Qdrant A Vector Search Engine in Rust



github.com/qdrant/qdrant

Who am I

- Arnaud Gourlay
- Full time contributor @qdrant
- OSS and Rust < 3
- github.com/agourlay
- agourlay.github.io



Agenda

- About Qdrant (pronounced quadrant)
- General introduction to vector search engines
- Use cases for the technology
- How it works internally
- What makes Rust a good fit for the job

What is Qdrant?

- Open source vector search engine
- Written in Rust
- Interactions via HTTP/JSON or gRPC
- Official clients in Python, Rust & Go
- Distributed deployment
- Saas cloud offering



Evolution of search

- Traditionally exact match on a text keyword
- Growing amount of unstructured data
- Recommendations are everywhere
- Similarity search

Reverse image search (Google Lens)

🗟 Find image source 🛛 🖸



French hydrangea Plant

G Search



Visual matches

Bigleaf Hydrangea

Hydrangea Blue

Hydrangea macrophyll...





🗑 missouri.edu Hydrangeas, the bold

Tips for Growing chameleon of plants |... Hydrangeas in Souther...



"What Makes The



pinterest.com

What Color Is Periwinkle Blue | Periwinkle Blue...



pinterest.com Hydrangeas So Blue?"







Best Hydrangeas for Shade and Sun - Grass...



Hydrengea my favorite

flower! Love all the ...

1 inquirer.com

Why your hydrangeas

🛦 covingtonnursery.co.. 🥖 bruns.de HYDPANGEA nantucket Hydrangea macrophylla

Nor flowerpower.com.au may go wild this year

Neural search

- Real example on (Simple) Wikipedia (170k documents)
- Query: What is the capital of the United States?
- Top-3 Hits

Lexical Search (BM25)

- Capital punishment (the death penalty) has existed in the United States [...]
- Ohio is one of the 50 states in the United States. Its capital is Columbus.
 [...]
- Nevada is one of the United States' states. Its capital [...]

Neural Search

- Washington, D.C. [...] is the capital of the United States. [...]
- A capital city (or capital town or just capital) is a city or town, [...]
- The United States Capitol is the building where the United States Congress meets [...]

source: Nils Reimer

Similarity models

- Trained via machine learning
- "similar" inputs have vectors "close to each other" in space



Vector search engine

- Enables similarity search
- Storage: persists durably vector embeddings
- Search: find vectors most similar to an input vector
- Efficiently!

Usage example

ython	
<pre>from sentence_transformers imp from tqdm import tqdm tqdm.pandas() # load the model model = SentenceTransformer('m</pre>	t SentenceTransformer ti-qa-MiniLM-L6-cos-v1')
# enco Python	
dfl"ve 1 from qdrant_clien 2 from qdrant_clien 3 client = QdrantC 5 client_recreate	<pre>import QdrantClienthttp.models import * #VectorParamsen</pre>
6 collection_n 7 vectors_conf 8)	<pre>le= 1 search_term = "earth observation" 2 3 search_result = client.search(4</pre>

Source: https://geo.rocks/post/geospatial-vector-search-qdrant/

Vector payload

- Attach additional data to a vector
- Filtered search on payload fields
- Text keyword, numeric, geo coordinates ...

```
from qdrant_client import QdrantClient
from qdrant_client.http import models
client = QdrantClient(host="localhost", port=6333)
client.upsert(
   collection name="{collection name}",
   points=[
       models.PointStruct(
           id=1,
           vector=[0.05, 0.61, 0.76, 0.74],
           payload={
               "city": "Berlin",
               "price": 1.99,
           },
        ),
       models.PointStruct(
           id=2,
           vector=[0.19, 0.81, 0.75, 0.11],
           payload={
               "city": ["Berlin", "London"],
               "price": 1.99,
           3,
        ),
       models.PointStruct(
           id=3.
           vector=[0.36, 0.55, 0.47, 0.94],
           payload={
               "city": ["Berlin", "Moscow"],
               "price": [1.99, 2.99],
           },
        ),
```

Naive vector search

- Store vectors in a "table" (4 dimensions in example)
- Compute similarity between input vector and **each** vector
- Return vector id with max similarity

id	W	х	У	Z
1	1.22	24.61	8.79	49.08
2	3.45	13.09	44.32	2.27
3	0.05	67.54	76.87	6.91

We need a vector index

- Traditional indexes do not fit
- Geospatial indexes (KD-trees)
- k-nearest neighbors (kNN)
- Curse of dimensionality
- How to handle very large dimensions?

