SingleStore

SingleStore: Do you need a specialized vector database?

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Specialized Database Systems

- Transaction processing
- Data warehousing
- Time series analysis
- Fulltext search
- …
- Vector search

Outline

- SingleStore Overview
- Vector Search Overview
- Vector Index at SingleStore
- Vector Search at SingleStore

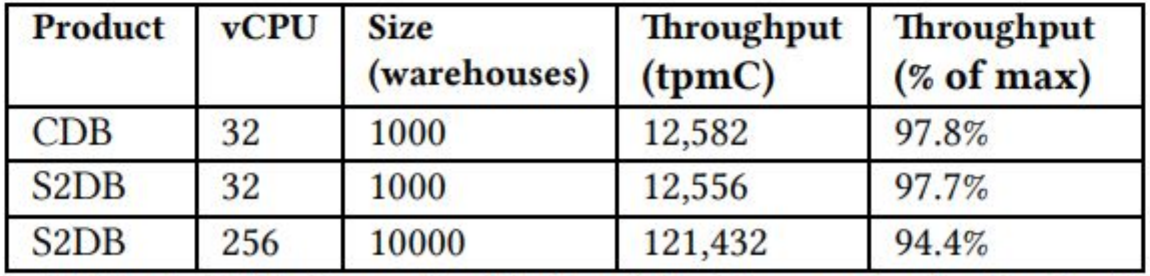
#

SingleStore Overview

What is SingleStore?

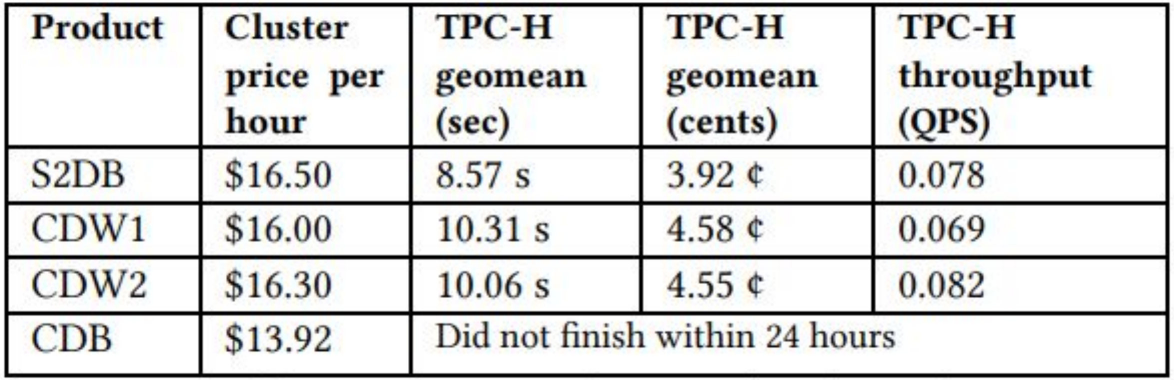
- SingleStore is a distributed general-purpose SQL database
- HTAP
  - Operational and analytical workloads
  - Can run TPC-H and TPC-DS competitively with data warehouses
  - Can run TPC-C competitively with operational databases
- Cloud-native
- Scale out to efficiently utilize 100s of hosts, 1000s of cores and 10s of TBs of RAM

Benchmarks



Product	vCPU	Size (warehouses)	Throughput (tpmC)	Throughput (% of max)
CDB	32	1000	12,582	97.8%
S2DB	32	1000	12,556	97.7%
S2DB	256	10000	121,432	94.4%

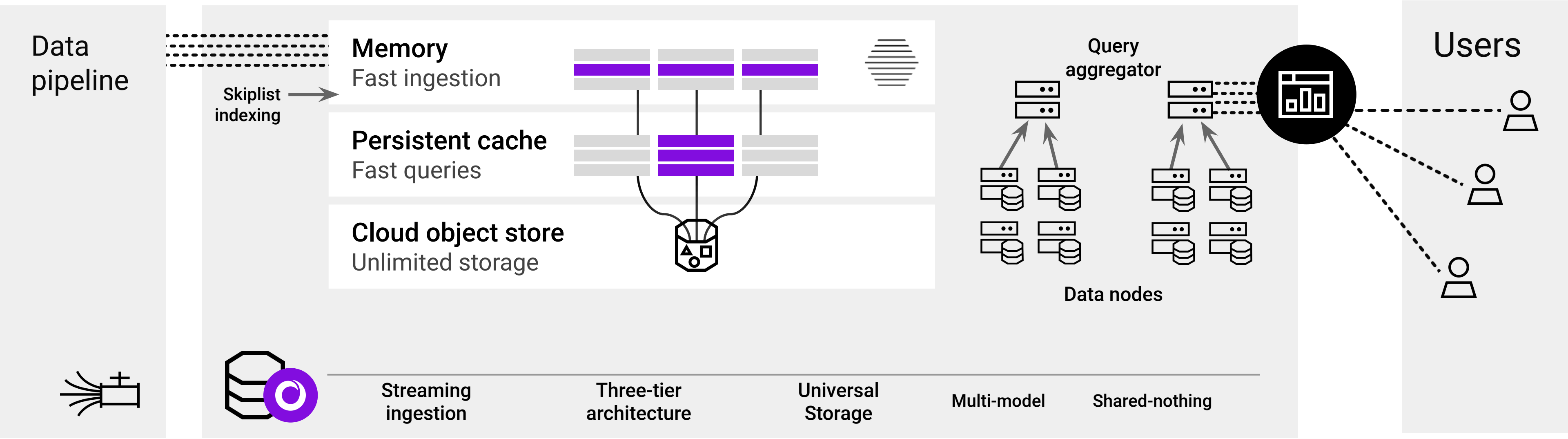
Table 1: TPC-C results (higher is better, up to the limit of 12.86 tpmC/warehouse)



Product	Cluster price per hour	TPC-H geomean (sec)	TPC-H geomean (cents)	TPC-H throughput (QPS)
S2DB	$16.50	8.57 s	3.92 ¢	0.078
CDW1	$16.00	10.31 s	4.58 ¢	0.069
CDW2	$16.30	10.06 s	4.55 ¢	0.082
CDB	$13.92	Did not finish within 24 hours		

