Vector data in Postgres

Size, TOAST, filters and performance

PGConf EU Oct 2025

Google Cloud

Contents

Speaker introduction

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Databases

- Live in Ottawa, Canada
- Earned a degree in oceanology and participated in expeditions dedicated to oceanic research in the Pacific.
- Runner. Next Marathons - Florence and the Boston 2026)

01
Vectors

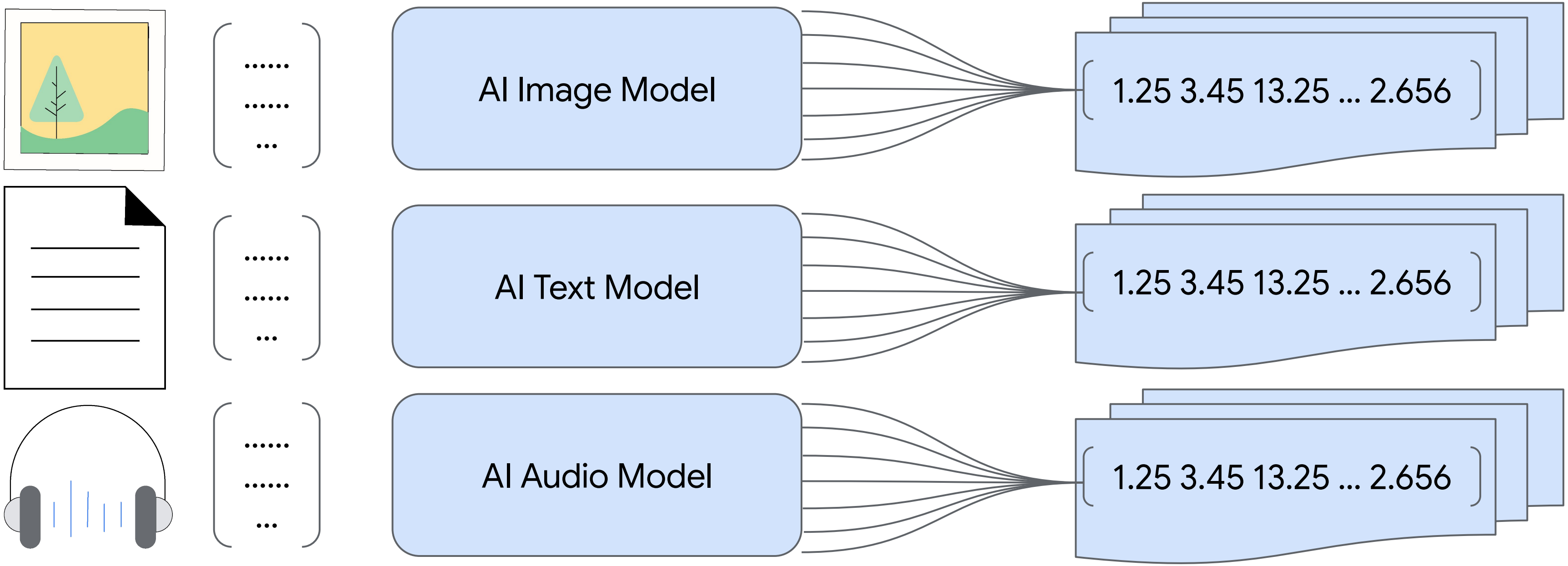
Why are we talking about vectors

Vector is an ordered list of numbers. These numbers represent magnitudes along different dimensions.

Vector embedding is a vector that represents a piece of data

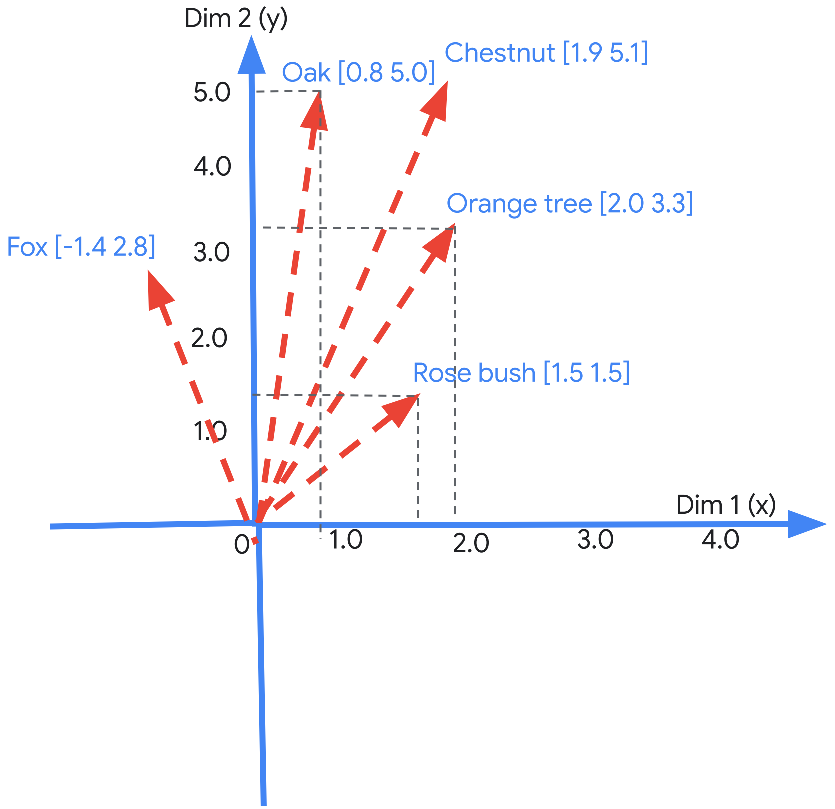
Vector embedding size depends on dimensions and doesn't depend on size of the source data

