Hashing Techniques

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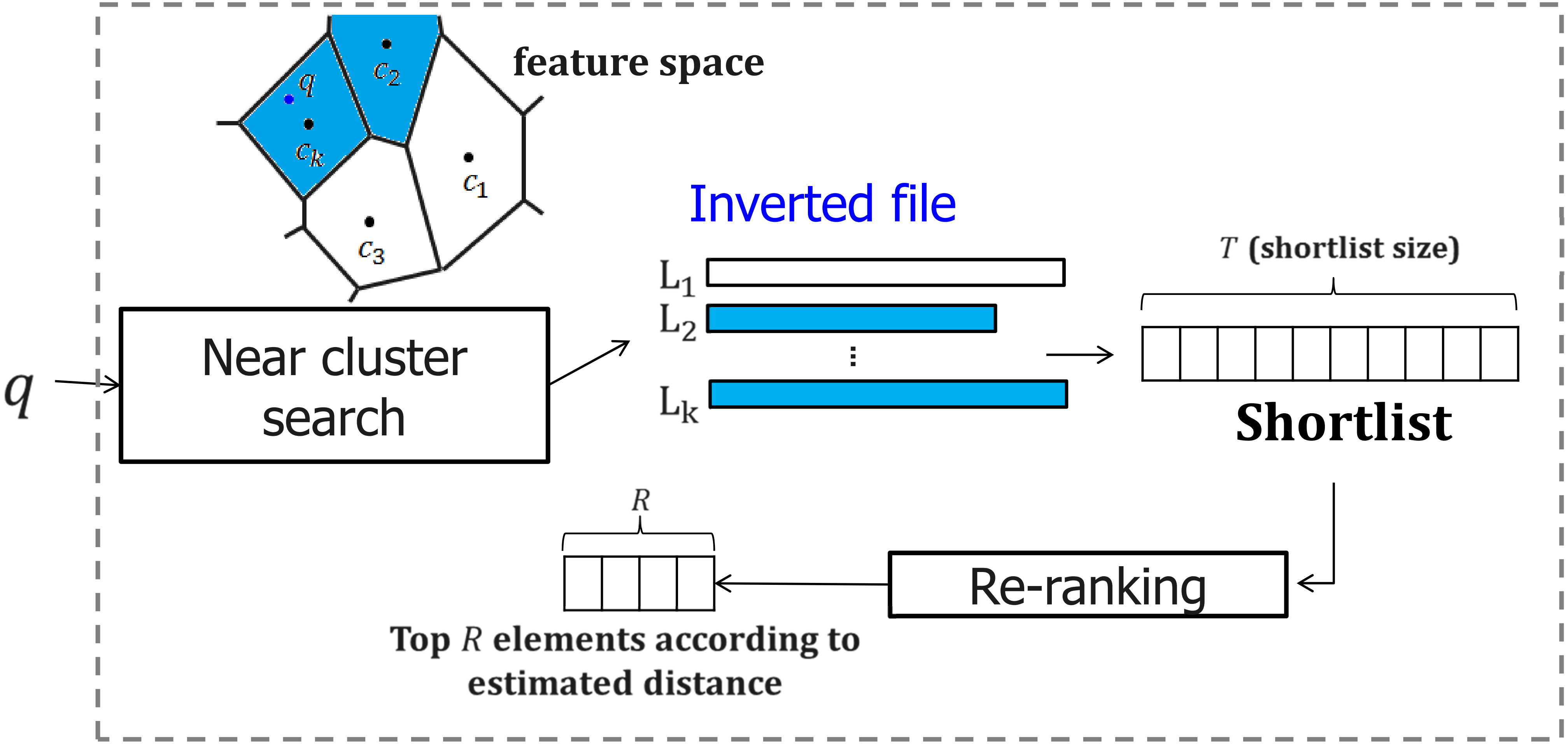
Class Objectives

- **Understand the basic hashing techniques based on hyperplanes**
  - **Unsupervised approach**
- **Supervised approach using deep learning**

- **At the last class:**
  - **Discussed re-ranking methods: spatial verification and query expansion**
  - **Talked about inverted index**

Review of Basic Image Search



Ack.: Dr. Heo

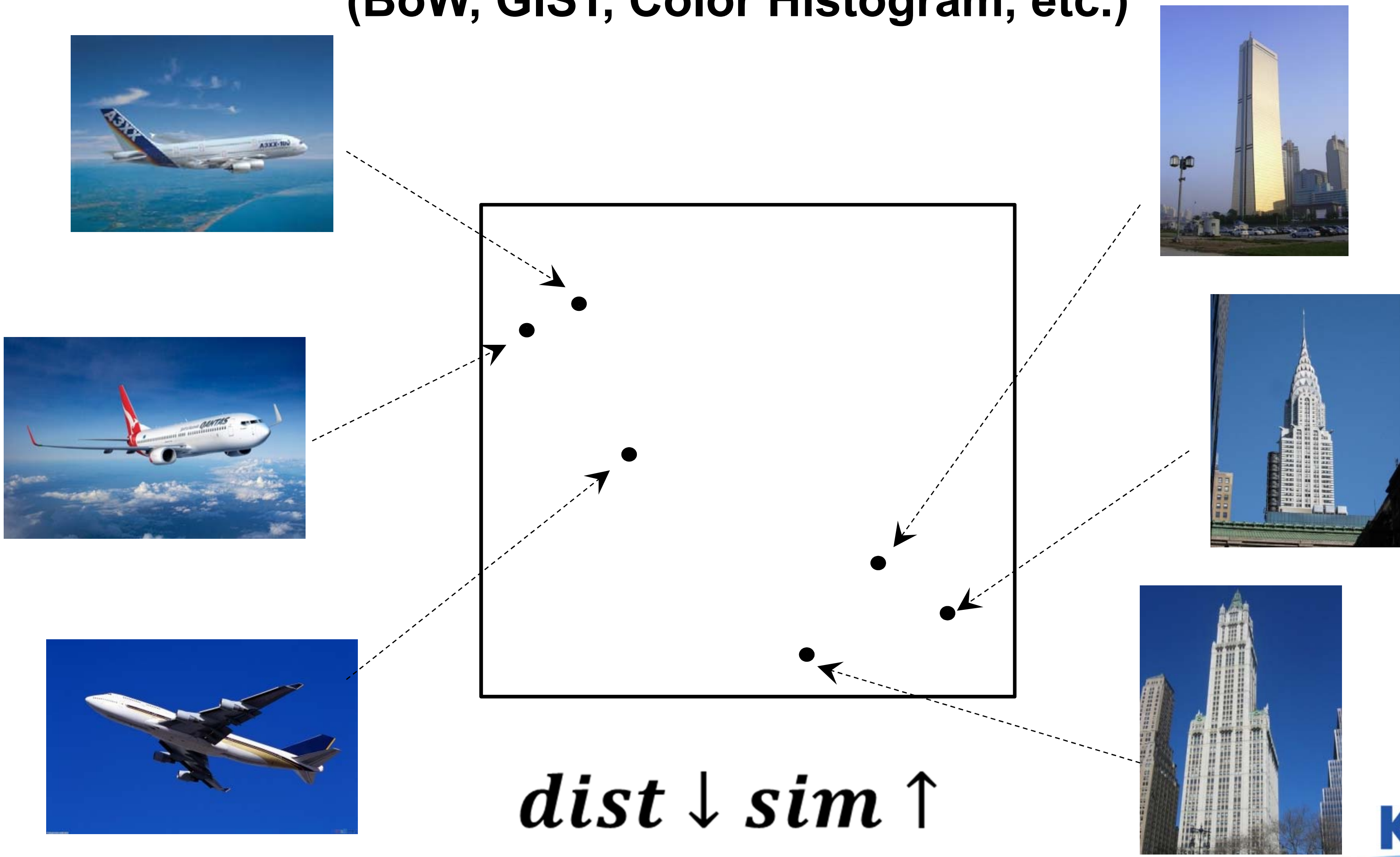
Image Search

Finding visually similar images

Image Descriptor

High dimensional point

(BoW, GIST, Color Histogram, etc.)

