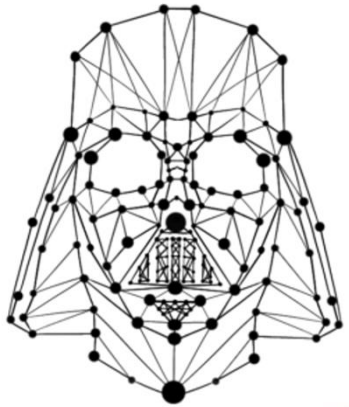

DARTH: Declarative Recall through Early Termination for Approximate Nearest Neighbor Search

Manos Chatzakis
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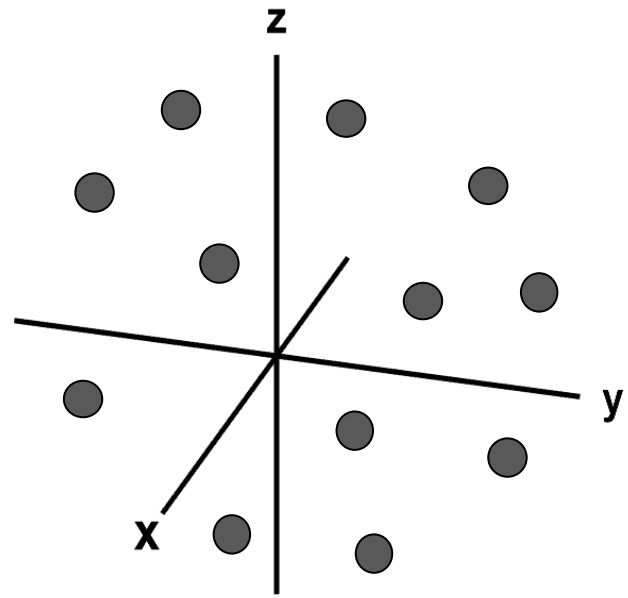
Laboratoire d'Informatique PAris DEscartes

Université Paris Cité

Google

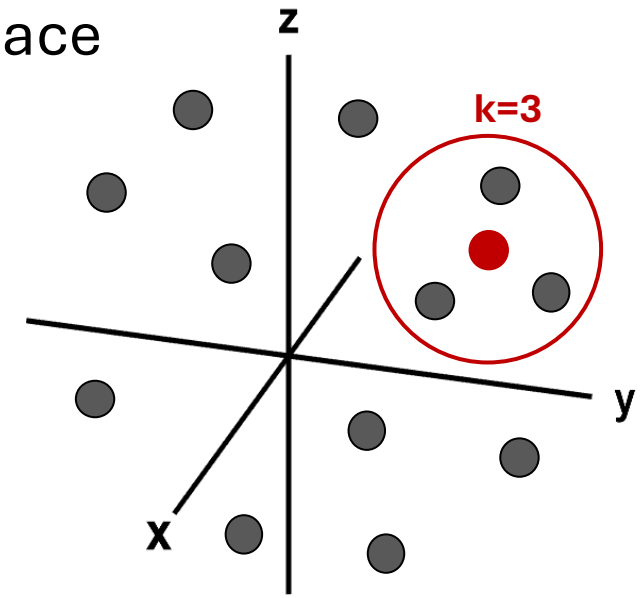
Nearest Neighbor Search

- Nearest Neighbor vector Search



Nearest Neighbor Search

- Nearest Neighbor vector Search
  - Find top-k nearest vectors of a **query** in a high-dimensional space



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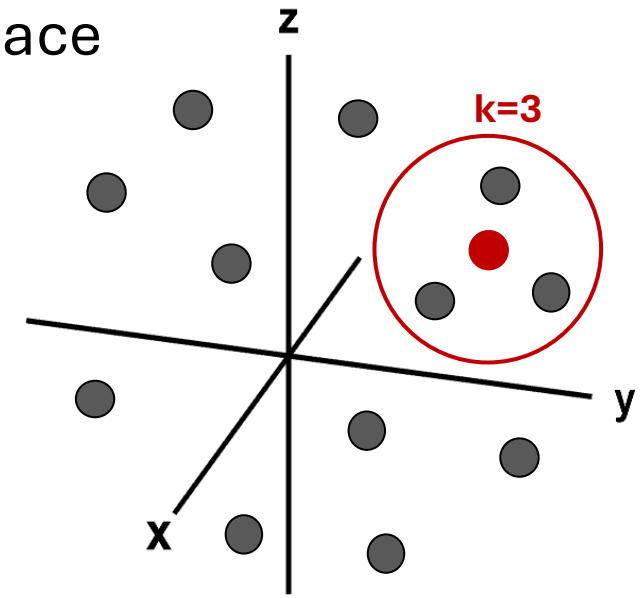

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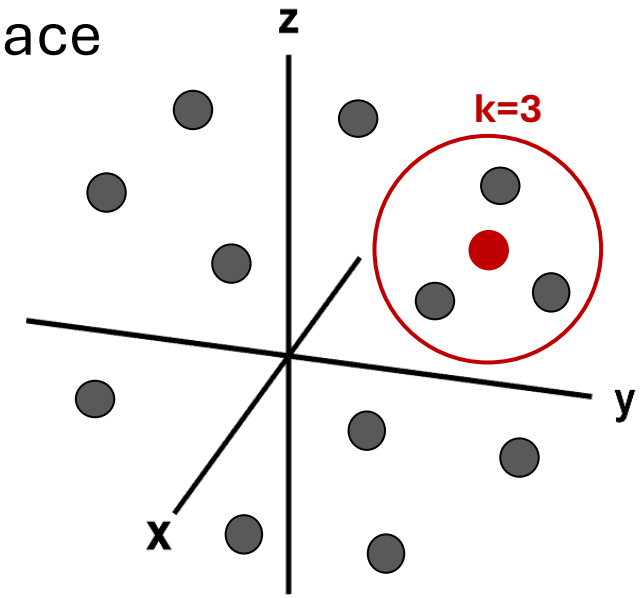

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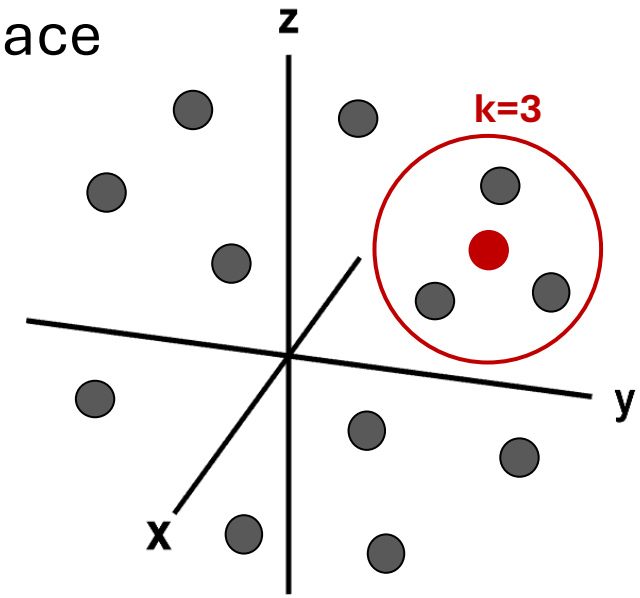
- Index the vector collection and then search
  - **ANNS(q, k, params)** → algorithm-dependent params
- Fundamental **tradeoff** of **latency** and **recall**
  - Users interested in specific **recall targets**
  - ANNS algorithms have different hyperparameters → **extensive tuning!**



ANNS comes with cumbersome tuning!

