Analyzing the Performance of Vector Databases

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About Me

- 3rd yr. PhD Student @ UC Santa Cruz
- Research Areas
  - Databases and Data Management
  - Programmable Storage Systems
  - Hardware Software Co-Design
- Working with the Centre for Research in Systems and Storage, UCSC
- Publications
  - Popper (CANOPIE-HPC ‘20)
  - Skyhook (CCGrid ‘22)
  - Apache Arrow Datafusion (SIGMOD ‘24)
- Internships
  - Princeton University (IRIS-HEP); Fall 2020, Winter 2021, Spring 202
  - InfluxData (InfluxDB); Summer 2023
  - NVIDIA (RAPIDs Team); Summer 2024

Background

Large Language Models (LLMs)

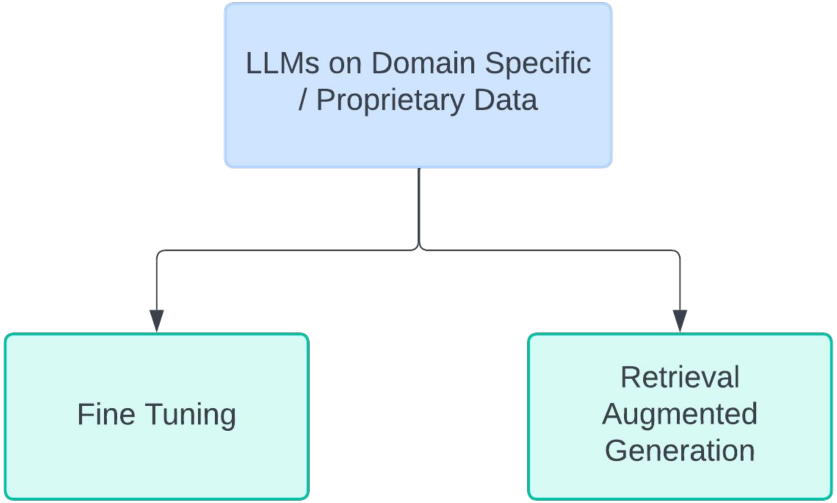
Massive “**Transformer-Decoder**” models trained on large amounts of data

Specifically focussed on language understanding and generation

Used for question answering, summarization, content creation, code development, translation, etc

Source: Google Images

Large Language Models (LLMs)



Fine Tuning

- High Infra Costs
- Time Consuming
- Training Data Dependent
- Loses Generic Capabilities

Retrieval Augmented Generation

- Minimal Costs
- Flexible Sources of Knowledge
- Retains Original Model Capabilities

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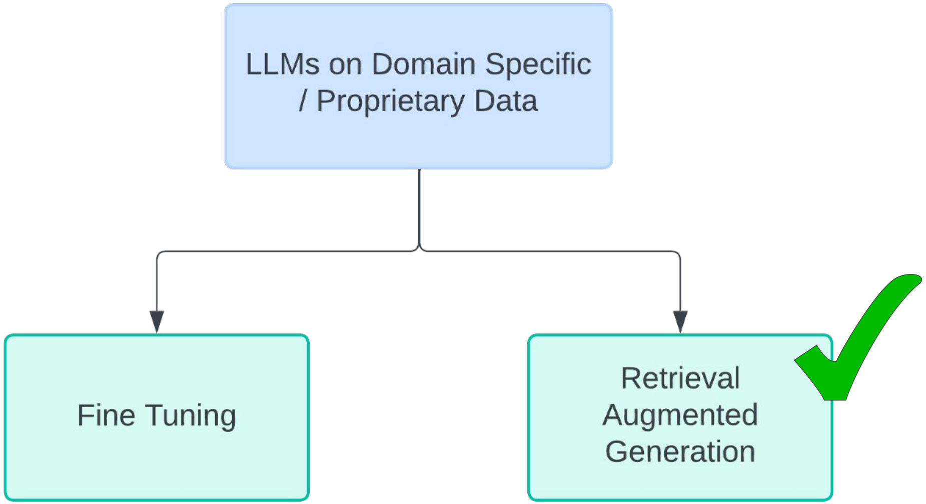

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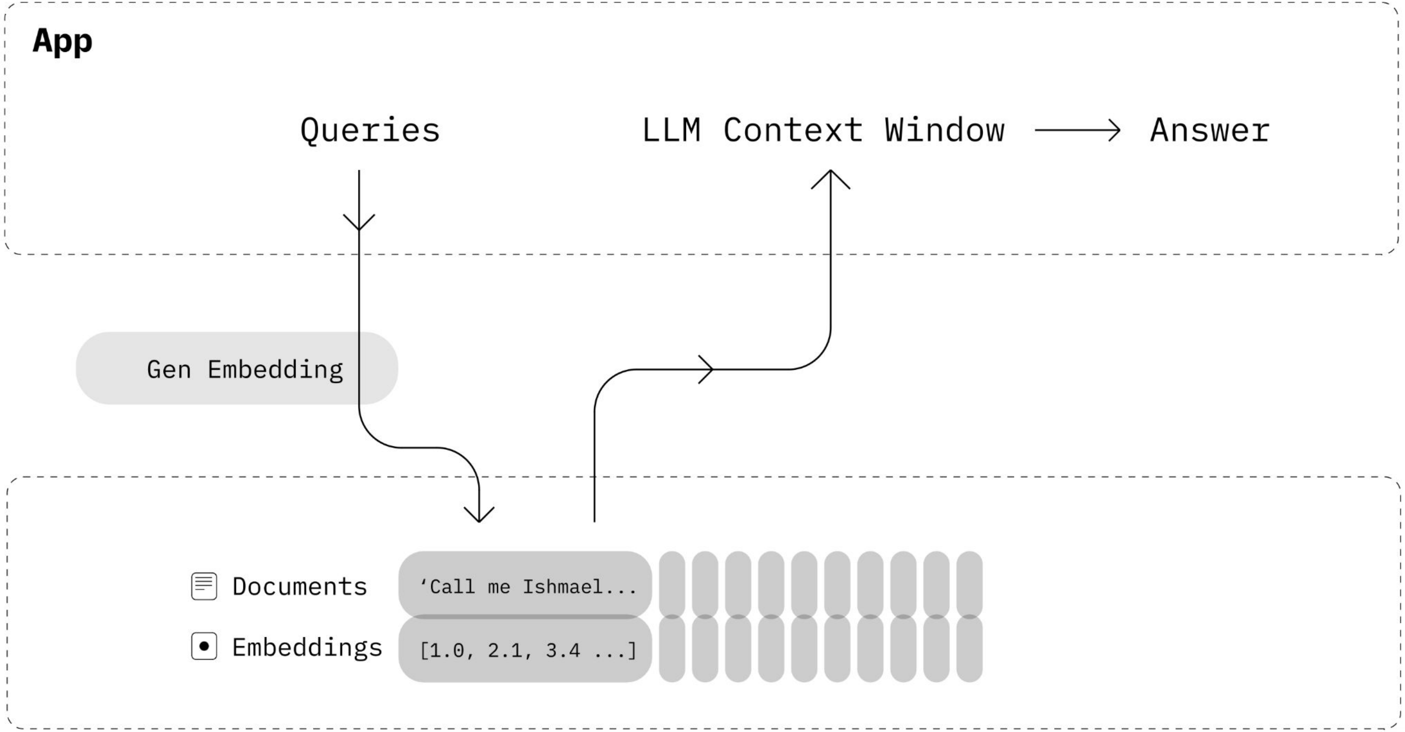
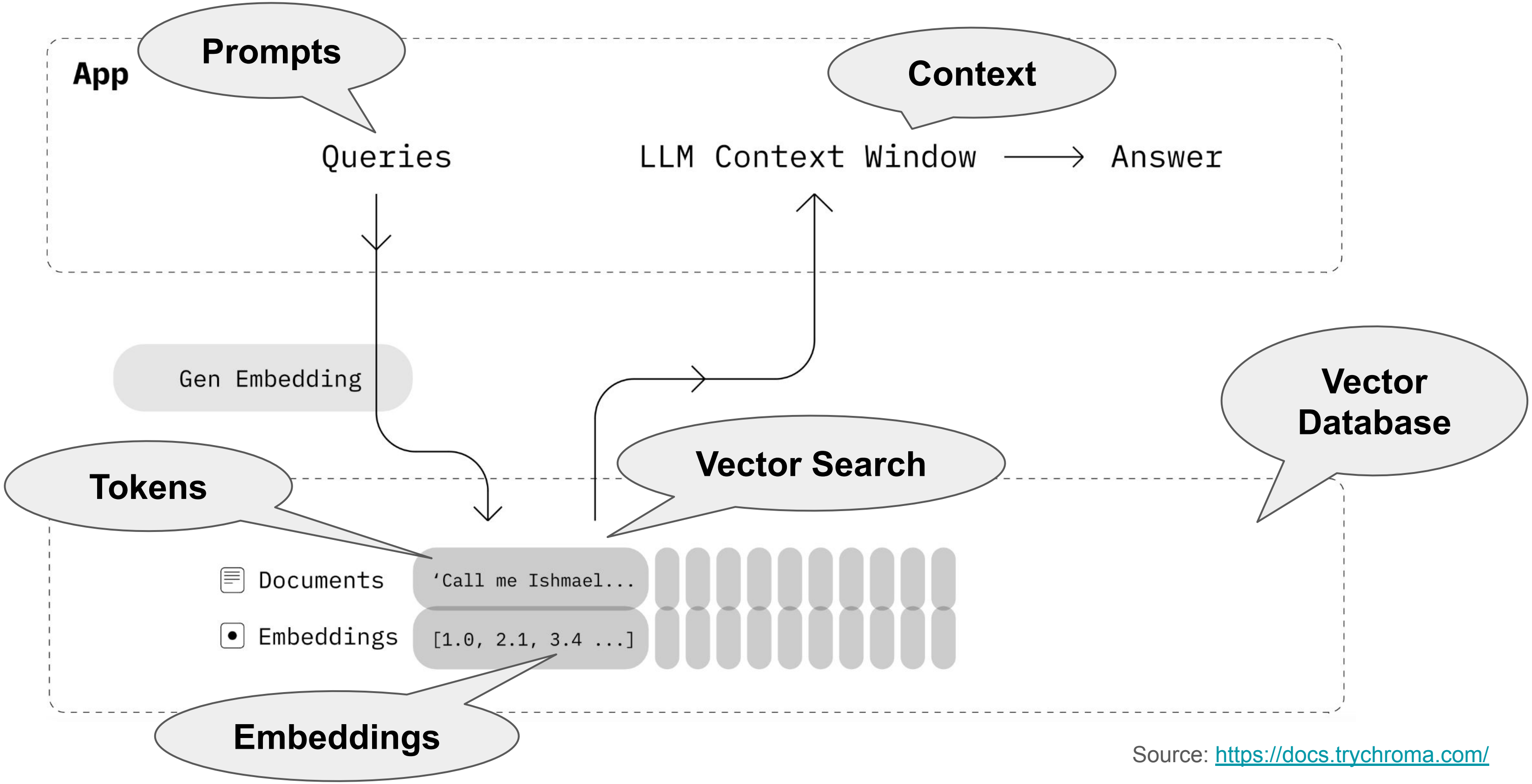
Retrieval Augmented Generation (RAG)



