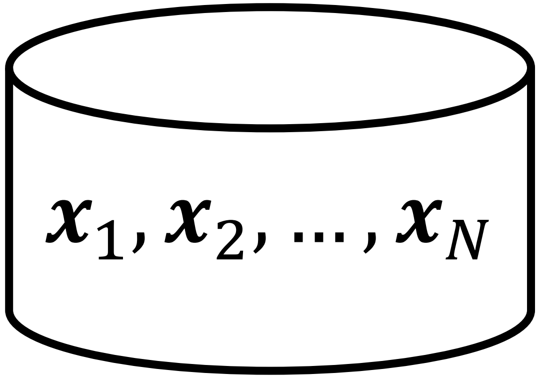
ACM Multimedia 2020 Tutorial on

Effective and Efficient: Toward Open-world Instance Re-identification

Billion-scale Approximate Nearest Neighbor Search

Yusuke Matsui
The University of Tokyo

Nearest Neighbor Search; NN

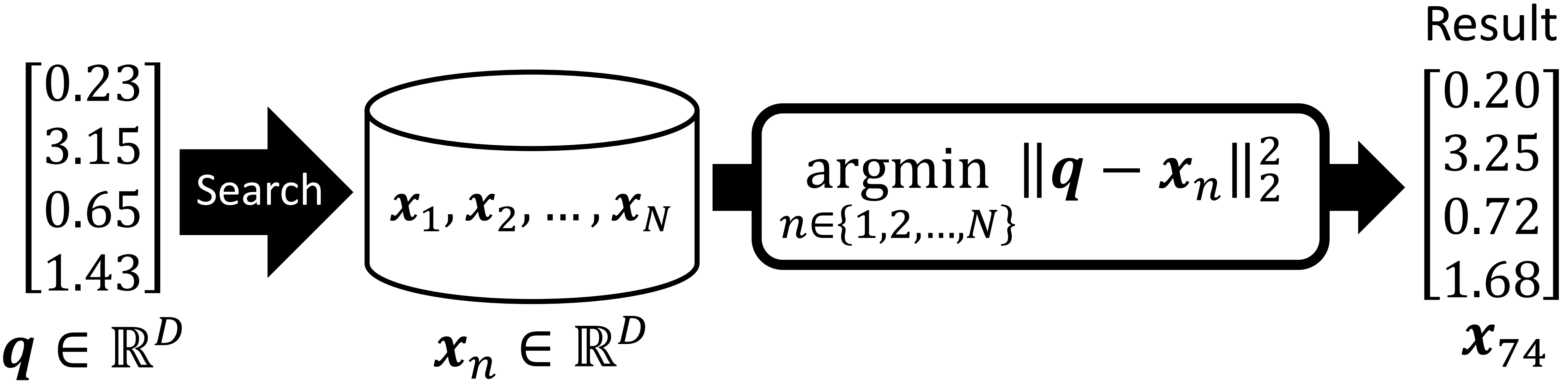


$\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N$

$\boldsymbol{x}_n \in \mathbb{R}^D$

- N D-dim database vectors: $\{\boldsymbol{x}_n\}_{n=1}^{N}$

Nearest Neighbor Search; NN



Result

$$\begin{bmatrix}0.23\\3.15\\0.65\\1.43\end{bmatrix} \xrightarrow{\text{Search}} \boxed{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N} \rightarrow \boxed{\operatorname*{argmin}_{n \in \{1,2,\dots,N\}} \|\boldsymbol{q} - \boldsymbol{x}_n\|_2^2} \rightarrow \begin{bmatrix}0.20\\3.25\\0.72\\1.68\end{bmatrix}$$

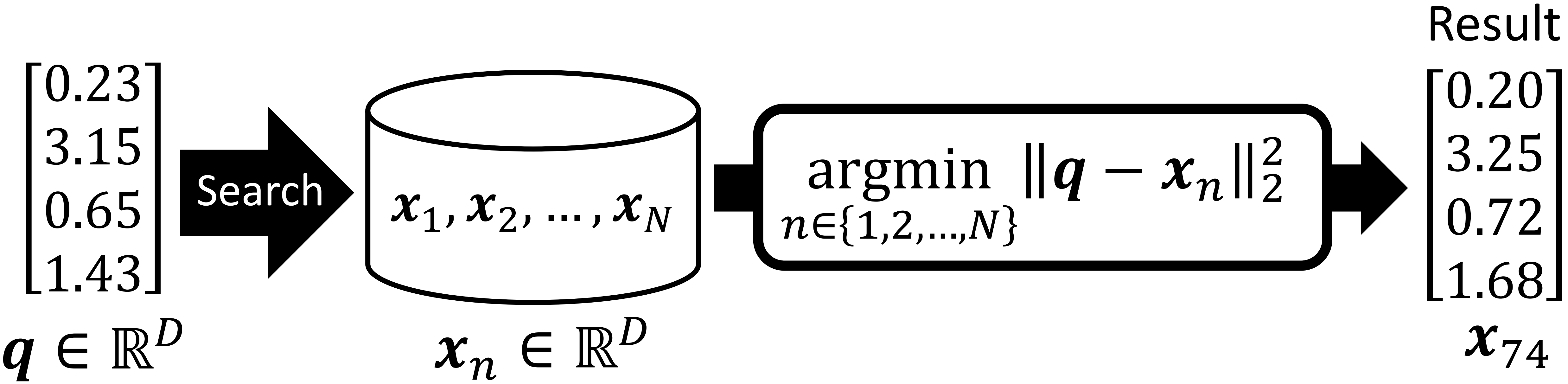
$\boldsymbol{q} \in \mathbb{R}^D$

$\boldsymbol{x}_n \in \mathbb{R}^D$

$\boldsymbol{x}_{74}$

- N D-dim database vectors: $\{\boldsymbol{x}_n\}_{n=1}^{N}$
- Given a query $\boldsymbol{q}$, find the closest vector from the database
- One of the fundamental problems in computer science
- Solution: linear scan, $O(ND)$, slow ☹

Approximate Nearest Neighbor Search; ANN



$$\begin{bmatrix}0.23\\3.15\\0.65\\1.43\end{bmatrix}$$

$\boldsymbol{q} \in \mathbb{R}^D$

Search

$\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N$

$\boldsymbol{x}_n \in \mathbb{R}^D$

$$\underset{n\in\{1,2,\dots,N\}}{\operatorname{argmin}} \|\boldsymbol{q} - \boldsymbol{x}_n\|_2^2$$

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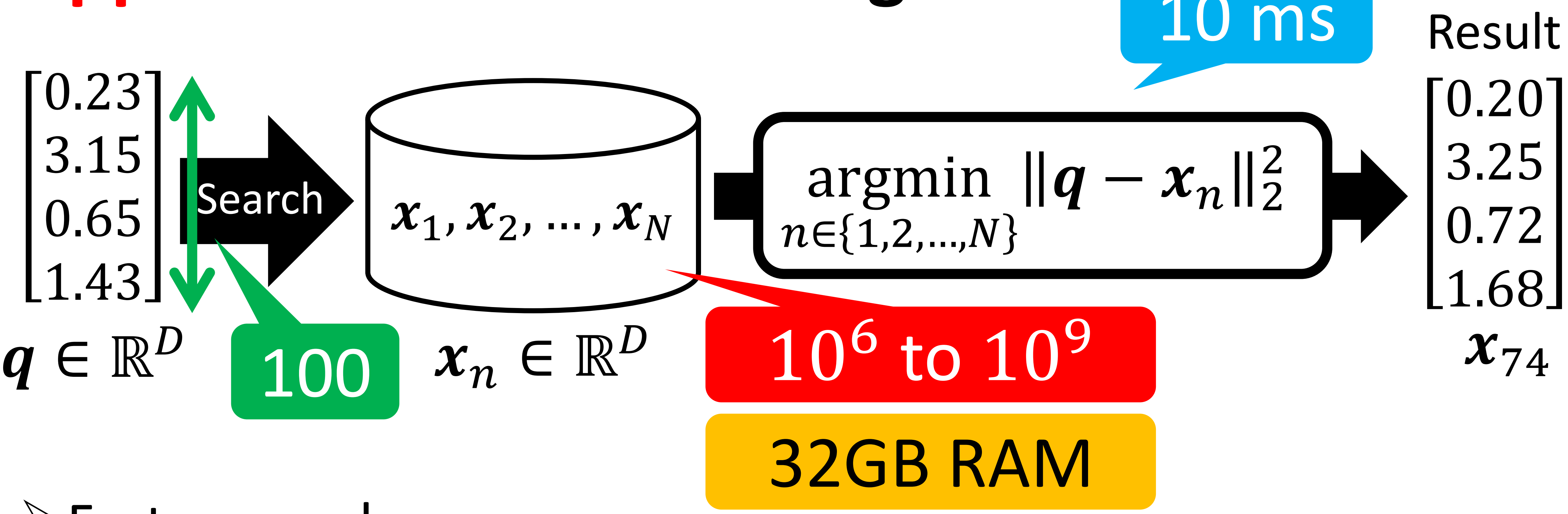
$\boldsymbol{x}_{74}$

- Faster search
- Don’t necessarily have to be exact neighbors
- Trade off: runtime, accuracy, and memory-consumption

Approximate Nearest Neighbor Search: ANN



10 ms

Result

$\begin{bmatrix} 0.23 \\ 3.15 \\ 0.65 \\ 1.43 \end{bmatrix}$

$\boldsymbol{q} \in \mathbb{R}^D$

100

Search

$\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N$

$\boldsymbol{x}_n \in \mathbb{R}^D$

$\underset{n \in \{1,2,\dots,N\}}{\operatorname{argmin}} \|\boldsymbol{q} - \boldsymbol{x}_n\|_2^2$

10^6 to 10^9

32GB RAM

$\begin{bmatrix} 0.20 \\ 3.25 \\ 0.72 \\ 1.68 \end{bmatrix}$

$\boldsymbol{x}_{74}$

- Faster search
- Don’t necessarily have to be exact neighbors
- Trade off: runtime, accuracy, and memory-consumption
- A sense of scale: billion-scale data on memory

NN/ANN for CV

https://about.mercari.com/press/news/article/20190318_image_search/

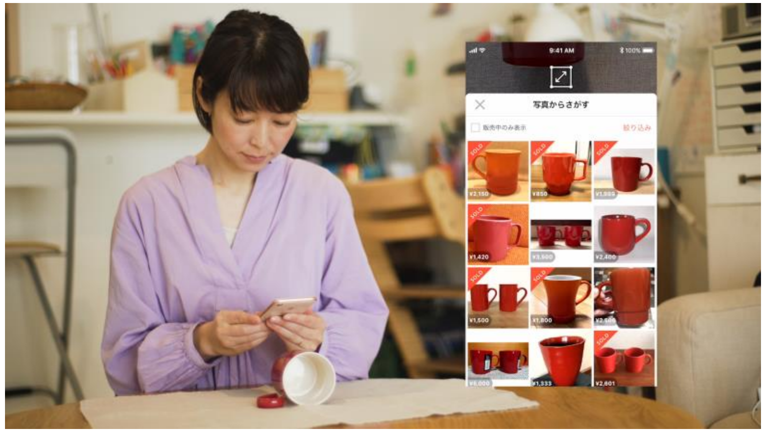
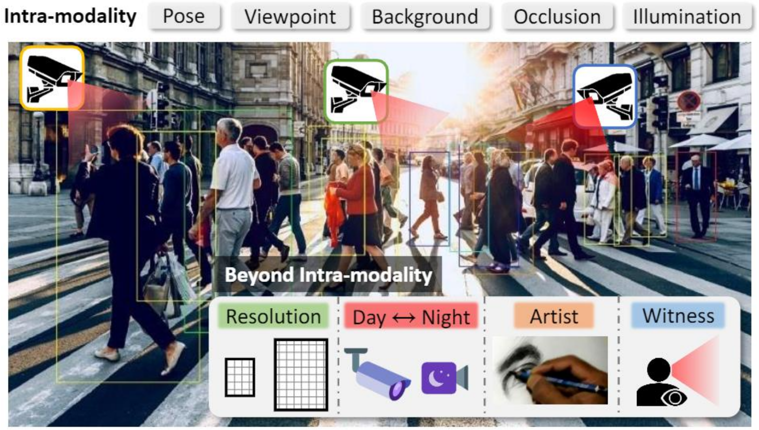
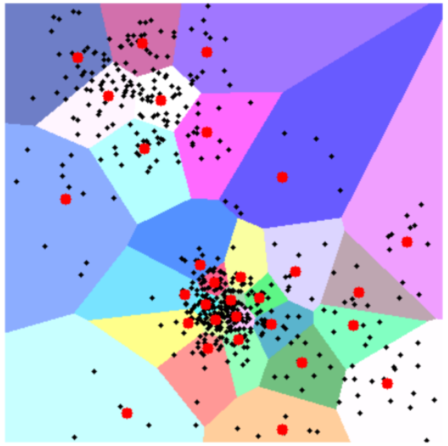


Image retrieval

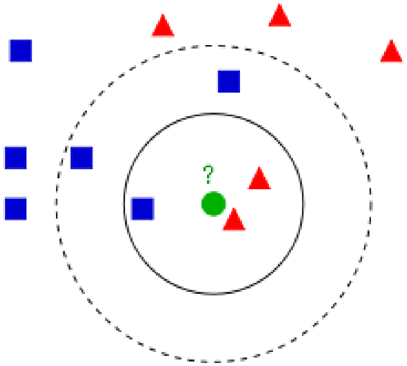


Person Re-identification



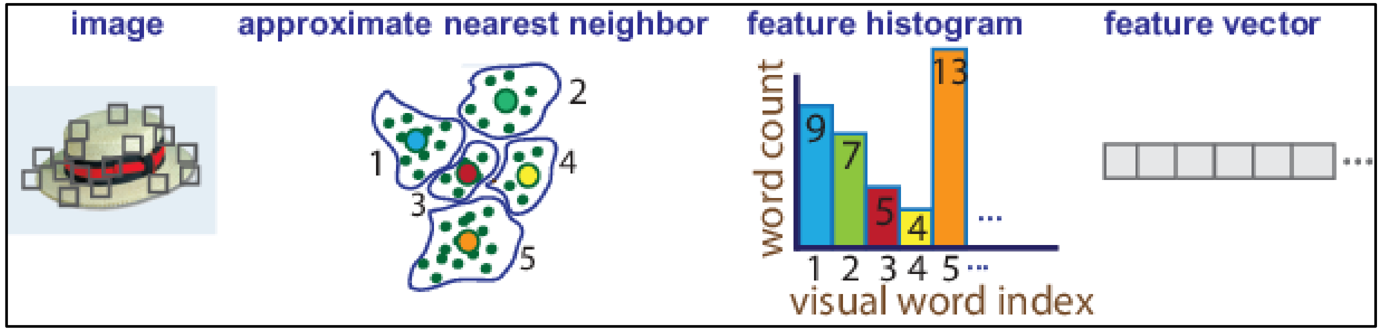
Clustering

https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm



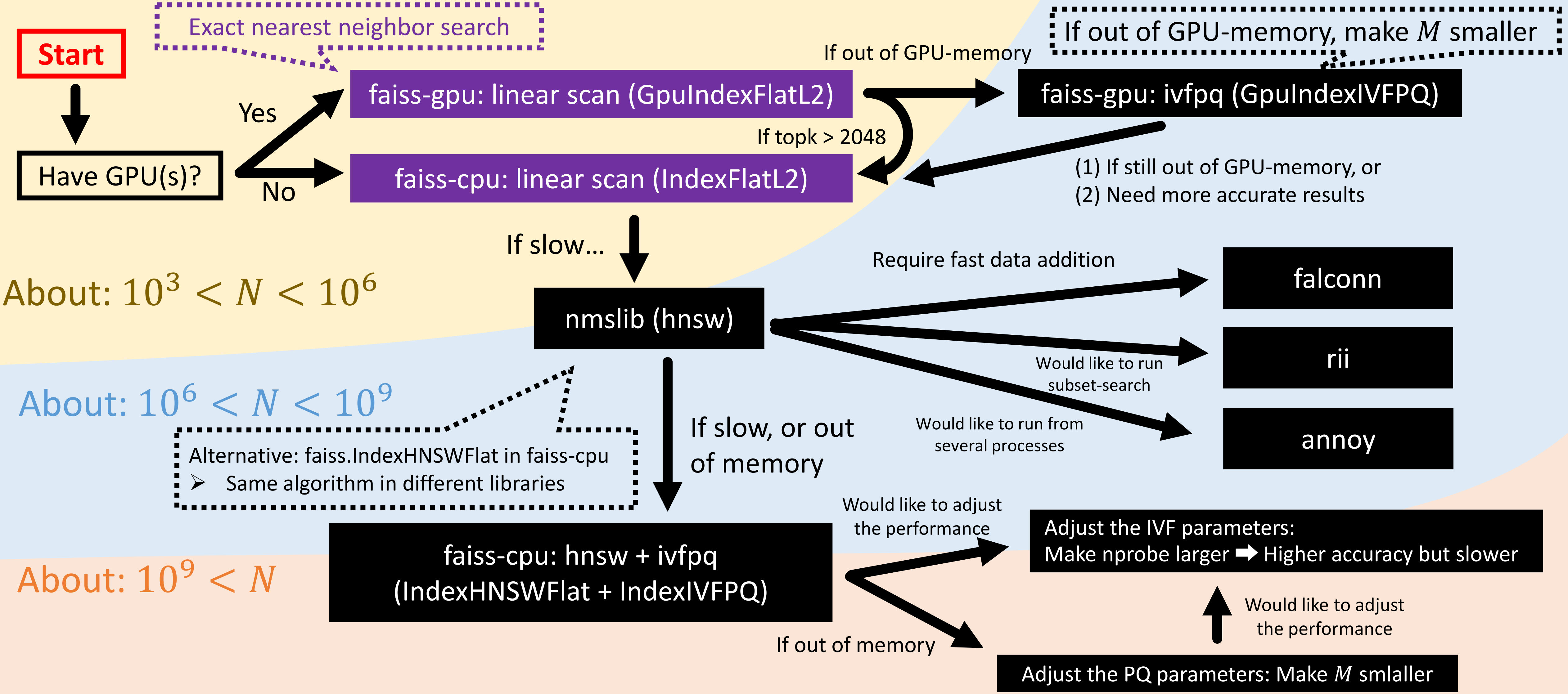
kNN recognition

https://jp.mathworks.com/help/vision/ug/image-classification-with-bag-of-visual-words.html



- Originally: fast construction of bag-of-features
- One of the benchmarks is still SIFT

cheat-sheet for ANN in Python （as of 2020. Can be installed by conda or pip）



Start

Have GPU(s)?

Yes

No

Exact nearest neighbor search

faiss-gpu: linear scan (GpuIndexFlatL2)

faiss-cpu: linear scan (IndexFlatL2)

If out of GPU-memory

If topk > 2048

If out of GPU-memory, make M smaller

faiss-gpu: ivfpq (GpuIndexIVFPQ)

(1) If still out of GPU-memory, or

(2) Need more accurate results

If slow…

About: $10^3 < N < 10^6$

nmslib (hnsw)

Require fast data addition

falconn

rii

Would like to run subset-search

annoy

Would like to run from several processes

About: $10^6 < N < 10^9$

Alternative: faiss.IndexHNSWFlat in faiss-cpu

- ➢ Same algorithm in different libraries

If slow, or out of memory

About: $10^9 < N$

faiss-cpu: hnsw + ivfpq

(IndexHNSWFlat + IndexIVFPQ)

Would like to adjust the performance

Adjust the IVF parameters:

Make nprobe larger ➡ Higher accuracy but slower

Would like to adjust the performance

If out of memory

Adjust the PQ parameters: Make M smlaller

Note: Assuming $D \cong 100$. The size of the problem is determined by DN. If $100 \ll D$, run PCA to reduce D to 100

Part 1:
Nearest Neighbor Search

Part 2:
Approximate Nearest Neighbor Search

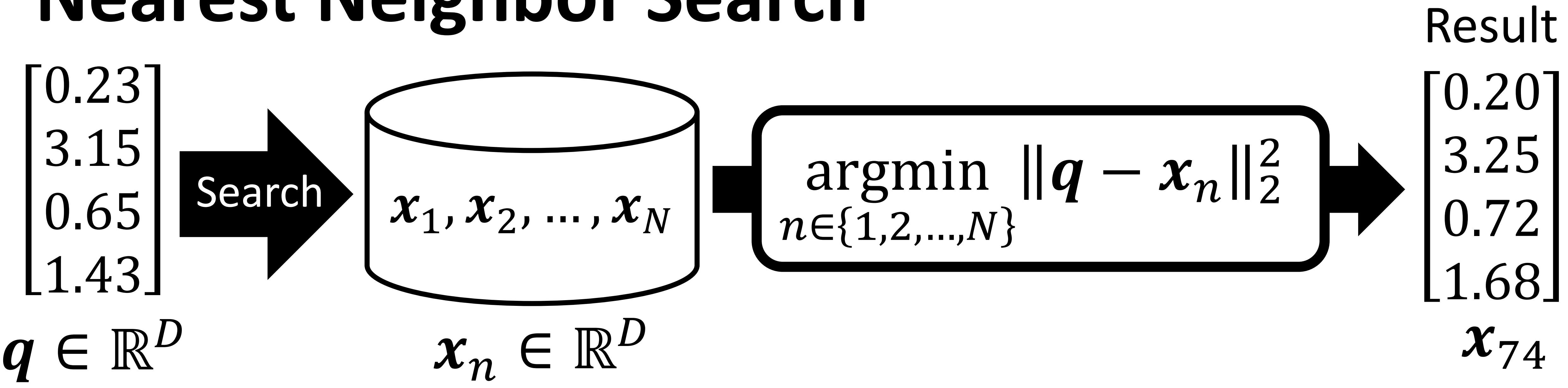
<u>Part 1:</u>

Nearest Neighbor Search

<u>Part 2:</u>

Approximate Nearest Neighbor Search

Nearest Neighbor Search



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$\boldsymbol{q} \in \mathbb{R}^D$ $\quad$ $\boldsymbol{x}_n \in \mathbb{R}^D$ $\quad$ $\boldsymbol{x}_{74}$

- ➢Should try this first of all
- ➢Introduce a naïve implementation
- ➢Introduce a fast implementation
  - ✓ **Faiss** library from FAIR (you'll see many times today. CPU & GPU)
- ➢Experience the drastic difference between the two impls

M D-dim query vectors $\mathcal{Q} = \{\boldsymbol{q}_1, \boldsymbol{q}_2, \dots, \boldsymbol{q}_M\}$

N D-dim database vectors $\mathcal{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$ $M \ll N$

Task：Given $\boldsymbol{q} \in \mathcal{Q}$ and $\boldsymbol{x} \in \mathcal{X}$, compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2$

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Naïve impl.

```
def l2sqr(q, x):
  diff = 0.0
  for (d = 0; d < D; ++d):
    diff += (q[d] – x[d])**2
  return diff
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parfor q in Q:
  for x in X:
    l2sqr(q, x)
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Parallelize query-side

Select min by heap, but omit it now

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faiss impl.

if $M < 20$:

compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2$ by SIMD

else :

compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2 = \|\boldsymbol{q}\|_2^2 - 2\boldsymbol{q}^\top \boldsymbol{x} + \|\boldsymbol{x}\|_2^2$ by BLAS

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$\|x-y\|_2^2$ by SIMD

Rename variables for the sake of explanation

```
float fvec_L2sqr (const float * x,
                  const float * y,
                  size_t d)
{
    __m256 msum1 = _mm256_setzero_ps();

    while (d >= 8) {
        __m256 mx = _mm256_loadu_ps (x); x += 8;
        __m256 my = _mm256_loadu_ps (y); y += 8;
        const __m256 a_m_b1 = mx - my;
        msum1 += a_m_b1 * a_m_b1;
        d -= 8;
    }

    __m128 msum2 = _mm256_extractf128_ps(msum1, 1);
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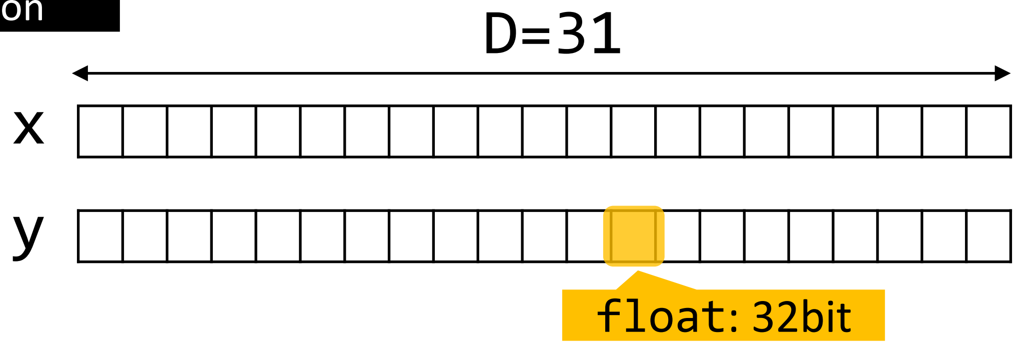

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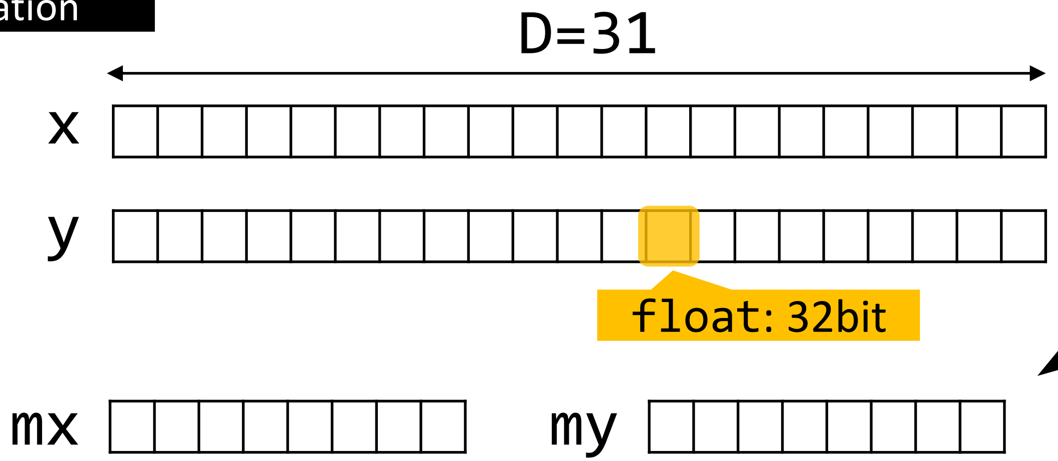

- 256bit SIMD Register
- Process eight floats at once

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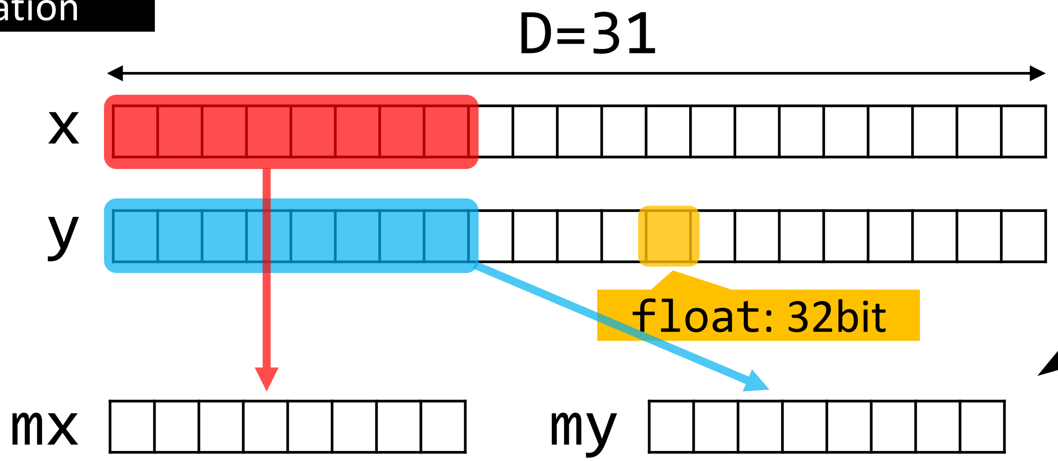

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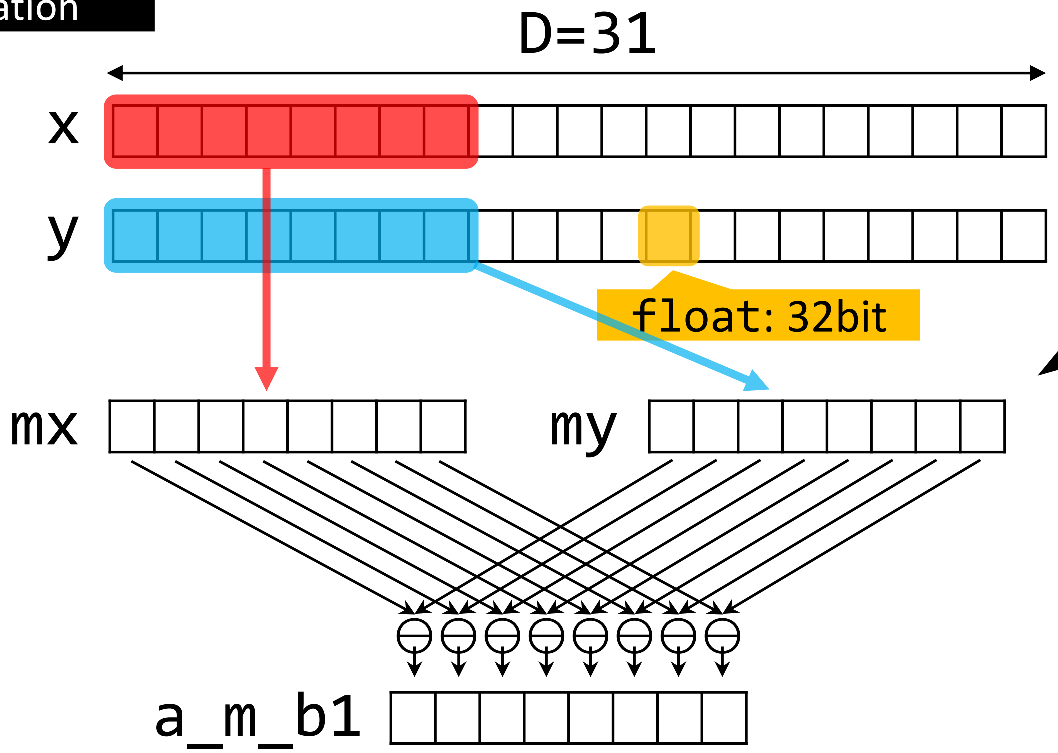

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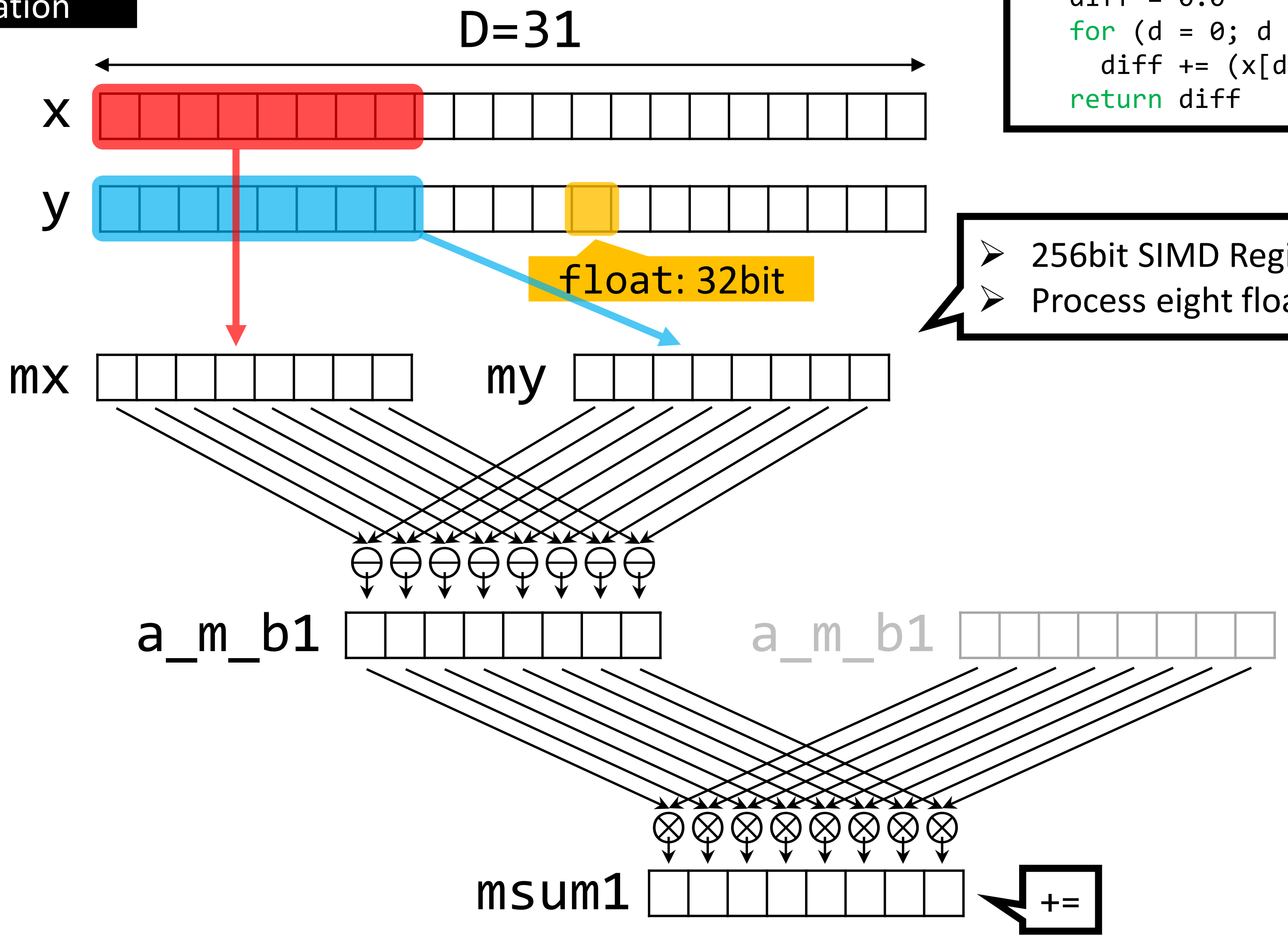

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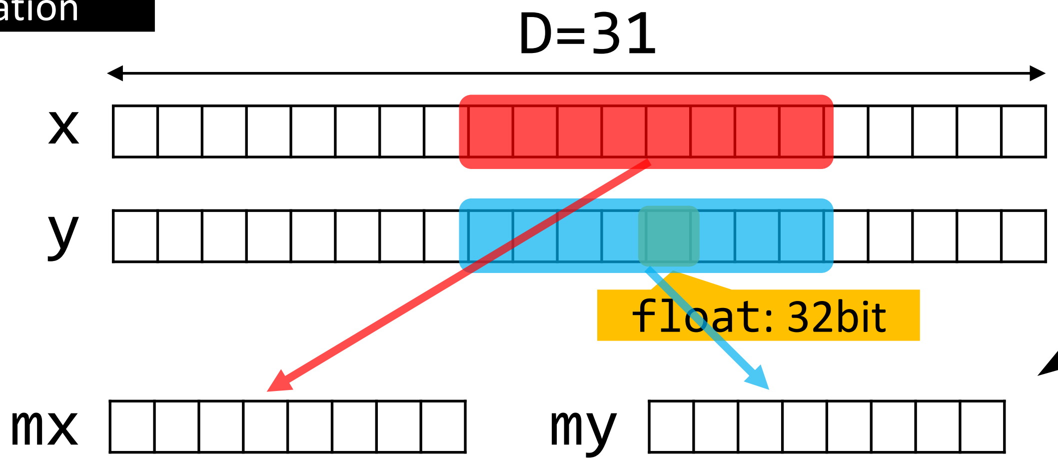

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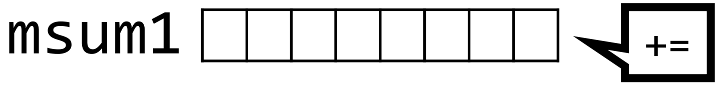

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$\|x - y\|_2^2$ by SIMD

Rename variables for the sake of explanation

```
float fvec_L2sqr (const float * x,
                  const float * y,
                  size_t d)
{
    __m256 msum1 = _mm256_setzero_ps();

    while (d >= 8) {
        __m256 mx = _mm256_loadu_ps (x); x += 8;
        __m256 my = _mm256_loadu_ps (y); y += 8;
        const __m256 a_m_b1 = mx - my;
        msum1 += a_m_b1 * a_m_b1;
        d -= 8;
    }

    __m128 msum2 = _mm256_extractf128_ps(msum1, 1);
    msum2 += _mm256_extractf128_ps(msum1, 0);

    if (d >= 4) {
        __m128 mx = _mm_loadu_ps (x); x += 4;
        __m128 my = _mm_loadu_ps (y); y += 4;
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        msum2 += a_m_b1 * a_m_b1;
        d -= 4;
    }

    if (d > 0) {
        __m128 mx = masked_read (d, x);
        __m128 my = masked_read (d, y);
        __m128 a_m_b1 = mx - my;
        msum2 += a_m_b1 * a_m_b1;
    }

    msum2 = _mm_hadd_ps (msum2, msum2);
    msum2 = _mm_hadd_ps (msum2, msum2);
    return  _mm_cvtss_f32 (msum2);
}
```

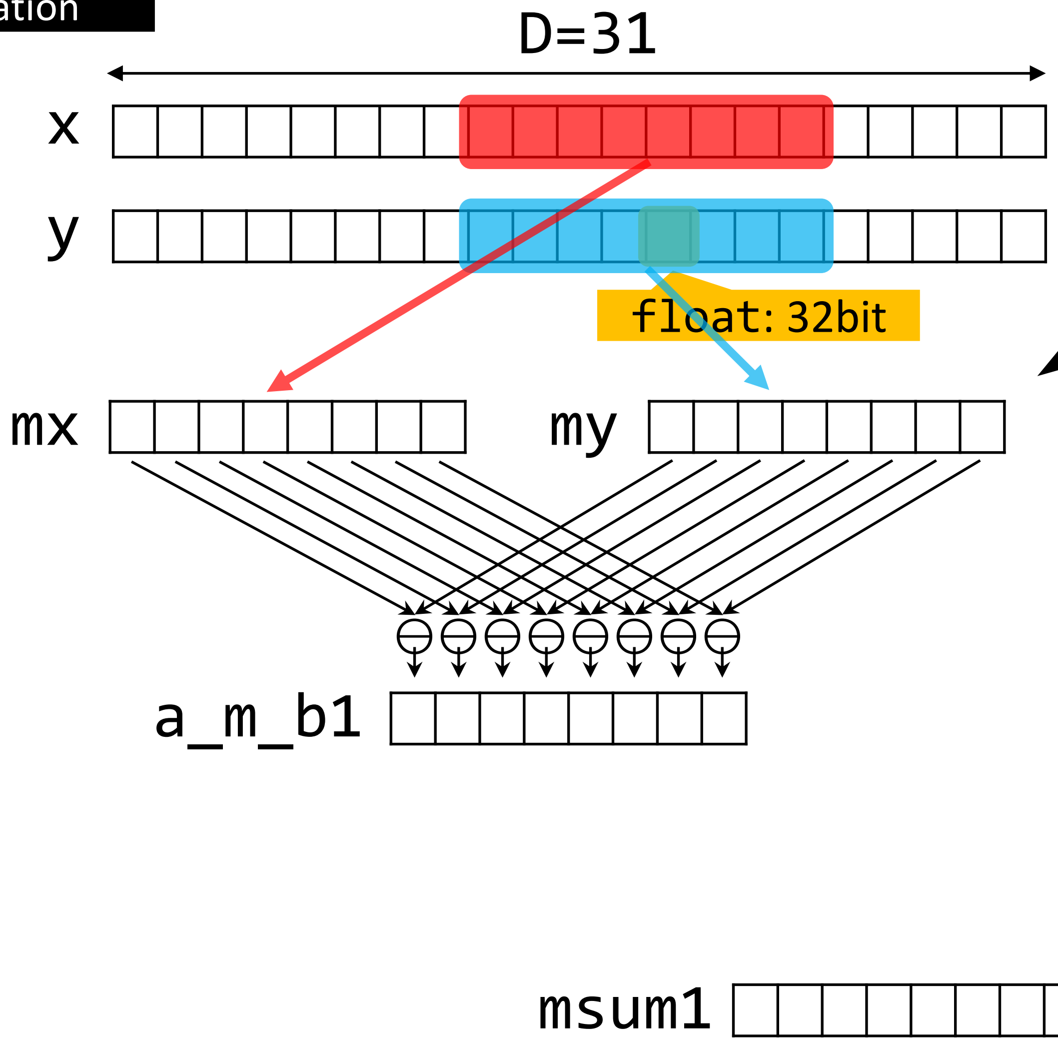

Ref.

```
def l2sqr(x, y):
  diff = 0.0
  for (d = 0; d < D; ++d):
    diff += (x[d] - y[d])**2
  return diff
```

- 256bit SIMD Register
- Process eight floats at once

+=

$\|x-y\|_2^2$ by SIMD

Rename variables for the sake of explanation

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float fvec_L2sqr (const float * x,
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        const __m128 a_m_b1 = mx - my;
        msum2 += a_m_b1 * a_m_b1;
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        __m128 mx = masked_read (d, x);
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        __m128 a_m_b1 = mx - my;
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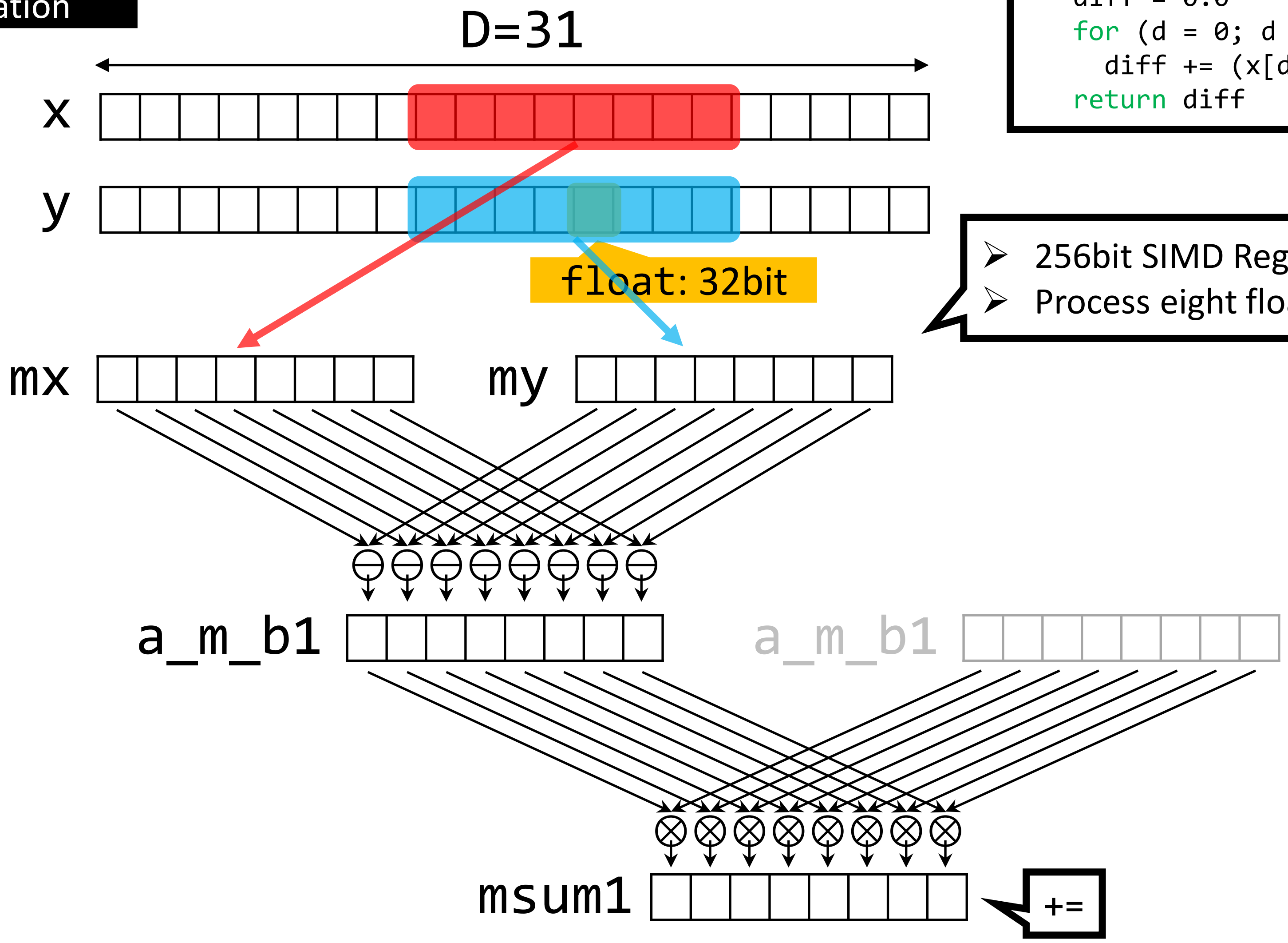
}
```



Ref.