The Tuning Process

- Tuning requires enormous time-consuming trial and error
  1. Select an ANNS algorithm
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  5. Check if chosen hyperparameters achieve **the recall target on average**
     - If not, **delete index**, pick new parameters, **start over**! ☹

Tuning is a resource- and time-intensive task!

Problems After Tuning

- Performance might still not be optimal: Parameters predefined **average** recall over the workload
  - Cannot **adapt** to individual query hardness
  - Suboptimal results for many queries

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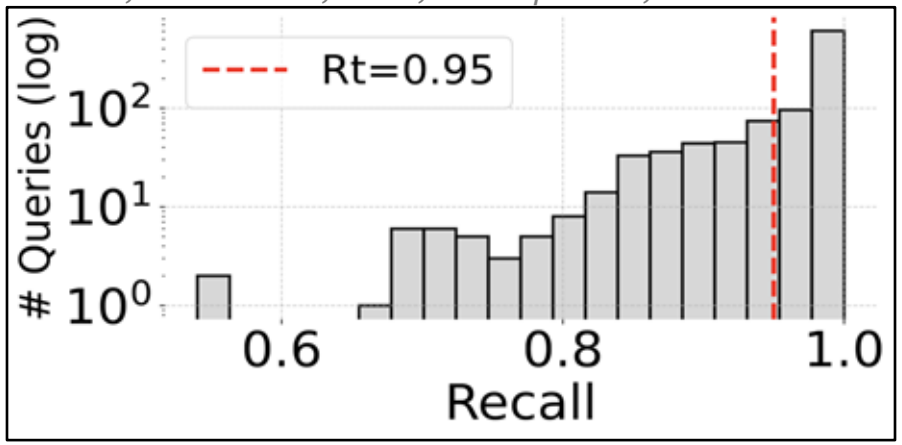
HNSW, DEEP100M, k=50, 1000 queries, efSearch=750



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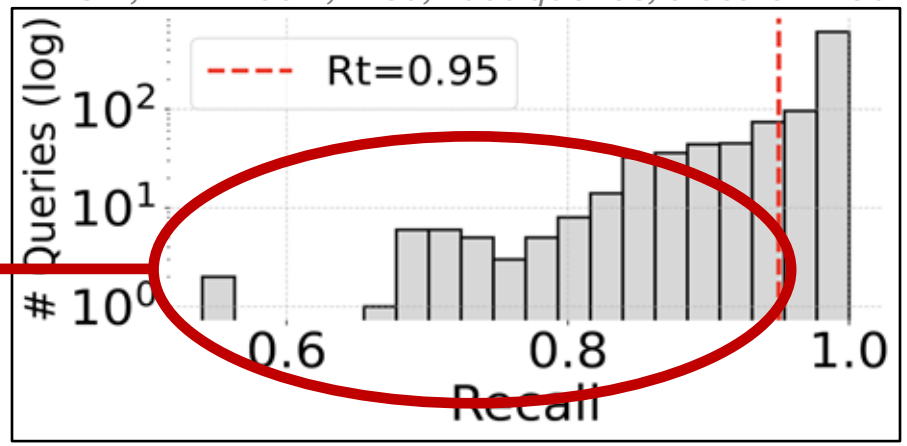

Semantically innacurate results!

Even after tuning, **many queries have suboptimal results!**

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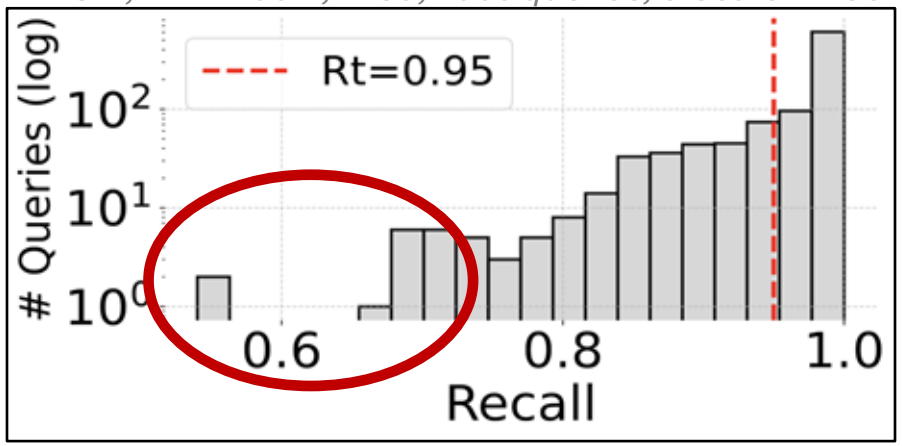

Even after tuning, **many queries have suboptimal results!**
some of them, **really bad results!**

Key Observation

- Query reaching very high recall satisfies all lower recalls as well
  - Early termination opportunities
  - Creating high-scoring index is easy

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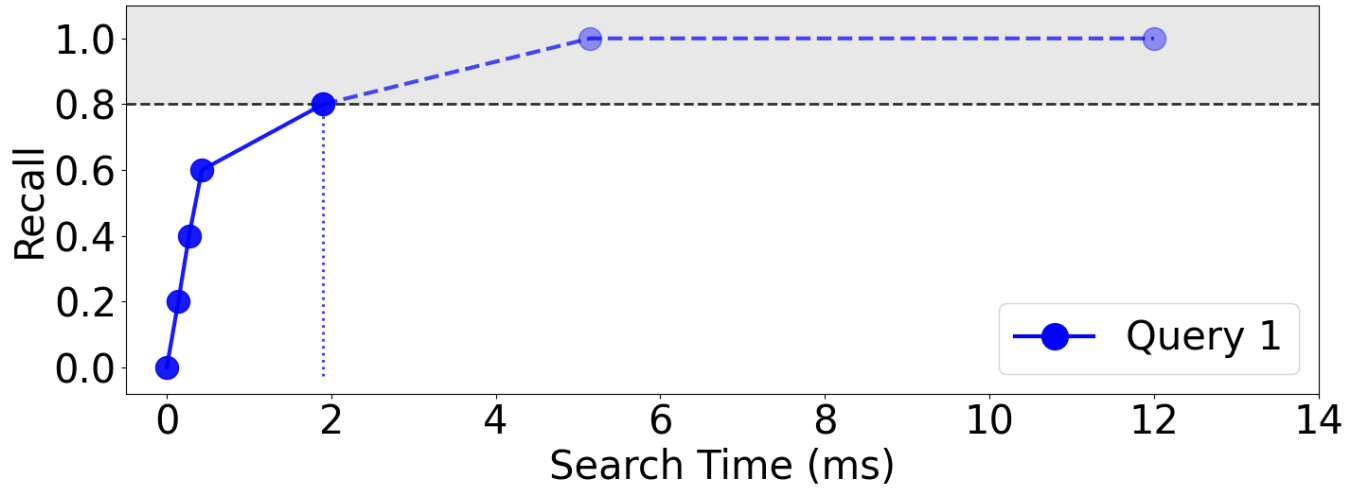

