A Vertical Layout for Vector Similarity Search

Leonardo Kuffo*, **Peter Boncz**
CWI Database Architectures group

DBDBD ‘24

Vector Similarity Search

















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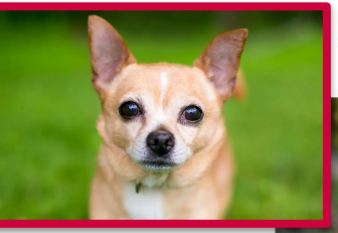
QUERY



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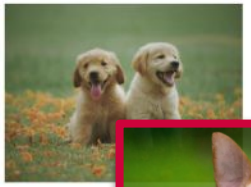




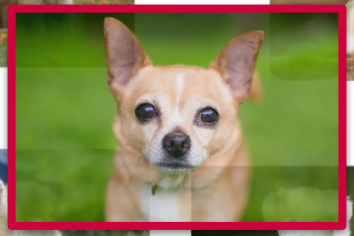

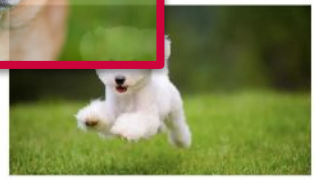








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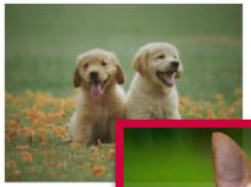
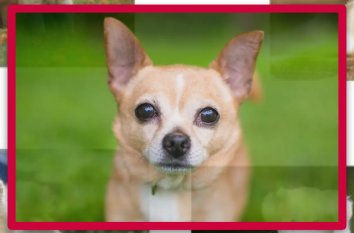
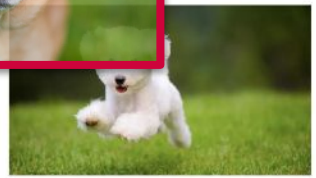
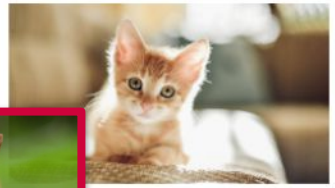
Result









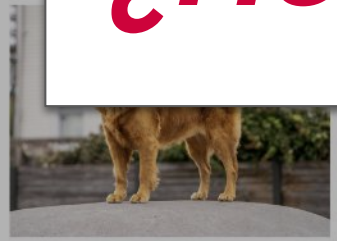
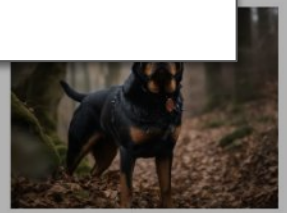
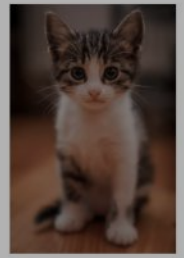




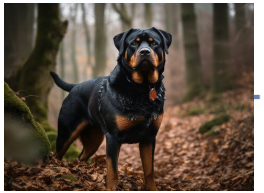


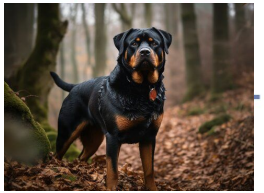




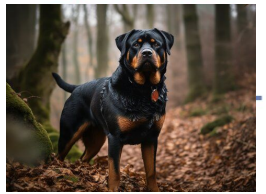






¿How?





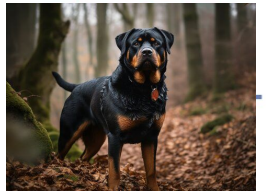
Embedding Model



Embedding Model

0.6	0.3	0.1	...
0.8	0.5	0.3	...
0.4	0.2	0.9	...

Objects as vectors



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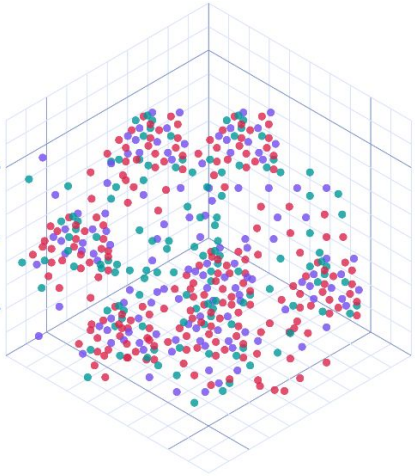

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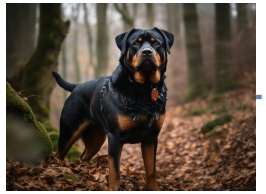

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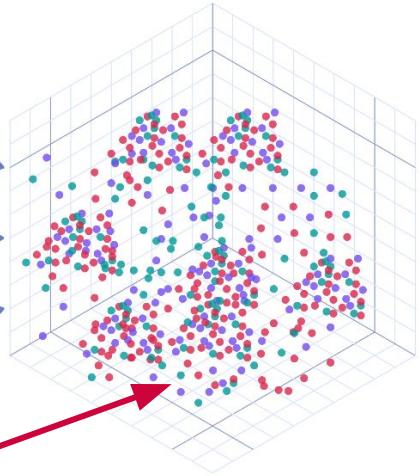


Objects as vectors

0.1	-0.3	0.8	...

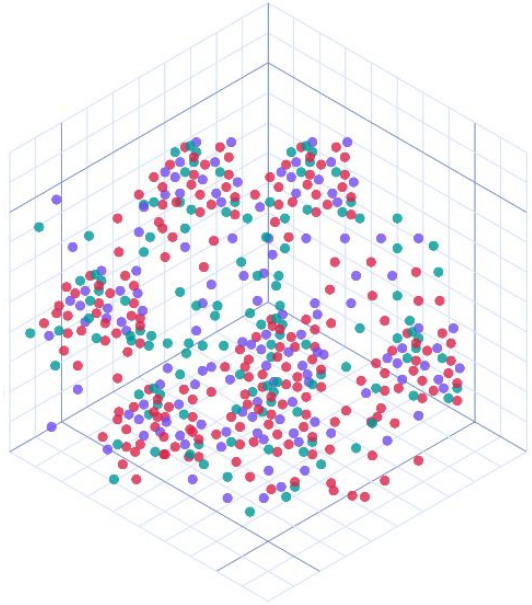
Euclidean Distance, Cosine Similarity, Dot Product, Manhattan...

Cool use cases

- Information Retrieval
- Recommendation Systems
- **In the LLMs era**: Retrieval Augmented Generation (RAG)

CWI

Vector similarity search is expensive



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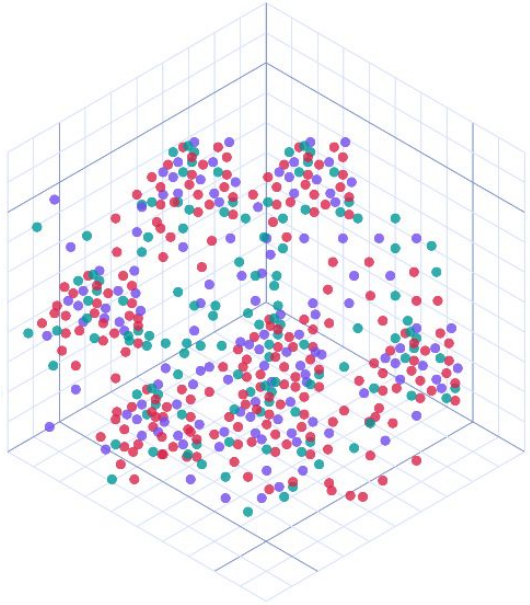
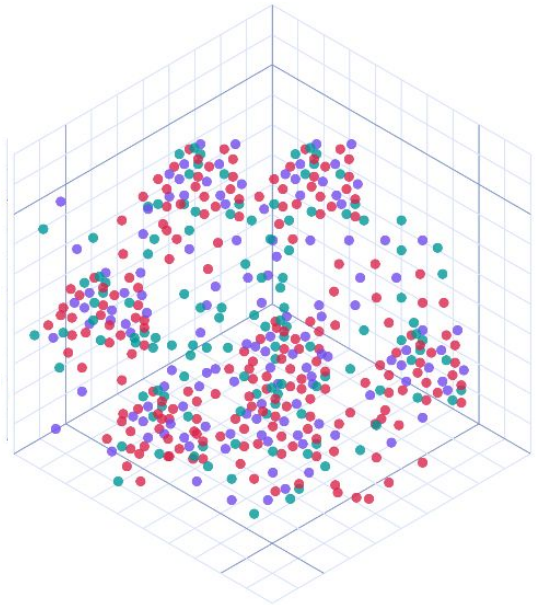
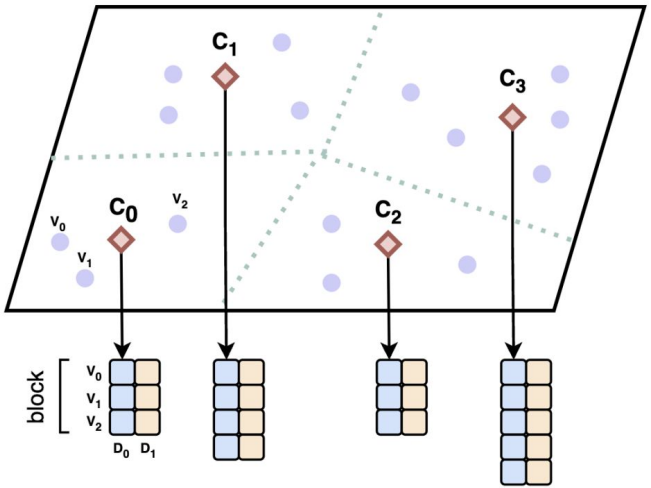


...unless we trade-off exactness

Vector indexes to speed up search





[2010] Jegou, Herve, Matthijs Douze, and Cordelia Schmid. "Product quantization for nearest neighbor search."