AI and Vectors



Vectors and dimensions

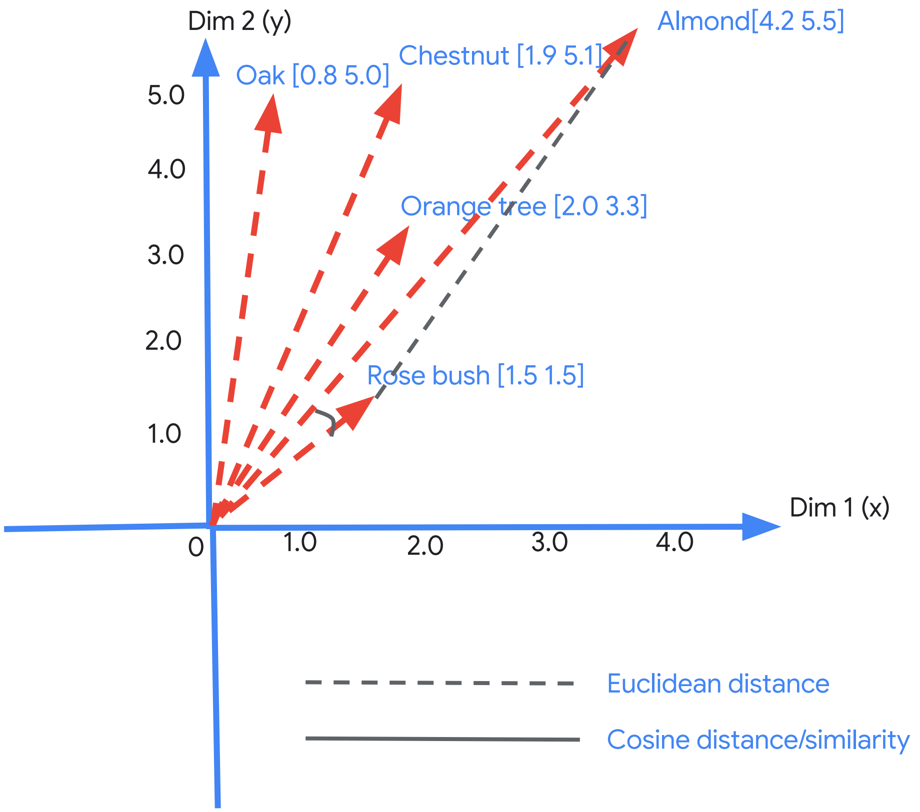
- Vector defined by coordinates in n-dimensional space
- Example for 2-dimensional space:
    - Coordinates in 2 dimensional space
    - Dimension 1 (x) - the first coordinate
    - Dimension 2 (y) - the second coordinate
    - Vector is direction from the center of coordinates



Distance between vectors

- Euclidean distance - straight line
- Cosine distance - based on angle
- Other ways(L2, Inner product)

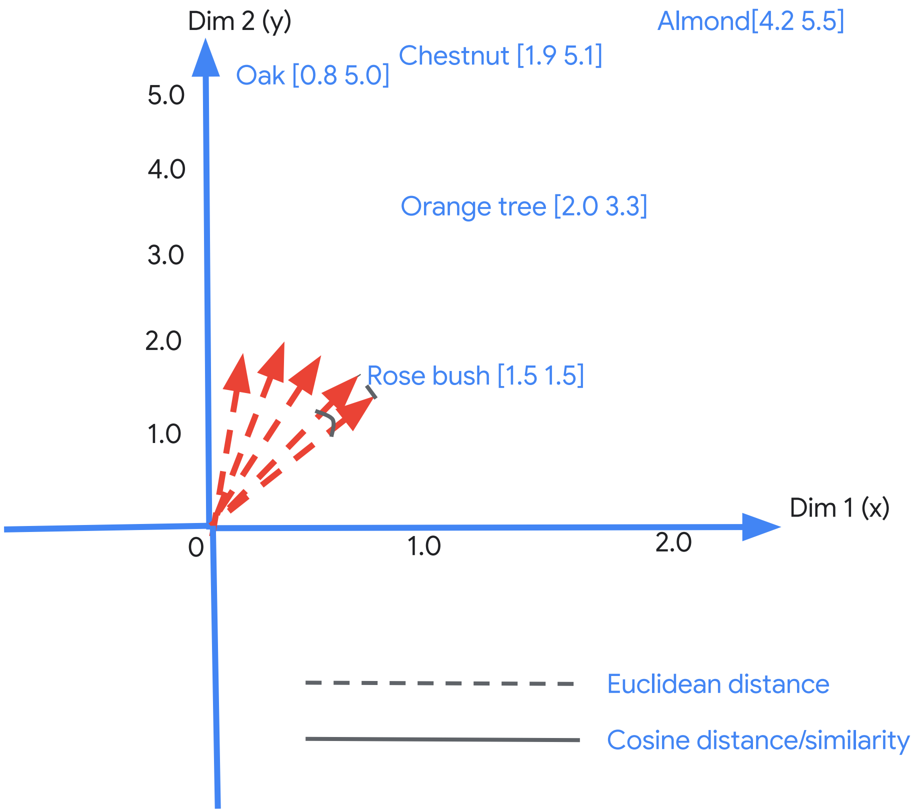
$$distance = \sqrt{(x_R - x_A)^2 + (y_R - y_A)^2}$$



Normalized vectors

- Focuses on Direction
- Simplifies Similarity Calculation
- Improves Consistency

$$\hat{\mathbf{v}} = \frac{\mathbf{v}}{\sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}}$$



02
Vector Data in PostgreSQL

How we store vectors in database

Vector embeddings

- Dimensions - from 25 to 3000 (or more)
- Precision for each value (dimension) - float32
- Stored in postgres as vector data type
    - As single-precision, half-precision, binary, and sparse vectors
    - Single-precision (real) - 4 bytes