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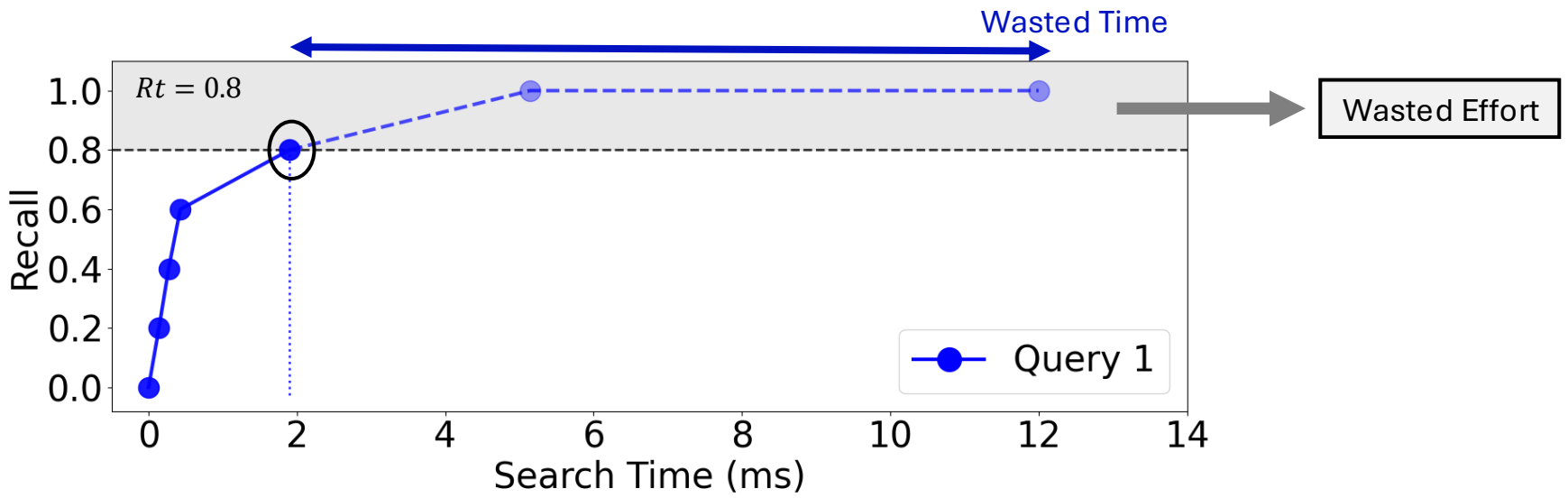

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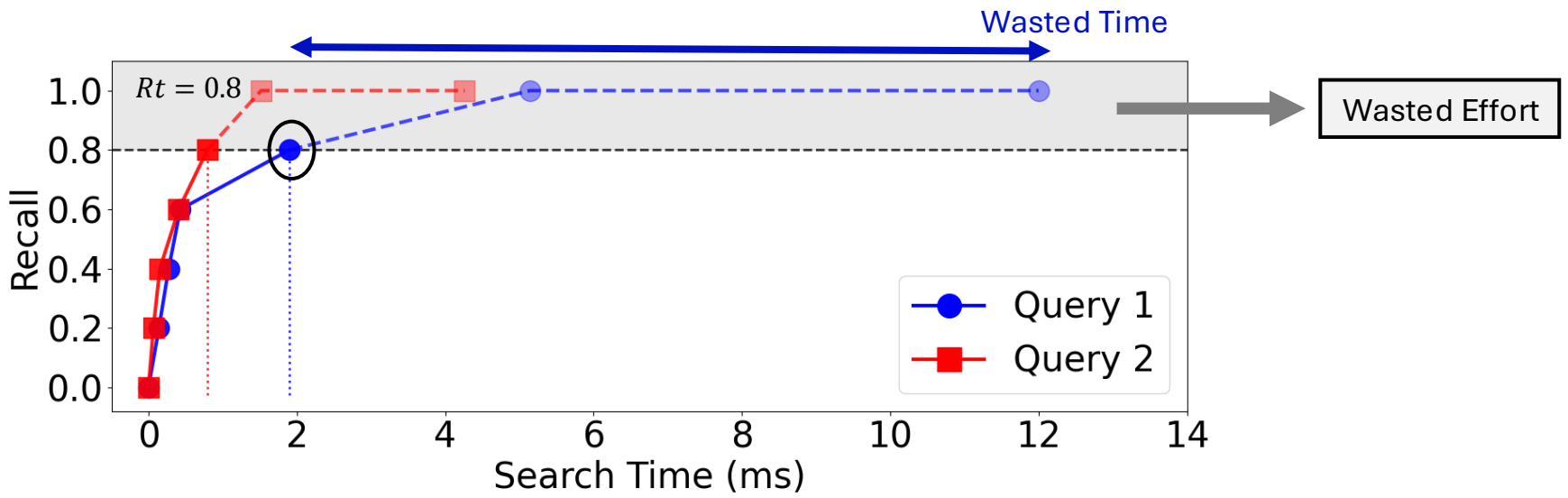

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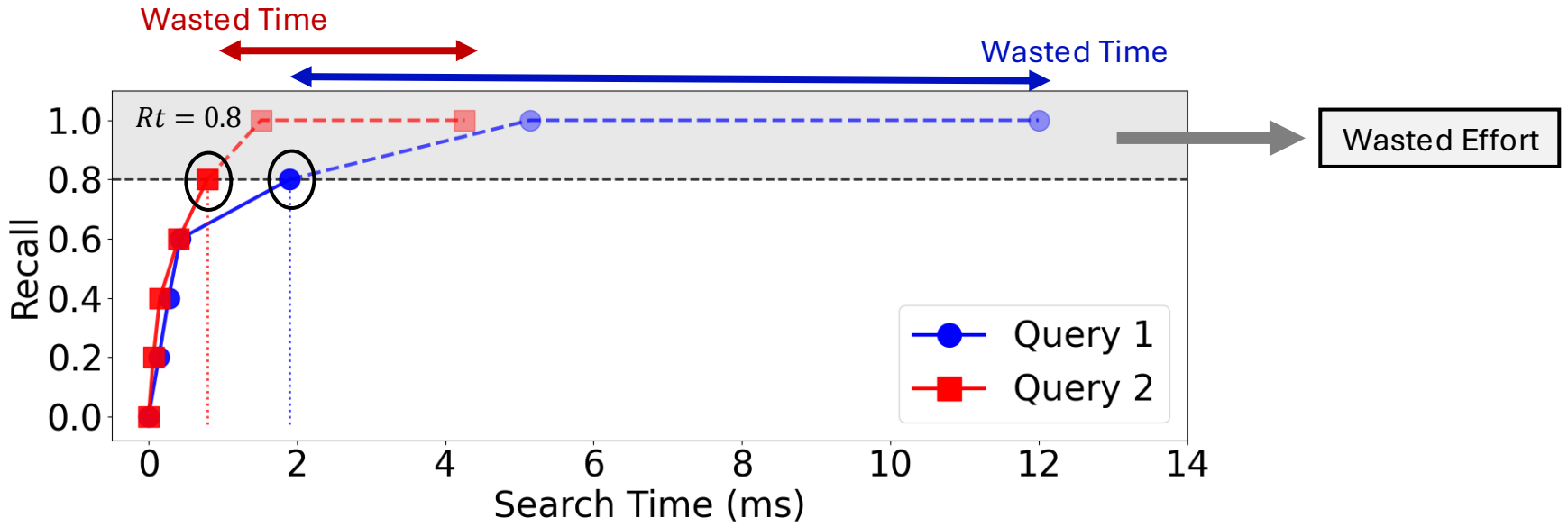
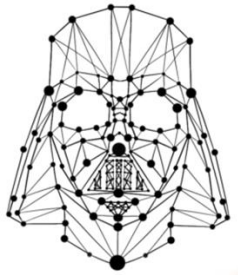


