GaussDB-Vector:
A Large-Scale Persistent Real-Time Vector Database for LLM Applications

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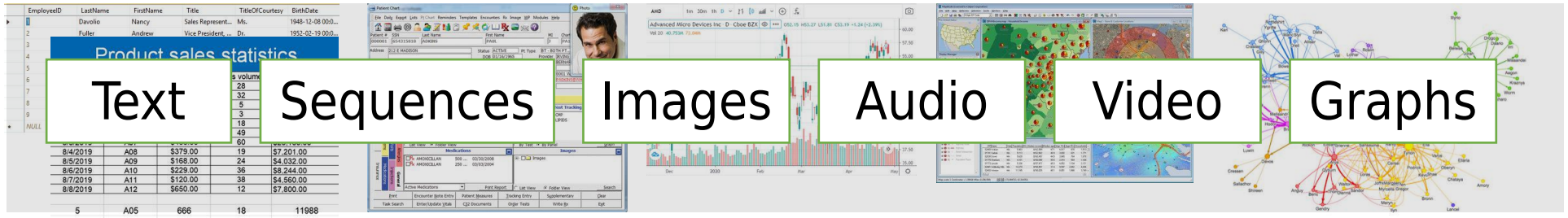
Embeddings: Building Blocks of Future

More and more applications rely on embedding vectors that are retrieved via similarity search

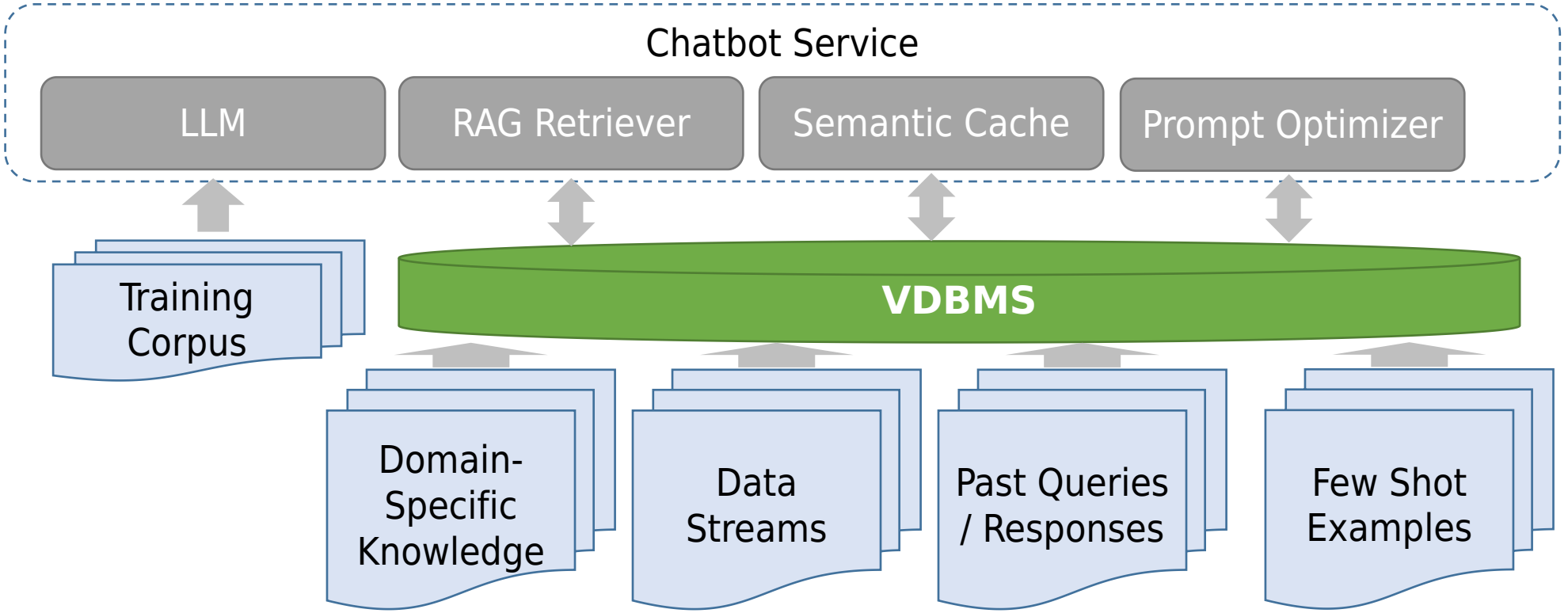
Forecasting
Classification
RecSys
Pattern Recognition
Reinforcement Learning
Object Detection
Semantic Retrieval
Segmentation
Generation

DeepMind
Hugging Face
OpenAI

MiniLM-L6
MPNet-Base
ResNet-50
CLIP VIT
Whisper
Multimodal Receiver



Vector Databases and LLMs



Search Capabilities	Performance	Quality	System-Level Features
• Support various queries, e.g. k-NN, Range NN, Predicated (Filtered) Search	• Low latency queries • High throughput • Memory efficient	• High recall • High semantic relevance	• Scalable • Available • Elastic • Consistent • Persistent

Vector Databases: Key Challenges

More and more applications rely on embedding vectors that are retrieved via similarity search

Goal: Store embeddings in a DB and retrieve for whatever downstream task

1) ***<u>Size</u>: Existing hardware not for large data units***
2) ***<u>Structure</u>: Lack of structure (e.g. attrs) makes embeddings hard to index***

Performance

- **Latency**
  - Fundamentally high I/O due to more frequent paging
  - Naive disk-resident HNSW is not I/O optimal
  - High latency of filtered search