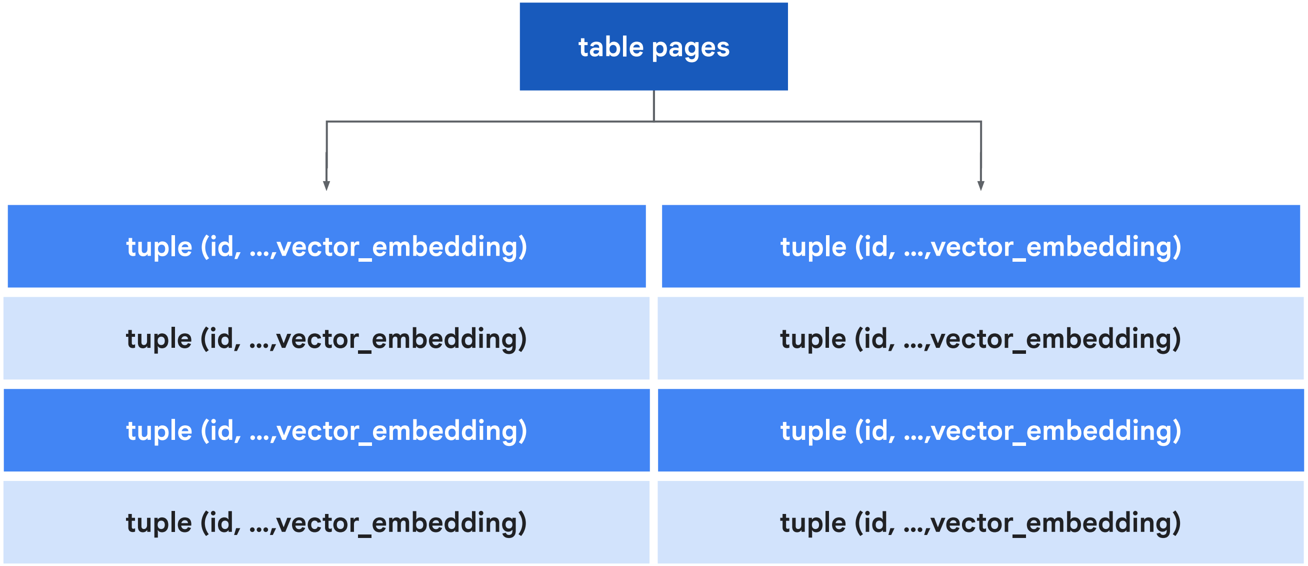
Vector - stored inline

Up to 500 dimensions is stored inline

4 bytes * 500 = 2000

Vector size is less than

TOAST_TUPLE_THRESHOLD

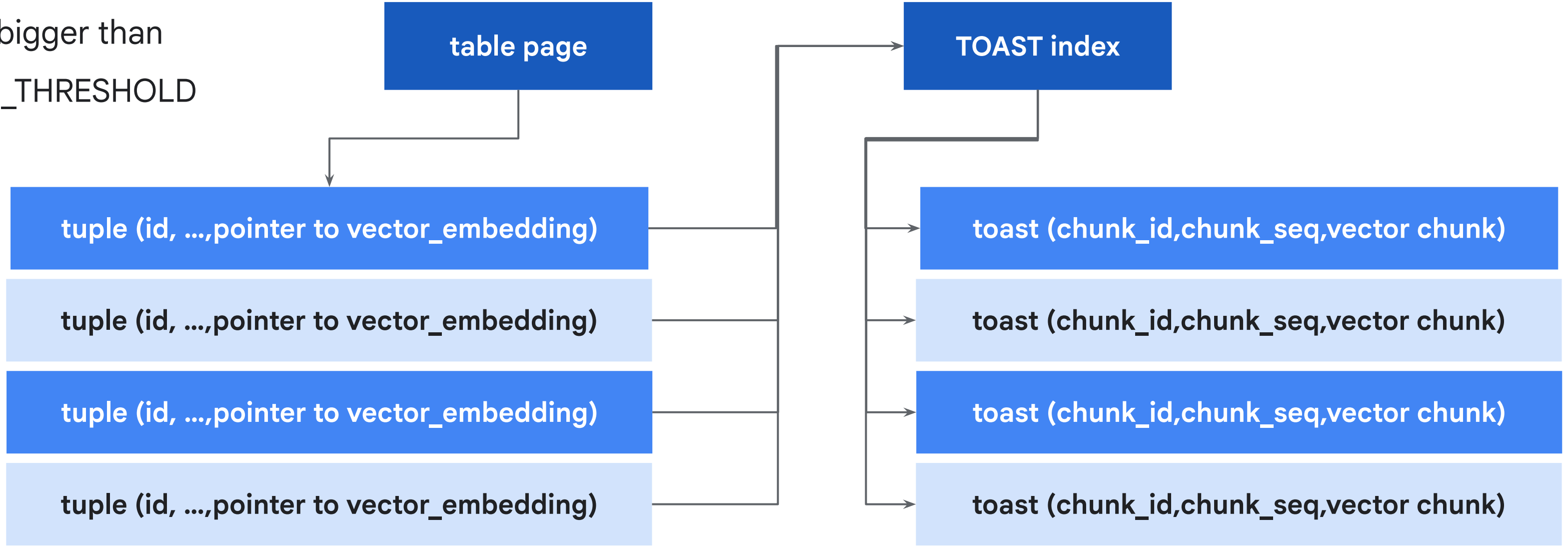


Vector - using TOAST

More than 500 dimensions is stored in TOAST chunks

Vector size is bigger than

TOAST_TUPLE_THRESHOLD



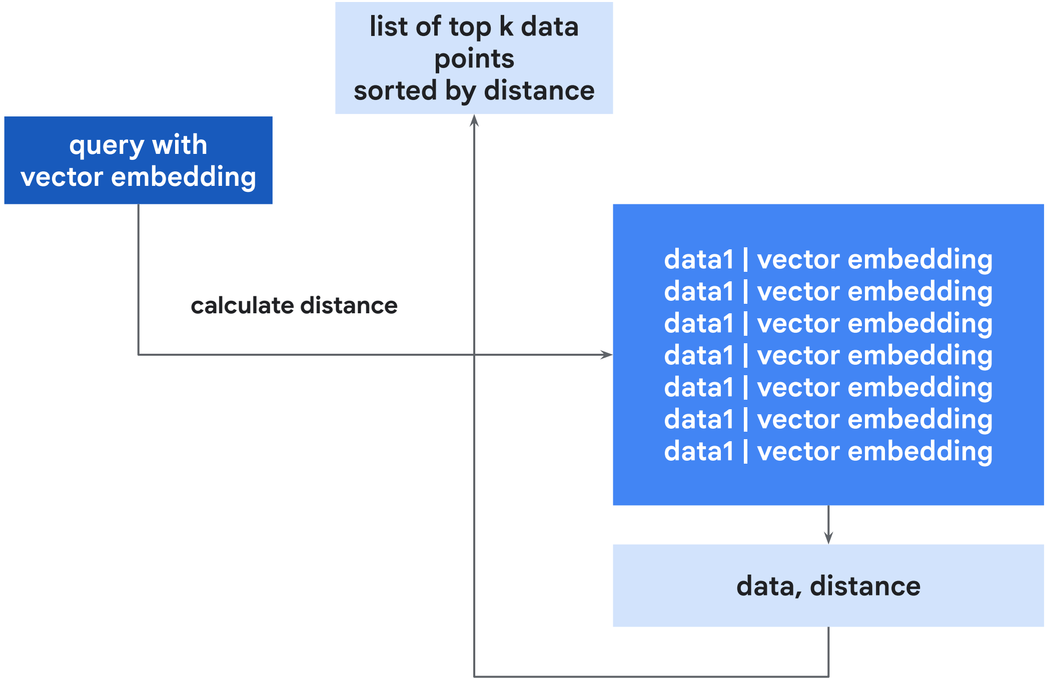
03
Vector Search - KNN

Compare vectors and finding similarities

KNN

What is KNN or kNN?

- It stands for k-nearest neighbor search
- Sometimes called exact search
- Linear - depends on the size of a dataset
- Uses different measurements:
  - L2 distance
  - Cosine distance
  - inner product
  - Others - https://github.com/pgvector/pgvector



KNN - how it works

What is KNN or kNN?