Different queries reach different recalls at different times!

Our Contributions

- Solution through **declarative recall**:
  - From ANNS(q, k, params) to **ANNS(q, k, Rt)!**

Our Contributions



- Solution through **declarative recall**:
  - From ANNS(q, k, params) to **ANNS(q, k, Rt)!**

- DARTH **predicts the query recall** at any point of the search → Early termination
  - Eliminate the need for parameter tuning
  - Support different indexes and distance measures
  - Support any Rt at query time and achieve it for each **individual** query →adapts to **query hardness**
  - Achieves **state-of-the-art results** when compared to baselines!

DARTH is SotA approach for declarative recall!

How to predict recall?

10K queries: 100M samples (many samples per query)

Dynamic search features
(distance calculations, search steps, descriptive nearest neighbors, ...)

Current Recall

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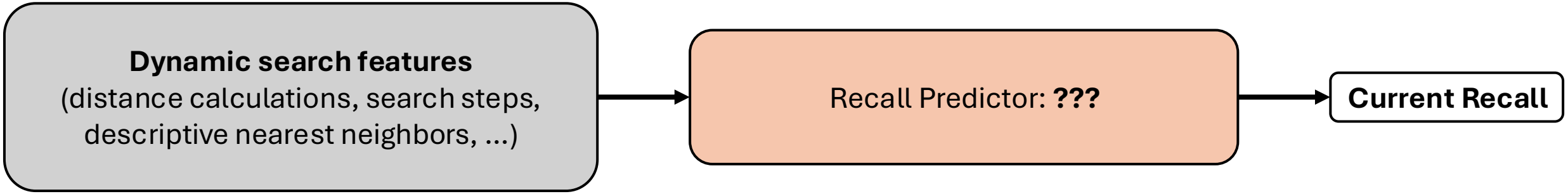

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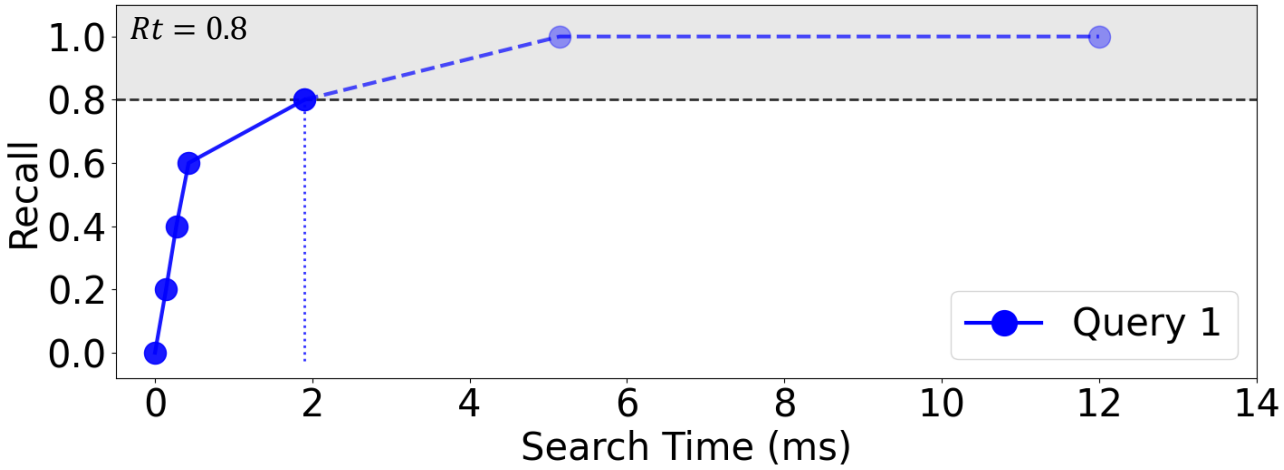

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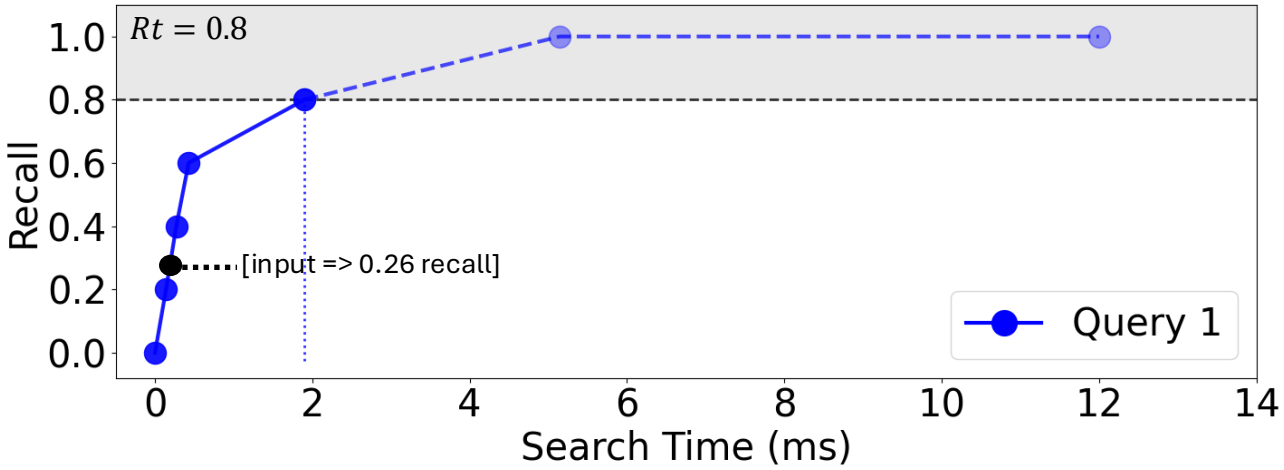

