Vector search engines

George Panchuk

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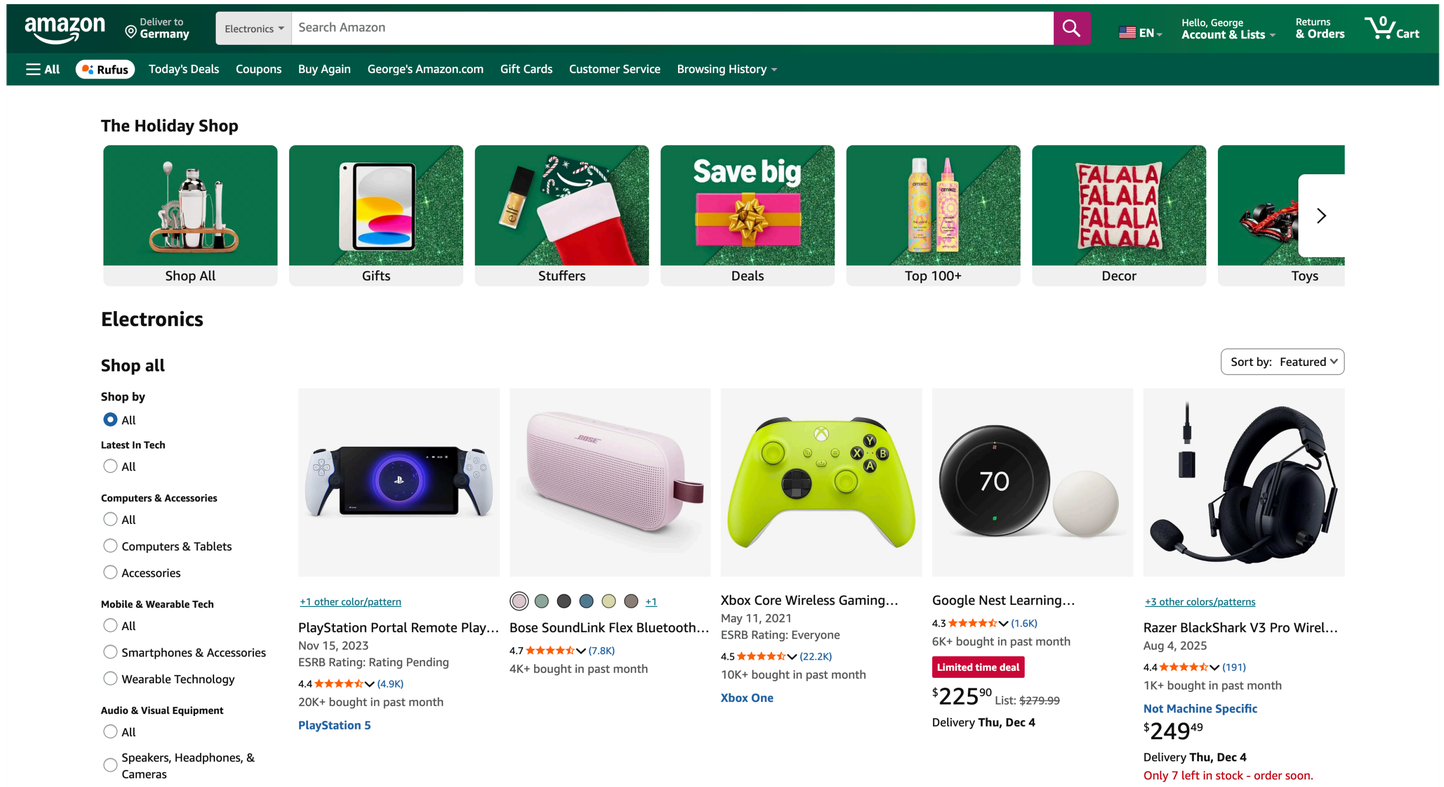
github.com/joein/vector-search-course

From ANN libraries to vector search engines

Are pure ANN libraries enough to build a real world app?

- ANN libraries are good at finding nearest neighbours to the query embeddings
- Can handle millions of records
- Have little to no overhead for compute
- But vectors and their nearest neighbours do not sound like enough to build a full-fledged product..



