Hashing Techniques

윤성의 (Sung-Eui Yoon)
Associate Professor
KAIST

http://sglab.kaist.ac.kr

Student Presentation Guidelines

- Good summary, not full detail, of the paper
  - Talk about motivations of the work
  - Give a broad background on the related work
  - Explain main idea and results of the paper
  - Discuss strengths and weaknesses of the method

- Prepare an overview slide
  - Talk about most important things and connect them well

High-Level Ideas

- Deliver most important ideas and results
  - Do not talk about minor details
  - Give enough background instead

- Deeper understanding on a paper is required
  - Go over at least two related papers and explain them in a few slides

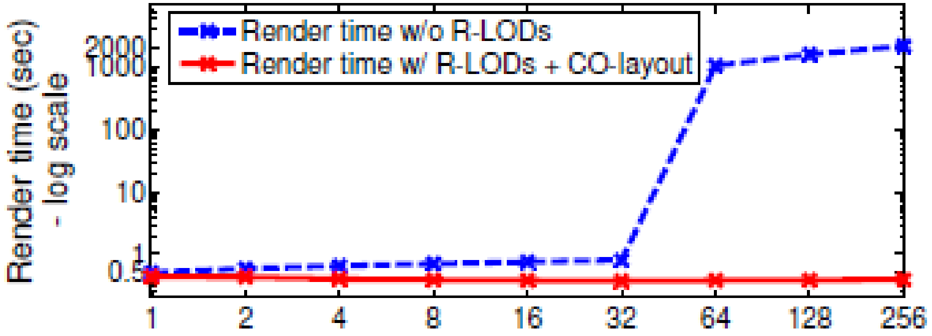
- Spend most time to figure out the most important things and prepare good slides for them

Be Honest

- Do not skip important ideas that you don't know
  - Explain as much as you know and mention that you don't understand some parts
- If you get questions you don't know good answers, just say it
- In the end, you need to explain them before the semester ends at KLMS board

Result Presentation

- **Give full experiment settings and present data with the related information**
  - **What does the x-axis mean in the below image?**



- **After showing the data, give a message that we can pull of the data**
- **Show images/videos, if there are**

Utilizing Existing Resources

- **Use author's slides, codes, and video, if they exist**
- **Give proper credits or citations**
  - **Without them, you are cheating!**

Deliver Main Ideas of the Paper

- **Identify main ideas/contributions of the paper and deliver them**

- **If there are prior techniques that you need to understand, study those prior techniques and explain them**
  - **For example, A paper utilizes B's technique in its main idea. In this case, you need to explain B to explain A well.**

Audience feedback form

Date:
Talk title:
Speaker:

1. Was the talk well organized and well prepared?
5: Excellent 4: good 3: okay 2: less than average 1: poor

2. Was the talk comprehensible? How well were important concepts covered?
5: Excellent 4: good 3: okay 2: less than average 1: poor