ANN Search

- Approximate Nearest Neighbors
- Tradeoff: precision vs speed



Source github.com/erikbern/ann-benchmarks/

Hierarchical Navigable Small Worlds

- Proximity graphs
- Skip-List
- 'M' friends per vector
- 'efSearch' per layer



HNSW filtering

- Custom implementation to support payload filters
- Post-filtering vs Pre-filtering
- Enrich graph with indexed payload info
- Single stage search
- <u>https://qdrant.tech/articles/filtrable-hnsw/</u>

Distance metrics

- Very common operation (indexing & search)
- Several similarity metrics available depending on encoder

```
pub trait Metric {
    /// Enum value
    fn distance() -> Distance;
    /// Greater the value - closer the vectors
    fn similarity(v1: &[f32], v2: &[f32]) -> f32;
    /// Necessary vector transformations performed before adding it to the collection (normalization)
    /// Return None if metric does not required preprocessing
    fn preprocess(vector: &[f32]) -> Option<Vec<f32>>;
```

Naive Dot product

```
impl Metric for DotProductMetric {
    fn distance() -> Distance {
        Distance::Dot
    }
    fn similarity(v1: &[f32], v2: &[f32]) -> ScoreType {
        v1.iter().zip(v2).map(|(a, b)| a * b).sum()
     }
}
```

Dot product performance

• 70% CPU in "core..iter..traits..accum..Sum\$GT\$::sum::"