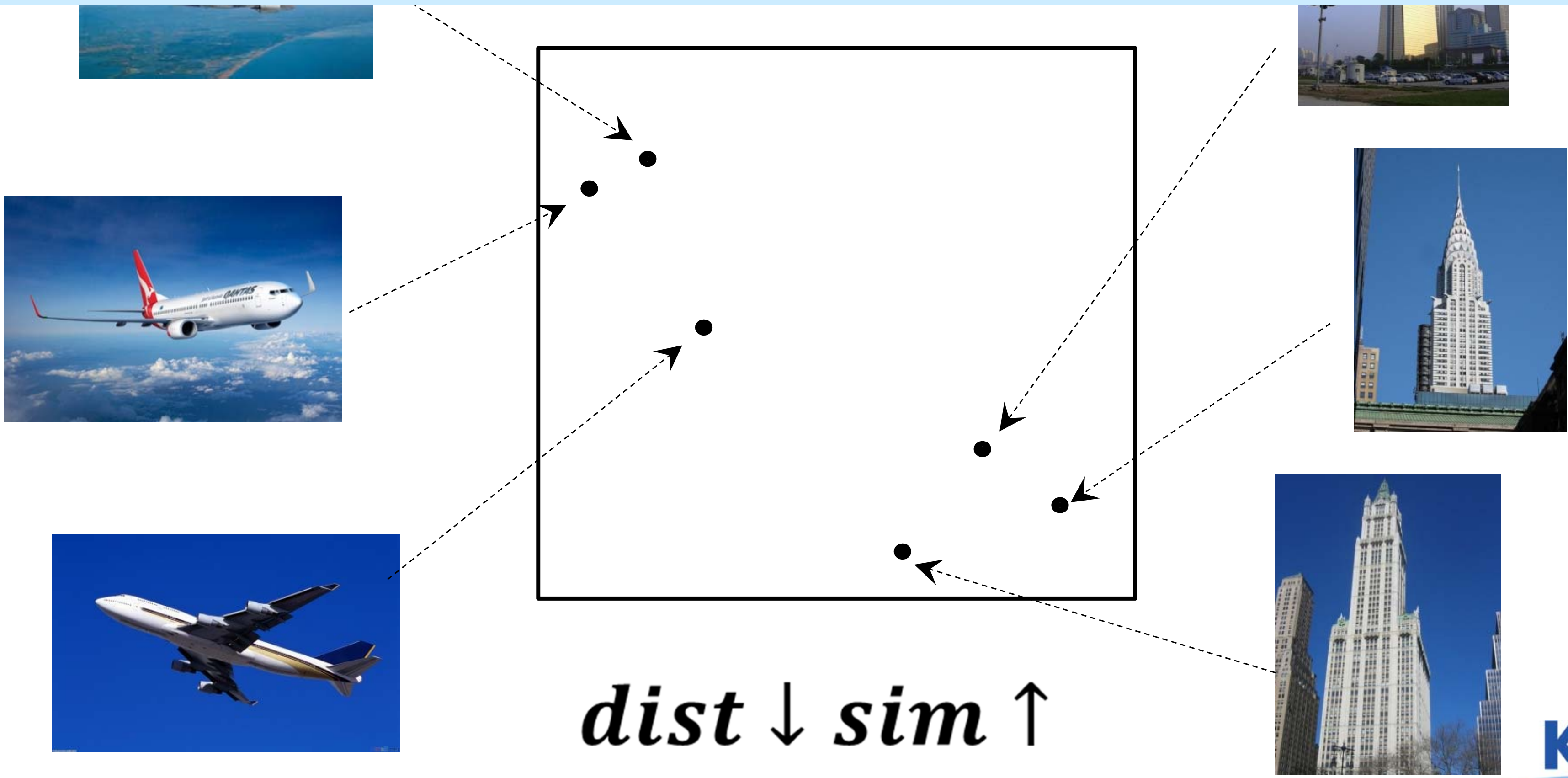


$$dist \downarrow sim \uparrow$$

Image Descriptor

High dimensional point

Nearest neighbor search (NNS) in high dimensional space

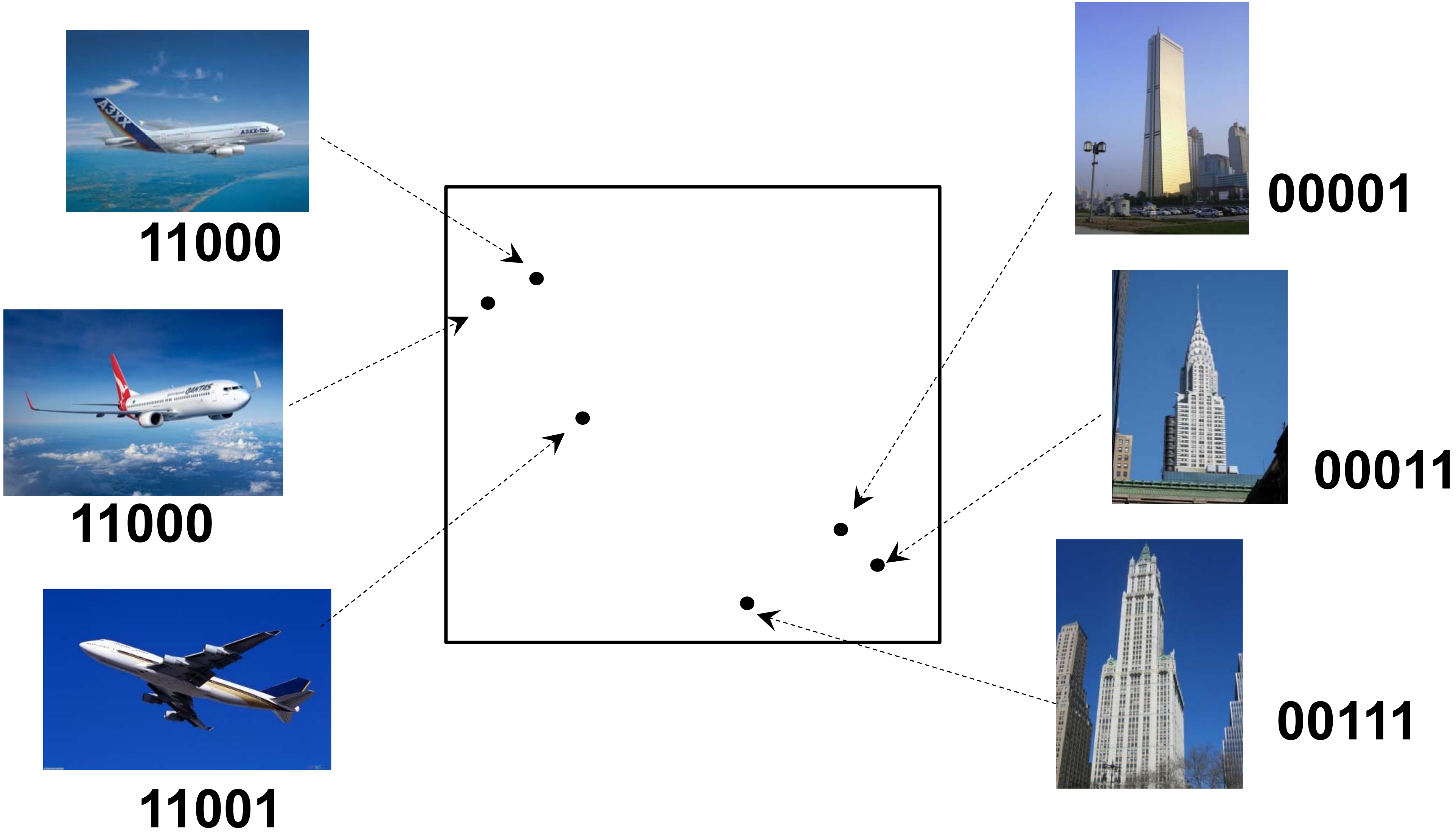


Challenge

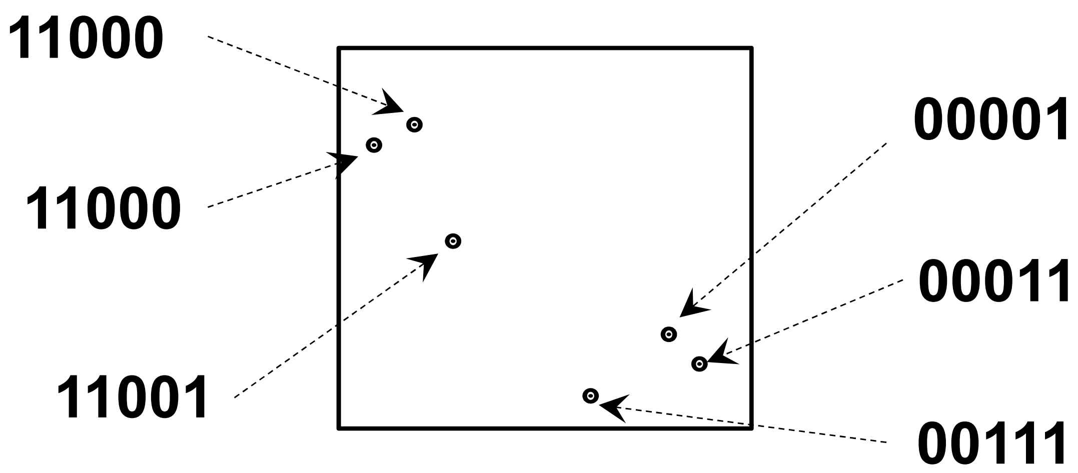
	BoW	CNN
Dimensions	1000+	4000+
1 image	4 KB+	16 KB+
1B images	4 TB+	16 TB+

$$\frac{144\ GB\ memory}{1\ billion\ images} \approx \frac{128\ bits}{1\ image}$$