Table 2: Summary of TPC-H (1TB) results

Product Overview



Data pipeline

Skiplist indexing

Memory
Fast ingestion

Persistent cache
Fast queries

Cloud object store
Unlimited storage

Query aggregator

Data nodes

Users

Streaming ingestion

Three-tier architecture

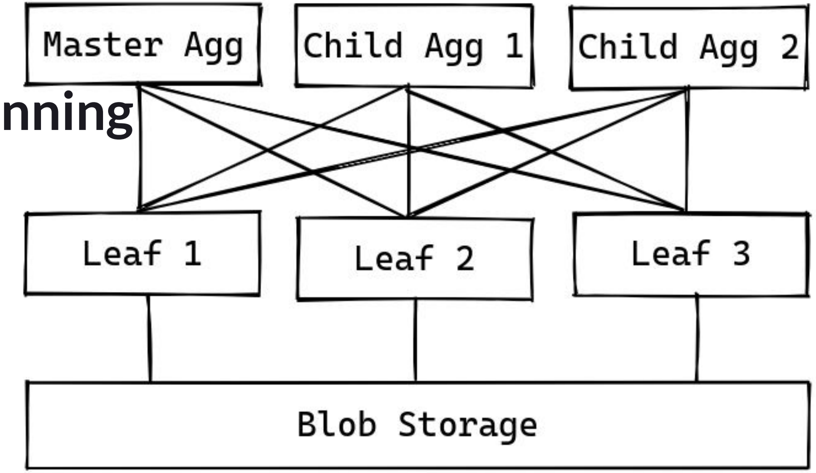
Universal Storage

Multi-model

Shared-nothing

Cluster Architecture

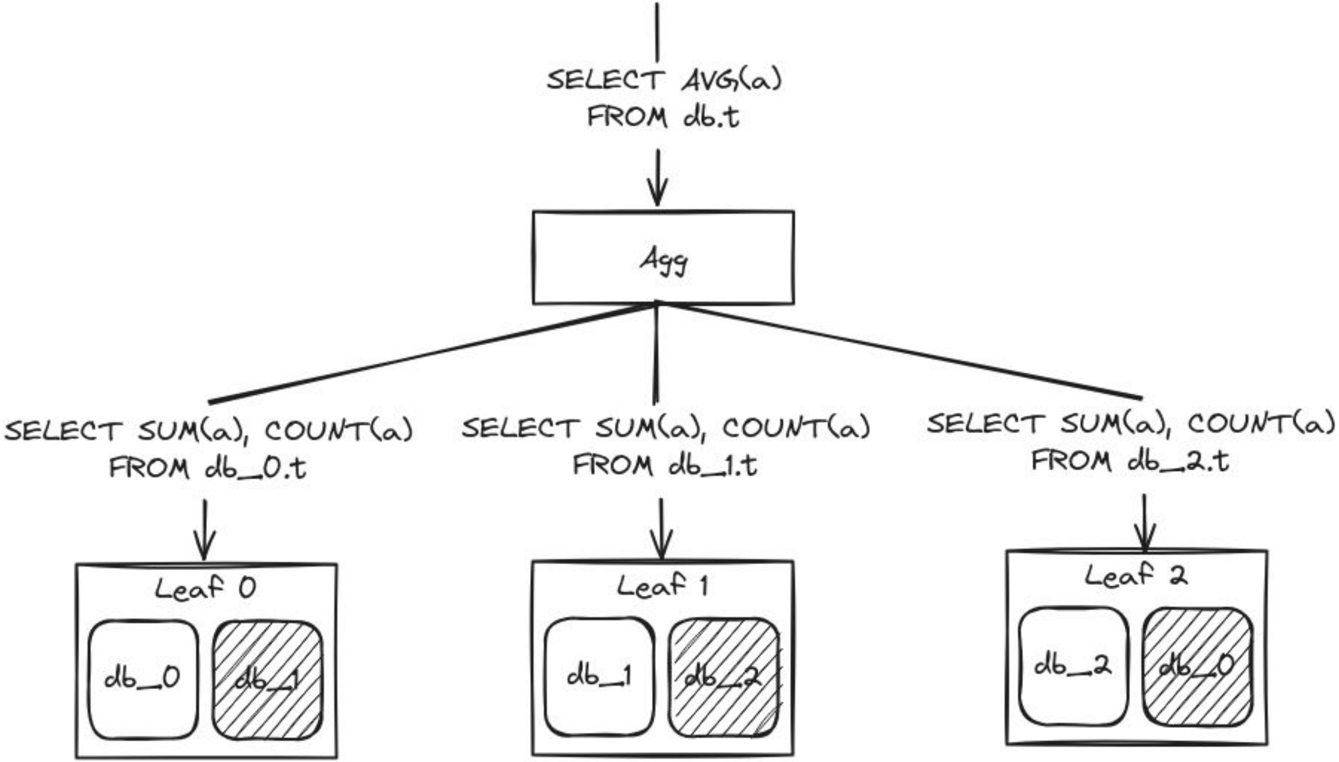
- SingleStore is a horizontally-partitioned, shared-nothing DBMS with an optional shared storage for cold data
- Aggregators
  - Clients connect to aggregators
  - Handle query optimization and planning
  - Coordinate distributed query
- Leaves
  - Perform most computation



Distributed Query Processing

- Tables are hash partitioned by shard key
- Distributed Join
  - Shard key matching, push down execution to individual partitions
  - Otherwise, redistribute data via broadcast or reshuffle
- Optimizer needs to take into account data movement cost
- Certain queries need to be transformed in order to be efficiently executed

Distributed Query Processing



Hybrid Workloads

- Analytical workloads
    - Scan 100s of millions to trillions of rows in a second
- Transactional workloads
    - Write or update millions of rows per second
- Real-time analytical workloads
    - Running analytics concurrently with high-concurrency point reads and writes

Unified Table Storage For Hybrid Workload

- Efficient for analytical workloads
- Efficient for transactional workloads
    - Operational-Optimized Columnstore

Operational-Optimized Columnstore

- On-disk columnstore LSM + in-memory rowstore segment
- Rows are first written into in-memory rowstore segment
- Flusher flushes a new segment when in-memory rowstore segment is full
- Merger merges segments
- Columnstore segments are immutable
    - `DELETE/UPDATE` mark rows as deleted in the segment

Optimized For Tiered Storage

- Immutable blobs
- No blob writes are on commit (no files either, only WAL)
- Out-of-order replication