\$LT\$f32\$u20\$jas\$u20\$coreitertraitsaccumSum\$GT\$::sum:: \$u7b\$\$u7b\$closure\$u7d\$\$u7d\$::h6969d7e6e9c9e336
core::iter::adapters::map::map_fold::_\$u7b\$\$u7b\$closure\$u7d\$\$:u7d5::hd2d1a5e6ee2934c0
core::iter::traits::iterator::Iterator::fold::h11259888030051a0
<pre>\$LT\$coreiteradaptersmapMap\$LT\$I\$C\$F\$GT\$\$u20\$as\$u20\$coreitertraitsiteratorIterator\$GT\$::fold::h2218f6b789d356d8</pre>
<pre>\$LT\$f32\$u20\$csfu20\$coreitertraitsaccumSum\$GT\$::sum::hfcf98caaff52283e</pre>
core::iter::traits::iterator::Ite
segment::spaces::simple::dot_similarity::he0bffc0d050e28f1
_\$LT\$segmentspacessimpleDotProductMetric\$u20\$as\$u20\$segmentspacesmetricMetric\$GT\$::similarity::h80142848b6452596
\$LT\$segmentvector_storagesimple_vector_storage\$LT\$tTMetric\$GT\$\$u20\$segmentvector_storagevector_storage\$LT\$trage\$LT\$trage*
core::ops::function::impls::_\$LT\$impl\$u20\$coreopsfunctionFnOnce\$LT\$A\$GT\$\$u20\$for\$u20\$\$RF\$mut\$u20\$F\$GT\$::call_once::ha55494437a593efc
core::option::Option\$LT\$T\$GT\$::map::h9a86f012f61ada30
_\$LT\$coreiteradaptersmapMap\$LT\$I\$C\$F\$GT\$\$u20\$as\$u20\$coreitertraitsiteratorIterator\$GT\$:::hab462cf4d9b73222
segment::spaces::tools::peek_top_largest_iterable::he7b0b6a6dec9a9d5
\$LT\$segmentvector_storagesimple_vector_storage\$LT\$tTMetric\$GT\$\$u28\$as\$u28\$segmentvector_storagevector_storage\$LT\$trage\$LT
segment::index::hnsw_index::point_scorer::FilteredScorer::score_points::h2e1661ca418eabb9
segment::index::hnsw_index::graph_layers::GraphLayersBase::_search_on_level::hecablc32f75072a0
segment::index::hnsw_index::graph_layers::GraphLayersBase::search_on_level::h507c991569bab4e6
segment::index::hnsw_index::graph_layers::GraphLayers\$LT\$TGraphLinks\$GT\$::search::h53bBf9d5997a628f
segment::index::hnsw_index::hnsw_iMBSWIndex\$LT\$TGraphLinks\$GT\$::search_with_graph::h694def1cecf1cd6d
segment::index::hnsw_index::hnsw_indexsif\$fGraphLinks\$GT\$::search_vectors_with_graph::_\$v7b\$\$v7b\$closure\$v7d\$\$v7d\$:ind556372b688552f8
core::iter::adapters::map_:map_fold::_\$u7b\$\$u7b\$closure\$u7d\$\$:u7d\$::hd2d1a5e6ee2934c0
core::iter::traits::iterator::fold::h112598803a0051a0
_\$LT\$coreiteradaptersmapMap\$LT\$I\$C\$F\$GT\$\$u20\$as\$u20\$coreitertraitsiteratorIterator\$GT\$::fold::h2218f6b789d356d8
_\$LT\$f32\$u20\$as\$u20\$coreitertraitsaccum5um\$GT\$::sum::hfcf98caaff52283e
core::iter::traits::iterator::Iterator::sum::h4b9da043o5b3d7b1
segment::spaces::simple::dot_similarity::he0bffc0d050e28f1
sLT\$segmentspacessimpleDotProductMetric\$u20\$as\$u20\$segmentspacesmetricMetric\$GT\$::similarity::h80142848b6452596
\$LT\$segmentvector_storage.simple_vector_storage\$LT\$::score_all:: \$u7b\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$\$u7b\$closure\$u7d\$torage\$LT\$rester at the sector_storage at the sector_storage at the sector_storage at the sector_storage at the sector
core::ops::function::impls::_\$LT\$impl\$u20\$coreopsfunctionFnOnce\$LT\$A\$GT\$\$u20\$for\$u20\$\$RF\$mut\$u20\$F\$GT\$::call_once::ha55494437a593efc
core::option::OptionsLT\$T\$GT\$::map::h9a06f012f61ada30
<pre>sLT\$coreiteradaptersmapMapsLT\$I\$C\$F\$GT\$\$u20\$as\$u20\$coreitertraitsiteratorIterator\$GT\$:::hab462cf4d9b73222</pre>
segment::spaces::tools::peek_top_largest_iterable::he7b0066a6dec9a9d5
\$LT\$segmentvector_storagesimple_vector_storage\$LT\$tTMetric\$GT\$\$u20\$segmentvector_storagevector_storage_baseVectorStorage\$GT\$::score_all::h35b722a7618011ed
sLT\$allocvecVec\$LT\$T\$GT\$\$u20\$cas\$u20\$coreitertraitscollectFromIterator\$LT\$T\$GT\$\$GT\$::from_iter::h1c828c5b7692b66e
core::iter::traits::iterator::Iterator::Collect::h71b2da614955e506
segment::index::hnsw_index::hnsw_iMBWIndex\$LT\$TGraphLinks\$GT\$::search_vectors_with_graph::hae4ce8aebab84414
_\$LT\$segmentindexhnsw_indexhnsw.iNtSWIndex\$LT\$TGraphLinks\$GT\$\$u20\$sas\$u20\$segmentindex_baseVectorIndex\$GT\$::search::h47d0f94e786dabdc
_\$LT\$segmentsegmentsegment\$u20\$sas\$u20\$segmententry.pointSegmentEntry\$GT\$::search_batch::h04555ba9bfe70f9e
collection::collection_manager::segments_searcher::search_in_segment::_\$u7b\$\$u7b\$closure\$u7d\$\$::h0655e57b02e8db87
tokio::rumtime::task::core::Core\$LT\$T\$C\$S\$GT\$::poll::_\$u7b\$\$u7b\$closure\$u7d\$\$u7b\$closure\$U7d\$\$u7b\$closure\$U7d\$\$u7b\$closure\$u7
tokio::loom::std::unsafe_cell:!UnsafeCell\$LT\$T\$GT\$::with_mut::h3da766a17374151e
tokio::runtime::task::raw::RawTask::poll::h385014b6ef18866a
tokio::runtime::task::LocalNotified\$LT\$S\$GT\$::run::h5acc35bcle8f13e1
tokio::runtime::scheduler::multi_thread::worker::Context::run_task::_\$u7b\$\$u7b\$closure\$u7d\$\$u7d\$::h43d9bc3a5bBca12d

SIMD

- Single Instruction Multiple Data.
- Same operation on multiple data simultaneously!
- X86: SSEs, AVXs
- ARM: NEON
- Hand-coded or auto-vectorizing compiler.