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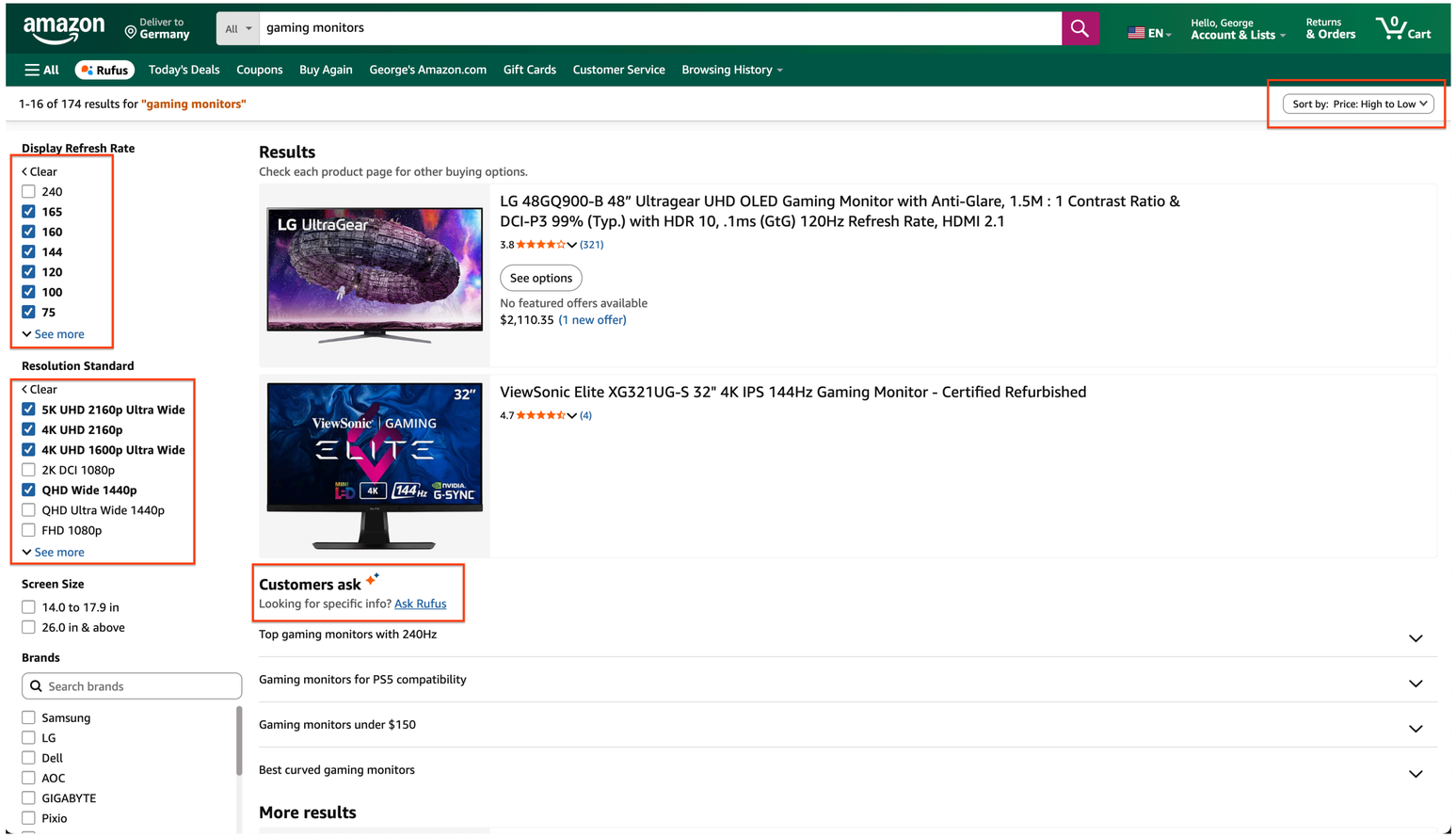
From ANN libraries to vector search engines

What else is required for the apps?

- Metadata filtering capabilities
- CRUD operations without full index rebuild
- Horizontal scaling
- Access control (RBAC)
- And many more..



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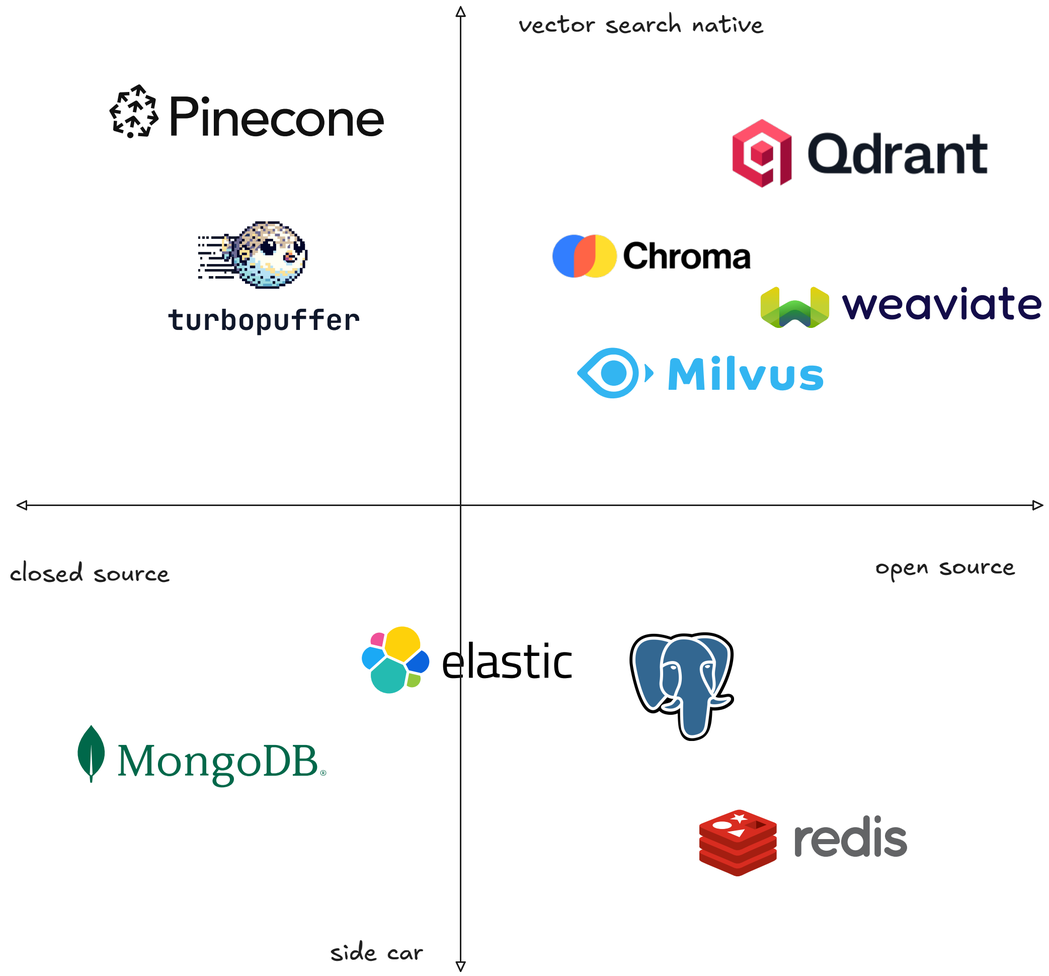
Vector search engine