Optimized for Analytical Workloads

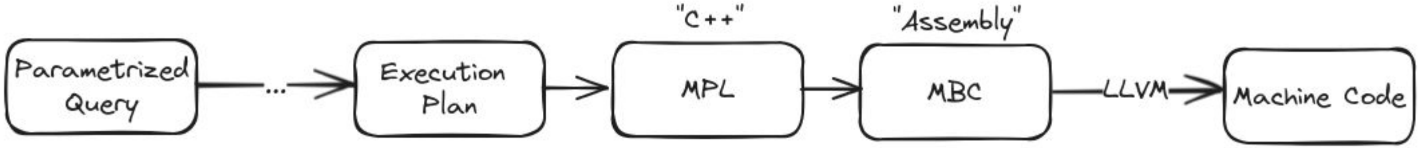
- Vectorized execution
- Encoded execution
- Late materialization

Optimized for Operational Workloads

- Seekable encoding
- Segment Elimination
  - In-memory metadata (MIN/MAX/deleted bits/…)
  - Sort key
- Secondary index
- Row-level locking

Full-Query Code Generation

- Queries are parametrized
    - SELECT a + 1 AS x FROM t WHERE b = “abc”
    - SELECT a + @ AS x FROM t WHERE b = ^
- Parameterized queries are compiled to MBC bytecodes
- Interpret MBC while compiling MBC to machine code in the background
- Switch to machine code when compilation completes



Secondary Indexes

- Common indexing approaches for LSM tree
  - External index: extra LSM tree lookup per matched row
  - Per-segment index: O(logn) write amplification
- Index generally have sub-linear search complexity
  - Searching a larger index is cheaper than several small ones
- Index LSM tree
  - Per-segment index + index merger
  - Index merger builds cross-segment indexes on multiple segments

Secondary Hash Index

- Two-level indexes
- Per-segment index
    - Posting lists: value -> [row offset]
- Cross-segment index
    - hash(value) -> [(segment id, posting list offset)]

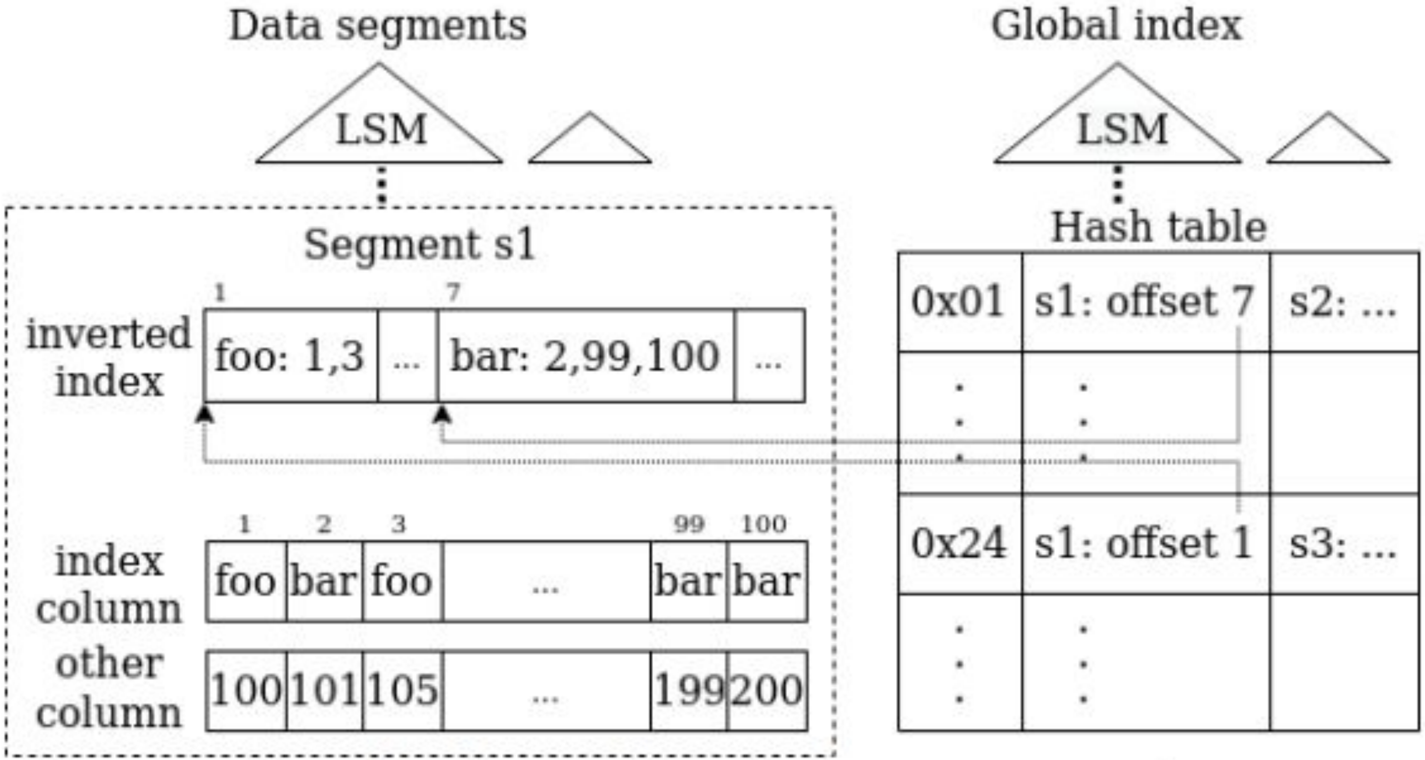


Figure 3: Two-level secondary index structure. A segment and a global hash table from the corresponding LSM trees are shown here

Unified Way To Identify A Row Efficiently

- Everything identifies a row by (segment id, row offset)
  - Columnar storage
  - Deleted bits
  - Secondary indexes
    - Hash index
    - Fulltext index
    - Row index
    - Vector index
- Can correlate between them efficiently