- Compares a vector to every other vector
- Sort it by distance
- Get top k values
- Keeping in memory on k top results
- Memory depends on K

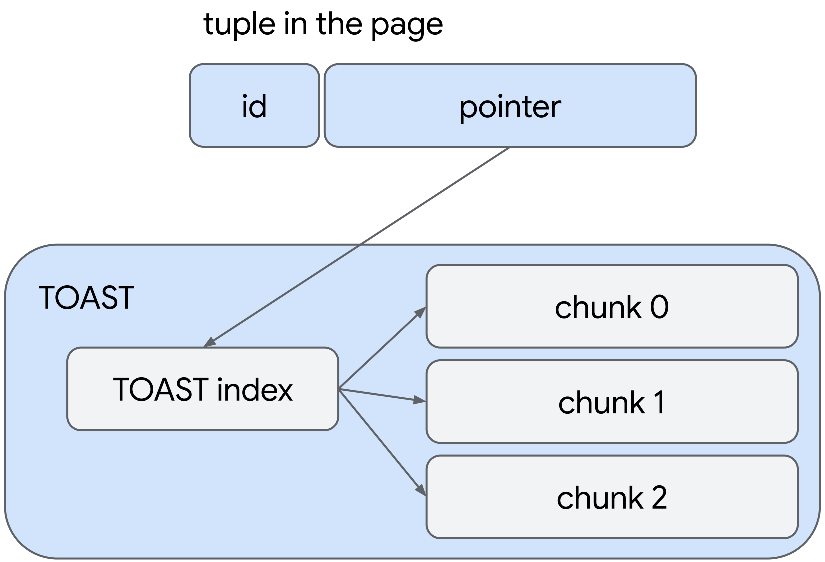
```sql
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM TV500
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 5;
```

```
Limit  (cost=265212.38..265212.97 rows=5 width=24) (actual time=881.220..916.180
rows=5 loops=1)
   ->  Gather Merge  (cost=265212.38..362441.47 rows=833334 width=24) (actual
time=878.233..913.190 rows=5 loops=1)
         Workers Planned: 2
         Workers Launched: 2
         ->  Sort  (cost=264212.36..265254.03 rows=416667 width=24) (actual
time=803.573..803.575 rows=4 loops=3)
               Sort Key: ((d <=>
'[0.31021905,0.42329416,0.2588454,.....,0.5502057]'::vector))
               Sort Method: top-N heapsort  Memory: 25kB
               Worker 0:  Sort Method: top-N heapsort  Memory: 25kB
               Worker 1:  Sort Method: top-N heapsort  Memory: 25kB
               ->  Parallel Seq Scan on tv500  (cost=0.00..257291.67 rows=416667

width=24) (actual time=8.299..630.664 rows=333333 loops=3)

 Planning Time: 0.121 ms

 Execution Time: 1045.325 ms
```

KNN - TOAST

How TOAST impact KNN search?

- For each vector additional IO
- In theory it least 3 IO buffers to get data



KNN - TOAST

How does TOAST impact KNN search?

- Execution longer
- IO is higher

```
Limit  (cost=22565.38..22565.97 rows=5 width=24) (actual time=9797.457..9845.396
rows=5 loops=1)
   ->  Gather Merge  (cost=22565.38..119794.47 rows=833334 width=24) (actual
time=9797.454..9845.391 rows=5 loops=1)
         Workers Planned: 2
         Workers Launched: 2
         ->  Sort  (cost=21565.36..22607.03 rows=416667 width=24) (actual
time=9721.322..9721.323 rows=4 loops=3)
               Sort Key: ((d <=> '[0.15708542,0.61898744, ...
,0.46348935]'::vector))
               Sort Method  top-N heapsort  Memory: 25kB
               Worker 0:  Sort Method: top-N heapsort  Memory: 25kB
               Worker 1:  Sort Method: top-N heapsort  Memory: 25kB
               ->  Parallel Seq Scan on tv501  (cost=0.00..14644.67 rows=416667
width=24) (actual time=0.285..9514.106 rows=333333 loops=3)
 Planning Time: 0.120 ms
 Execution Time: 9845.434 ms
```