Horizontal vs vertical

• Horizontal

• Vertical





*source: CMU CS Andy Pavlo

SIMD dynamic feature detections

```
similarity(v1: &[VectorElementType], v2: &[VectorElementType]) -> ScoreType {
         && is_x86_feature_detected!("fma")
         && v1.len() >= MIN_DIM_SIZE_AVX
        return unsafe { dot_similarity_avx(v1, v2) };
     if is_x86_feature_detected!("sse") && v1.len() >= MIN_DIM_SIZE_SIMD {
         return unsafe { dot_similarity_sse(v1, v2) };
 dot_similarity(v1, v2)
```

AVX SIMD dot product

```
use std::arch::x86_64::*;
#[target_feature(enable = "avx")]
#[target_feature(enable = "fma")]
pub unsafe fn dot_avx(v1: &[f32], v2: &[f32]) -> f32 {
    let mut sum256: __m256 = _mm256_setzero_ps(); // accumulated sum
    for i :usize in 0..v1.len() / 8 {
        let v1_256: __m256 = _mm256_loadu_ps( mem_addr: v1[8 * i..].as_ptr()); // vector floats from v1
        let v2_256: __m256 = _mm256_loadu_ps( mem_addr: v2[8 * i..].as_ptr()); // vector floats from v2
        sum256 = mm256 fmadd ps( a: v1 256, b: v2 256, c: sum256); // sum256 += v1 256 * v2 256
    let sum128: __m128 = _mm_add_ps( a: _mm256_extractf128_ps( a: sum256, 1), b: _mm256_castps256_ps128( a: sum256));
    let sum64: __m128 = _mm_add_ps( a sum128, b _mm_movehl_ps( a sum128, b sum128));
    let sum32: __m128 = _mm_add_ss( a: sum64, b: _mm_shuffle_ps( a: sum64, b: sum64, 0x55));
    _mm_cvtss_f32( a sum32)
```

Criterion benchmark

dot-product-group/dot_iter



dot-product-group/dot_simd



SIMD indexing impact

- 100k vectors of dim. 500
- HNSW index with dot product
- Dot iterator: 333 seconds
- Dot SIMD: 95 seconds

Vector collection

- Several segments per collection
- Persistence with RocksDB
- Optimizers keeping things clean
- In memory vs memmap



Concurrent programing

- Qdrant is inherently stateful
- Manage concurrent accesses
- Threads sharing data via Channel
- Threads synchronizing on Mutex/RwLock

RwLock

- API enforces proper usage
- No unlock method!
- Read guard impl. Deref
- Write guard impl. DerefMut
- Check out parking_lot

```
use std::sync::RwLock;
   let r1 = lock.read().unwrap();
   let r2 = lock.read().unwrap();
   assert_eq!(*r1, 5);
   assert_eq!(*r2, 5);
   let mut w = lock.write().unwrap();
```

Dead locks

- Threads waiting for each other
- Double reads on the same thread
- Not only locks
- Not caught by rustc
- Requires discipline



Runtime deadlock detector

• parking_lot "deadlock_detection" build feature



Static deadlock detector

• github.com/BurtonQin/lockbud



Going distributed

- Stay available
- Scaling out on commodity machines
- Shards & replicas per collection
- No leader shard for writes
- Transactional vector operations are opt-in

Raft consensus

- Used to synchronize cluster & collection topology
- Agree on sequence of operations (log)
- Leader commits after entry replicated by majority
- raft.rs is not easy but maintainers are responsive
- Debugging can be very difficult

Takeaways

- Demystified vector search engine
- New indexing schemes (ANN/HNSW)
- Apply SIMD to bottlenecks if possible
- Mind the deadlocks
- Distributed systems are hard
- Another data point in favor of Rust

Farewell links

- <u>https://github.com/qdrant/qdrant</u>
- https://qdrant.tech/documentation
- <u>https://qdrant.tech/benchmarks</u>
- <u>https://blog.qdrant.tech</u>
- <u>https://qdrant.to/discord</u>