```
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  for (d = 0; d < D; ++d):
    diff += (x[d] - y[d])**2
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```

- ➢ 256bit SIMD Register
- ➢ Process eight floats at once

$\|x - y\|_2^2$ by SIMD

Rename variables for the sake of explanation

```
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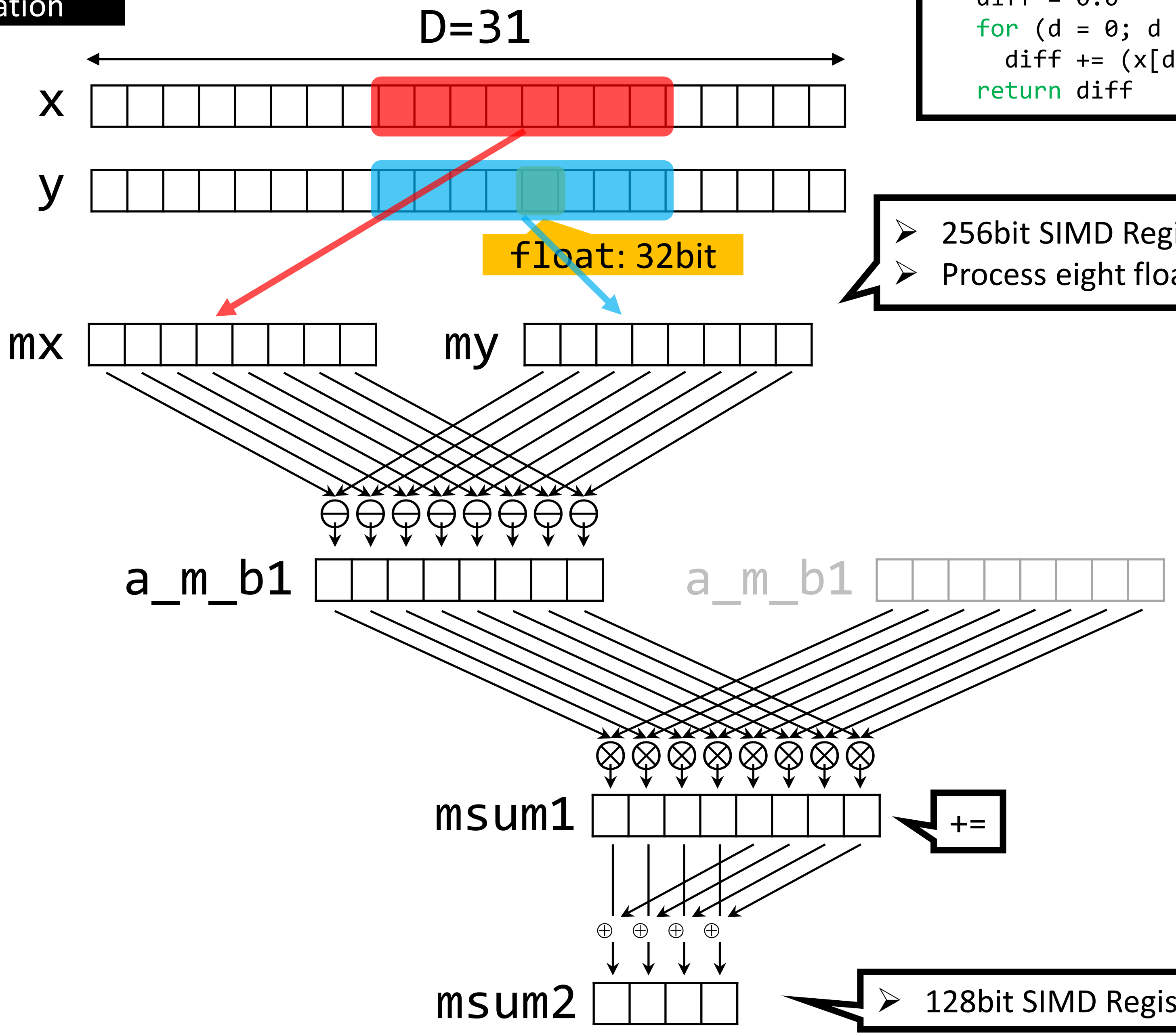

- 256bit SIMD Register
- Process eight floats at once

+=

- 128bit SIMD Register

$\|x - y\|_2^2$ by SIMD

Rename variables for the sake of explanation

```
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        const __m256 a_m_b1 = mx - my;
        msum1 += a_m_b1 * a_m_b1;
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        msum2 += a_m_b1 * a_m_b1;
        d -= 4;
    }

    if (d > 0) {
        __m128 mx = masked_read (d, x);
        __m128 my = masked_read (d, y);
        __m128 a_m_b1 = mx - my;
        msum2 += a_m_b1 * a_m_b1;
    }

    msum2 = _mm_hadd_ps (msum2, msum2);
    msum2 = _mm_hadd_ps (msum2, msum2);
    return  _mm_cvtss_f32 (msum2);
}
```

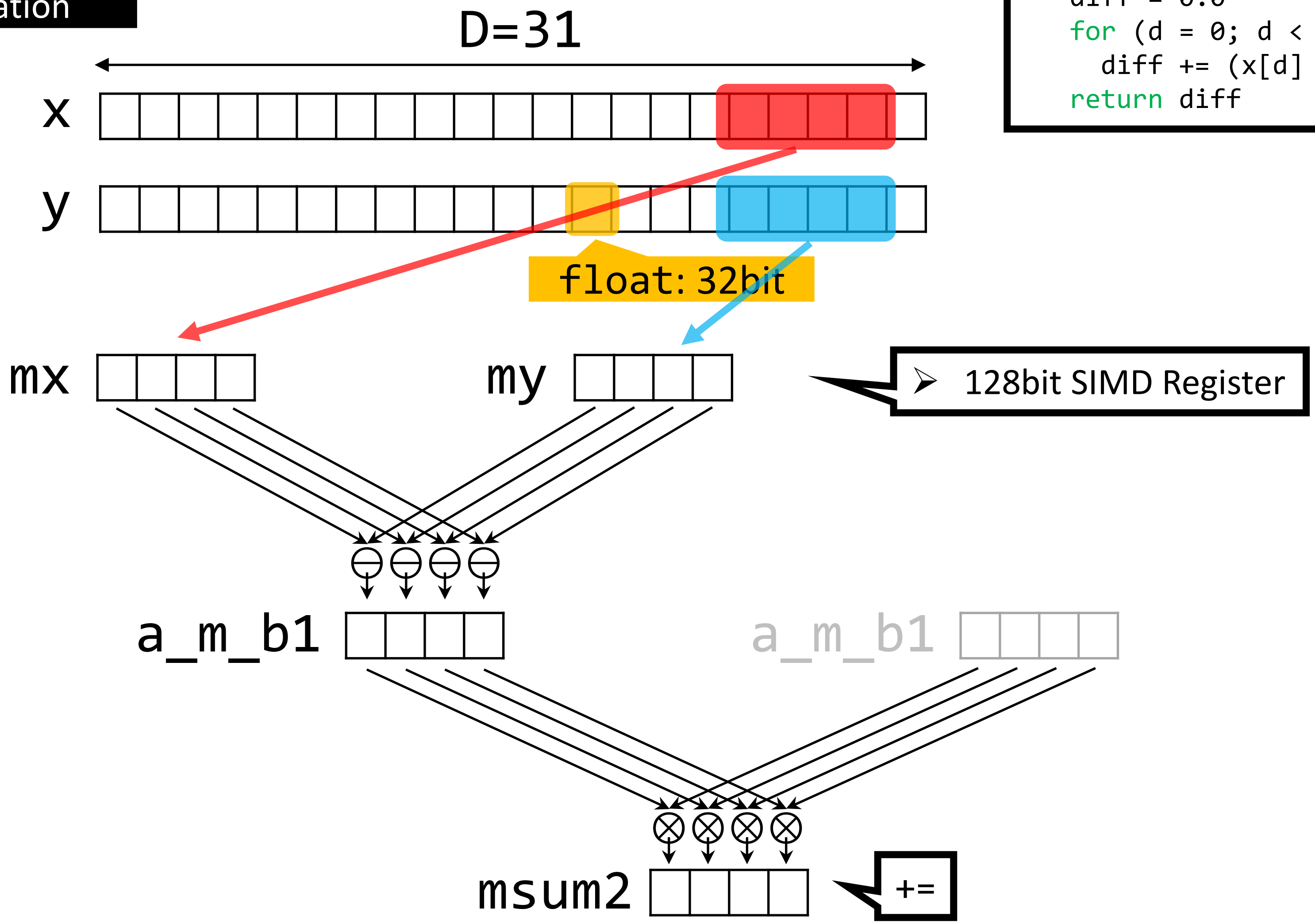

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```
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  for (d = 0; d < D; ++d):
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```

$\|x - y\|_2^2$ by SIMD

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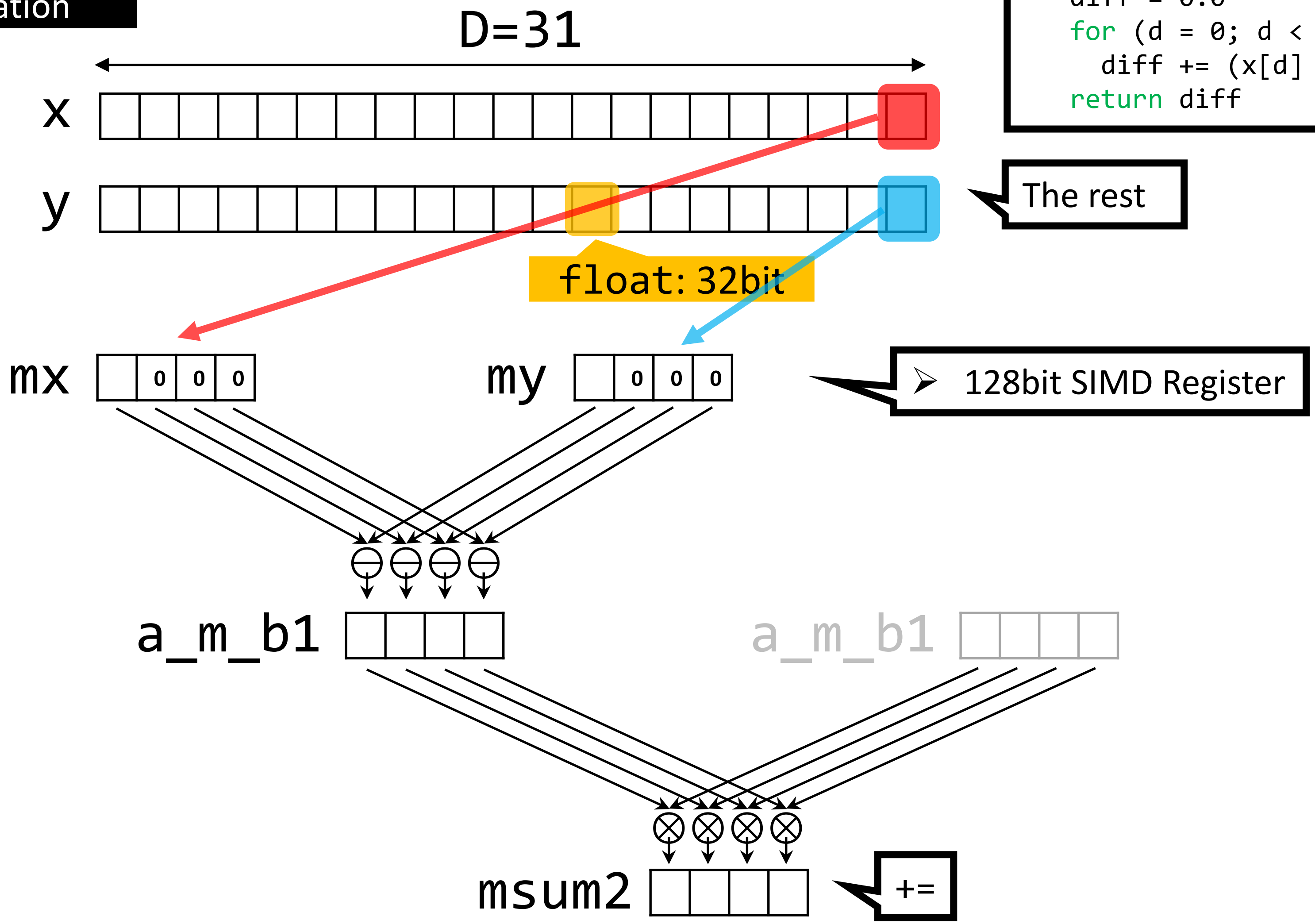

$\|\boldsymbol{x} - \boldsymbol{y}\|_2^2$ by SIMD

Rename variables for the sake of explanation

```
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        const __m256 a_m_b1 = mx - my;
        msum1 += a_m_b1 * a_m_b1;
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```
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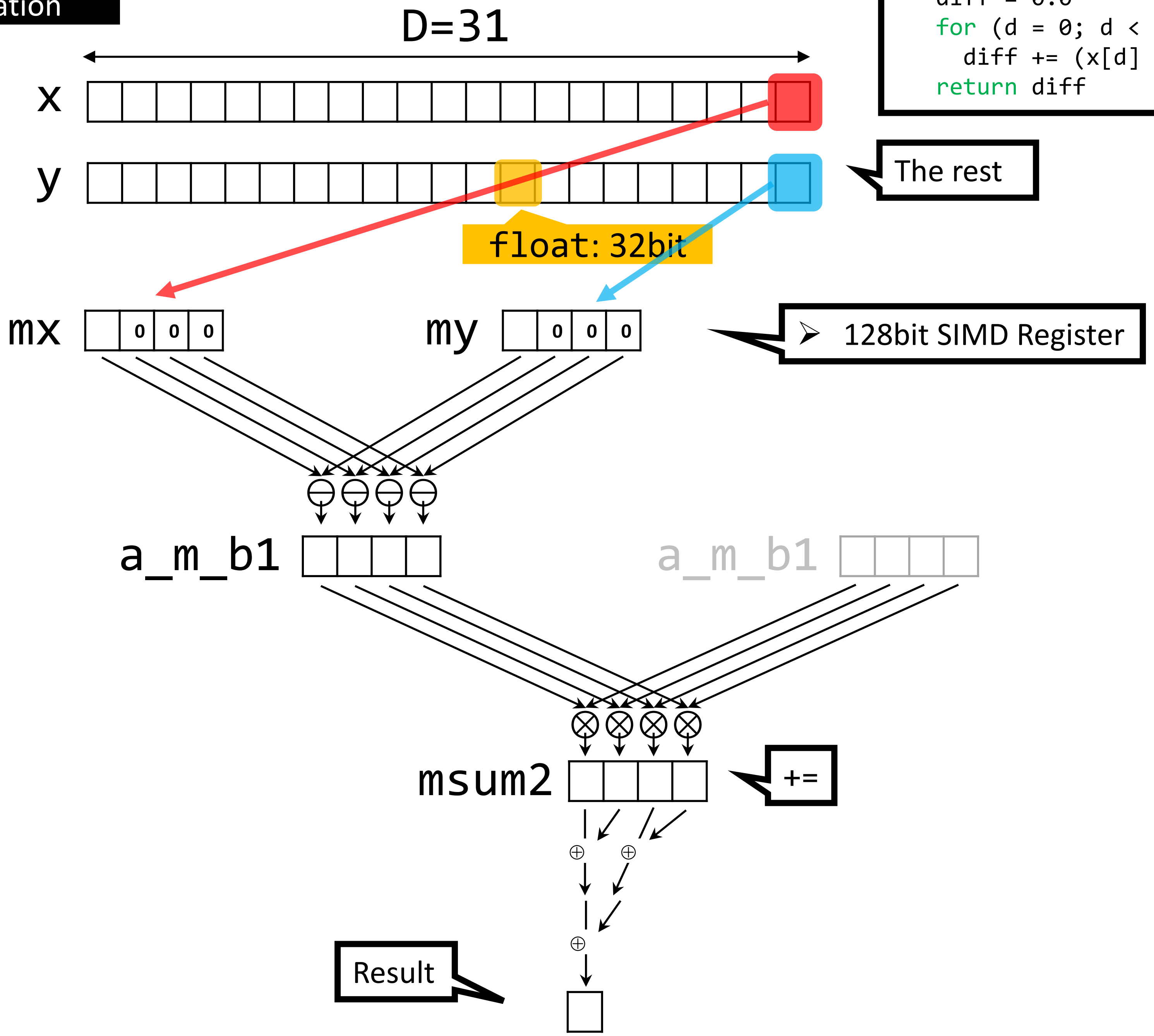

The rest

float: 32bit

➢ 128bit SIMD Register

+=

Result

$\|x-y\|_2^2$ by SIMD

Rename variables for the sake of explanation

```
float fvec_L2sqr (const float * x,
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                  size_t d)
{
    __m256 msum1 = _mm256_setzero_ps();
```
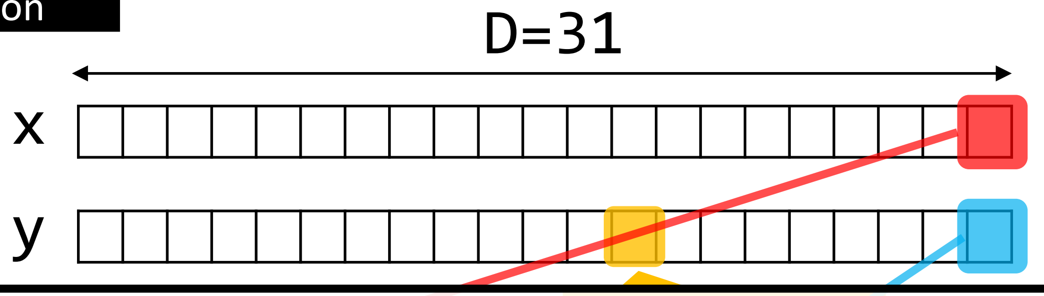



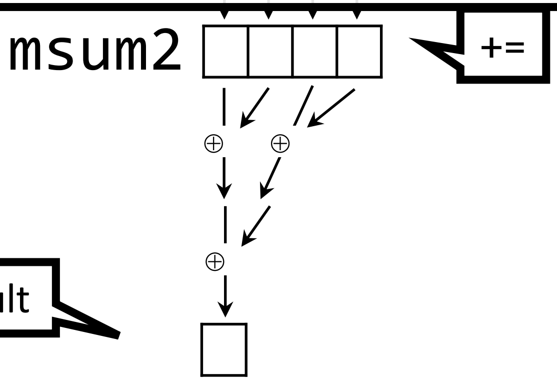
The rest

Ref.

```
def l2sqr(x, y):
  diff = 0.0
  for (d = 0; d < D; ++d):
    diff += (x[d] - y[d])**2
  return diff
```

- SIMD codes of faiss are simple and easy to read
- Being able to read SIMD codes comes in handy sometimes; *why this impl is super fast*
- Another example of SIMD L2sqr from HNSW: https://github.com/nmslib/hnswlib/blob/master/hnswlib/space_l2.h

```
        __m128 mx = masked_read (d, x);
        __m128 my = masked_read (d, y);
        __m128 a_m_b1 = mx - my;
        msum2 += a_m_b1 * a_m_b1;
    }

    msum2 = _mm_hadd_ps (msum2, msum2);
    msum2 = _mm_hadd_ps (msum2, msum2);
    return  _mm_cvtss_f32 (msum2);
}
```



+=

Result

M D-dim query vectors $\mathcal{Q} = \{\boldsymbol{q}_1, \boldsymbol{q}_2, \ldots, \boldsymbol{q}_M\}$

N D-dim database vectors $\mathcal{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\}$

Task：Given $\boldsymbol{q} \in \mathcal{Q}$ and $\boldsymbol{x} \in \mathcal{X}$, compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2$

Naïve impl.

```
def l2sqr(q, x):
  diff = 0.0
  for (d = 0; d < D; ++d):
    diff += (q[d] - x[d])**2
  return diff
```

```
parfor q in Q:
  for x in X:
    l2sqr(q, x)
```

Parallelize query-side

Select min by heap, but omit it now

---

faiss impl.

if $M < 20$:

compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2$ by SIMD

else :

compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2 = \|\boldsymbol{q}\|_2^2 - 2\boldsymbol{q}^\top\boldsymbol{x} + \|\boldsymbol{x}\|_2^2$ by BLAS

Compute $\|\boldsymbol{q} - \boldsymbol{x}\|_2^2 = \|\boldsymbol{q}\|_2^2 - 2\boldsymbol{q}^\top \boldsymbol{x} + \|\boldsymbol{x}\|_2^2$ with BLAS

Stack M D-dim query vectors to a $D \times M$ matrix: $Q = [\boldsymbol{q}_1, \boldsymbol{q}_2, \dots, \boldsymbol{q}_M] \in \mathbb{R}^{D \times M}$

Stack N D-dim database vectors to a $D \times N$ matrix: $X = [\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N] \in \mathbb{R}^{D \times N}$

```
# Compute tables
q_norms = norms(Q)        # $\|\boldsymbol{q}_1\|_2^2, \|\boldsymbol{q}_2\|_2^2, \dots, \|\boldsymbol{q}_M\|_2^2$
x_norms = norms(X)        # $\|\boldsymbol{x}_1\|_2^2, \|\boldsymbol{x}_2\|_2^2, \dots, \|\boldsymbol{x}_N\|_2^2$
ip = sgemm_(Q, X, …)      # $Q^\top X$

# Scan and sum
parfor (m = 0; m < M; ++m):
  for (n = 0; n < N; ++n):
    dist = q_norms[m] + x_norms[n] – ip[m][n]
```

SIMD-accelerated function

- Matrix multiplication by BLAS
- Dominant if Q and X are large
- The difference of the background matters:
  - ✓ Intel MKL is 30% faster than OpenBLAS

$\|\boldsymbol{q}_m - \boldsymbol{x}_n\|_2^2$ $\|\boldsymbol{q}_m\|_2^2$ $\|\boldsymbol{x}_n\|_2^2$ $(Q^\top X)_{mn}$

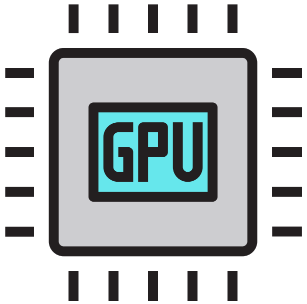
NN in GPU (faiss-gpu) is 10x faster than NN in CPU (faiss-cpu)

Benchmark: https://github.com/facebookresearch/faiss/wiki/Low-level-benchmarks

- ➢ NN-GPU always compute $\|\boldsymbol{q}\|_2^2 - 2\boldsymbol{q}^\top\boldsymbol{x} + \|\boldsymbol{x}\|_2^2$

- ➢ k-means for 1M vectors (D=256, K=20000)
- ✓ 11 min on CPU
- ✓ 55 sec on 1 Pascal-class P100 GPU (float32 math)
- ✓ 34 sec on 1 Pascal-class P100 GPU (float16 math)
- ✓ 21 sec on 4 Pascal-class P100 GPUs (float32 math)
- ✓ 16 sec on 4 Pascal-class P100 GPUs (float16 math)

x10 faster



- ➢ If GPU is available and its memory is enough, try GPU-NN
- ➢ The behavior is little bit different (e.g., a restriction for top-k)

Reference

- Switch implementation of L2sqr in faiss: [https://github.com/facebookresearch/faiss/wiki/Implementation-notes#matrix-multiplication-to-do-many-l2-distance-computations]

- Introduction to SIMD: a lecture by Markus Püschel (ETH) [How to Write Fast Numerical Code - Spring 2019], especially [SIMD vector instructions]
  - ✓ https://acl.inf.ethz.ch/teaching/fastcode/2019/
  - ✓ https://acl.inf.ethz.ch/teaching/fastcode/2019/slides/07-simd.pdf

- SIMD codes for faiss [https://github.com/facebookresearch/faiss/blob/master/utils/distances_simd.cpp]

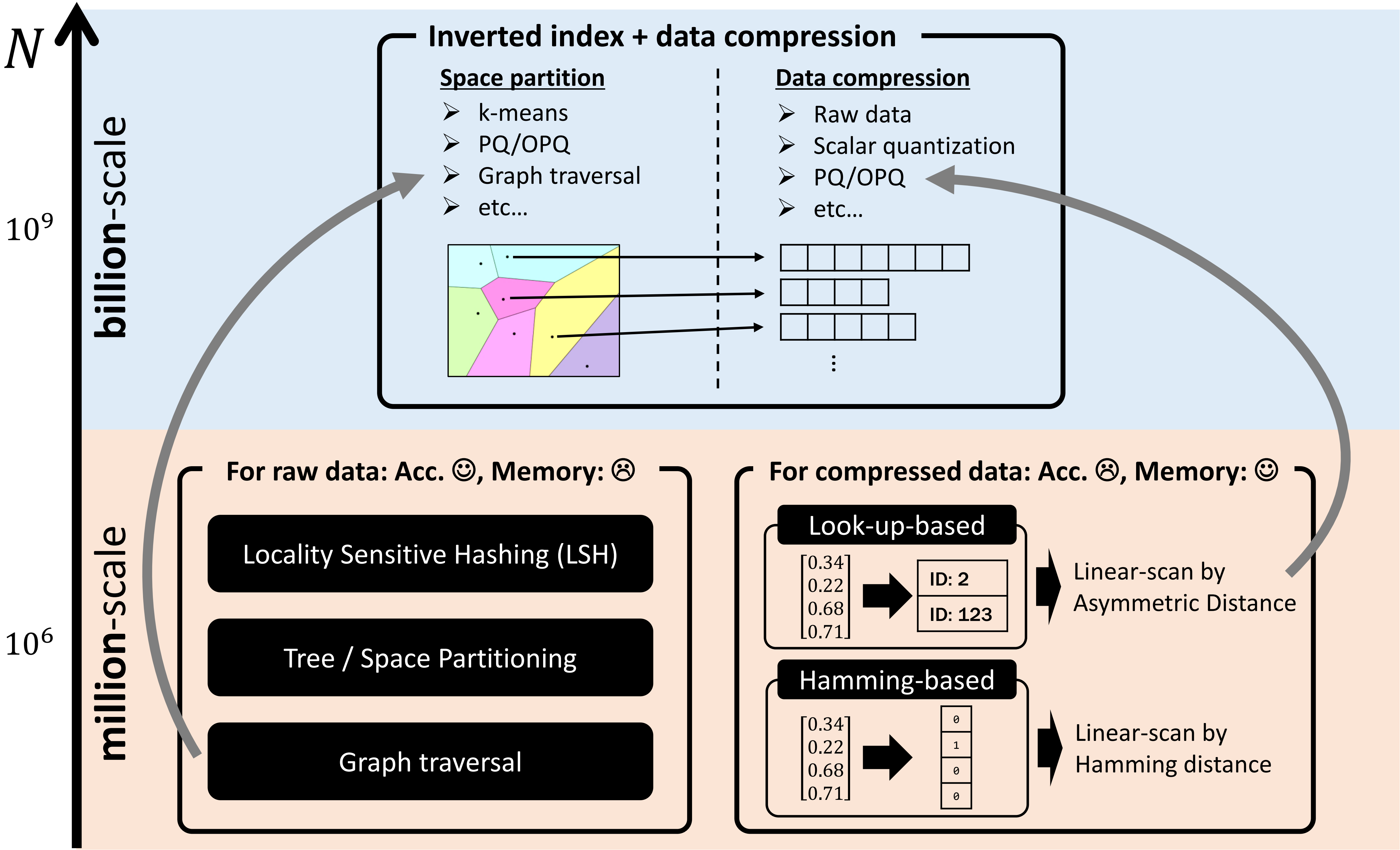
- L2sqr benchmark including AVX512 for faiss-L2sqr [https://gist.github.com/matsui528/583925f88fcb08240319030202588c74]

Part 1:

Nearest Neighbor Search

Part 2:

Approximate Nearest Neighbor Search



Inverted index + data compression

Space partition

- k-means
- PQ/OPQ
- Graph traversal
- etc…

Data compression

- Raw data
- Scalar quantization
- PQ/OPQ
- etc…

For raw data: Acc. ☺, Memory: ☹

- Locality Sensitive Hashing (LSH)
- Tree / Space Partitioning
- Graph traversal

For compressed data: Acc. ☹, Memory: ☺

Look-up-based

$$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$$

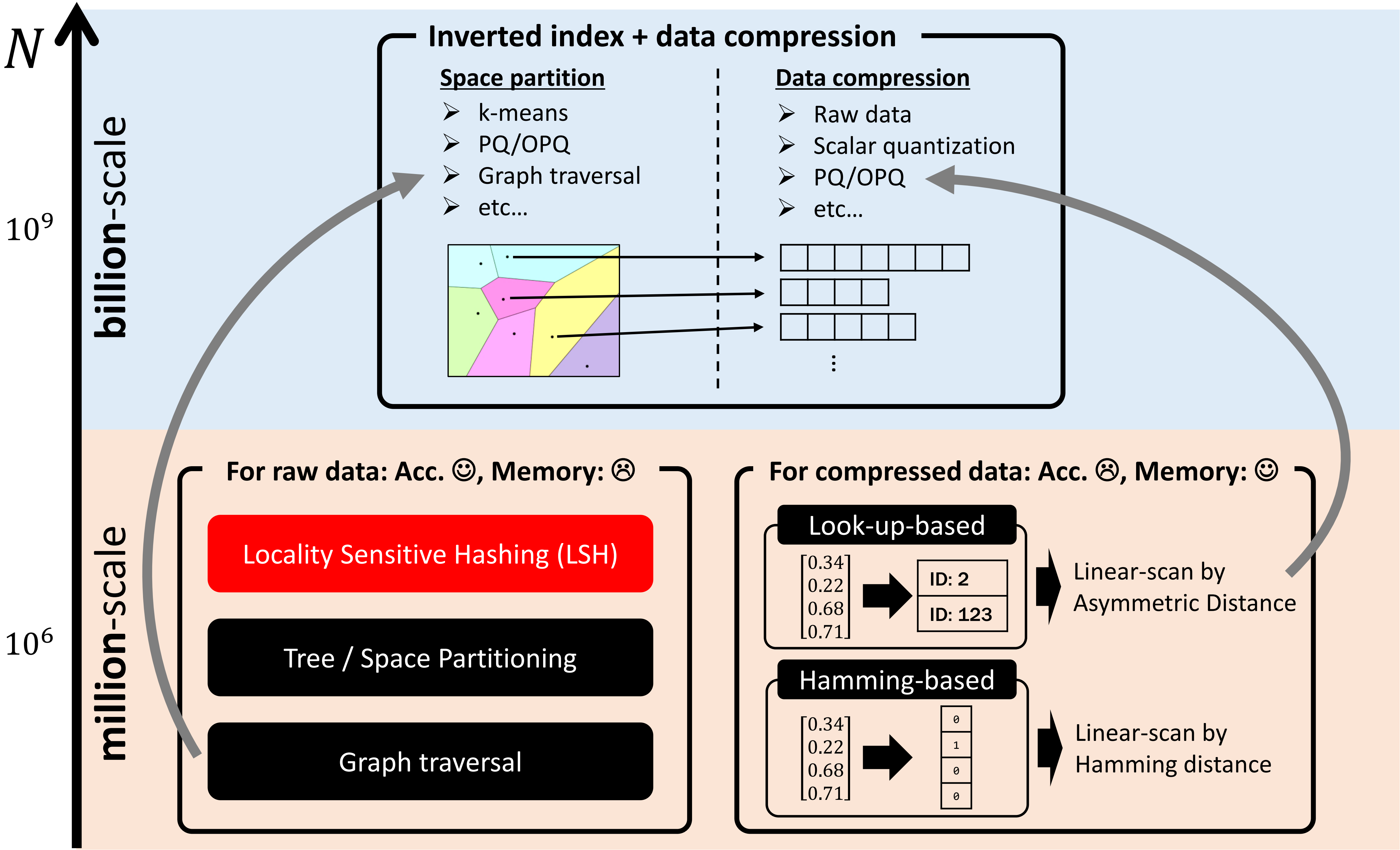
ID: 2
ID: 123

Linear-scan by Asymmetric Distance

Hamming-based

$$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$$

Linear-scan by Hamming distance



N

10^9

10^6

billion-scale

million-scale

Inverted index + data compression

Space partition

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- Graph traversal
- etc…

Data compression

- Raw data
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For raw data: Acc. ☺, Memory: ☹

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Graph traversal

For compressed data: Acc. ☹, Memory: ☺

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$\begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 0.71 \end{bmatrix}$

ID: 2

ID: 123

Linear-scan by Asymmetric Distance

Hamming-based

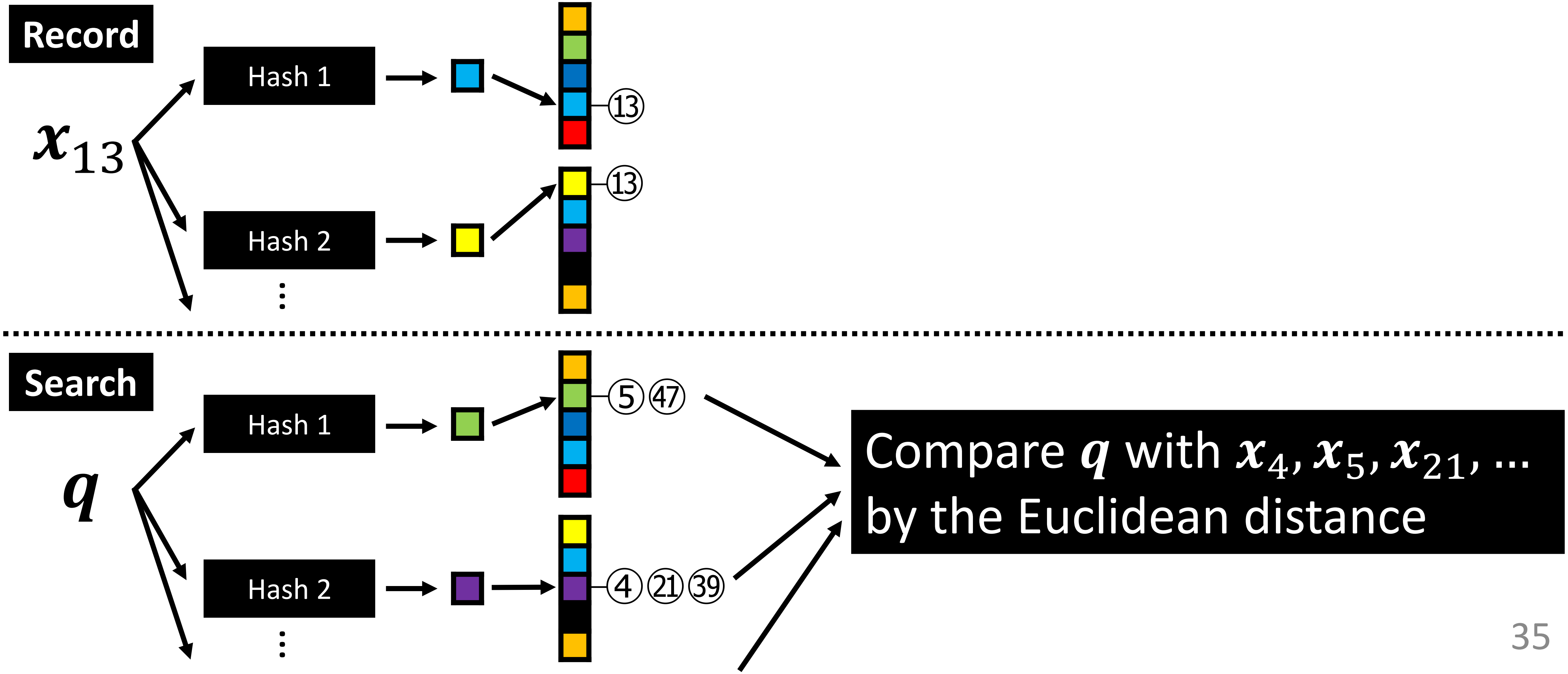
$\begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 0.71 \end{bmatrix}$