Any comments to the speaker

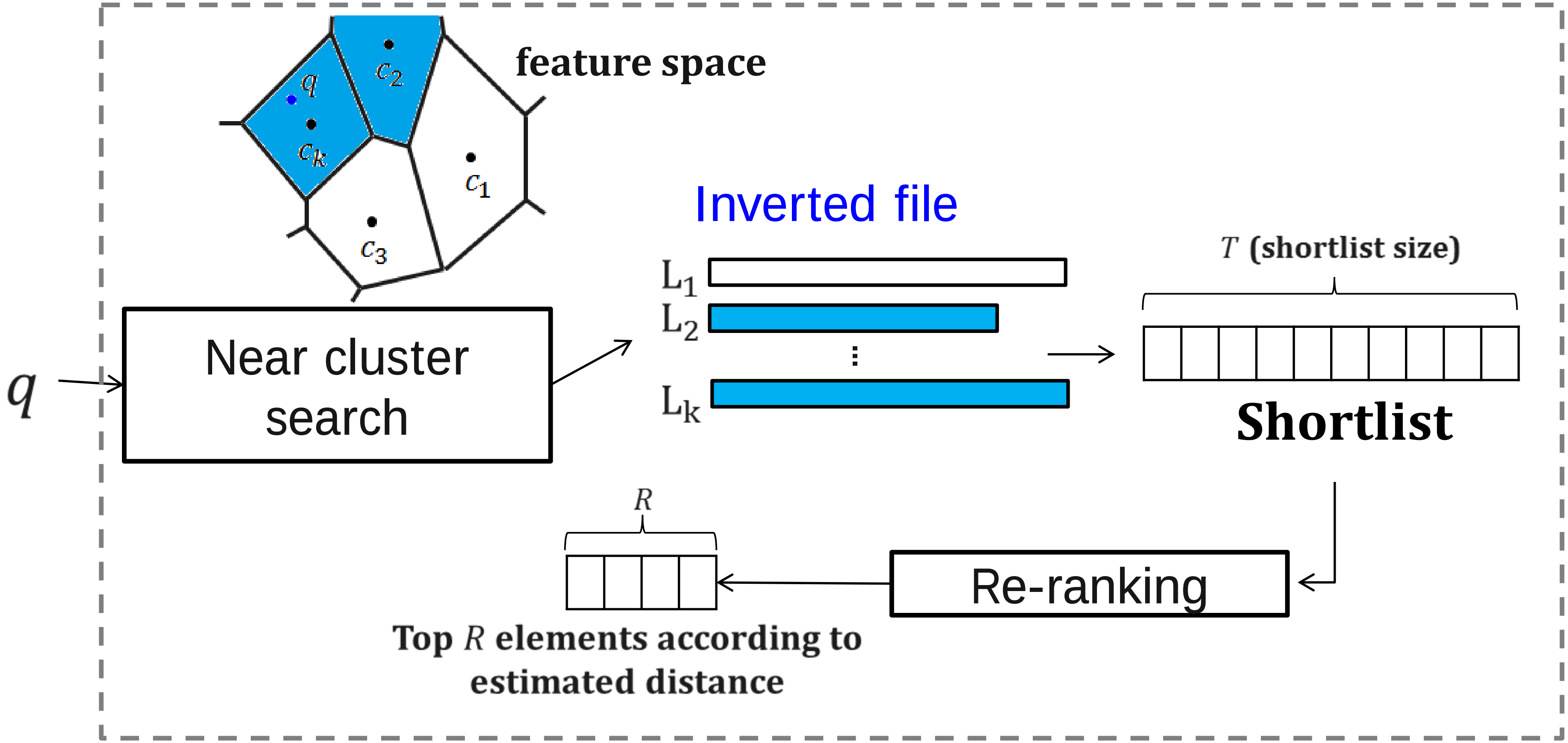
Prepare Quiz

- Review most important concepts of your talk
- Prepare two multiple-choices questions
- Example: What is the biased algorithm?
  - A: Given N samples, the expected mean of the estimator is I
  - B: Given N samples, the exp. Mean of the estimator is I + e
  - C: Given N samples, the exp. Mean of the estimator is I + e, where e goes to zeor, as N goes to infinite

Class Objectives

- Understand the basic hashing techniques based on hyperplanes
- Get to know a recent one based on hyperspheres