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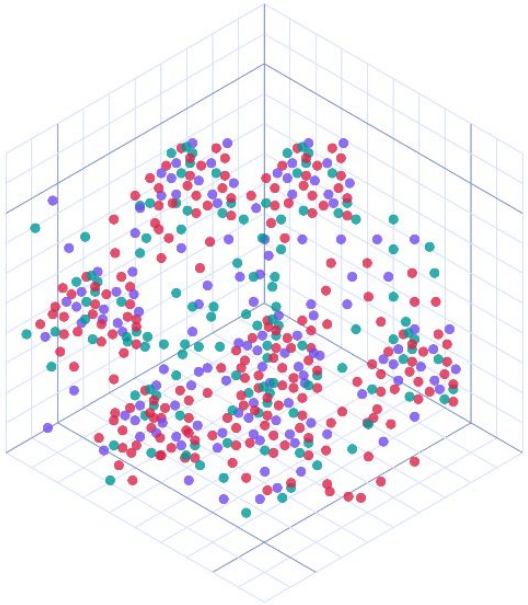
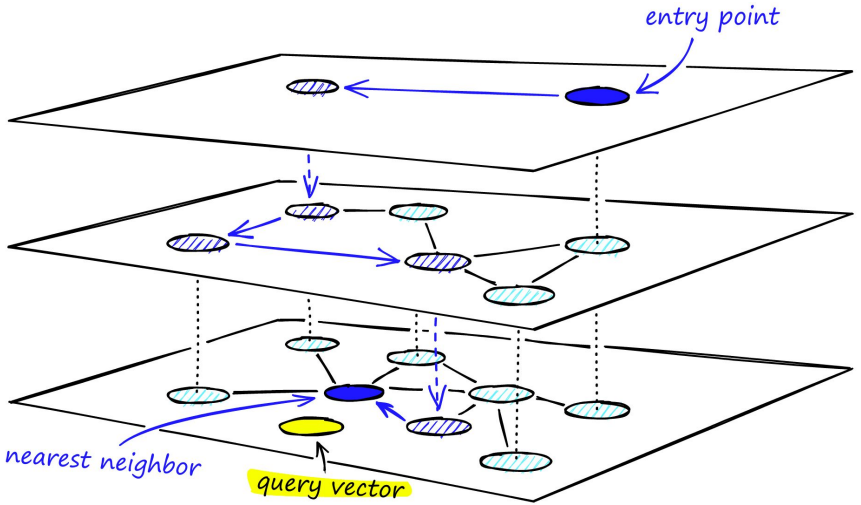
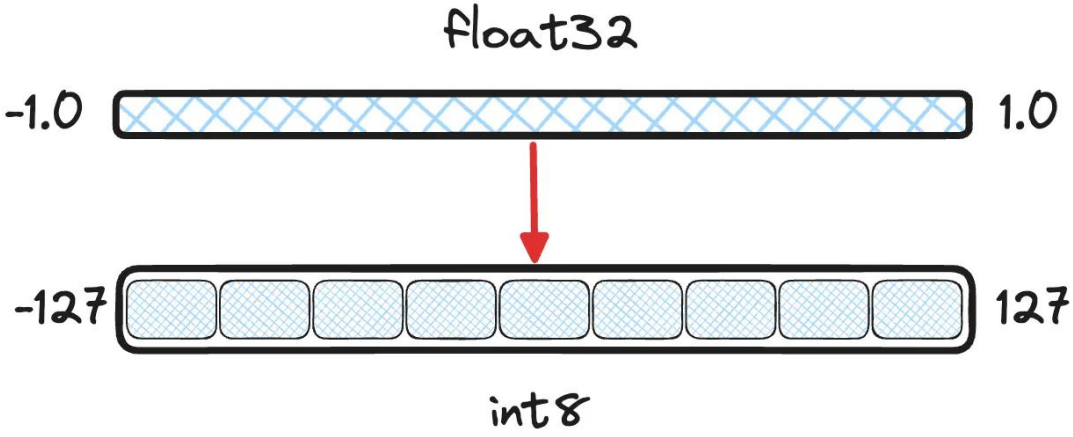




[2018] Malkov, Yu A., and Dmitry A. Yashunin. "Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs."

Quantization to speed up search



Challenges of Vector Similarity Search

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- Facing similar challenges of **Analytical Databases**

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  - **Heavy-weight indexes** that are hard to maintain (HNSW)

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  - How to efficiently **pushdown predicates** (hybrid search)

[2024] Patel, L., et al. ACORN: Performant and Predicate-Agnostic Search Over Vector Embeddings and Structured Data.

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  - Most quantization techniques lack **locality adaption**

[2023] Aguerrebere, C., et al. Similarity search in the blink of an eye with compressed indices.
[2024] Aguerrebere, C., et al. Locally-Adaptive Quantization for Streaming Vector Search. https://github.com/intel/ScalableVectorSearch

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Recent research proposes **pruning** of dimensions on the distance calculation

However, they can still lose to full **SIMD** distance calculations

[2002] de Vries, Arjen P., et al. Efficient k-NN search on vertically decomposed data.
[2023] Gao, J., & Long, C. High-dimensional ANNS: with reliable and efficient distance comparison operations.
[2024] Yang, M., et al. Bridging Speed and Accuracy to Approximate k-Nearest Neighbor Search.

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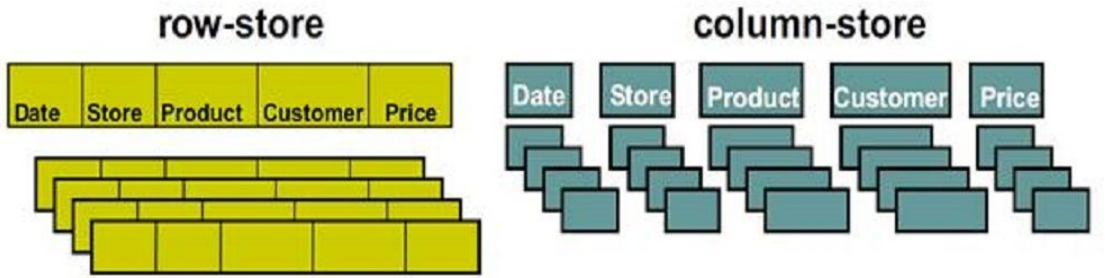
Can we borrow ideas
from Analytical Databases?

Storage



- Better opportunities for **compression**
- **Efficient scans** of attributes
- **Vectorized** query execution

What if we store vectors in a Vertical Layout?