Quality

- **Recall**
  - Accuracy degradation of IVF due to data drift following updates

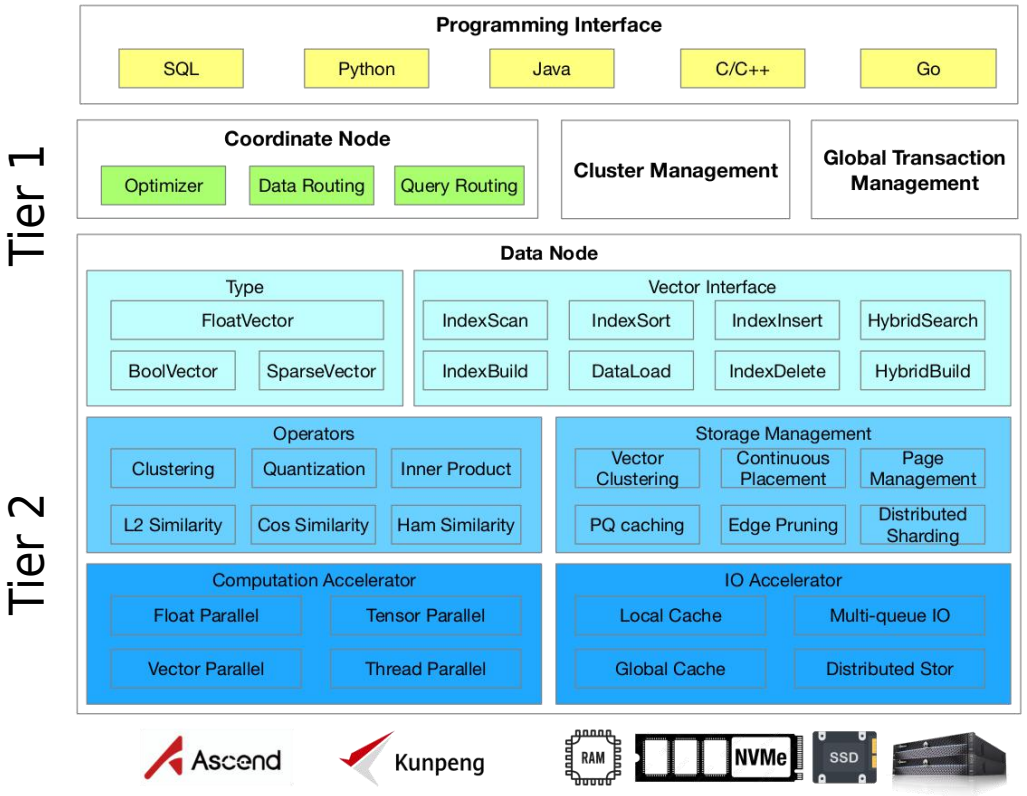
System-Level Features

- **Scalability**
  - Unclear sharding and query routing strategy for distributed deployments

GaussDB-Vector

Build a distributed persistent real-time database based on IVF & DiskANN

- ***Architecture*: Two-Tiered Distributed Database to provide scalability / availability**
- ***Techniques*: IVF & DiskANN but make it easier to build, update, and search**



Index Storage & Construction

- Two-Phase Neighborhood Pruning
- **Tailored Storage Structures to reduce I/O**
- **Data Sharding with Drift Detection & Auto Rebalancing**
- **Balanced Tree Hybrid Index**

Search

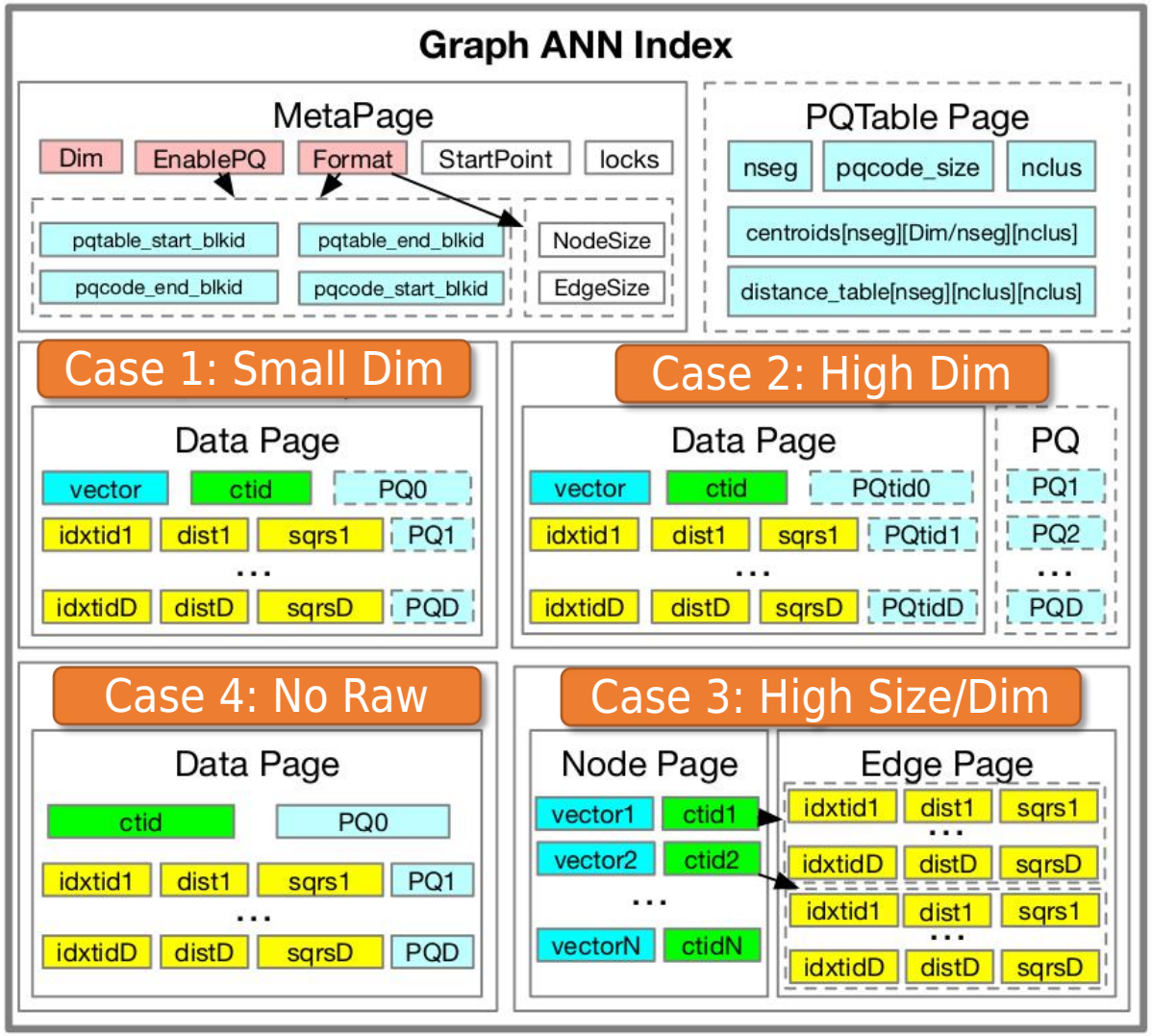
- Hot Nodes Buffering
- **Cardinality-Based Query Routing for Distributed Search**
- I/O Efficient Search Algorithms