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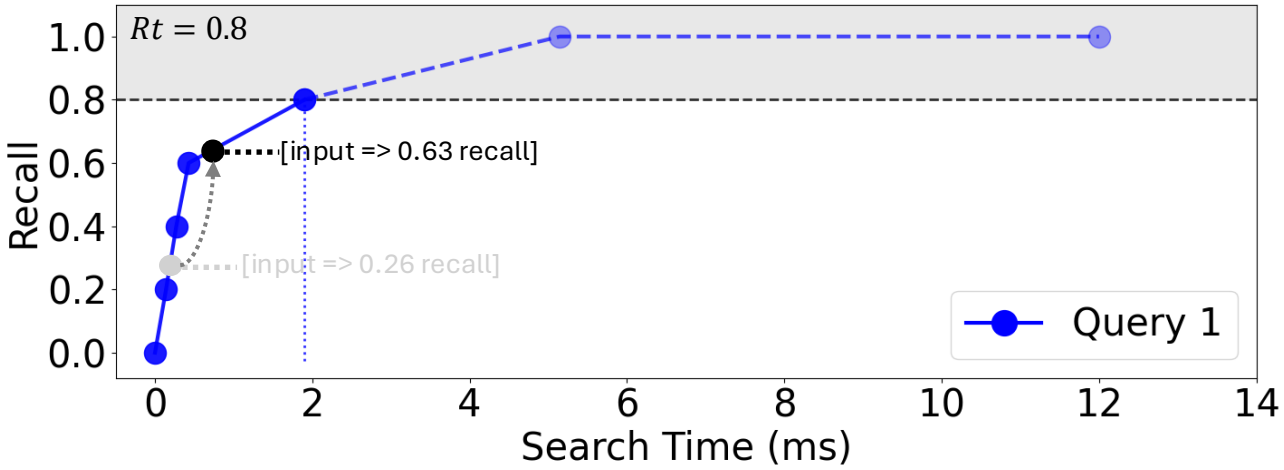

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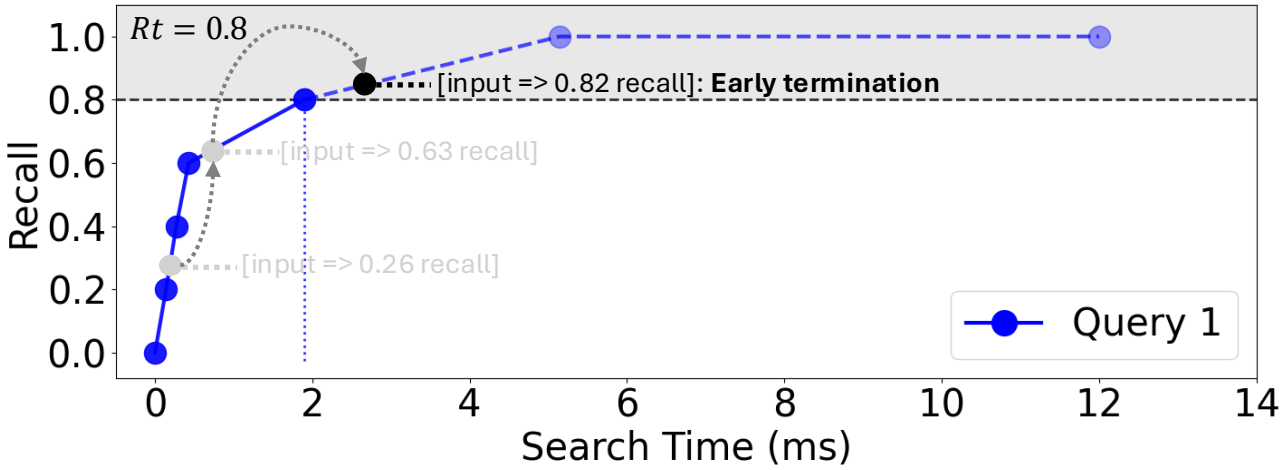

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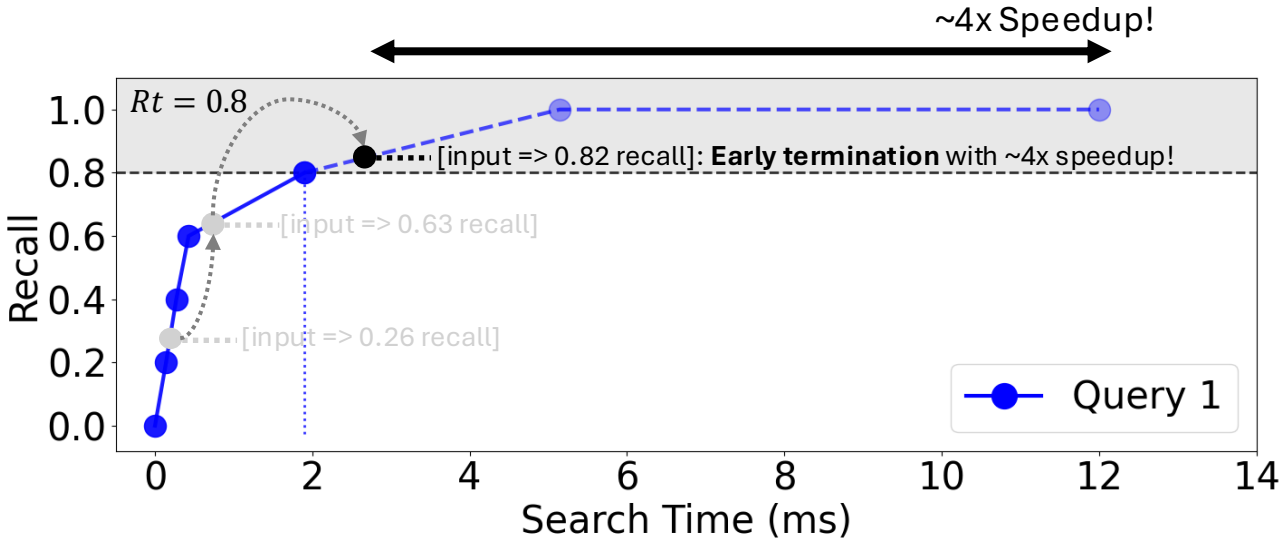