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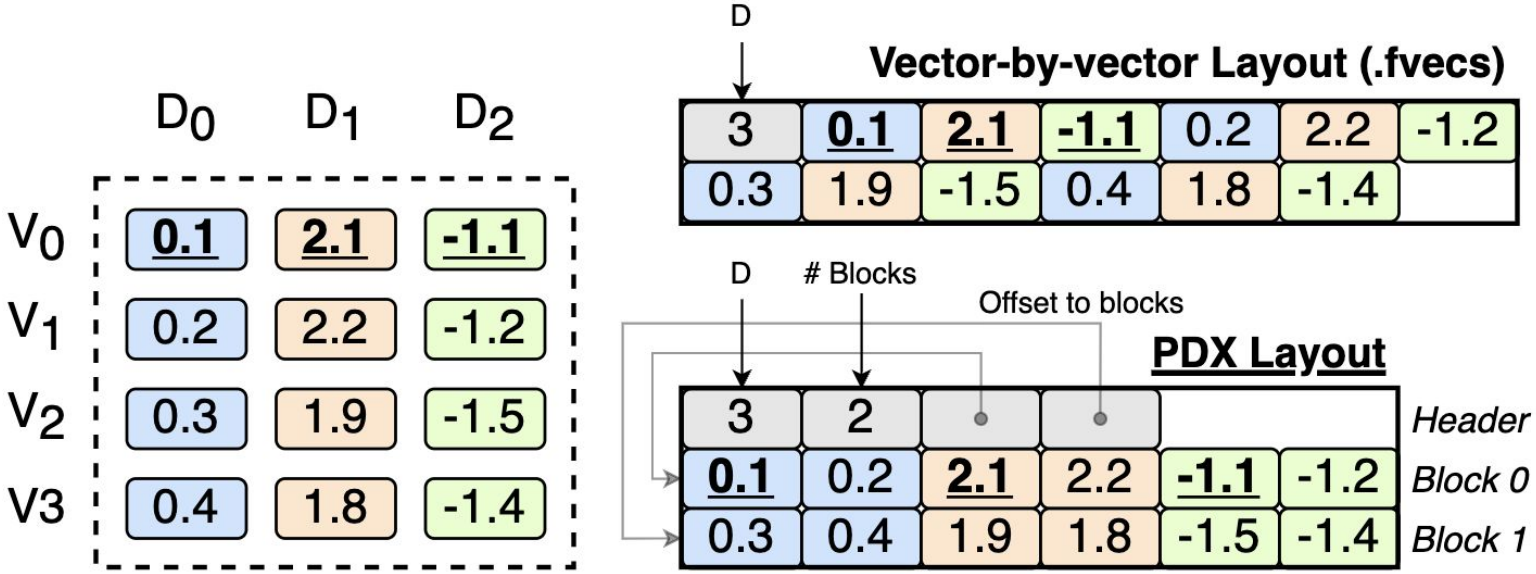
Storage

- **PDX: Vertical Layout** for Vectors

Storage

- **PDX: Vertical Layout** for Vectors



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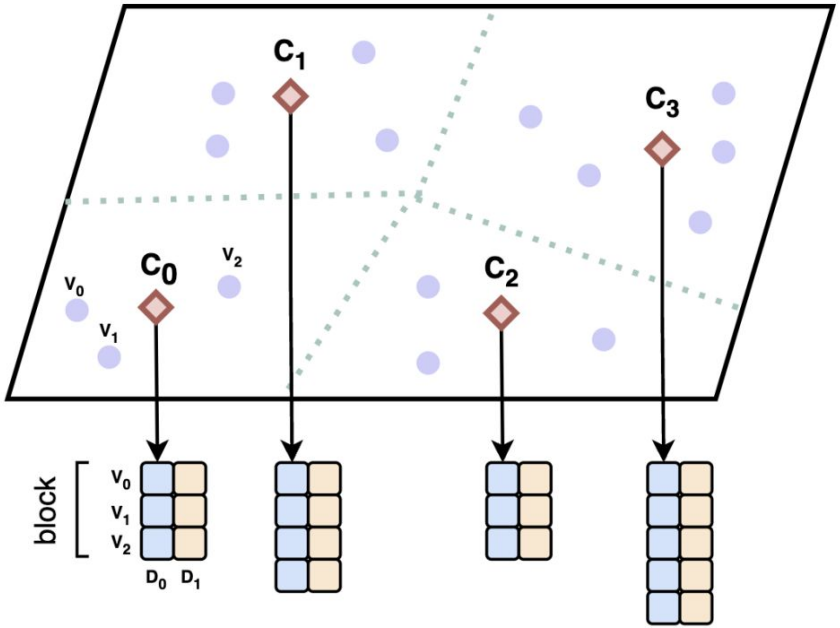
Storage: A foundational change

- **PDX: Vertical Layout** for Vectors
- Allows for efficient **dimensions-pruning** during search

A search that (reliably) prunes dimensions



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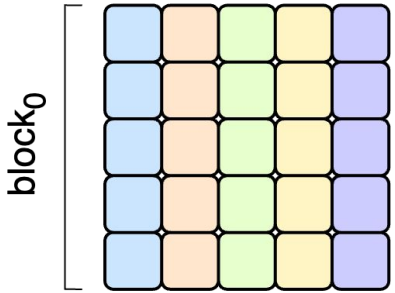

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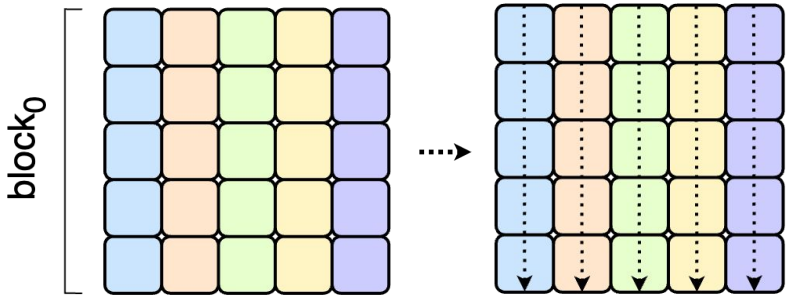

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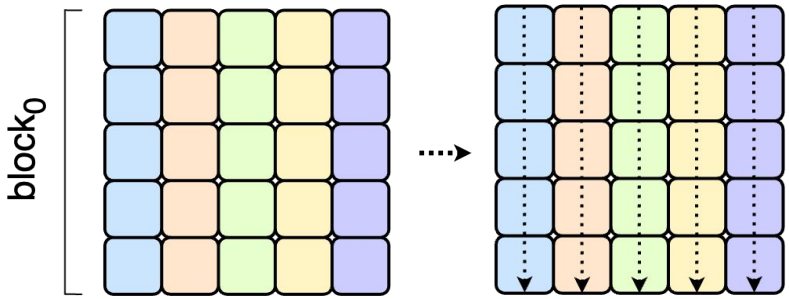

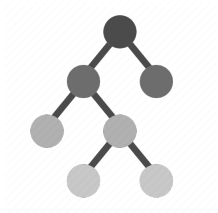

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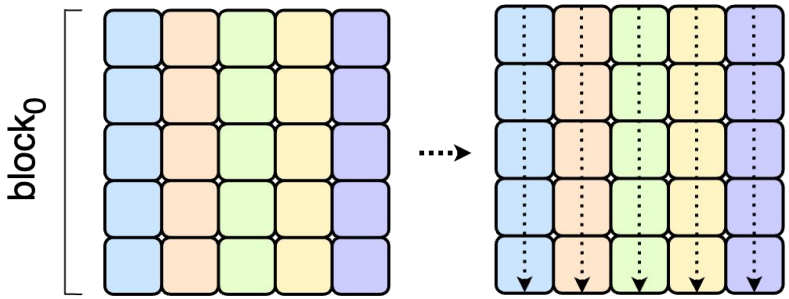

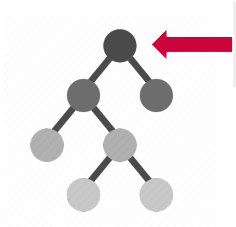

Pruning threshold

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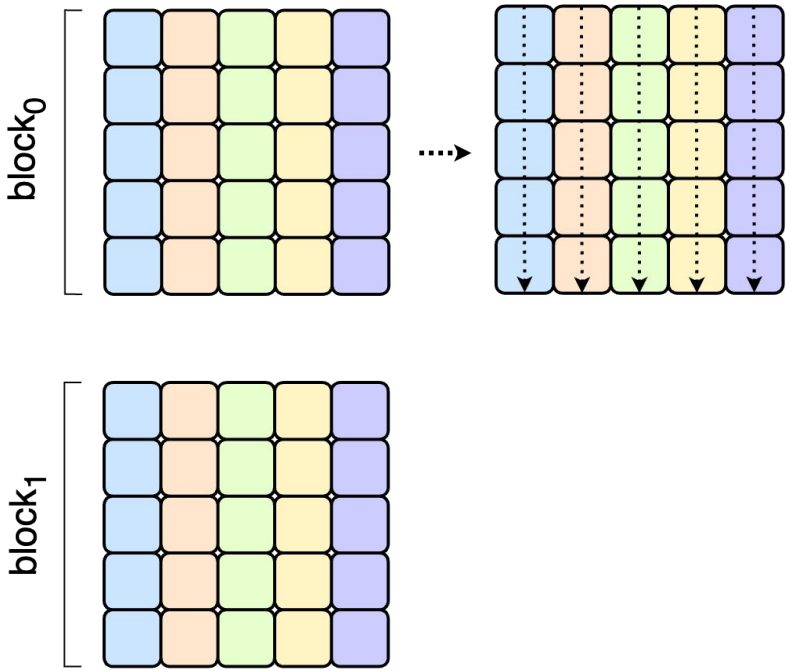