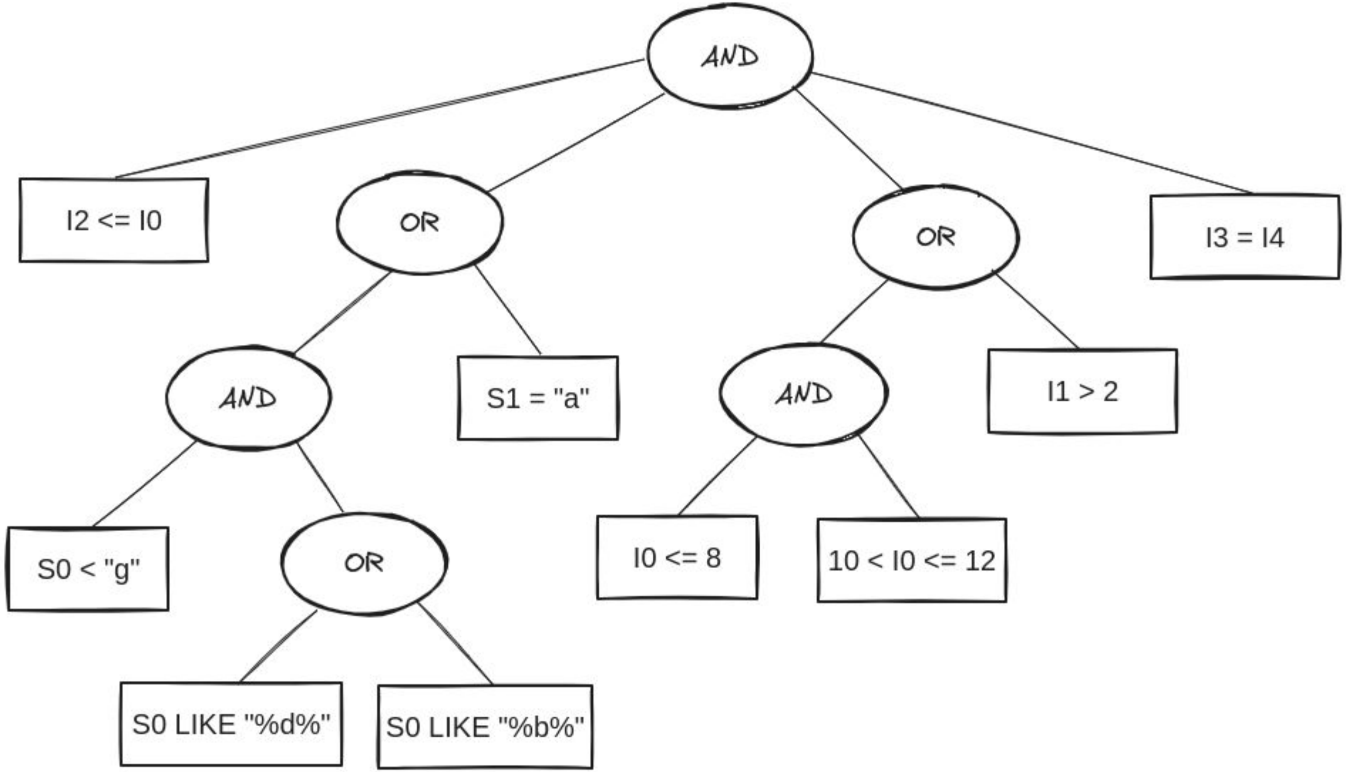
Adaptive Table Scan

- Hybrid workloads needs to combine different access methods and apply them in the optimal order
- Static decision made by optimizer doesn’t always work
    - Cost depends highly on query parameters and encodings used

Adaptive Table Scan

- Per-partition segment selection
  - segment elimination with index or MIN/MAX
- Per-segment row selection
  - filter reordering in next slide
- Per-block row projection
  - Seek or scan?
  - Use column group?
  - Selective column decoding or send encoded values upstream to AGGREGATE or JOIN

Filter Tree


AND
I2 <= I0
OR
OR
I3 = I4
AND
S1 = "a"
AND
I1 > 2
S0 < "g"
OR
I0 <= 8
10 < I0 <= 12
S0 LIKE "%d%"
S0 LIKE "%b%"

Filtering

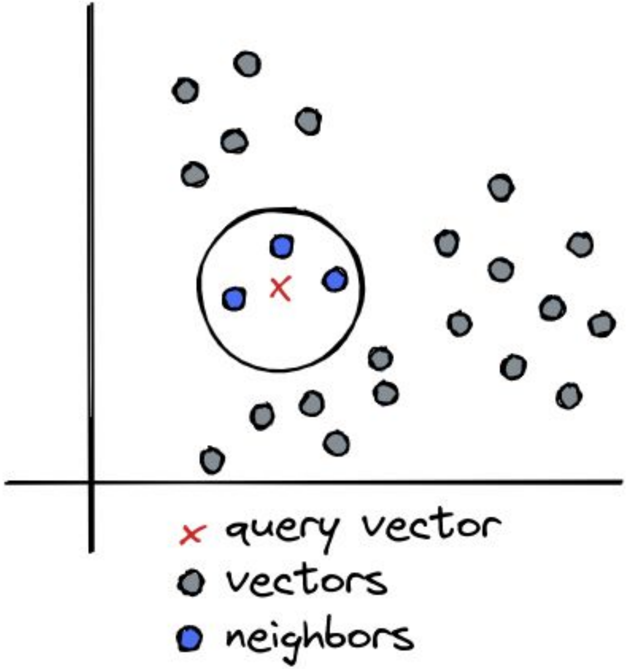
- Different ways to evaluate filters each with different tradeoffs
  - Regular filter
  - Encoded filter
  - Group filter
  - Index filter
- Adaptive filter reordering for each block
  - Each segment estimates the cost of each strategy by timing it on a small number of rows
  - Each block reorders the filters based on the cost estimate and selectivity from previous block