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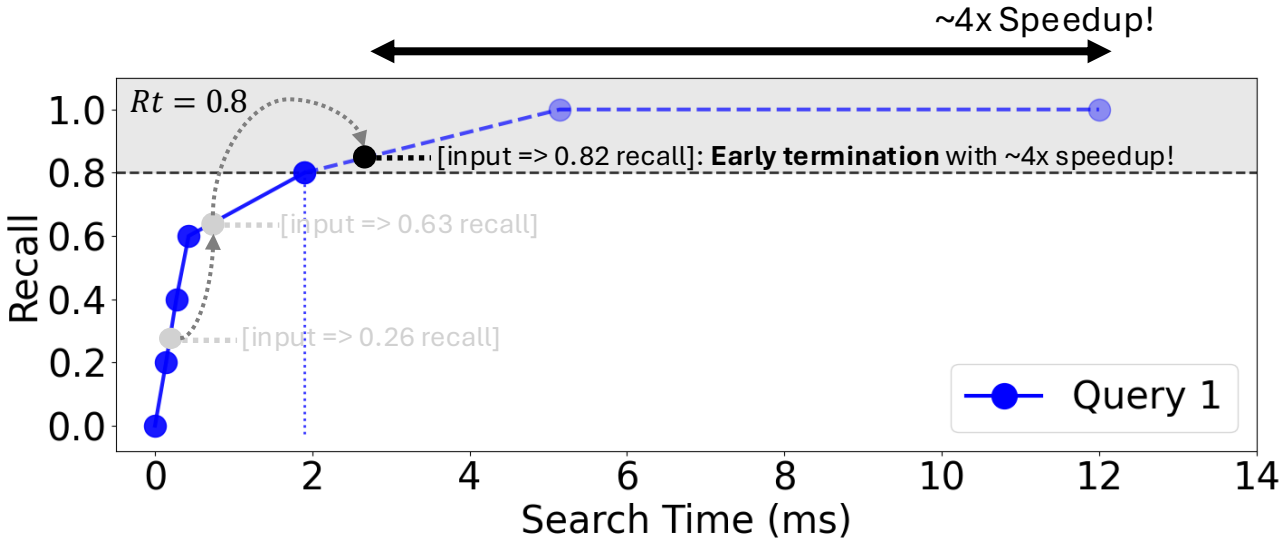

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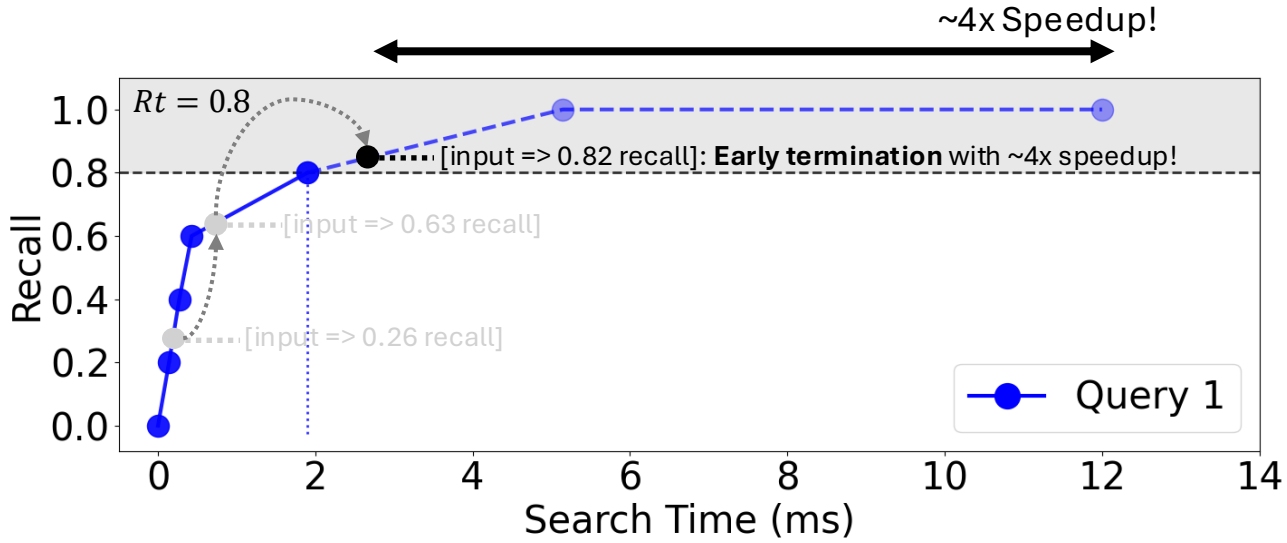

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Very fast training and inference, optimized invocations!

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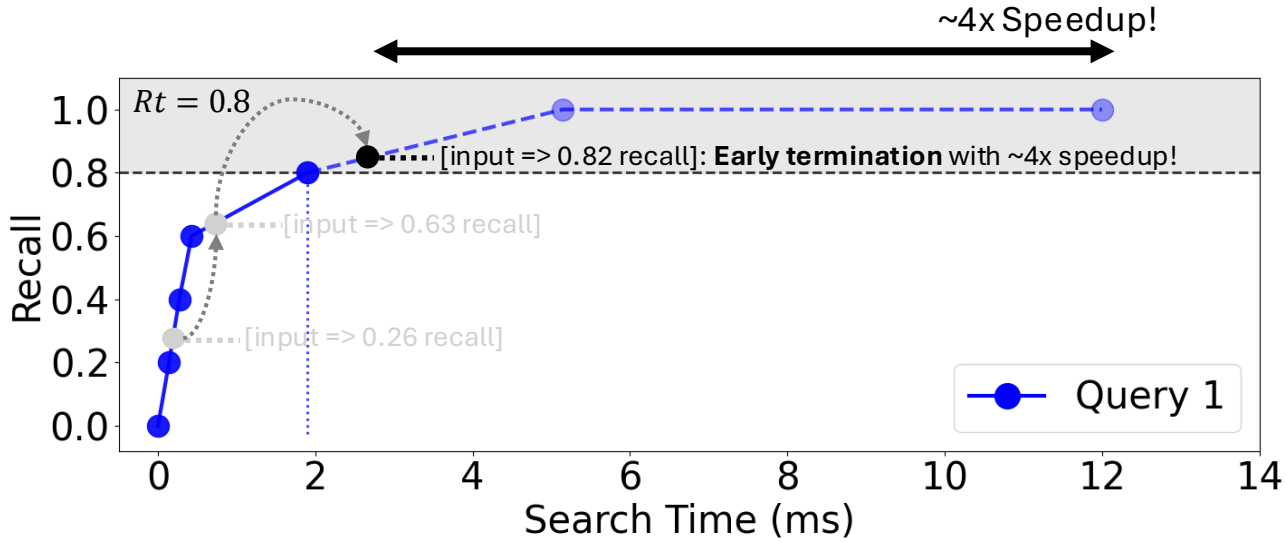

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FAISS & LightGBM (C/C++), k=50, 1000 queries

SIFT100M DEEP100M GLOVE1M GIST1M

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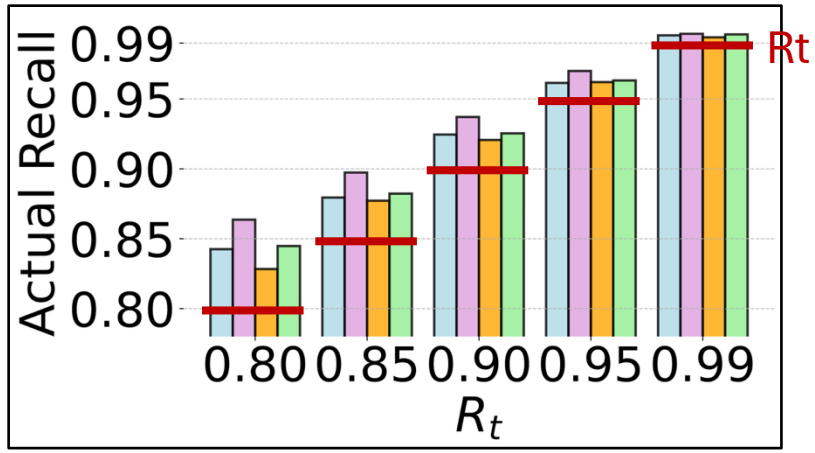