Update

- Asynchronous Delete
- **Incremental Index Updates for data freshness**

Tailored Storage Structures

Use Tailored Storage Structures based on dataset size/dimensions to reduce I/O



Case 1: Small Dimensionality

- Raw Vectors + PQ Codes stored together
- Each node is stored with all its neighbors on a single page to reduce I/O during neighborhood scan

Case 2: High Dimensionality

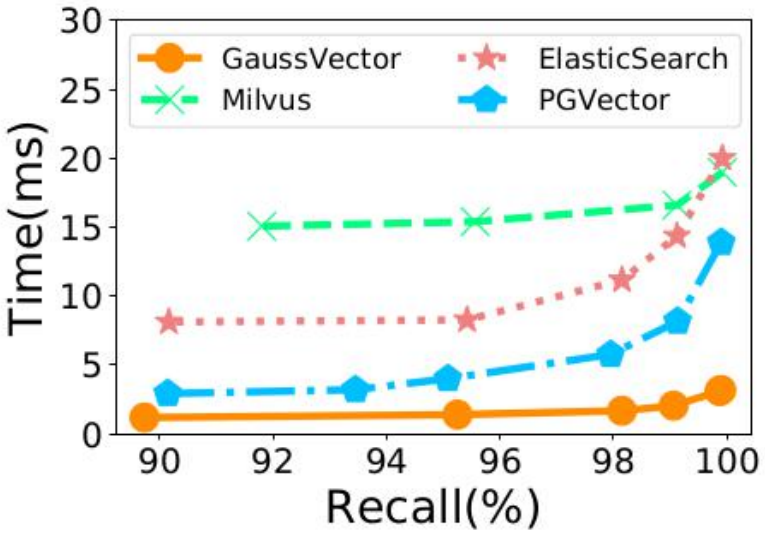
- Raw Vectors are too large and cannot be stored together with PQ Codes
- PQ Codes stored in separately pages and cached in memory

Case 3: High Size/Dimensionality

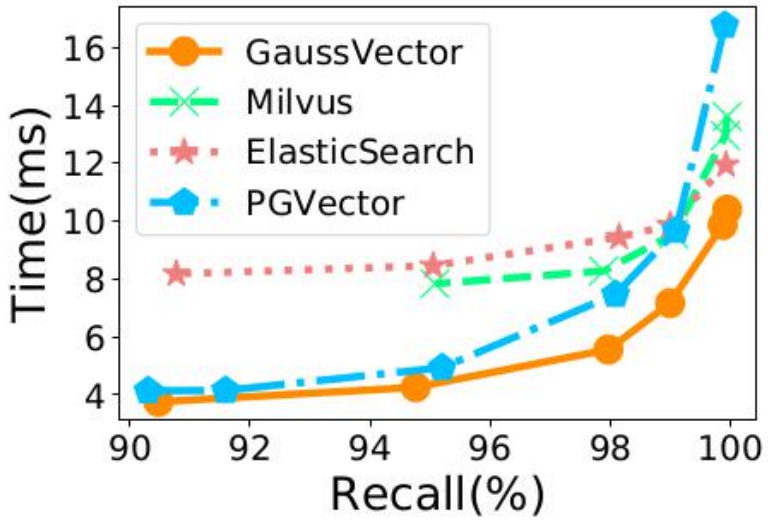
- Raw Vectors are too large and cannot be stored with PQ Codes nor Neighbors
- Store Nodes and Neighborhoods separately

Tailored Storage Structures

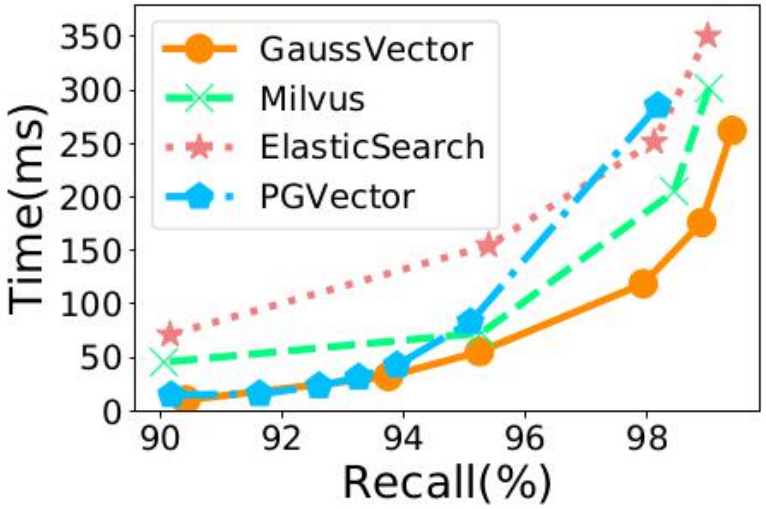
Use Tailored Storage Structures based on dataset size/dimensions to reduce I/O



(a) SIFT dataset.