#

Vector Search Overview

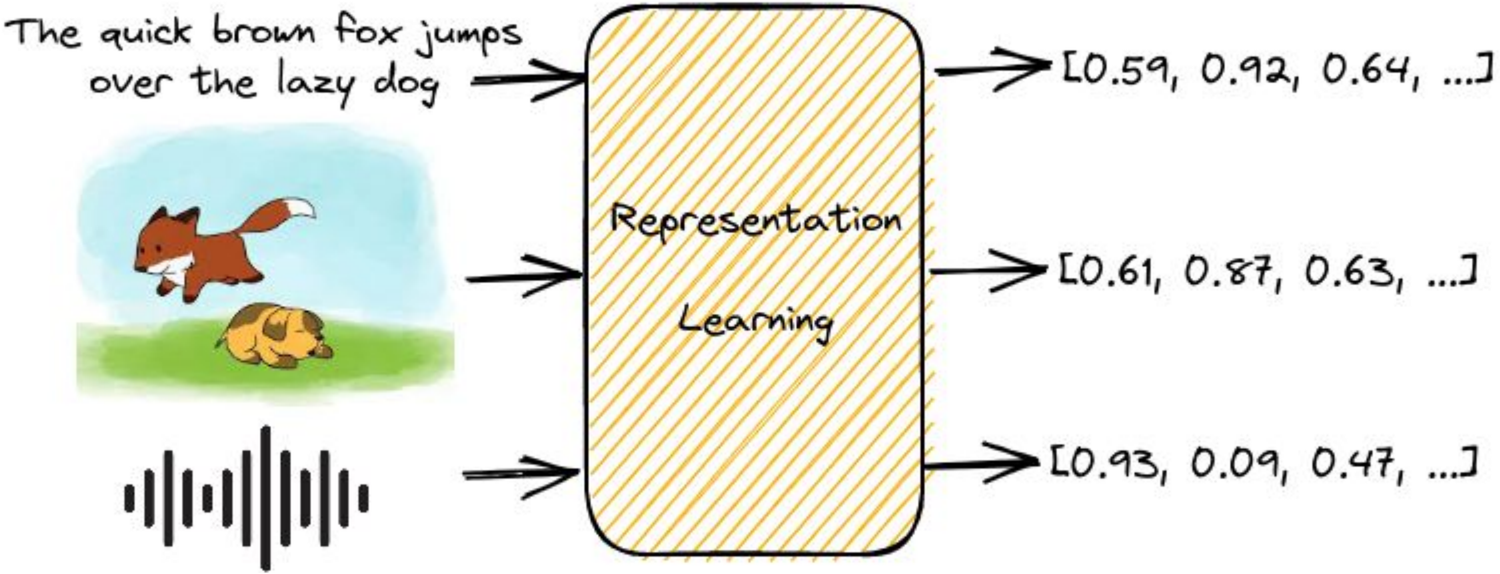
Vector Search

- Given n vectors and another query vector
- Find k nearest neighbors to the query vector
- Dense vectors in d-dimensional space
- Distance metrics
- Approximate nearest neighbors (ANN)



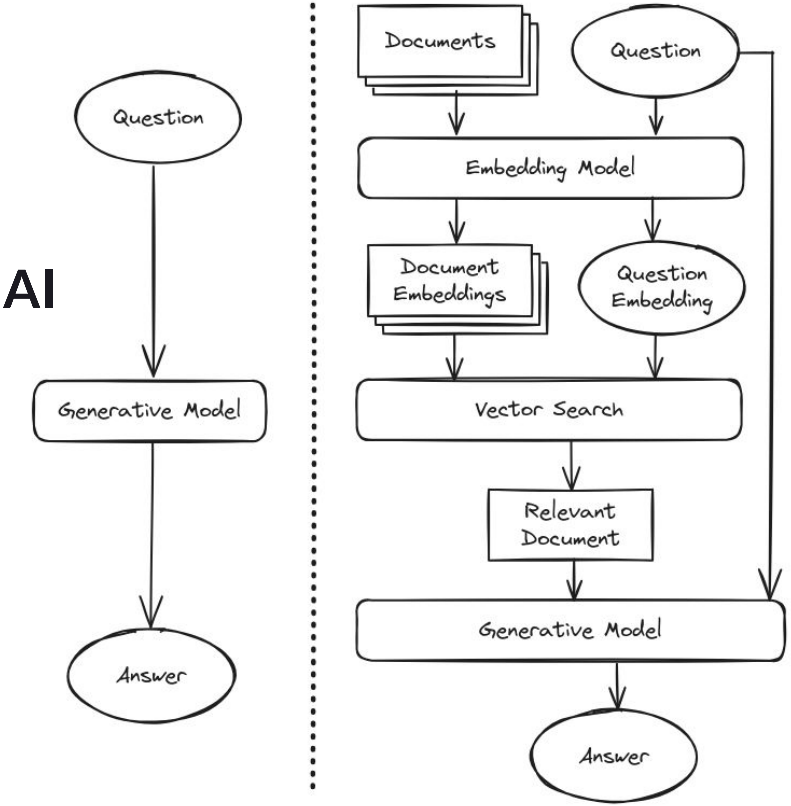
Representation Learning

- Learn to represent objects with vector embeddings
- Semantic similar objects are closer to each other



Retrieval Augmented Generation (RAG)

- LLMs are inefficient and costly to train/fine-tune
- RAG as a cost-efficient approach to GenAI
  - Up-to-date knowledge
  - Domain-specific knowledge
  - Source citation



SingleStore

Vector Search vs Fulltext Search

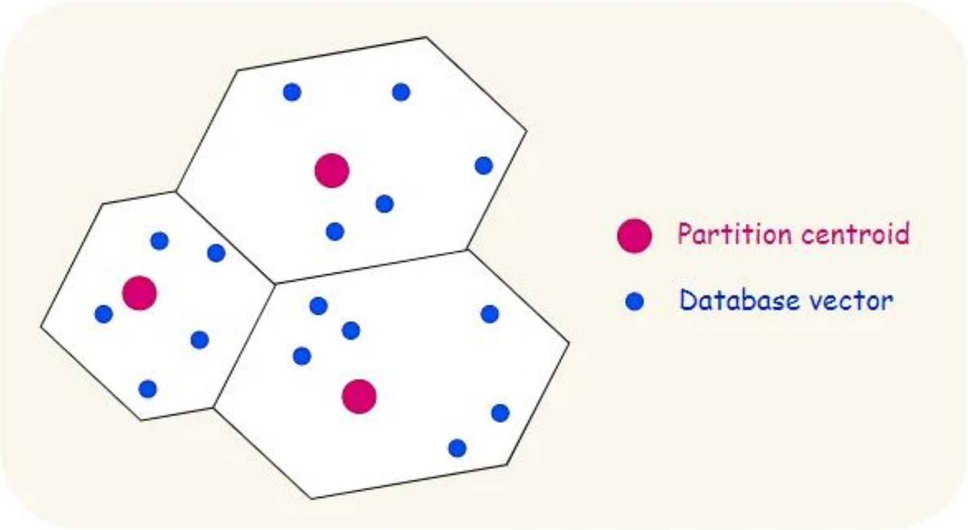
- Fulltext search relies on keyword matching and can’t capture semantics
  - I like apple
  - I don’t like apple
  - I don’t dislike the fruit company
- Vector search can be multimodal: text, image, audio, video etc
- Vector search is more computationally costly