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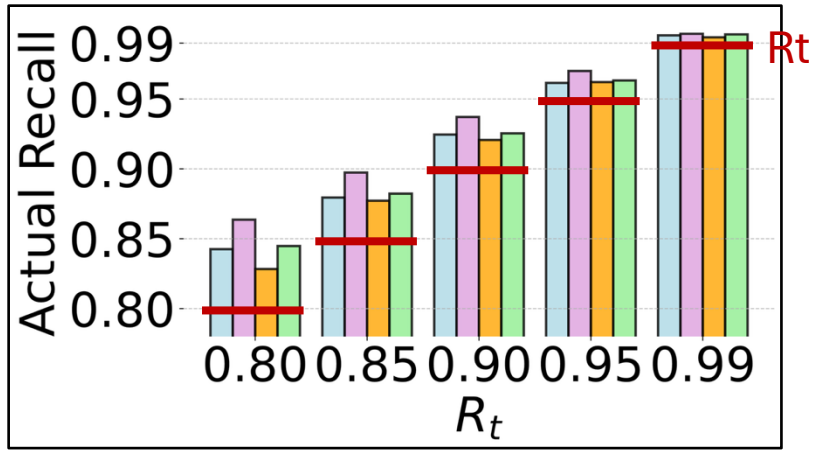

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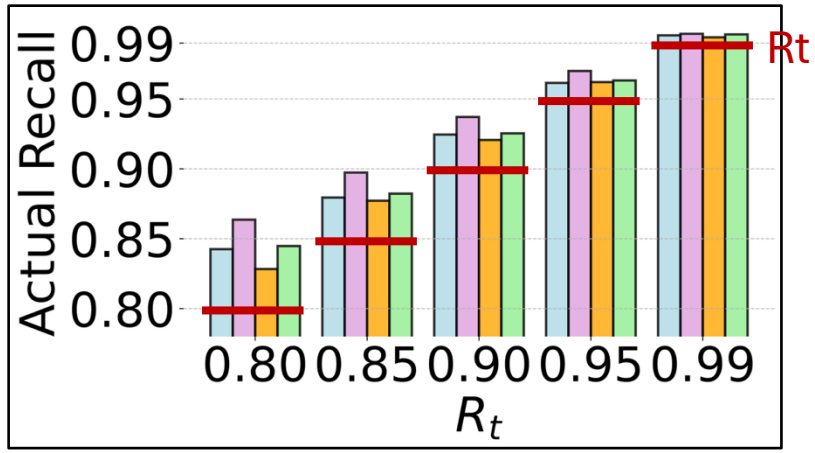

DARTH query answering speed:
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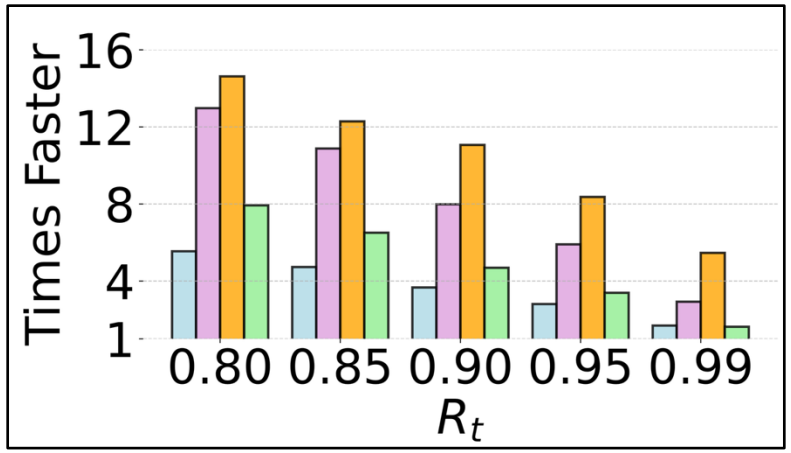

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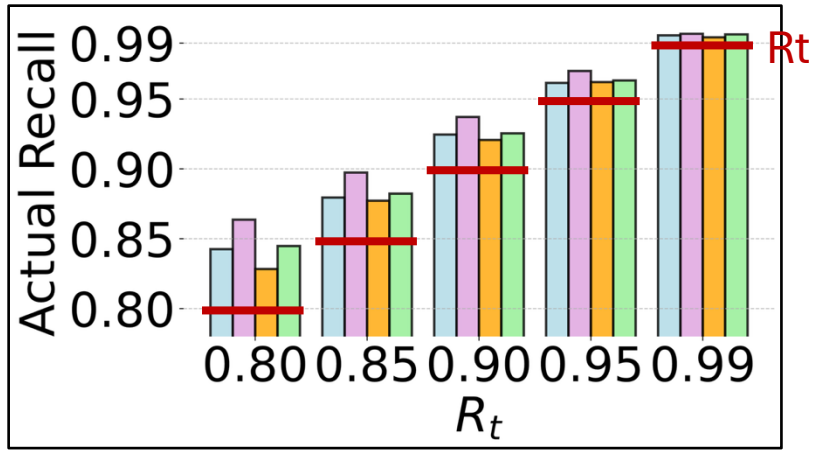

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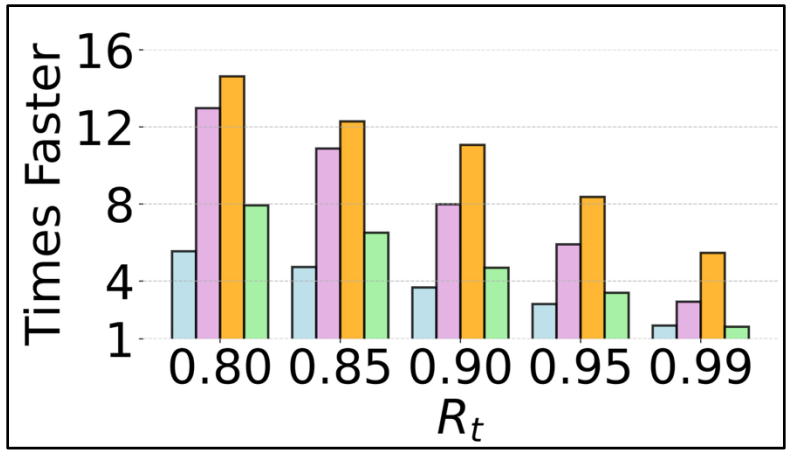

speedups **up to 15x compared to plain search** without early termination!