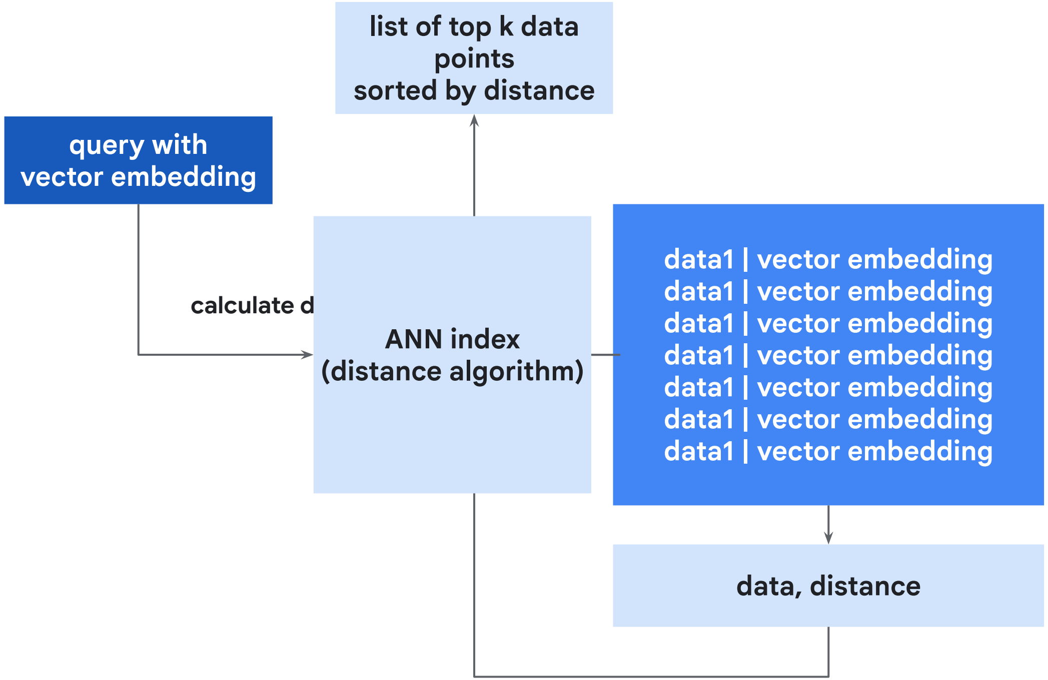
04
Vector Search - ANN

Compare vectors and finding approximate similarities

ANN - what it is

ANN - Approximate Nearest Neighbours

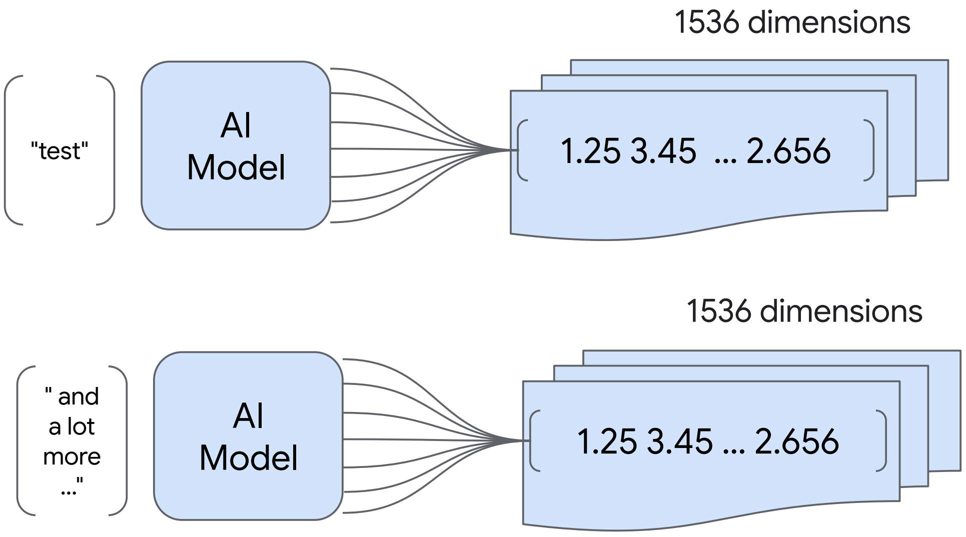
- KNN is too expensive and slow
- ANN trades recall to speed
- Enabled by using ANN index for vectors
- Search top-k value using distance algorithm
- Distance algorithm is part of the index



ANN and dimensions

More dimensions - bigger size for vector

- Data size in a row >2k - TOAST
- What about index ?
- Size limited by 2k for index value
- Over 2000 dimensions limit in pgvector?
  - Half-Precision Indexing (halfvec)
  - Quantization - changing precision (and size)



05
Indexes

What kind of indexes we can use with the vectors

Vector Indexes

IVFFlat

- Tree-based
- Fast rebuild

HNSW

- Graph-based
- Fast quality recall

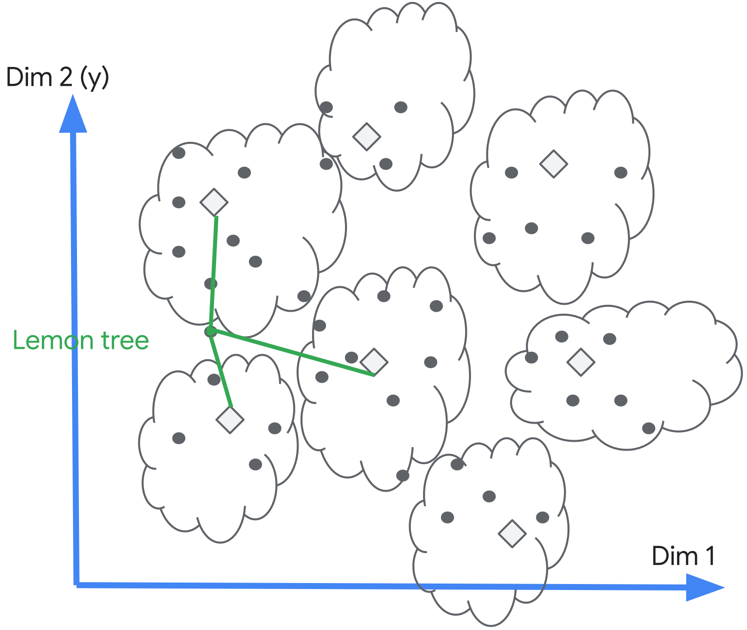
AlloyDB ScaNN

- Tree-based
- Uses Google algorithm

IVFFlat

IVFFlat - Inverted File with Flat Compression

- Tree-based with centroids
- Define number of lists
- Create centroids for each list
- Assign each vector to a centroid
- Search only for probed lists
- Parameters:
  - lists - number of centroids (during creation)
  - ivfflat.probes - number of lists to try (execution)



ivflat lists - 7
ivflat.probes - 3

IVFFlat - execution

IVFFlat - vector inline

- Lists = 100
- Cosine distance
- Default parameters

```
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM tvtest
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 10;
```

```
Limit  (cost=634.12..650.58 rows=10 width=24) (actual time=0.905..0.946 rows=10
loops=1)
  ->  Index Scan using tvtest_d_idx on tvtest  (cost=634.12..165162.50 rows=100000
width=24) (actual time=0.903..0.942 rows=10 loops=1)
        Order By: (d <=> '[0.5356429,0.07264433, ... ,0.7928642]'::vector)
Planning Time: 0.108 ms
Execution Time: 0.973 ms
```

IVFFlat - execution

IVFFlat - vector in TOAST

- Lists = 100
- Cosine distance
- Default parameters

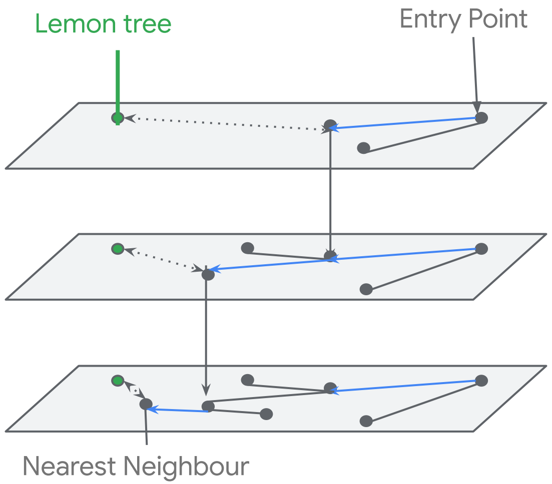
```
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM tvtest
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 10;
```

```
Limit  (cost=633.95..640.70 rows=10 width=24) (actual time=1.537..1.672 rows=10
loops=1)
   ->  Index Scan using tvtest_d_idx on tvtest  (cost=633.95..68089.00 rows=100000
width=24) (actual time=1.535..1.668 rows=10 loops=1)
         Order By: (d <=> '[0.65339184,0.92753774, ... ,0.7215546]'::vector)
 Planning Time: 0.101 ms
 Execution Time: 1.698 ms
```