Vector Index Algorithms

- Tree-Based: KD-Tree
- Hash-Based
- Quantization-Based: IVF, SPANN
- Graph-Based: HNSW, DiskANN, CAGRA

Inverted File (IVF)

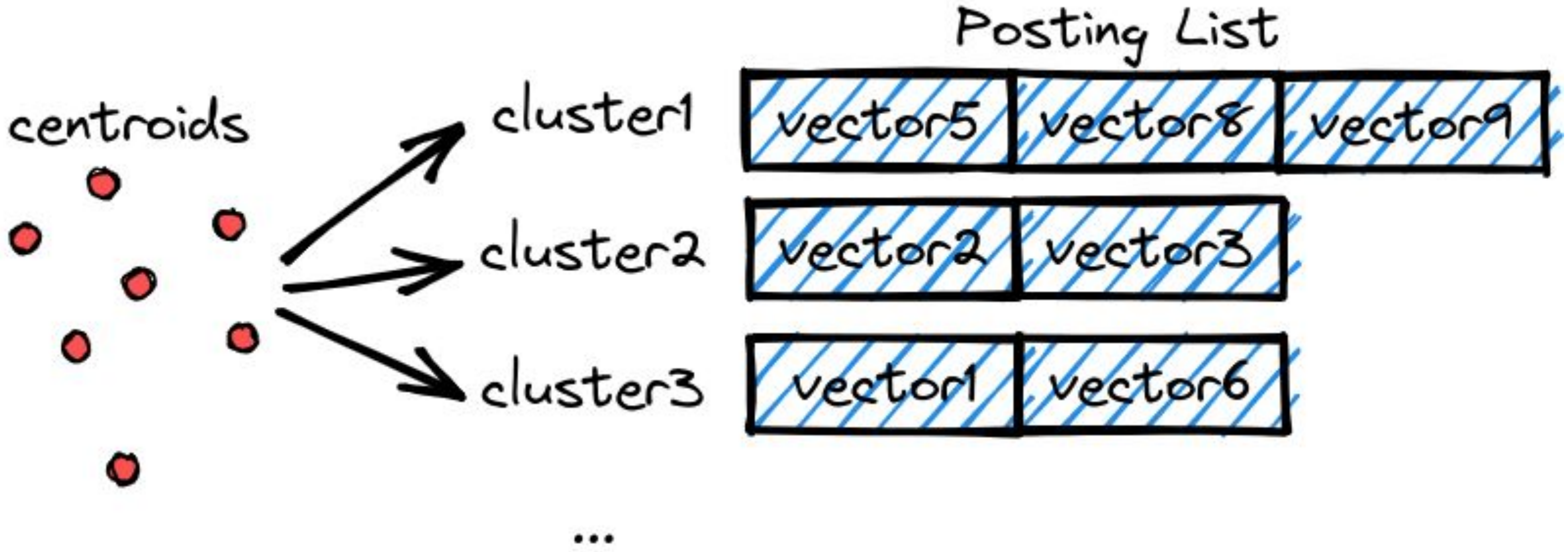
- Partition vectors into clusters
- Use the centroids to represent each cluster



Credit: Pinecone

Inverted File (IVF)

- Build an inverted index from clusters to vectors

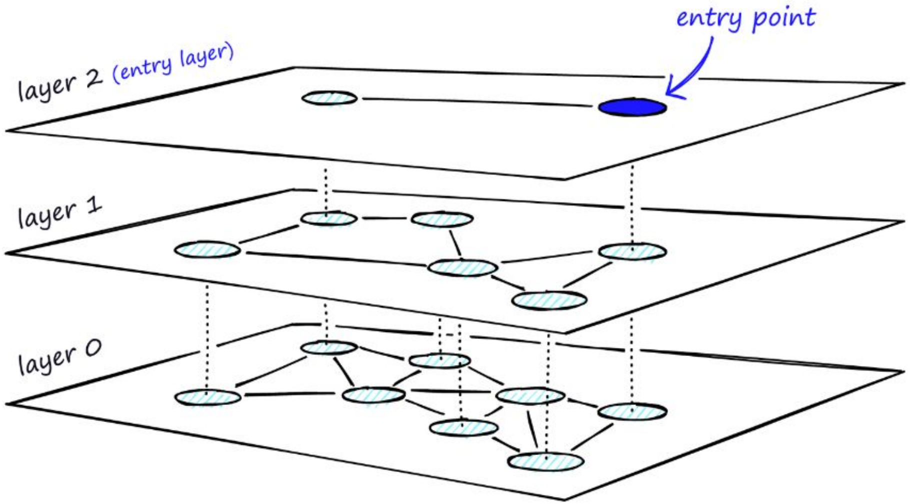


Inverted File (IVF): Search

- Find nearby centroids to the query vector
- Only search within nearby clusters

Hierarchical Navigable Small World (HNSW)

- Skiplist over proximity graph
- Each node is only connected to a small number of neighbors
- Greedy search starts from coarsest layer and refine with finer layers



Credit: Pinecone

IVF vs HNSW

- HNSW has higher recall
- HNSW is faster to search
    - O(logn) vs O(sqrt(n))
- IVF is faster to build
- IVF has much smaller index size