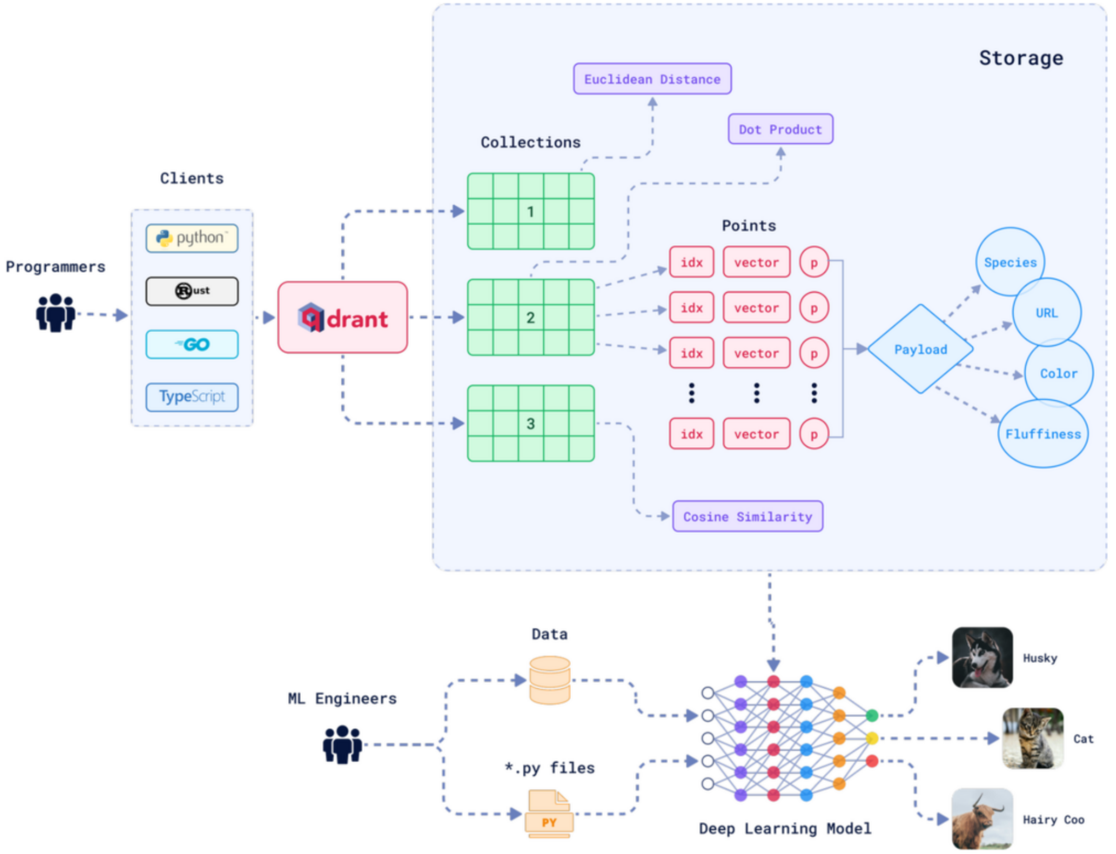
What is a vector search engine?

Vector search engine - is a specialised system which combines ANN indexing with storage, filtering, and scaling to support real-world applications.



A service, not a library

- No need to wrap search layer into an API, HTTP/gRPC/GraphQL APIs are usually available out-of-the-box
- Deploy easily (e.g. with docker), scale vertically and horizontally, or use managed cloud versions
- SDK for various languages, not limited to python and C++
- Built-in schemas, collections, payloads, backup tools



What is a vector database?