`0` `1` `0` `0`

Linear-scan by Hamming distance

Locality Sensitive Hashing (LSH)

- LSH = Hash functions + Hash tables
- Map similar items to the same symbol with a high probability



Compare q with $x_4, x_5, x_{21}, \ldots$ by the Euclidean distance

Locality Sensitive Hashing (LSH)

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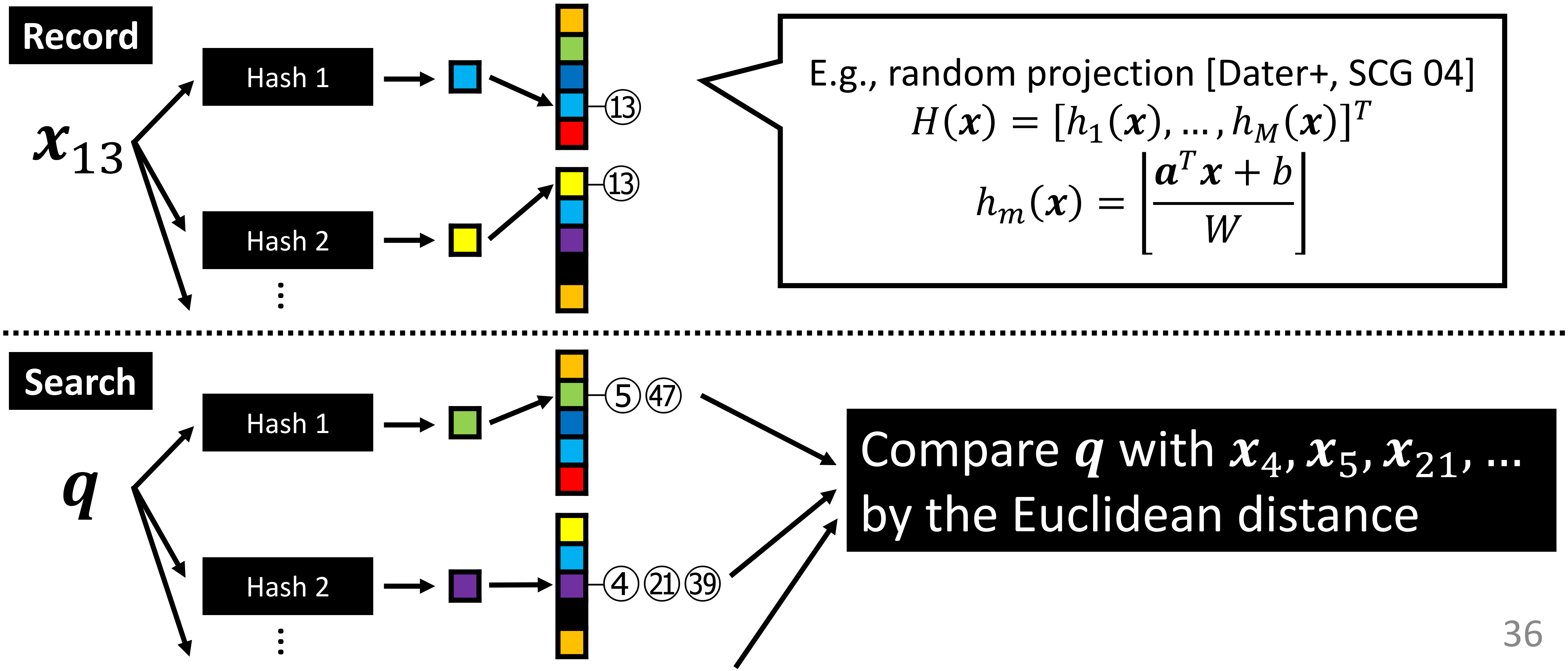


E.g., random projection [Dater+, SCG 04]

$$H(\boldsymbol{x}) = [h_1(\boldsymbol{x}), \dots, h_M(\boldsymbol{x})]^T$$

$$h_m(\boldsymbol{x}) = \left\lfloor \frac{\boldsymbol{a}^T \boldsymbol{x} + b}{W} \right\rfloor$$

Compare $\boldsymbol{q}$ with $\boldsymbol{x}_4, \boldsymbol{x}_5, \boldsymbol{x}_{21}, \dots$ by the Euclidean distance

Locality Sensitive Hashing (LSH)

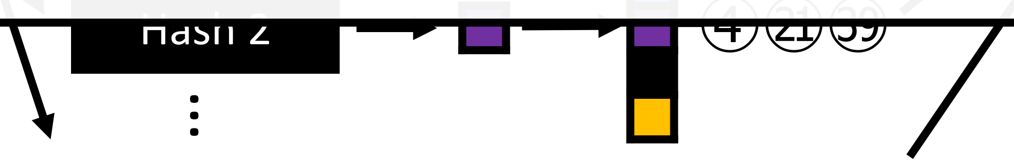
- LSH = Hash functions + Hash tables

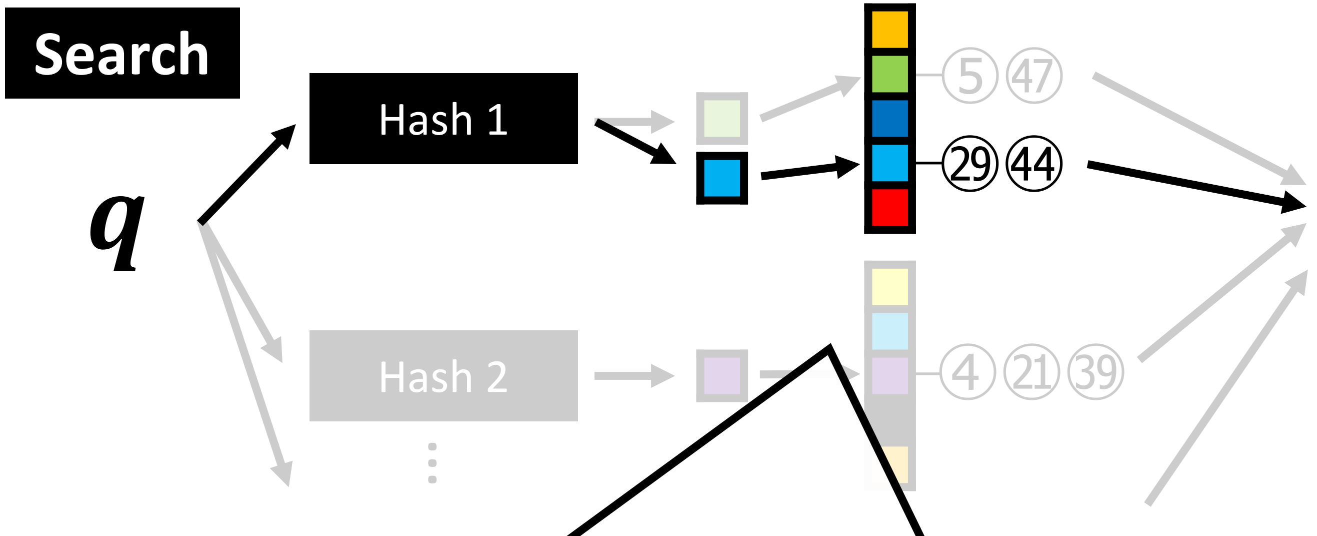
☺:

- Math-friendly
- Popular in the theory area (FOCS, STOC, …)

☹:

- Large memory cost
  - ✓ Need several tables to boost the accuracy
  - ✓ Need to store the original data, $\{\boldsymbol{x}_n\}_{n=1}^{N}$, on memory
- Data-dependent methods such as PQ are better for real-world data
- Thus, in recent CV papers, LSH has been treated as a classic-method ☹☹☹





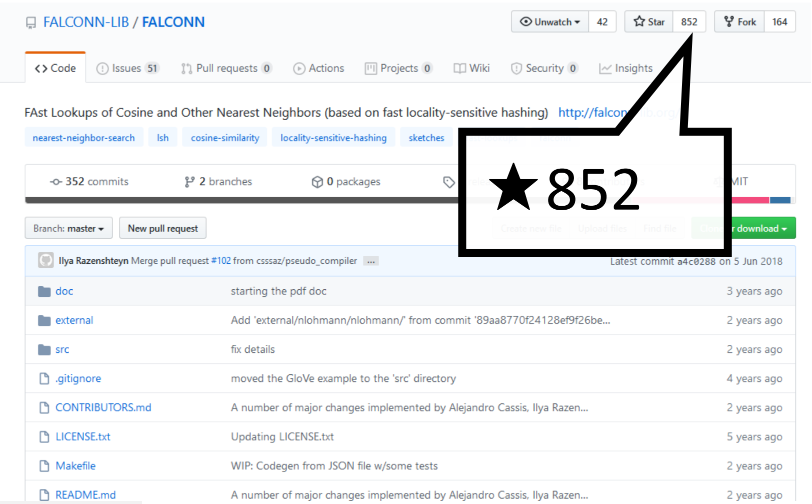
Compare $\boldsymbol{q}$ with $\boldsymbol{x}_4, \boldsymbol{x}_5, \boldsymbol{x}_{21}, \ldots$ by the Euclidean distance

In fact:

- ➢Consider a next candidate ➡ practical memory consumption （Multi-Probe [Lv+, VLDB 07]）
- ➢A library based on the idea: **FALCONN**

Falconn

https://github.com/falconn-lib/falconn



FAst Lookups of Cosine and Other Nearest Neighbors (based on fast locality-sensitive hashing) http://falcon

Ilya Razenshteyn Merge pull request #102 from csssaz/pseudo_compiler … Latest commit a4c0288 on 5 Jun 2018

doc	starting the pdf doc	3 years ago
external	Add 'external/nlohmann/nlohmann/' from commit '89aa8770f24128ef9f26be...	2 years ago
src	fix details	2 years ago
.gitignore	moved the GloVe example to the 'src' directory	4 years ago
CONTRIBUTORS.md	A number of major changes implemented by Alejandro Cassis, Ilya Razen...	2 years ago
LICENSE.txt	Updating LICENSE.txt	5 years ago
Makefile	WIP: Codegen from JSON file w/some tests	2 years ago
README.md	A number of major changes implemented by Alejandro Cassis, Ilya Razen...	2 years ago

```
$> pip install FALCONN
```

```
table = falconn.LSHIndex(params_cp)
table.setup(X-center)
query_object = table.construct_query_object()
# query parameter config here
query_object.find_nearest_neighbor(Q-center, topk)
```

- ☺ Faster data addition (than annoy, nmslib, ivfpq)
- ☺ Useful for on-the-fly addition
- ☹ Parameter configuration seems a bit non-intuitive

Reference

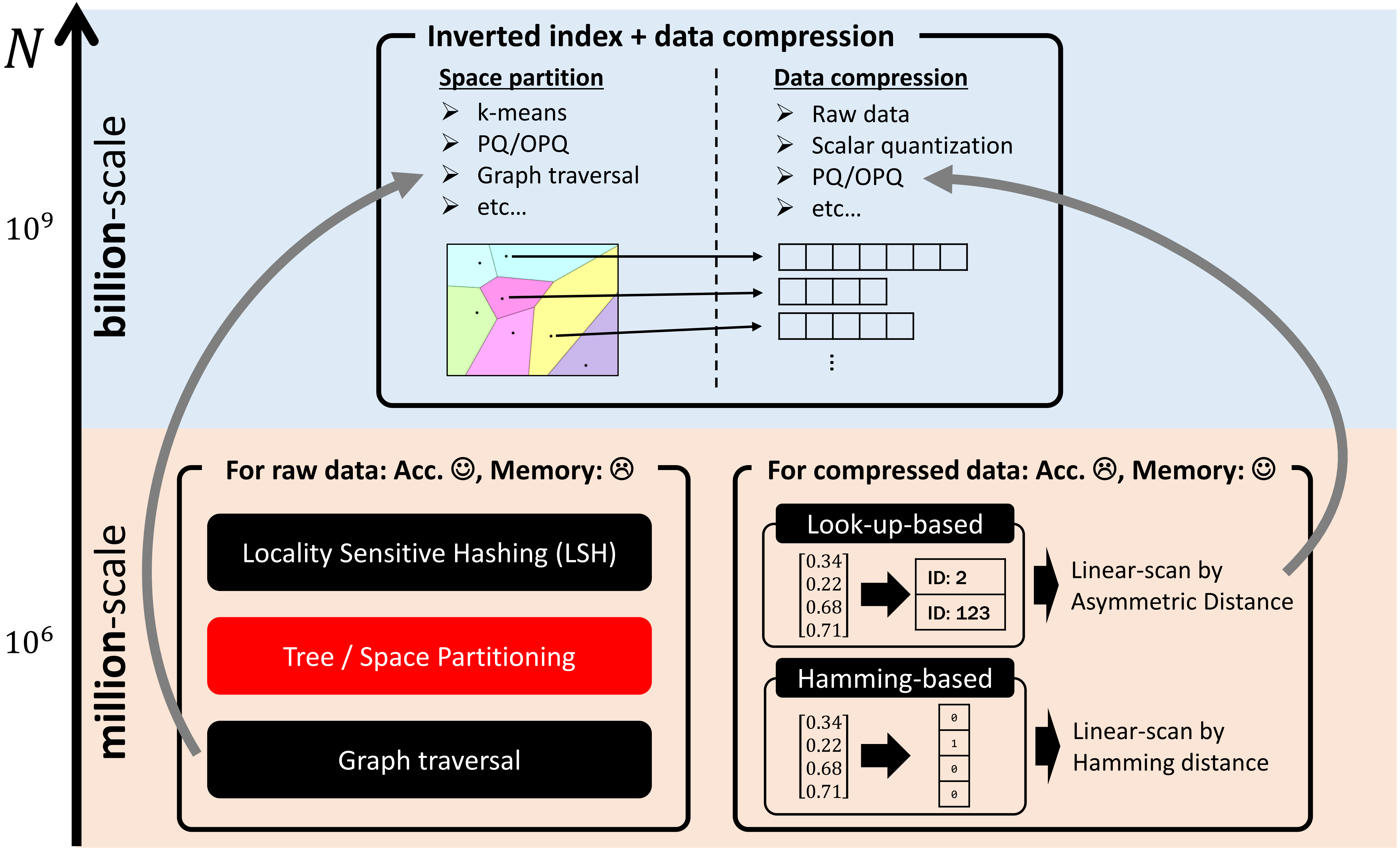
- Good summaries on this field: CVPR 2014 Tutorial on Large-Scale Visual Recognition, Part I: Efficient matching, H. Jégou [https://sites.google.com/site/lsvrtutorialcvpr14/home/efficient-matching]

- Practical Q&A: FAQ in Wiki of FALCONN [https://github.com/FALCONN-LIB/FALCONN/wiki/FAQ]

- Hash functions: M. Datar et al., “Locality-sensitive hashing scheme based on p-stable distributions,” SCG 2004.

- Multi-Probe: Q. Lv et al., “Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search”, VLDB 2007

- Survey: A. Andoni and P. Indyk, “Near-Optimal Hashing Algorithms for Approximate Nearest Neighbor in High Dimensions,” Comm. ACM 2008



Inverted index + data compression

Space partition

- k-means
- PQ/OPQ
- Graph traversal
- etc…

Data compression

- Raw data
- Scalar quantization
- PQ/OPQ
- etc…

For raw data: Acc. ☺, Memory: ☹

- Locality Sensitive Hashing (LSH)
- Tree / Space Partitioning
- Graph traversal

For compressed data: Acc. ☹, Memory: ☺

Look-up-based

$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ → ID: 2, ID: 123

Linear-scan by Asymmetric Distance

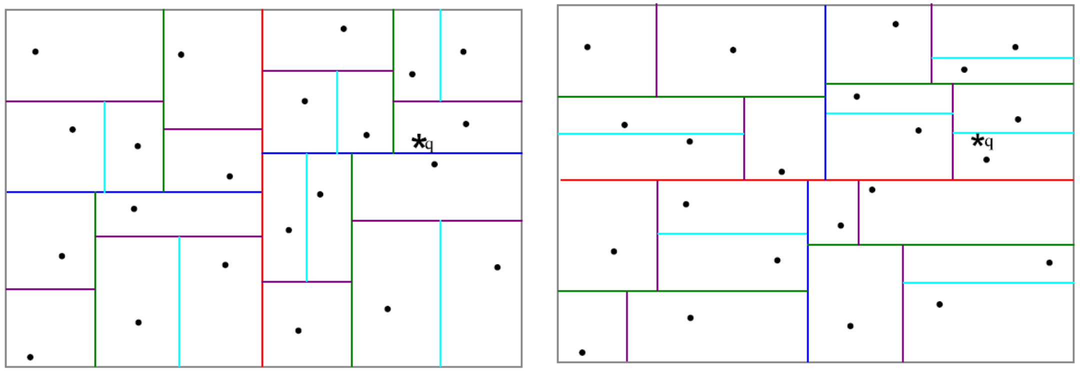
Hamming-based

$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ → 0, 1, 0, 0

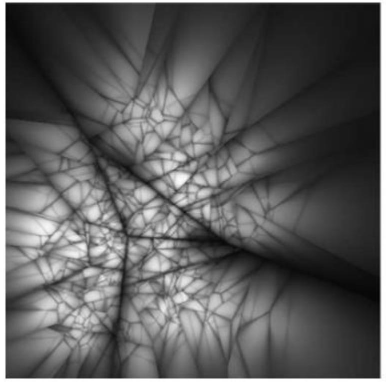
Linear-scan by Hamming distance

FLANN: Fast Library for Approximate Nearest Neighbors

Images are from [Muja and Lowe, TPAMI 2014]



Randomized KD Tree



k-means Tree

- Automatically select "Randomized KD Tree" or "k-means Tree"
  https://github.com/mariusmuja/flann

☺ Good code base. Implemented in OpenCV and PCL

☺ Very popular in the late 00's and early 10's

☹ Large memory consumption. The original data need to be stored

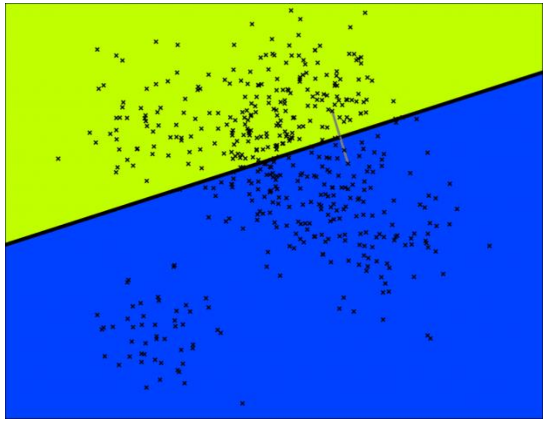
☹ Not actively maintained now

All images are cited from the author's blog post (https://erikbern.com/2015/10/01/nearest-neighbors-and-vector-models-part-2-how-to-search-in-high-dimensional-spaces.html)

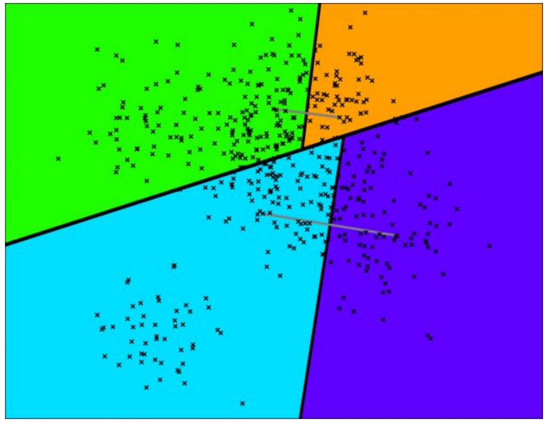
Annoy

"2-means tree"+ "multiple-trees" + "shared priority queue"

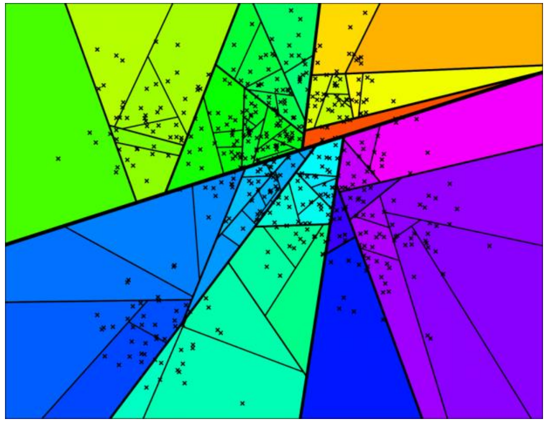
Record



Select two points randomly

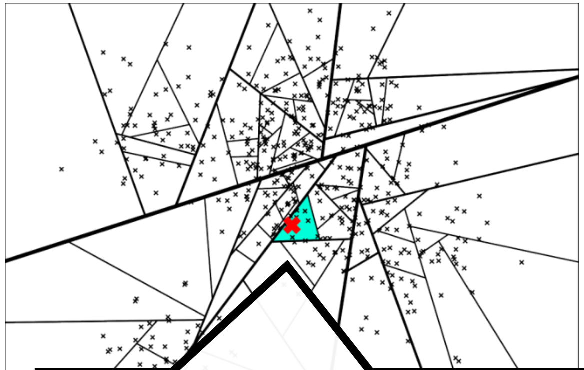


Divide up the space

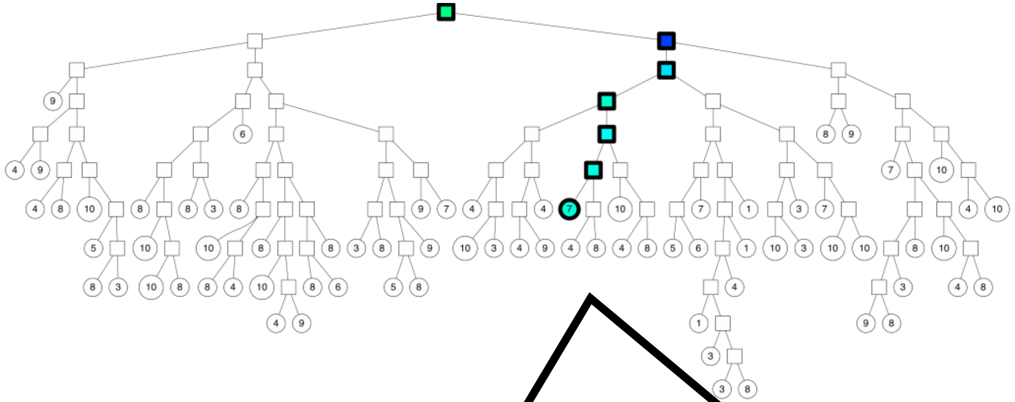


Repeat hierarchically

Search



- Focus the cell that the query lives
- Compare the distances



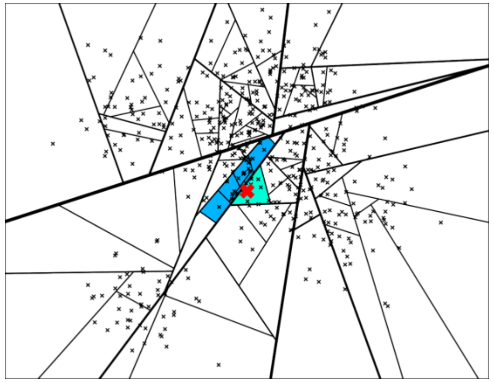
Can traverse the tree by log-times comparisons

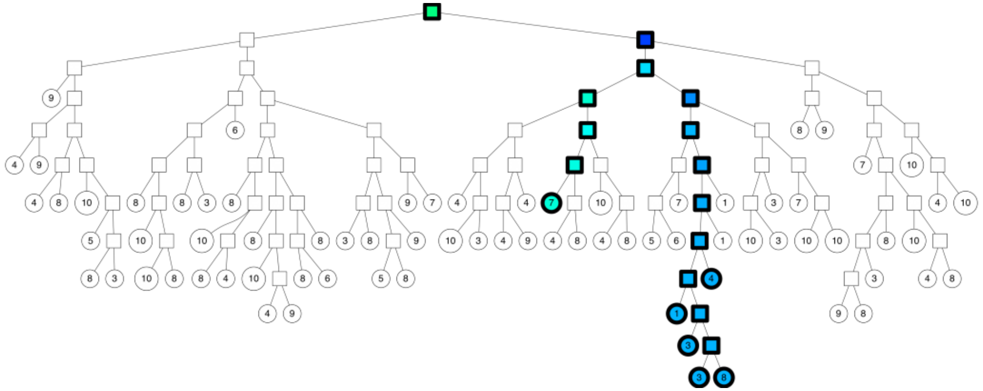
All images are cited from the author's blog post (https://erikbern.com/2015/10/01/nearest-neighbors-and-vector-models-part-2-how-to-search-in-high-dimensional-spaces.html)

Annoy

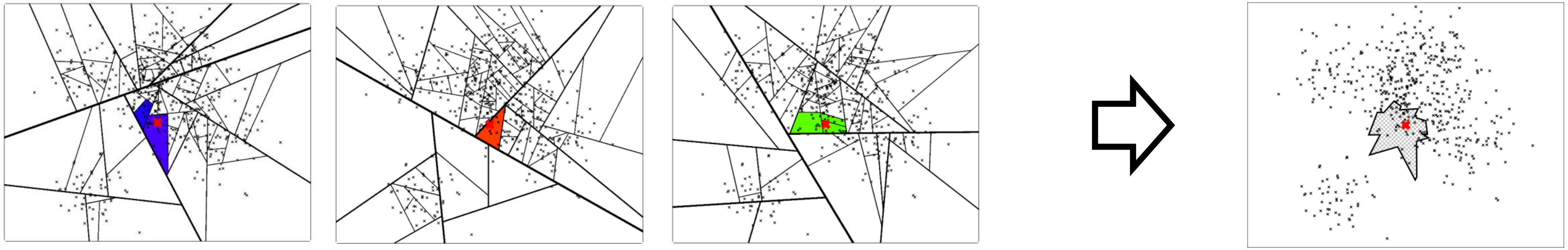
"2-means tree"+ "multiple-trees" + "shared priority queue"

Feature 1 If we need more data points, use a priority queue





Feature 2 Boost the accuracy by multi-tree with a shared priority queue



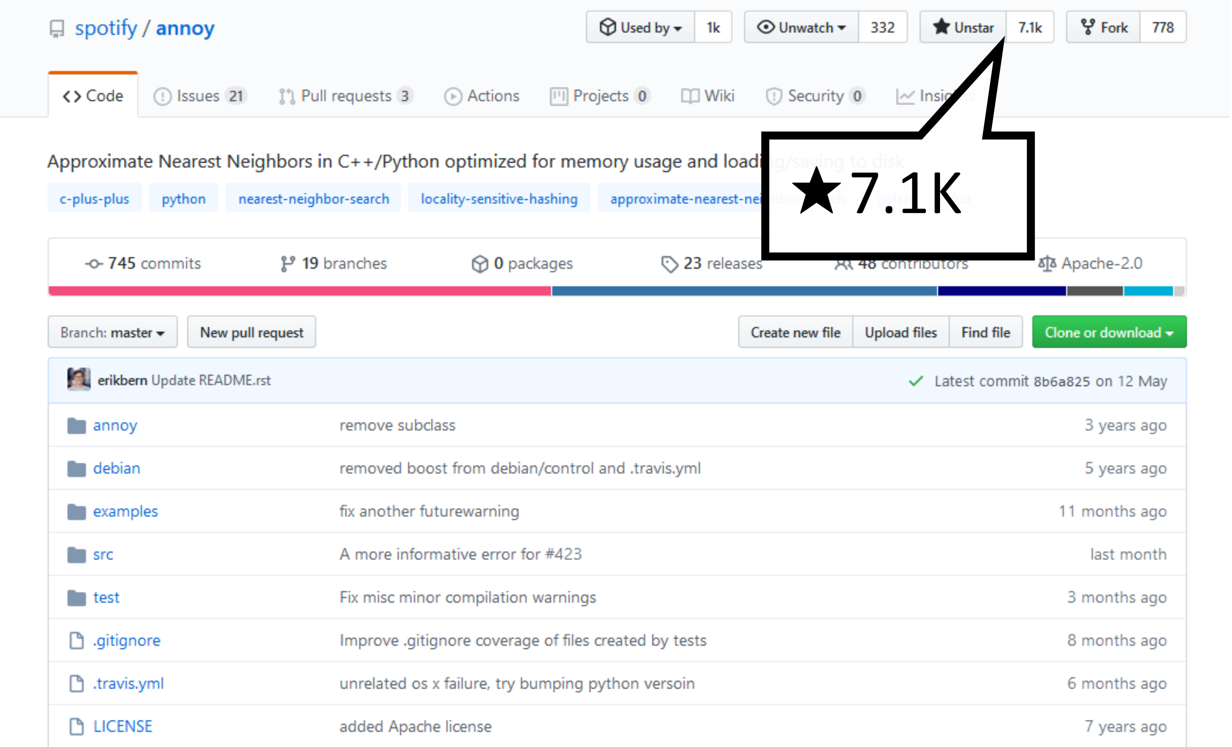
Annoy

https://github.com/erikbern/annoy

```
$> pip install annoy
```

```
t = AnnoyIndex(D)
for n, x in enumerate(X):
    t.add_item(n, x)
t.build(n_trees)

t.get_nns_by_vector(q, topk)
```



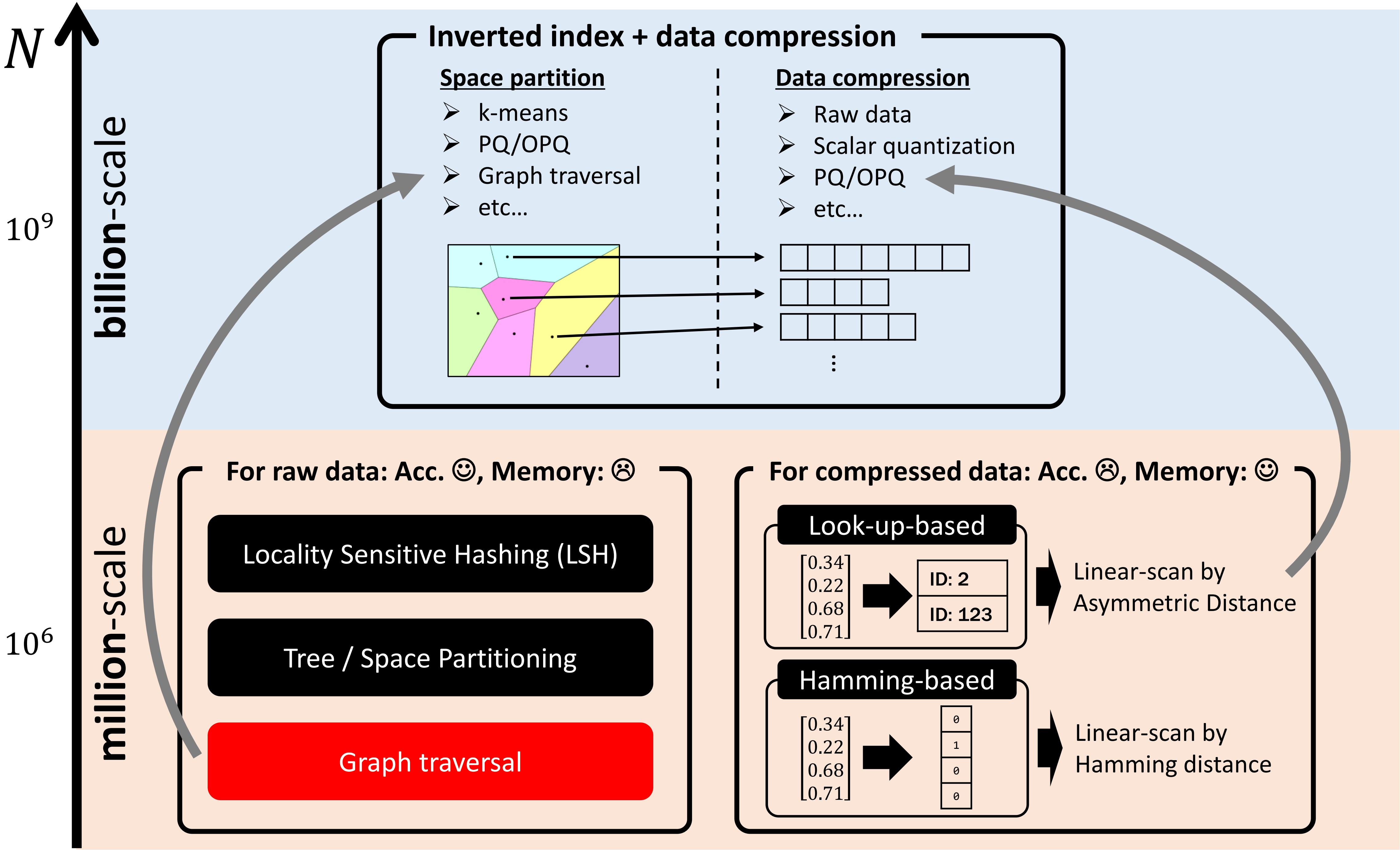
Approximate Nearest Neighbors in C++/Python optimized for memory usage and loadi

erikbern Update README.rst ✓ Latest commit 8b6a825 on 12 May

annoy	remove subclass	3 years ago
debian	removed boost from debian/control and .travis.yml	5 years ago
examples	fix another futurewarning	11 months ago
src	A more informative error for #423	last month
test	Fix misc minor compilation warnings	3 months ago
.gitignore	Improve .gitignore coverage of files created by tests	8 months ago
.travis.yml	unrelated os x failure, try bumping python versoin	6 months ago
LICENSE	added Apache license	7 years ago

★7.1K

- ☺ Developed at Spotify. Well-maintained. Stable
- ☺ Simple interface with only a few parameters
- ☺ Baseline for million-scale data
- ☺ Support mmap, i.e., can be accessed from several processes
- ☹ Large memory consumption
- ☹ Runtime itself is slower than HNSW



Inverted index + data compression

Space partition

- k-means
- PQ/OPQ
- Graph traversal
- etc…

Data compression

- Raw data
- Scalar quantization
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For raw data: Acc. ☺, Memory: ☹

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- Graph traversal

For compressed data: Acc. ☹, Memory: ☺

Look-up-based

Linear-scan by Asymmetric Distance

Hamming-based

Linear-scan by Hamming distance

Graph traversal

- **Very popular** in recent years

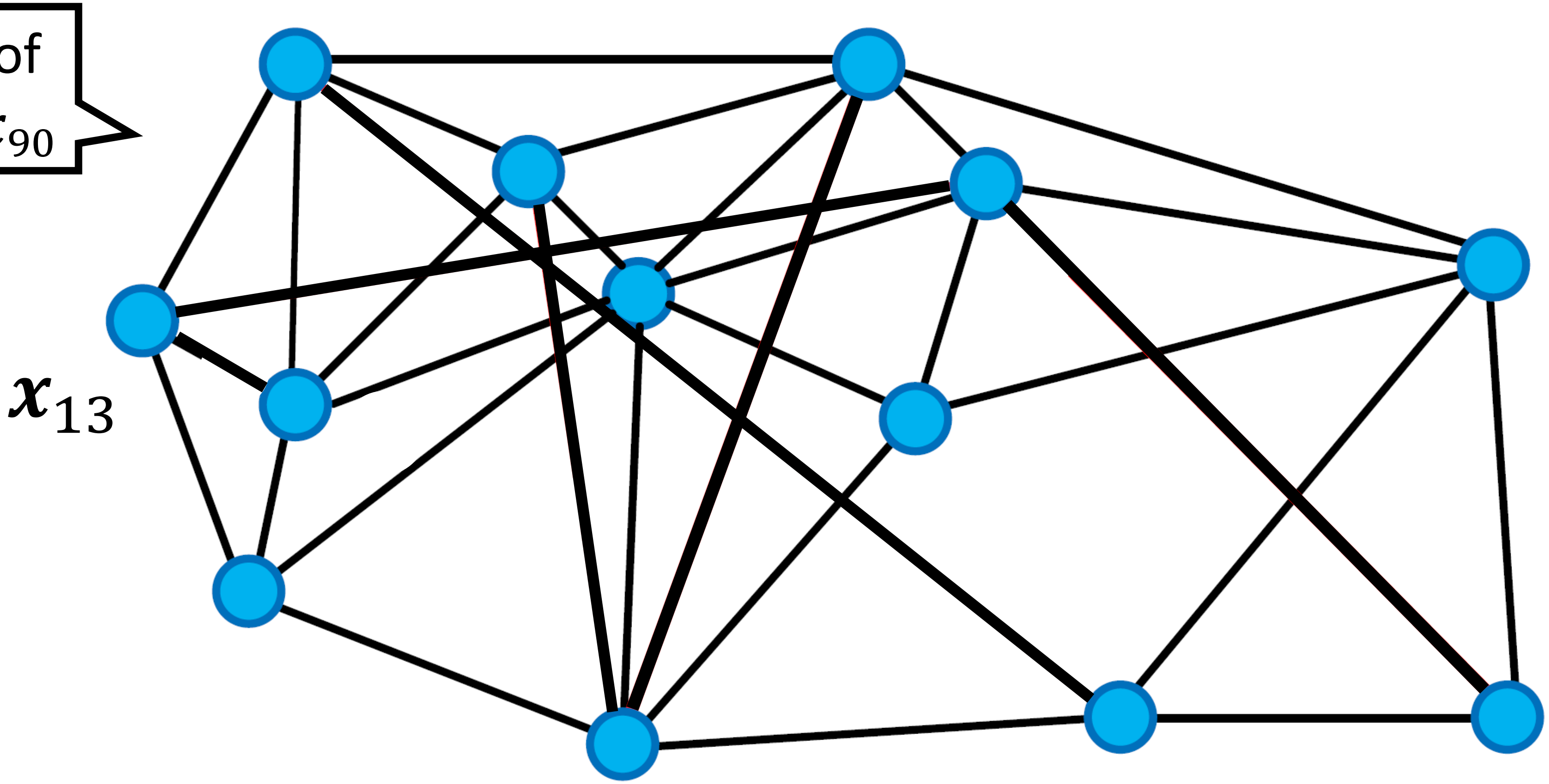
- Around 2017, it turned out that the graph-traversal-based methods work well for million-scale data

- Pioneer:
  - ✓ Navigable Small World Graphs (NSW)
  - ✓ Hierarchical NSW (**HNSW**)

- Implementation: nmslib, hnsw, faiss

Record Images are from [Malkov+, Information Systems, 2013]