HNSW

HNSW - Hierarchical Navigable Small Worlds

- Split to layers
- Long links on the top
- Shorter links to bottom
- Starting on top from long distances
- Down in layers - shorter distances
- Graph based - handles updates



HNSW - execution

HNSW - vector inline

- Cosine distance
- Default parameters

```
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM tvtest
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 10;
```

```
Limit  (cost=921.81..945.30 rows=10 width=24) (actual time=2.460..2.493 rows=10
loops=1)
   ->  Index Scan using tvtest_d_idx on tvtest  (cost=921.81..235840.00 rows=100000
width=24) (actual time=2.458..2.489 rows=10 loops=1)
         Order By: (d <=> '[0.5356429,0.07264433, ... ,0.7928642]'::vector)
 Planning Time: 0.103 ms
 Execution Time: 2.518 ms
```

HNSW - execution

HNSW - vector in TOAST

- Cosine distance
- Default parameters

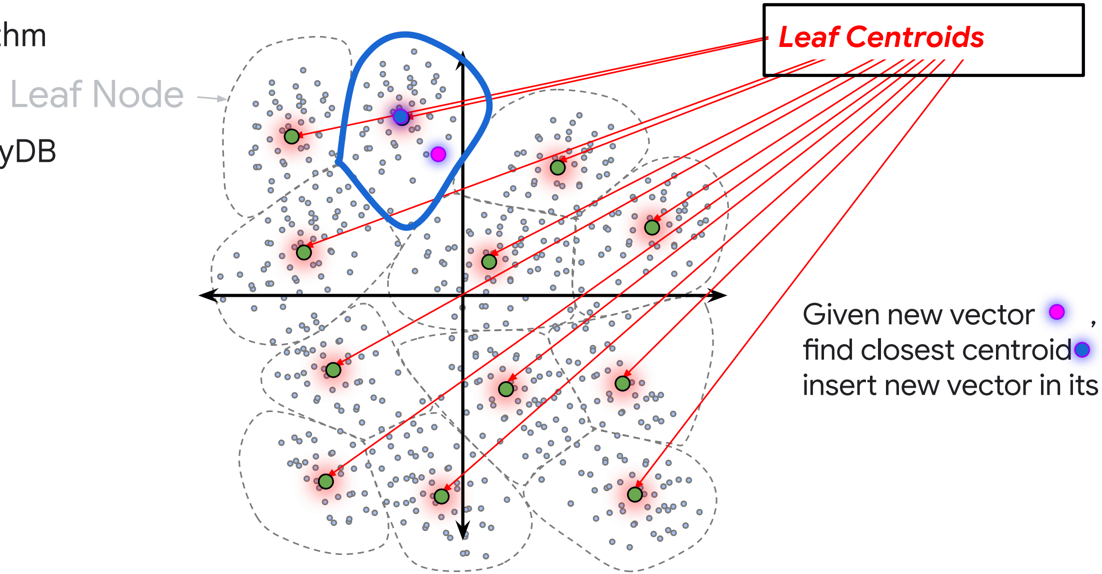
```
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM tvtest
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 10;
```

```
Limit  (cost=921.81..935.59 rows=10 width=24) (actual time=3.677..3.806 rows=10
loops=1)
   ->  Index Scan using tvtest_d_idx on tvtest  (cost=921.81..138784.00 rows=100000
width=24) (actual time=3.675..3.802 rows=10 loops=1)
         Order By: (d <=> '[0.65339184,0.92753774, ... ,0.7215546]'::vector)
 Planning Time: 0.114 ms
 Execution Time: 3.832 ms
```

ScaNN for AlloyDB

AlloyDB - Scalable Nearest Neighbors

- ScaNN vector search algorithm from Google Research
- Natively integrated with AlloyDB
- Fast build
- Quality recall
- Auto-maintenance



Given new vector ,
find closest centroid ,
insert new vector in its leaf

- Algorithm open-sourced in 2019 (https://github.com/google-research/google-research/tree/master/scann)

AlloyDB ScaNN - execution

ScaNN - vector inline

- Cosine distance
- Default parameters

```
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM tvtest
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 10;
```

```
Limit  (cost=320.00..320.47 rows=10 width=24) (actual time=0.774..0.808 rows=10
loops=1)
   ->  Index Scan using tvtest_d_idx on tvtest  (cost=320.00..5004.00 rows=100000
width=24) (actual time=0.771..0.803 rows=10 loops=1)
         Order By: (d <=> '[0.9267122,0.2705454, ... ,0.3225359]'::vector)
         Limit: 10
 Planning Time: 0.146 ms
 Execution Time: 0.855 ms
```

AlloyDB ScaNN - execution

ScaNN - vector in TOAST

- Cosine distance
- Default parameters

```
EXPLAIN ANALYZE
SELECT
    ID, 1 - (D <=> :'SAMPLE_VECTOR'::VECTOR) AS SIMILARITY
FROM tvtest
ORDER BY D <=> :'SAMPLE_VECTOR'::VECTOR LIMIT 10;
```

```
Limit  (cost=342.50..342.81 rows=10 width=24) (actual time=0.935..1.088 rows=10
loops=1)
   ->  Index Scan using tvtest_d_idx on tvtest  (cost=342.50..3486.50 rows=100000
width=24) (actual time=0.931..1.083 rows=10 loops=1)
         Order By: (d <=> '[0.14669167,0.53945506, ... ,0.34823254]'::vector)
         Limit: 10
 Planning Time: 0.186 ms
 Execution Time: 1.160 ms
```

Indexes Build Time

Default parameters, index doesn't fit to the maintenance_work_mem, 100k rows

	IVFFLAT	HNSW	ScaNN
Build on 498 dimension	5,047 ms	282,323 ms	11,816 ms
Build on 501 dimension	6,042 ms	386,666 ms	14,594 ms

1. Numbers can be different on your system and shown only for comparison
2. The ScaNN build time tested using AlloyDB Omni on the same VM type with the same storage