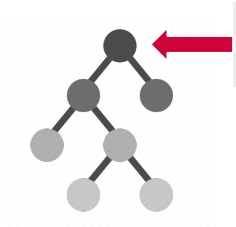

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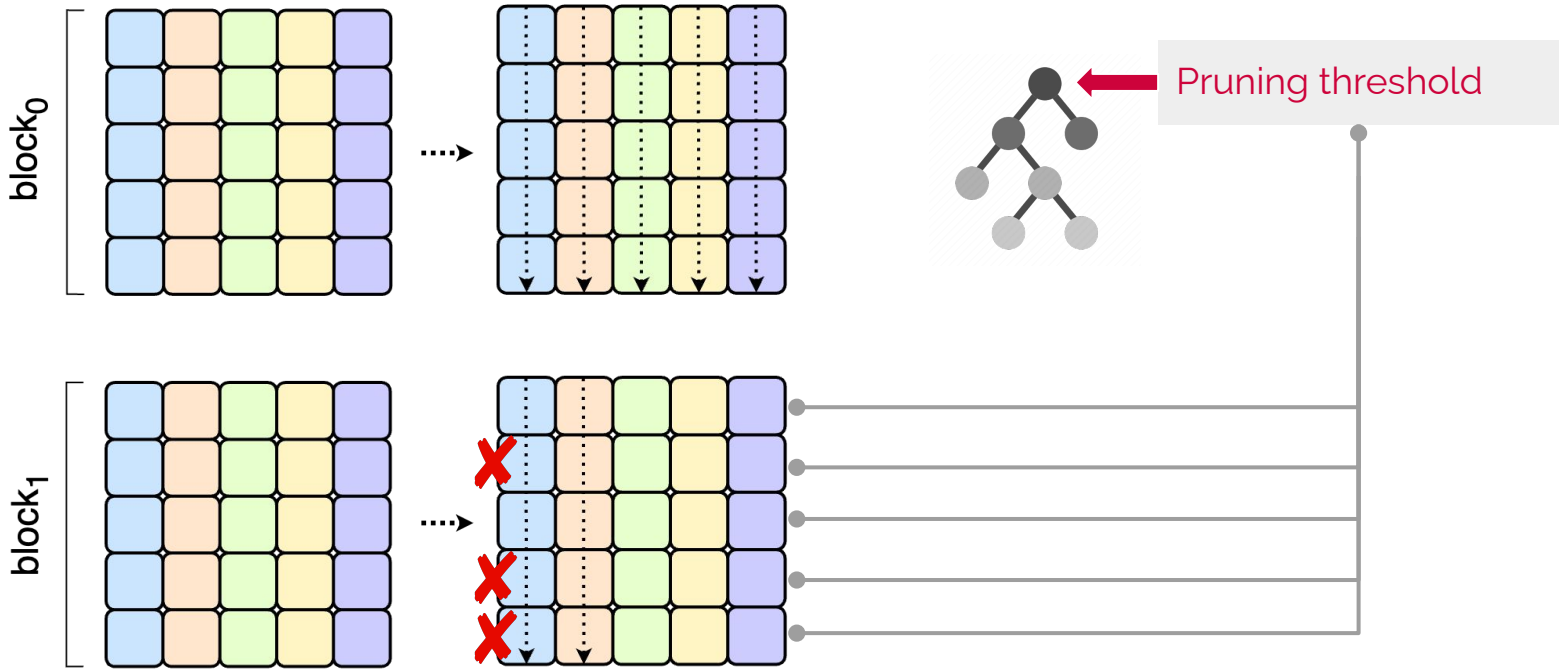
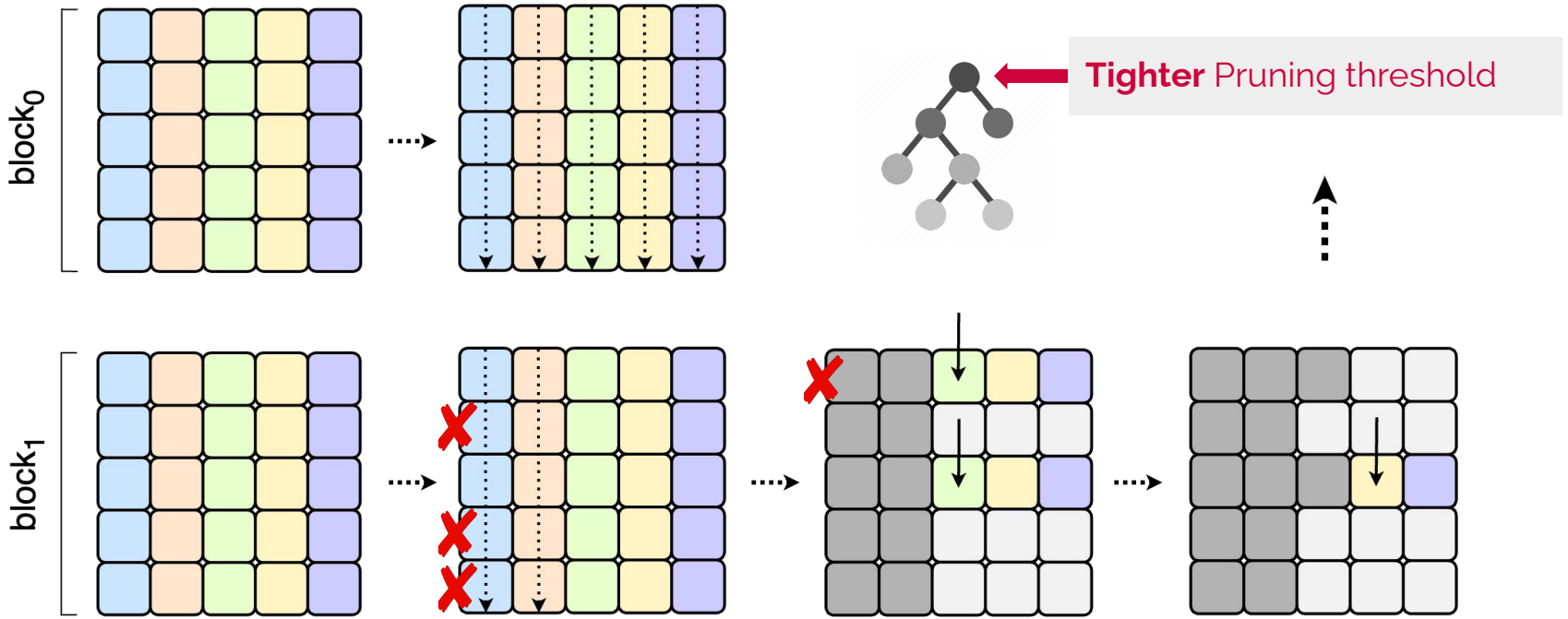


A search that (reliably) prunes vectors



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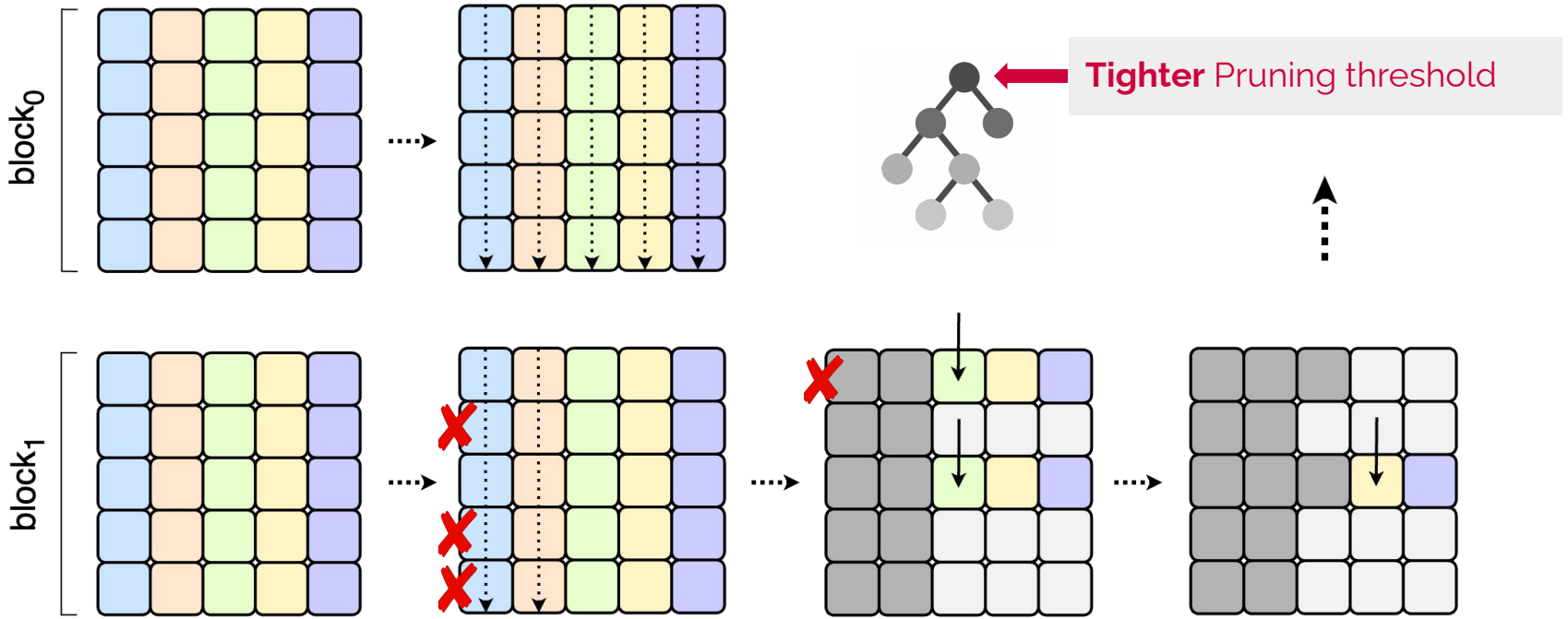
PDXearch