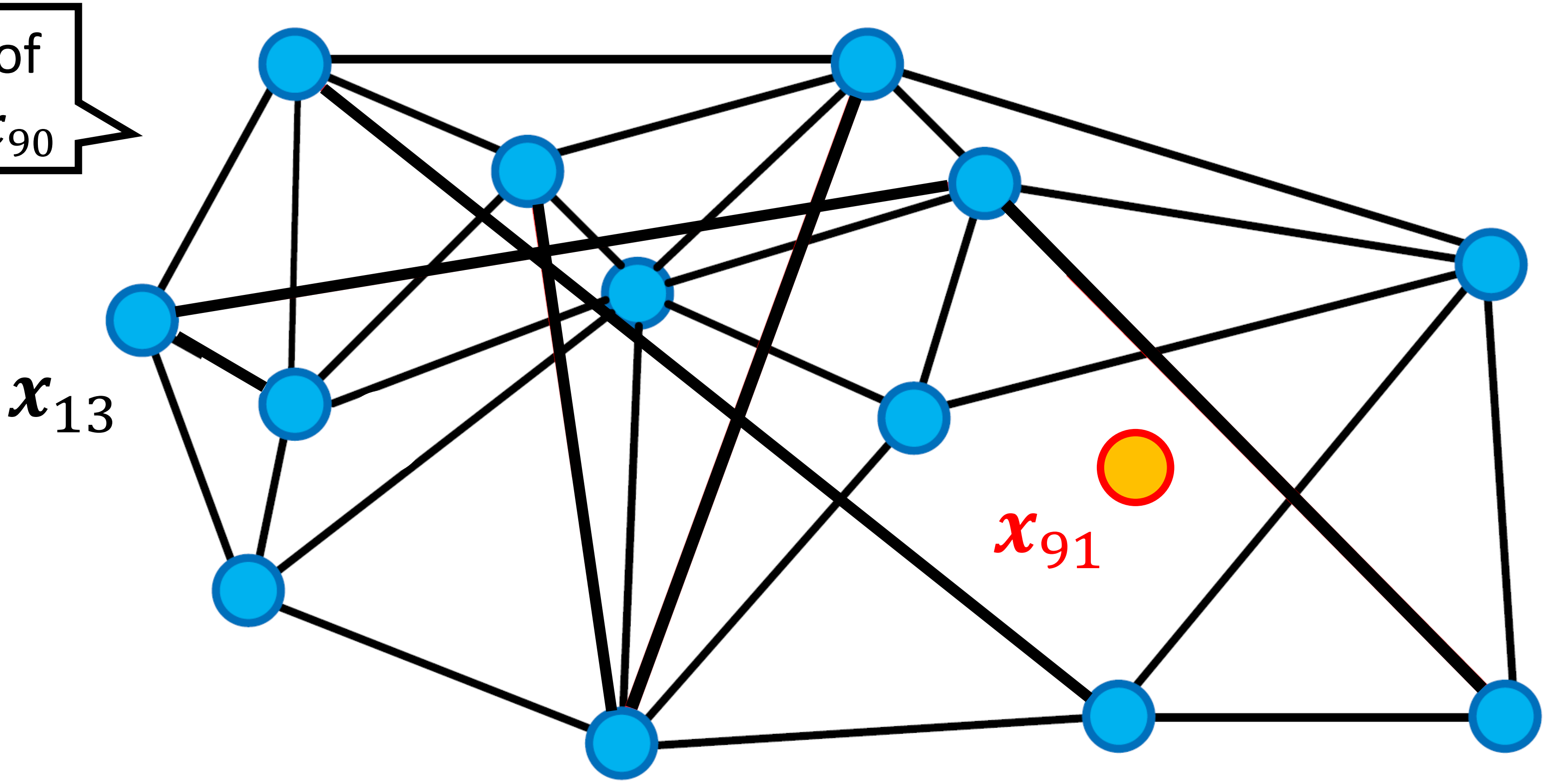
Graph of $x_1, \ldots, x_{90}$



- ➢Each node is a database vector

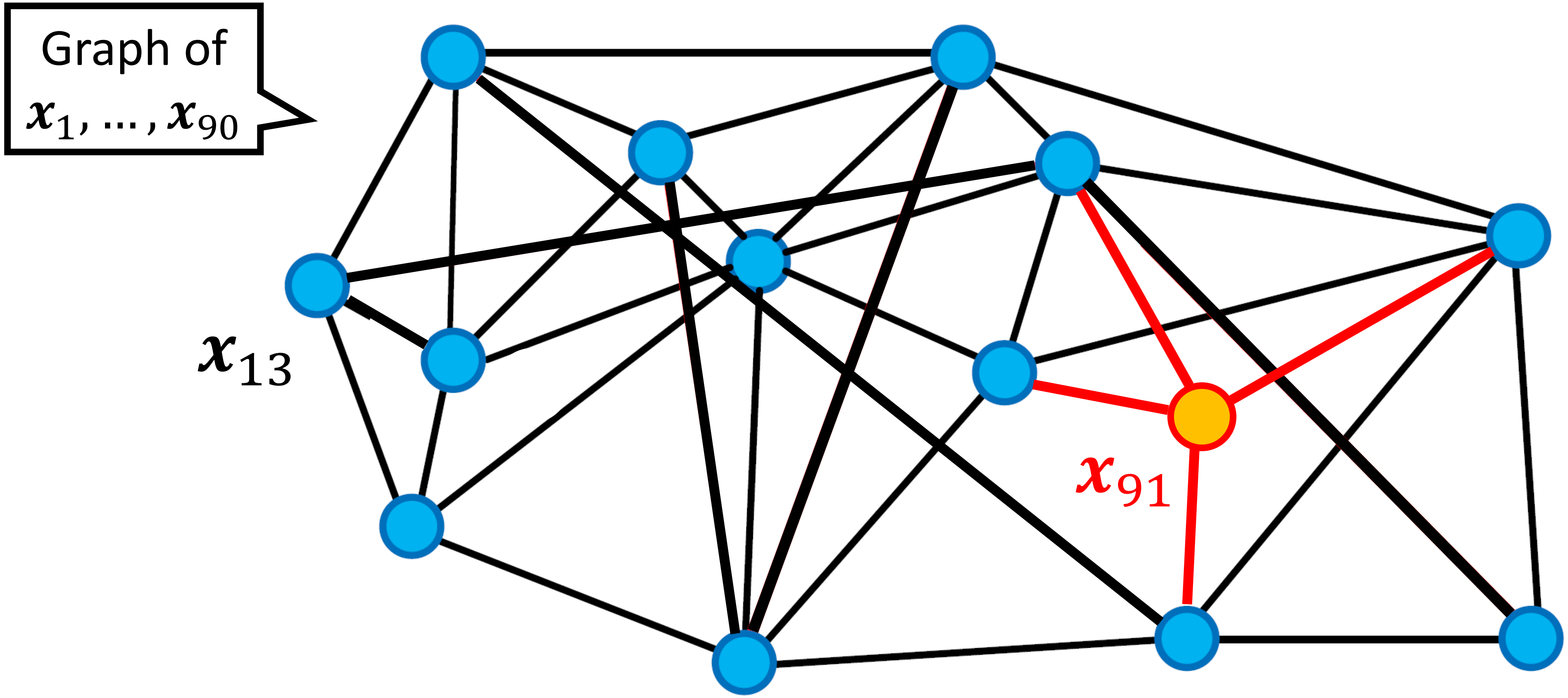
Record Images are from [Malkov+, Information Systems, 2013]

Graph of $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_{90}$



- ➢Each node is a database vector
- ➢Given a new database vector, create new edges to neighbors

Record Images are from [Malkov+, Information Systems, 2013]



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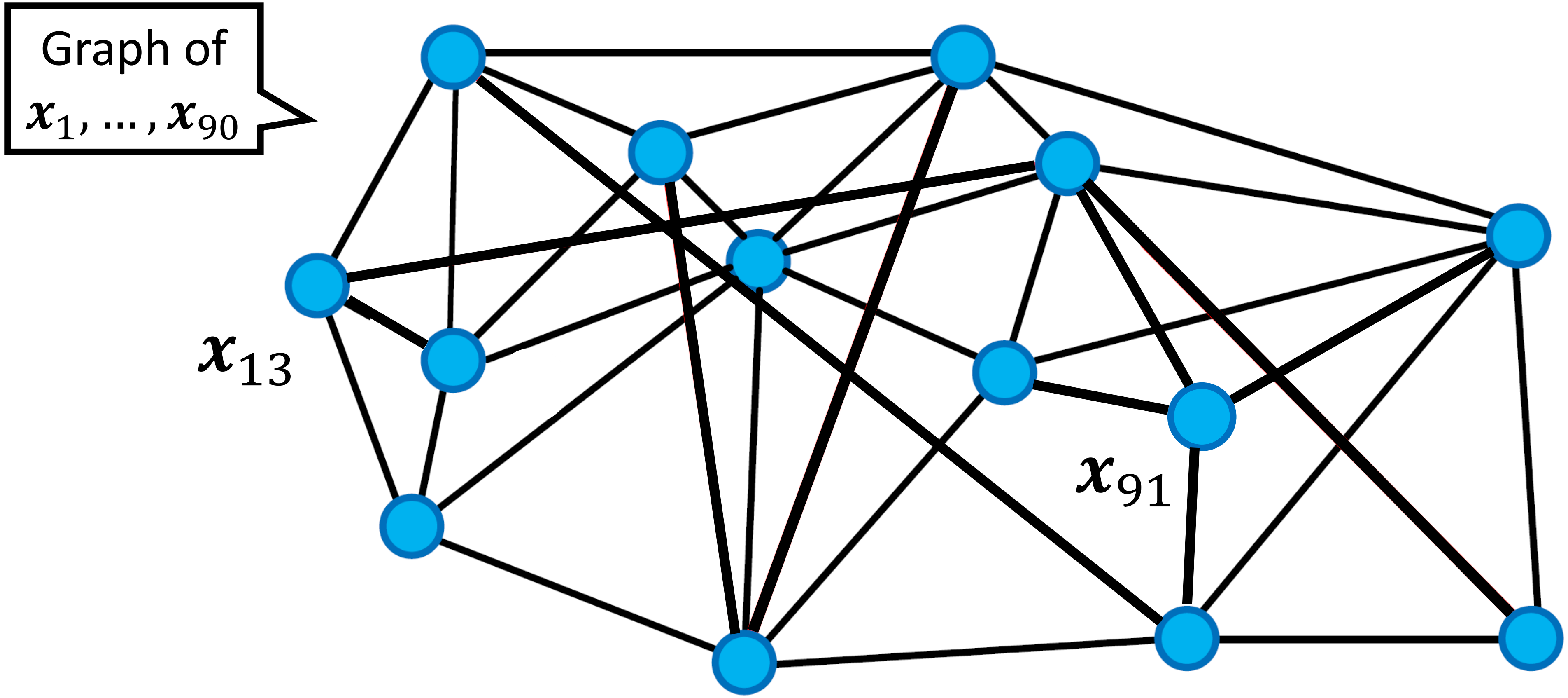
Record Images are from [Malkov+, Information Systems, 2013]



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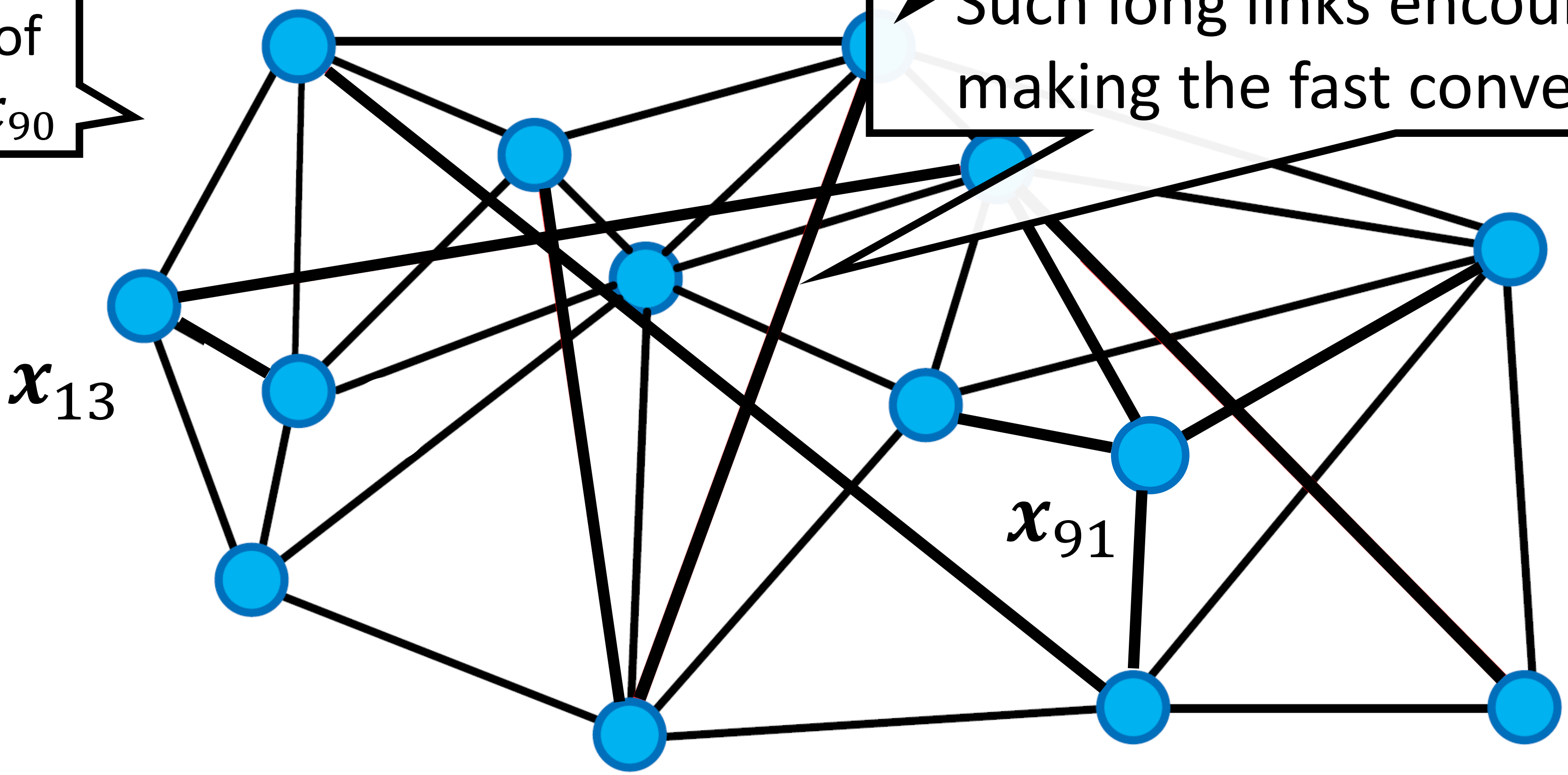


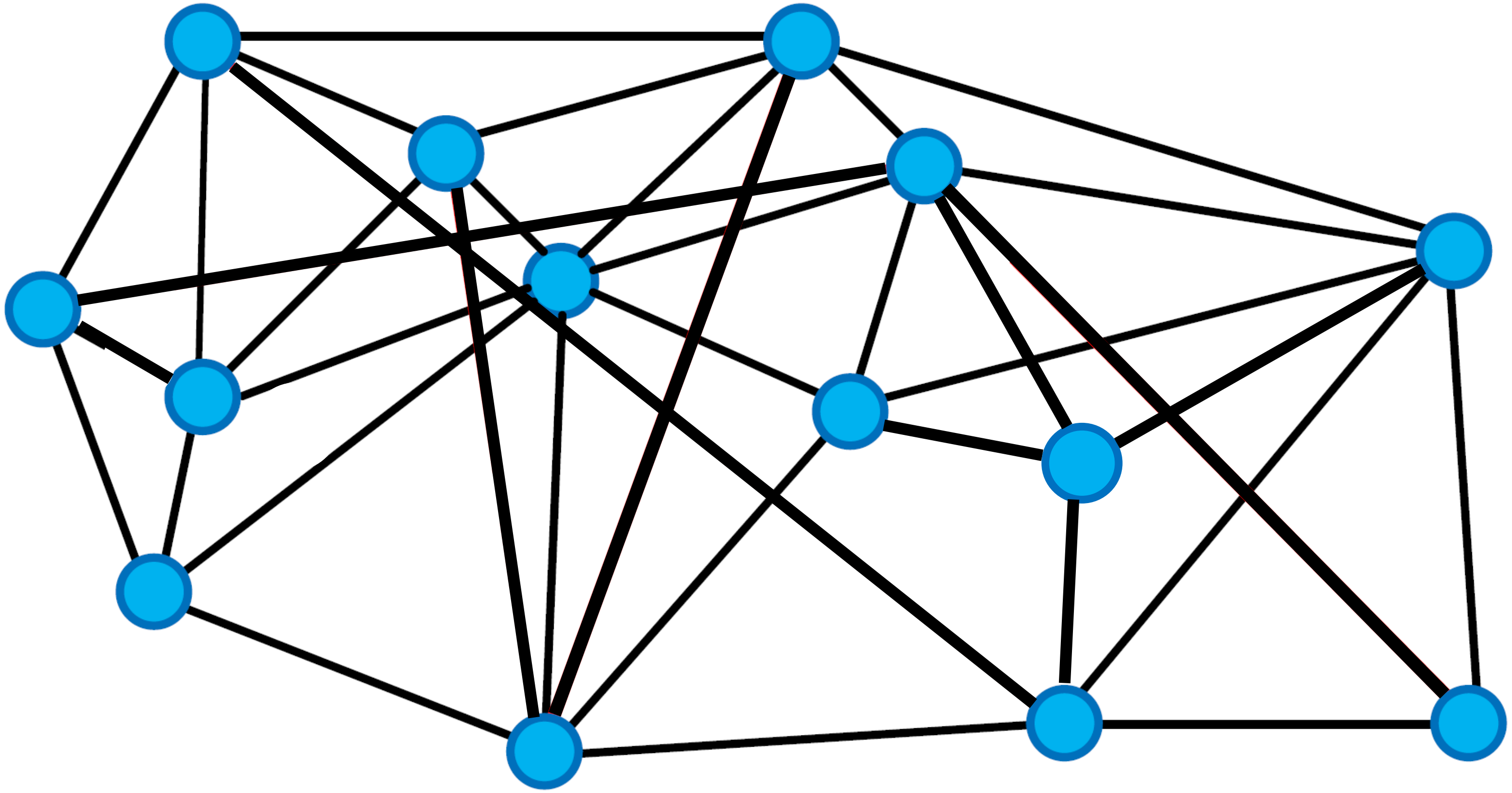
Graph of $x_1, \dots, x_{90}$

- Early links can be long
- Such long links encourage a large hop, making the fast convergence for search

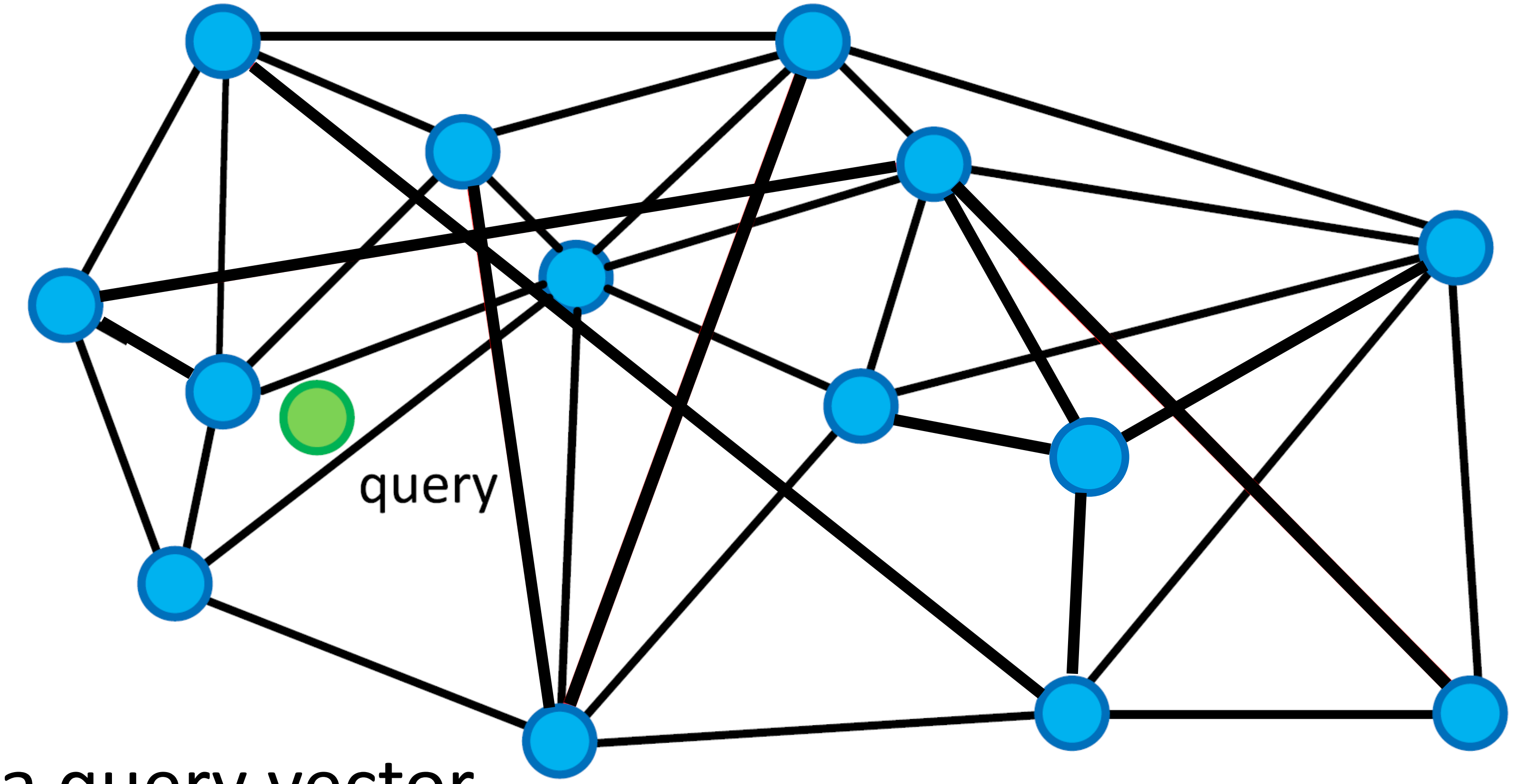
- Each node is a database vector
- Given a new database vector, create new edges to neighbors

Search

Images are from [Malkov+, Information Systems, 2013]

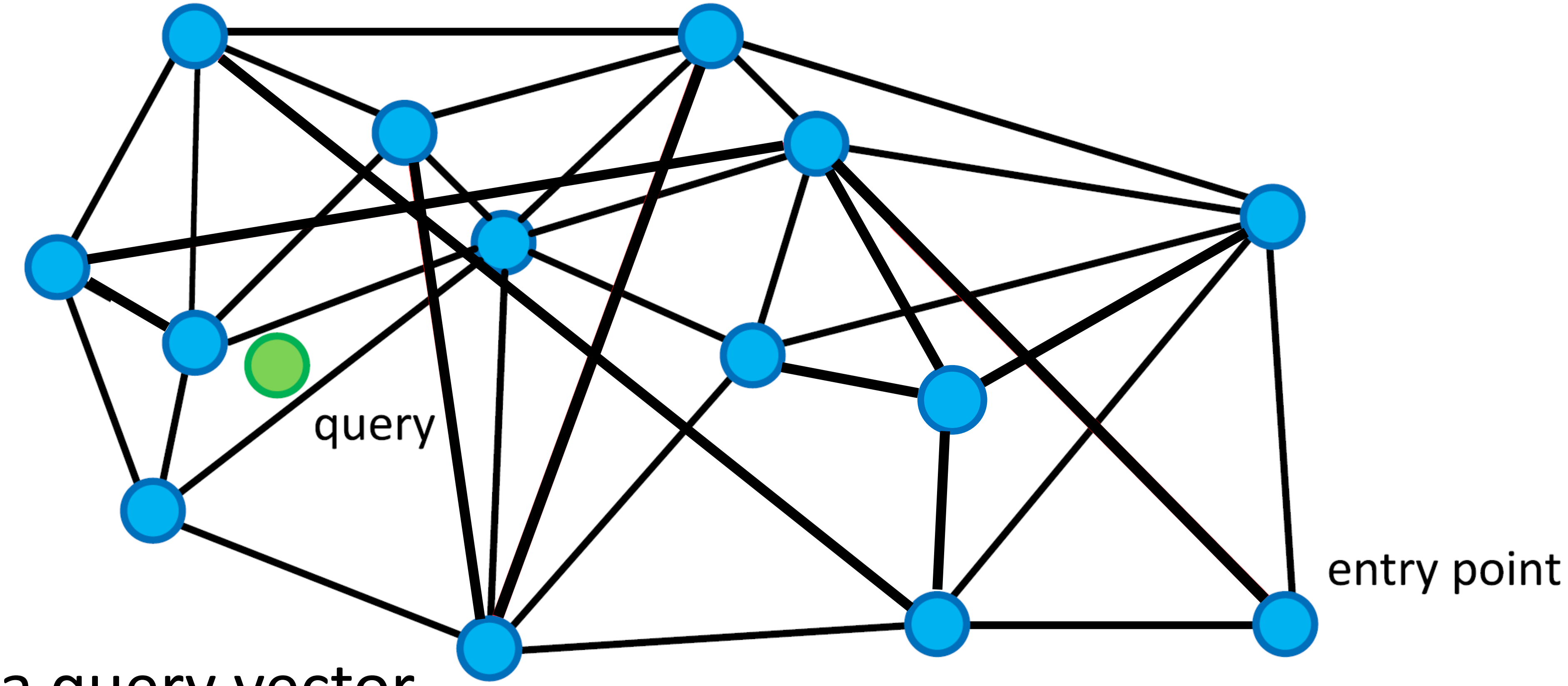


Search Images are from [Malkov+, Information Systems, 2013]



- Given a query vector

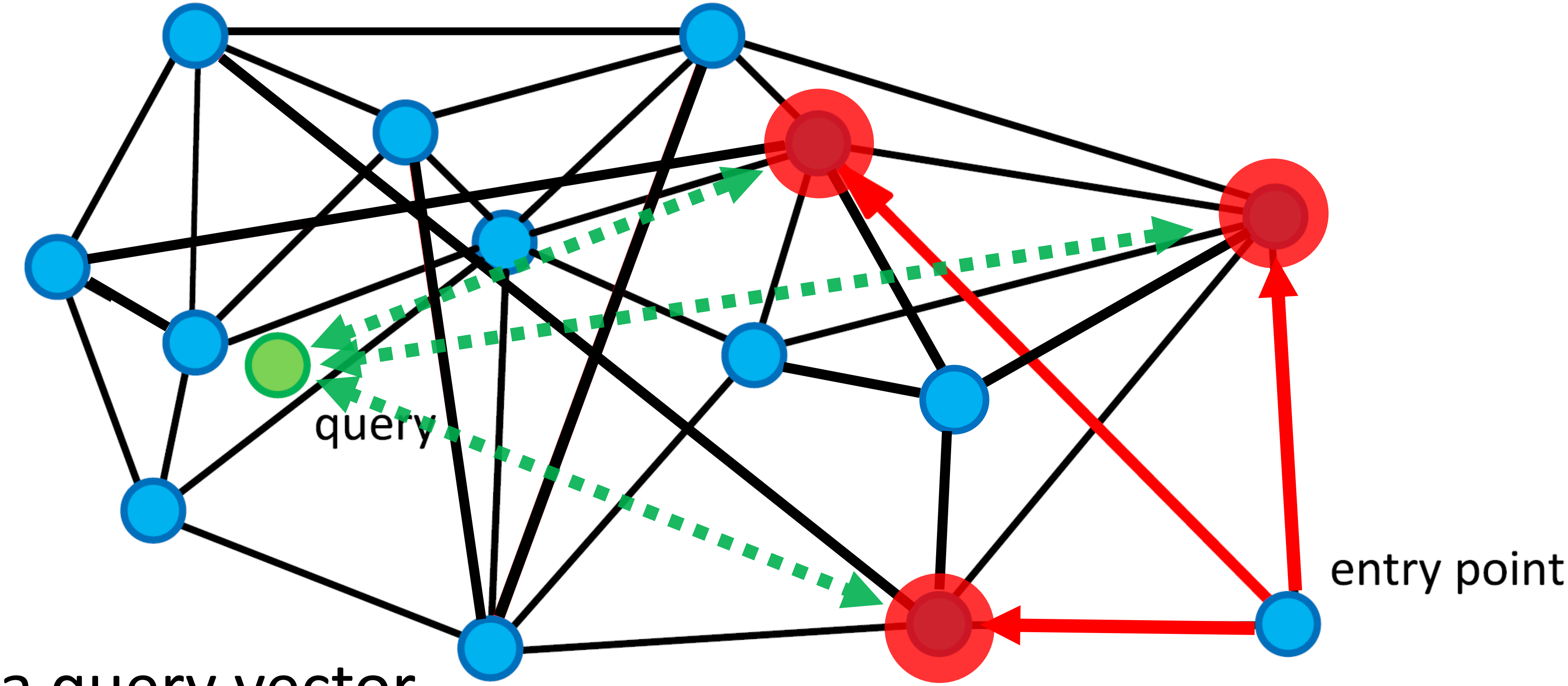
Search Images are from [Malkov+, Information Systems, 2013]



- Given a query vector
- Start from a random point

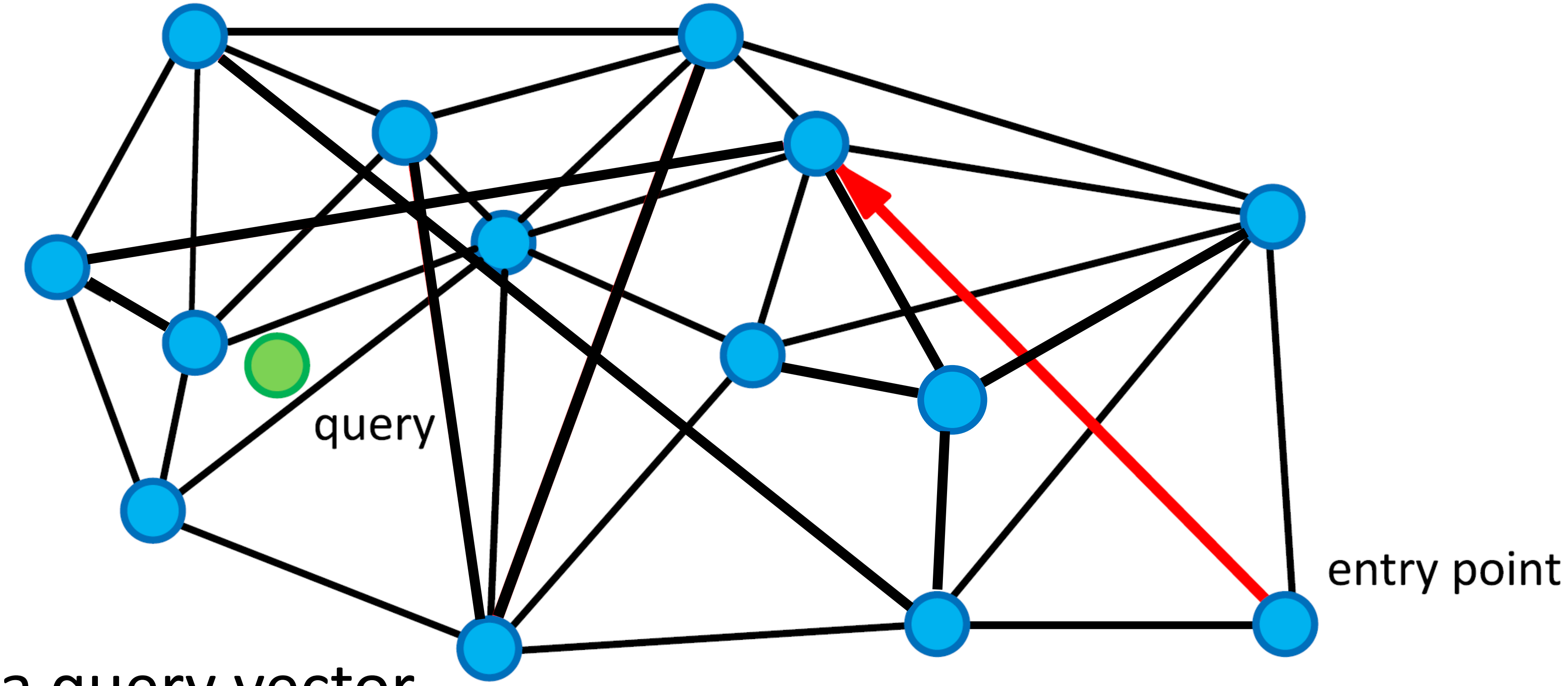
Search

Images are from [Malkov+, Information Systems, 2013]



- ➢ Given a query vector
- ➢ Start from a random point
- ➢ From the connected nodes, find the closest one to the query

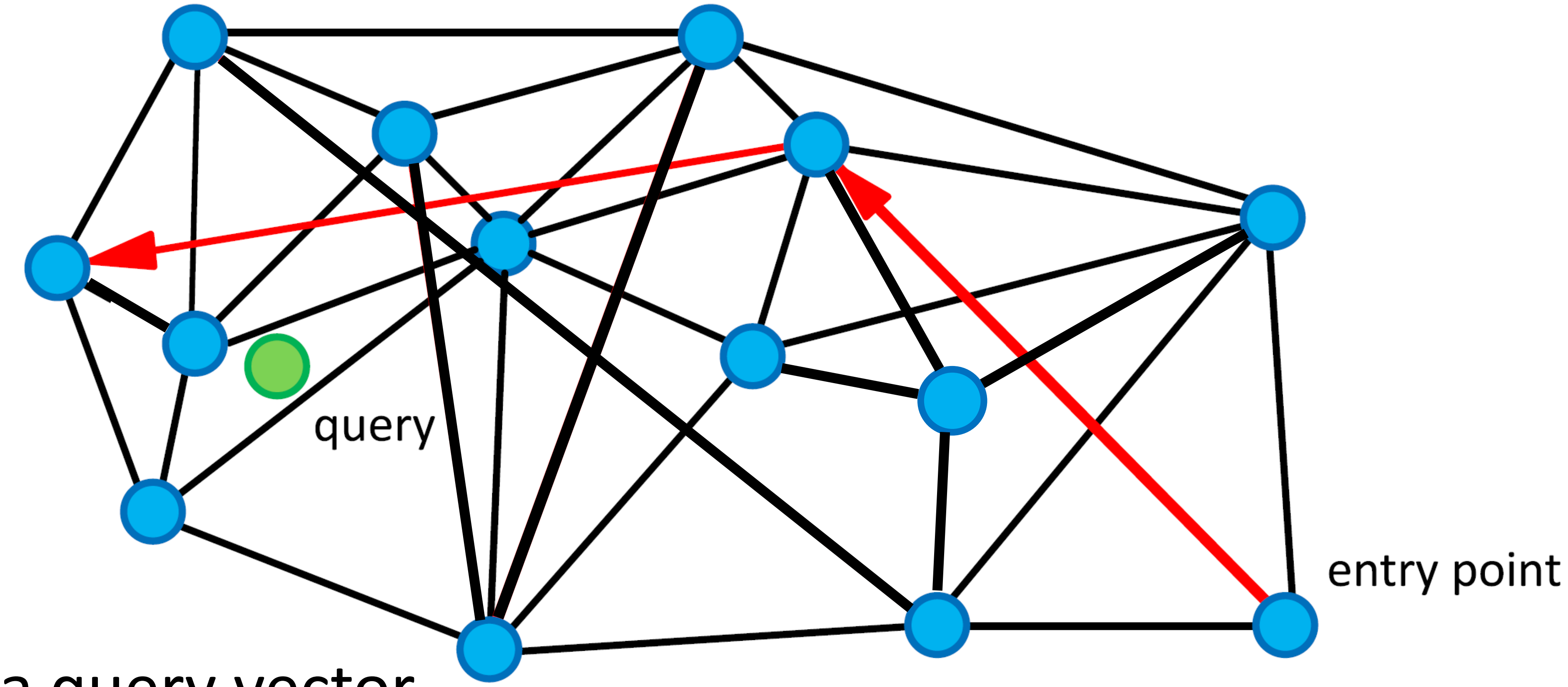
Search Images are from [Malkov+, Information Systems, 2013]



- Given a query vector
- Start from a random point
- From the connected nodes, find the closest one to the query

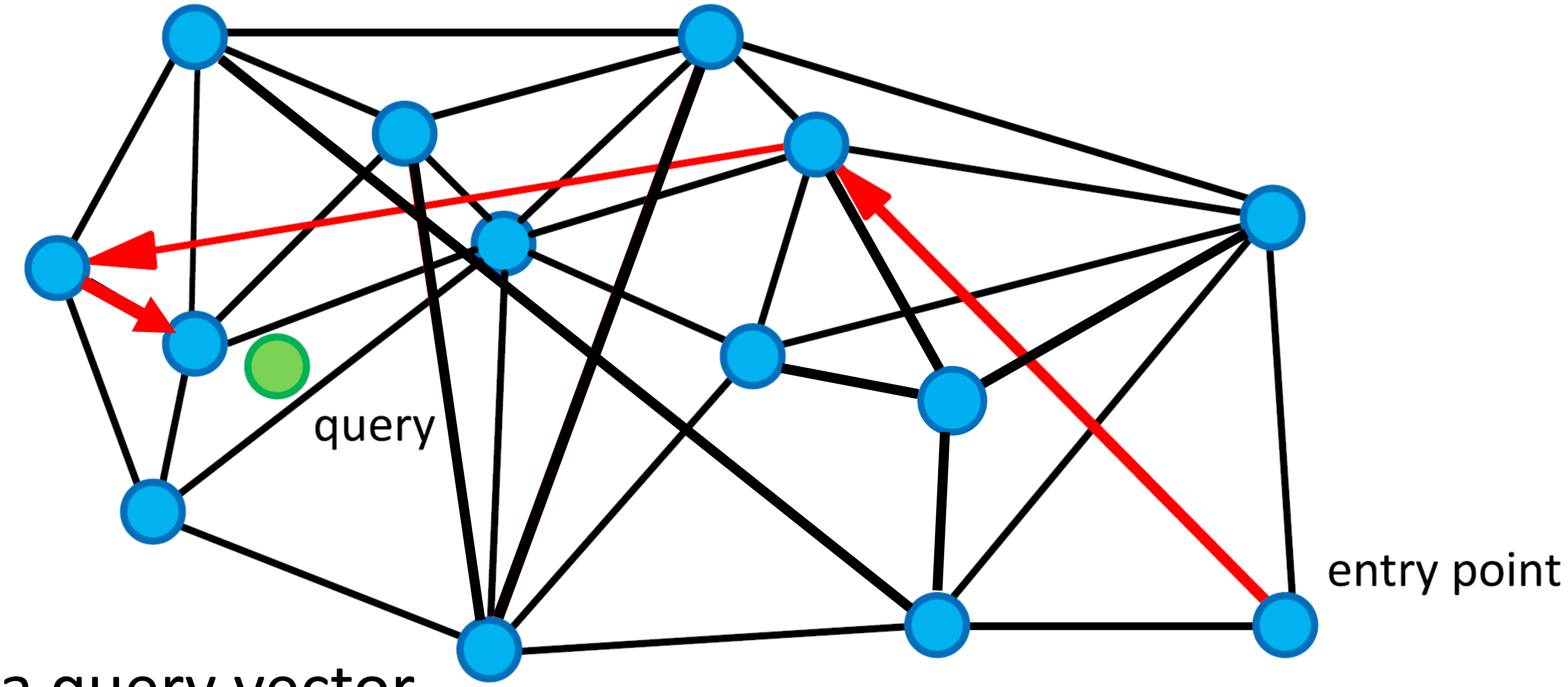
Search

Images are from [Malkov+, Information Systems, 2013]



- Given a query vector
- Start from a random point
- From the connected nodes, find the closest one to the query
- Traverse in a greedy manner

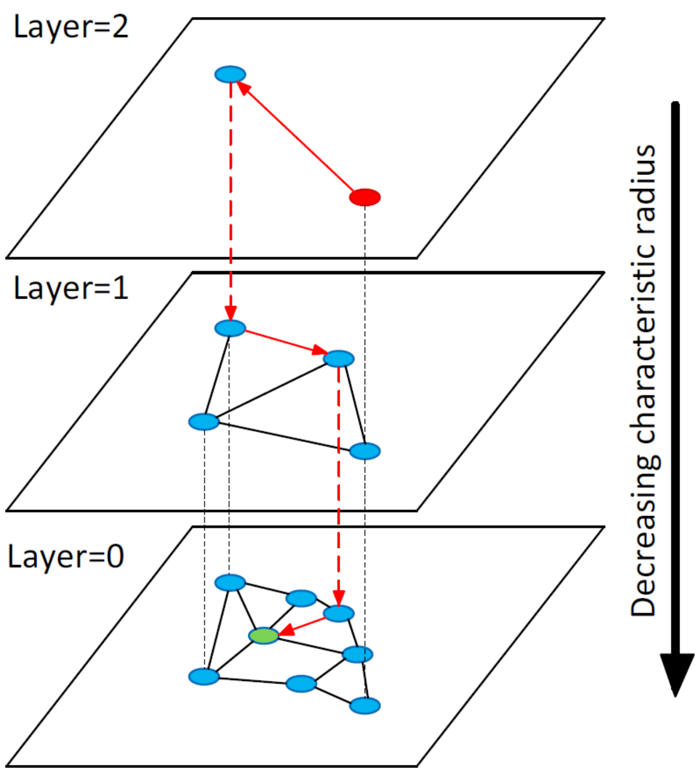
Search Images are from [Malkov+, Information Systems, 2013]



- Given a query vector
- Start from a random point
- From the connected nodes, find the closest one to the query
- Traverse in a greedy manner

Extension: Hierarchical NSW; HNSW

- Construct the graph hierarchically [Malkov and Yashunin, TPAMI, 2019]
- This structure works pretty well for real-world data



[Malkov and Yashunin, TPAMI, 2019]