Indexes Build Time

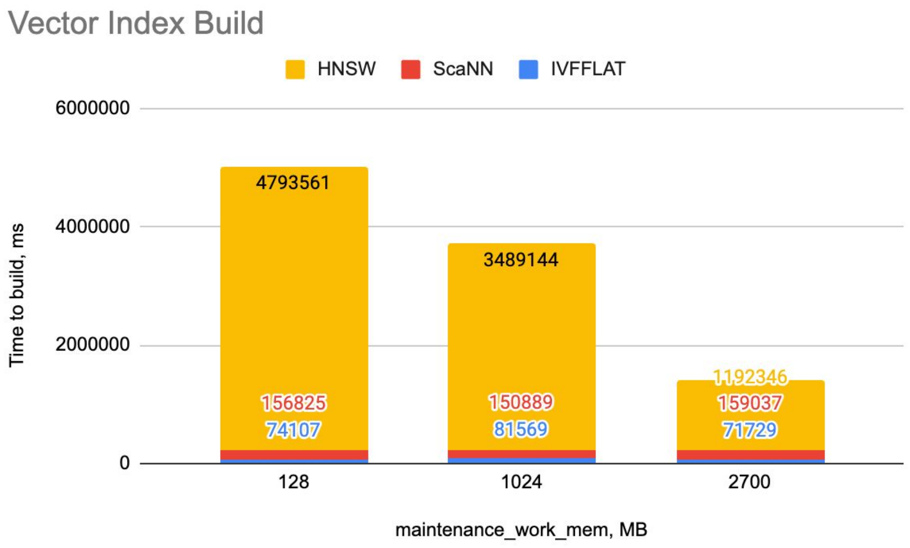
Default parameters, 501 dimensions, different maintenance_work_mem, 1M rows

maintenance_work_mem, MB	IVFFLAT	HNSW	ScaNN
128	74,107 ms	4,793,561 ms	156,825 ms
1024	81,569 ms	3,489,144 ms	150,889 ms
2700	71,729 ms	1,192,346 ms	159,037 ms

1. Numbers can be different on your system and shown only for comparison
2. The ScaNN build time tested using AlloyDB Omni on the same VM type with the same storage

Indexes Build Time

- Memory allocation and CPU are the keys
- The maintenance_work_mem to fit the graphs for HNSW
- Parallel might help to improve speed



“

Index reduces scan area and as result reduces number of work you need to do to retrieve and compare the data”

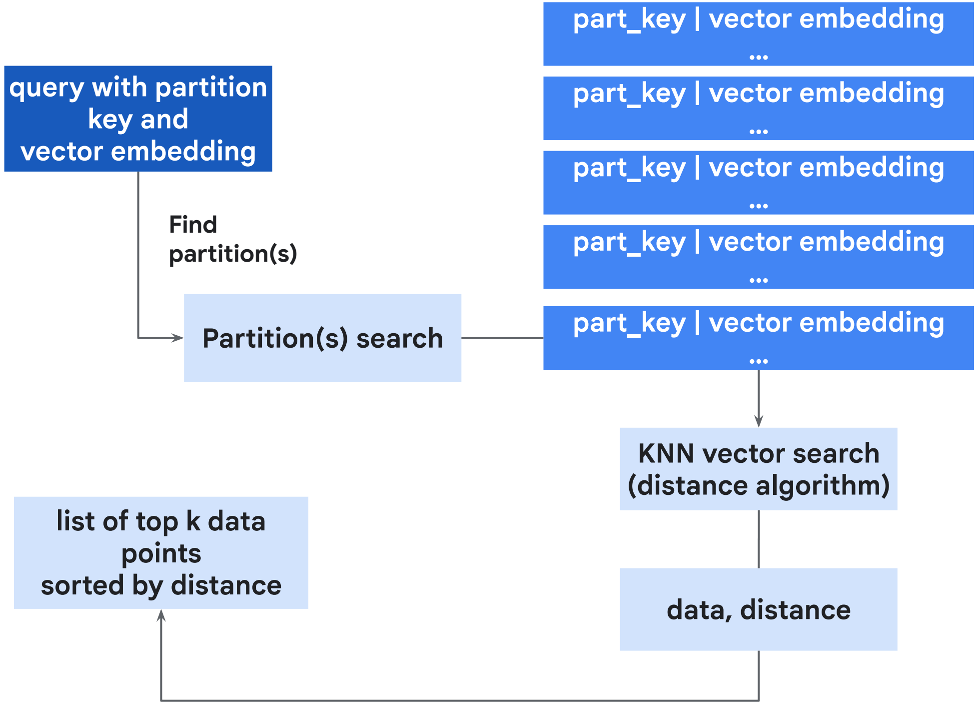
06
Partitions

Compare vectors and finding approximate similarities

Partitions

Partitions reduce search area for Nearest Neighbours

- Query should have partition key in the query
- Data distribution directly impact performance
- Partition scan reduces number of vectors for search
- Vector index might be still faster to retrieve the data



07
Vector Search & Filters

Vector search with filters on another columns

Pre-Filtering

When: High selectivity on the filtered value

Use a standard B-tree index on the metadata column *before* the vector search.

- **Filter First:** The database uses the B-tree to quickly find the small set of rows matching the filter.
- **Vector Search Second:** An KNN search is performed only on this small, pre-filtered subset of vectors.

Post-Filtering

When: Low selectivity on the filtered value

Perform the ANN vector search first, then filter the results after:

- **Vector search First:** The database performs a full ANN search to find the top K nearest neighbors from the entire dataset.
- **Filter Second:** The metadata filter is applied to this small list of K candidate results.

Inline-Filtering

When: Uniform distributions (mid-range) of the filtered values (Iterative index scan)

The filter is applied during the ANN index scan (e.g., HNSW graph traversal).

- **Integrated Search:** As the ANN index algorithm explores the graph...
- **Check As It Goes:** ...it checks if each node/vector also matches the metadata filter before adding it to the candidate list.
- Best for: A good "all-rounder" when selectivity is moderate. Supported by modern ANN indexes.

How pgvector Handles This

The pgvector approach

- Pre-filtering: The Postgres planner might choose this. (with or without index on the column)
- Post-filtering: This is supposed to be a default
- Inline-filtering (Iterative Index Scans HNSW): pgvector (0.8.0+) supports this for HNSW indexes.
- Inline-filtering (Iterative Index Scans IVF): IVF indexes in pgvector have supported this.

Parameters:

- (ivfflat)hnsw.iterative_scan = relaxed_order
- hnsw.max_scan_tuples = 20000
- ivfflat.max_probes = 100

"With approximate indexes, filtering is applied after the index is scanned …" - default behaviour from README

https://github.com/pgvector/pgvector?tab=readme-ov-file#filtering

Filtering Strategy

Strategy	Best For Selectivity	Data Access	Key Benefit
Pre-Filtering	High	B-Tree Index ⟶ KNN	Drastically reduces kNN search space
Post-Filtering	Low	ANN ⟶ Filter	Fastest when ANN is already selective
Inline-Filtering	Mid-range	Iterative index scan	Balanced performance in a single operation.