Source: https://docs.trychroma.com/

Retrieval Augmented Generation (RAG)



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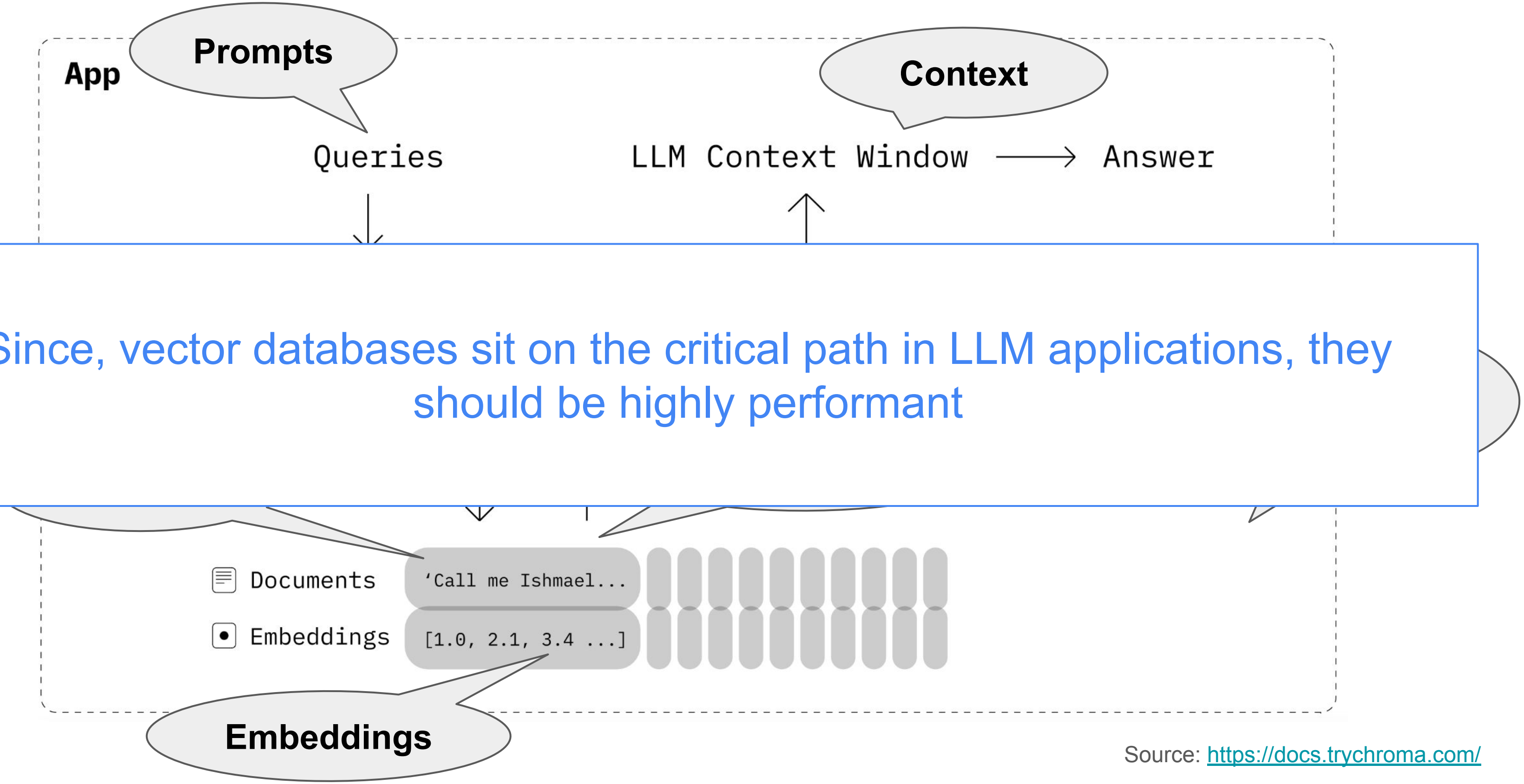
Retrieval Augmented Generation (RAG)



Since, vector databases sit on the critical path in LLM applications, they should be highly performant

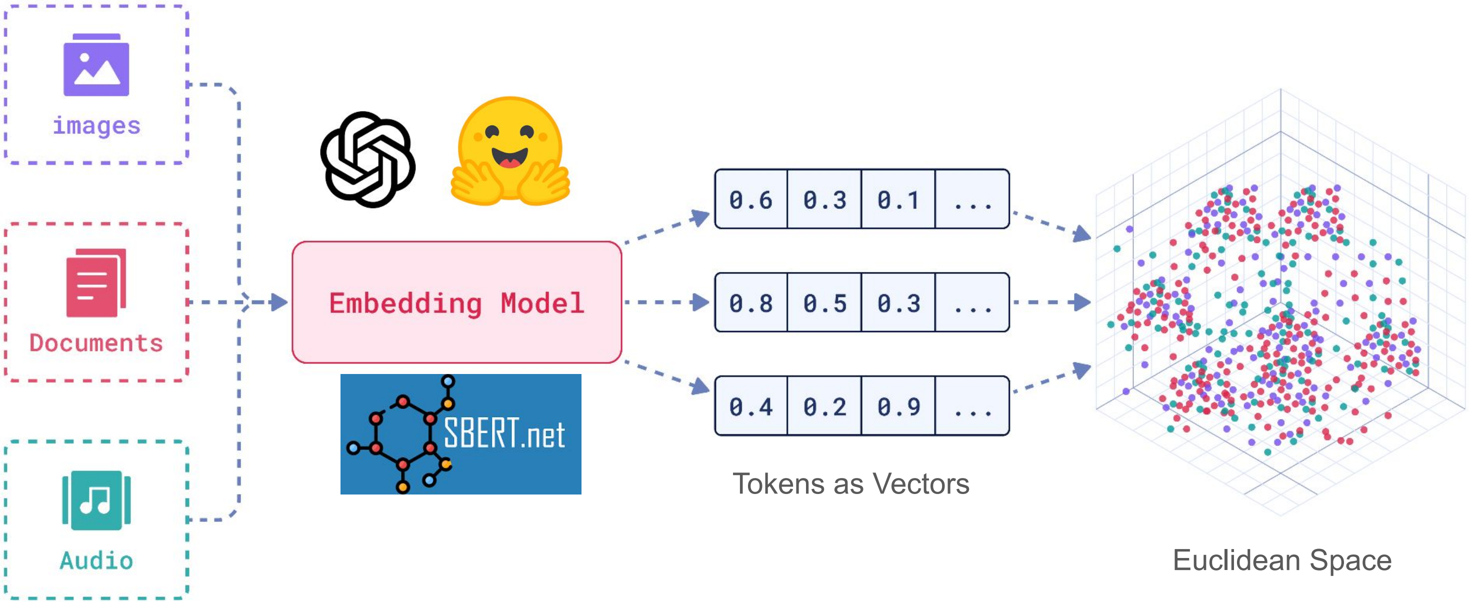
Source: https://docs.trychroma.com/

Tokens / Tokenization

- Tokens are the basic units of data processed by an LLM
  - Words
  - Subwords
  - Sentences
- Tokenization is the process of splitting large corpus of texts into smaller pieces or tokens
- Recommendations for Tokenization
  - Simple searches, smaller chunks; Complex searches, larger chunks
  - Larger chunks = More Context = But less tokens that fit in the LLM context window
- Examples of Tokenizers
  - nltk.tokenize
  - Hugging Face Tokenizer API
  - `BertTokenizer` and `AutoTokenizer` from transformers

NLTK

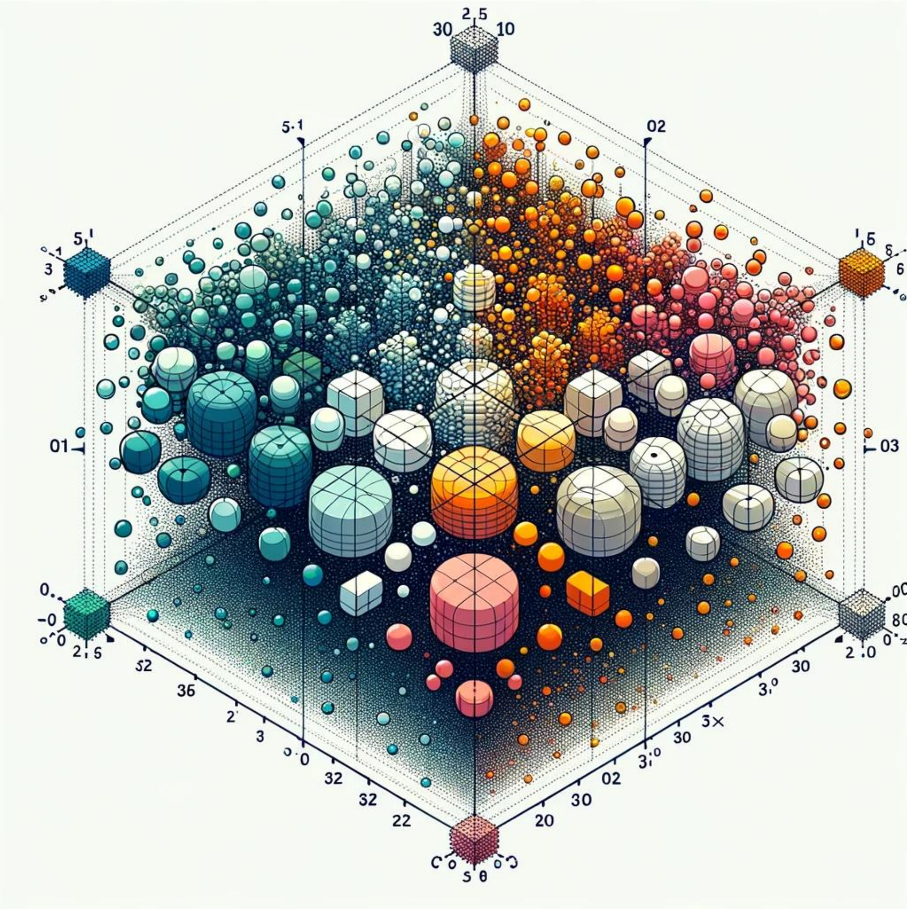
Embeddings



Tokens from Multimodal Data

Source: https://qdrant.tech/articles/what-are-embeddings/

Vector embeddings when laid out in a multi-dimensional space form clusters of **semantically similar** tokens