(b) GIST dataset.



(c) HUAWEINet dataset.

Case 1: Small Dim

ElasticSearch & Milvus require loading multiple disk segments into memory

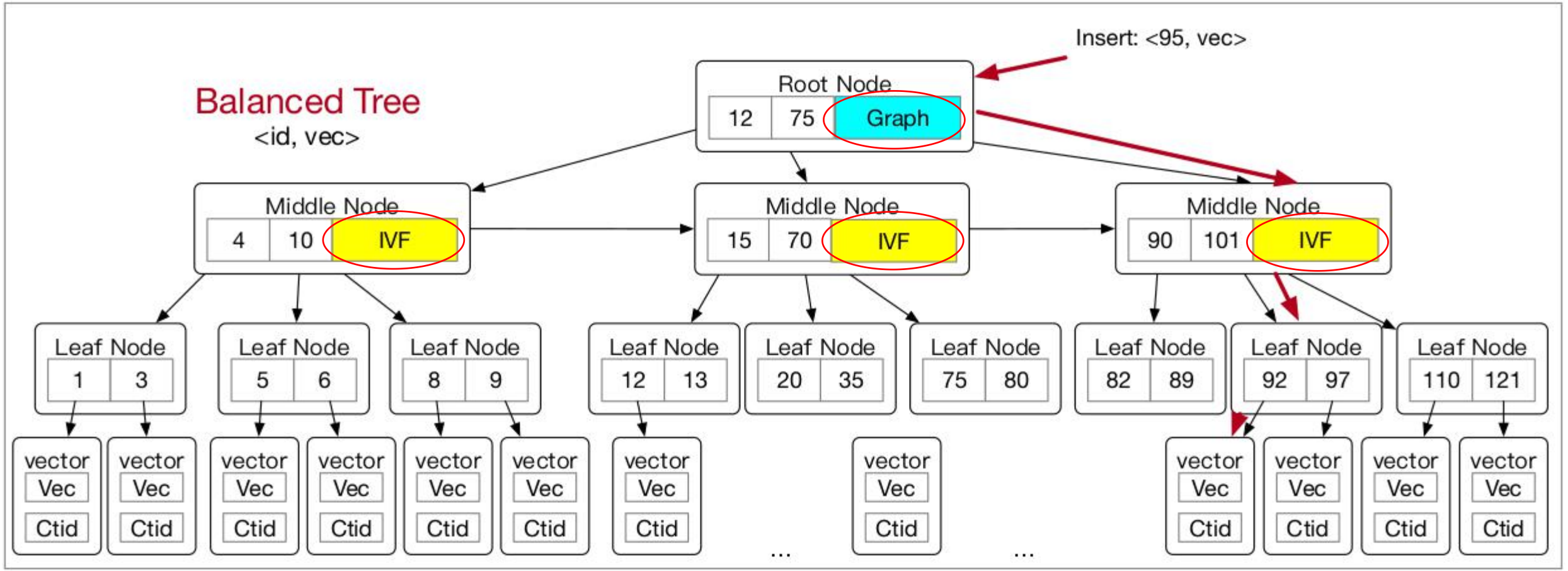
Case 2: High Dim

GaussDB-Vector adapts to high-dim scenarios to maintain high search performance

Balanced Tree Hybrid Index

Use Balanced Tree with intermediate sub-indexes to support fast pre- / single-stage filtering

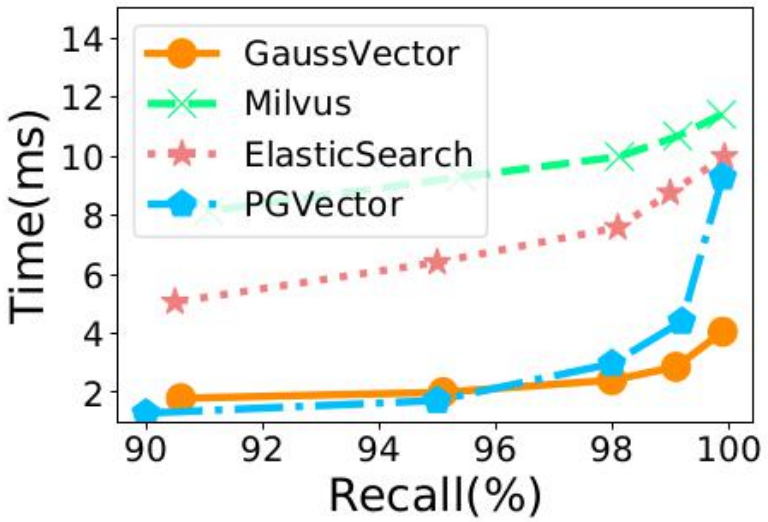
- ***High Selectivity** (few satisfying records): Sequential Scan over leaf nodes*
- ***Low Selectivity** (many satisfying records): Single-Stage Scan over sub-indexes*