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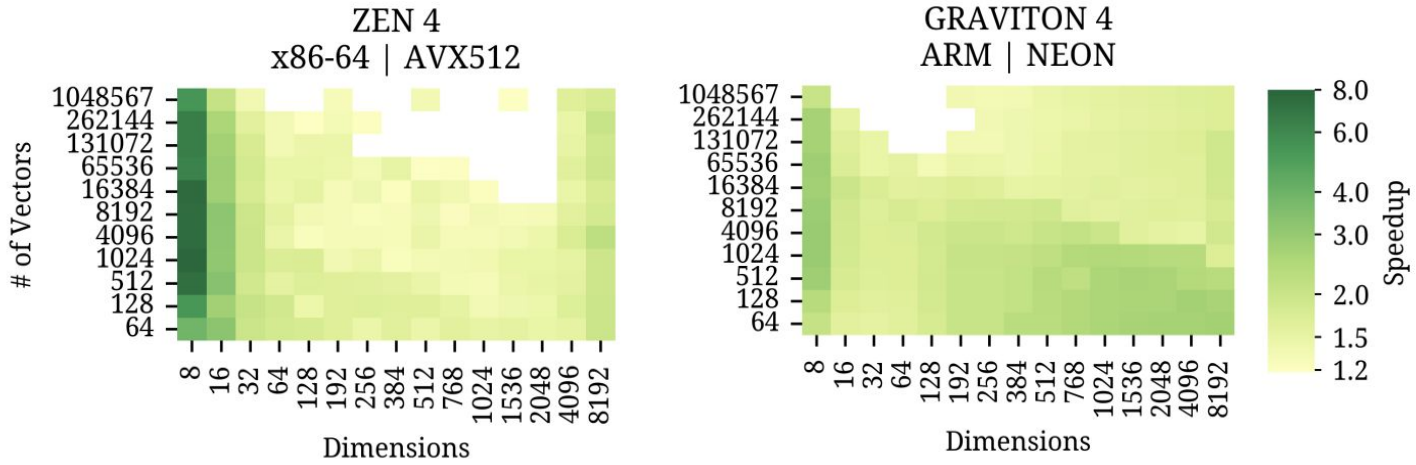
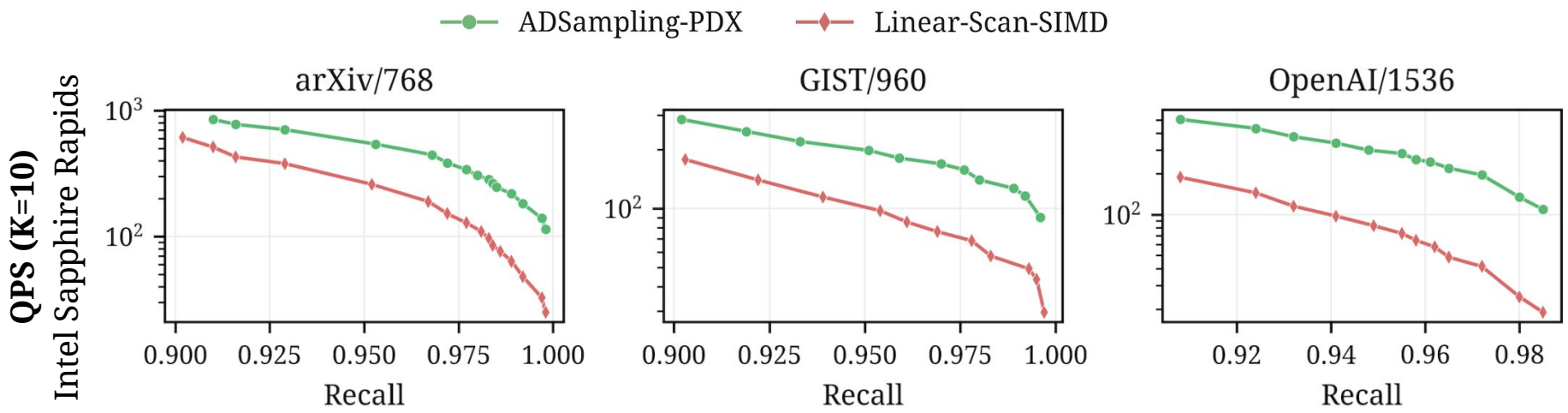
- **PDX: Vertical Layout** for Vectors
- Allows for efficient **dimensions-pruning** during search ✔
- Distance computation (L2) **faster** than SIMD kernels
  - Only using **Scalar code** that is auto-vectorized (in NEON, AVX2 and AVX512)

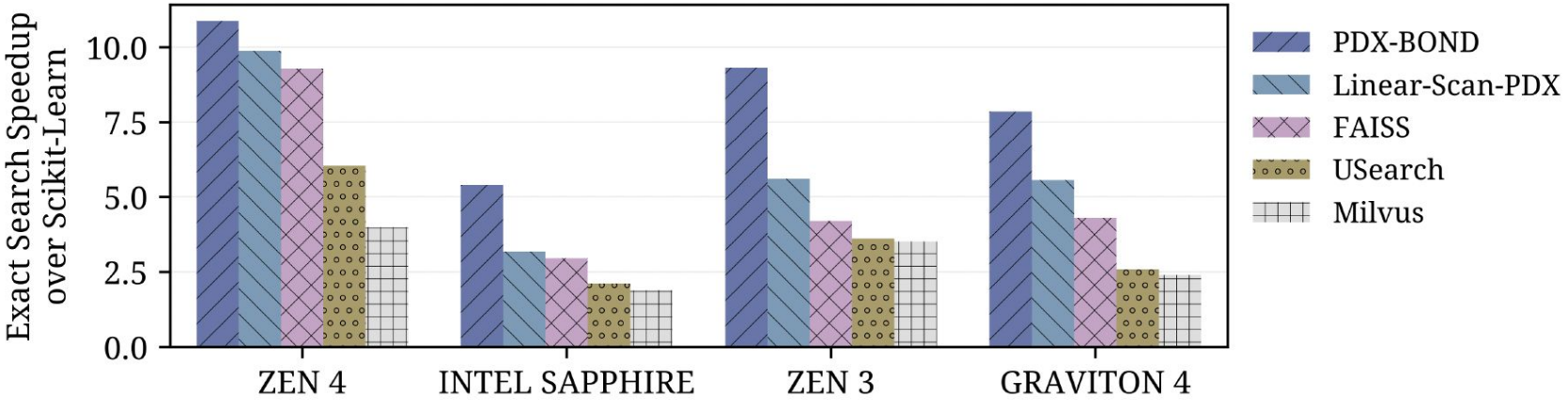


A search that (reliably) prunes vectors → on IVF



arXiv	D=768	N=2.25M
GIST	D=960	N=1M
OpenAI (dbpedia)	D=1536	N=1M

A search that (reliably) prunes vectors



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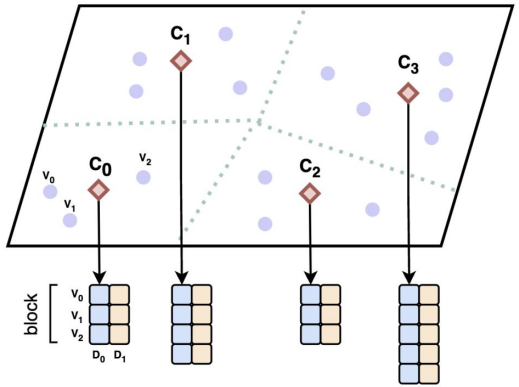
- Allows for efficient **dimensions-pruning** during search ✔
- Distance computation (L2) **faster** than SIMD kernels ✔
- Lightweight **Compression**

LEP: Lossily Encoded floating-Points (WIP)

- Local adaptivity per dimension & per block
  - Specially effective on space-partitioning indexes (IVF)
  - Thanks to the **PDX** layout
- ALP without lossless verification (in a nutshell)
- Encoding of out-of-distribution values
- Encoding of repetition



[2023] Afroozeh, Azim, Leonardo X. Kuffo, and Peter Boncz. "ALP: Adaptive Lossless floating-Point Compression."

