Maintain max connections per node (M)

Visualization:

RETRIEVING SIMILAR CHUNKS

Code:

```
# Create a query vector
query_text = "Which fruit is red?"
query_vector = model.encode([query_text])[0].astype('float32')

# Search the index
k = 2  # Return top 2 results
distances, indices =
index.search(np.array([query_vector]).astype('float32'), k)

# Display results
print(f"Top {k} matches for '{query_text}':")
for i, (dist, idx) in enumerate(zip(distances[0], indices[0])):
    print(f"{i+1}. Text: '{texts[idx]}' (Distance: {dist:.4f})")
```

Behind the Scenes:

1. Query text is converted to a vector using same model
2. Vector DB performs distance calculations:
   - For Flat index: Computes distance to EVERY vector (O(n))
   - For HNSW index: Traverses graph structure (O(log n))
3. Returns indices of closest vectors and their distances

Output:

```
Top 2 matches for 'Which fruit is red?':
1. Text: 'Apples are sweet and red.' (Distance: 0.7234)
2. Text: 'Bananas are yellow and soft.' (Distance: 1.2156)
```

HOW SIMILARITY IS CALCULATED

Different similarity metrics can be used, affecting how "closeness" is measured:

Euclidean Distance (L2):

```
# Already used in our FAISS example
index = faiss.IndexFlatL2(d)  # Lower value = more similar
```

Cosine Similarity:

```
# Normalize vectors for cosine similarity
faiss.normalize_L2(embeddings_np)  # In-place normalization

# Create index that measures inner product (dot product)
index_ip = faiss.IndexFlatIP(d)    # Higher value = more similar
index_ip.add(embeddings_np)        # Add normalized vectors

# Normalize query for search
query_vector_norm = query_vector.copy()
faiss.normalize_L2(np.array([query_vector_norm]).astype('float32'))
```

Mathematical Understanding:

- Euclidean: Straight-line distance between points in vector space
  - Formula: sqrt(sum((a_i - b_i)²))
- Cosine: Angle between vectors (ignores magnitude)
  - Formula: dot(a, b) / (||a|| * ||b||)
  - After normalization, dot product = cosine similarity

REAL-WORLD USE CASE: BUILDING A SIMPLE Q&A SYSTEM

Complete Working Example:

import numpy as np
from sentence_transformers import SentenceTransformer
import faiss

```
# 1. Create a knowledge base
documents = [
    "Apples are red or green fruits that grow on trees.",
    "Bananas are yellow fruits with a soft texture inside.",
    "Oranges are citrus fruits known for vitamin C content.",
    "Strawberries are red berries with seeds on the outside.",
    "Blueberries are small blue fruits rich in antioxidants."
]

# 2. Convert to embeddings
model = SentenceTransformer('all-MiniLM-L6-v2')
document_embeddings =
model.encode(documents).astype('float32')

# 3. Create and populate index
dimension = document_embeddings.shape[1]
index = faiss.IndexFlatL2(dimension)
index.add(document_embeddings)

# 4. Function to answer questions
def answer_question(question, index, documents, model, k=2):
    # Convert question to vector
    query_vector = model.encode([question]).astype('float32')
```

```
    # Search
    distances, indices = index.search(query_vector, k)

    print(f"Question: {question}\n")
    print("Top relevant information:")
    for i, (idx, dist) in enumerate(zip(indices[0], distances[0])):
        print(f"{i+1}. {documents[idx]} (Distance: {dist:.4f})")

    print("\n---\n")

# 5. Try it out
questions = [
    "What color are apples?"
]

for question in questions:
    answer_question(question, index, documents, model)
```

System Output:

Question: What color are apples?

Top relevant information:

1. Apples are red or green fruits that grow on trees. (Distance: 0.5008)
2. Bananas are yellow fruits with a soft texture inside. (Distance: 1.0824)

REAL-LIFE ANALOGY

Vector databases are like Google Maps for ideas:

- Vector space is like a vast landscape of meaning
- Embedding model is like a coordinate system
- Indexing creates highways and shortcuts for faster travel
- Query is your starting point
- Similarity search finds the closest "locations" in meaning-space
-

Applications:

- Semantic search engines
- Chatbot memory & knowledge retrieval
- Recommendation systems
- Content discovery
- Document deduplication

SUMMARY

Step	Description	Code Example	What Happens
1. Embedding	Convert text to vectors	model.encode(texts)	Neural network transforms text to numerical representation
2. Storage	Save vectors in DB	collection.add(...)	Vectors stored in specialized structures + metadata in KV store
3. Indexing	Build efficient search structure	faiss.IndexHNSWFlat(d, M)	Creates graph or clusters for fast navigation
4. Query	Convert question to vector	model.encode([query])	Same process as original text
5. Retrieval	Find similar vectors	index.search(query_vector, k)	Finds nearest neighbors using distance metric

Key Insight: Vector databases bridge the gap between human language and machine understanding, enabling semantic search beyond keyword matching.