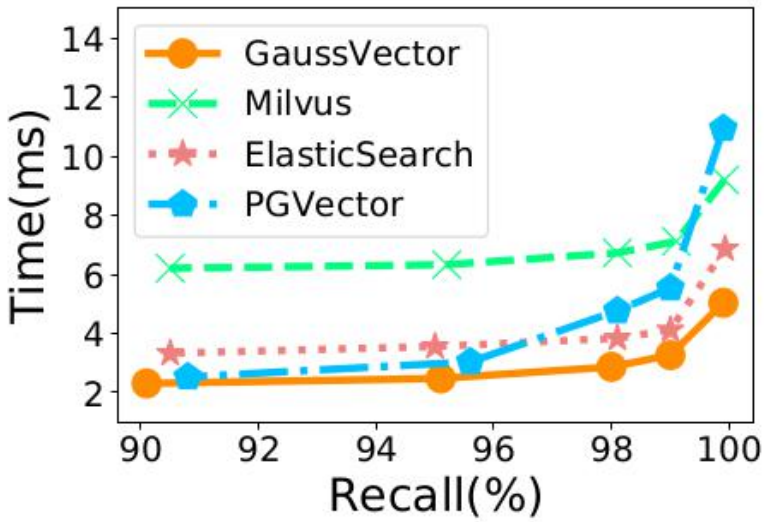
Balanced Tree Hybrid Index

Use Balanced Tree with intermediate sub-indexes to support fast pre- / single-stage filtering

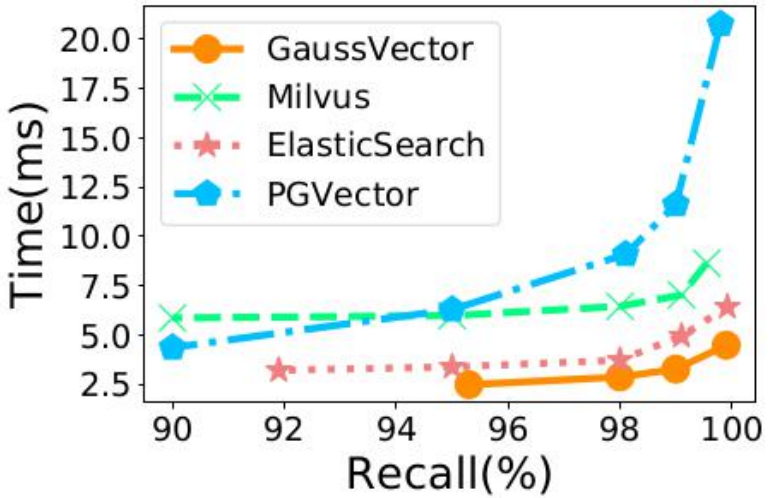
- ***High Selectivity* (few satisfying records): Sequential Scan over leaf nodes**
- ***Low Selectivity* (many satisfying records): Single-Stage Scan over sub-indexes**



(a) SIFT dataset, 90% scalar selectivity.



(b) SIFT dataset, 50% scalar selectivity.



(c) SIFT dataset, 10% scalar selectivity.

Many Satisfying Records

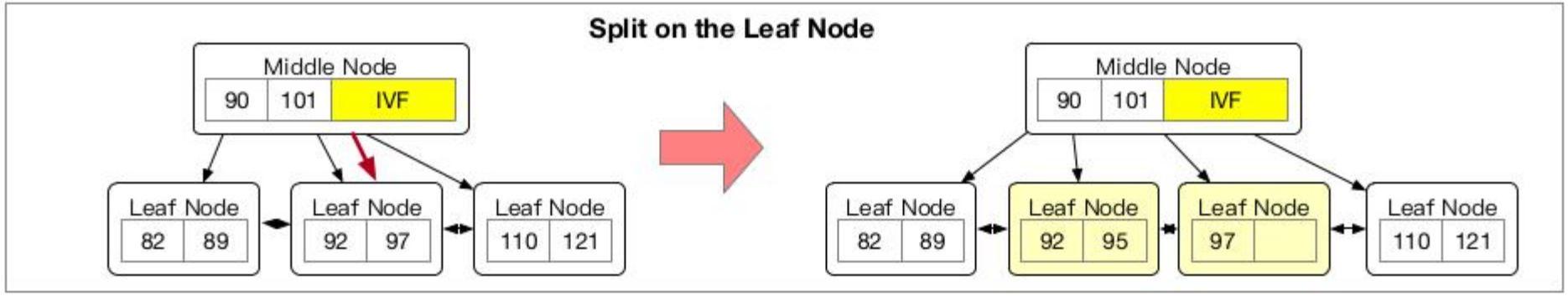
ElasticSearch & Milvus require merging across many segments

Few Satisfying Records

Pre-Filtering via index followed by Sequential Scan beats single-stage scan over segments