Review of Basic Image Search



Ack.: Dr. Heo

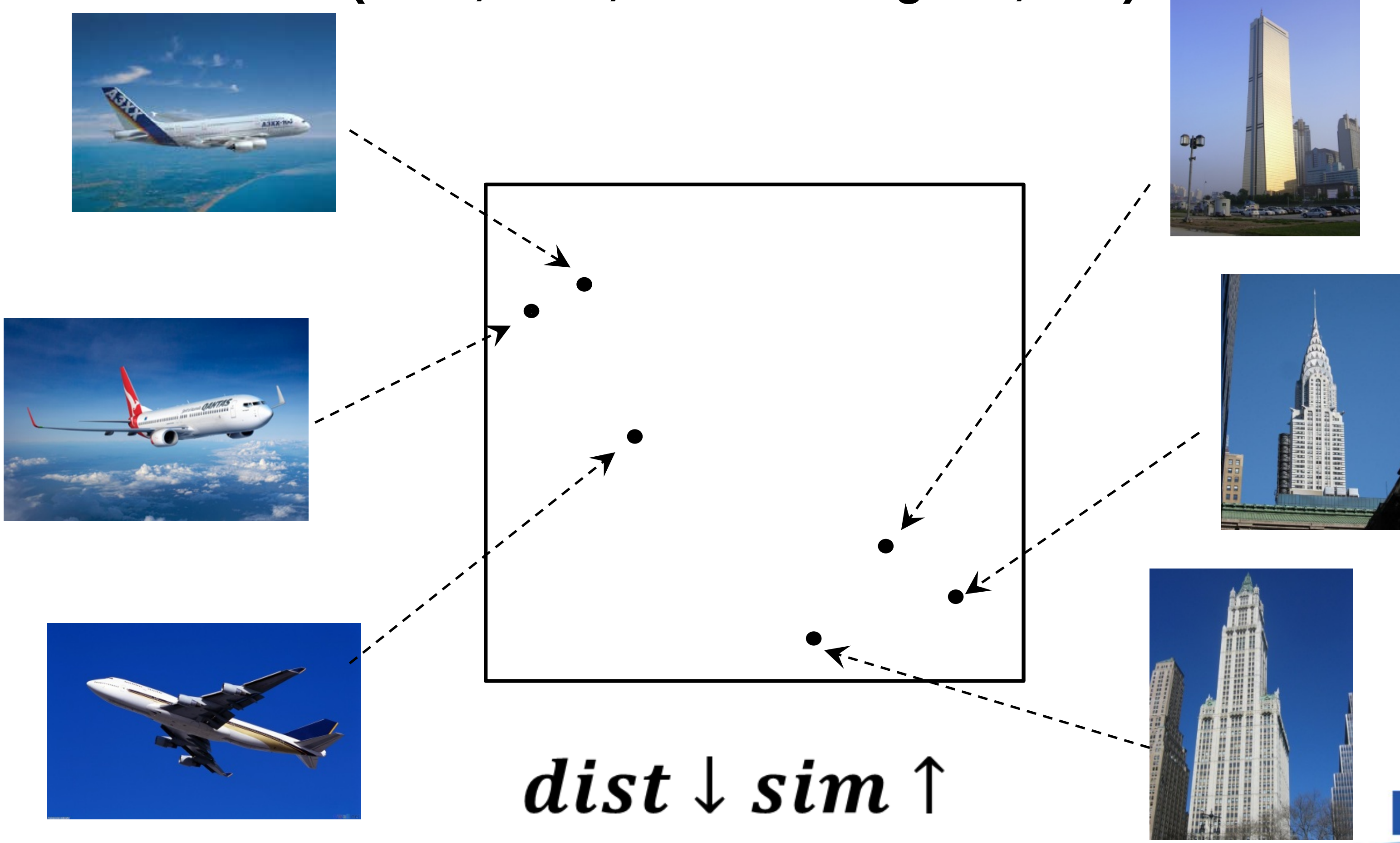
Image Search

Finding visually similar images

Image Descriptor

High dimensional point

(BoW, GIST, Color Histogram, etc.)