Search on a coarse graph

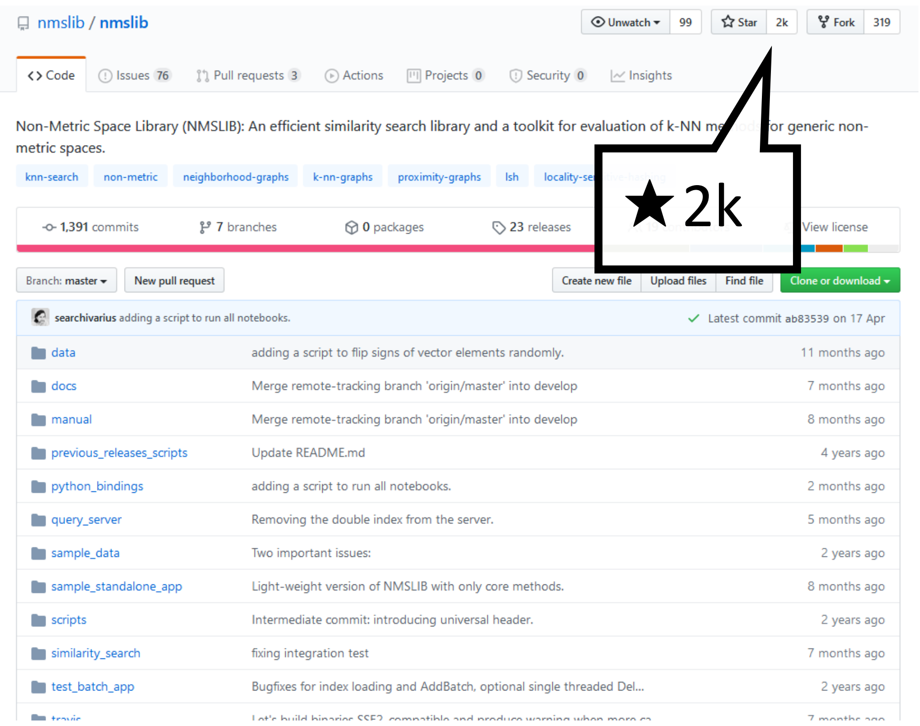
Move to the same node on a finer graph

Repeat

NMSLIB (Non-Metric Space Library)

https://github.com/nmslib/nmslib

```
$> pip install nmslib
```



Non-Metric Space Library (NMSLIB): An efficient similarity search library and a toolkit for evaluation of k-NN methods for generic non-metric spaces.

searchivarius adding a script to run all notebooks. Latest commit ab83539 on 17 Apr

data	adding a script to flip signs of vector elements randomly.	11 months ago
docs	Merge remote-tracking branch 'origin/master' into develop	7 months ago
manual	Merge remote-tracking branch 'origin/master' into develop	8 months ago
previous_releases_scripts	Update README.md	4 years ago
python_bindings	adding a script to run all notebooks.	2 months ago
query_server	Removing the double index from the server.	5 months ago
sample_data	Two important issues:	2 years ago
sample_standalone_app	Light-weight version of NMSLIB with only core methods.	8 months ago
scripts	Intermediate commit: introducing universal header.	2 years ago
similarity_search	fixing integration test	7 months ago
test_batch_app	Bugfixes for index loading and AddBatch, optional single threaded Del...	2 years ago
travis	Let's build binaries SSE2 compatible and produce warning when more ca	7 months ago

```
index = nmslib.init(method=‘hnsw’)
index.addDataPointBatch(X)
index.createIndex(params1)

index.setQueryTimeParams(params2)
index.knnQuery(q, topk)
```

- ☺ The “hnsw” is the best method as of 2020 for million-scale data
- ☺ Simple interface
- ☺ If memory consumption is not the problem, try this
- ☹ Large memory consumption
- ☹ Data addition is not fast

Other implementations of HNSW

Hnswlib: https://github.com/nmslib/hnswlib

- ➢ Spin-off library from nmslib
- ➢ Include only hnsw
- ➢ Simpler; may be useful if you want to extend hnsw

Faiss: https://github.com/facebookresearch/faiss

- ➢ Libraries for PQ-based methods. Will Introduce later
- ➢ This lib also includes hnsw

Other graph-based approaches

- From Alibaba:

C. Fu et al., “Fast Approximate Nearest Neighbor Search with the Navigating Spreading-out Graph”, VLDB19
https://github.com/ZJULearning/nsg

- From Microsoft Research Asia. Used inside Bing:

J. Wang and S. Lin, “Query-Driven Iterated Neighborhood Graph Search for Large Scale Indexing”, ACMMM12 (This seems the backbone paper)
https://github.com/microsoft/SPTAG

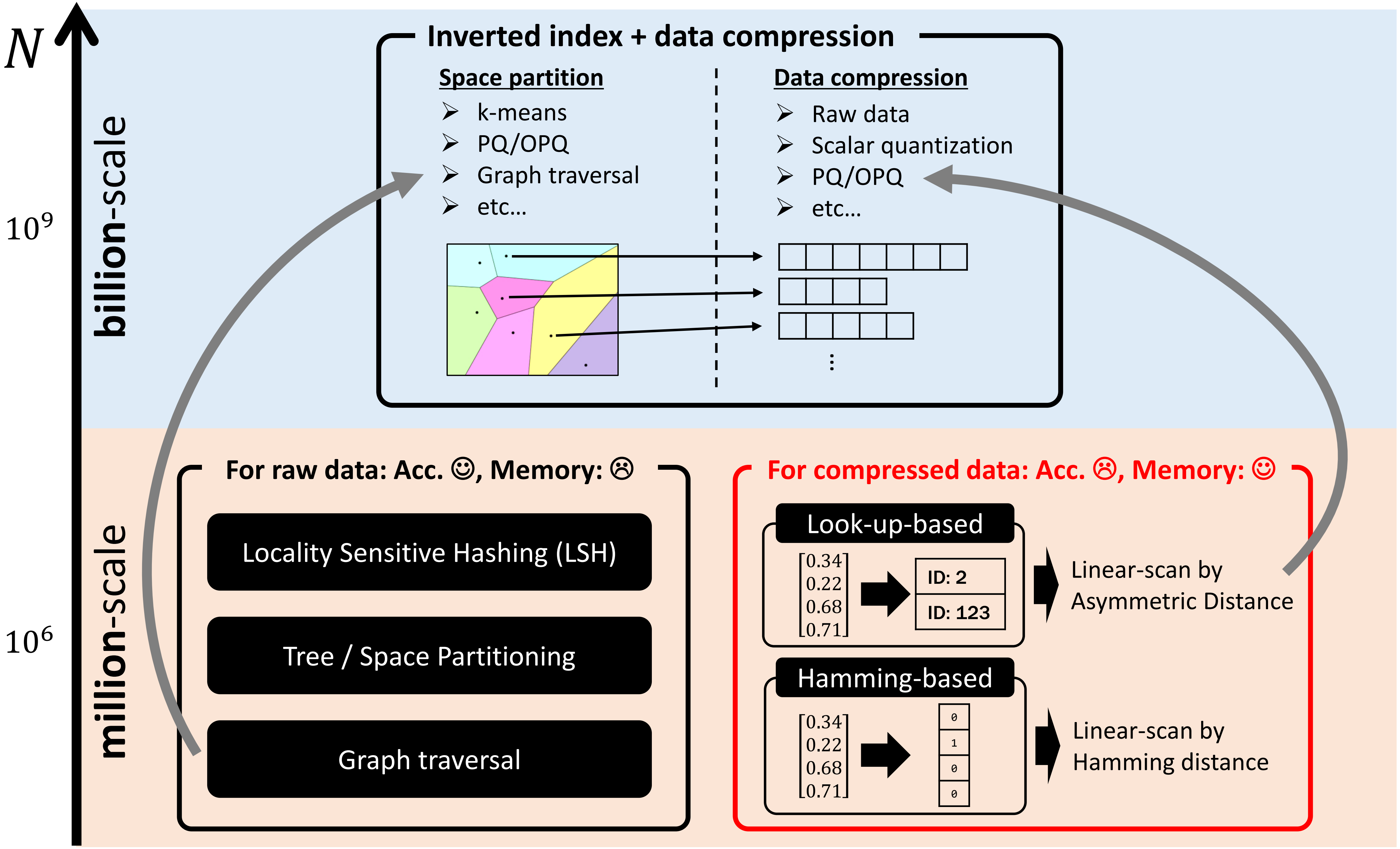
- From Yahoo Japan. Competing with NMSLIB for the 1st place of benchmark:

M. Iwasaki and D. Miyazaki, “Optimization of Indexing Based on k-Nearest Neighbor Graph for Proximity Search in High-dimensional Data”, arXiv18
https://github.com/yahoojapan/NGT

Reference

- The original paper of Navigable Small World Graph: Y. Malkov et al., “Approximate Nearest Neighbor Algorithm based on Navigable Small World Graphs,” Information Systems 2013

- The original paper of Hierarchical Navigable Small World Graph: Y. Malkov and D. Yashunin, “Efficient and Robust Approximate Nearest Neighbor search using Hierarchical Navigable Small World Graphs,” IEEE TPAMI 2019



Inverted index + data compression

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- k-means
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- Graph traversal
- etc…

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- Raw data
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For raw data: Acc. ☺, Memory: ☹

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For compressed data: Acc. ☹, Memory: ☺

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$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ → ID: 2 / ID: 123

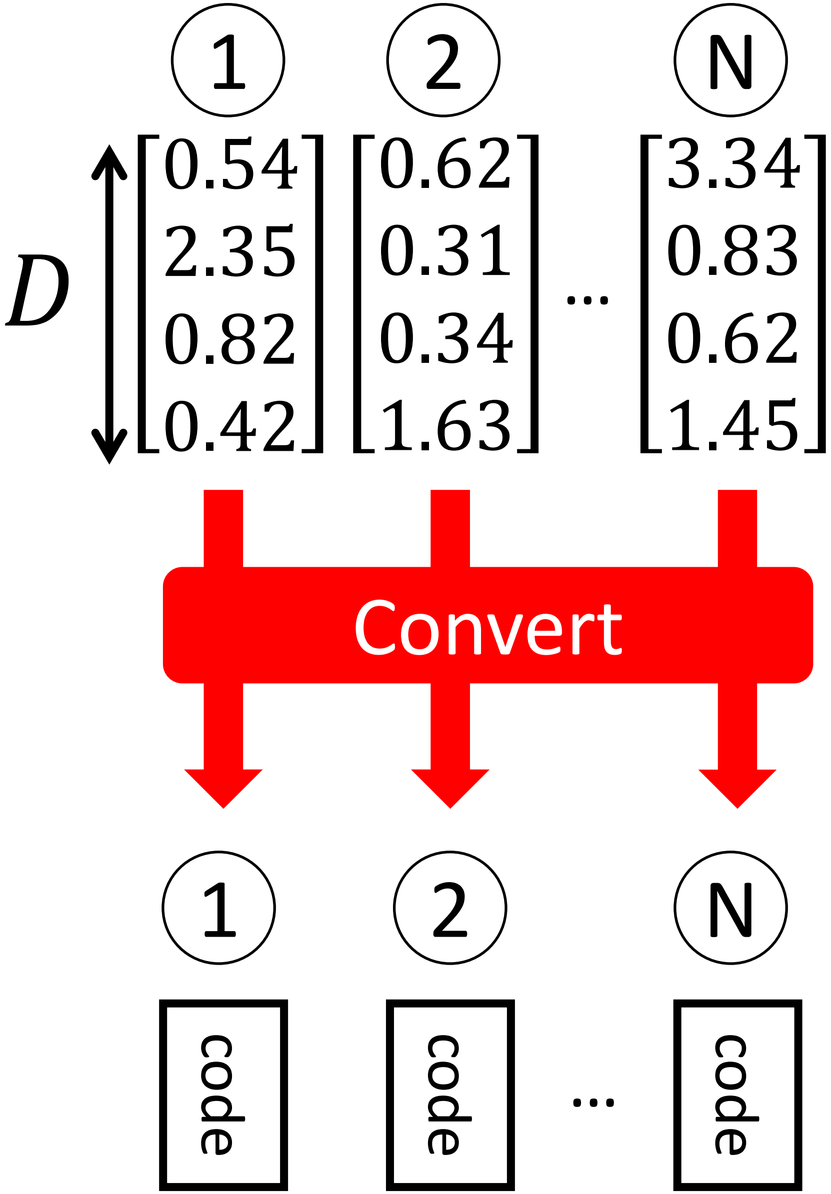
Linear-scan by Asymmetric Distance

Hamming-based

$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ → 0 / 1 / 0 / 0

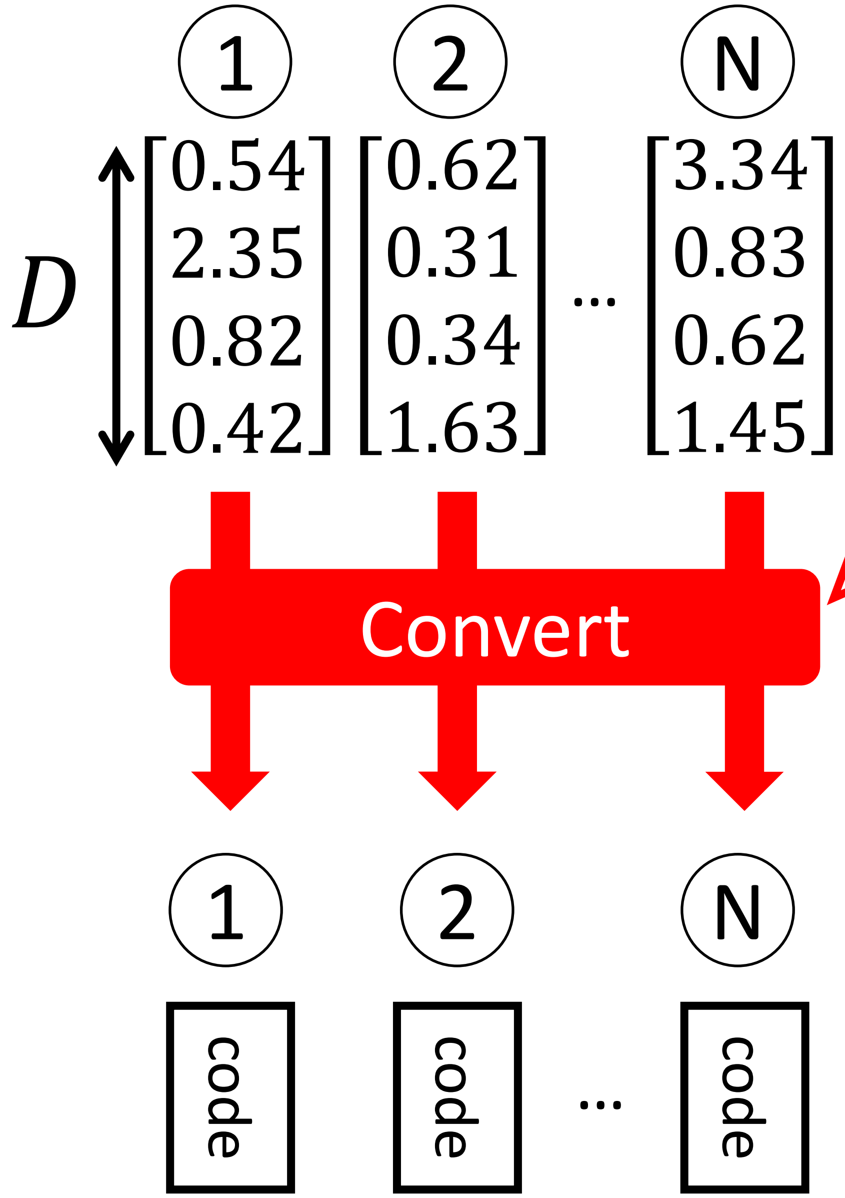
Linear-scan by Hamming distance

Basic idea



- Need $4ND$ byte to represent N real-valued vectors using floats
- If N or D is too large, we cannot read the data on memory
  - ✓ E.g., 512 GB for $D = 128, N = 10^9$
- Convert each vector to a **short-code**
- Short-code is designed as memory-efficient
  - ✓ E.g., 4 GB for the above example, with 32-bit code
- Run search for short-codes

Basic idea



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- Convert each vector to a **short-code**
- Short-code is designed as memory-efficient
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- Run search for short-codes

What kind of conversion is preferred?

1. The “distance” between two codes can be calculated (e.g., Hamming-distance)
2. The distance can be computed quickly
3. That distance approximates the distance between the original vectors (e.g., L_2)
4. Sufficiently small length of codes can achieve the above three criteria

- Convert $\boldsymbol{x}$ to a B-bit binary vector:

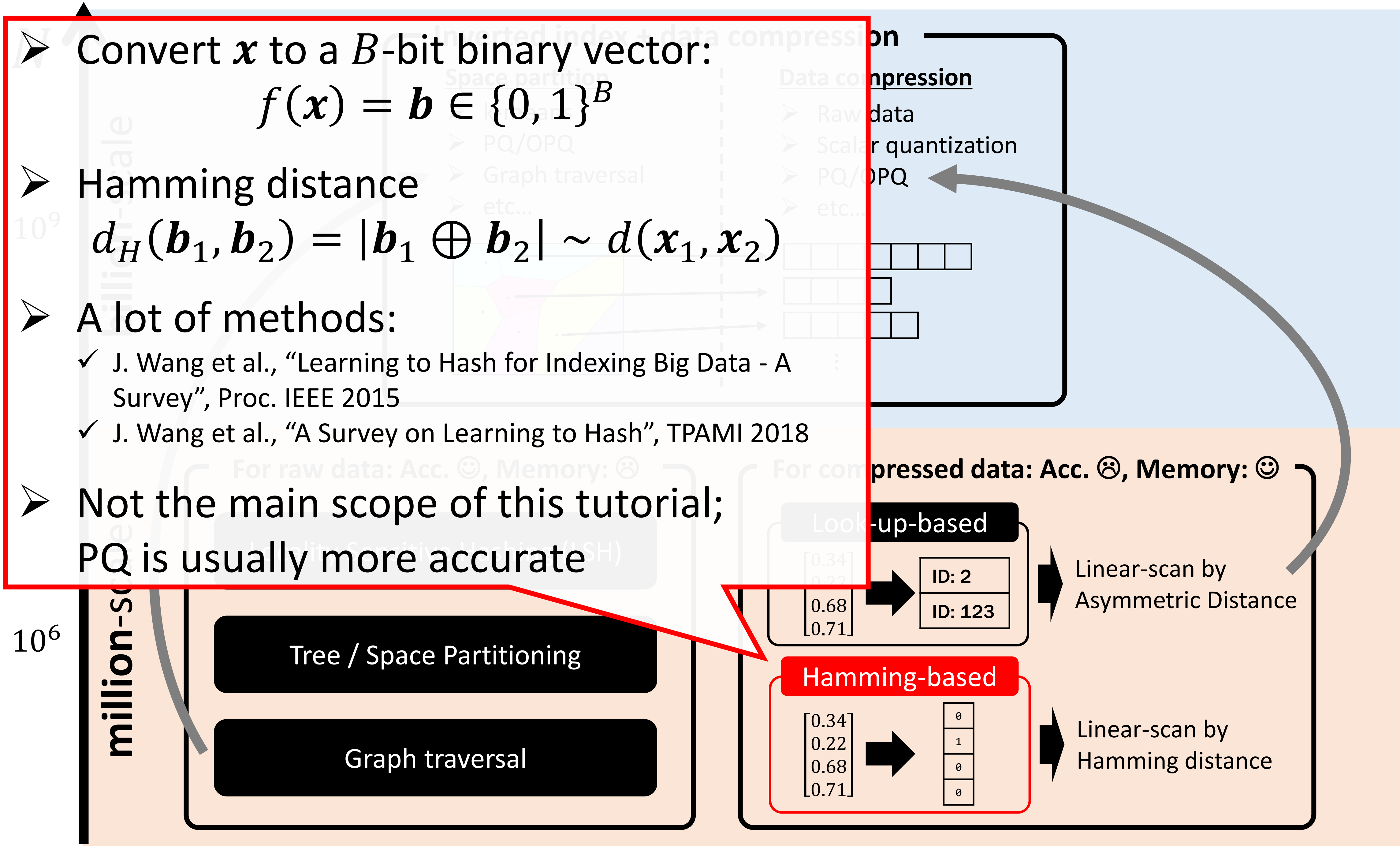
$$f(\boldsymbol{x}) = \boldsymbol{b} \in \{0,1\}^B$$

- Hamming distance

$$d_H(\boldsymbol{b}_1, \boldsymbol{b}_2) = |\boldsymbol{b}_1 \oplus \boldsymbol{b}_2| \sim d(\boldsymbol{x}_1, \boldsymbol{x}_2)$$

- A lot of methods:
  - ✓ J. Wang et al., “Learning to Hash for Indexing Big Data - A Survey”, Proc. IEEE 2015
  - ✓ J. Wang et al., “A Survey on Learning to Hash”, TPAMI 2018

- Not the main scope of this tutorial; PQ is usually more accurate



N

10^9

billion-scale

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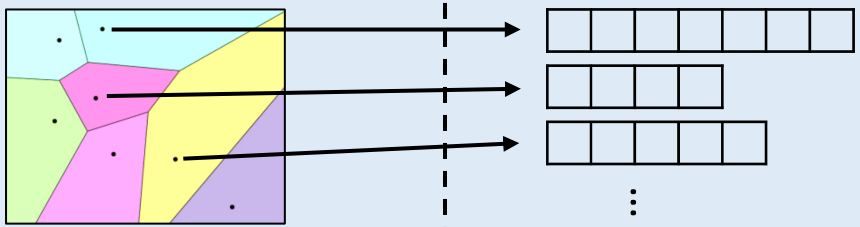

10^6

million-scale

For raw data: Acc. ☺, Memory: ☹

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For compressed data: Acc. ☹, Memory: ☺

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$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ ➡ ID: 2, ID: 123

Linear-scan by Asymmetric Distance

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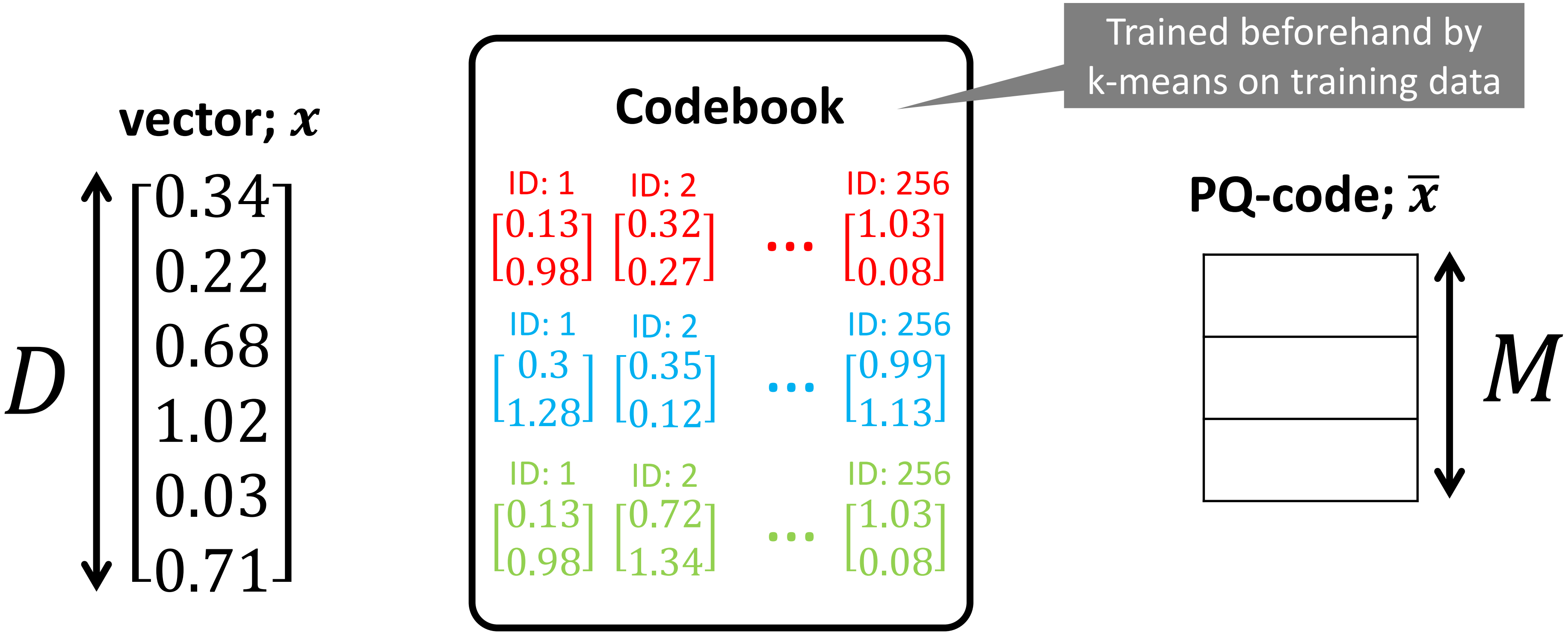
Linear-scan by Hamming distance

Product Quantization; PQ [Jégou, TPAMI 2011]

- Split a vector into sub-vectors, and quantize each sub-vector



vector; x

$$D \begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$$

Codebook

Trained beforehand by k-means on training data

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.32\\0.27\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.3\\1.28\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.35\\0.12\end{bmatrix}$ … ID: 256 $\begin{bmatrix}0.99\\1.13\end{bmatrix}$

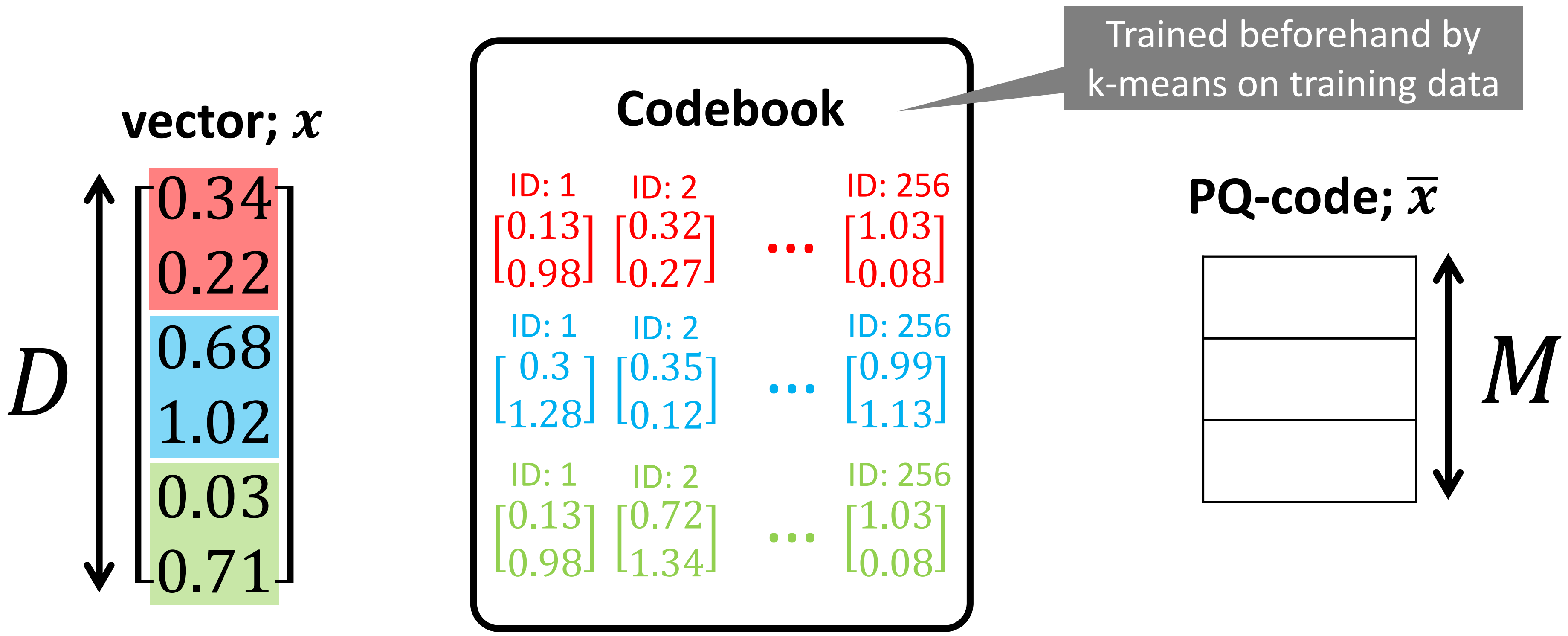
ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.72\\1.34\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

PQ-code; $\bar{x}$

M

Product Quantization; PQ [Jégou, TPAMI 2011]

- Split a vector into sub-vectors, and quantize each sub-vector



vector; x

$$D \quad \begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 1.02 \\ 0.03 \\ 0.71 \end{bmatrix}$$

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Trained beforehand by k-means on training data

ID: 1 $\begin{bmatrix} 0.13 \\ 0.98 \end{bmatrix}$ ID: 2 $\begin{bmatrix} 0.32 \\ 0.27 \end{bmatrix}$ … ID: 256 $\begin{bmatrix} 1.03 \\ 0.08 \end{bmatrix}$

ID: 1 $\begin{bmatrix} 0.3 \\ 1.28 \end{bmatrix}$ ID: 2 $\begin{bmatrix} 0.35 \\ 0.12 \end{bmatrix}$ … ID: 256 $\begin{bmatrix} 0.99 \\ 1.13 \end{bmatrix}$

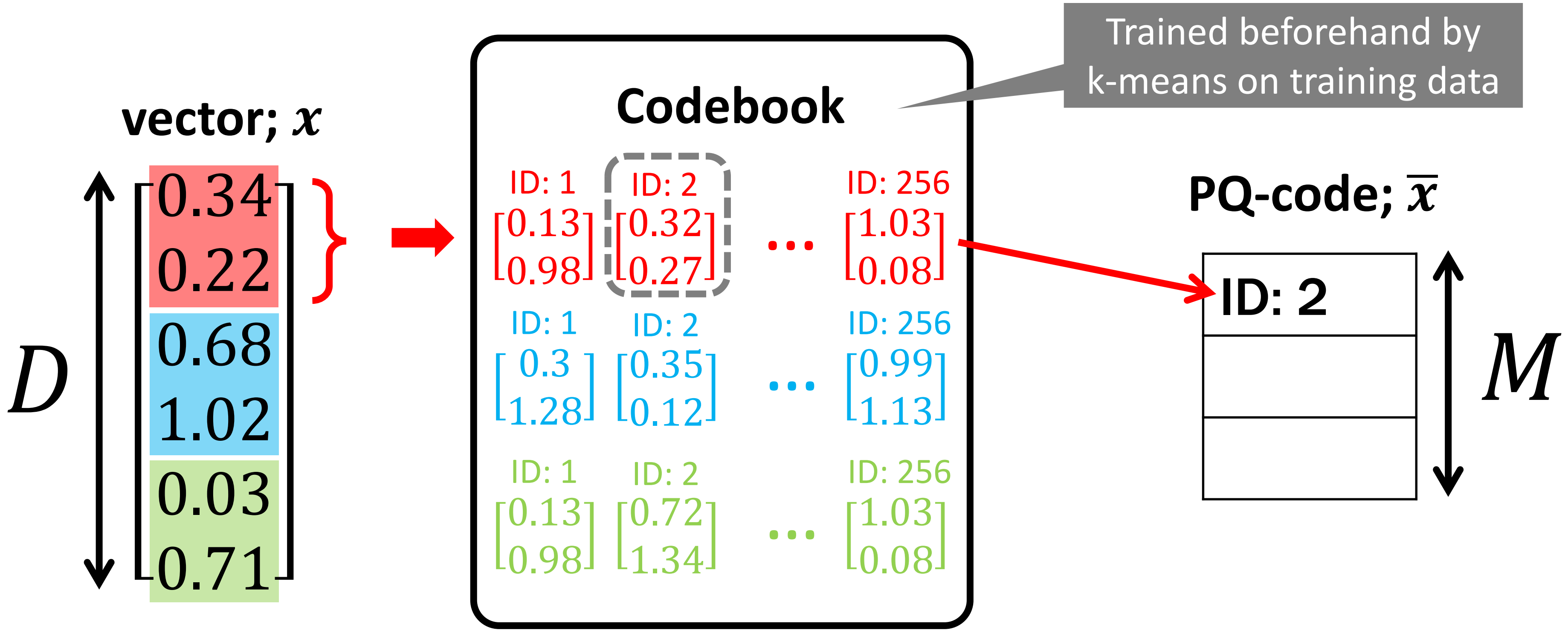
ID: 1 $\begin{bmatrix} 0.13 \\ 0.98 \end{bmatrix}$ ID: 2 $\begin{bmatrix} 0.72 \\ 1.34 \end{bmatrix}$ … ID: 256 $\begin{bmatrix} 1.03 \\ 0.08 \end{bmatrix}$

PQ-code; $\bar{x}$

M

Product Quantization; PQ [Jégou, TPAMI 2011]

- Split a vector into sub-vectors, and quantize each sub-vector



vector; x

D

$$\begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$$

Codebook

Trained beforehand by k-means on training data

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.32\\0.27\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.3\\1.28\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.35\\0.12\end{bmatrix}$ … ID: 256 $\begin{bmatrix}0.99\\1.13\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.72\\1.34\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

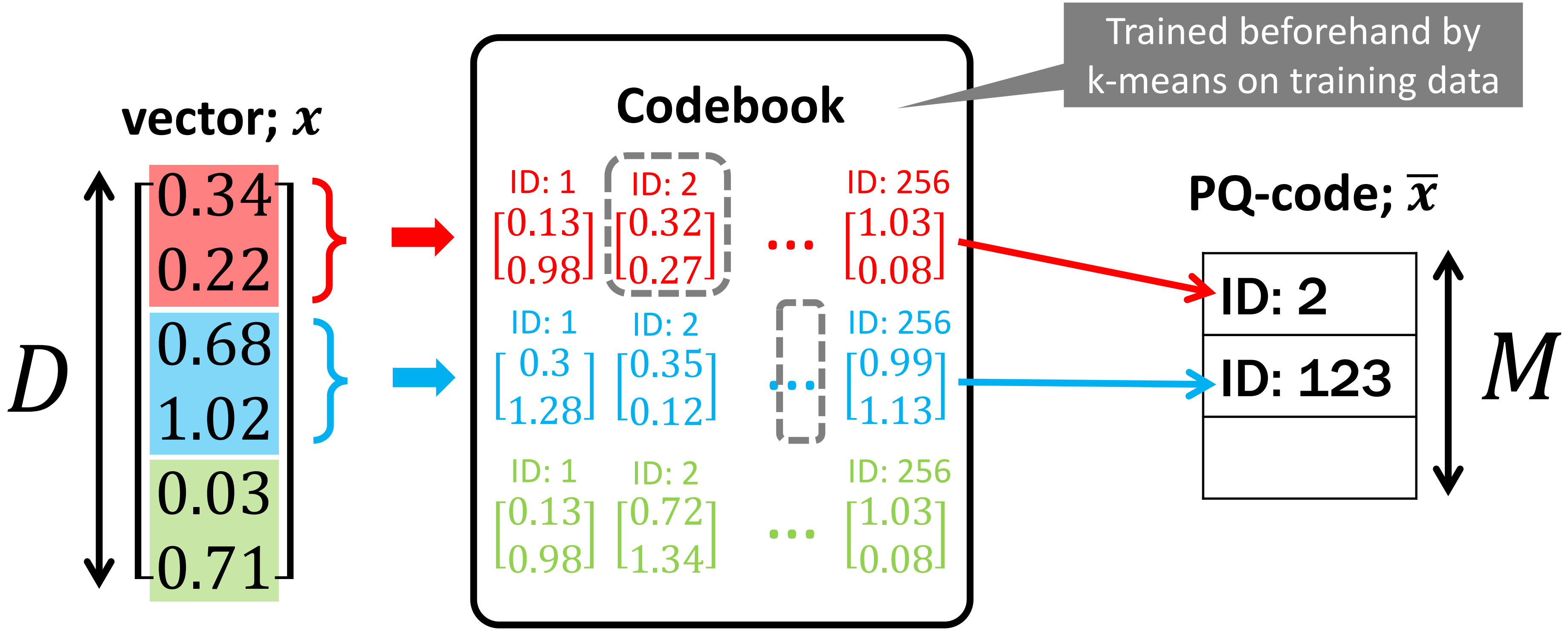
PQ-code; $\bar{x}$

ID: 2

M

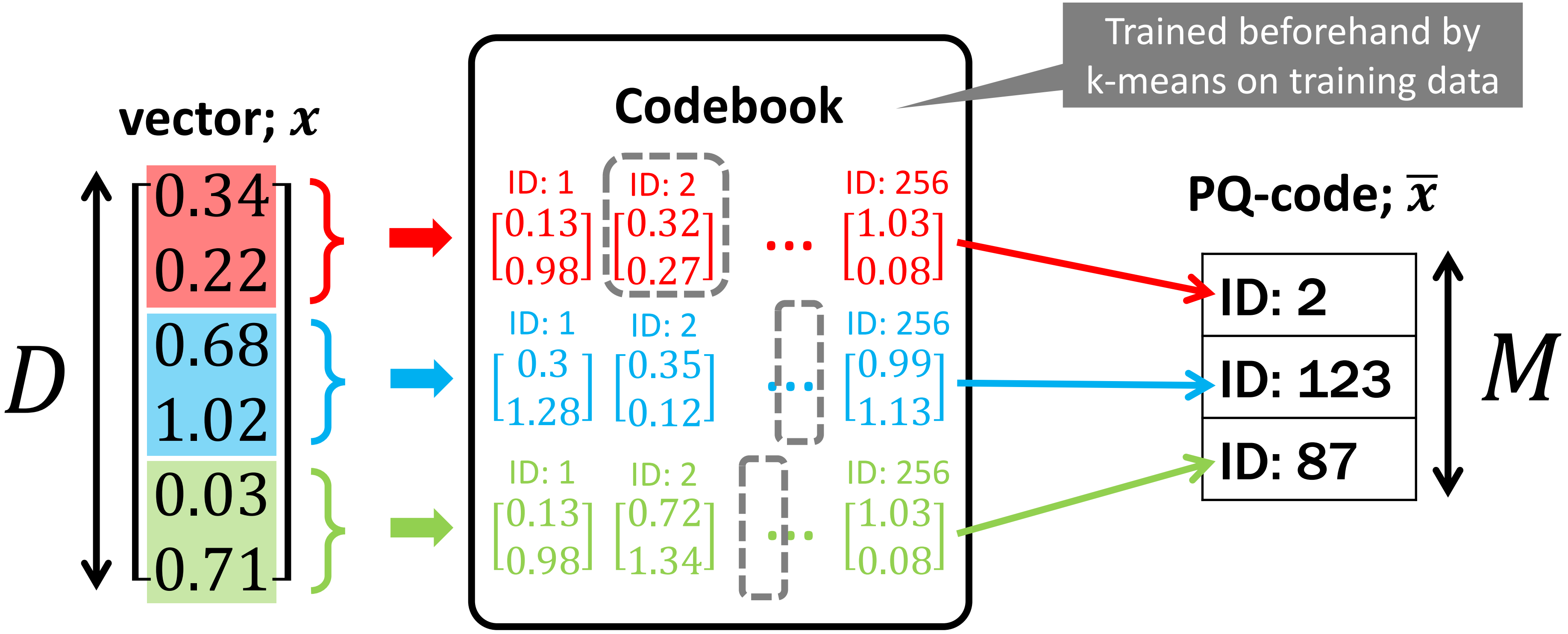
Product Quantization; PQ [Jégou, TPAMI 2011]

- Split a vector into sub-vectors, and quantize each sub-vector



Product Quantization; PQ [Jégou, TPAMI 2011]