[2025] Krippner, E. Rethinking Vector Embeddings Search for Analytical Database Systems. (MSc thesis)

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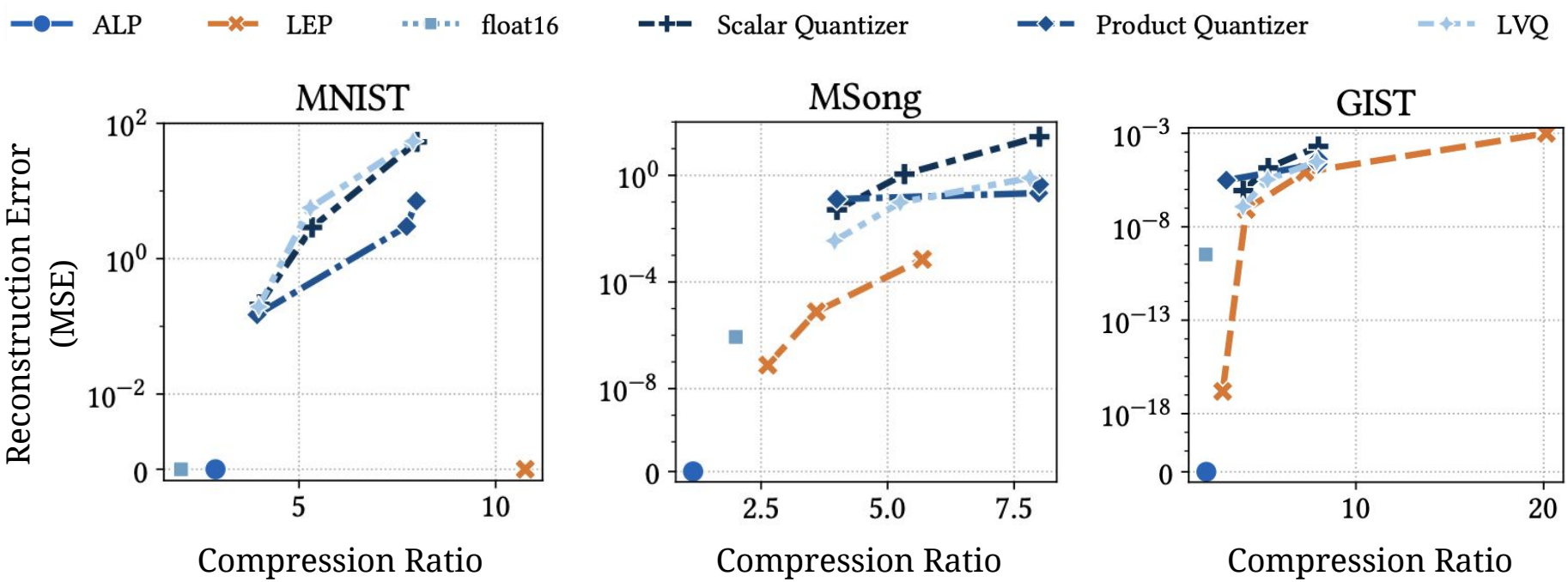

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Summary

PDX | **A Vertical Layout** for Vectors

- Distance calculations **faster** than SIMD kernels ✔
- Improve distance evaluation latency by **pruning dimensions** ✔
- Adaptive lightweight **compression per dimension (wip)** ✔

Future Work

- Better **pruning strategies**
- Implement PDXearch on **GPUs**
- Do IVF indexes *the right way*
    - *Lightweight* | *Updatable* | *Compressed* | *Pruning*

A Vertical Layout for Vector Similarity Search

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22/11/24

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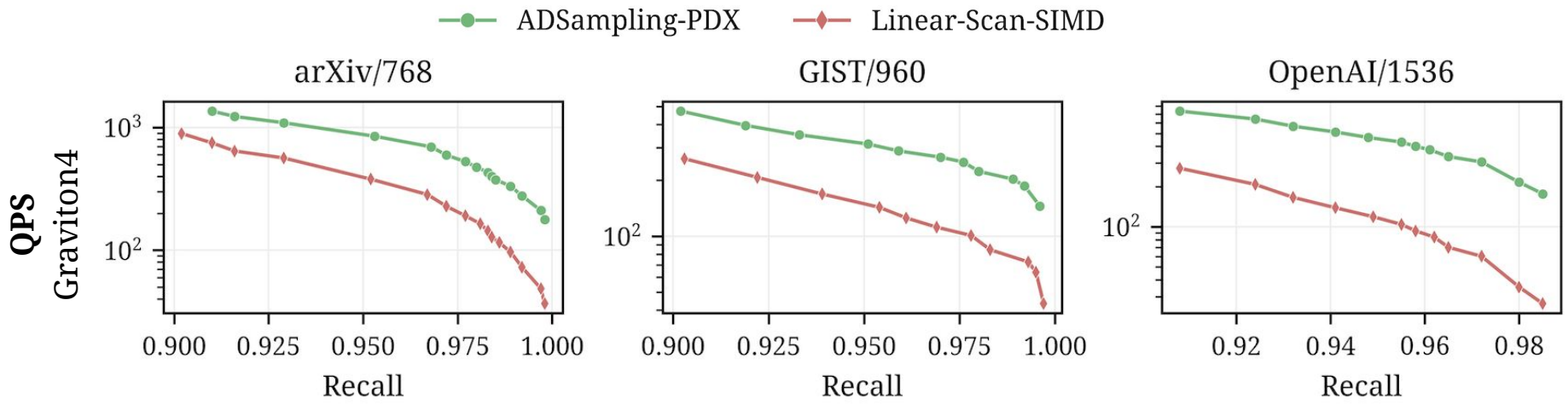
SUPPLEMENTARY SLIDES

A search that (reliably) prunes vectors → on IVF



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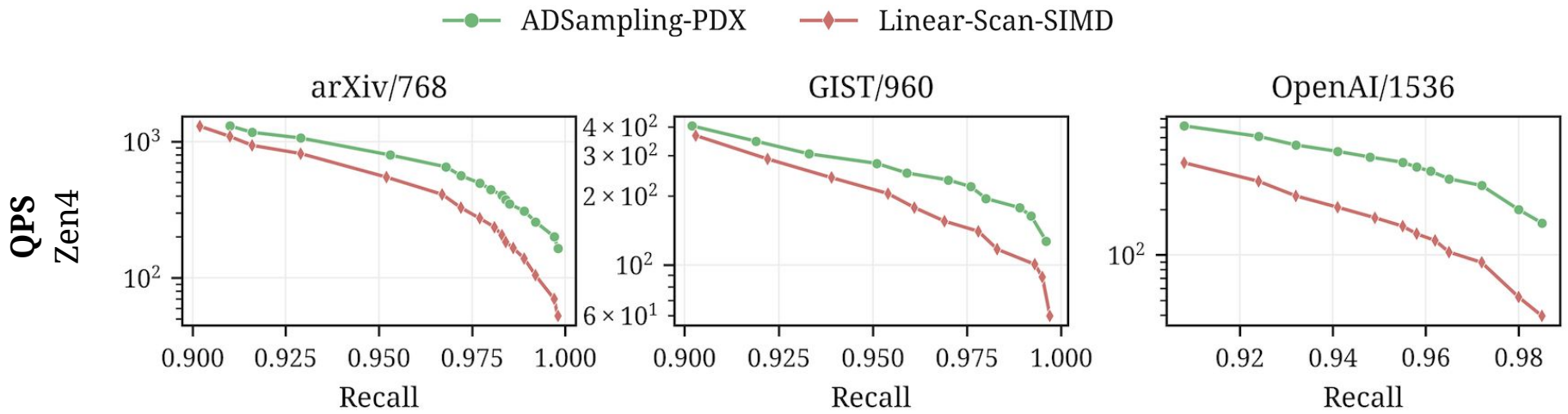
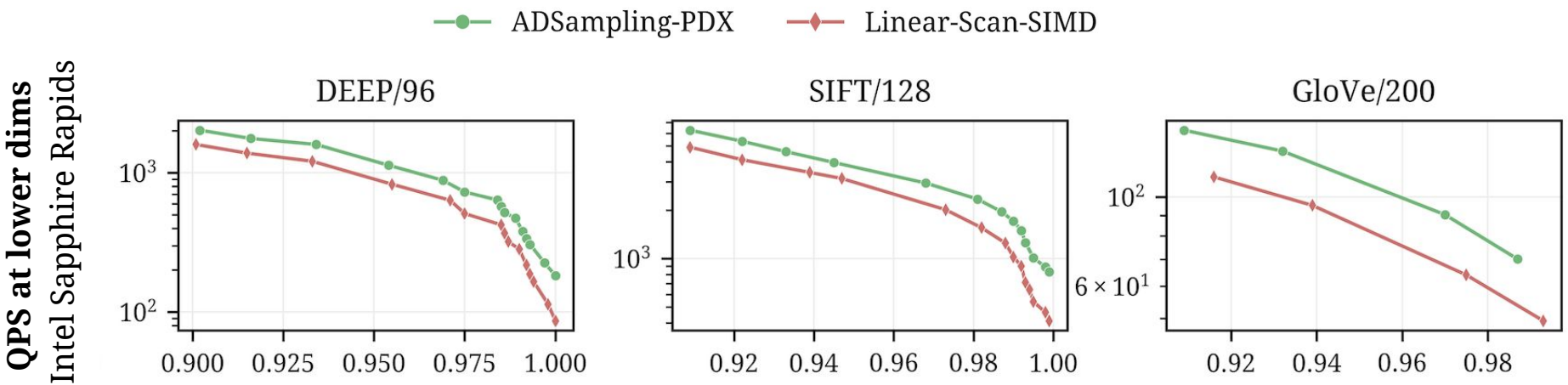
OpenAI (dbpedia)	D=1536	N=1M