CRUD operations

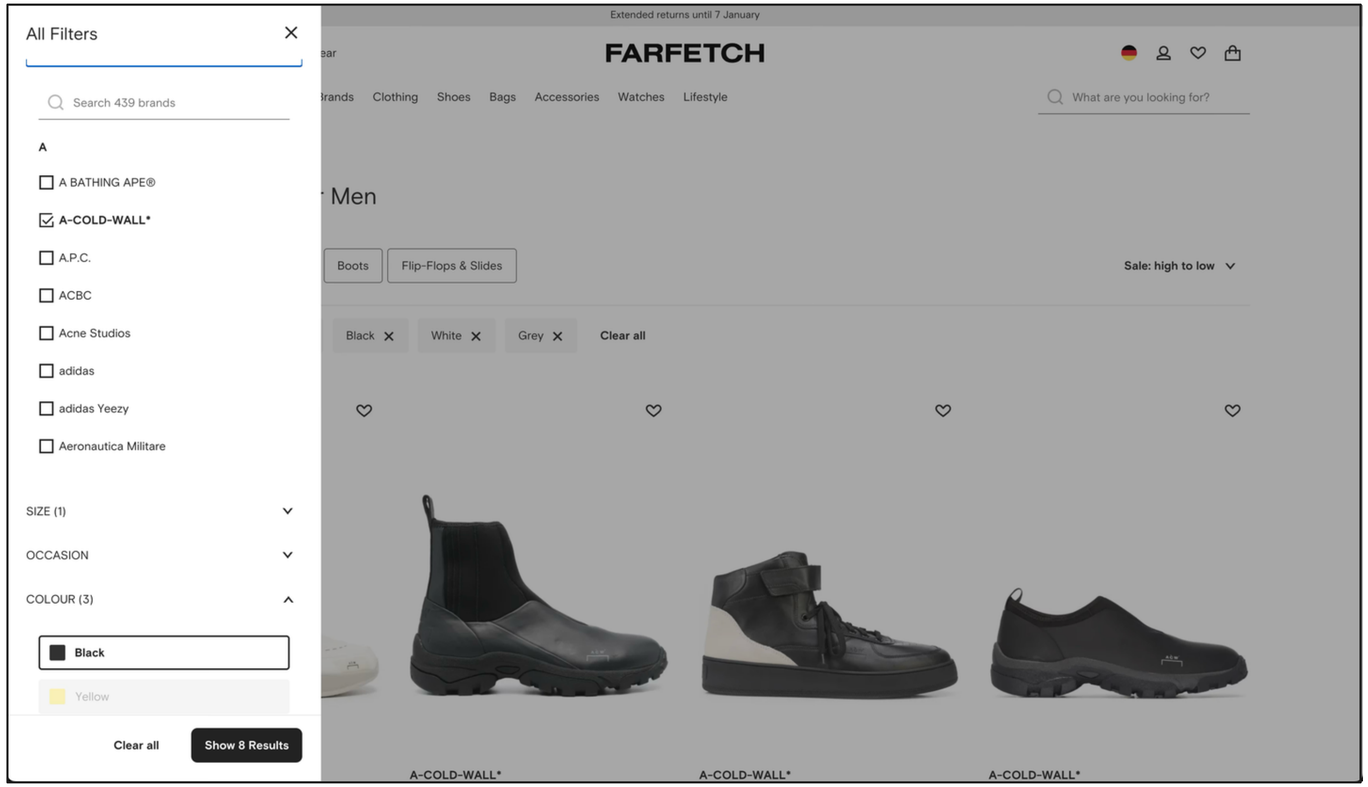
- Insert new vectors without rebuilding the entire index
- Update payload or replace a vector
- Delete documents (soft delete + background cleanup)
- Consistency provided via WAL/raft, etc.
- Real-time indexing and searching, data is available for search as soon as it is inserted

```python
import numpy as np
from qdrant_client import QdrantClient, models

client = QdrantClient()
client.create_collection(
    collection_name,
    vectors_config=models.VectorParams(
      size=512,
      distance=models.Distance.COSINE
    )
)
client.upload_collection(
    collection_name,
    ids=range(10),
    vectors=np.random.random((10, 512)),
    payload=[{"index": i} for i in range(10)],
)
client.delete(collection_name, points_selector=[0, 1, 4])
client.update_vectors(
    collection_name,
    points=[models.PointVectors(id=2, vector=np.random.random(512))]
)
client.set_payload(collection_name, payload={"name": "George"}, points=[7])
client.clear_payload(collection_name, points_selector=[3, 5])
```

Payload filtering

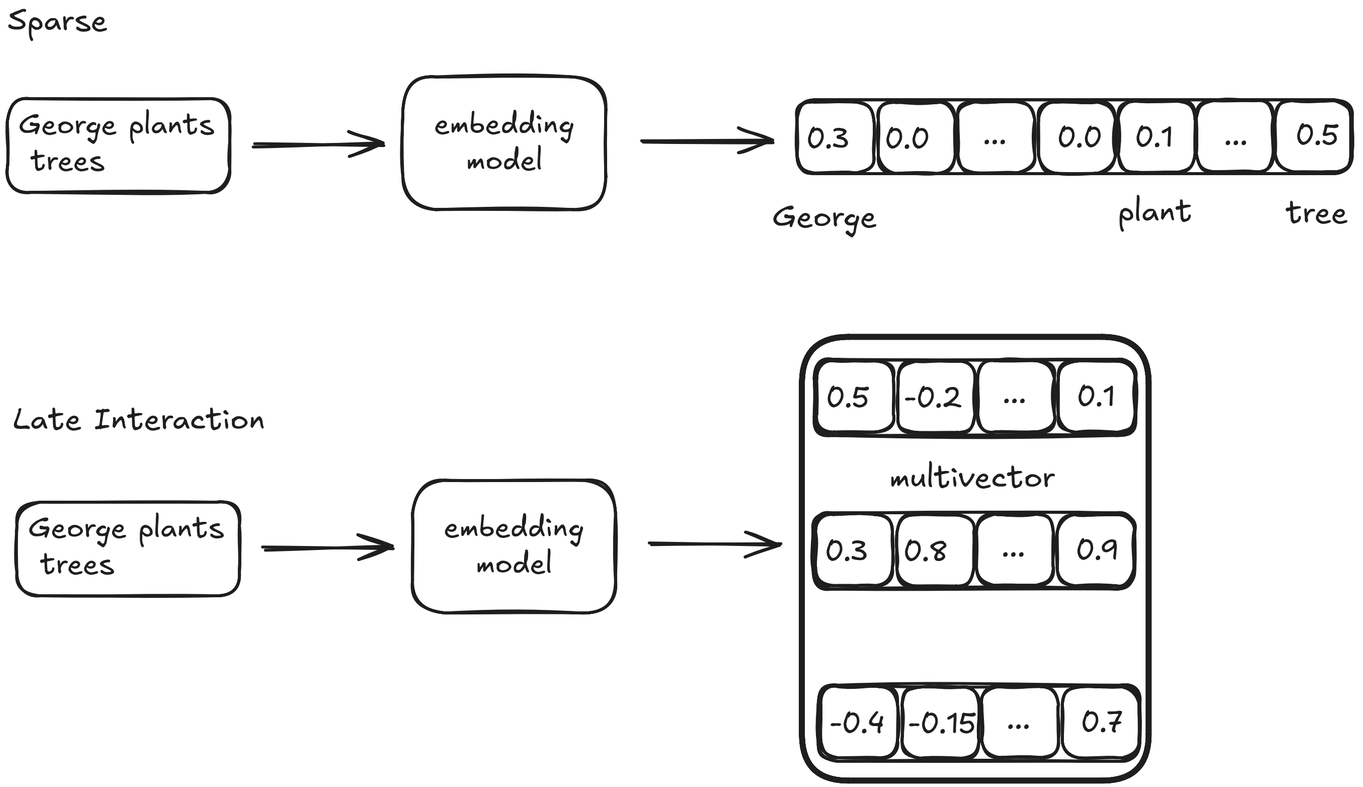
- It’s usually not enough to just run nearest neighbours search for a real app, users might want to apply extra rules for the search
- Pre-filtering and brute-force might be too slow if a filter is not strict
- Post-filtering might filter out too many results if filter is too selective
- ANN-aware filtering techniques are required for better performance (filtrable hnsw, ACORN)
- Query planners are essential for balancing workload
- Additional structures and indexes are crucial for an efficient search