Binary Code

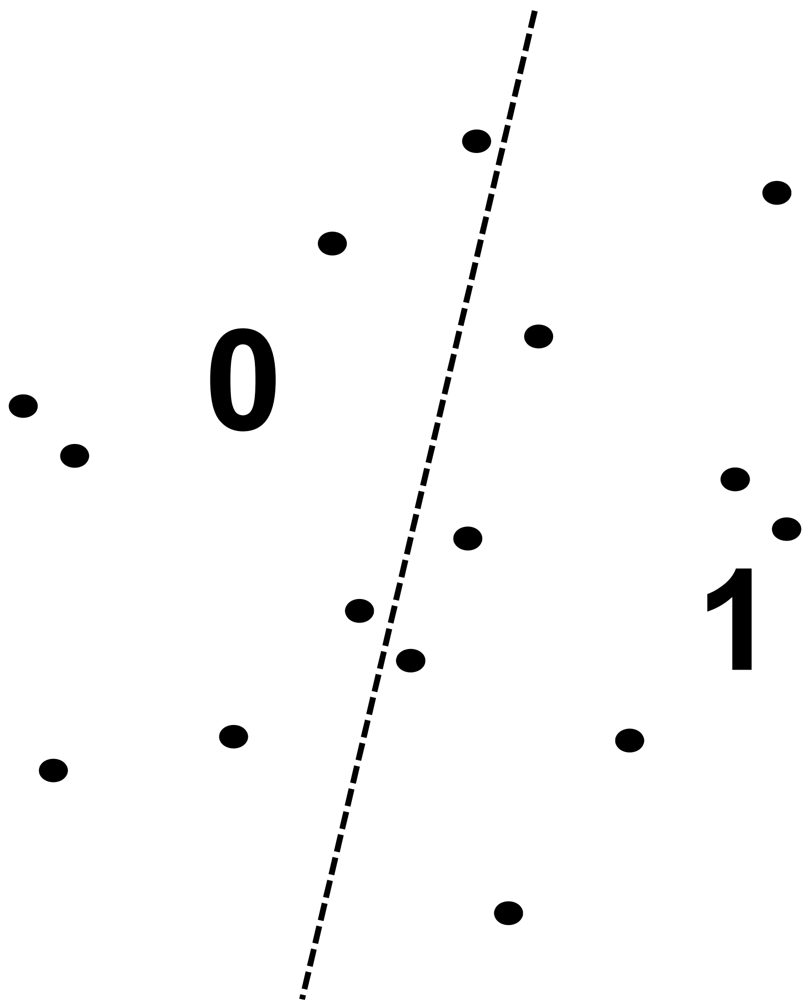


Binary Code

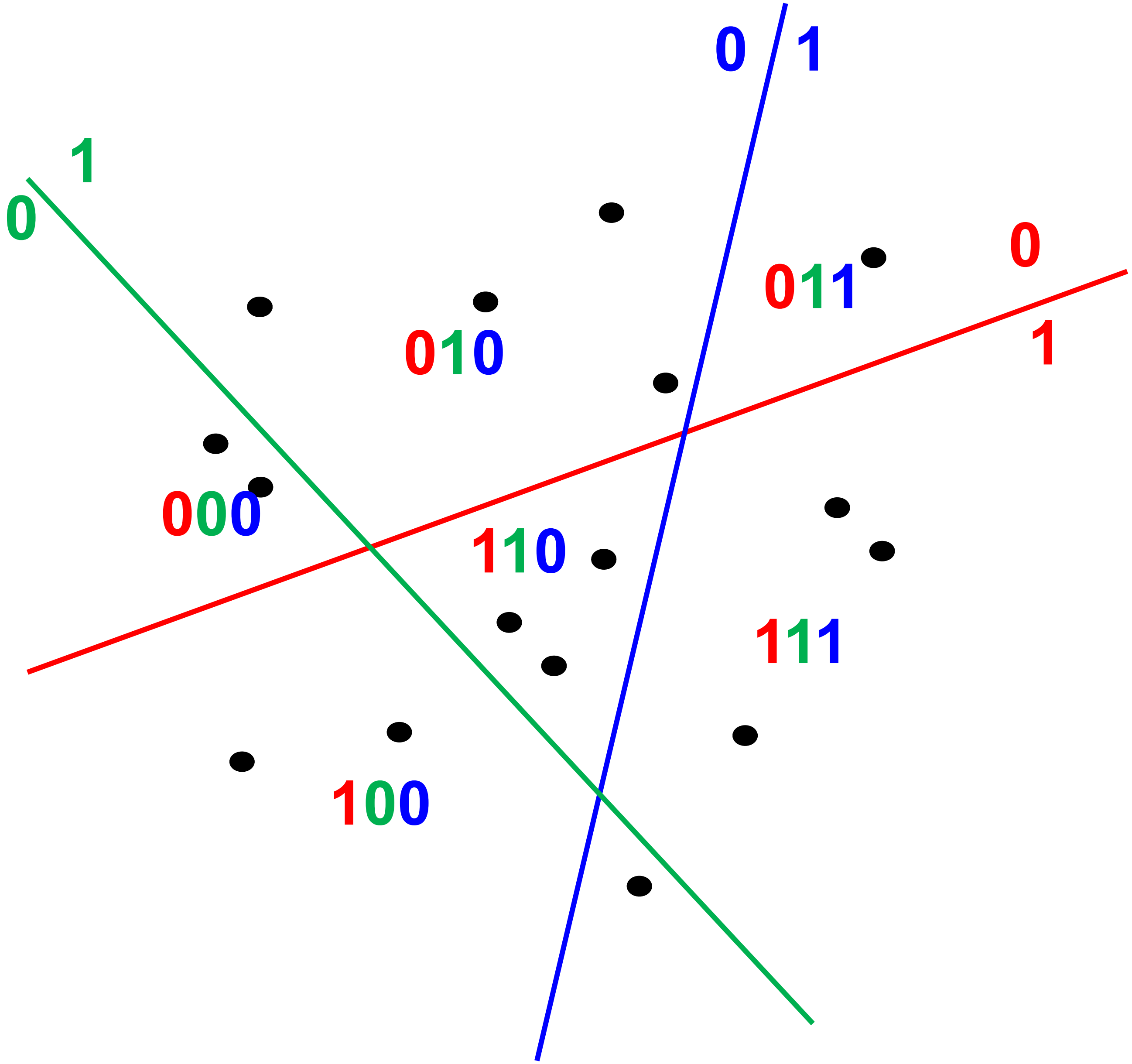


* Benefits
- Compression
- Very fast distance computation (Hamming Distance, XOR)

Hyper-Plane based Binary Coding



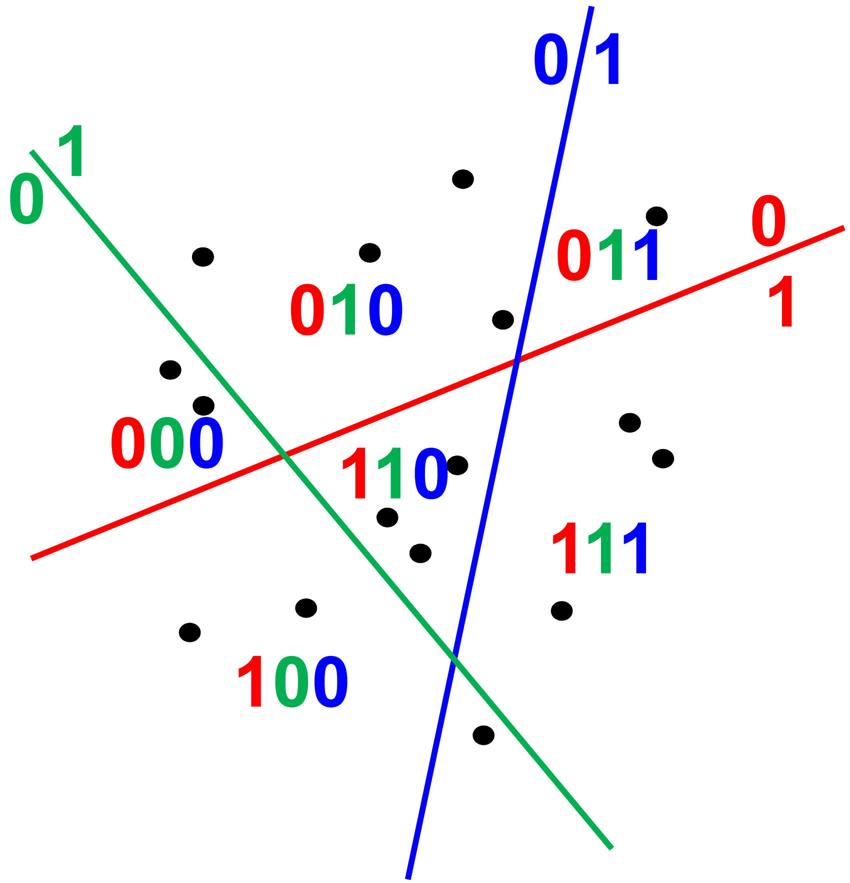
Hyper-Plane based Binary Coding



Distance between Two Points

- Measured by bit differences, known as Hamming distance
- Efficiently computed by XOR bit operations