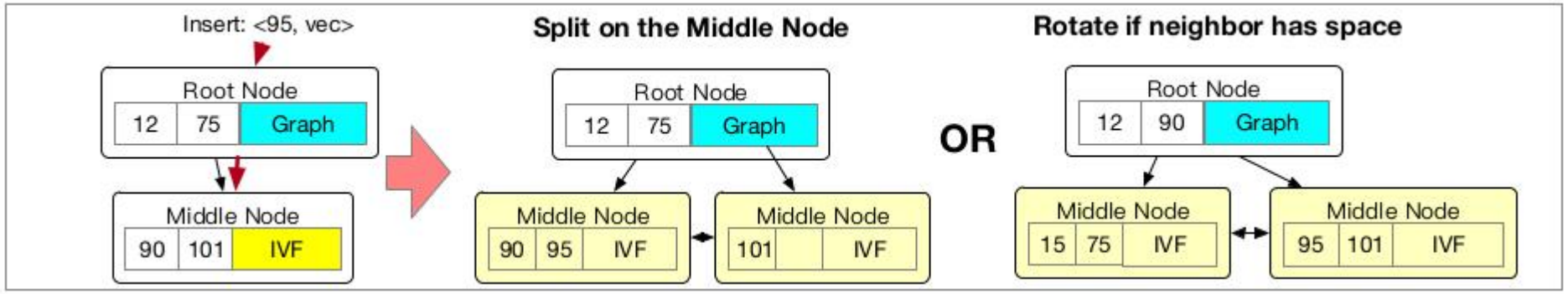
Incremental Index Updates

Balanced Tree with intermediate sub-indexes enables incremental updates for data freshness



Leaf node split requires no index update

(a) Splitting a leaf node following an insert

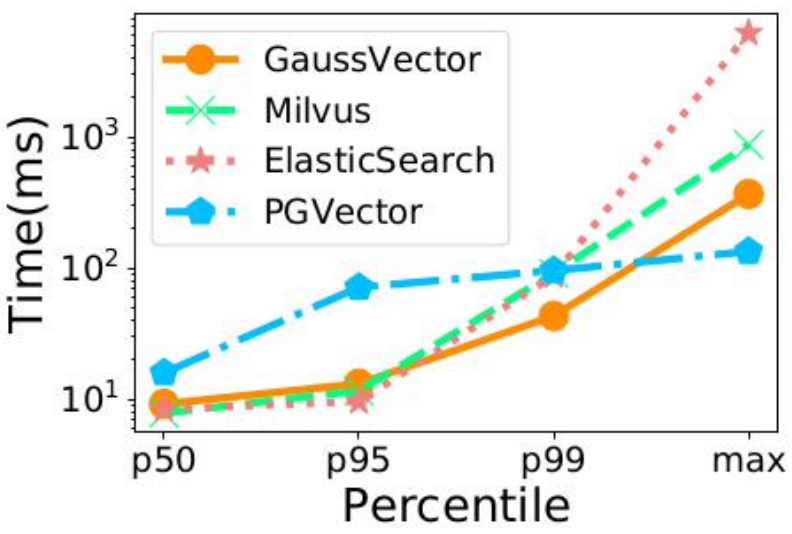


Inner node with IVF index is easy to update

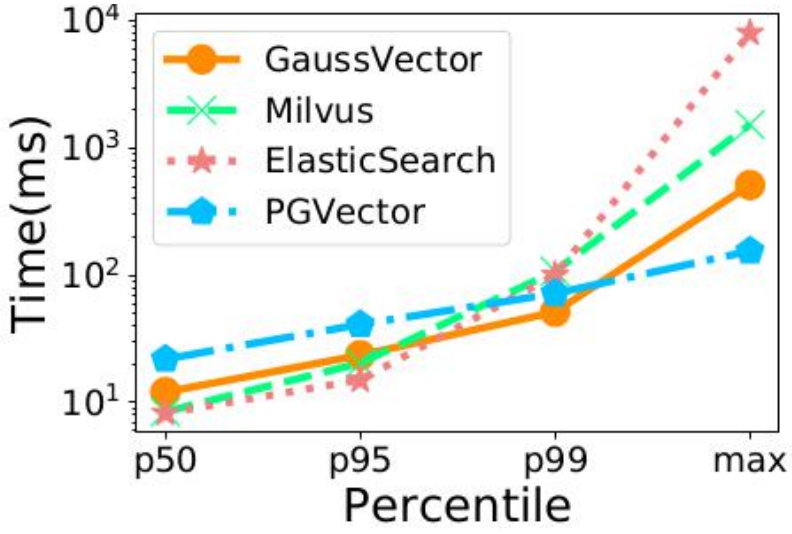
(b) Splitting an inner node following an insert

Incremental Index Updates

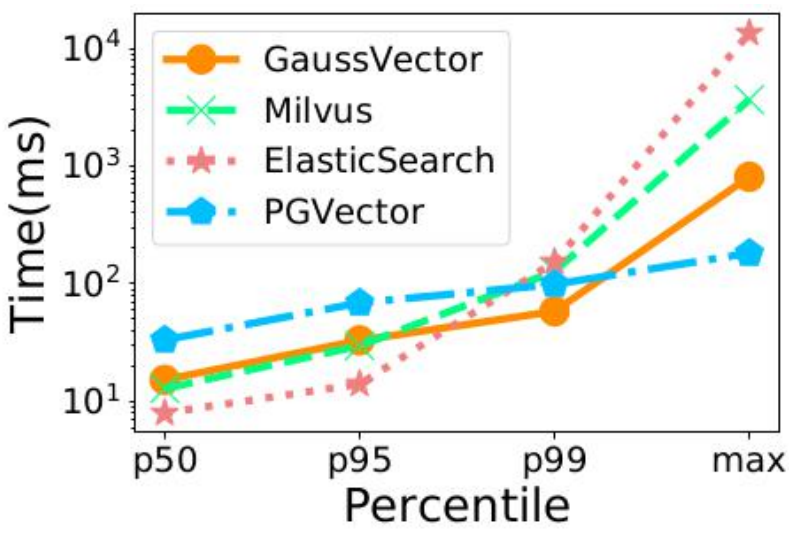
Balanced Tree with intermediate sub-indexes enables incremental updates for data freshness



(a) SIFT dataset.



(b) GIST dataset.