Farfetch

Different types of vectors

- Vector search does not rely solely on dense embeddings
- Typical embedding types also include sparse (BM25, SPLADE, etc) and late-interaction embeddings (ColBERT)
- Traditional ANN libraries mainly support only dense vectors



Multistage and Hybrid search

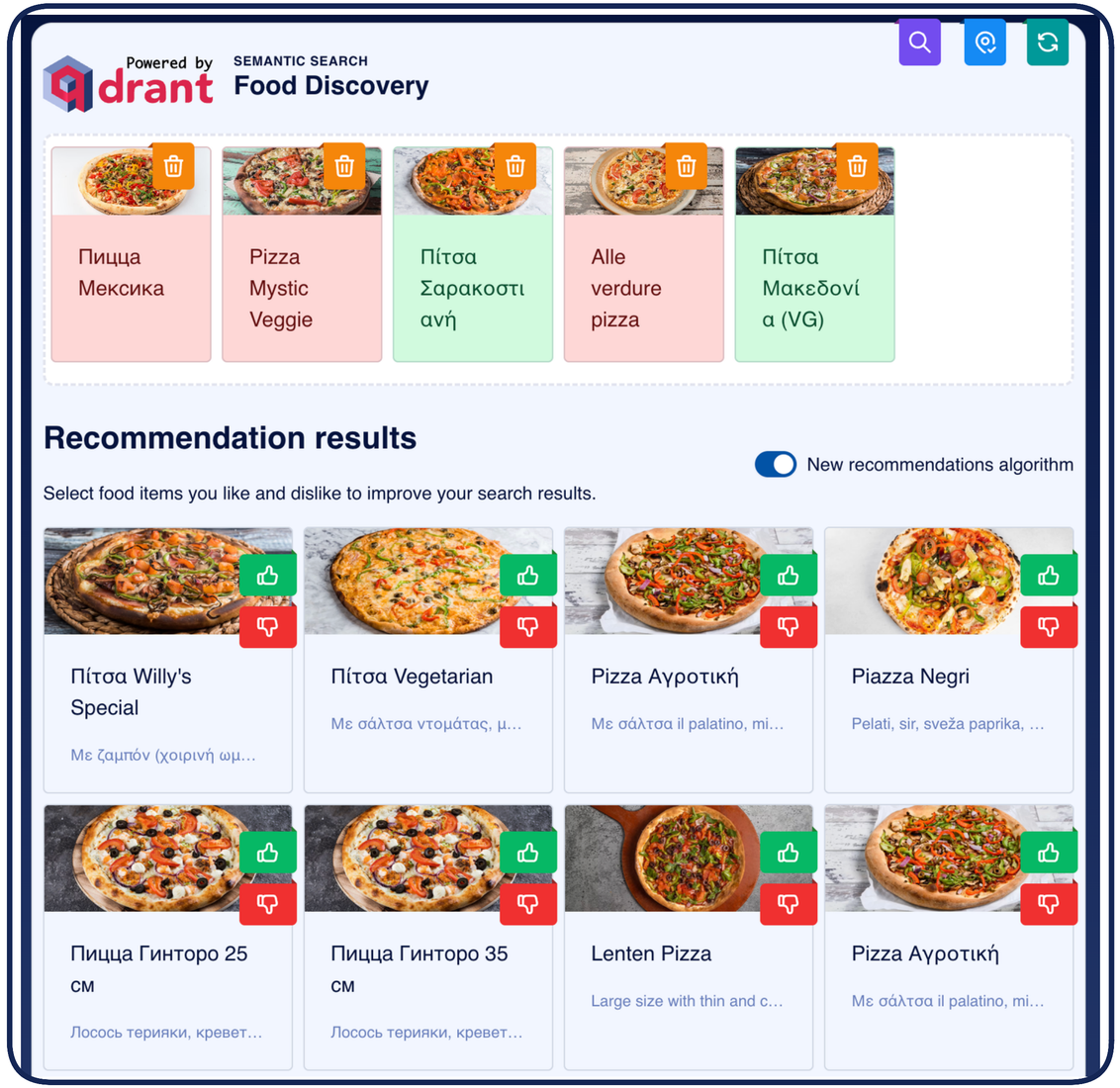
- To balance speed and recall, production systems often adopt two-stage retrieval:
    1. A lightweight model retrieves a broader candidate set,
    2. A larger, more accurate model re-scores those candidates
- Hybrid retrieval might mix dense semantic search with sparse lexical signals (BM25, SPLADE) for better coverage
- Multimodal approaches can search among both textual and image data simultaneously
- Certain results can be boosted or down-weighted using payload-driven decay functions (e.g., time-based scoring).

```python
from qdrant_client import QdrantClient, models

client = QdrantClient()
client.create_collection(
    collection_name,
    vectors_config={
        "large-dense": models.VectorParams(size=1024, distance=models.Distance.COSINE),
        "small-dense": models.VectorParams(size=384, distance=models.Distance.COSINE),
    },
    sparse_vectors_config={"bm25": models.SparseVectorParams(modifier=models.Modifier.IDF)},
)
# <upsert>
client.query_points(
    collection_name,
    query=models.Document(
        text="What is the capital of France?", model="intfloat/multilingual-e5-large"
    ),
    using="large-dense",
    prefetch=[
        models.Prefetch(
            query=models.Document(
                text="What is the capital of France?",
                model="sentence-transformers/all-minilm-l6-v2",
            ),
            limit=50,
            using="small-dense",
        ),
        models.Prefetch(
            query=models.Document(
                text="What is the capital of France?",
                model="Qdrant/bm25",
            ),
            limit=50,
            using="bm25",
        ),
    ],
    limit=10,
)
```