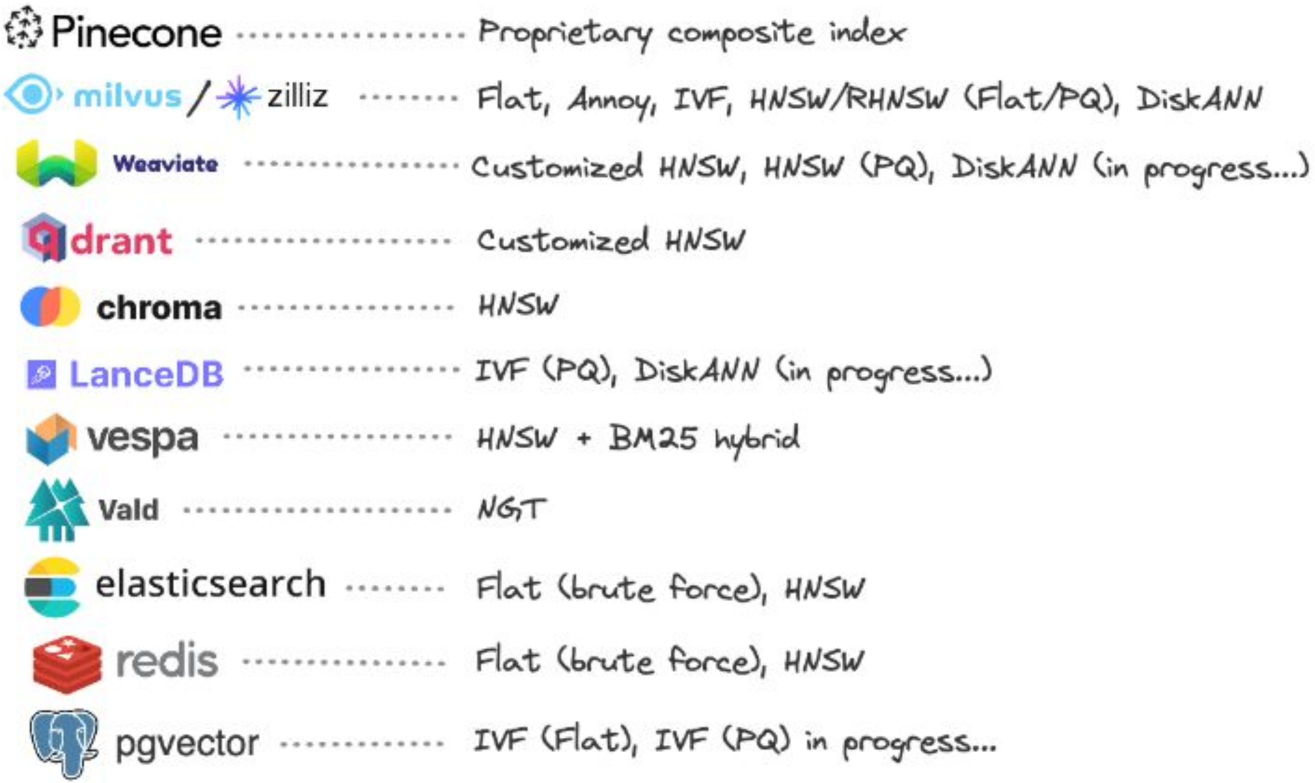
Product Quantization (PQ)

- Vector compression technique that applies to various algorithms
  - IVF_PQ
  - HNSW_PQ
- Not only saves space, but also speeds up distance computation
- Even faster with PQ Fast Scan
- Compression is lossy so need to refine the results for better recall

Index Composition

- In IVF, searching nearest centroids is yet another ANN
- Can build another vector index on centroids: IVF + HNSW
  - Centroids are much smaller
  - Searching nearest centroids requires very high recall

Vector Search Offerings (08/19/2023)



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...

Credit: https://thedataquarry.com/posts/vector-db-4/

#

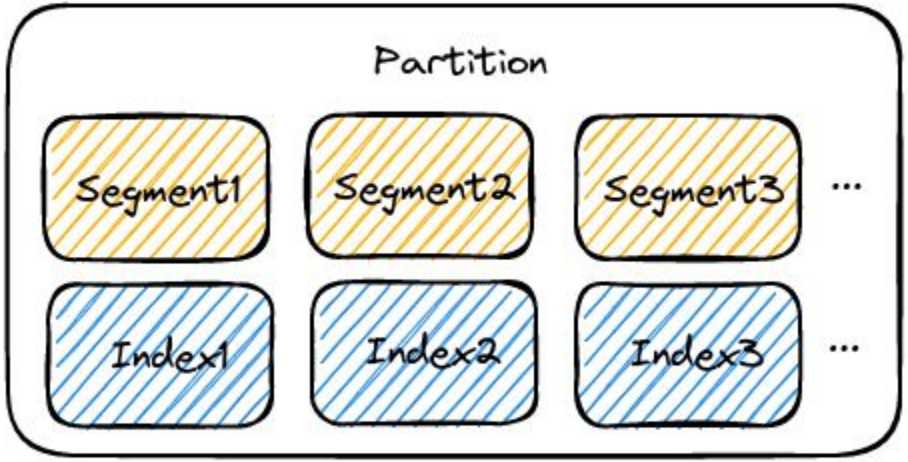
Vector Index at SingleStore

Overview

- On-disk columnstore LSM + in-memory rowstore segment
- In-memory rowstore segment is small
    - No vector index, just full scan
- Build vector index for on-disk columnstore LSM
    - Per-segment vector index + vector index merger

Per-Segment Vector Index

- Background flusher/merger create a new vector index for each new segment created
- ALTER TABLE creates a new vector index for each segment
- If too many rows are deleted in a segment, its vector index gets rebuild



Vector Index Merger

- Vector indexes have sub-linear search complexity
    - Searching a larger index is cheaper than several small indexes
- Vector index LSM tree
    - Build cross-segment vector indexes on multiple segments
- Vector index is expensive to build so O(logn) write amplification due to merge can be significant
    - Merge only cold data

Pluggable Vector Index Algorithms

- We are using vector index algorithm as a black box
- This allows us to plug in any vector index algorithm
- In 8.5, we support many popular in-memory vector index algorithms:
  - IVF_FLAT, IVF_PQ, IVF_PQFS
  - HNSW_FLAT, HNSW_PQ
- Post 8.5, we are planning to support on-disk vector index algorithms
- Vector index can be built in an external service
  - Build vector index on GPU

Auto Vector Index

- It’s hard for average users to pick which vector index algorithm to use and to tune various parameters for the given algorithm
- Note that our vector index is always build on immutable data
- We can make smart decision for the users
- The user just need to tell us what the requirements are
    - High-recall
    - Cost-effective

#

Vector Search at SingleStore

Example 1: ANN

```
SELECT
  t.v <-> vector AS d
FROM t
ORDER BY d
LIMIT k;
```

ORDER BY … LIMIT Pushdown

- Agg already pushes down `ORDER BY … LIMIT` to leaves
  - Currently `Merge TopSort`, but we can prob do better
- Leaf pushes down `ORDER BY … LIMIT` to table scan as a `Top` filter