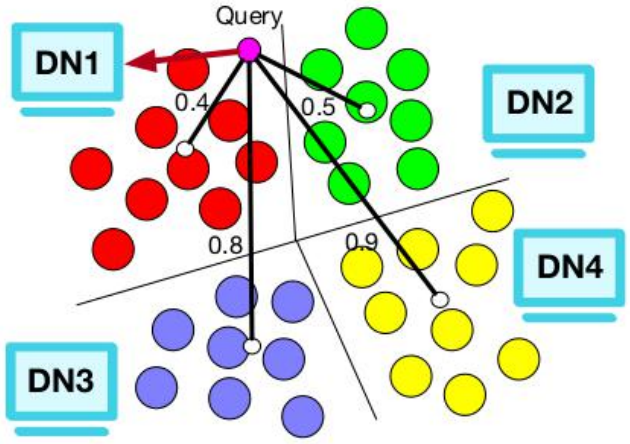


(c) HUAWEINet dataset.

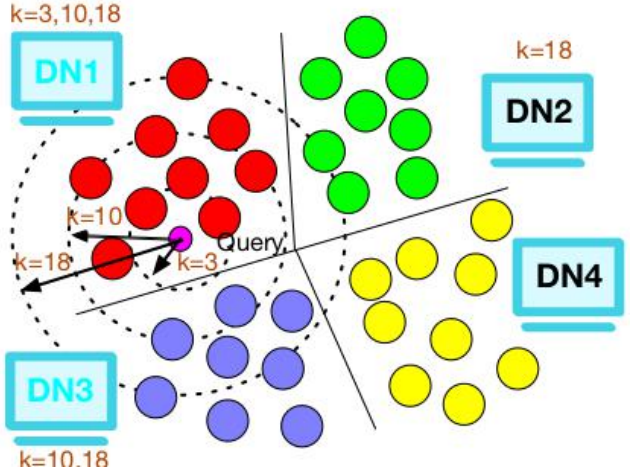
- Large max latency due to inner node / root node splits but otherwise competitive with baselines
- Insert / search latency balanced by adjusting indexing granularity

Data Sharding & Distributed Search

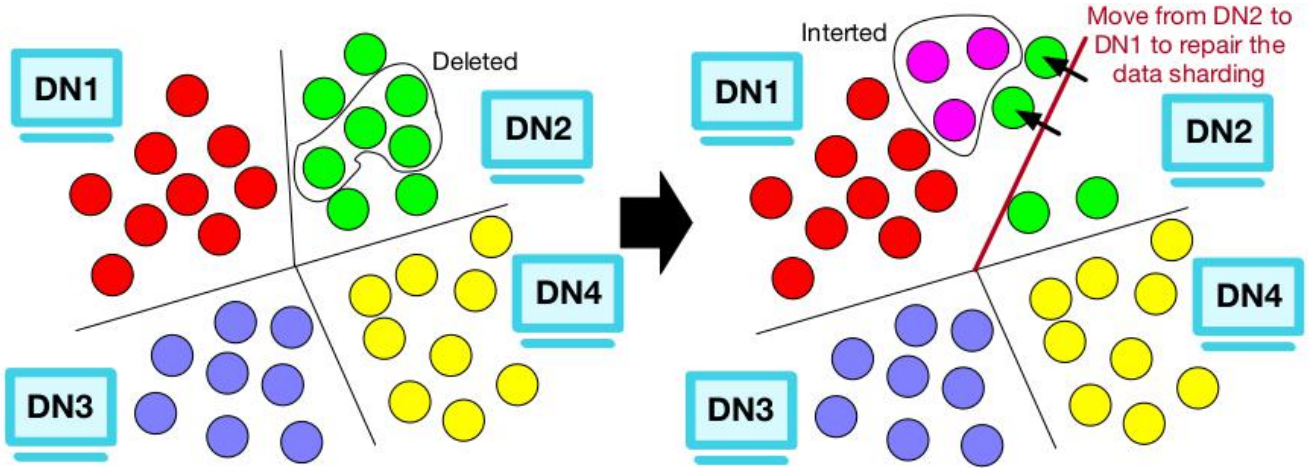
Balanced Tree with intermediate sub-indexes enables incremental updates for data freshness



(a) Insert into Nearest Shard



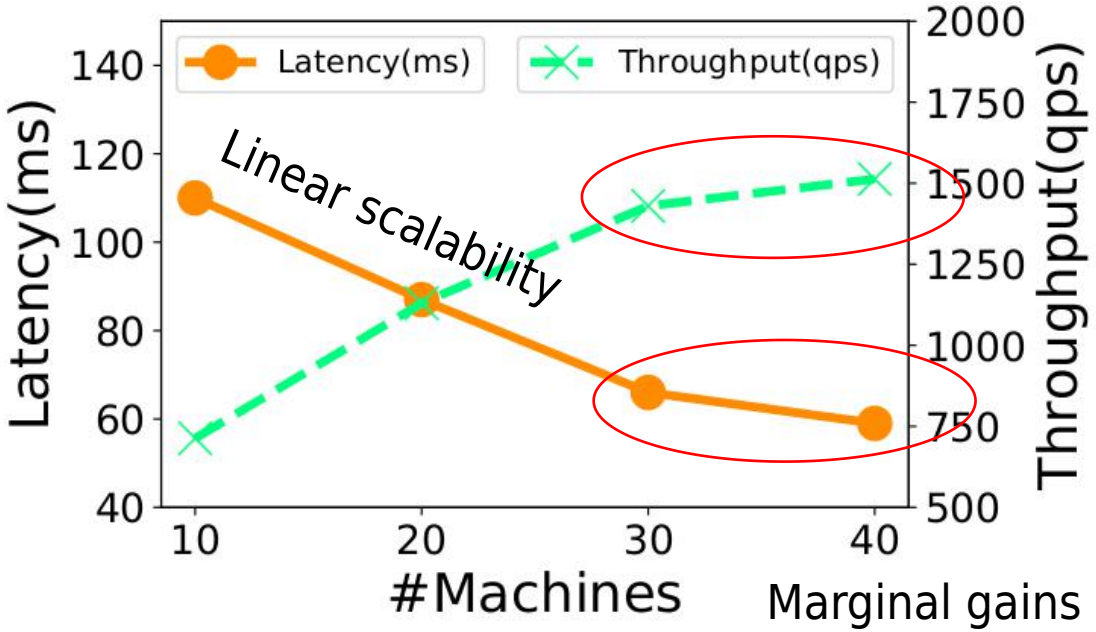
(b) Search Shards based on Estimated Cardinality