Advanced methods: Exploration

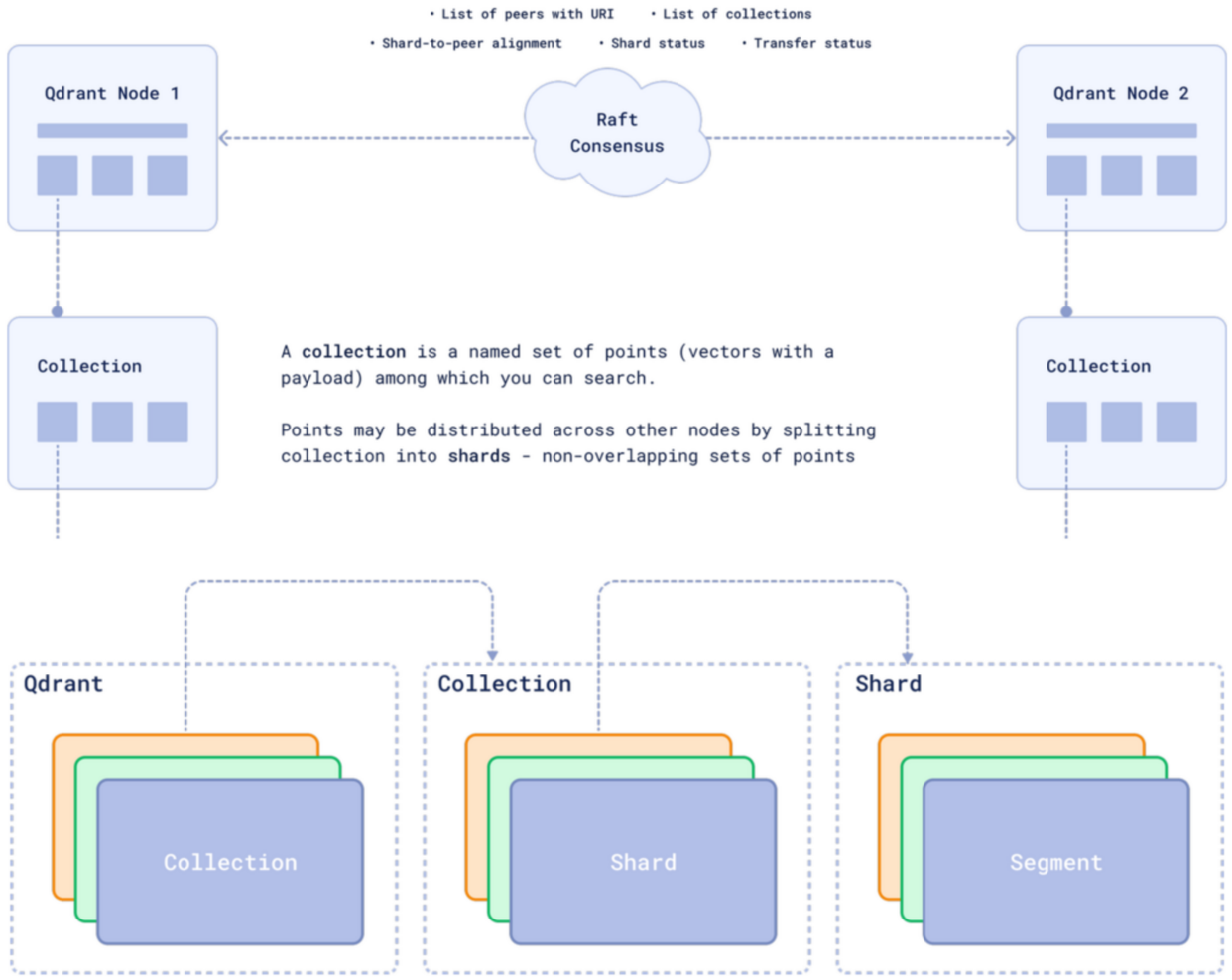
- Vector search is not limited to looking for a point nearest to one query, e.g. it also allows to do a directed traversal of the embedding space
- Neighbourhood exploration: expand from seed points to uncover clusters and local structure
- Discovery / context search: use positive examples to define the target semantic region and negative examples to exclude unwanted directions
- Distance-based exploration tools (distance matrices, local graphs) for analysis and visualisation of the vector space