$$d_{hd}(b_i, b_j) = |b_i \oplus b_j|$$



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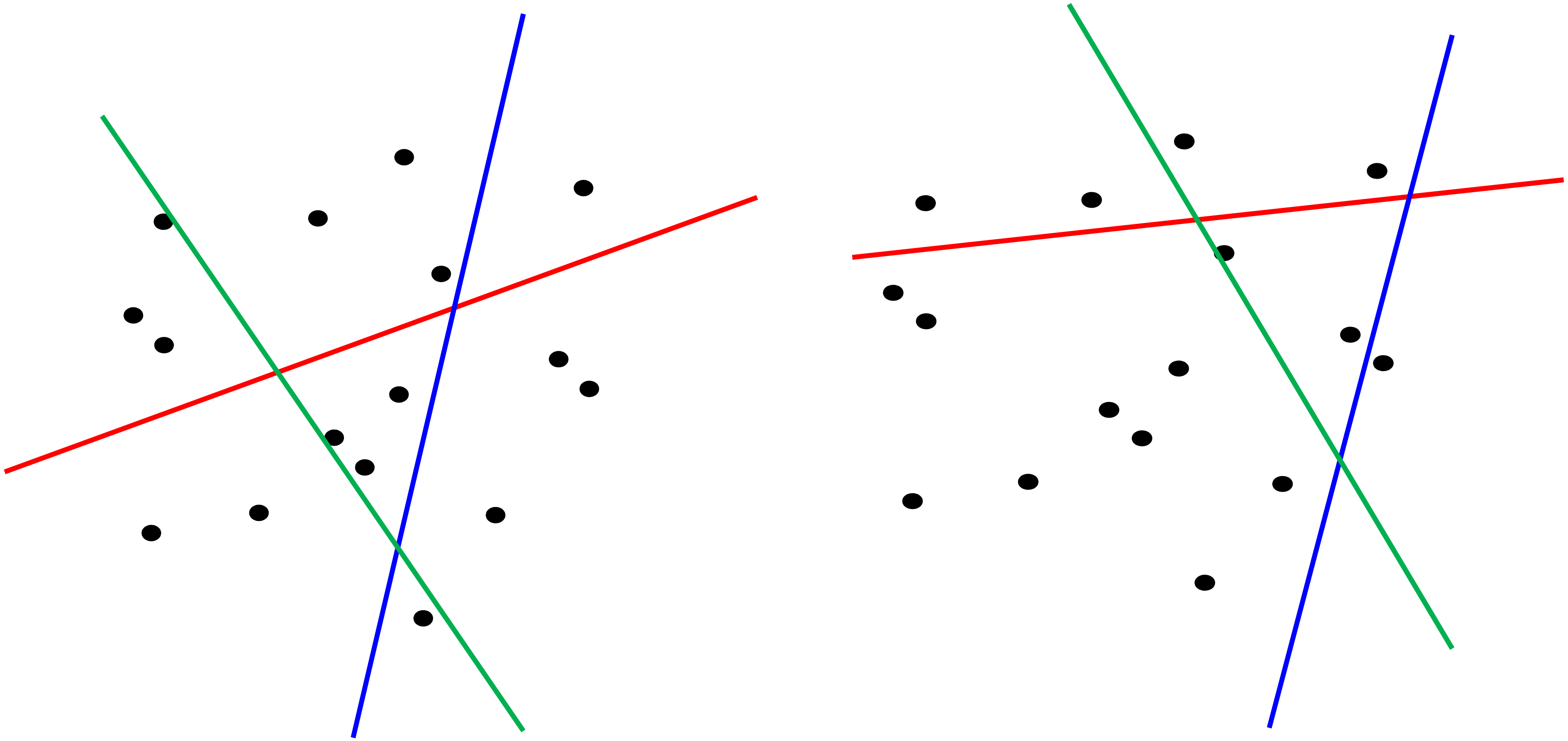
Good and Bad Hyper-Planes



Previous work focused on how to determine good hyper-planes

Components of Spherical Hashing

- **Spherical hashing**
- **Hyper-sphere setting strategy**
- **Spherical Hamming distance**

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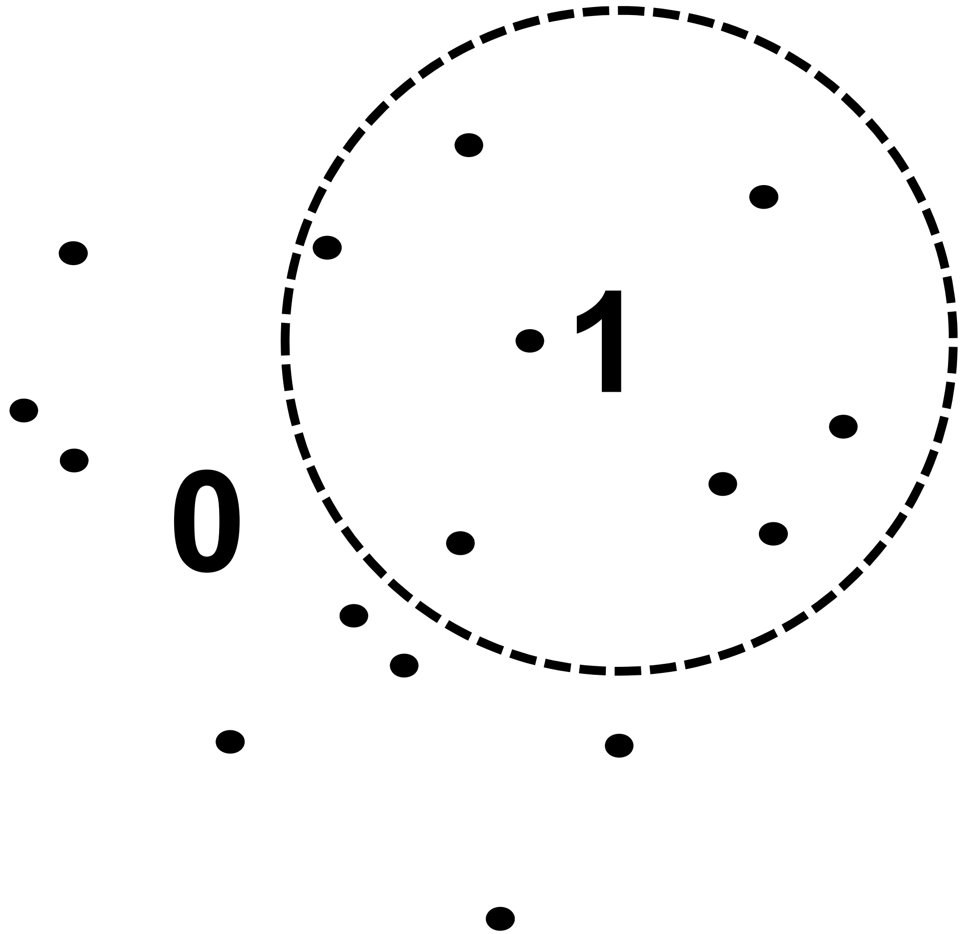
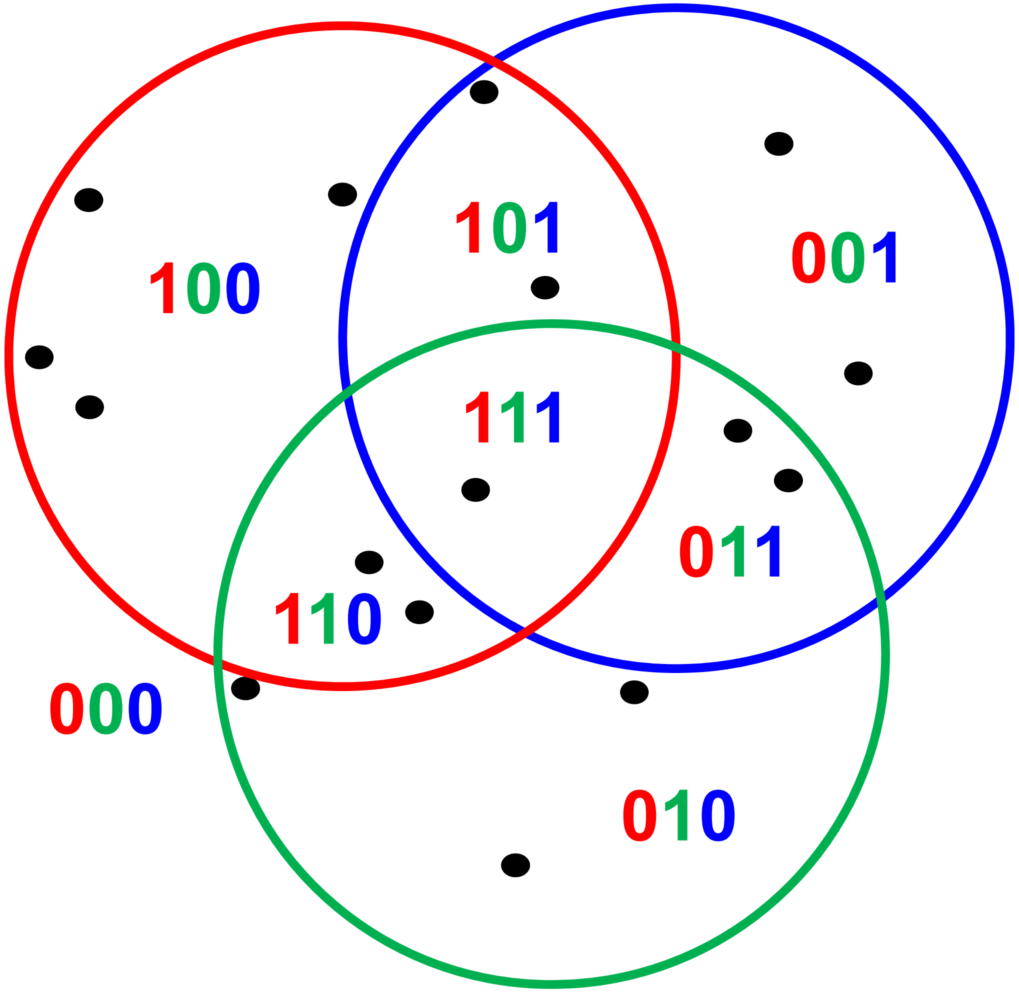
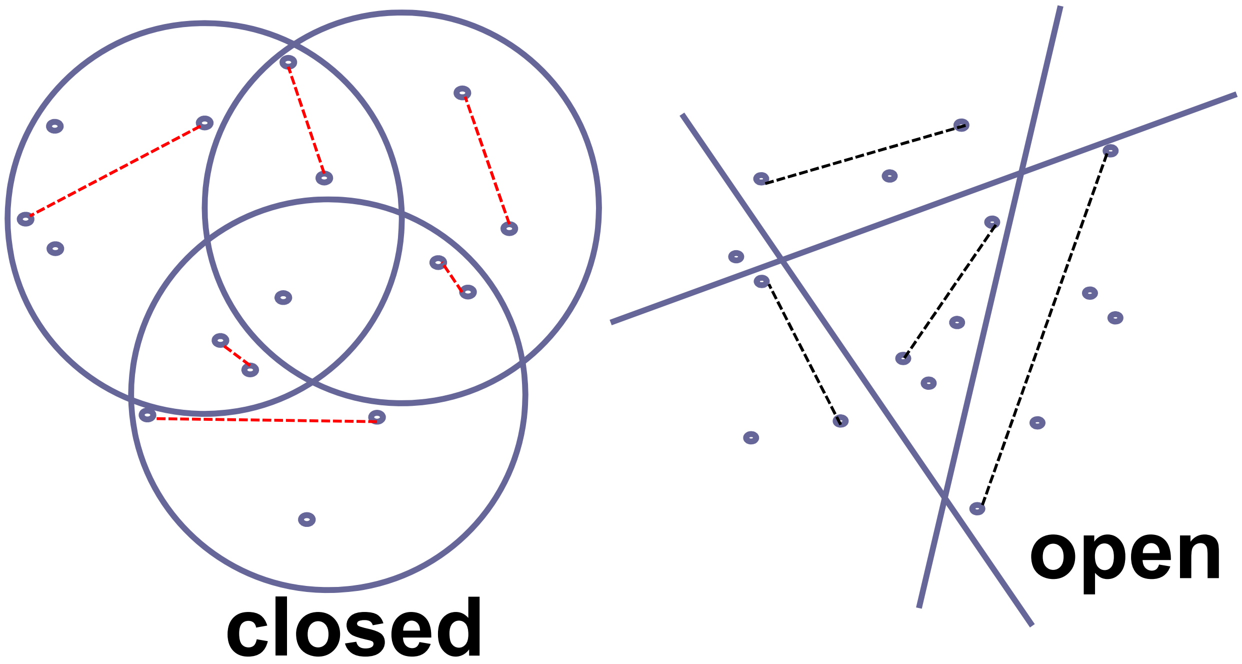
Spherical Hashing [Heo et al., CVPR 12]