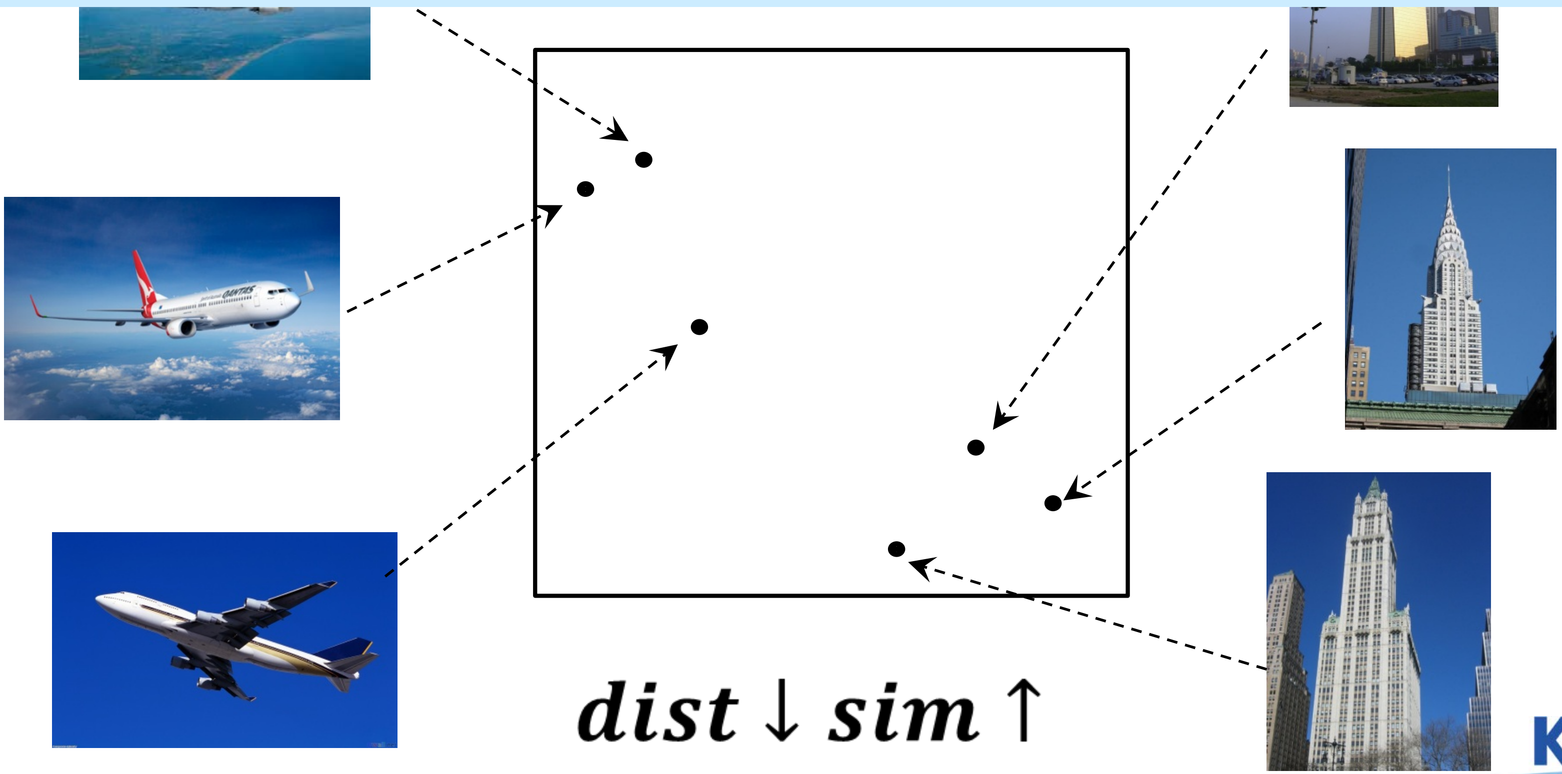


$$dist \downarrow \; sim \uparrow$$

Image Descriptor

High dimensional point

Nearest neighbor search (NNS) in high dimensional space