Qdrant: Food discovery demo

Horizontal scaling

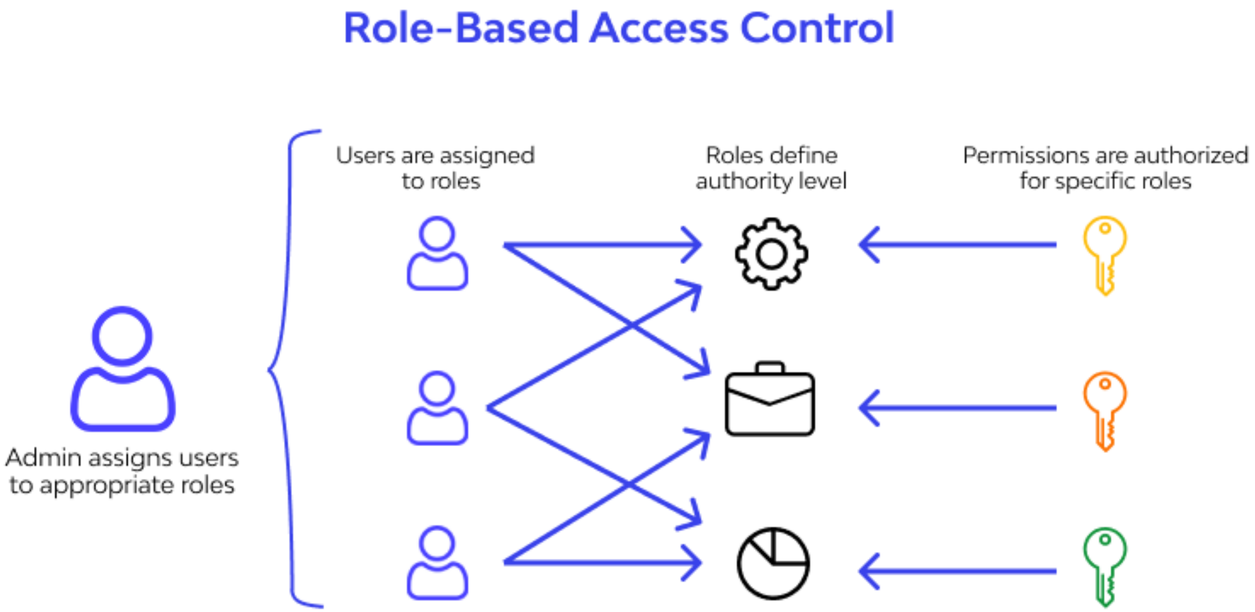
- A single machine eventually hits limits in memory, CPU, storage and I/O
- Distributed search engines split data into shards, each holding a non-overlapping subset of the collection
- Shards can be spread among multiple nodes
- Data is automatically distributed across shard, queries are routed to all relevant nodes
- Replication is used for high availability, failover, and increased read throughput
- Query results from multiple shards are merged into a final ranked list
- Horizontal scaling allows the system to grow with data size and traffic without major architectural changes
- With ANN libraries all this has to be done manually



What is a vector database?

Security and access control

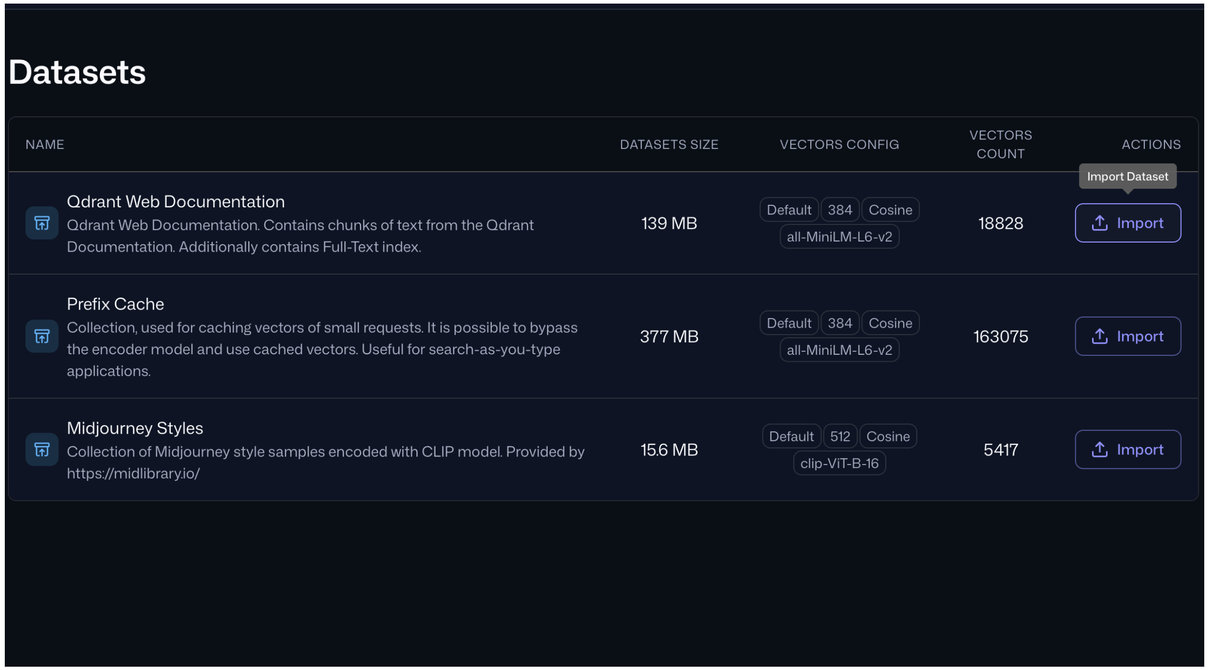
- Data stored in vector search engines is often proprietary and may include sensitive information
- Original data could potentially be reconstructed from the embeddings via “embedding inversion attack”
- Vector search engines are usually not secured by default
- API-keys and TLS encryption can be used if all-or-nothing access is acceptable
- Role-based access control (RBAC) provides more granular approach by defining user roles and corresponding permissions, often with JWT
- Useful for multi-team setups, production environments and managed deployments



What is RBAC?