A search that (reliably) prunes vectors → on IVF

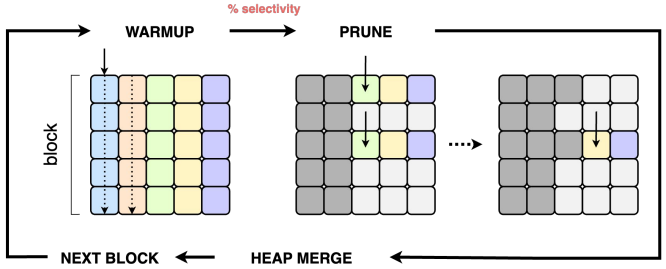


arXiv	D=768	N=2.25M
GIST	D=960	N=1M
OpenAI (dbpedia)	D=1536	N=1M

A search that (reliably) prunes vectors → on IVF



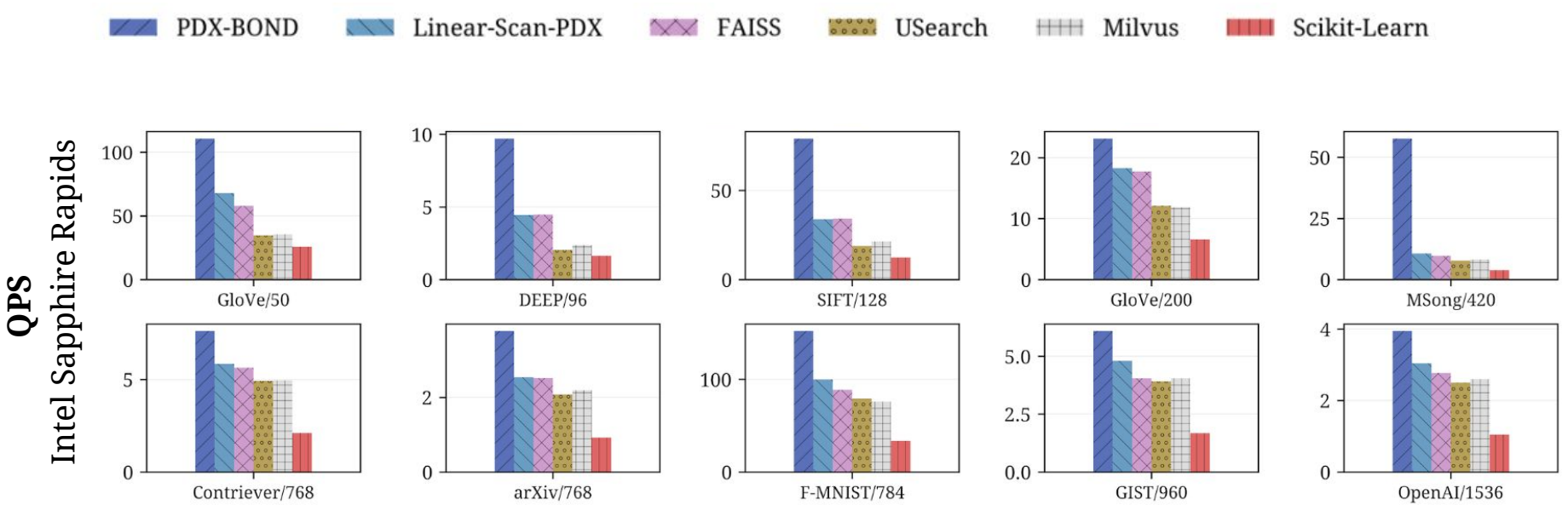
A search that (reliably) prunes vectors



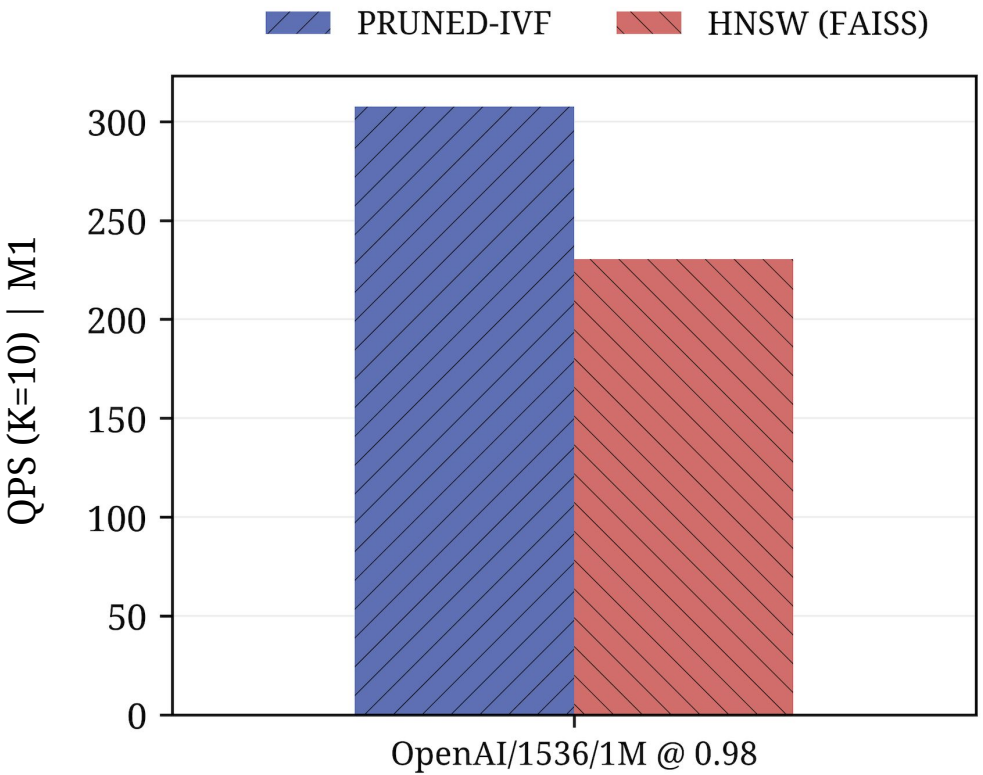
- Which **distance metrics**?
  - Monotonic ones (L2, Dot in normalized vectors [0, 1])
- How ***early*** does pruning happen?
  - As early as 2% of dimensions in some datasets
  - Depends on the query, dataset and pruning algorithm
- Find benefits only with the PDX layout
- Pruning Algorithms:
  - **ADSampling** → Approximate (<0.001 loss of recall)
  - **BSA** → Approximate
  - **PDX-BOND** → Exact | Prioritize dimensions at query-time
- ↑ gains at ↑ dimensionalities

[2023] Gao, J., & Long, C. High-dimensional ANNS: with reliable and efficient distance comparison operations.
[2024] Yang, M., et al. Bridging Speed and Accuracy to Approximate k-Nearest Neighbor Search.
[2025] Kuffo, L., Krippner E., & Boncz, P. PDX: A Data Layout for Vector Similarity Search *(under-review)*