Source: Generated by DALL-E

Top Embedding Models

Retrieval English leaderboard 🔎

- **Metric:** Normalized Discounted Cumulative Gain @ k (ndcg_at_10)
- **Languages:** English

Metric: Normalized Discounted Cumulative Gain (NDCG)

Rank	Model	Model Size (Million Parameters)	Memory Usage (GB, fp32)	Average	ArguAna	ClimateFEVER	CQADupstackRetrieval	DBPedi
1	Linq-Embed-Mistral	7111	26.49	60.19	69.65	39.11	47.27	51.32
2	NV-Embed-v1			59.36	68.2	34.72	50.51	48.29
3	SFR-Embedding-Mistral	7111	26.49	59	67.17	36.41	46.49	49.06
4	voyage-large-2-instruct			58.28	64.06	32.65	46.6	46.03
5	gte-large-en-v1.5	434	1.62	57.91	72.11	48.36	42.16	46.3
6	GritLM-7B	7242	26.98	57.41	63.24	30.91	49.42	46.6
7	e5-mistral-7b-instruct	7111	26.49	56.89	61.88	38.35	42.97	48.89
8	LLM2Vec-Meta-Llama-3-supervis	7505	27.96	56.63	62.78	34.27	48.25	48.34
9	voyage-lite-02-instruct	1220	4.54	56.6	70.28	31.95	46.2	39.79
10	SE_v1			56.55	61.42	30.33	49.94	49.03
11	gte-Qwen1.5-7B-instruct	7099	26.45	56.24	62.65	44	40.64	48.04

Source: https://huggingface.co/spaces/mteb/leaderboard

Scale of Embeddings

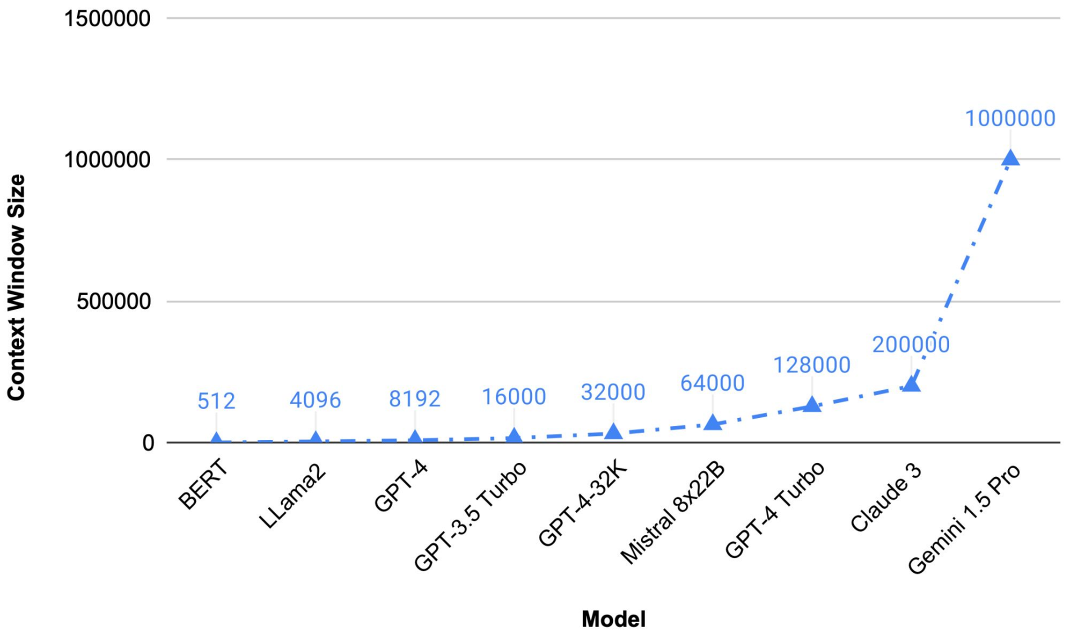
- OpenAI
  - text-embedding-3-small: 1536 dims
    - 1536 * 4 bytes = 6 KB
    - 6 KB * 1B = **6 TB**
    - 6 KB * 1T = **6 PB**
  - text-similarity-davinci-001: 12288 dims
    - 12288 * 4 bytes = 49 KB
    - 49 KB * 1B = **49 TB**
    - 49 KB * 1T = **49 PB**

Huge DRAM capacities required for processing billion / trillion scale vector datasets

Source: openai.com

Context Windows in LLMs

The maximum amount of text in the form of “tokens” that an LLM can consider at any given time while generating a response



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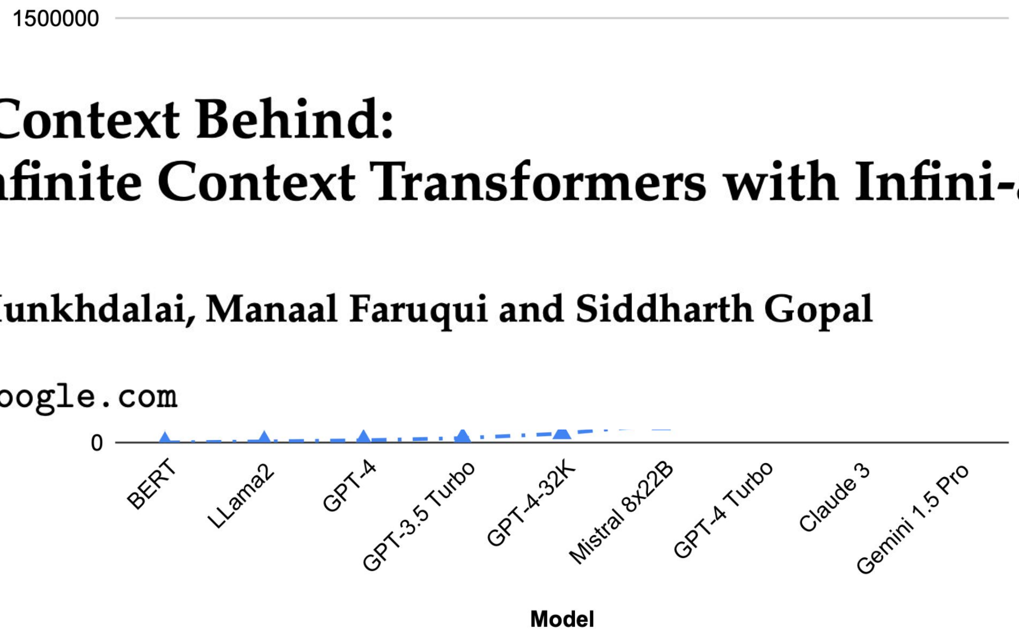


Leave No Context Behind:
Efficient Infinite Context Transformers with Infini-attention

Tsendsuren Munkhdalai, Manaal Faruqui and Siddharth Gopal
Google
tsendsuren@google.com

Vector Databases

- Indexes and stores high-dimensional vector embeddings and tokens for fast similarity searches and retrieval

- Consistency guarantees, multi-tenancy, cloud-native, CRUD, logging and recovery, serverless, etc

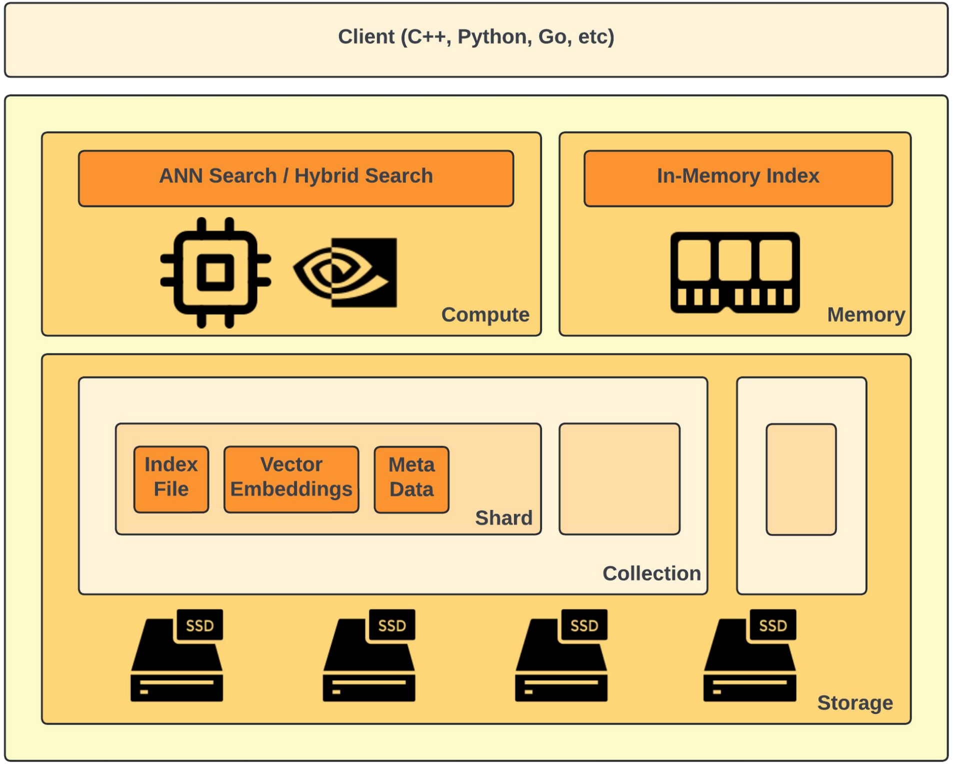
Source: Google Images

Vector Databases

How do vector databases compare to relational databases ?