(c) Background Monitoring & Remigration

Data Sharding & Distributed Search

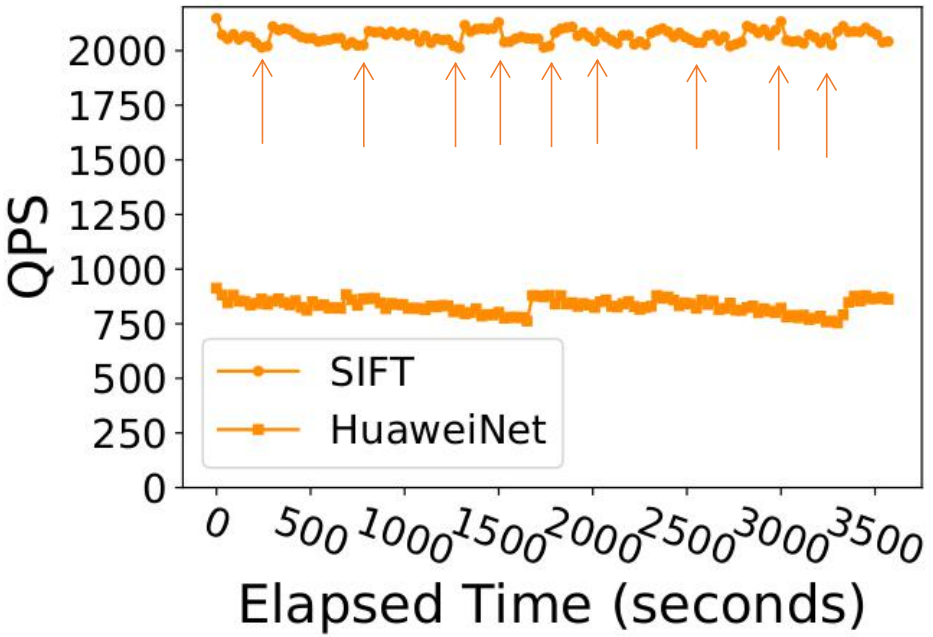
Balanced Tree with intermediate sub-indexes enables incremental updates for data freshness



Marginal gains due to higher merge costs

(a) Scalability

Rebalancing Spikes



(b) Update Throughput

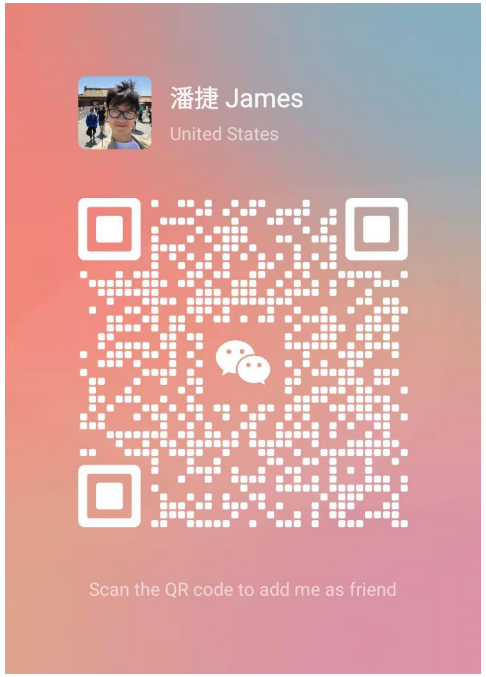
Summary & Conclusion

GaussDB-Vector integrates vector search capabilities within existing data management system

	Query Processor	Storage & Indexing	Query Optimizer	Query Executor
Milvus 	• k-NN • Range NN • Predicated k-NN • Multi-vector search • Grouping Search • Full Text Search • Reranking	• Replicas • Data Partitions • Multiple index types • Blob storage (backup & persistence)	• Cost-based predicated query planning	• Scatter-gather • R/W Disagg. • CPU/Store Disagg. • Log-backed durable writes • Cache & SIMD acceleration • GPU acceleration • Tunable consistency
PostgreSQL (pgvector) 	• k-NN • Range NN • Predicated k-NN • Full Text Search • ***Relational queries***	• Page-Based Storage • Shards & Replicas • HNSW, IVF • Quantization	• Cost-based predicated query planning	• MVCC • Scatter-gather • Log-backed durable writes • etc.
GaussDB-Vector 	• k-NN • Range NN • Predicated k-NN • ***Relational queries***	• **Page-Based Storage** • **Shards & Replicas** • HNSW, IVF, **Hybrid Index** • Quantization	• Cost-based predicated query planning	• GaussDB Transaction Manager • **Scatter-gather** • Log-backed durable writes • Cache & SIMD acceleration • NPU/GPU acceleration

Thanks!

GaussDB-Vector:
A Large-Scale Persistent Real-Time Vector Database for LLM Applications PVLDB (2025)



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Slides:

https://dbgroup.cs.tsinghua.edu.cn/ligl/activities.html