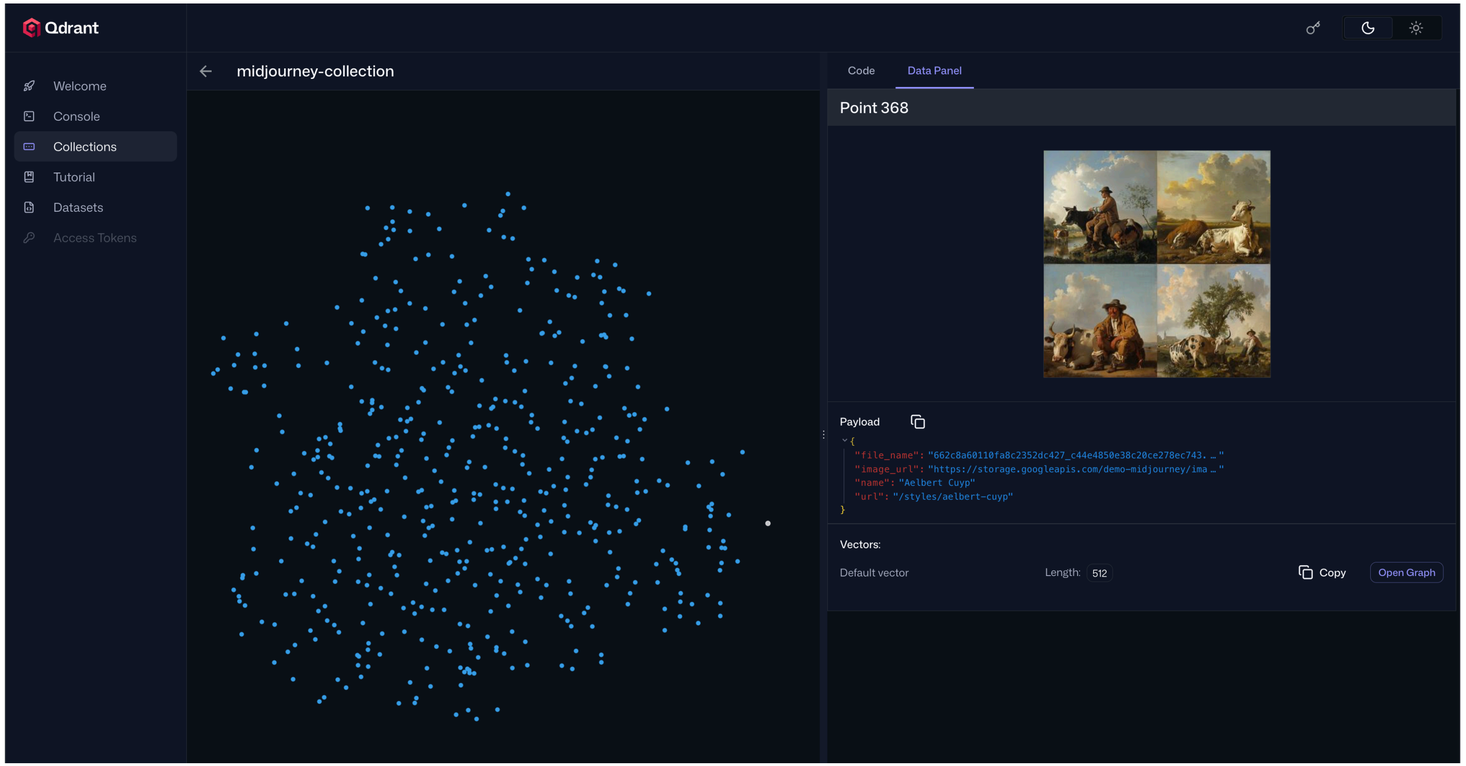
Snapshots & recovery

- Production system require reliable recovery mechanisms to prevent data loss and index corruption
- Write-ahead logs (WAL) record all writes so the system can restore after crashes
- Snapshot is a consistent point-in-time image of the database or a collection
- Can be used for recovery, migration, safe upgrades, and cloning environments
- Combining WAL with snapshots enables restoring the system to an exact previous state



Bells & whistles

- There are lots of other things which vector search engines implement, it's hard to cover them all in one lecture
- Those could include various quantisation mechanisms (PQ, SQ, BQ, etc.) for memory and/or speed optimisations, or targeting particular real world scenarios, such as multitenacy
- Libraries or modules for inference
- Monitoring, telemetry and visualisation tools
- In-memory or local modes for fast experimentation



Engines comparison

- This slide could have been a huge comparison table...
  but these tables get outdated quickly, since the vector search engine space evolves fast
- Most engines are open-source, and unique features spread across the ecosystem within weeks or months
- Instead of memorising tables, focus on choosing the right category for your use case

Side-car search (ElasticSearch, Redis, Postgres, Mongo, OpenSearch, etc.)

- Choose this if you app is small, or you already run one of these systems in production
- Good when vector search is a convenience feature, not a core component

Dedicated vector search engine (Qdrant, Milvus, Weaviate, Pinecone, Turbopuffer, Chroma, etc.)

- Prefer this when vector search is central to the product, or your dataset/workload will grow
- Evaluate based on your workload patterns, required features, and unique capabilities available at the moment
- Run your own benchmarks

Questions?