	Relational Database	Vector Database
Indexing	B/B+ Tree, LSM-Tree	HNSW, IVF, LSH
Compute	Filter, Project, Aggregate, Sort	ANN, KNN, Hybrid Search
Data Access	Index loaded page-by-page	Entire index in memory
Query Interface	SQL, JDBC, ODBC	Python, C++, REST APIs
Performance Metric	Transactions / Second	Queries / Second, Recall

Architecture of Vector Databases



Types of Vector Databases

- Client-Server
  - Milvus, **Qdrant**, Weaviate
- Embedded
  - LanceDB, Chroma, DeepLake
- Extensions
  - **PGVector**, DuckDB Vector, Redis Vector Search
- Libraries
  - FAISS, **HNSWLIB**, usearch, NVIDIA Raft (CAGRA)

Indexing Algorithms in Vector Databases

Pinecone	Proprietary composite index
milvus / zilliz	Flat, Annoy, IVF, HNSW/RHNSW (Flat/PQ), DiskANN
Weaviate	Customized HNSW, HNSW (PQ), DiskANN (in progress...)
qdrant	Customized HNSW
chroma	HNSW
LanceDB	IVF (PQ), DiskANN (in progress...)
vespa	HNSW + BM25 hybrid
Vald	NGT
elasticsearch	Flat (brute force), HNSW
redis	Flat (brute force), HNSW
pgvector	IVF (Flat), IVF (PQ) in progress... HNSW

Source: http://thedataquarry.com/posts/vector-db-1/

Indexing Algorithms in Vector Databases

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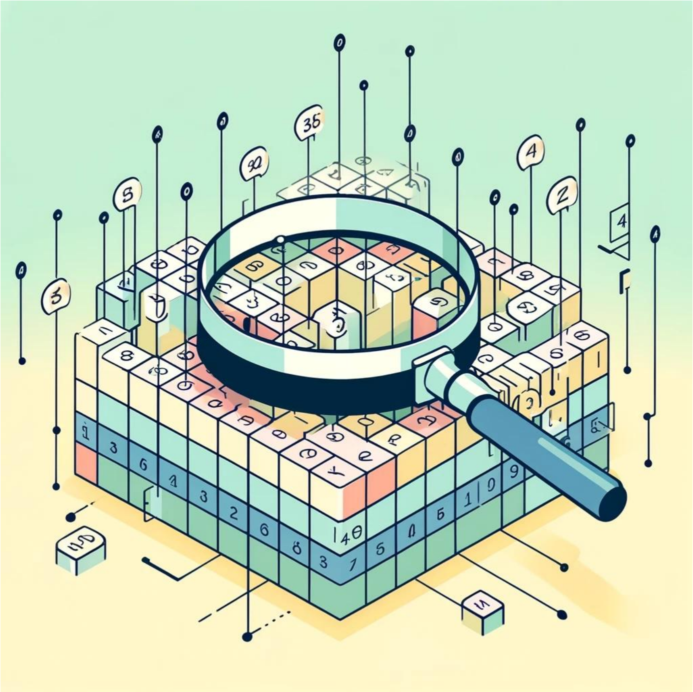
HNSW is the Most Widely Supported Indexing Algorithm

elasticsearch	Flat (brute force), HNSW
redis	Flat (brute force), HNSW
pgvector	IVF (Flat), IVF (PQ) in progress... HNSW

Source: http://thedataquarry.com/posts/vector-db-1/

Vector Search

- Finding tokens similar to a query using nearest neighbor searches
- Traditionally, **KNN** has been used
  - But on billions / trillions of data points, not feasible
- Using **ANN** (Approximate Nearest Neighbor) algorithms allows **trading off accuracy for search speed**
- Use Cases
  - Retrieval Augmented Generation, Recommendation Models, Classification, Clustering



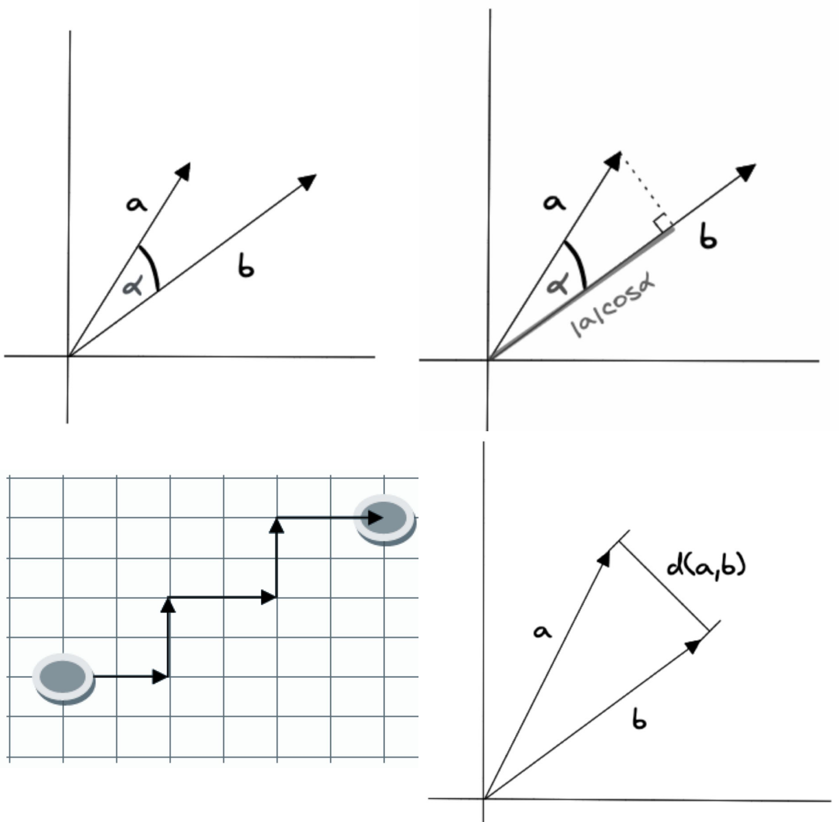
Source: Generated by DALL-E

Hybrid Search

- Hybrid search combines the results of a **vector search** and a **keyword search** by fusing the two result sets
- Uses inverted index for keyword lookups and vector index for vector similarity searches
- How does it work ?
  - First, both vector and keyword search are run independently on the dataset to generate unique top K result sets
  - Then, the above two lists are combined in a single unified list using a special re-ranking algorithm
    - **RRF (Reciprocal Rank Fusion)**: Give more weight to the top-ranked item in each individual list when building the fused list
    - Example: If a record X is ranked 3 in one list and 9 in the other, then its score would be 1/3 + 1/9 = 0.444
  - The items are ranked in descending order to their scores in the fused list

Vector Similarity Metrics

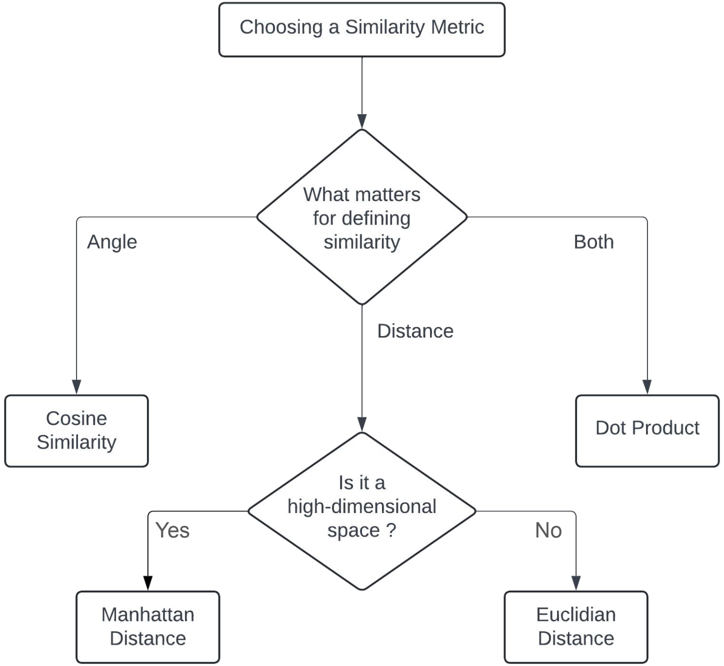
- Cosine Similarity
- Dot Product
- Manhattan Distance (L1)
- **Euclidean Distance (L2)**



Source: https://www.pinecone.io/learn/vector-similarity/

Vector Similarity Metrics

- Choosing a metric ?
  - To define similarity b/w two vectors, follow the chart given here
  - For indexing, use the similarity metric used to train your embedding model
  - For searches, use the similarity metric used to create your index
  - Calculation Speed
    - Manhattan > Cosine > Dot Product > L2