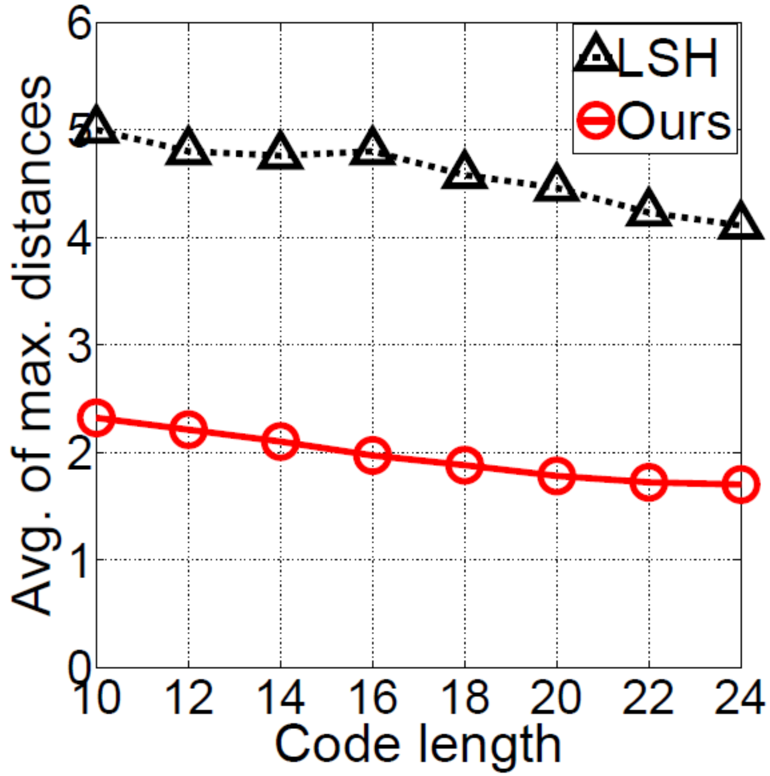


Spherical Hashing [Heo et al., CVPR 12]



Hyper-Sphere vs Hyper-Plane





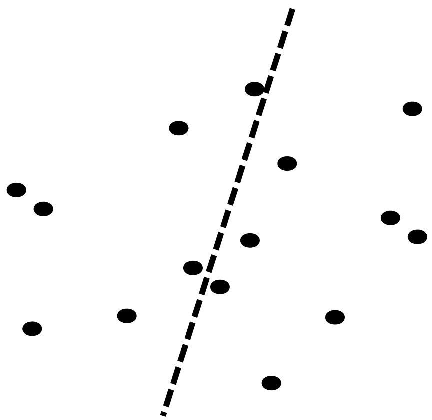
Average of maximum distances within a partition:
- Hyper-spheres gives tighter bound!

Components of Spherical Hashing

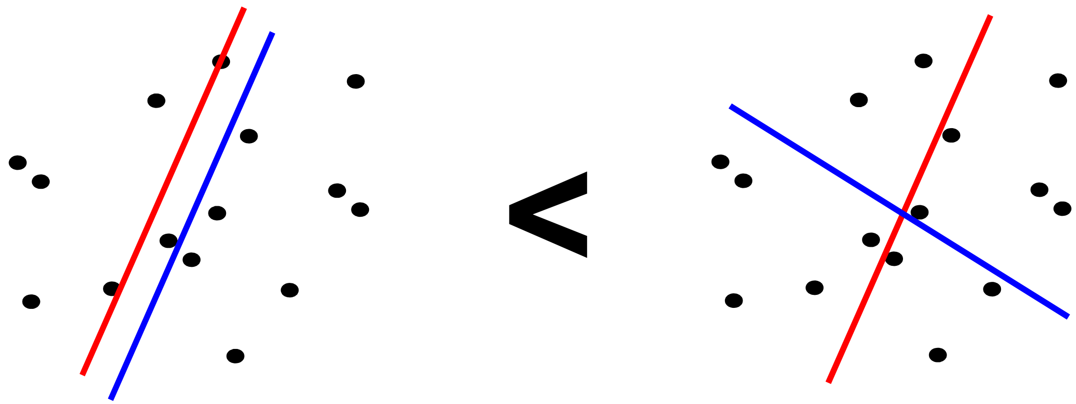
- Spherical hashing
- **Hyper-sphere setting strategy**
- Spherical Hamming distance

Good Binary Coding [Yeiss 2008, He 2011]