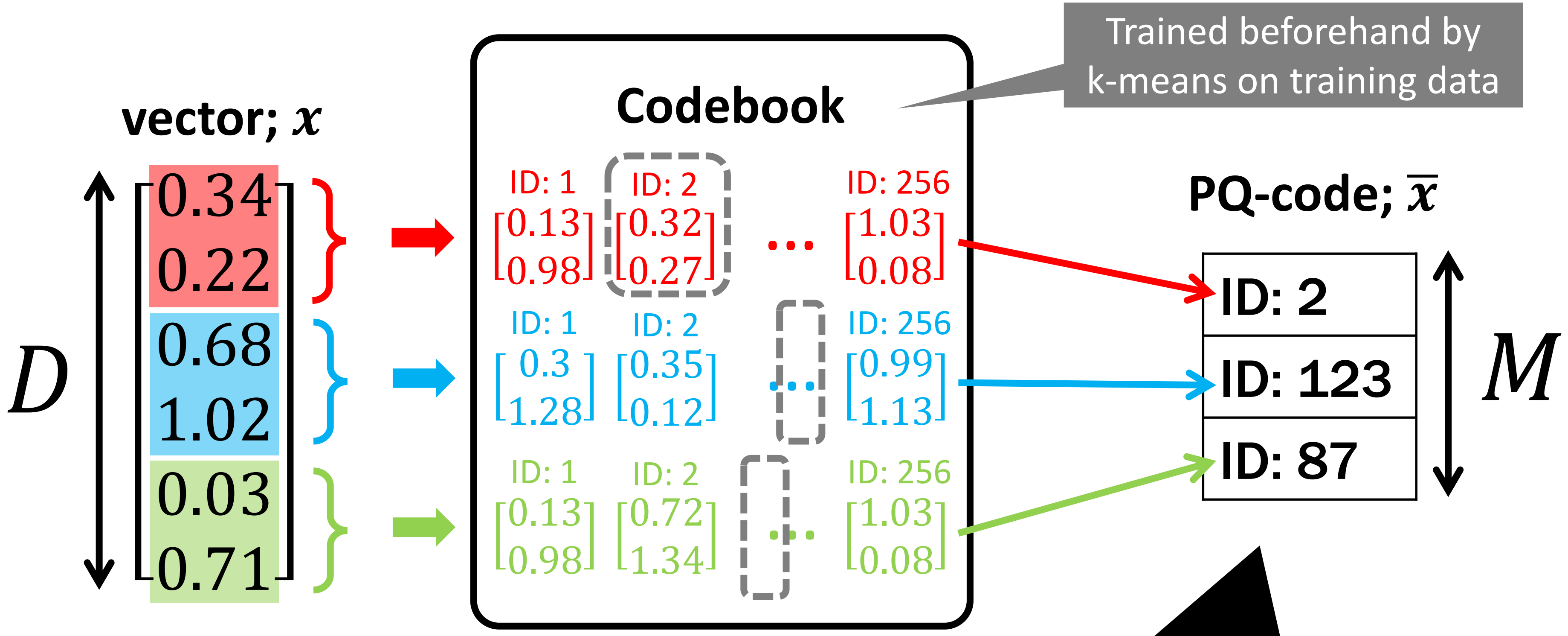
- Split a vector into sub-vectors, and quantize each sub-vector



Trained beforehand by k-means on training data

Product Quantization; PQ [Jégou, TPAMI 2011]

- Split a vector into sub-vectors, and quantize each sub-vector



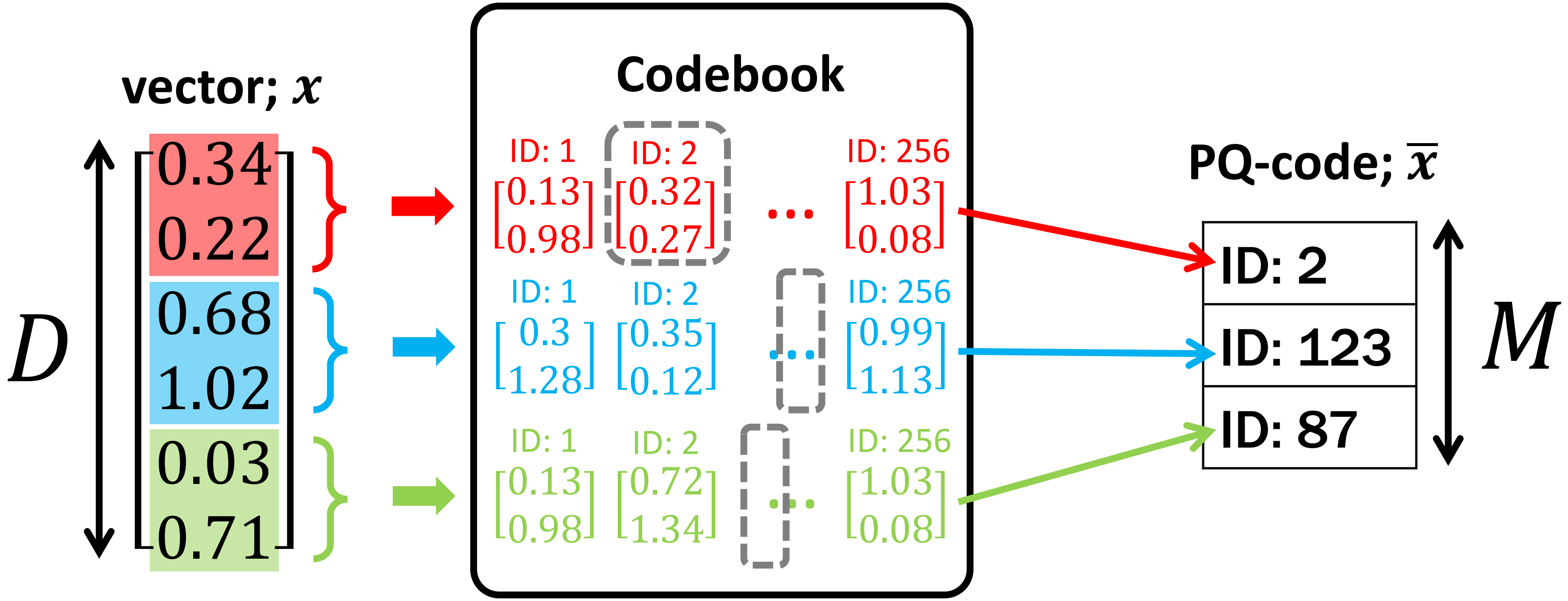
Trained beforehand by
k-means on training data

Bar notation for PQ-code in this tutorial:

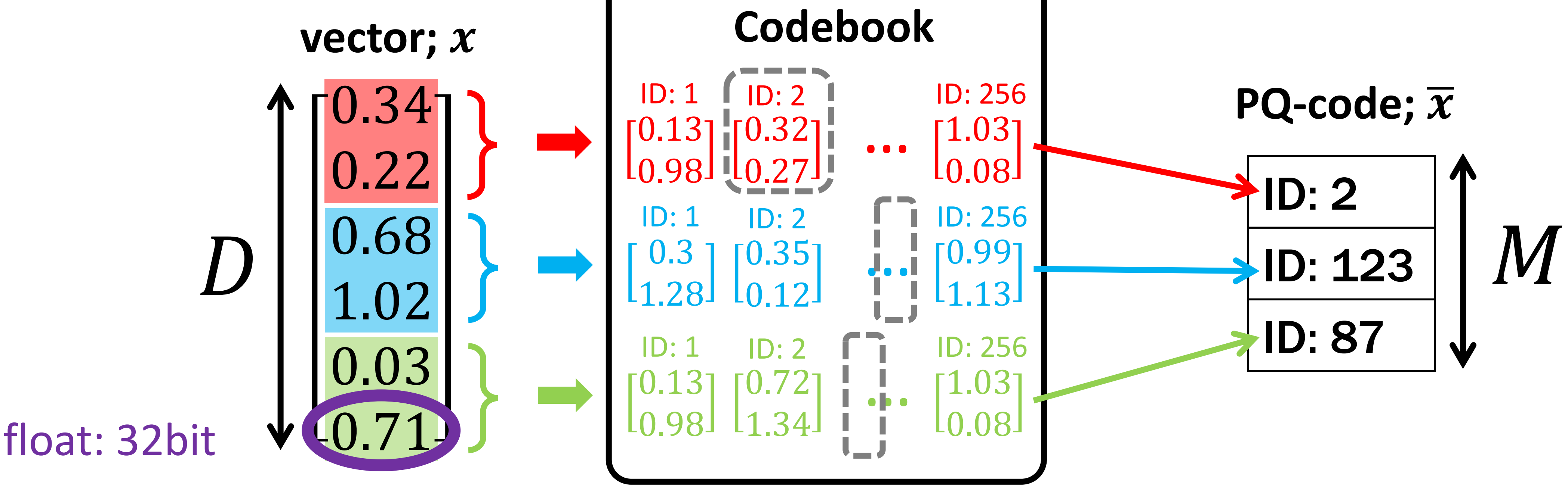
$$\boldsymbol{x} \in \mathbb{R}^D \quad \mapsto \quad \bar{\boldsymbol{x}} \in \{1, \dots, 256\}^M$$

- Simple
- Memory efficient
- Distance can be esimated

Product Quantization: Memory efficient



Product Quantization: Memory efficient



vector; x

D

$\begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$

float: 32bit

Codebook

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.32\\0.27\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.3\\1.28\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.35\\0.12\end{bmatrix}$ … ID: 256 $\begin{bmatrix}0.99\\1.13\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.72\\1.34\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

PQ-code; $\bar{x}$

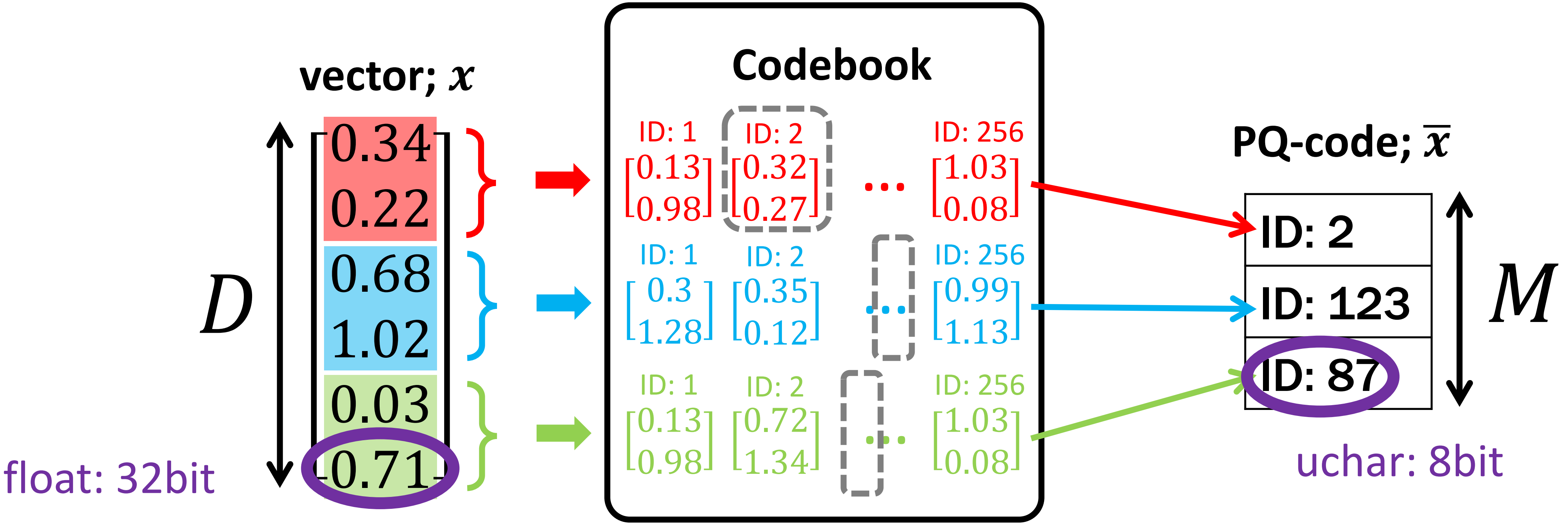
ID: 2
ID: 123
ID: 87

M

e.g., $D = 128$

$128 \times 32 = 4096$ [bit]

Product Quantization: Memory efficient



vector; x

D

$\begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$

float: 32bit

Codebook

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.32\\0.27\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.3\\1.28\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.35\\0.12\end{bmatrix}$ … ID: 256 $\begin{bmatrix}0.99\\1.13\end{bmatrix}$

ID: 1 $\begin{bmatrix}0.13\\0.98\end{bmatrix}$ ID: 2 $\begin{bmatrix}0.72\\1.34\end{bmatrix}$ … ID: 256 $\begin{bmatrix}1.03\\0.08\end{bmatrix}$

PQ-code; $\bar{x}$

ID: 2

ID: 123

ID: 87

M

uchar: 8bit

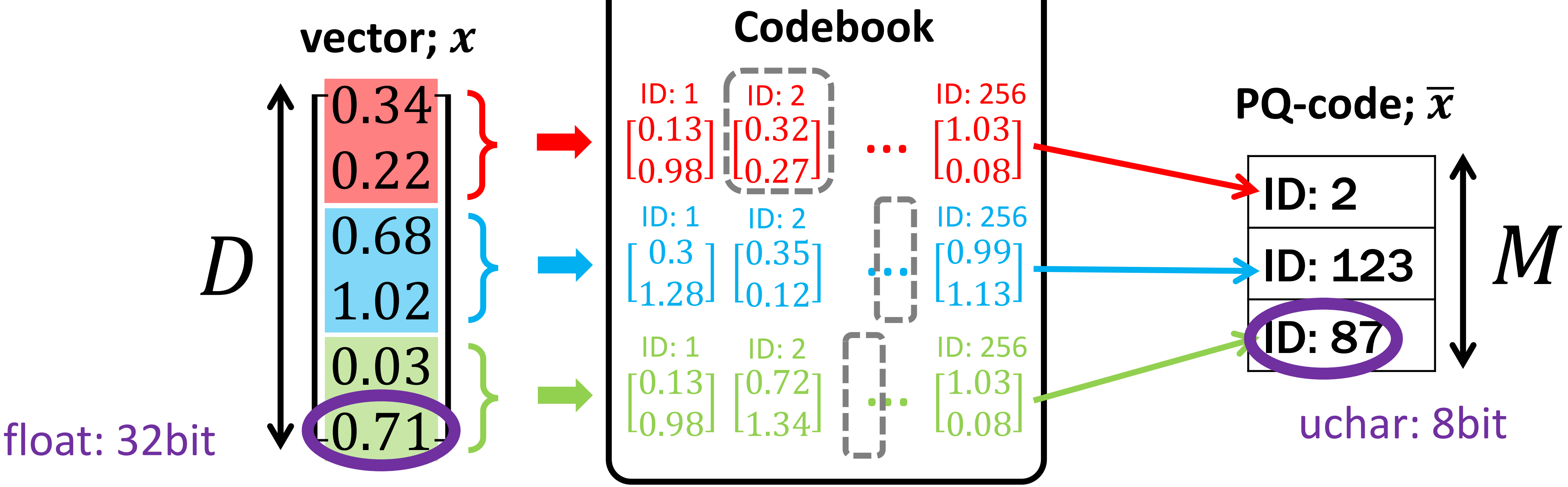
e.g., $D = 128$

$128 \times 32 = 4096$ [bit]

e.g., $M = 8$

$8 \times 8 = 64$ [bit]

Product Quantization: Memory efficient



e.g., $D = 128$
$128 \times 32 = 4096$ [bit]

e.g., $M = 8$
$8 \times 8 = 64$ [bit]

1/64

Product Quantization: Distance estimation

Query; $\boldsymbol{q} \in \mathbb{R}^D$

$$\begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$$

Database vectors

$$\begin{array}{cccc} \boldsymbol{x}_1 & \boldsymbol{x}_2 & & \boldsymbol{x}_N \\ \begin{bmatrix}0.54\\2.35\\0.82\\0.42\\0.14\\0.32\end{bmatrix} & \begin{bmatrix}0.62\\0.31\\0.34\\1.63\\1.43\\0.74\end{bmatrix} & \cdots & \begin{bmatrix}3.34\\0.83\\0.62\\1.45\\0.12\\2.32\end{bmatrix} \end{array}$$

Product Quantization: Distance estimation

Query; $\boldsymbol{q} \in \mathbb{R}^D$

$$\begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 1.02 \\ 0.03 \\ 0.71 \end{bmatrix}$$

Database vectors

$$\begin{array}{cccc} \boldsymbol{x}_1 & \boldsymbol{x}_2 & & \boldsymbol{x}_N \\ \begin{bmatrix} 0.54 \\ 2.35 \\ 0.82 \\ 0.42 \\ 0.14 \\ 0.32 \end{bmatrix} & \begin{bmatrix} 0.62 \\ 0.31 \\ 0.34 \\ 1.63 \\ 1.43 \\ 0.74 \end{bmatrix} & \cdots & \begin{bmatrix} 3.34 \\ 0.83 \\ 0.62 \\ 1.45 \\ 0.12 \\ 2.32 \end{bmatrix} \end{array}$$

Product quantization

Product Quantization: Distance estimation

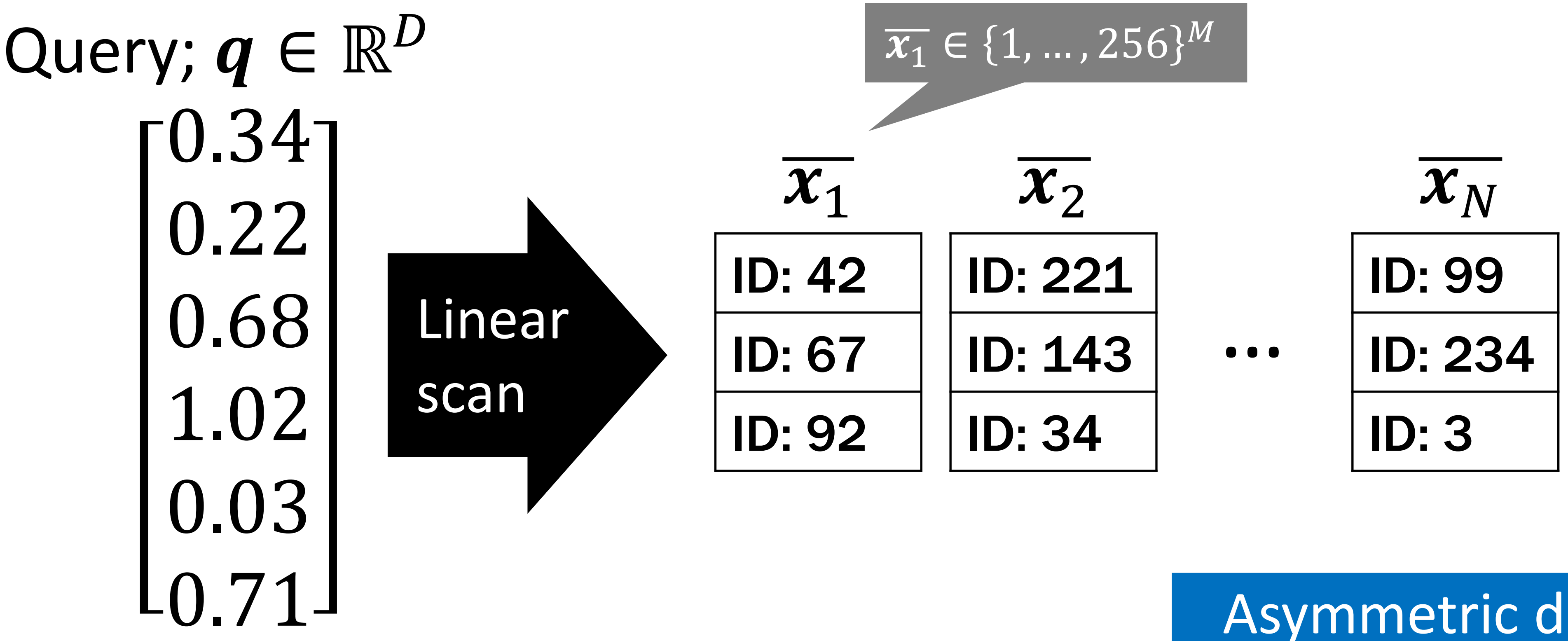
Query; $\boldsymbol{q} \in \mathbb{R}^D$

$$\begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 1.02 \\ 0.03 \\ 0.71 \end{bmatrix}$$

$\overline{\boldsymbol{x}_1} \in \{1, \dots, 256\}^M$

$\overline{\boldsymbol{x}_1}$	$\overline{\boldsymbol{x}_2}$		$\overline{\boldsymbol{x}_N}$
ID: 42	**ID: 221**		**ID: 99**
ID: 67	**ID: 143**	…	**ID: 234**
ID: 92	**ID: 34**		**ID: 3**

Product Quantization: Distance estimation



Query; $\boldsymbol{q} \in \mathbb{R}^D$

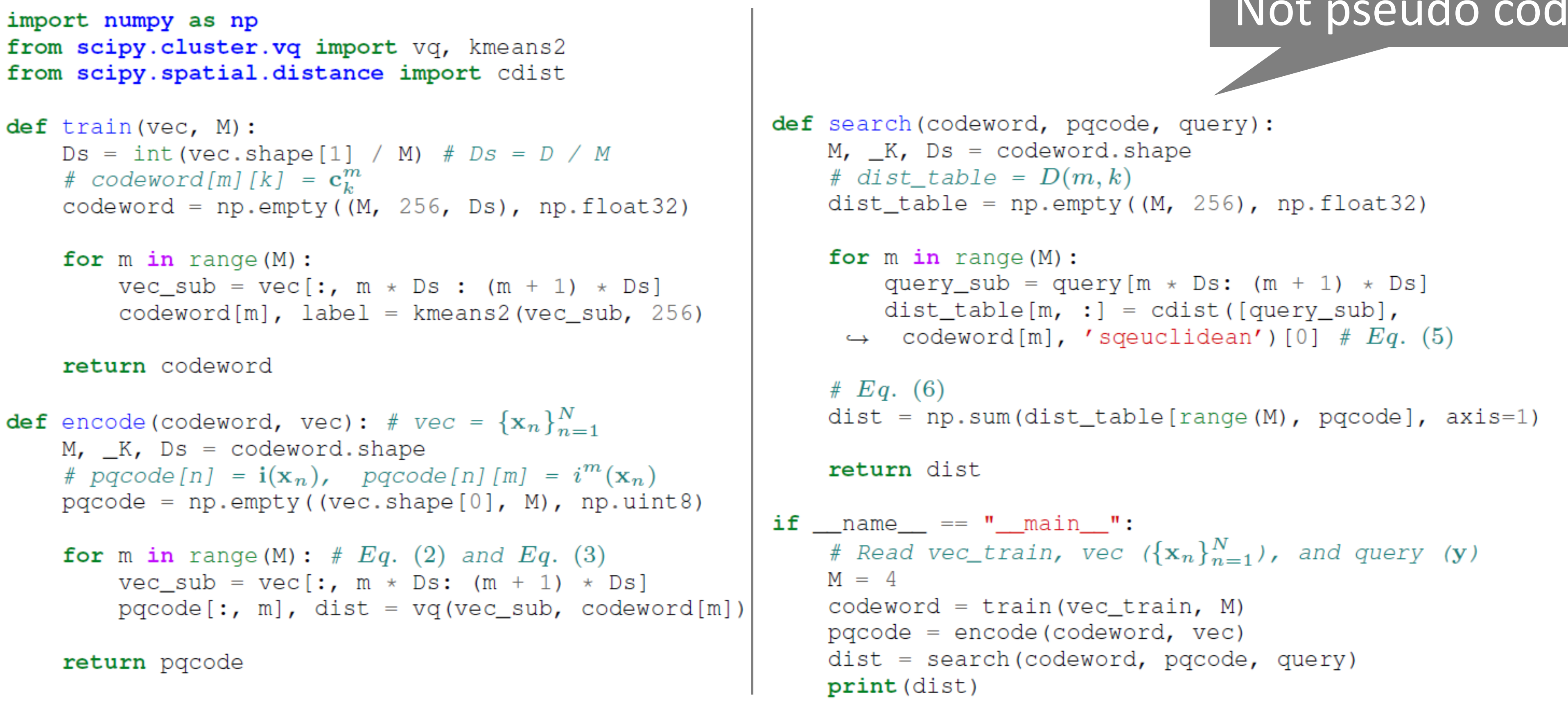
$$\begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 1.02 \\ 0.03 \\ 0.71 \end{bmatrix}$$

$\overline{\boldsymbol{x}_1} \in \{1, \dots, 256\}^M$

$\overline{\boldsymbol{x}_1}$	$\overline{\boldsymbol{x}_2}$	…	$\overline{\boldsymbol{x}_N}$
ID: 42	ID: 221		ID: 99
ID: 67	ID: 143		ID: 234
ID: 92	ID: 34		ID: 3

Asymmetric distance

- ➢ $d(\boldsymbol{q}, \boldsymbol{x})^2$ can be efficiently approximated by $d_A(\boldsymbol{q}, \overline{\boldsymbol{x}})^2$
- ➢ Lookup-trick: Looking up pre-computed distance-tables
- ➢ Linear-scan by d_A



Not pseudo codes

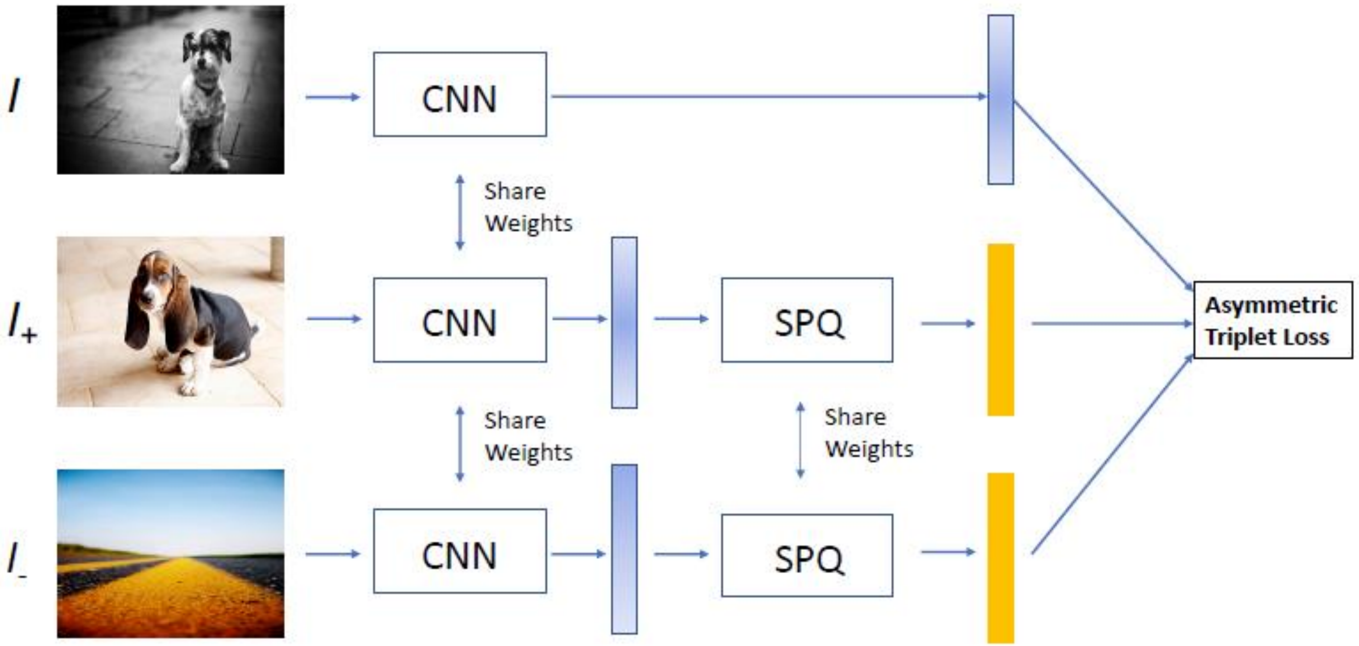
```
import numpy as np
from scipy.cluster.vq import vq, kmeans2
from scipy.spatial.distance import cdist

def train(vec, M):
    Ds = int(vec.shape[1] / M)  # Ds = D / M
    # codeword[m][k] = c_k^m
    codeword = np.empty((M, 256, Ds), np.float32)

    for m in range(M):
        vec_sub = vec[:, m * Ds : (m + 1) * Ds]
        codeword[m], label = kmeans2(vec_sub, 256)

    return codeword

def encode(codeword, vec):  # vec = {x_n}_{n=1}^N
    M, _K, Ds = codeword.shape
    # pqcode[n] = i(x_n),   pqcode[n][m] = i^m(x_n)
    pqcode = np.empty((vec.shape[0], M), np.uint8)

    for m in range(M):  # Eq. (2) and Eq. (3)
        vec_sub = vec[:, m * Ds: (m + 1) * Ds]
        pqcode[:, m], dist = vq(vec_sub, codeword[m])

    return pqcode
```

```
def search(codeword, pqcode, query):
    M, _K, Ds = codeword.shape
    # dist_table = D(m, k)
    dist_table = np.empty((M, 256), np.float32)

    for m in range(M):
        query_sub = query[m * Ds: (m + 1) * Ds]
        dist_table[m, :] = cdist([query_sub],
    ↪   codeword[m], 'sqeuclidean')[0]  # Eq. (5)

    # Eq. (6)
    dist = np.sum(dist_table[range(M), pqcode], axis=1)

    return dist

if __name__ == "__main__":
    # Read vec_train, vec ({x_n}_{n=1}^N), and query (y)
    M = 4
    codeword = train(vec_train, M)
    pqcode = encode(codeword, vec)
    dist = search(codeword, pqcode, query)
    print(dist)
```

- Only tens of lines in Python
- Pure Python library: nanopq https://github.com/matsui528/nanopq
- `pip install nanopq`

Deep PQ

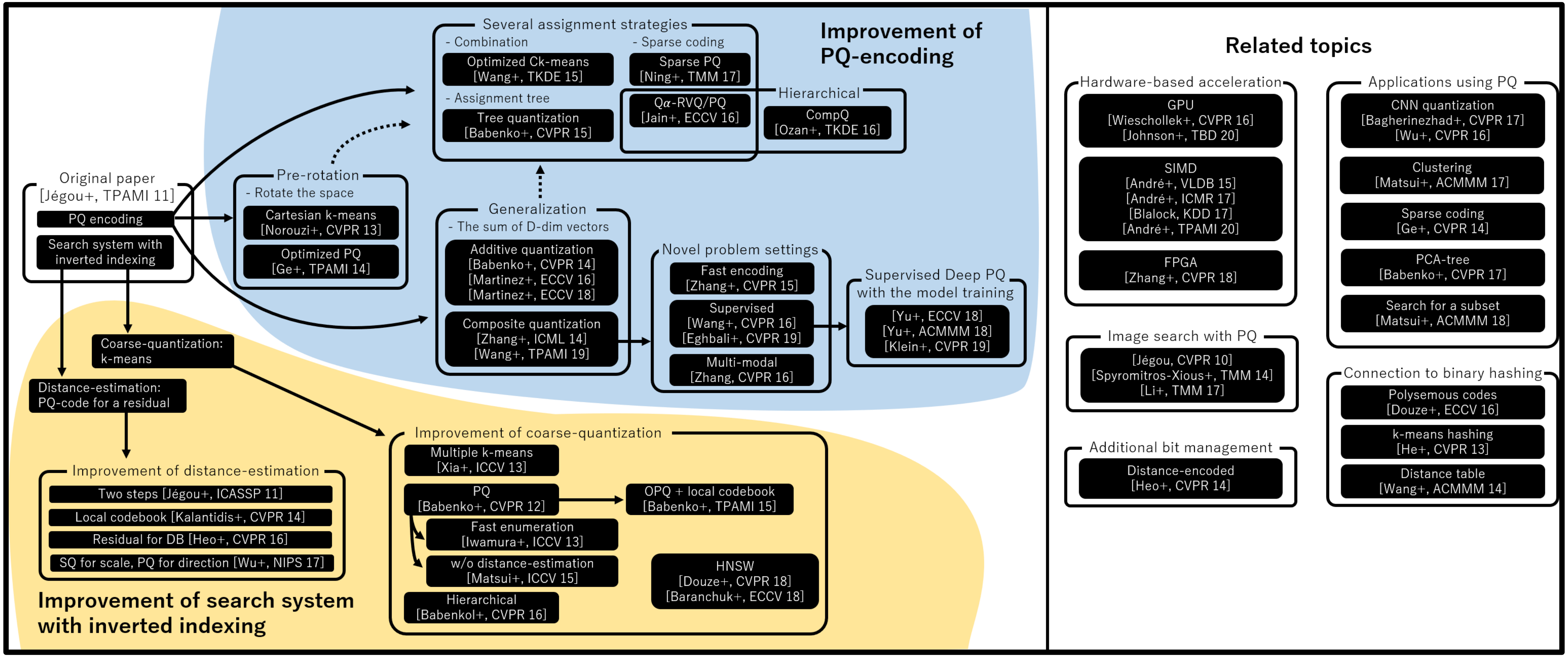
- Supervised search (unlike the original PQ)
- Base-CNN + PQ-like-layer + Some-loss
- Need class information



From T. Yu et al., “Product Quantization Network for Fast Image Retrieval”, ECCV 18

- T. Yu et al., “Product Quantization Network for Fast Image Retrieval”, ECCV 18, IJCV20
- L. Yu et al., “Generative Adversarial Product Quantisation”, ACMMM 18
- B. Klein et al., “End-to-End Supervised Product Quantization for Image Search and Retrieval”, CVPR 19

More extensive survey for PQ



Original paper [Jégou+, TPAMI 11]
- PQ encoding
- Search system with inverted indexing

Improvement of PQ-encoding

Pre-rotation
- Rotate the space
- Cartesian k-means [Norouzi+, CVPR 13]
- Optimized PQ [Ge+, TPAMI 14]

Several assignment strategies
- Combination
  - Optimized Ck-means [Wang+, TKDE 15]
- Sparse coding
  - Sparse PQ [Ning+, TMM 17]
- Assignment tree
  - Tree quantization [Babenko+, CVPR 15]
  - Qα-RVQ/PQ [Jain+, ECCV 16]

Hierarchical
- CompQ [Ozan+, TKDE 16]

Generalization
- The sum of D-dim vectors
- Additive quantization [Babenko+, CVPR 14] [Martinez+, ECCV 16] [Martinez+, ECCV 18]
- Composite quantization [Zhang+, ICML 14] [Wang+, TPAMI 19]

Novel problem settings
- Fast encoding [Zhang+, CVPR 15]
- Supervised [Wang+, CVPR 16] [Eghbali+, CVPR 19]
- Multi-modal [Zhang, CVPR 16]

Supervised Deep PQ with the model training
- [Yu+, ECCV 18] [Yu+, ACMMM 18] [Klein+, CVPR 19]

Improvement of search system with inverted indexing

Coarse-quantization: k-means

Distance-estimation: PQ-code for a residual

Improvement of distance-estimation
- Two steps [Jégou+, ICASSP 11]
- Local codebook [Kalantidis+, CVPR 14]
- Residual for DB [Heo+, CVPR 16]
- SQ for scale, PQ for direction [Wu+, NIPS 17]

Improvement of coarse-quantization
- Multiple k-means [Xia+, ICCV 13]
- PQ [Babenko+, CVPR 12]
  - OPQ + local codebook [Babenko+, TPAMI 15]
  - Fast enumeration [Iwamura+, ICCV 13]
  - w/o distance-estimation [Matsui+, ICCV 15]
- Hierarchical [Babenkol+, CVPR 16]
- HNSW [Douze+, CVPR 18] [Baranchuk+, ECCV 18]

Related topics

Hardware-based acceleration
- GPU [Wieschollek+, CVPR 16] [Johnson+, TBD 20]
- SIMD [André+, VLDB 15] [André+, ICMR 17] [Blalock, KDD 17] [André+, TPAMI 20]
- FPGA [Zhang+, CVPR 18]

Image search with PQ
- [Jégou, CVPR 10] [Spyromitros-Xious+, TMM 14] [Li+, TMM 17]

Additional bit management
- Distance-encoded [Heo+, CVPR 14]

Applications using PQ
- CNN quantization [Bagherinezhad+, CVPR 17] [Wu+, CVPR 16]
- Clustering [Matsui+, ACMMM 17]
- Sparse coding [Ge+, CVPR 14]
- PCA-tree [Babenko+, CVPR 17]
- Search for a subset [Matsui+, ACMMM 18]

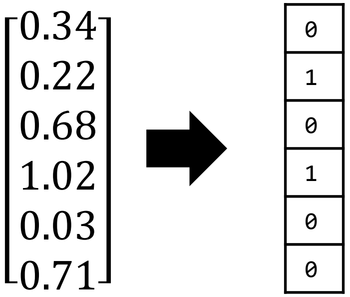
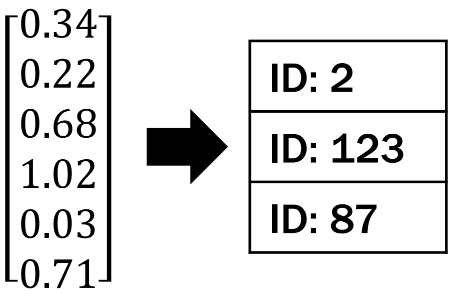
Connection to binary hashing
- Polysemous codes [Douze+, ECCV 16]
- k-means hashing [He+, CVPR 13]
- Distance table [Wang+, ACMMM 14]

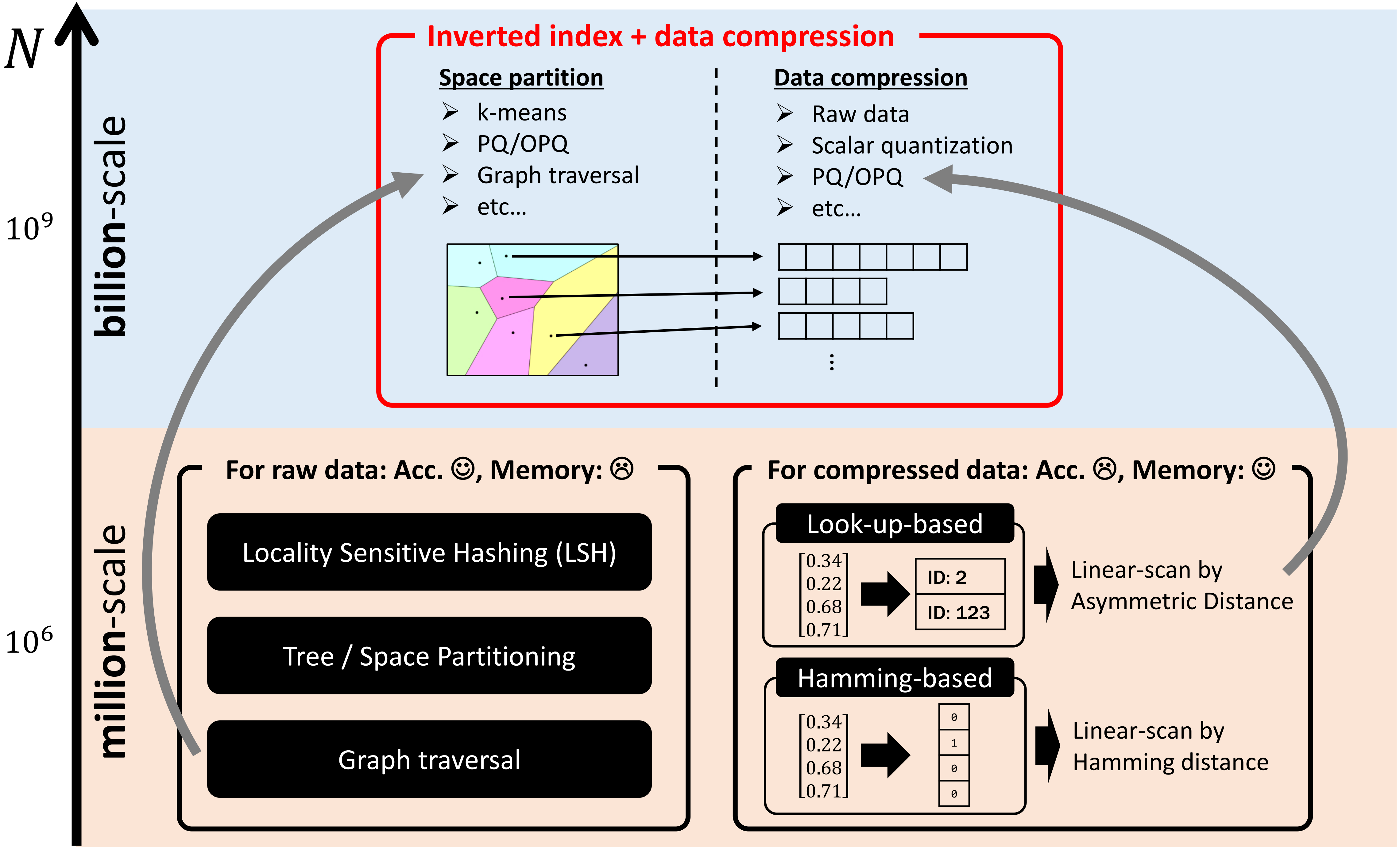
➢ https://github.com/facebookresearch/faiss/wiki#research-foundations-of-faiss

➢ http://yusukematsui.me/project/survey_pq/survey_pq_jp.html

➢ Y. Matsui, Y. Uchida, H. Jégou, S. Satoh "A Survey of Product Quantization", ITE 2018.