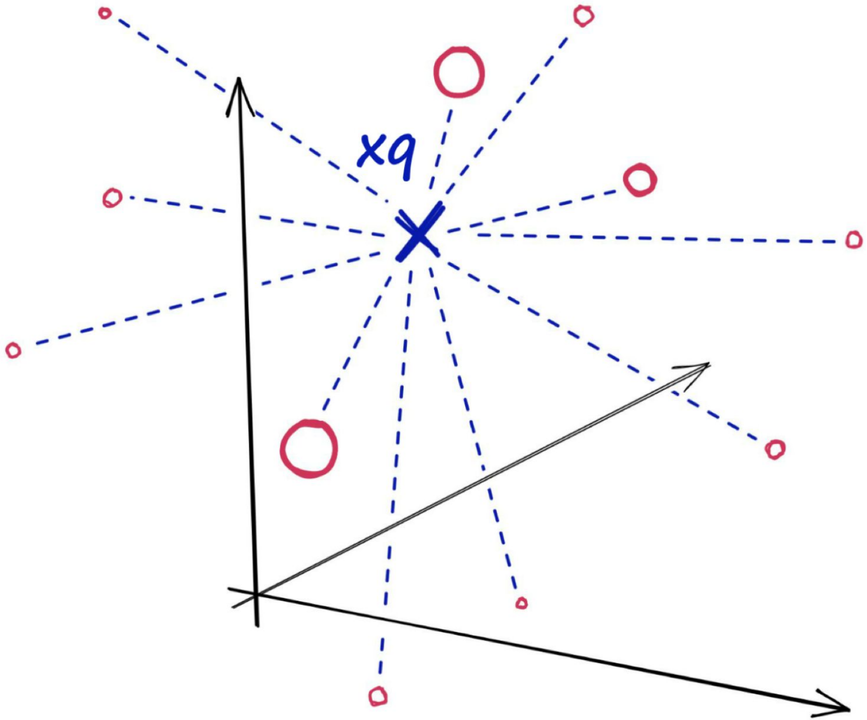


Vector Indexing Algorithms

- Flat
- IVF or Inverted File Index (clustering-based)
- LSH or Locality Sensitive Hashing (hashing-based)
- **HNSW or Hierarchical Navigable Small Worlds** (graph-based)
- Others
  - Microsoft DiskANN
  - Spotify ANNOY
  - Google ScaNN
  - NVIDIA Cagra

Flat Index

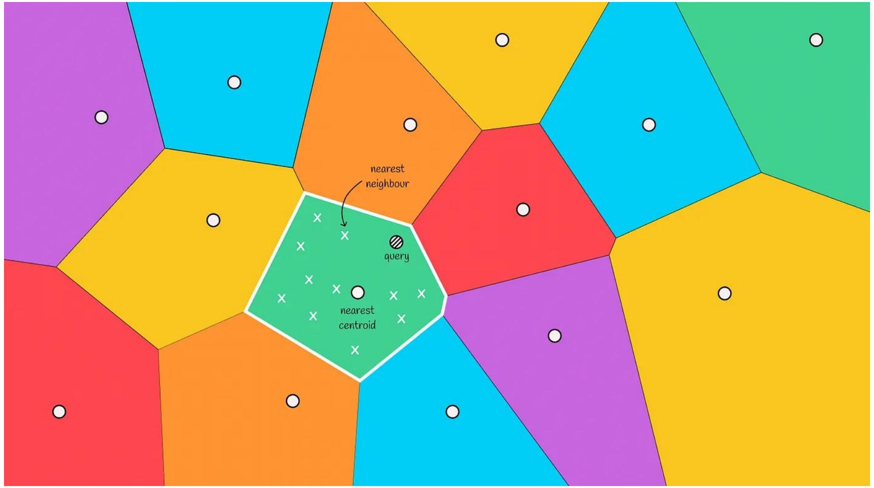
- ❖ Vectors simply laid out in space
- ❖ Perform simple K-nearest neighbors search
- ❖ Search duration grows linearly, but provides accurate results



Source: https://www.pinecone.io/learn/series/faiss/vector-indexes/

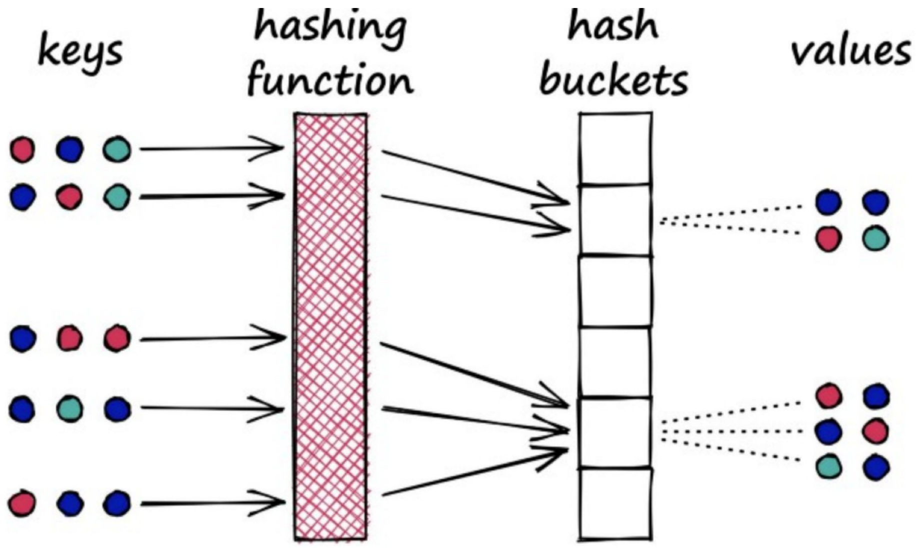
Inverted File Index (IVF)

- ❖ Cluster similar vectors using K-Means
- ❖ Find the centroid nearest to the query vector, then zoom into the cluster, and search for K-nearest neighbors
- ❖ Parameters
  - ➢ `n_list`: Number of cluster to create
  - ➢ `n_probe`: Number of nearest clusters to search



Locality Sensitive Hashing (LSH)

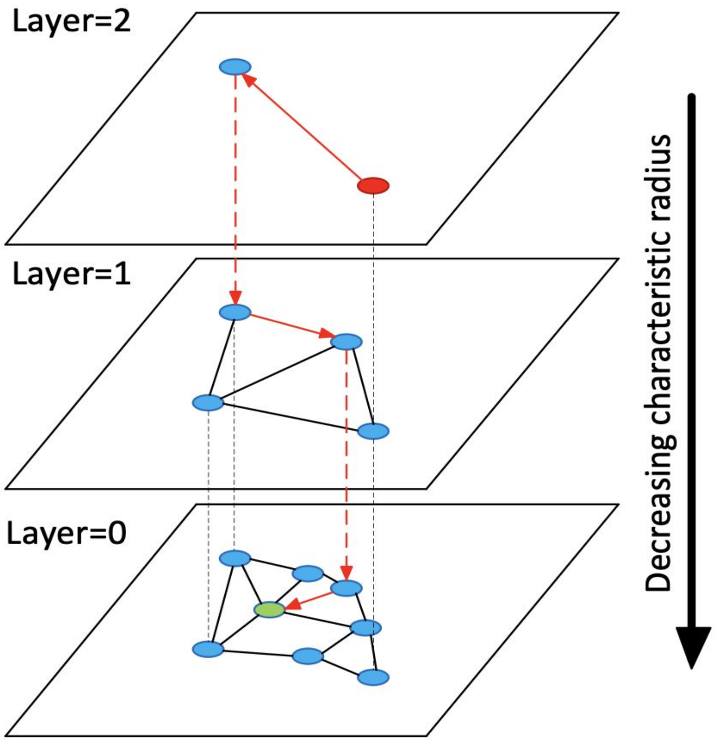
- ❖ Hash input vectors so that similar vectors land in the same bucket with high probability
- ❖ Query is hashed using the same hash function into the closest buckets within which KNN is performed
- ❖ Parameters
  - ➢ `nbits`: No. of bits used per stored vector (The number of hash buckets would be 2^{nbits})



Source: https://www.pinecone.io/learn/series/faiss/vector-indexes/

Hierarchical Navigable Small World (HNSW)

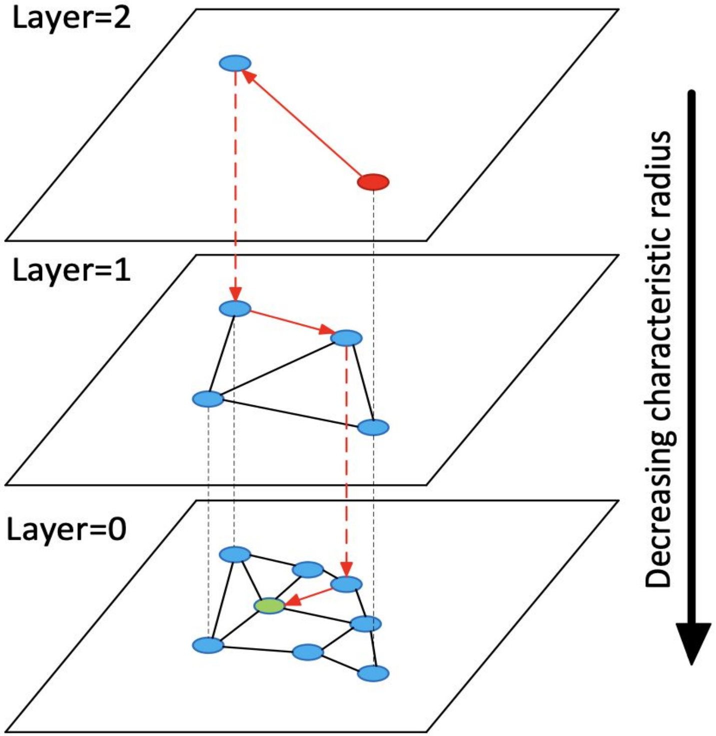
- Search
  - We start from the top layer by picking a node as the entrypoint
  - Compare its neighbors with the query vector and move the closest neighbor
  - Once we find a local minima, we move to the exact node in the next layer and start the search from there
  - The local minima that we find in the last layer is the nearest neighbor of our query vector
- Parameters
  - `ef_search`: The number of nearest neighbors searched for in every layer



Source: https://arxiv.org/abs/1603.09320

Hierarchical Navigable Small World (HNSW)

- Construction
  - Calculate a layer (L) for the incoming node using a probabilistic function
  - Assign the node to all the layers starting from L to 0
  - Run the search algorithm from the topmost layer, and connect the new node with its nearest neighbors
- Parameters
  - `ef_construction`: The number of nearest neighbors searched for in every layer
  - `M`: The maximum degree allowed for any node