1. Balanced partitioning

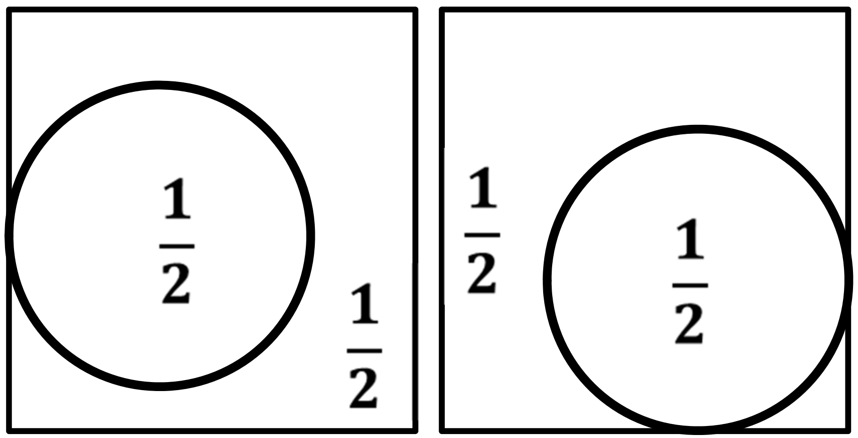


2. Independence

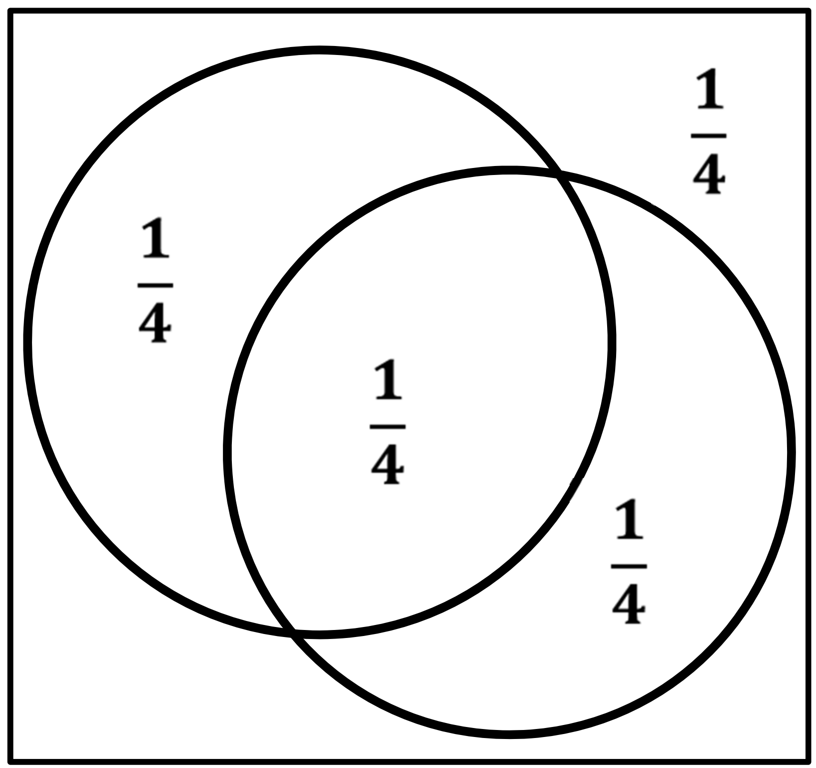


Intuition of Hyper-Sphere Setting

1. Balance

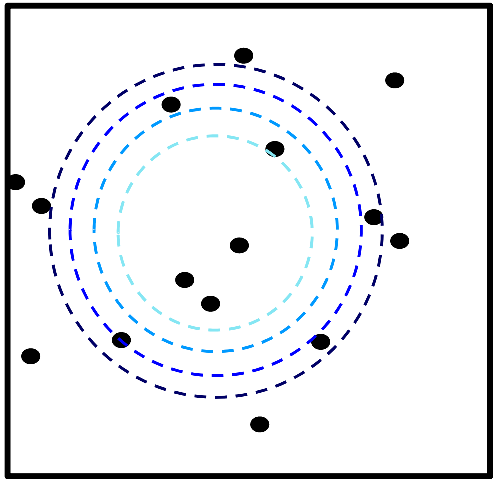


2. Independence

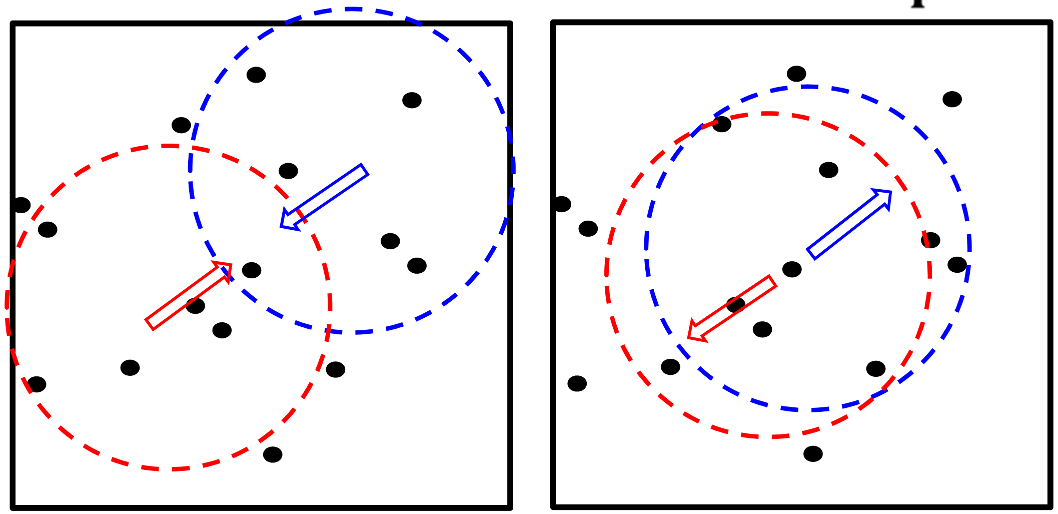


Hyper-Sphere Setting Process

1. Balance
- by controlling radius for $n(S) = \frac{N}{2}$



2. Independence
- by moving two hyper-spheres for $n(S_1 \cap S_2) = \frac{N}{4}$

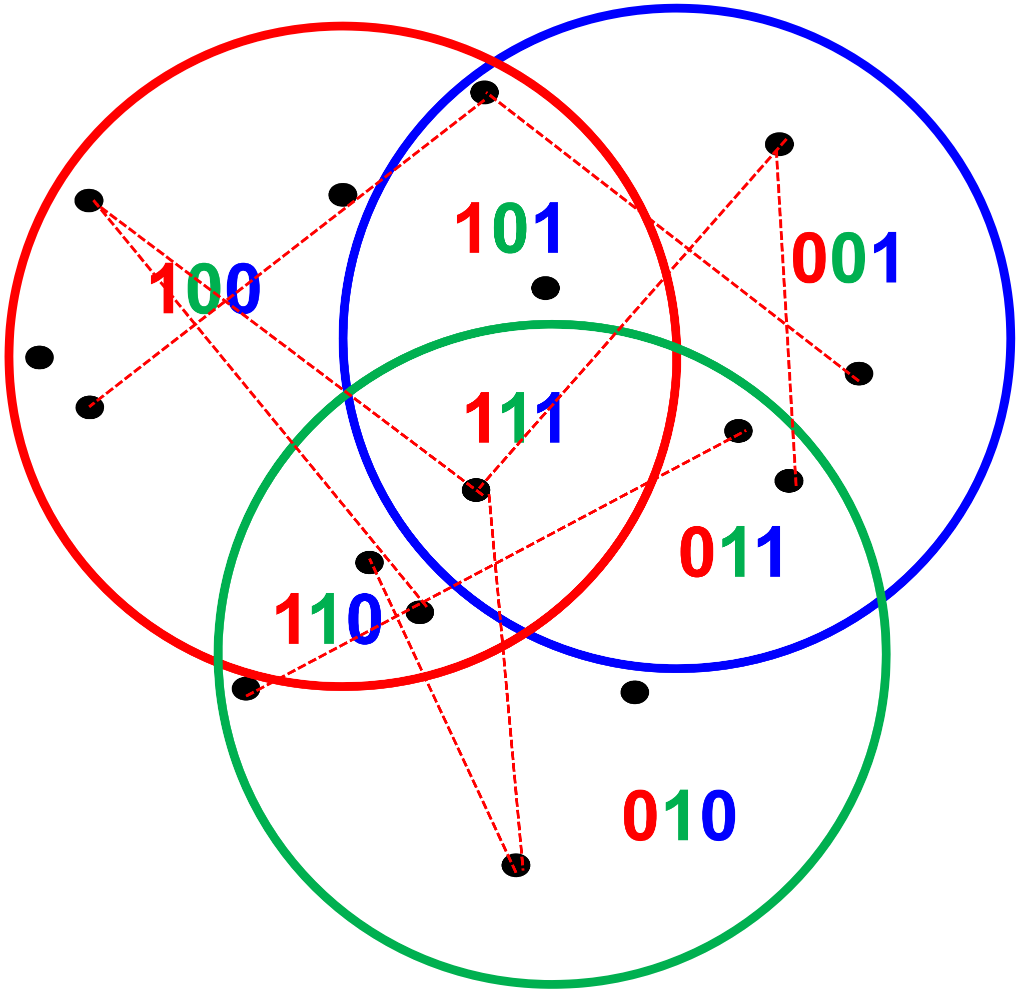


Iteratively repeat step 1, 2 until convergence.