Hamming-based vs Look-up-based

	Hamming-based	**Look-up-based**
	 $\begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$ → 0 1 0 1 0 0	 $\begin{bmatrix}0.34\\0.22\\0.68\\1.02\\0.03\\0.71\end{bmatrix}$ → **ID: 2** **ID: 123** **ID: 87**
Representation	Binary code : $\{0,1\}^B$	PQ code : $\{1,\ldots,256\}^M$
Distance	Hamming distance	Asymmetric distance
Approximation	☺	☺☺
Runtime	☺☺	☺
Pros	No auxiliary structure	Can reconstruct the original vector
Cons	Cannot reconstruct the original vector	Require an auxiliary structure (codebook)



Inverted index + data compression

Space partition

- k-means
- PQ/OPQ
- Graph traversal
- etc…

Data compression

- Raw data
- Scalar quantization
- PQ/OPQ
- etc…

For raw data: Acc. ☺, Memory: ☹

- Locality Sensitive Hashing (LSH)
- Tree / Space Partitioning
- Graph traversal

For compressed data: Acc. ☹, Memory: ☺

Look-up-based

$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ → **ID: 2** **ID: 123**

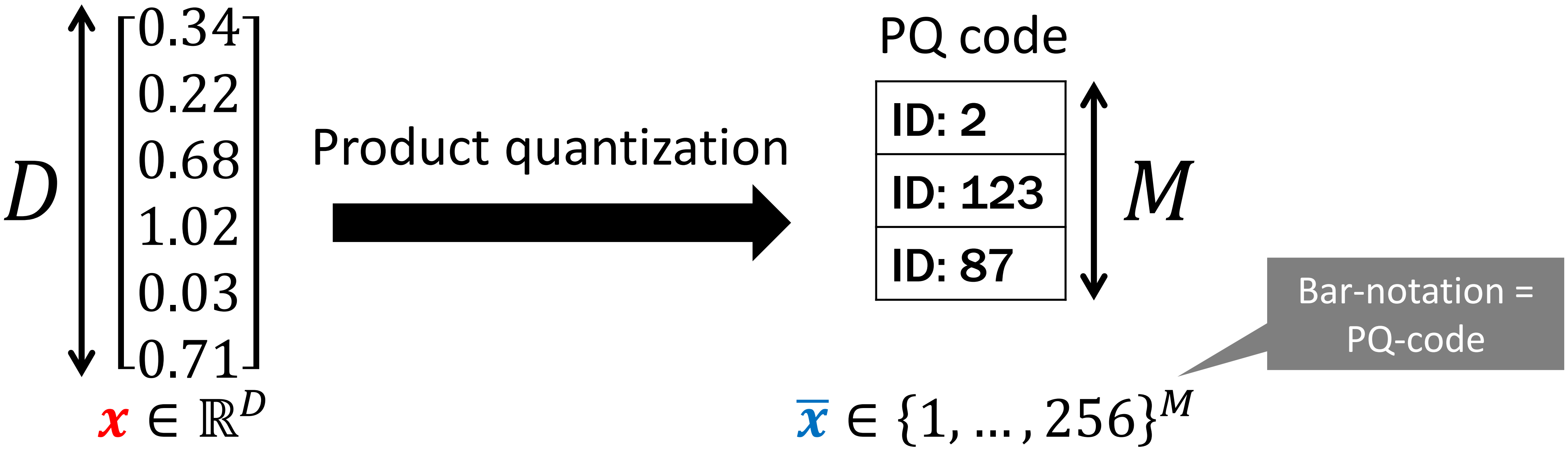
Linear-scan by Asymmetric Distance

Hamming-based

$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix}$ → `0 1 0 0`

Linear-scan by Hamming distance

Inverted index + PQ: Recap the notation



$$D \begin{bmatrix} 0.34 \\ 0.22 \\ 0.68 \\ 1.02 \\ 0.03 \\ 0.71 \end{bmatrix}$$

$\boldsymbol{x} \in \mathbb{R}^D$

Product quantization

PQ code

ID: 2
ID: 123
ID: 87

M

Bar-notation = PQ-code

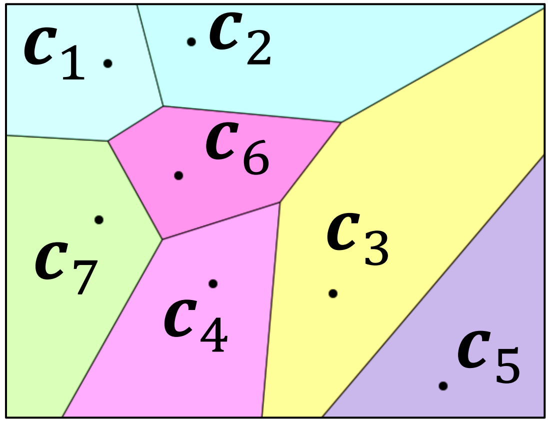
$\overline{\boldsymbol{x}} \in \{1, \ldots, 256\}^M$

- Suppose $\boldsymbol{q}, \boldsymbol{x} \in \mathbb{R}^D$, where $\boldsymbol{x}$ is quantized to $\overline{\boldsymbol{x}}$
- $d(\boldsymbol{q}, \boldsymbol{x})^2$ can be efficiently approximated by $\overline{\boldsymbol{x}}$:

$$d(\boldsymbol{q}, \boldsymbol{x})^2 \sim d_A(\boldsymbol{q}, \overline{\boldsymbol{x}})^2$$

Just by a PQ-code.
Not the original vector $\boldsymbol{x}$

Inverted index + PQ: Record



Coarse quantizer

$k = 1$

$k = 2$

$\vdots$

$k = K$

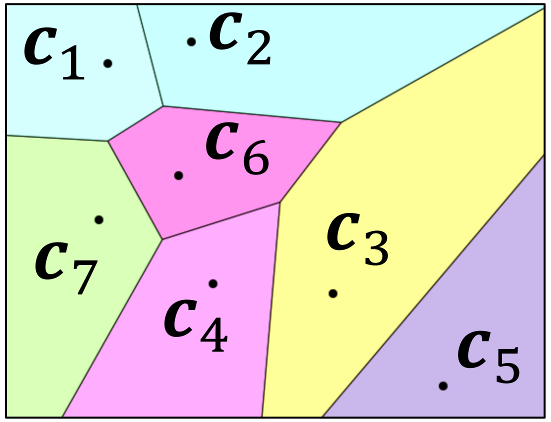
Prepare a **coarse quantizer**
- ✓ Split the space into K sub-spaces
- ✓ $\{\boldsymbol{c}_k\}_{k=1}^{K}$ are created by running k-means on training data

Inverted index + PQ: Record

Record $\boldsymbol{x}_1$

$$\begin{bmatrix} 1.02 \\ 0.73 \\ 0.56 \\ 1.37 \\ 1.37 \\ 0.72 \end{bmatrix}$$

$\boldsymbol{x}_1$



Coarse quantizer

$k = 1$

$k = 2$

$\vdots$

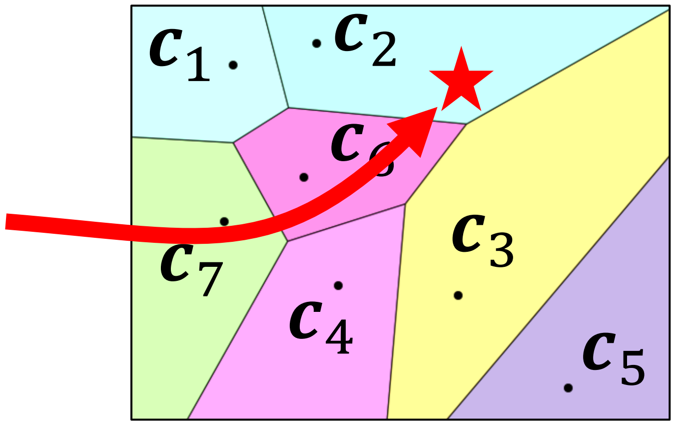
$k = K$

Inverted index + PQ: Record

Record $\boldsymbol{x}_1$

$$\begin{bmatrix} 1.02 \\ 0.73 \\ 0.56 \\ 1.37 \\ 1.37 \\ 0.72 \end{bmatrix}$$

$\boldsymbol{x}_1$



Coarse quantizer

$k = 1$

$k = 2$

$\vdots$

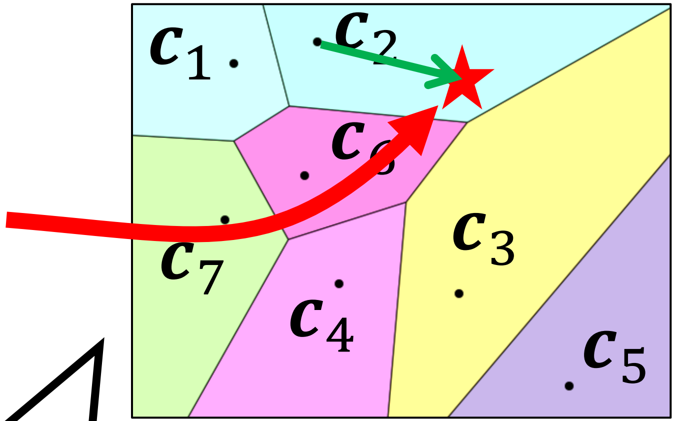
$k = K$

Inverted index + PQ: Record

Record $\boldsymbol{x}_1$

$$\begin{bmatrix} 1.02 \\ 0.73 \\ 0.56 \\ 1.37 \\ 1.37 \\ 0.72 \end{bmatrix}$$

$\boldsymbol{x}_1$



Coarse quantizer

$k = 1$

$k = 2$

$\vdots$

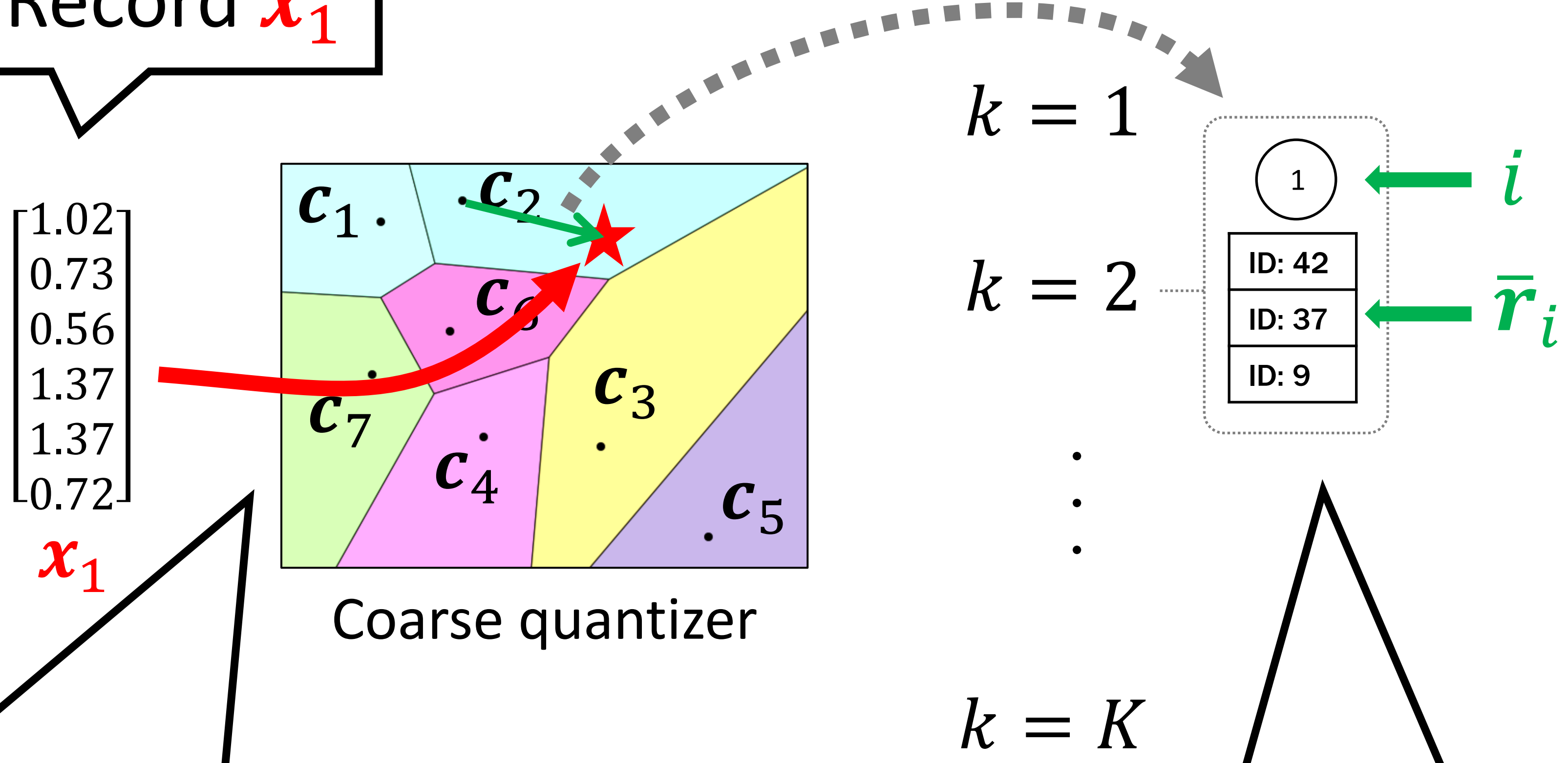
$k = K$

- ➢ $\boldsymbol{c}_2$ is closest to $\boldsymbol{x}_1$
- ➢ Compute a **residual** r_1 between $\boldsymbol{x}_1$ and $\boldsymbol{c}_2$:

$$\boldsymbol{r}_1 = \boldsymbol{x}_1 - \boldsymbol{c}_2 \quad (\ \longrightarrow\ )$$

Inverted index + PQ: Record

Record $\boldsymbol{x}_1$



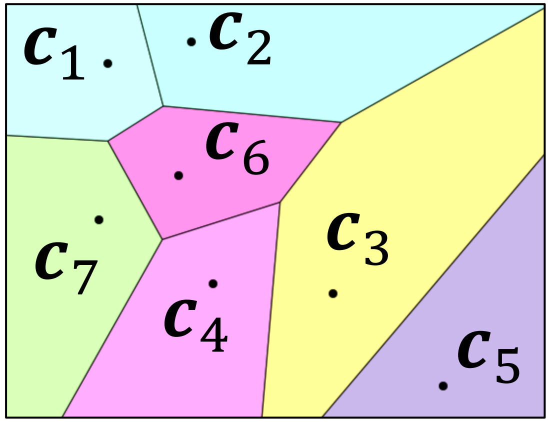
- ➢ $\boldsymbol{c}_2$ is closest to $\boldsymbol{x}_1$
- ➢ Compute a **residual** r_1 between $\boldsymbol{x}_1$ and $\boldsymbol{c}_2$:

$$\boldsymbol{r}_1 = \boldsymbol{x}_1 - \boldsymbol{c}_2 \quad (\longrightarrow)$$

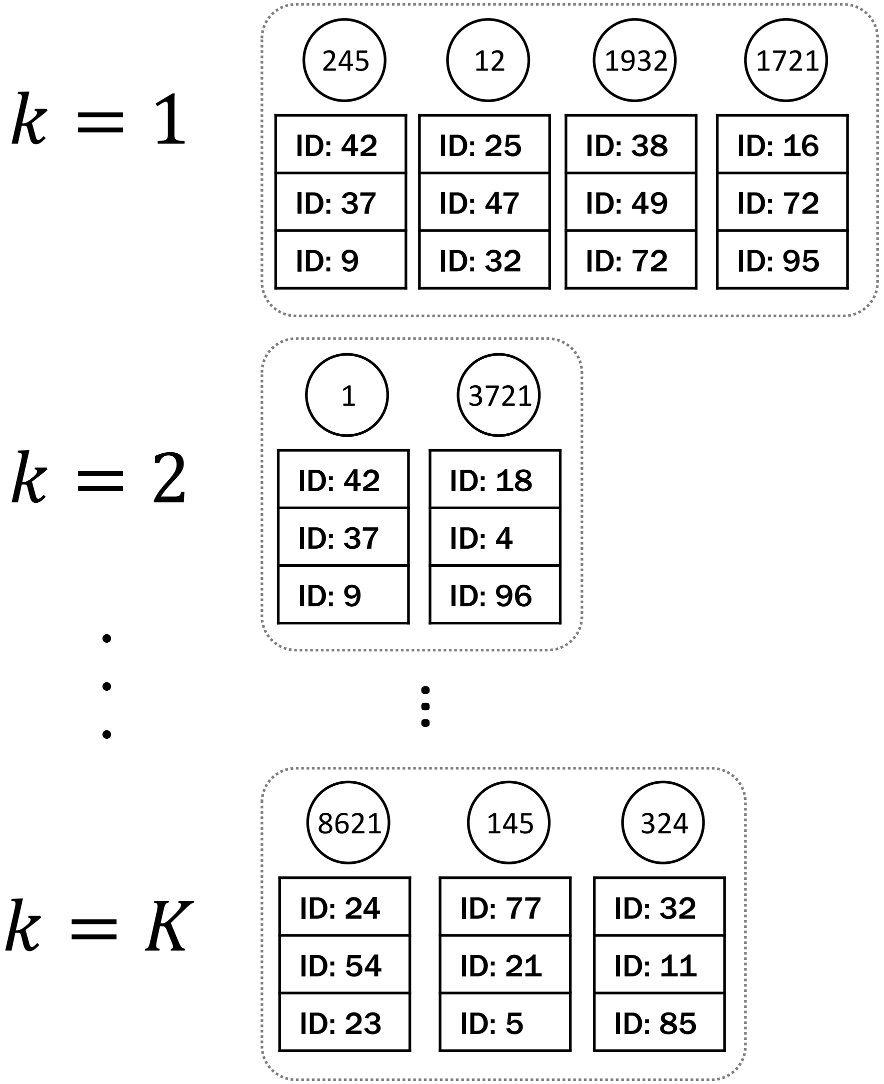
- ➢ Quantize $\boldsymbol{r}_1$ to $\bar{\boldsymbol{r}}_1$ by PQ
- ➢ Record it with the ID, “1”
- ➢ i.e., record $(i, \bar{\boldsymbol{r}}_i)$

Inverted index + PQ: Record

- ➢ For all database vectors, record [ID + PQ(res)] as pointing lists



coarse quantizer



$k = 1$

245 | 12 | 1932 | 1721

ID: 42	ID: 25	ID: 38	ID: 16
ID: 37	ID: 47	ID: 49	ID: 72
ID: 9	ID: 32	ID: 72	ID: 95

$k = 2$

1 | 3721

ID: 42	ID: 18
ID: 37	ID: 4
ID: 9	ID: 96

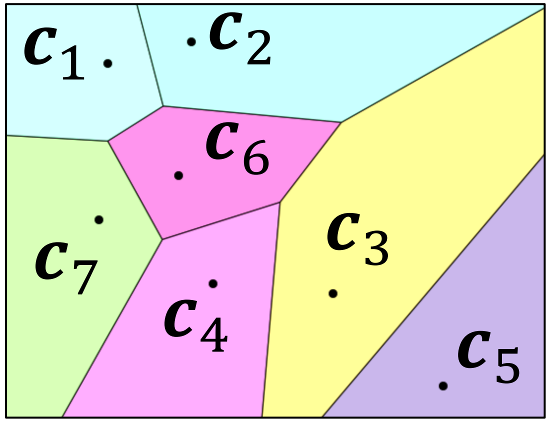
⋮

$k = K$

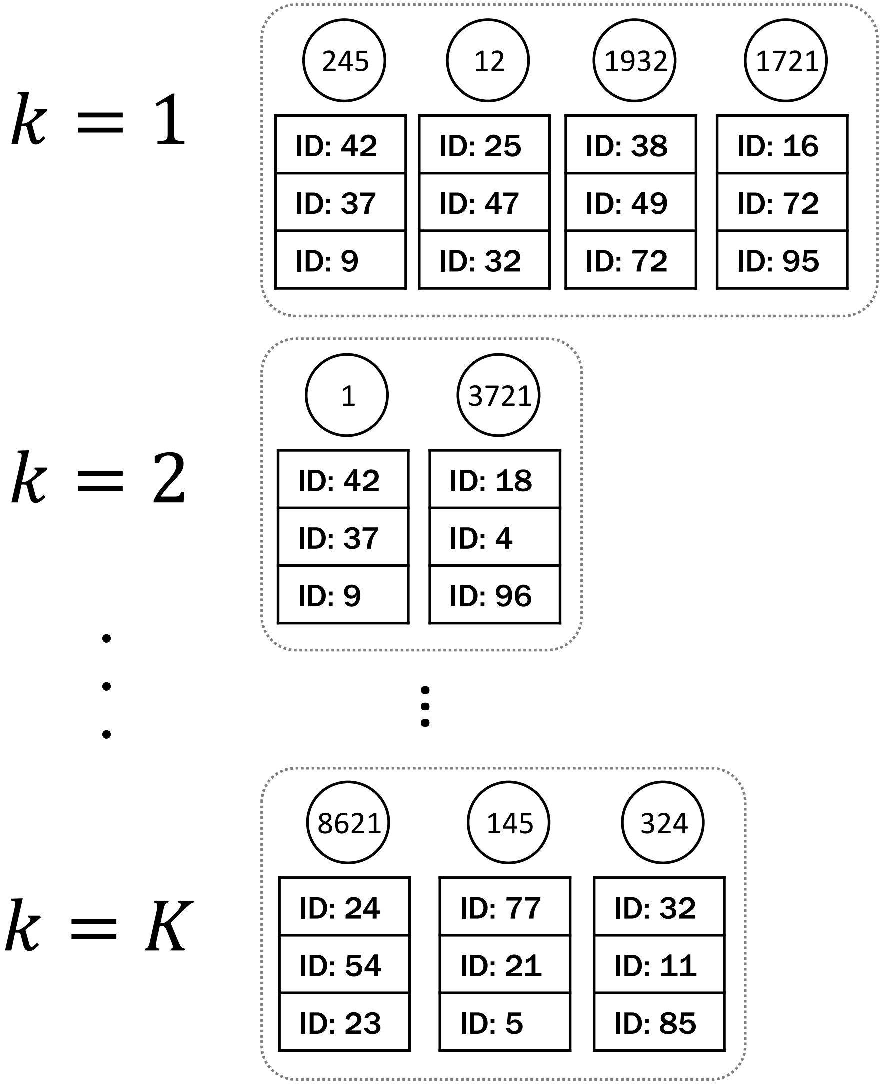
8621 | 145 | 324

ID: 24	ID: 77	ID: 32
ID: 54	ID: 21	ID: 11
ID: 23	ID: 5	ID: 85

Inverted index + PQ: Search



coarse quantizer



$k = 1$

245	12	1932	1721
ID: 42	ID: 25	ID: 38	ID: 16
ID: 37	ID: 47	ID: 49	ID: 72
ID: 9	ID: 32	ID: 72	ID: 95

$k = 2$

1	3721
ID: 42	ID: 18
ID: 37	ID: 4
ID: 9	ID: 96

⋮

$k = K$

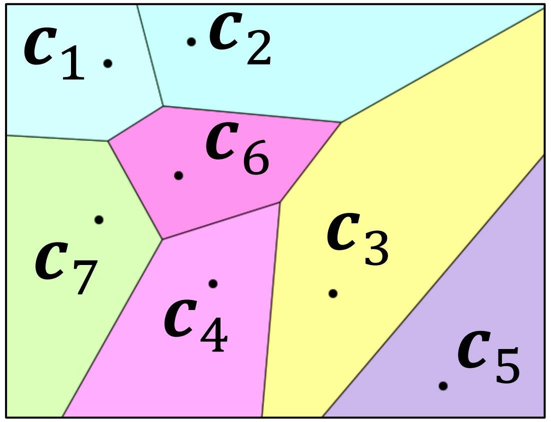
8621	145	324
ID: 24	ID: 77	ID: 32
ID: 54	ID: 21	ID: 11
ID: 23	ID: 5	ID: 85

Inverted index + PQ: Search

Find the nearest vector to $\boldsymbol{q}$

$$\begin{bmatrix}0.54\\2.35\\0.82\\0.42\\0.14\\0.32\end{bmatrix}$$

$\boldsymbol{q}$



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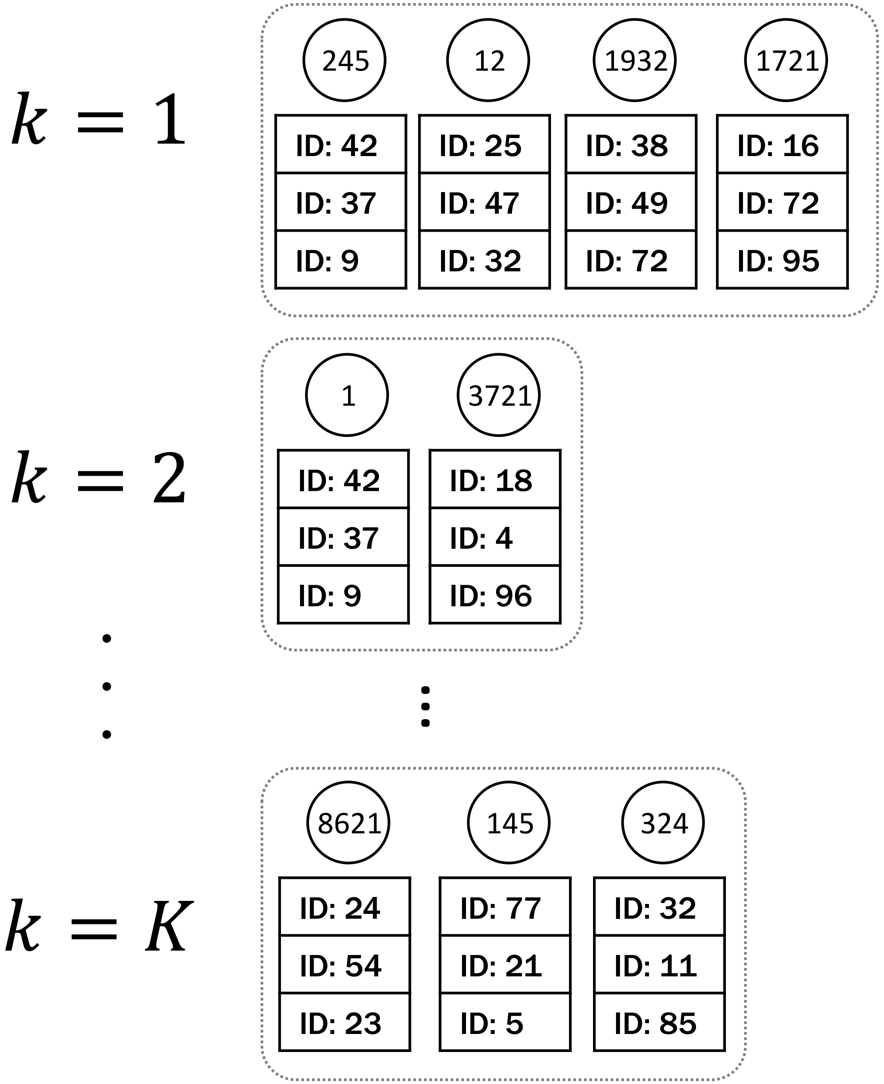

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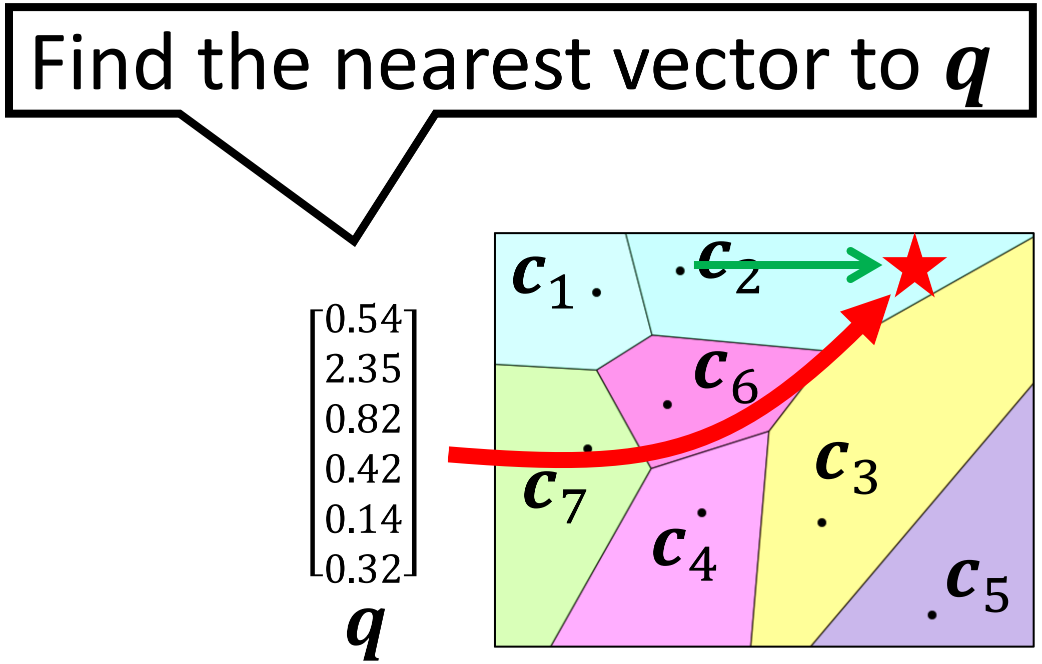

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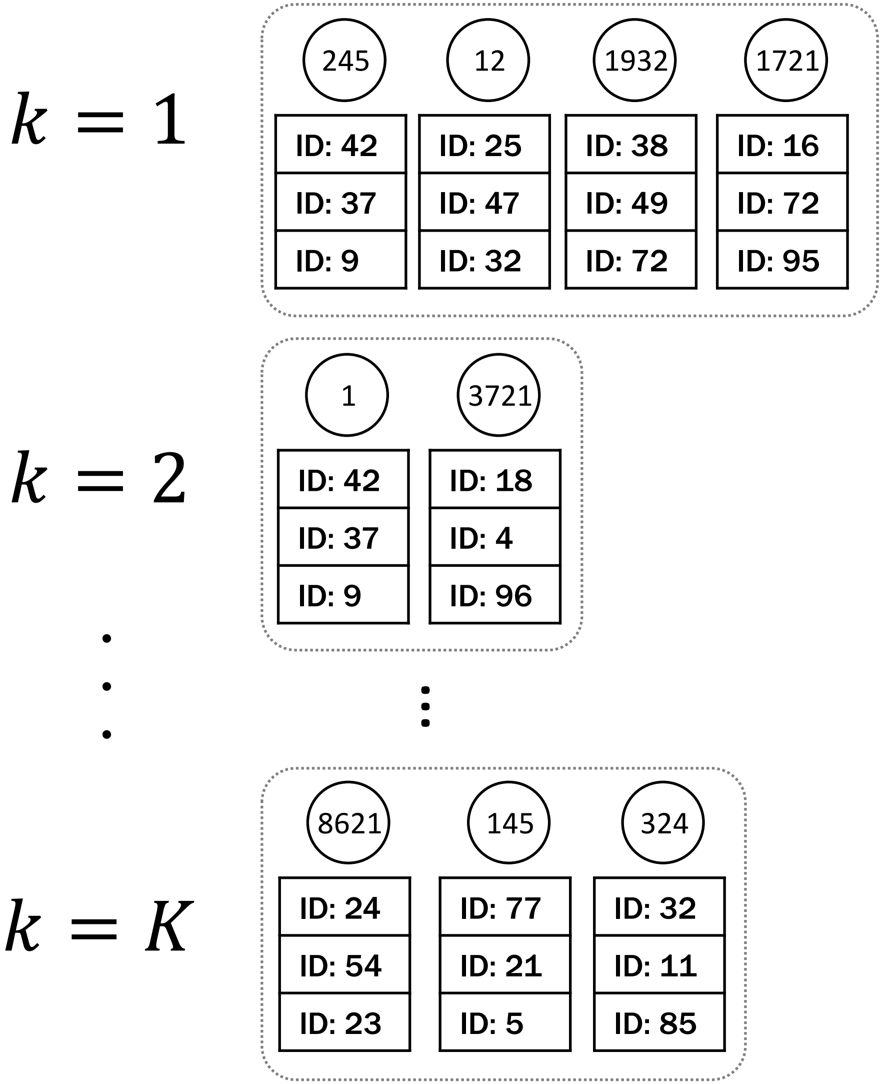

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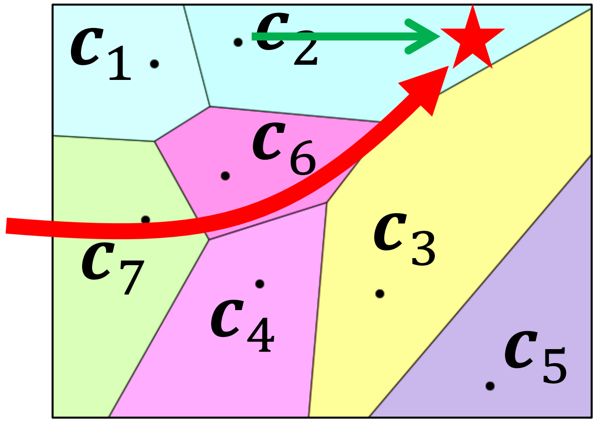

coarse quantizer

- ➢ $\boldsymbol{c}_2$ is the closest to $\boldsymbol{q}$
- ➢ Compute the residual: $\boldsymbol{r}_q = \boldsymbol{q} - \boldsymbol{c}_2$

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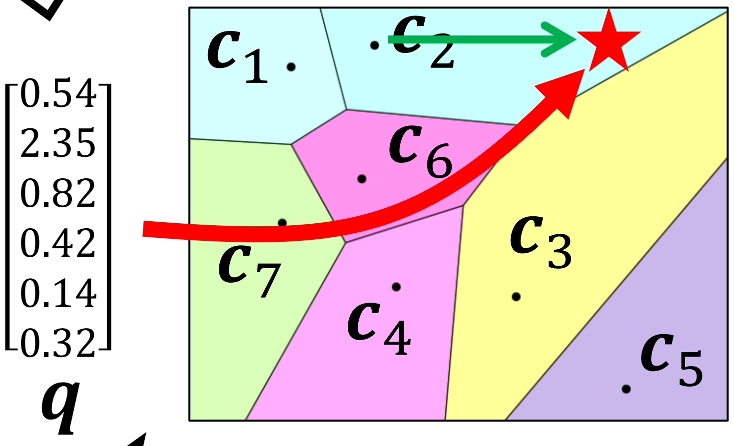

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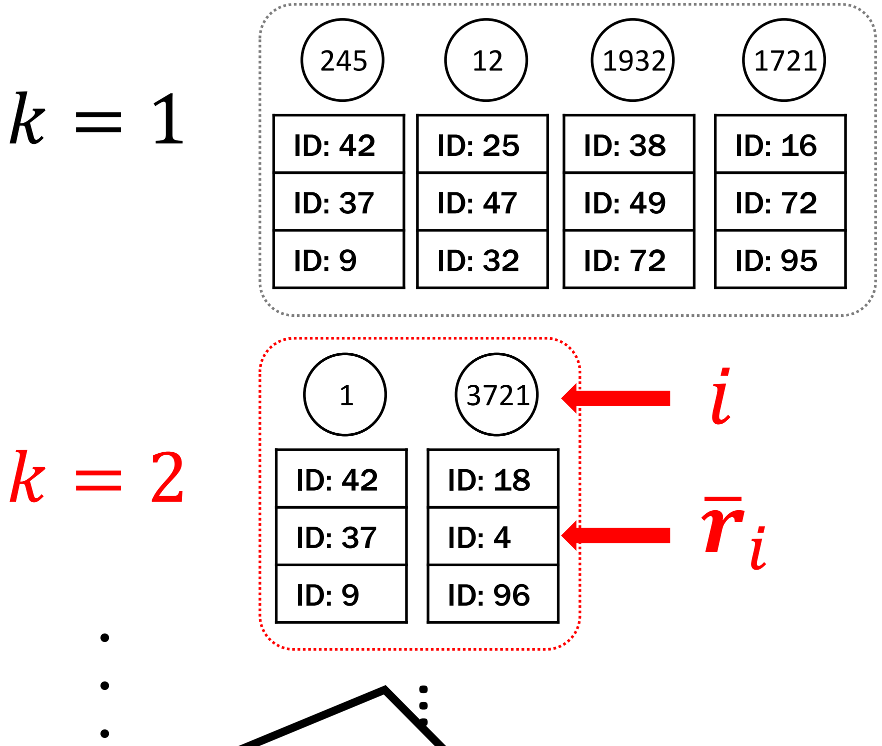


- For all $(i, \bar{\boldsymbol{r}}_i)$ in $k = 2$, compare $\bar{\boldsymbol{r}}_i$ with $\boldsymbol{r}_q$:

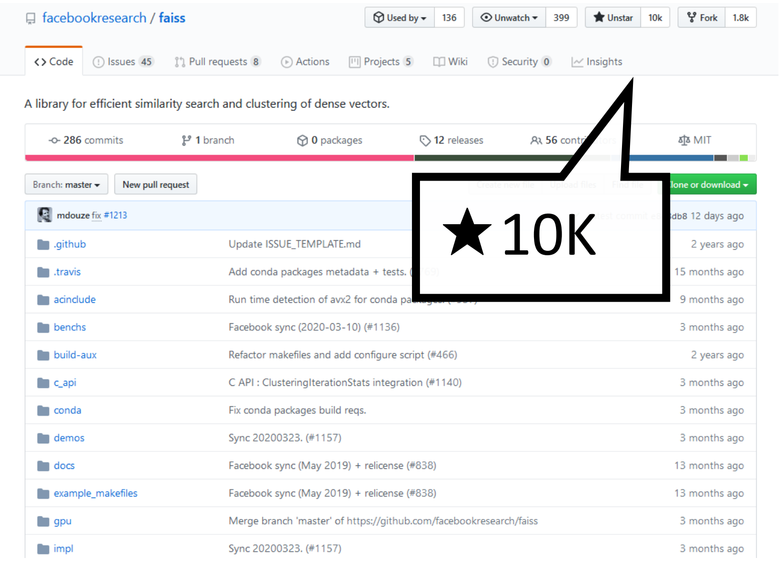
$$d(\boldsymbol{q}, \boldsymbol{x}_i)^2 = d(\boldsymbol{q} - \boldsymbol{c}_2, \boldsymbol{x}_i - \boldsymbol{c}_2)^2$$
$$= d\left(\boldsymbol{r}_q, \boldsymbol{r}_i\right)^2 \sim d_A\left(\boldsymbol{r}_q, \bar{\boldsymbol{r}}_i\right)^2$$

- Find the smallest one (several strategies)

Faiss

https://github.com/facebookresearch/faiss

```
$> conda install faiss-cpu -c pytorch
$> conda install faiss-gpu -c pytorch
```



A library for efficient similarity search and clustering of dense vectors.

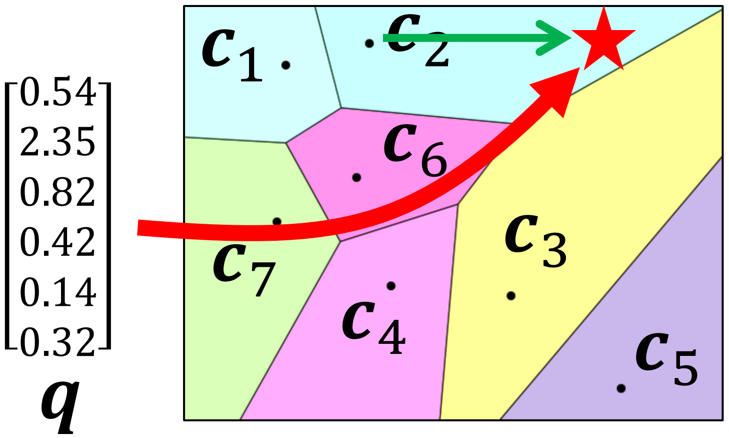
mdouze fix #1213 db8 12 days ago

.github	Update ISSUE_TEMPLATE.md	2 years ago
.travis	Add conda packages metadata + tests.	15 months ago
acinclude	Run time detection of avx2 for conda pa	9 months ago
benchs	Facebook sync (2020-03-10) (#1136)	3 months ago
build-aux	Refactor makefiles and add configure script (#466)	2 years ago
c_api	C API : ClusteringIterationStats integration (#1140)	3 months ago
conda	Fix conda packages build reqs.	3 months ago
demos	Sync 20200323. (#1157)	3 months ago
docs	Facebook sync (May 2019) + relicense (#838)	13 months ago
example_makefiles	Facebook sync (May 2019) + relicense (#838)	13 months ago
gpu	Merge branch 'master' of https://github.com/facebookresearch/faiss	3 months ago
impl	Sync 20200323. (#1157)	3 months ago

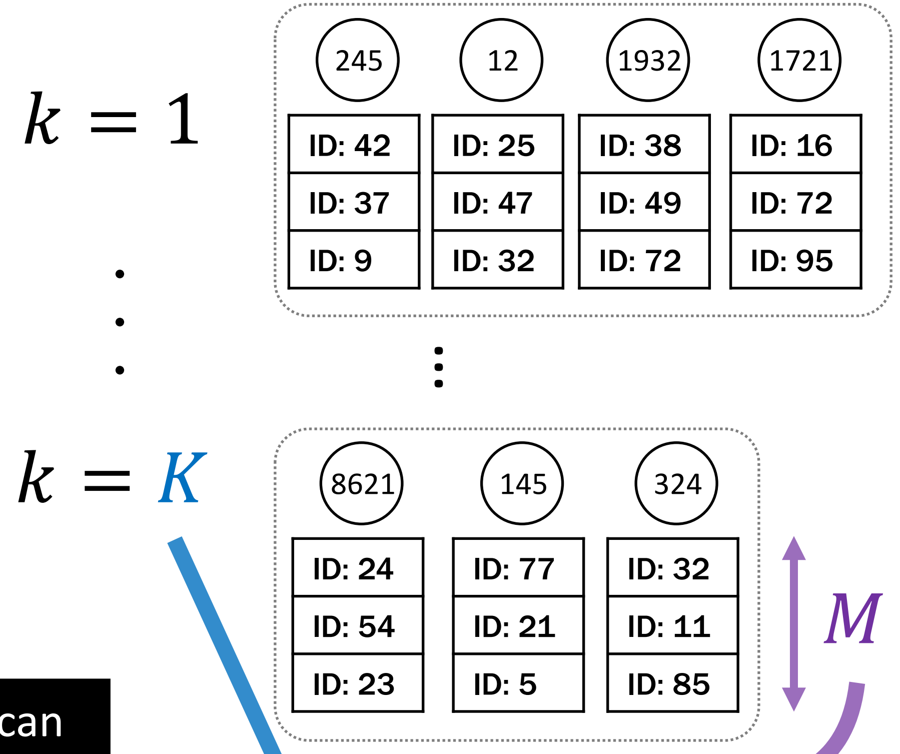
★10K

- From the original authors of the PQ and a GPU expert, FAIR
- CPU-version: all PQ-based methods
- GPU-version: some PQ-based methods
- Bonus:
    - NN (not ANN) is also implemented, and quite fast
    - k-means (CPU/GPU). Fast.