Source: https://arxiv.org/abs/1603.09320

Benchmarking Vector Databases

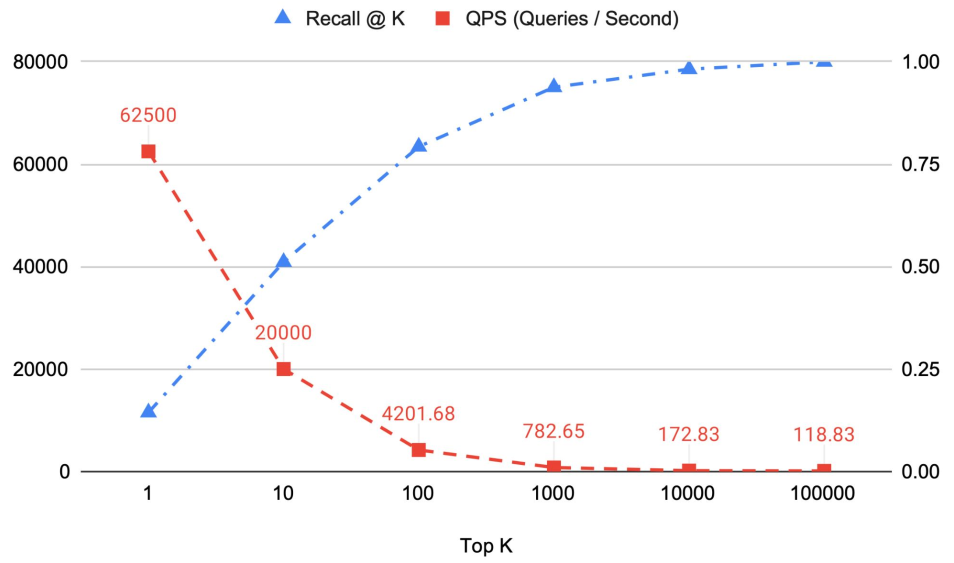
- Popular Datasets

Dataset	Dimensions	Train Set	Test Set	Distance Metric
DEEP1B	96	1B	10K	Cosine
SIFT 1M / 1B	128	1M / 1B	10K	Euclidean
GIST	960	1M	1K	Euclidean
GloVe	25	1.2M	10K	Cosine
dbpedia-openai	1536	1M	Need to split	Cosine

- Frameworks / Examples
  - ANN Benchmarks
  - Qdrant Vector DB Benchmarks
  - Ziliz VectorDBBench

Metrics for Comparison

- Queries / Second (QPS)
- Recall @ K
  - # of *true* K-nearest neighbors / K



On a 100K learn / 1K query / GIST dataset / HNSWLIB

Metrics for Comparison

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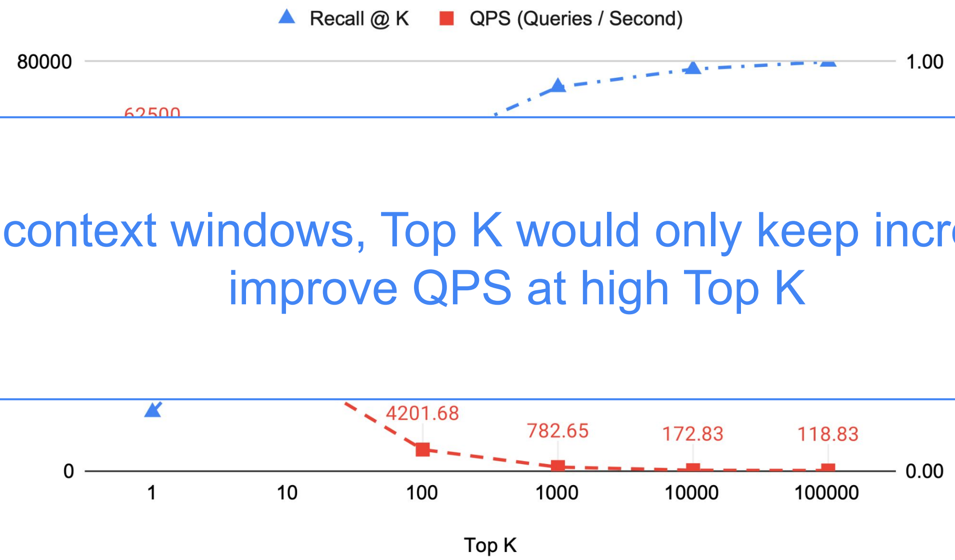


With bigger context windows, Top K would only keep increasing; Need to improve QPS at high Top K

On a 100K learn / 1K query / GIST dataset / HNSWLIB

Performance Comparison of Indexing Techniques

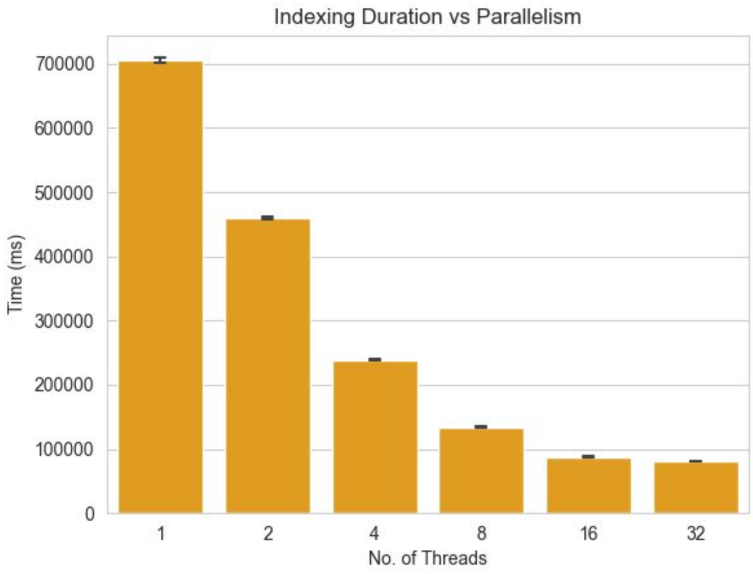
Index	Memory (MB)	Query Time (ms)	Recall @ 10
Flat (L2 or IP)	~500	~18	1.0
LSH	20 - 600	1.7 - 30	0.4 - 0.85
HNSW	600 - 1600	0.6 - 2.1	0.5 - 0.95
IVF	~520	1 - 9	0.7 - 0.95

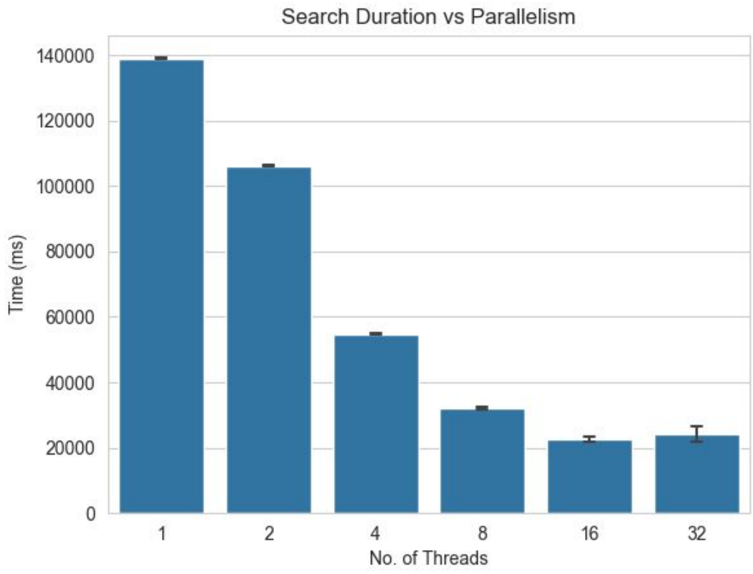
HNSW is the fastest algorithm with efficient memory usage and high recall