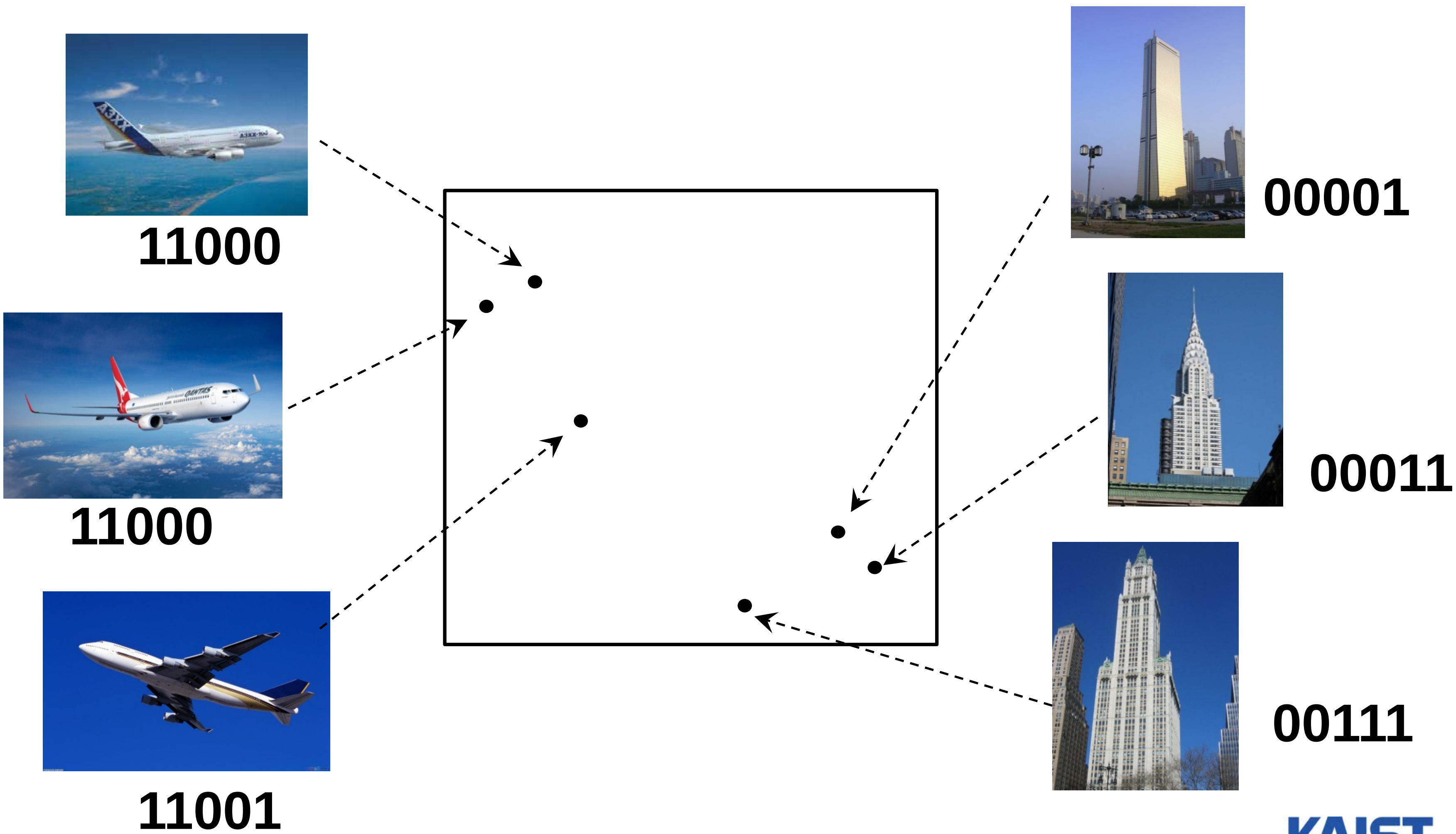


Challenge

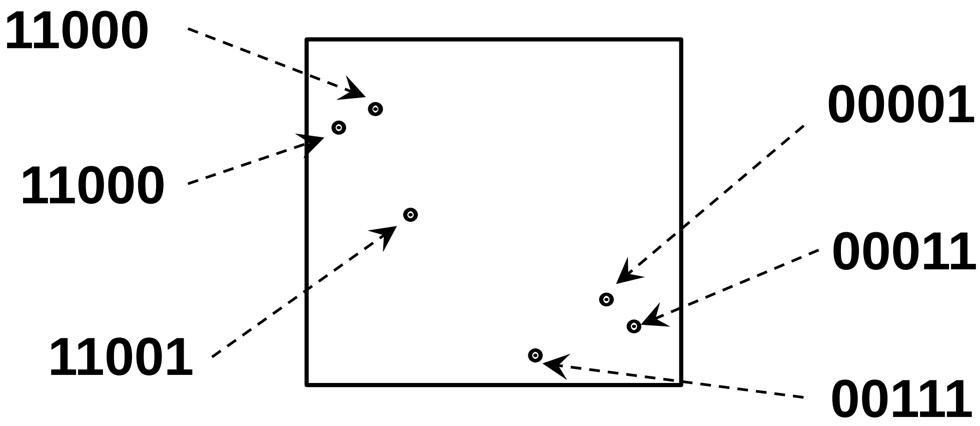
	BoW	GIST
Dimensions	1000+	300+
1 image	4 KB+	1.2 KB+
1B images	3 TB+	1 TB+