Components of Spherical Hashing

- Spherical hashing
- Hyper-sphere setting strategy
- **Spherical Hamming distance**

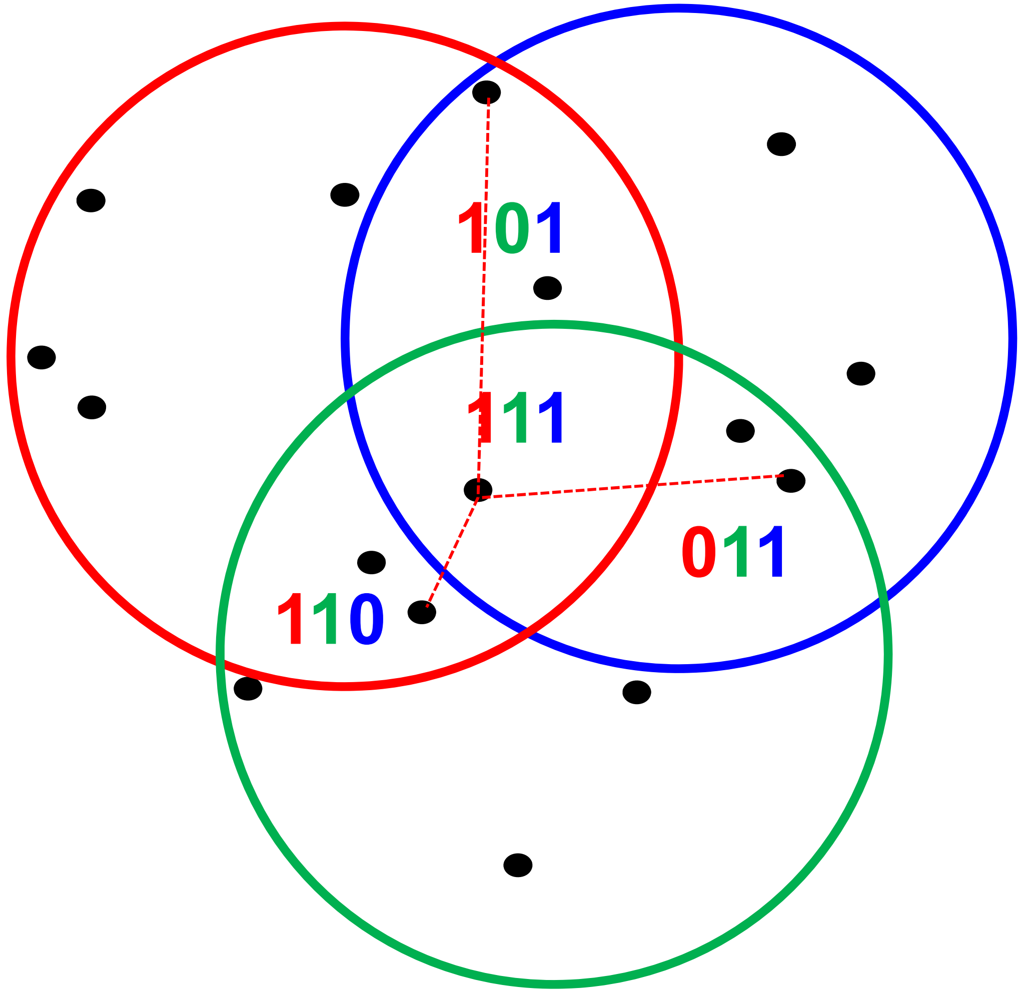
Max Distance and Common ‘1’



Common ‘1’s

: 1

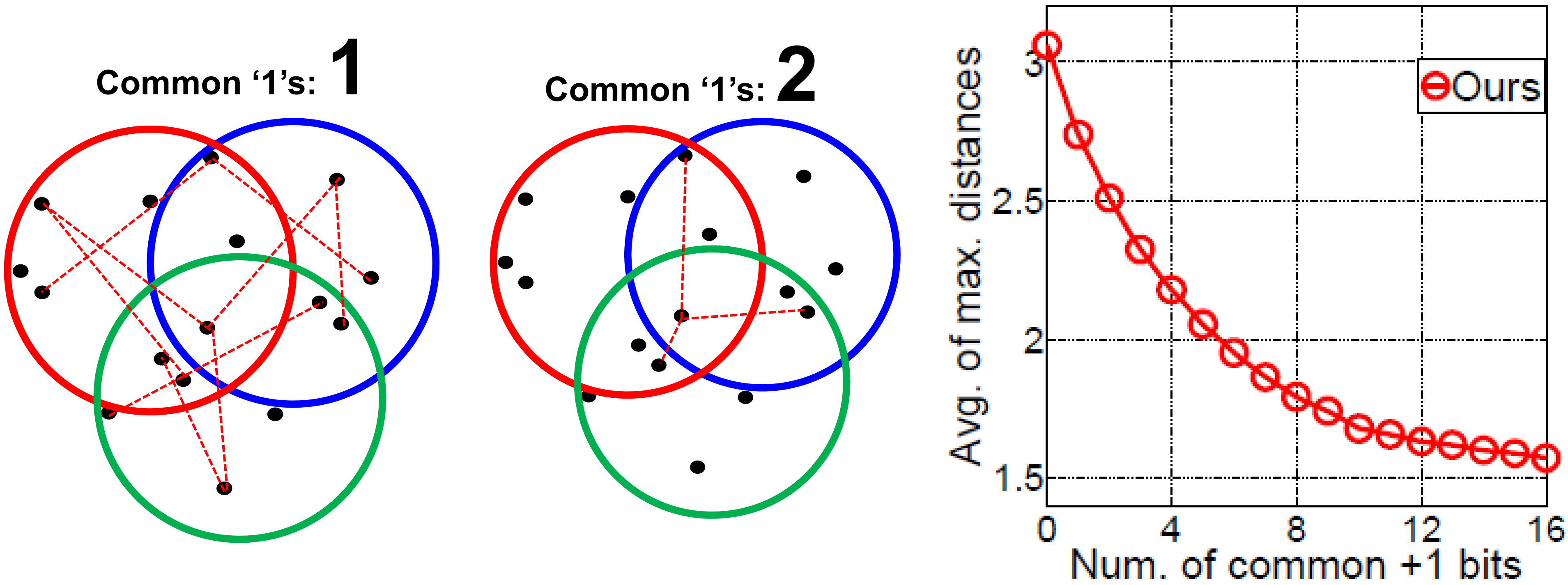
Max Distance and Common '1'



Common '1's

: **2**

Max Distance and Common '1'



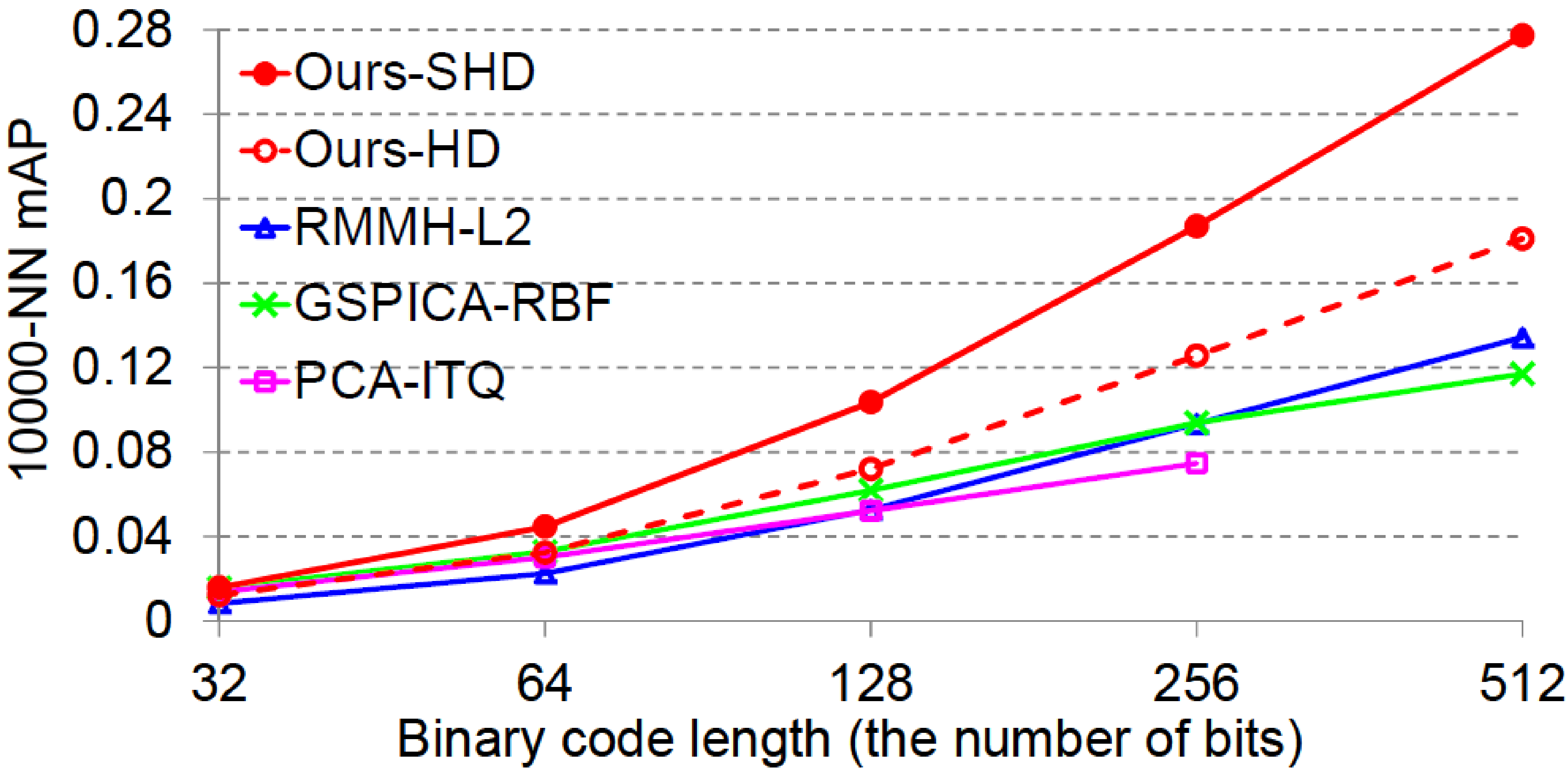
Average of maximum distances between two partitions: decreases as number of common '1'

Spherical Hamming Distance (SHD)

$$d_{shd}(b_i, b_j) = \frac{|b_i \oplus b_j|}{|b_i \wedge b_j|}$$

SHD: Hamming Distance divided by the number of common '1's.