Example 1: ANN

```
Project [t.v <-> vector AS d]
TopSort limit:k [t.v <-> vector]
ColumnStoreFilter [Top(t.v <-> vector, k) index]
ColumnStoreScan t
```

Example 1: ANN

- Per-partition segment selection
  - Scan all vector indexes within the partition and select top-k for the entire partition
  - Select segments that contain these top-k rows
- Per-segment row selection
  - `Top` filter evaluates to true iff the row is selected above
- Per-block row projection

Example 2: Pre-Filtered ANN

```
SELECT
  t.v <-> vector AS d
FROM t
WHERE <filters>
ORDER BY d
LIMIT k;
```

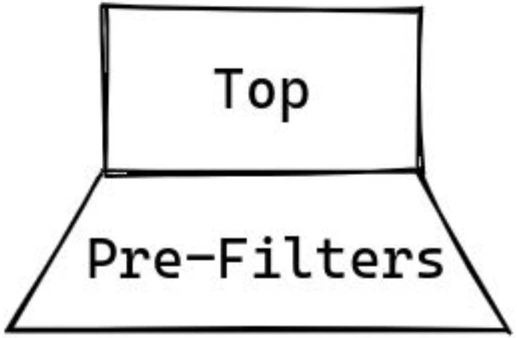
Pre-Filters

- If `<filters>` are executed after vector index scan
  - There will be less rows after filters
  - We can let vector index scan to output more rows at the beginning, but in practice it's very hard to predict
- `<filters>` need to be executed before vector index scan
  - Make vector index filter aware of its pre-filters

Example 2: Pre-Filtered ANN

```
Project [t.v <-> vector AS d]
TopSort limit:k [t.v <-> vector]
ColumnStoreFilter [Top(t.v <-> vector, <filters>, k) index]
ColumnStoreScan t
```

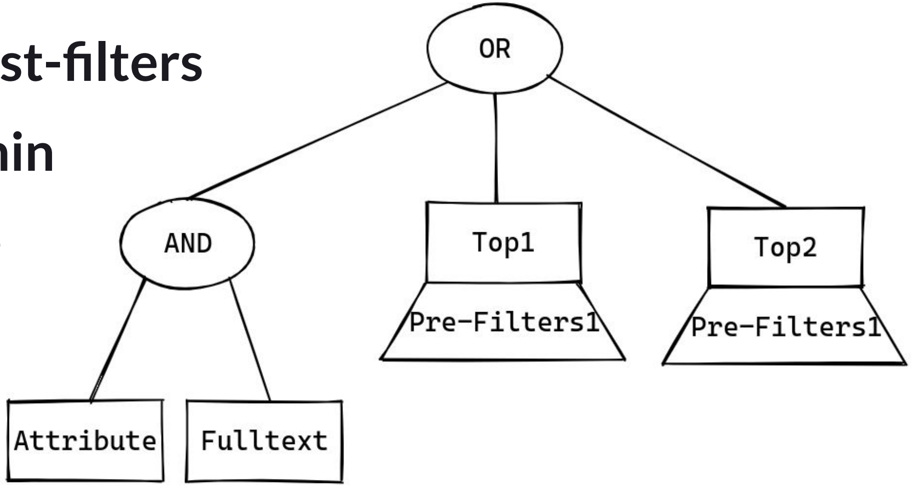
Example 2: Pre-Filtered ANN



- Per-partition segment selection
  a. Segment elimination with pre-filters
  b. Scan all vector indexes within the filtered segments and select top-l for the entire partition
  c. Run pre-filters on these top-l rows
    - If there are at least k output rows, select top-k.
    - If there are less than k output rows
      - Either retry b with a larger l
      - Or fall back to not using vector index scan

Top Filter

- `Top(expr, <filters>, k)` **is** `true` **iff** `expr` **of this row ranks within the top-**`k` **among all the rows that pass** `<filters>`
- `Top` **filter is just a regular leaf node in the filter tree**
- **Can have many** `Top` **filters in the filter tree with different pre-filters**
- **Filters outside of** `Top` **filter are post-filters**
- **Filter reordering can happen within pre-filter tree and post-filter tree**
- **Retry happens within** `Top` **filter**



Example 3: Join

```
SELECT
  t.v <-> vector AS d
FROM t JOIN s
ON t.id = s.id
WHERE <s.filters>
ORDER BY d
LIMIT k;
```

Example 3: Join

```
Project [t.v <-> vector AS d]
TopSort limit:k [t.v <-> vector]
HashJoin
|---HashTableProbe [t.id = s.id]
|   HashTableBuild alias s
|   ColumnStoreFilter [<s.filter>]
|   ColumnStoreScan s
ColumnStoreFilter [Top(t.v <-> vector, t.id = s.id, k) join index]
ColumnStoreScan t
```

Example 4: Combining Fulltext and Vector Search

- Each query contains multiple subqueries
- Each subquery has its own type: fulltext or knn
- For a given row
    - Each subquery produces a score
    - The final score is a weighted sum of all individual scores
- The query selects rows with the highest final score

Example 4: Combining Fulltext and Vector Search

- Execute each subquery individually as a filter to select rows that have a positive score for that subquery
- Union all rows selected by each subquery
- Compute the final score for all rows in Step 2 and output the highest ones

Example 4: Combining Fulltext and Vector Search

```
SELECT
  MATCH(t.s) AGAINST (‘pattern’) AS score1,
  t.v <-> vector AS score2
FROM t
WHERE <filters>
ORDER BY weight1 * score1 + weight2 * score2
LIMIT k;
```

Example 4: Combining Fulltext and Vector Search

```
Project [
    MATCH(t.s) AGAINST (‘pattern’) AS score1,
    t.v <-> vector AS score2]
TopSort limit:k [weight1 * score1 + weight2 * score2]
ColumnStoreFilter [
    (<filters> AND MATCH(t.a) AGAINST (‘pattern’) index) OR
    Top(t.v <-> vector, <filters>, k) index]
ColumnStoreScan t
```

More Examples

- Vector index join
- Cross apply
  - Batched workload, good for GPU

Other Vector Index Filters

- Vector range search
  - `t.v <-> vector > threshold`
- Maximal Marginal Relevance (MMR)
  - Representatives of nearest neighbors
  - New neighbor can’t be too close to previously selected neighbors

SingleStore

Thank You