“

The best filtering strategy depends entirely on your data's selectivity. ”

08
DML on Vector Data

Inserting and Updating Vectors

High Level Overview

Add Tuple

Inserting tuple to the page

Verifying Size

Can all values be stored inline

Compression

Check if we can compress values

Add to TOAST

Inserting chunks to TOAST

TOAST Index

Updating TOAST index

Complete Insert

Commit transaction

Write WAL

Flash WALL record to persistent storage

Insert with ANN Index

Add Tuple

Inserting tuple to the page

Verifying Size

Can all values be stored inline

Compression

Check if we can compress values

Add to TOAST

Inserting chunks to TOAST

TOAST Index

Updating TOAST index

Update Index

Insert new value to the index

Finish Insert

Commit transaction

Write WAL

Flash WALL record to persistent storage

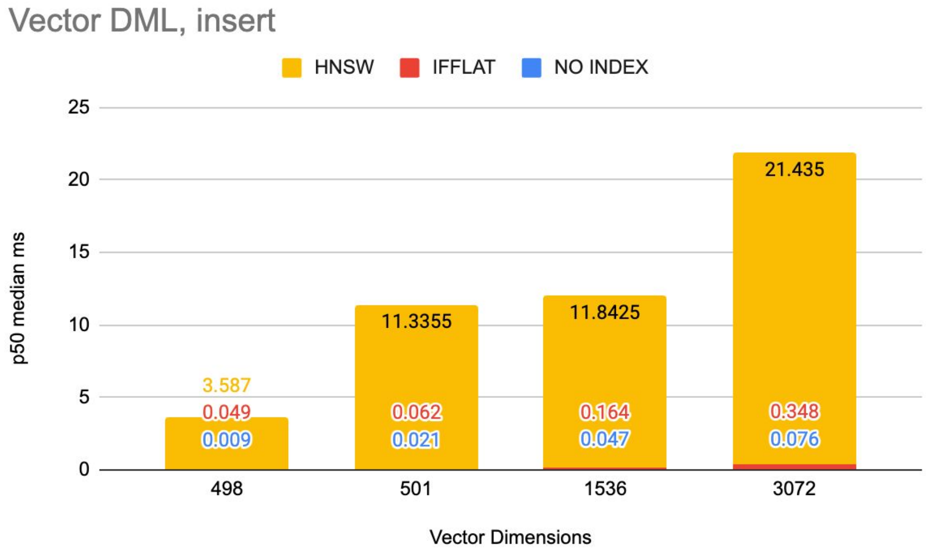
DML on Vectors - Insert

	No Index	HNSW	IVFFLAT	TOAST chunks
Insert 1M 498 dimension	0.009 ms	3.587 ms	0.049 ms	0
Insert 1M 501 dimension	0.021 ms	11.335 ms	0.062 ms	2
Insert 1M 1536 dimension	0.047 ms	11.842 ms	0.164 ms	4
Insert 1M 3072 dimension	0.076 ms	21.435 ms	0.348 ms	7

1. Latency measured for p50 median
2. Numbers can be different on your system and shown only for comparison
3. For 3072 dimensions a casting to halfvec was used to build HNSW and IVFFlat indexes

DML - Insert

- Depends on TOAST - TOAST slows down inserts
- Depends on dimensions - how many TOAST chunks
- Indexes have significant performance impact
- HNSW is more expensive in overhead than IVFFlat



Update

Create New Tuple

Inserting tuple to the page

Verifying Size

Can all values be stored inline

Compression

Check if we can compress values

Add to TOAST

Inserting chunks to TOAST

TOAST Index

Updating TOAST index

Update Index

Insert new value to the index

Finish Update

Commit transaction

Write WAL

Flash WALL record to persistent storage

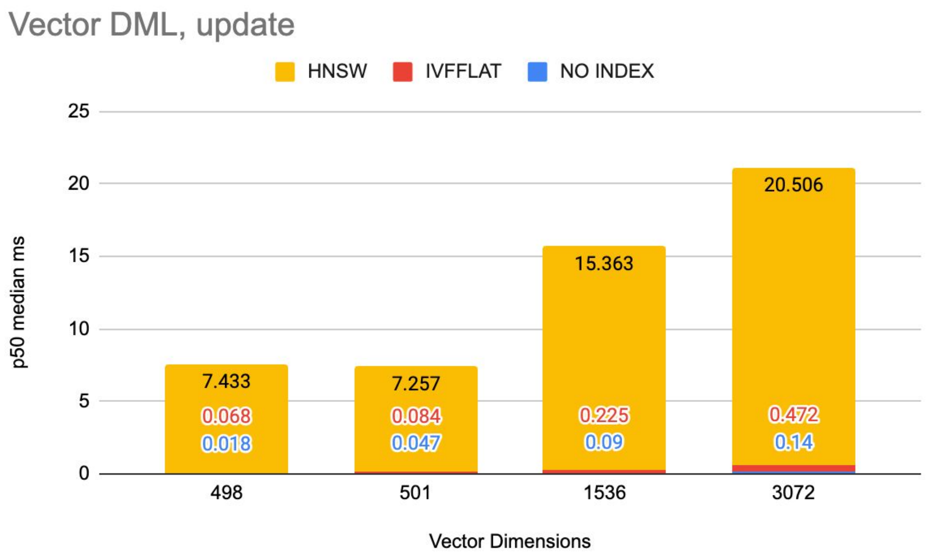
DML on Vectors - Updates

	No Index	HNSW	IVFFLAT	TOAST chunks
Update 1M 498 dimension	0.018 ms	7.433 ms	0.068 ms	0
Update 1M 501 dimension	0.047 ms	7.257 ms	0.084 ms	2
Update 1M 1536 dimension	0.090 ms	15.363 ms	0.225 ms	4
Update 1M 3072 dimension	0.140 ms	20.506 ms	0.472 ms	7

1. Latency measured for p50 median
2. Numbers can be different on your system and shown only for comparison
3. For 3072 dimensions a casting to halfvec was used to build HNSW and IVFFlat indexes

DML - Update

- Depends on TOAST - TOAST slows down updates
- Depends on dimensions - how many TOAST chunks
- Indexes have significant performance impact
- HNSW is more expensive in overhead than IVFFlat
- Dead tuples for inline vectors and in TOAST
- Indexes fragmentation
- TOAST bloating



Basic Recommendations

- Keep vector data in separate tables if it is feasible - models are changing
- Dimensions and size matter - check if you can reduce it
- Indexes have significant performance impact on DML
- HNSW is more expensive in overhead than IVFFLAT
- But HNSW might be a better choice if your data are static
- Use partitioning to reduce search area

Here is supposed to be a very opinionated slide with detailed instructions but ...

Q&A

Google Cloud

Thank you

Google Cloud