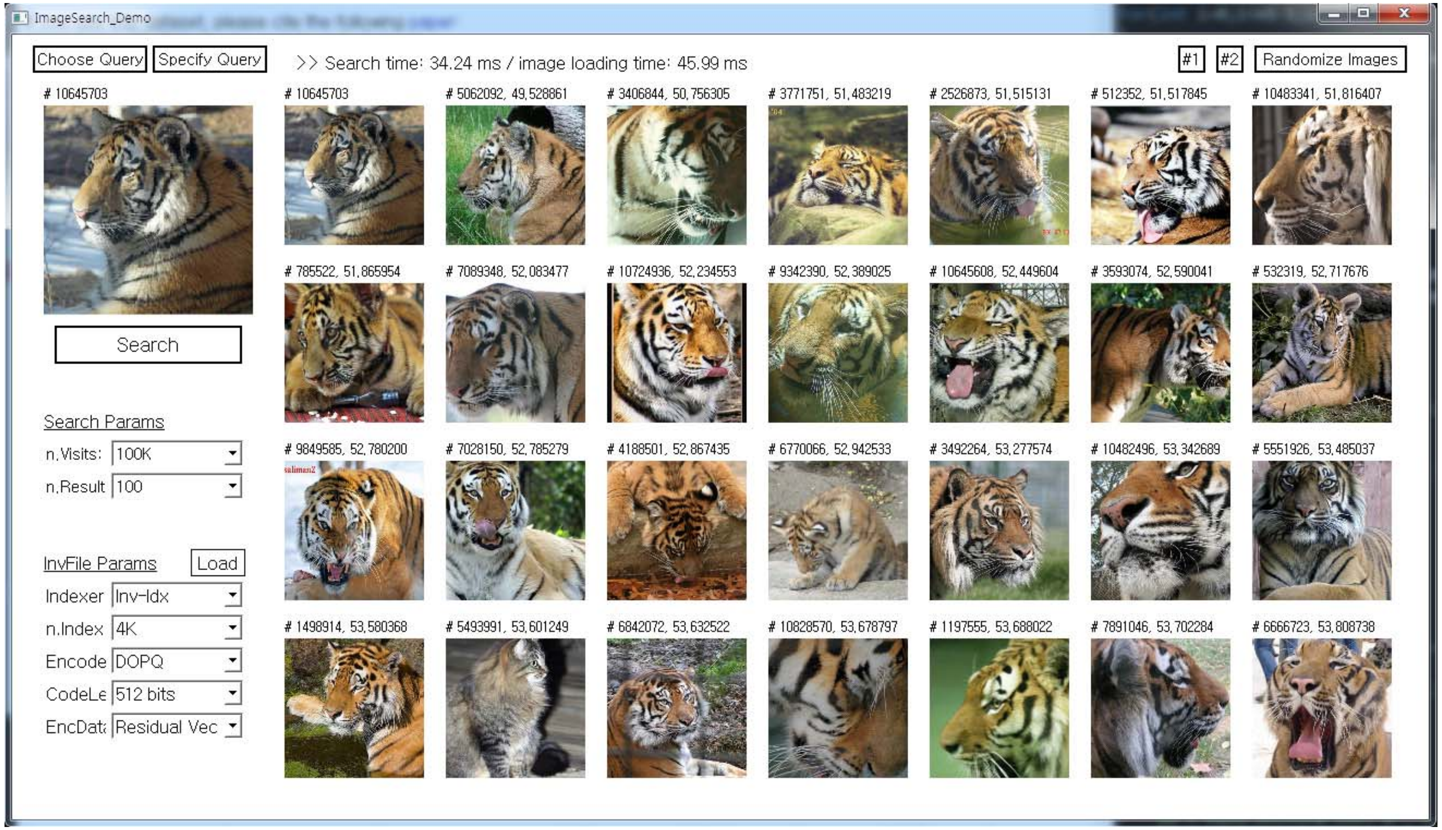
Results



384 dimensional 75 million GIST descriptors

Results of Image Retrieval

- **Collaborated with Adobe**
  - **11M images**
  - **Use deep neural nets for image representations**
  - **Spend only 35 ms for a single CPU thread**

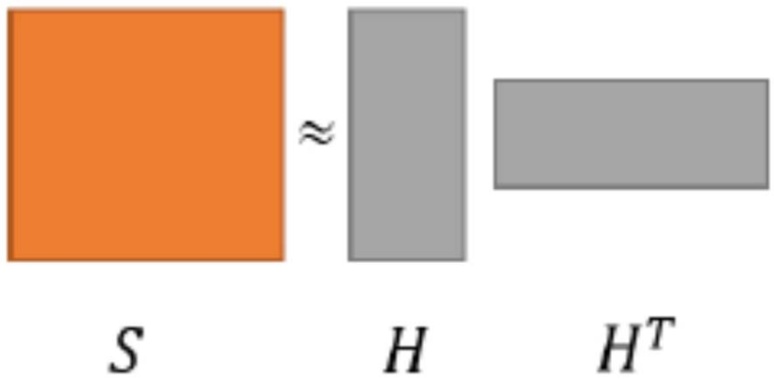


Supervised Hashing

- **Utilize image labels**
  - **Conducted by using deep learning**

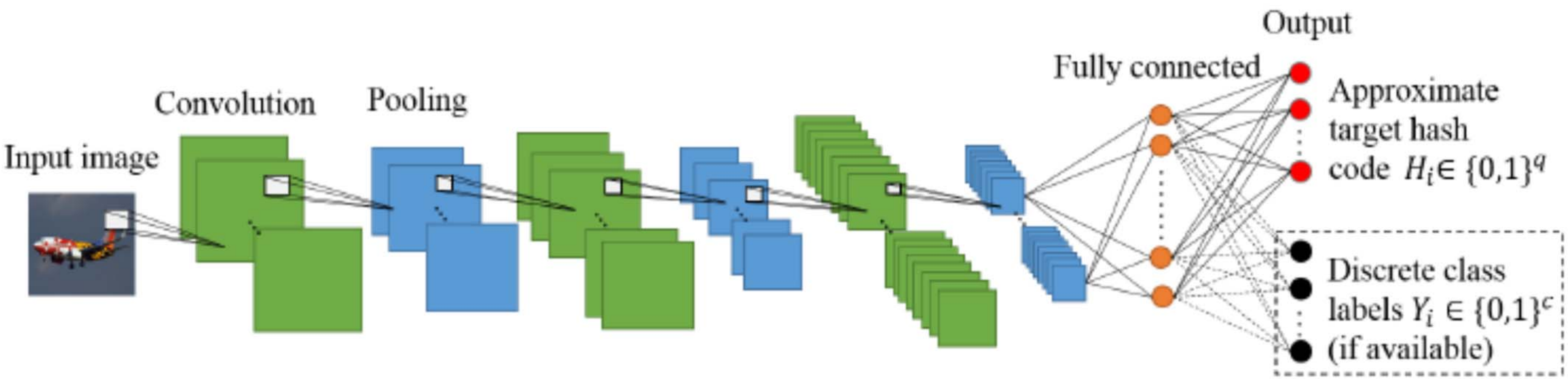
Supervised hashing for image retrieval via image representation learning, AAA 14

- **First step: approximate hash codes**
  - **S (similarity matrix, i.e., 1 when two images i & j have same label)**
  - **H (Hamming embedding, binary codes): dot products between two similar codes gives 1**
  - **Minimize the reconstruction error between S and similarity between codes**



Supervised hashing for image retrieval via image representation learning, AAA 14

- **Second step: learning image features and hash functions**
  - **Use Alexnet by utilizing approximate target hash codes and optionally class labels**
  - **Once the network is trained, it is used for test images**



Class Objectives were:

- **Understand the basic hashing techniques based on hyperplanes**
  - **Unsupervised approach**
- **Supervised approach using deep learning**

- **Codes are available**

  http://sglab.kaist.ac.kr/software.htm

Homework for Every Class

- **Go over the next lecture slides**
- **Come up with one question on what we have discussed today**
    - **Write questions three times**
- **Go over recent papers on image search, and submit their summary before Tue. class**

Next Time…

- **CNN based image search techniques**

Fig