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DARTH resilience:
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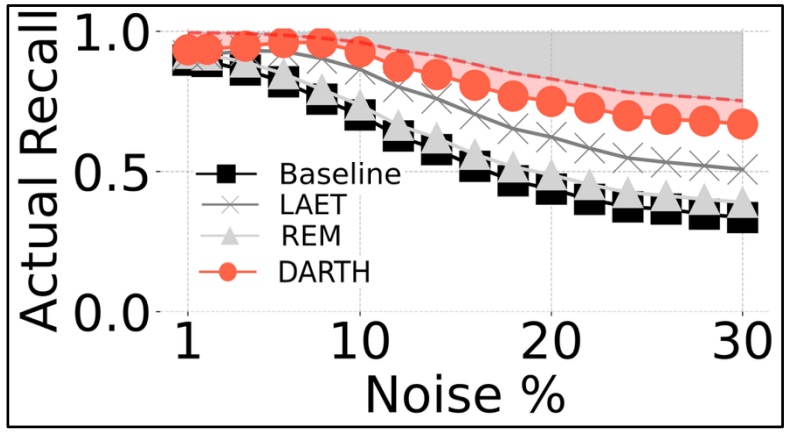

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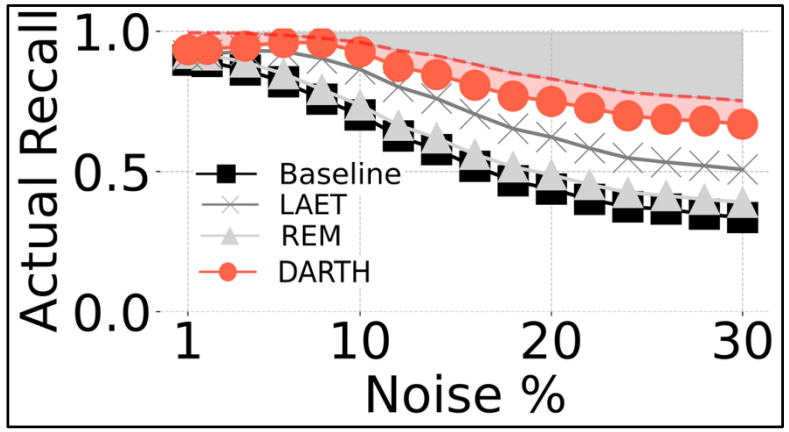

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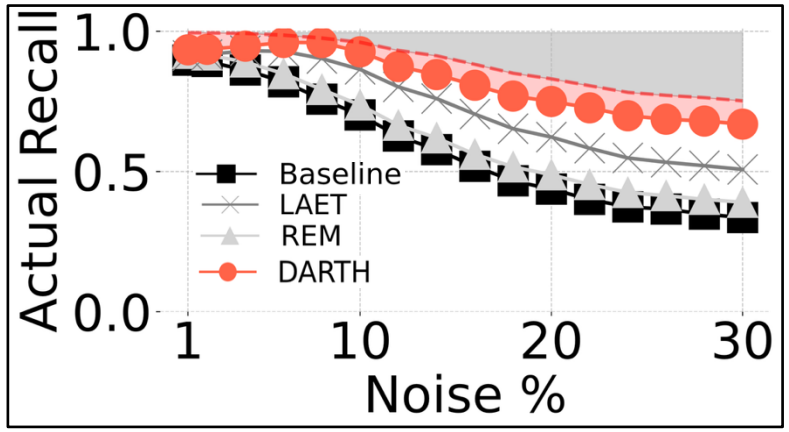

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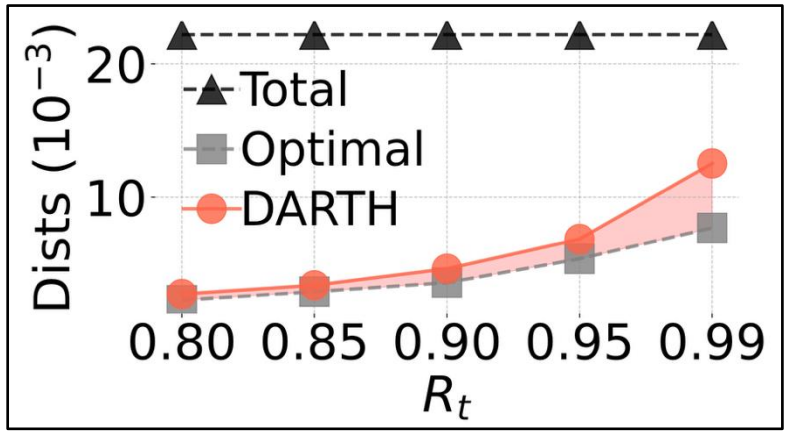

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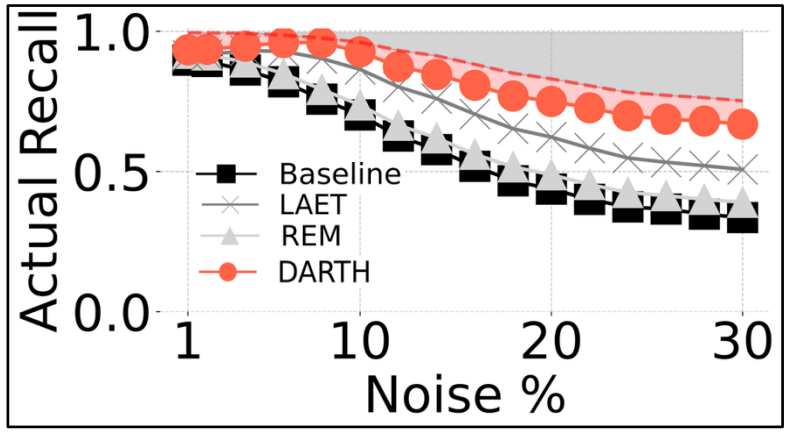

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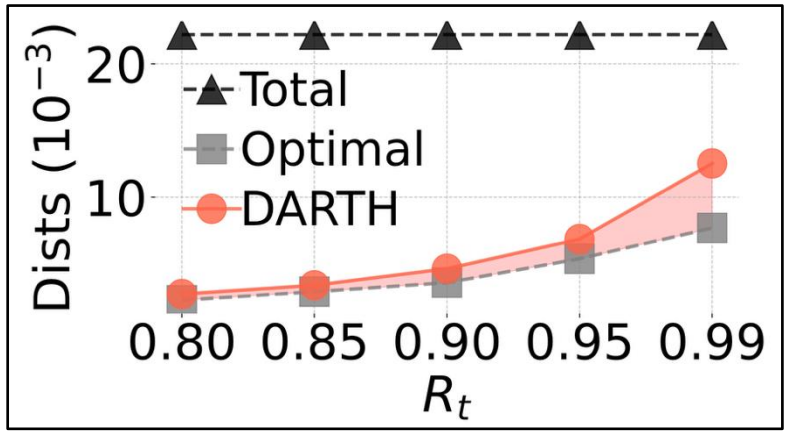

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Near-optimal early termination quality!

Conclusions

- Declarative recall can provide a very useful interface for ANNS
- DARTH
  - Accurate and efficient approach for declarative target recall
  - Early termination through recall prediction and adaptive intervals
  - SotA results!
- Future work
  - Probabilistic quality guarantees for predictions
  - Filtered vector search

Artifacts, ongoing works, and more!

Thank you!