A search that (reliably) prunes vectors → on Exact

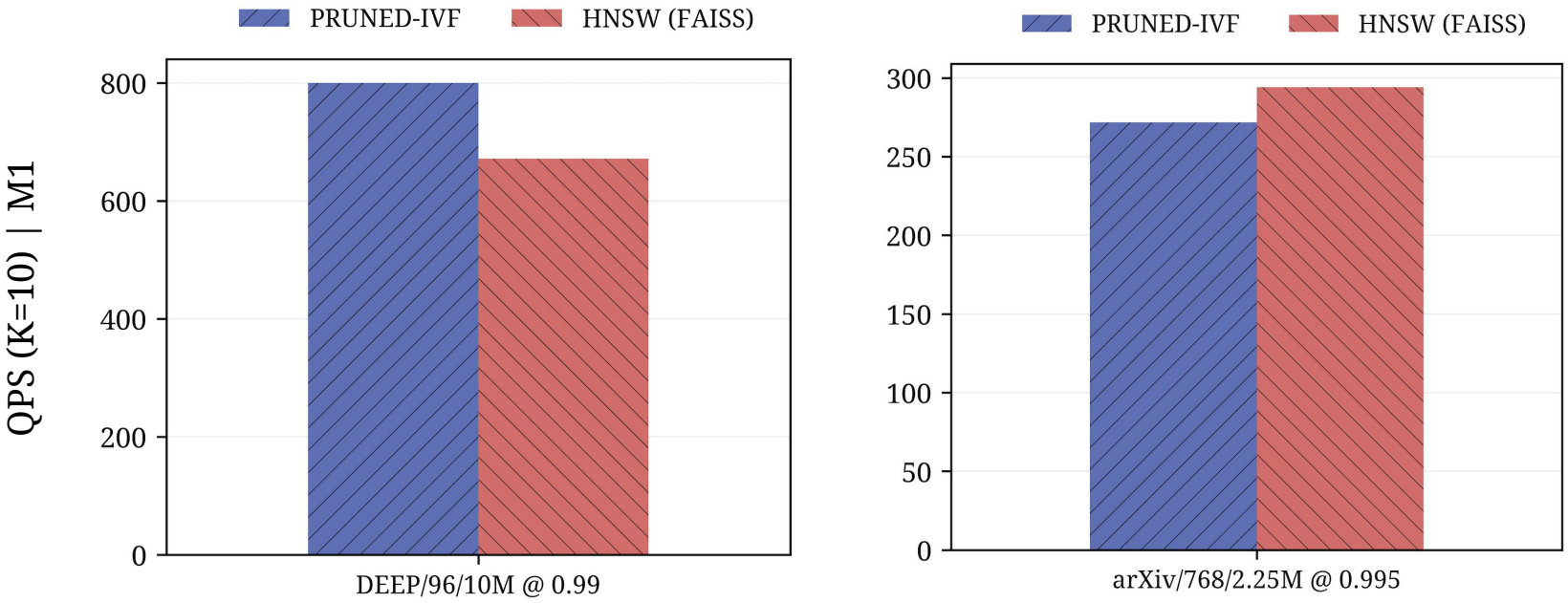


A search that (reliably) prunes vectors → vs HNSW (wip)

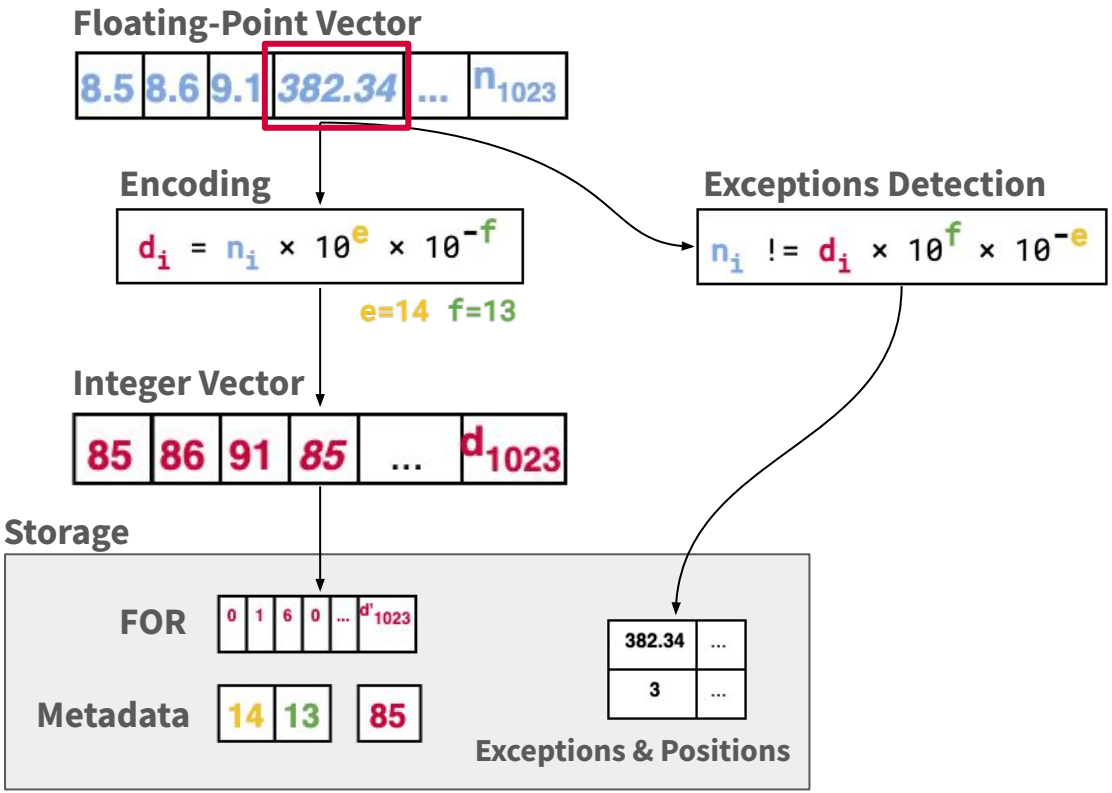


- **K = 10**
- HNSW **efConstruction = 64**
- HNSW **M = 24**
- IVF **N° Probed = 256**

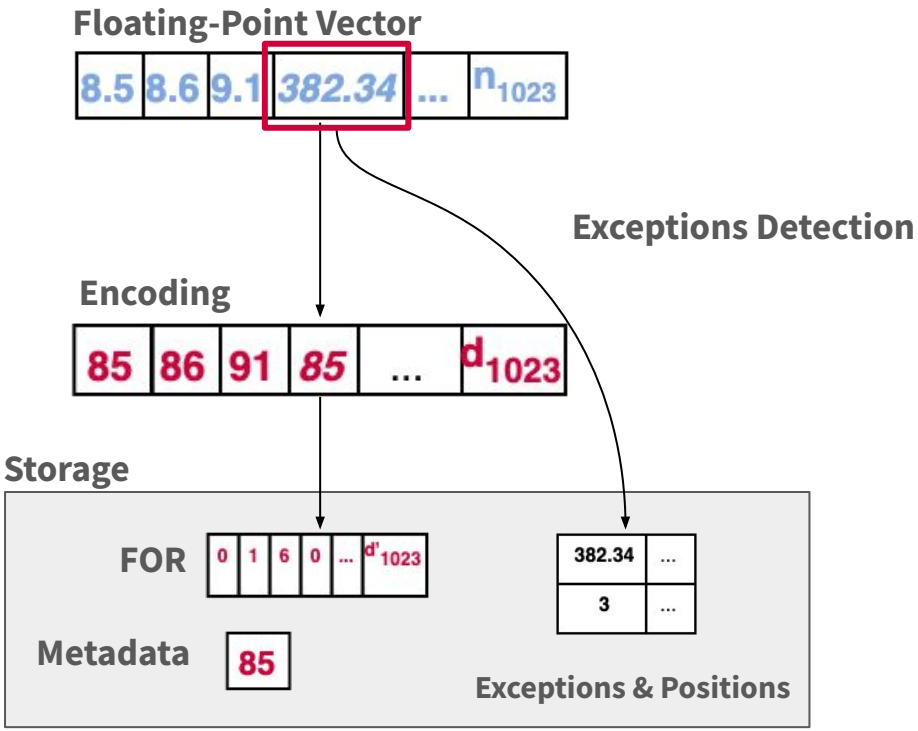
A search that (reliably) prunes vectors → vs HNSW (wip)



Lightweight Compression: ALP (lossless)



Lightweight Compression: ALP (lossless)



Across Architectures