Source: https://www.pinecone.io/learn/series/faiss/vector-indexes/

SIFT-1M-128; K = 10

Effect Of Parallelism on HNSW

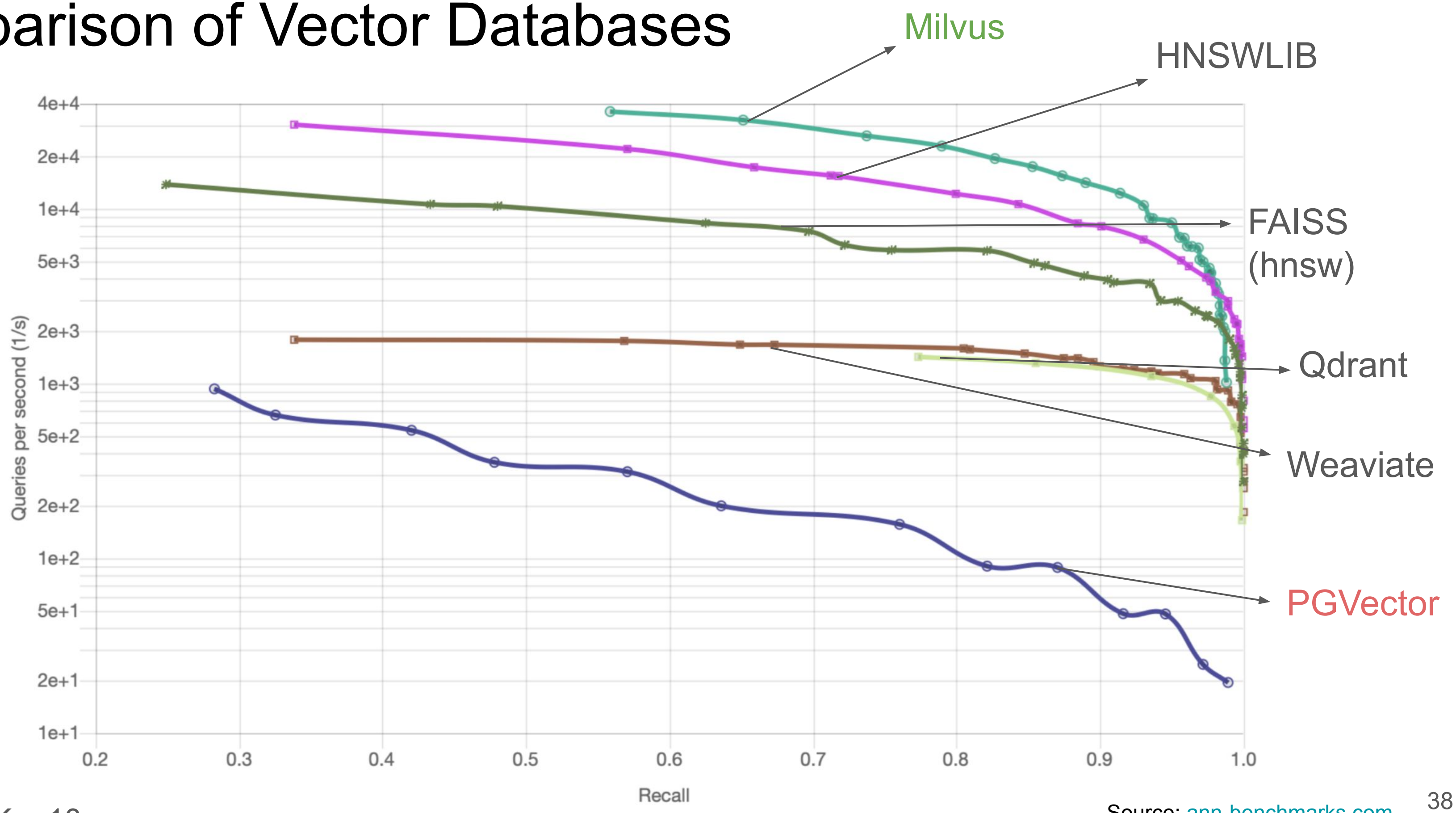




*Indexing and Search are **parallelizable** operations in HNSW*

GIST-1M-960 / HNSWLIB

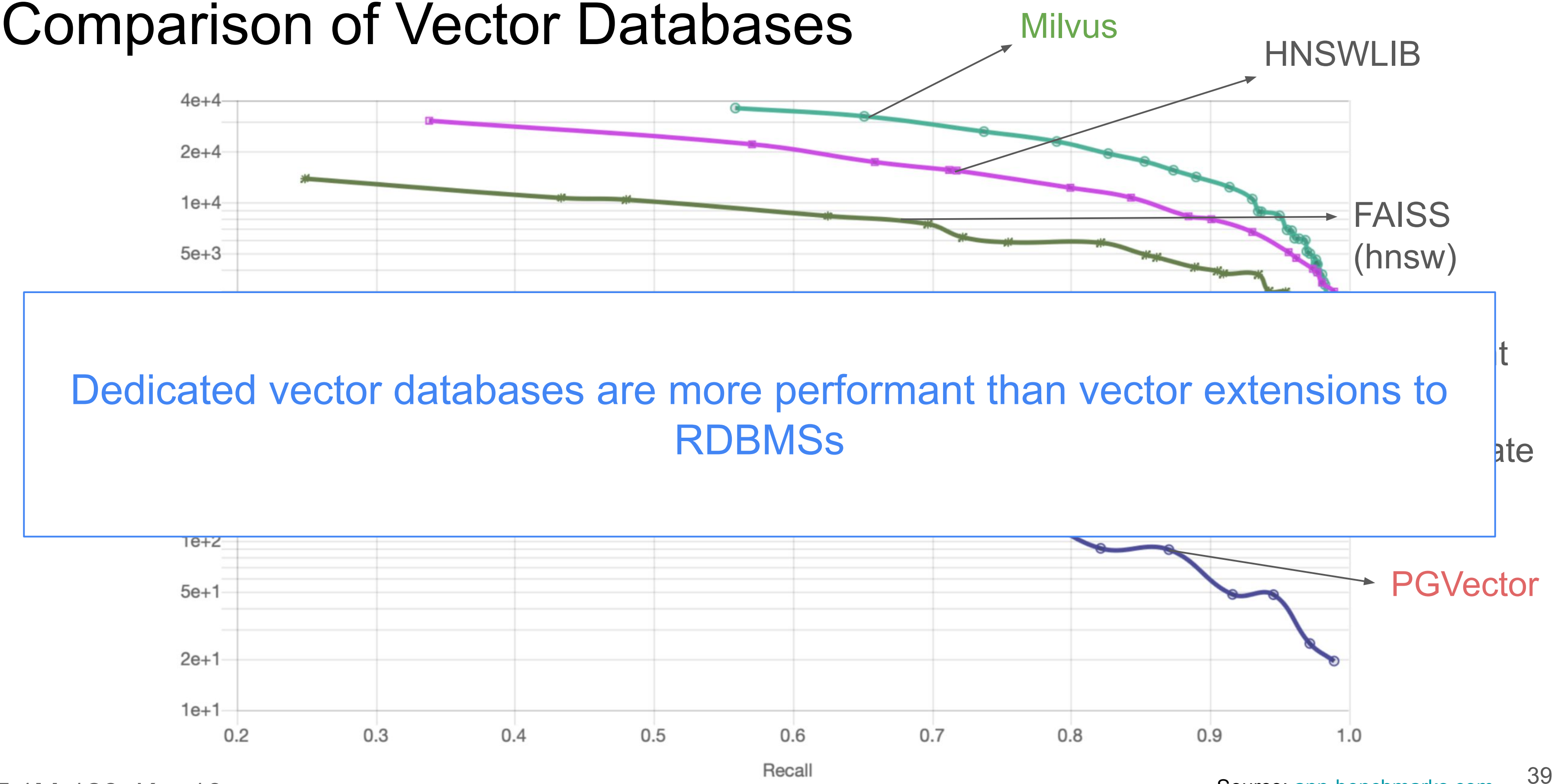
Comparison of Vector Databases



SIFT-1M-128; K = 10

Source: ann-benchmarks.com

Comparison of Vector Databases



SIFT-1M-128; K = 10

Source: ann-benchmarks.com

Profiles

(HNSWLIB, Qdrant, PGVector)

Machine Information

- Hardware
  - Processor
    - Dual Socket Intel Xeon Silver 4114 CPU @ 2.20 GHz
    - 10 Cores / Socket
    - Hyperthreading enabled
  - Cache
    - L1i / L1d: 640 KB
    - L2: 20 MB
    - L3: 27.5 MB
  - Memory
    - 192 GB DDR4
- Software
  - Intel VTune Profiler 2024.0.1
  - Perf 5.4.248

HNSWLIB: Performance Comparison

Dataset: GIST (960)

Train / Test Split: 100K / 1K

No. of Threads: 40

	Flat	**HNSW** (ef_cons = 64, ef_search = 100, M = 32)
Index Size	367 MB	393 MB
Index Duration	0.239 s	7.198 s
Query Duration (Top K = 100)	1.757 s	0.247 s

HNSWLIB: Performance Comparison

Dataset: GIST (960)

Train / Test Split: 100K / 1K

No. of Threads: 40

Index calculation is a highly expensive operation as compared to searches in HNSW

	Flat	**HNSW** (ef_cons = 64, ef_search = 100, M = 32)
Index Size	367 MB	393 MB
Index Duration	0.239 s	7.198 s
Query Duration (Top K = 100)	1.757 s	0.247 s

HNSWLIB: CPU Hotspot Analysis

Flat

```
91.76%  profile_hnswlib  profile_hnswlib     [.] hnswlib::L2SqrSIMD16ExtSSE
 3.36%  profile_hnswlib  libgomp.so.1.0.0    [.] omp_get_num_procs
 0.90%  swapper          [kernel.kallsyms]   [k] intel_idle
 0.79%  profile_hnswlib  [kernel.kallsyms]   [k] copy_user_enhanced_fast_string
 0.48%  profile_hnswlib  libc-2.31.so        [.] __memcpy_avx_unaligned_erms
 0.27%  profile_hnswlib  [kernel.kallsyms]   [k] _raw_spin_lock
 0.23%  profile_hnswlib  profile_hnswlib     [.] hnswlib::BruteforceSearch<float>::searchKnn
```

HNSW

```
45.59%  profile_hnswlib  profile_hnswlib      [.] hnswlib::L2SqrSIMD16ExtSSE
11.74%  profile_hnswlib  libgomp.so.1.0.0     [.] omp_get_num_procs
 5.93%  swapper          [kernel.kallsyms]    [k] intel_idle
 5.81%  profile_hnswlib  [kernel.kallsyms]    [k] copy_user_enhanced_fast_string
 4.82%  profile_hnswlib  profile_hnswlib      [.] hnswlib::HierarchicalNSW<float>::searchBas
 3.13%  profile_hnswlib  libc-2.31.so         [.] __memcpy_avx_unaligned_erms
 2.56%  swapper          [unknown]            [.] 0000000000000000
```

Distance calculations (L2) takes a major chunk of the execution time

HNSWLIB: Memory Access Analysis

Instruction	% of `L2SqrSIMD` in Flat	% of `L2SqrSIMD` in HNSW
`movups`	41.18	86.74
`addps`	43.43	7.27
`subps`	0.61	1.24
`mulps`	7.38	0.78

Distance calculation (L2) in HNSW is more memory bound than Flat due to aggressive prefetching

Qdrant: CPU Hotspot Analysis

Elapsed Time: 122.915s

CPU Time:	239.192s
Total Thread Count:	449
Paused Time:	0s

Top Hotspots

This section lists the most active functions in your application. Optimizing these hotspot functions typically results in improving overall application performance.

Function	Module	CPU Time	% of CPU Time
segment::spaces::simple_avx::dot_similarity_avx::he0656f57d193c9aa	qdrant	232.215s	97.1%
_LTsegment..vector_storage..raw_scorer..RawScorerImplLTTVector$C$TQueryScorer$GT$$u20asu20$segment..vector_storage..raw_scorer..RawScorerGT::peek_top_all::h7f7a0572eaed0ae9	qdrant	1.864s	0.8%
common::fixed_length_priority_queue::FixedLengthPriorityQueueLTTGT::push::h9555933f1b8054be	qdrant	0.808s	0.3%
epoll_wait	libc.so.6	0.760s	0.3%
_LTsegment..spaces..simple..DotProductMetric$u20$as$u20$segment..spaces..metric..MetricGT::similarity::h788ac744465c6b5a	qdrant	0.684s	0.3%
[Others]	N/A*	2.860s	1.2%

Flat

Elapsed Time: 122.332s

CPU Time:	87.370s
Total Thread Count:	200
Paused Time:	0s

Top Hotspots

This section lists the most active functions in your application. Optimizing these hotspot functions typically results in improving overall application performance.