Benchmark of k-means:
https://github.com/DwangoMediaVillage/pqkmeans/blob/master/tutorial/4_comparison_to_faiss.ipynb



coarse quantizer



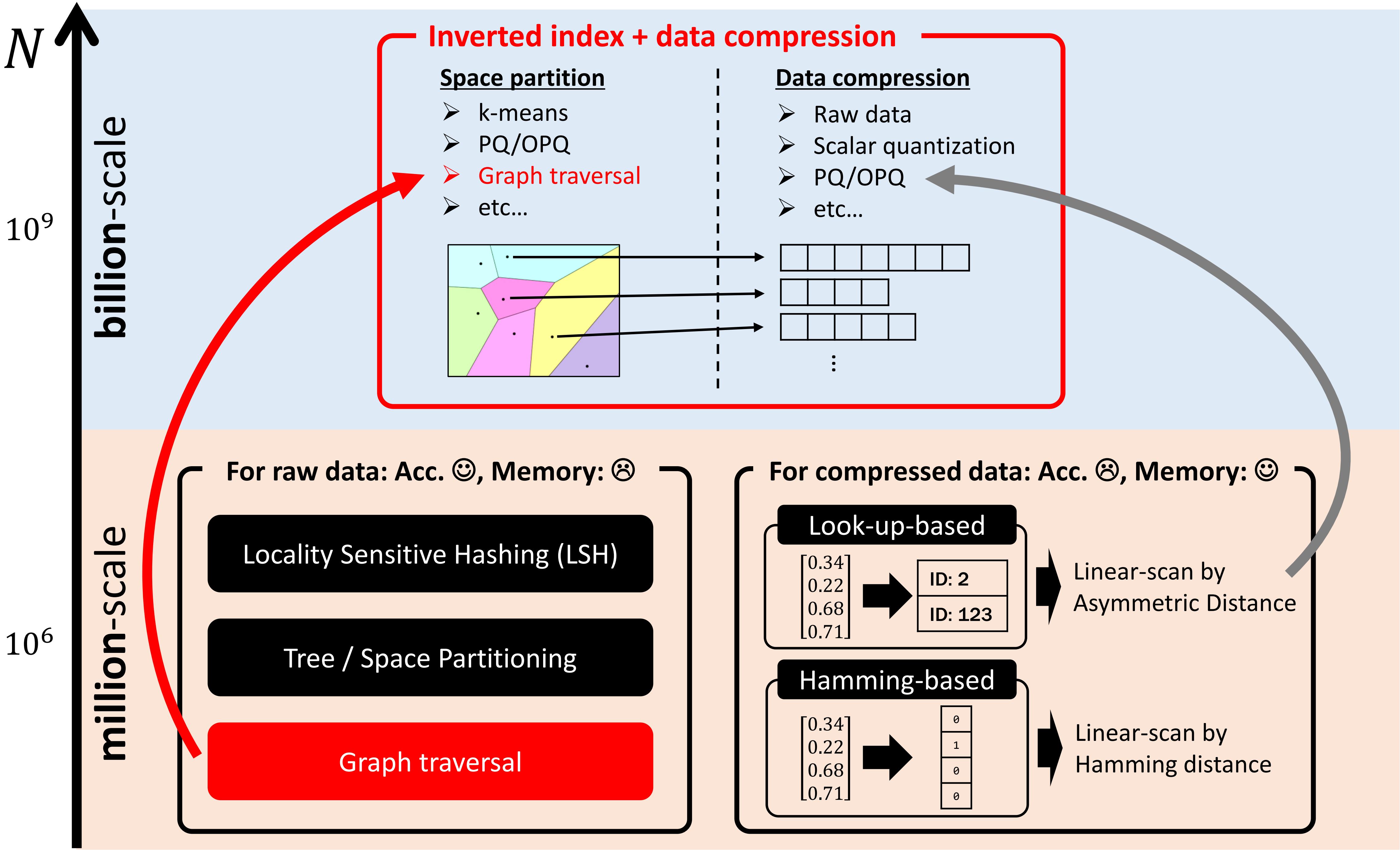
Simple linear scan

```
quantizer = faiss.IndexFlatL2(D)
index = faiss.IndexIVFPQ(quantizer, D, nlist, M, nbits)

index.train(Xt)  # Train
index.add(X)  # Record data
index.nprobe = nprobe  # Search parameter
dist, ids = index.search(Q, topk)  # Search
```

Select a coarse quantizer

Usually, 8 bit



Inverted index + data compression

Space partition
- ➢ k-means
- ➢ PQ/OPQ
- ➢ Graph traversal
- ➢ etc…

Data compression
- ➢ Raw data
- ➢ Scalar quantization
- ➢ PQ/OPQ
- ➢ etc…

For raw data: Acc. ☺, Memory: ☹

- Locality Sensitive Hashing (LSH)
- Tree / Space Partitioning
- Graph traversal

For compressed data: Acc. ☹, Memory: ☺

Look-up-based

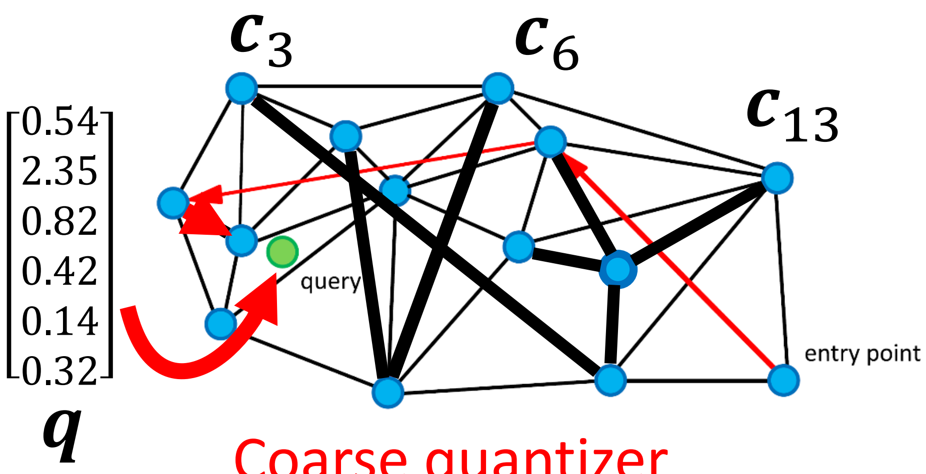
$$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix} \Rightarrow \begin{array}{|l|}\hline \text{ID: 2}\\\hline \text{ID: 123}\\\hline\end{array}$$

Linear-scan by Asymmetric Distance

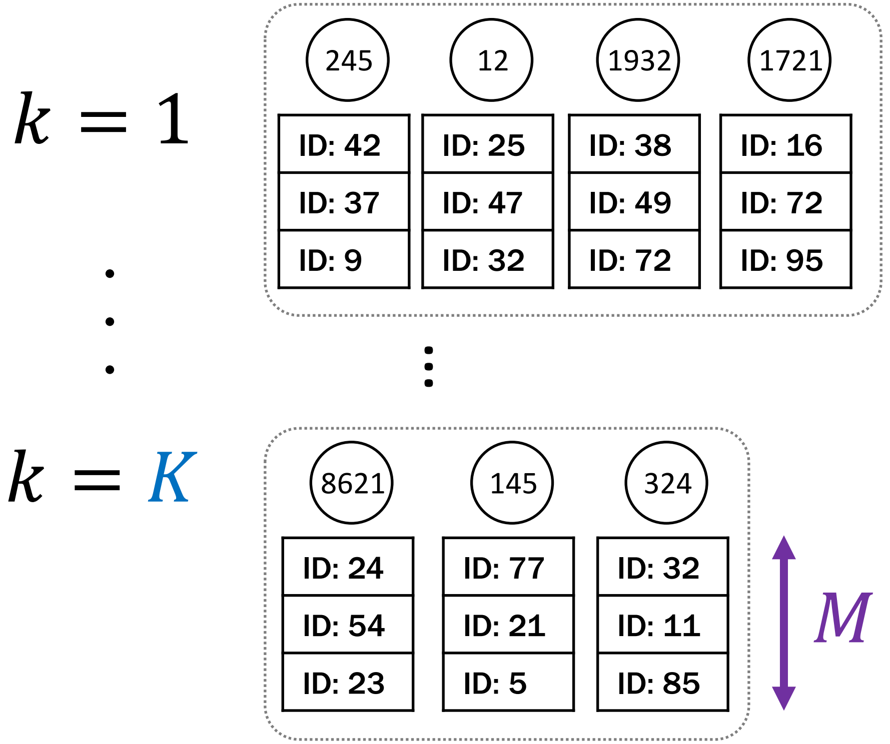
Hamming-based

$$\begin{bmatrix}0.34\\0.22\\0.68\\0.71\end{bmatrix} \Rightarrow \begin{array}{|c|}\hline 0\\\hline 1\\\hline 0\\\hline 0\\\hline\end{array}$$

Linear-scan by Hamming distance



Coarse quantizer



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⋮

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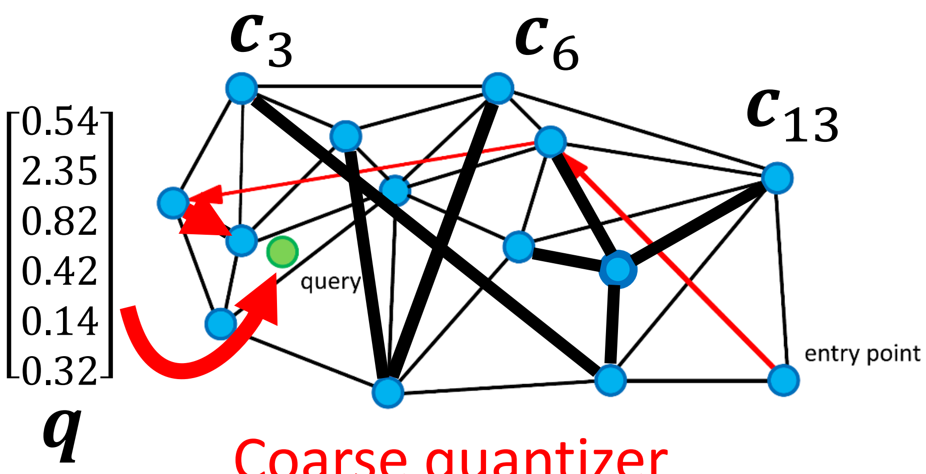
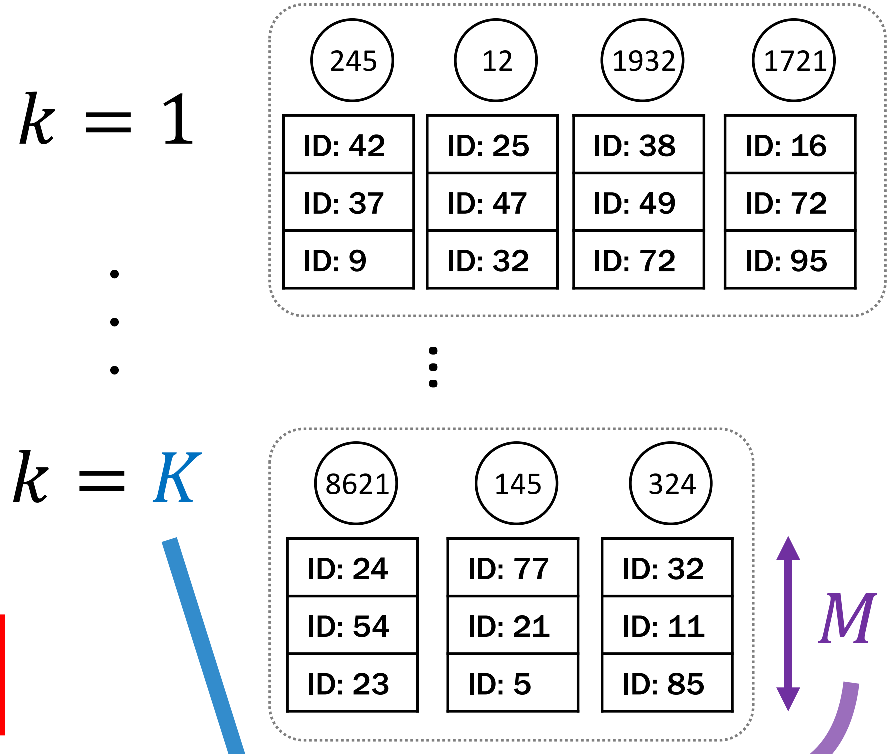


Coarse quantizer



HNSW

```
quantizer = faiss.IndexHNSWFlat(D, hnsw_m)
index = faiss.IndexIVFPQ(quantizer, D, nlist, M, nbits)
```

Select a coarse quantizer

Usually, 8 bit

- Switch a coarse quantizer from linear-scan to HNSW
- The best approach for billion-scale data as of 2020
- The backbone of [Douze+, CVPR 2018] [Baranchuk+, ECCV 2018]

☺ From the original authors of PQ. Extremely efficient (theory & impl)
☺ Used in a real-world product (Mercari, etc)
☺ For billion-scale data, Faiss is the best option
☺ Especially, large-batch-search is fast; #query is large

☹ Lack of documentation (especially, python binding)
☹ Hard for a novice user to select a suitable algorithm
☹ As of 2020, anaconda is required. Pip is not supported officially

Reference

- Faiss wiki: [https://github.com/facebookresearch/faiss/wiki]

- Faiss tips: [https://github.com/matsui528/faiss_tips]

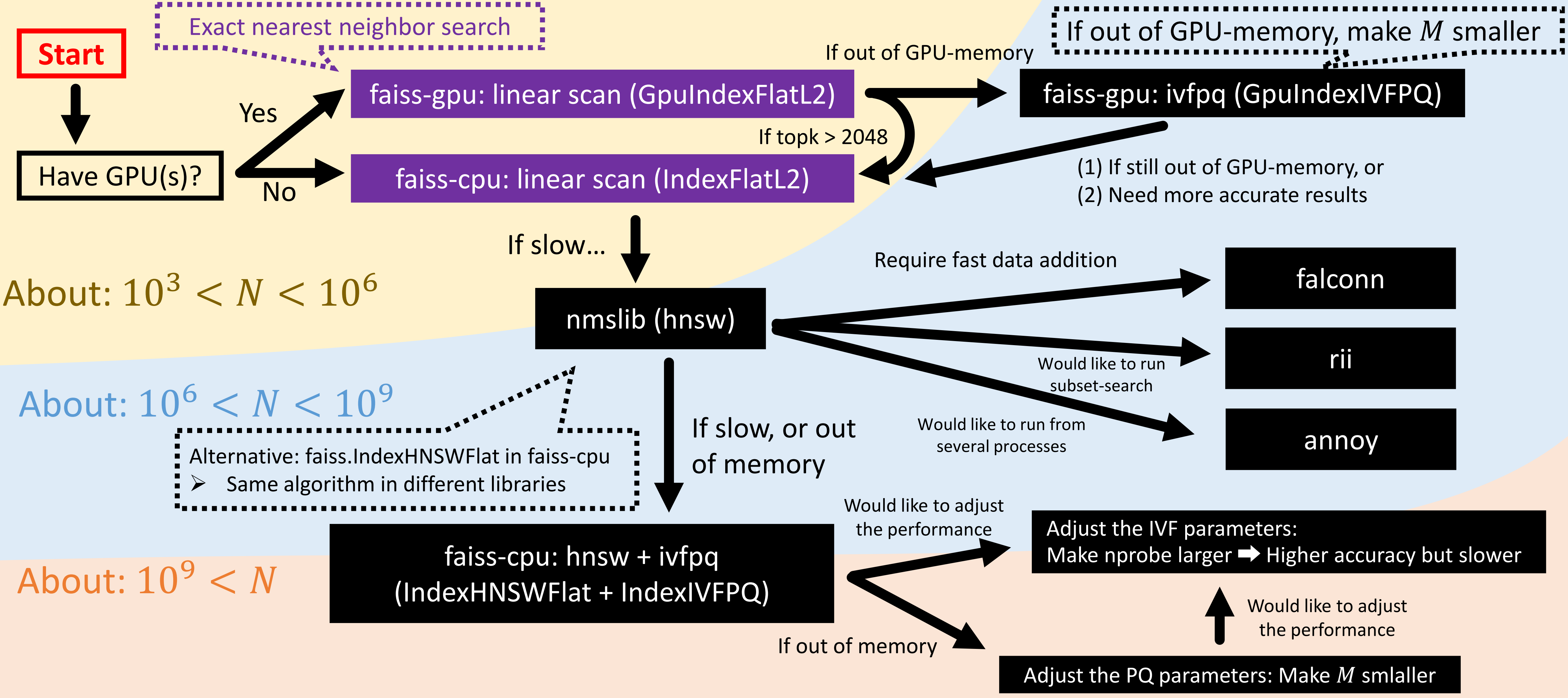
- Julia implementation of lookup-based methods [https://github.com/una-dinosauria/Rayuela.jl]

- PQ paper: H. Jégou et al., “Product quantization for nearest neighbor search,” TPAMI 2011

- IVFADC + HNSW (1): M. Douze et al., “Link and code: Fast indexing with graphs and compact regression codes,” CVPR 2018

- IVFADC + NHSW (2): D. Baranchuk et al., “Revisiting the Inverted Indices for Billion-Scale Approximate Nearest Neighbors,” ECCV 2018

cheat-sheet for ANN in Python （as of 2020. Can be installed by conda or pip）



Start

Have GPU(s)?

Yes

No

Exact nearest neighbor search

faiss-gpu: linear scan (GpuIndexFlatL2)

faiss-cpu: linear scan (IndexFlatL2)

If out of GPU-memory

If topk > 2048

If out of GPU-memory, make M smaller

faiss-gpu: ivfpq (GpuIndexIVFPQ)

(1) If still out of GPU-memory, or
(2) Need more accurate results

If slow…

About: $10^3 < N < 10^6$

nmslib (hnsw)

Require fast data addition

falconn

Would like to run subset-search

rii

Would like to run from several processes

annoy

About: $10^6 < N < 10^9$

Alternative: faiss.IndexHNSWFlat in faiss-cpu

- Same algorithm in different libraries

If slow, or out of memory

faiss-cpu: hnsw + ivfpq
(IndexHNSWFlat + IndexIVFPQ)

About: $10^9 < N$

Would like to adjust the performance

Adjust the IVF parameters:
Make nprobe larger ➡ Higher accuracy but slower

Would like to adjust the performance

If out of memory

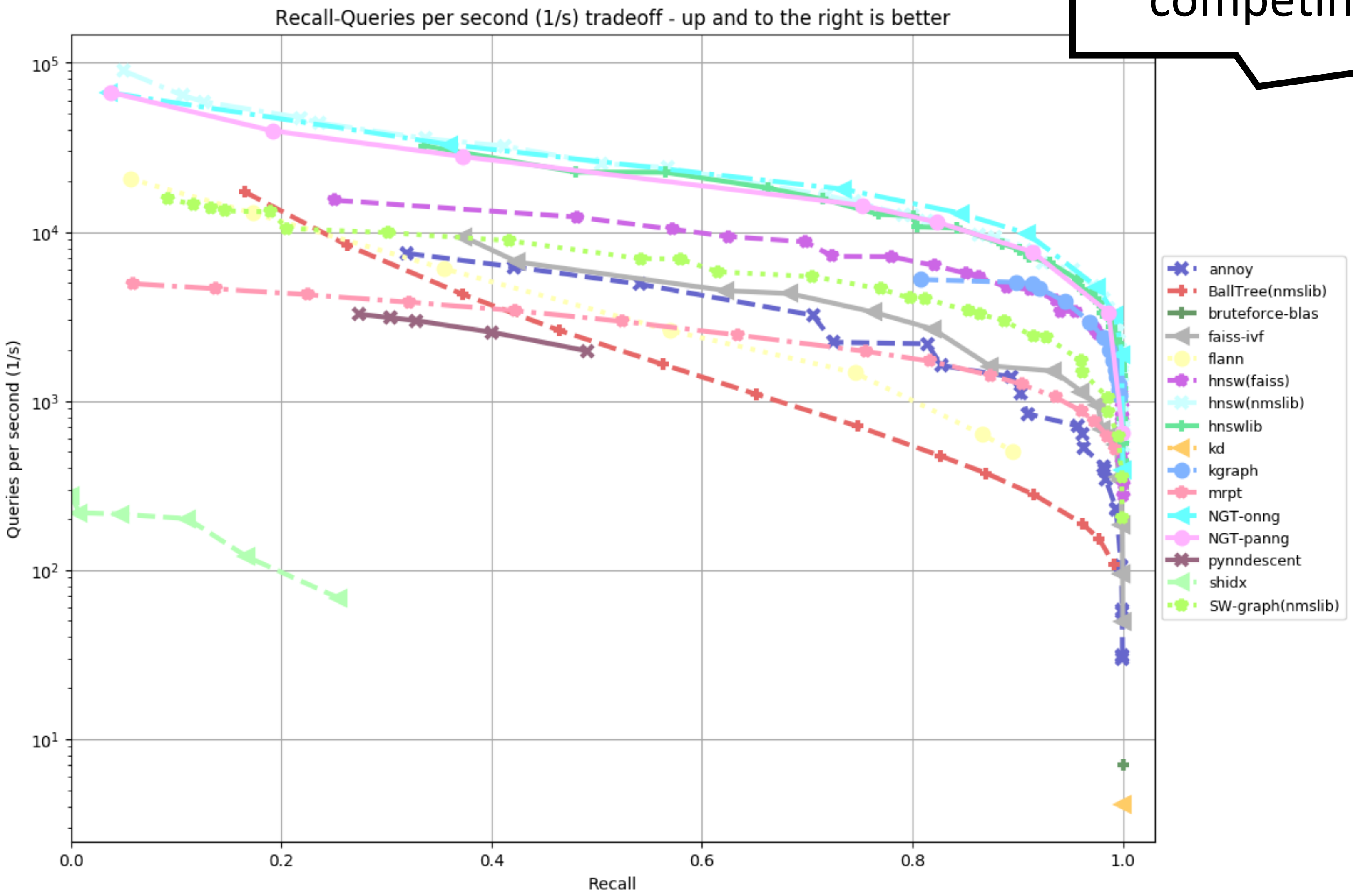
Adjust the PQ parameters: Make M smlaller

Note: Assuming $D \cong 100$. The size of the problem is determined by DN. If $100 \ll D$, run PCA to reduce D to 100

Benchmark 1: ann-benchmarks

- https://github.com/erikbern/ann-benchmarks
- Comprehensive and thorough benchmarks for various libraries. Docker-based

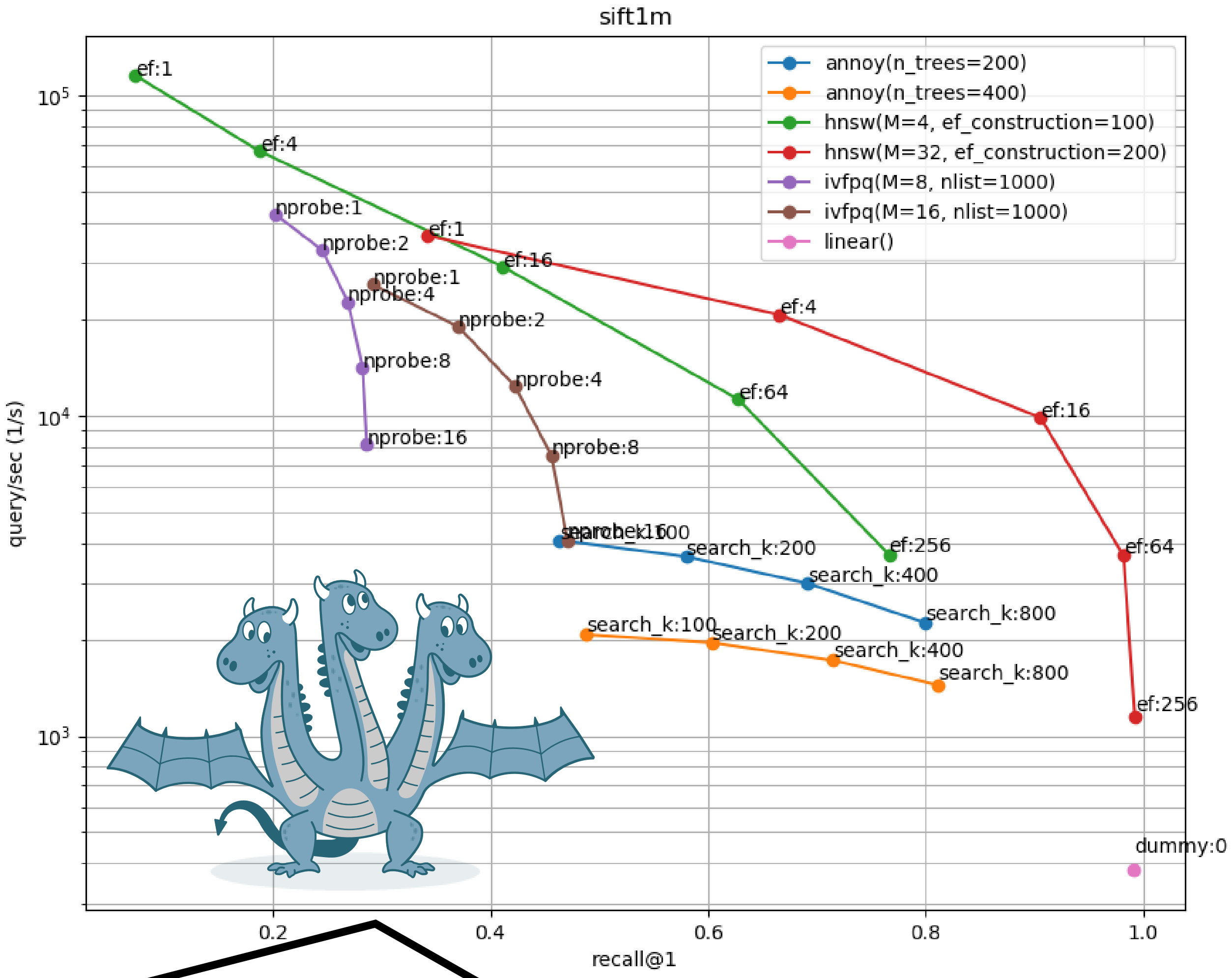
- Top right, the better
- As of June, 2020, NMSLIB and NGT are competing each other for the first place



Benchmark 2: annbench

- https://github.com/matsui528/annbench
- Lightweight, easy-to-use

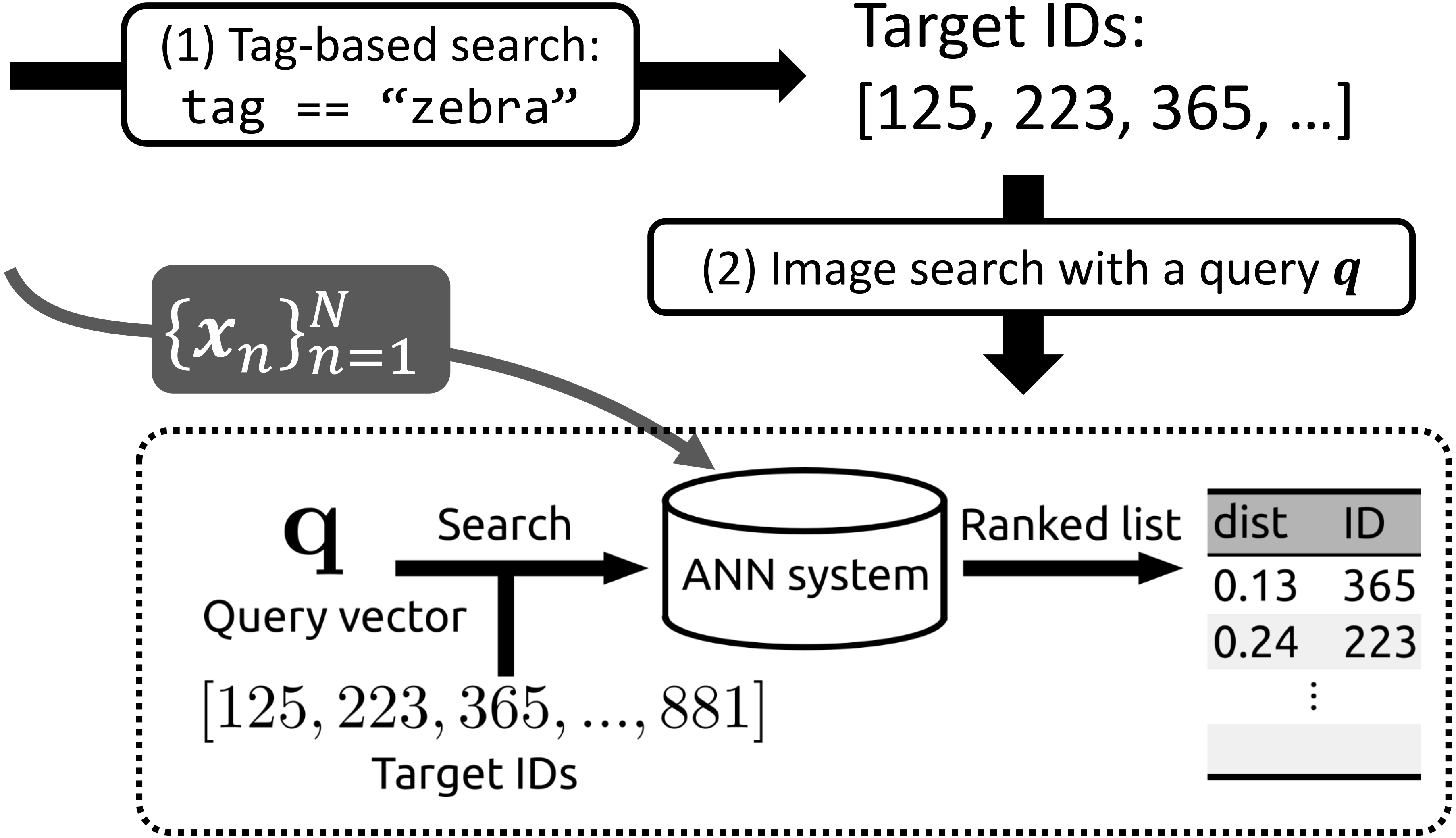
```
# Install libraries
pip install -r requirements.txt

# Download dataset on ./dataset
python download.py dataset=siftsmall

# Evaluate algos. Results are on ./output
python run.py dataset=siftsmall algo=annoy

# Visualize
python plot.py
```



```
# Multi-run by Hydra
python run.py --multirun dataset=siftsmall,sift1m algo=linear,annoy,ivfpq,hnsw
```

Search for a "subset"

ID	Img	Tag
1		"cat"
2		"bird"
	⋮	
125		"zebra"
126		"elephant"
	⋮	



(1) Tag-based search:
`tag == "zebra"`

Target IDs:
[125, 223, 365, …]

(2) Image search with a query $\boldsymbol{q}$

$\{\boldsymbol{x}_n\}_{n=1}^{N}$

$\mathbf{q}$
Query vector

Search

$[125, 223, 365, ..., 881]$
Target IDs

ANN system

Ranked list

dist	ID
0.13	365
0.24	223
⋮	

Subset-search

Y. Matsui+, "Reconfigurable Inverted Index", ACMMM 18

Trillion-scale search: $N = 10^{12}$ (1T)

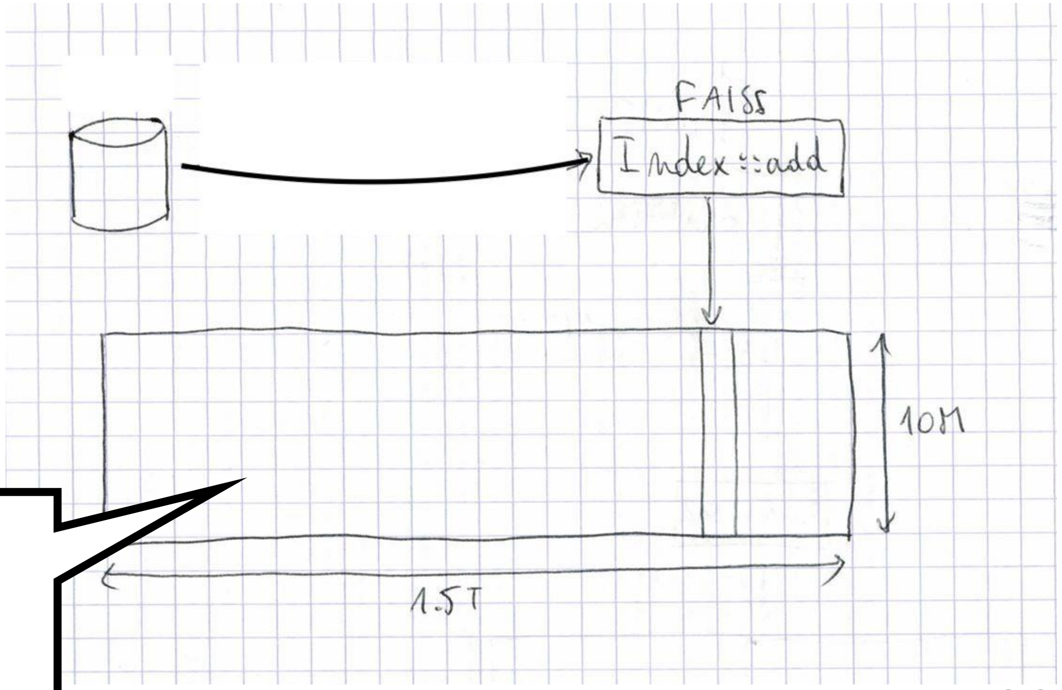
Sense of scale

- K($= 10^3$) Just in a second on a local machine
- M($= 10^6$) All data can be on memory. Try several approaches
- G($= 10^9$) Need to compress data by PQ. Only two datasets are available (SIFT1B, Deep1B)
- T($= 10^{12}$) Cannot even imagine

https://github.com/facebookresearch/faiss/wiki/Indexing-1T-vectors

- Only in Faiss wiki
- Distributed, mmap, etc.

https://github.com/facebookresearch/faiss/wiki/Indexing-1T-vectors



A sparse matrix of 15 Exa elements? 🤔

Nearest neighbor search engine: something like **ANN + SQL**

- The algorithm inside is faiss, nmslib, or NGT

VEARCH

https://github.com/vearch/vearch

Open Distro
for Elasticsearch

Elasticsearch KNN

https://github.com/opendistro-for-elasticsearch/k-NN

Milvus

https://github.com/milvus-io/milvus

Vald

https://github.com/vdaas/vald

Problems of ANN

- ➢ No mathematical background.
  - ✓ Only actual measurements matter: recall and runtime
  - ✓ The ANN problem was mathematically defined 10+ years ago (LSH), but recently no one cares the definition.

- ➢ Thus, when the score is high, it’s not clear the reason:
  - ✓ The method is good?
  - ✓ The implementation is good?
  - ✓ Just happens to work well for the target dataset?
  - ✓ E.g.: The difference of math library (OpenBLAS vs Intel MKL) matters.

- ➢ If one can explain “why this approach works good for this dataset”, it would be a great contribution to the field.

- ➢ Not enough dataset. Currently, only two datasets are available for billion-scale data: SIFT1B and Deep1B

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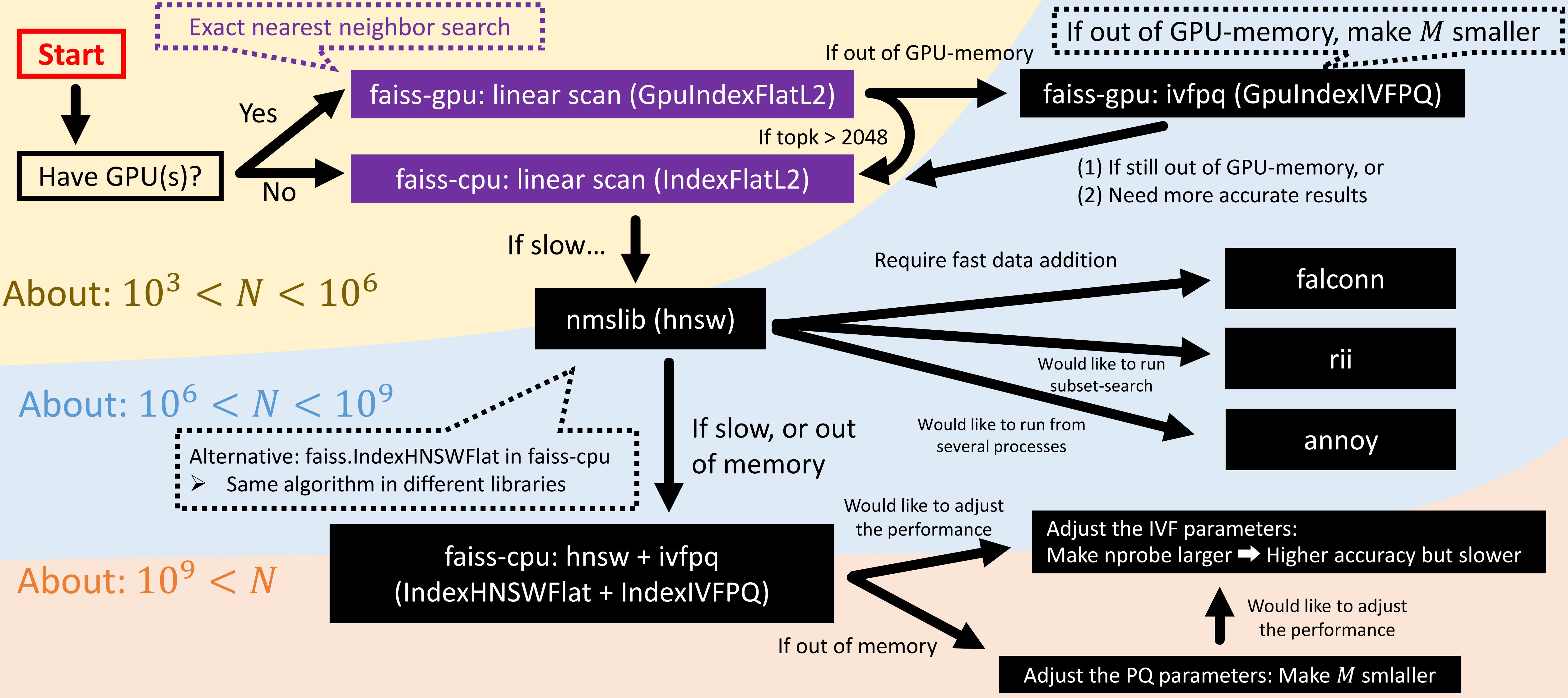

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