Function	Module	CPU Time	% of CPU Time
segment::spaces::simple_avx::dot_similarity_avx::he0656f57d193c9aa	qdrant	46.463s	53.2%
epoll_wait	libc.so.6	4.458s	5.1%
segment::index::hnsw_index::hnsw::HNSWIndexLTTGraphLinksGT::search_with_graph::h5aad91e8607d78ab	qdrant	2.729s	3.1%
syscall	libc.so.6	2.607s	3.0%
write	libpthread.so.0	1.688s	1.9%
[Others]	N/A*	29.425s	33.7%

*N/A is applied to non-summable metrics

HNSW

Distance calculations (Dot Product) dominate the execution time

Qdrant: Memory Access Analysis

Function / Call Stack	CPU Time	Memory Bound	Loads	Stores	LLC Miss Count	Average Latency (cycles)	Module
segment::spaces::simple_avx::dot_similarity_avx::he06	217.755s	80.0%	112,072,553,108	10,047,542	16,394,674,965	120	qdrant
_LTsegment..vector_storage..raw_scorer..RawScorer	2.040s	82.9%	3,950,180,460	5,093,750,253	0	7	qdrant
smp_call_function_single	1.415s	37.9%	20,053,973	10,047,542	0	586	vmlinux
swapgs_restore_regs_and_return_to_usermode	1.040s	0.0%	70,250,572	10,006,431	0	8	vmlinux

Flat

Function / Call Stack	CPU Time	Memory Bound	Loads	Stores	LLC Miss Count	Average Latency (cycles)	Module
segment::spaces::simple_avx::dot_similarity_avx::he06	28.205s	84.1%	8,834,440,834	25,485,511	1,087,687,953	69	qdrant
segment::index::hnsw_index::hnsw::HNSWIndexLTT	2.670s	62.0%	314,894,531	138,670,884	0	31	qdrant
serde_json::de::DeserializerLTRGT::parse_decima	2.250s	21.6%	954,465,540	808,302,238	0	7	qdrant
serde::de::Deserializer::__deserialize_content::h9d9545	1.875s	0.0%	1,034,131,175	587,516,780	0	30	qdrant
regex::backtrack::BoundedLTIGT::backtrack::hf360	1.795s	2.0%	1,392,025,584	621,750,220	0	7	qdrant

HNSW

Distance calculations (Dot Product) are highly memory-bound

PGVector: Performance Comparison

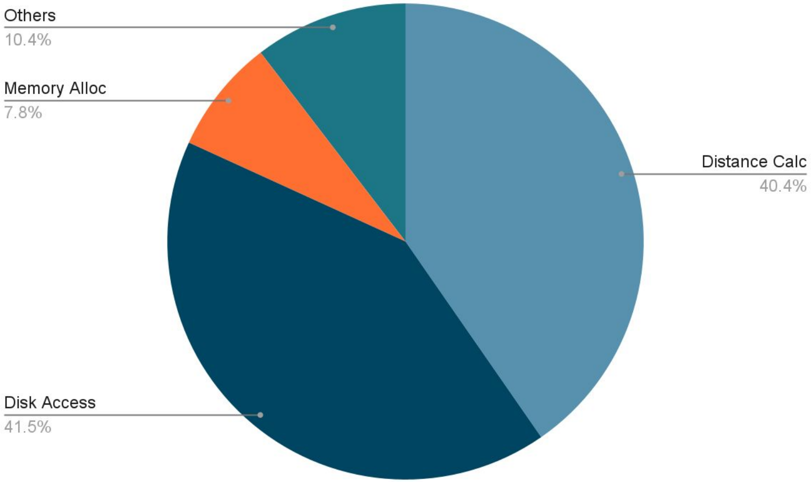
Dataset: dbpedia-entities-openai-1M (1536)

Train / Test Split: 100K / 1K

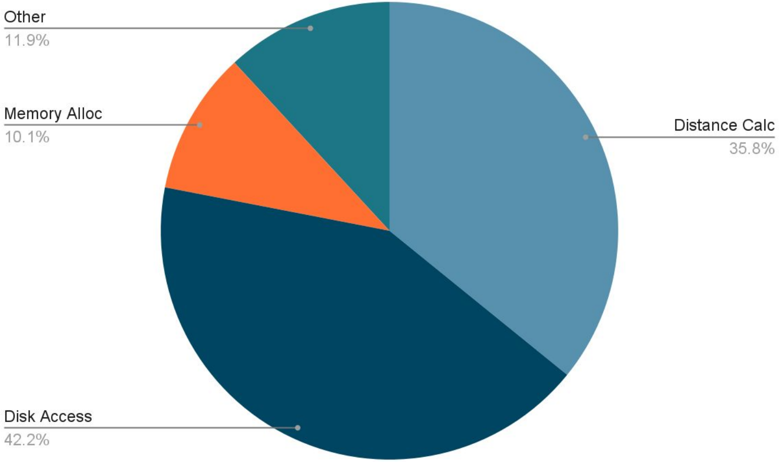
No. of Threads: 1

	IVF Flat (n_list = 100, n_probe = 10)	**HNSW** (ef_cons = 64, ef_search = 100, M = 32)
Index Size	782 MB	781 MB
Index Duration	27.50 s	150.24 s
Query Duration (Top K = 100)	147.63 s	89.82 s

PGVector: CPU Hotspot Analysis



IVF Flat



HNSW

After distance calculations, file reads comprise a significant chunk of the execution time

PGVector: Performance Comparison

Dataset: dbpedia-entities-openai-1M (1536)

Train / Test Split: 100K / 1K

No. of Threads: 1

Not much diff due to high overhead of disk access

	IVF Flat (n_list = 100, n_probe = 10)	**HNSW** (ef_cons = 64, ef_search = 100, M = 32)
Index Size	782 MB	781 MB
Index Duration	27.50 s	150.24 s
Query Duration (Top K = 100)	147.63 s	89.82 s

PGVector: Memory Access Analysis

```
Percent │   for (int i = 0; i < dim; i++)
        │     mov     $0x0,%eax
        │   float           distance = 0.0;
  0.06  │     vxorps  %xmm1,%xmm1,%xmm1
        │   for (int i = 0; i < dim; i++)
        │9:   cmp     %edi,%eax
  0.07  │   ↓ jge     26
        │   {
        │   float           diff = ax[i] - bx[i];
 25.44  │     movslq  %eax,%rcx
  0.74  │     vmovss  (%rsi,%rcx,4),%xmm0
  0.15  │     vsubss  (%rdx,%rcx,4),%xmm0,%xmm0
        │
        │   distance += diff * diff;
 23.49  │     vmulss  %xmm0,%xmm0,%xmm0
 49.96  │     vaddss  %xmm0,%xmm1,%xmm1
        │   for (int i = 0; i < dim; i++)
        │     inc     %eax
        │   ↑ jmp     9
        │   }
        │
        │   return distance;
        │   }
        │26:  vmovaps %xmm1,%xmm0
  0.08  │   ← retq
```

IVF Flat

compute ops dominate

```
Percent │   for (int i = 0; i < dim; i++)
  0.21  │     mov     $0x0,%eax
        │   float           distance = 0.0;
        │     vxorps  %xmm1,%xmm1,%xmm1
        │   for (int i = 0; i < dim; i++)
        │9:   cmp     %edi,%eax
        │   ↓ jge     26
        │   {
        │   float           diff = ax[i] - bx[i];
 26.24  │     movslq  %eax,%rcx
        │     vmovss  (%rsi,%rcx,4),%xmm0
        │     vsubss  (%rdx,%rcx,4),%xmm0,%xmm0
        │
        │   distance += diff * diff;
 27.25  │     vmulss  %xmm0,%xmm0,%xmm0
 46.12  │     vaddss  %xmm0,%xmm1,%xmm1
        │   for (int i = 0; i < dim; i++)
  0.18  │     inc     %eax
        │   ↑ jmp     9
        │   }
        │
        │   return distance;
        │   }
        │26:  vmovaps %xmm1,%xmm0
        │   ← retq
```

HNSW

PGVector: Memory Access Analysis

```
Percent │  for (int i = 0; i < dim; i++)
        │    mov     $0x0,%eax
        │  float             distance = 0.0;
   0.06 │    vxorps  %xmm1,%xmm1,%xmm1
        │  for (int i = 0; i < dim; i++)
        │ 9:  cmp     %edi,%eax
   0.07 │  ↓ jge     26
        │  {
        │  float             diff = ax[i] - bx[i];
  25.44 │    movslq  %eax,%rcx
   0.74 │    vmovss  (%rsi,%rcx,4),%xmm0
   0.15 │    vsubss  (%rdx,%rcx,4),%xmm0,%xmm0
        │
        │  distance += diff * diff;
  23.49 │    vmulss  %xmm0,%xmm0,%xmm0
  49.96 │    vaddss  %xmm0,%xmm1,%xmm1
        │  for (int i = 0; i < dim; i++)
        │    inc     %eax
```

```
Percent │  for (int i = 0; i < dim; i++)
   0.21 │    mov     $0x0,%eax
        │  float             distance = 0.0;
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        │  for (int i = 0; i < dim; i++)
        │ 9:  cmp     %edi,%eax
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        │  {
        │  float             diff = ax[i] - bx[i];
  26.24 │    movslq  %eax,%rcx
        │    vmovss  (%rsi,%rcx,4),%xmm0
        │    vsubss  (%rdx,%rcx,4),%xmm0,%xmm0
        │
        │  distance += diff * diff;
  27.25 │    vmulss  %xmm0,%xmm0,%xmm0
  46.12 │    vaddss  %xmm0,%xmm1,%xmm1
        │  for (int i = 0; i < dim; i++)
   0.18 │    inc     %eax
```

CPU is waiting for disk I/O, and can't issue memory load instructions, so its compute bound

IVF Flat   HNSW

Future Work

- Perform billion-scale experiments / profiles (Please provide me hardware !)
- Study GPU-based indexes and their performance characteristics
- Explore offloading distance calculations to specialized accelerators
- Leverage far memory to store larger-than-memory indexes
- Explore offloading vector search to computational storage devices

Thank You

Questions ?

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