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

Binary Code



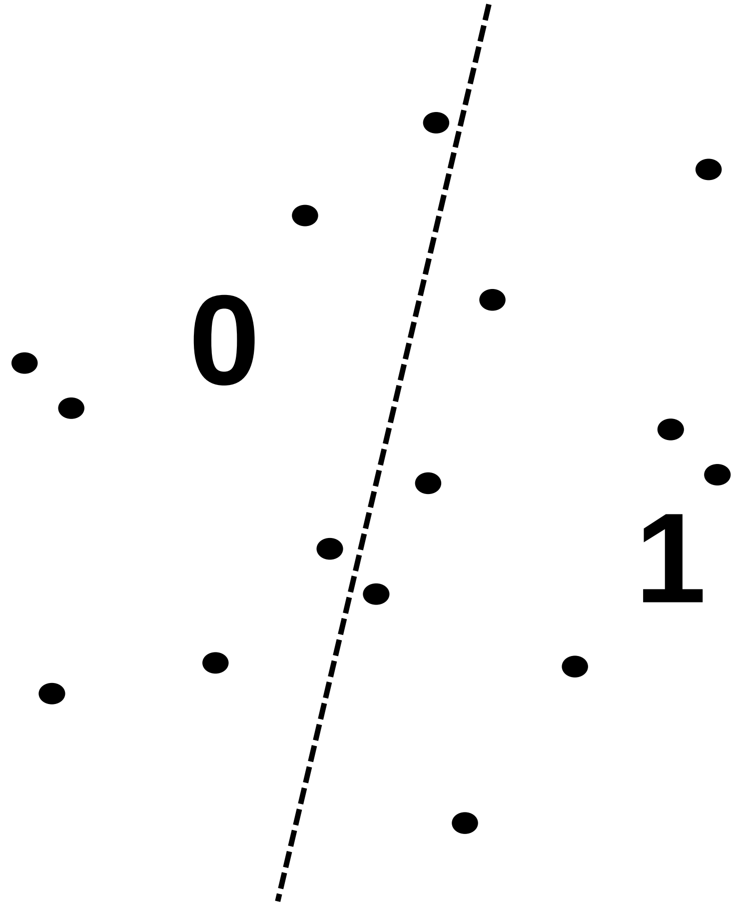
Binary Code



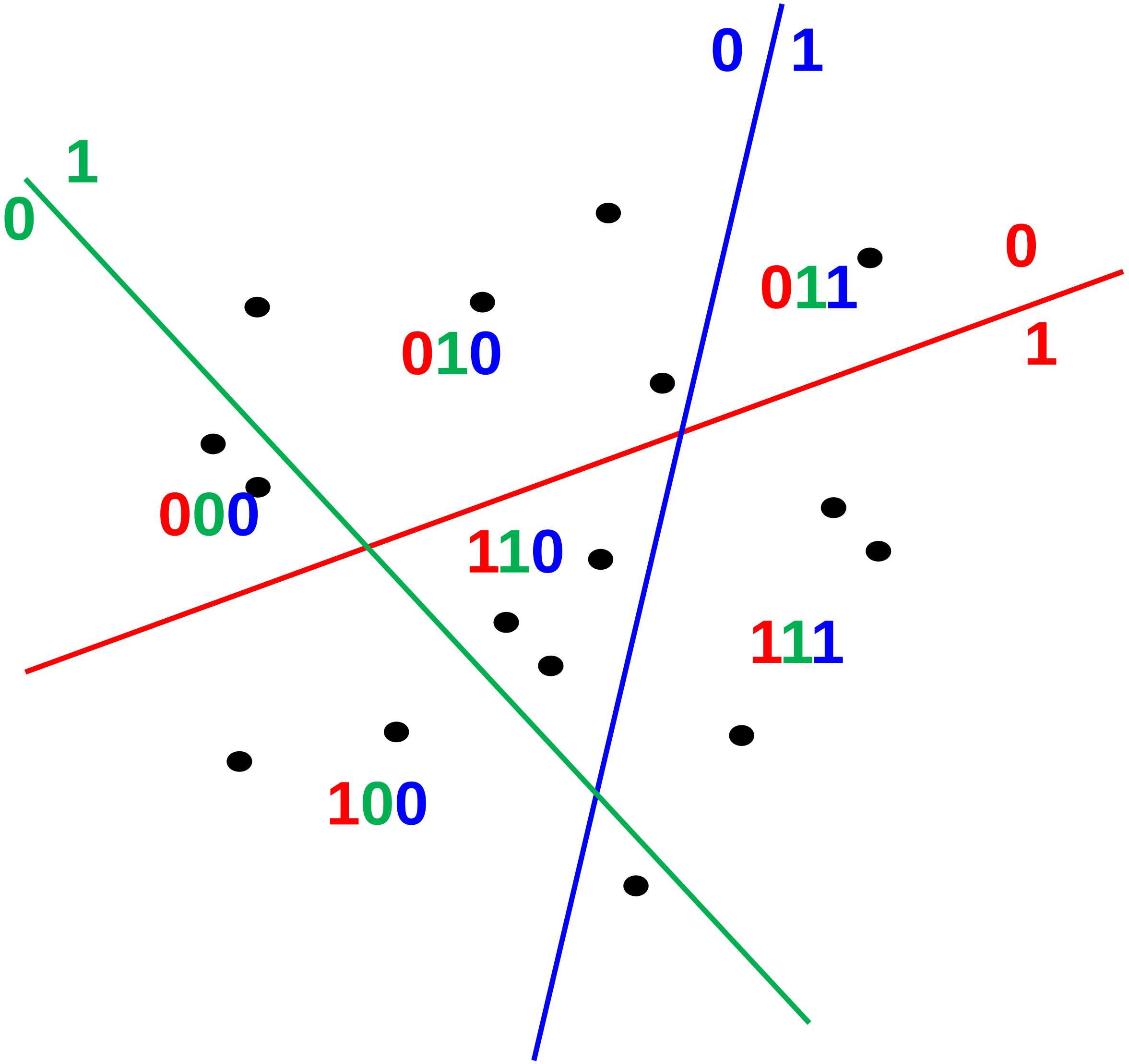
* Benefits

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

Hyper-Plane based Binary Coding



Hyper-Plane based Binary Coding

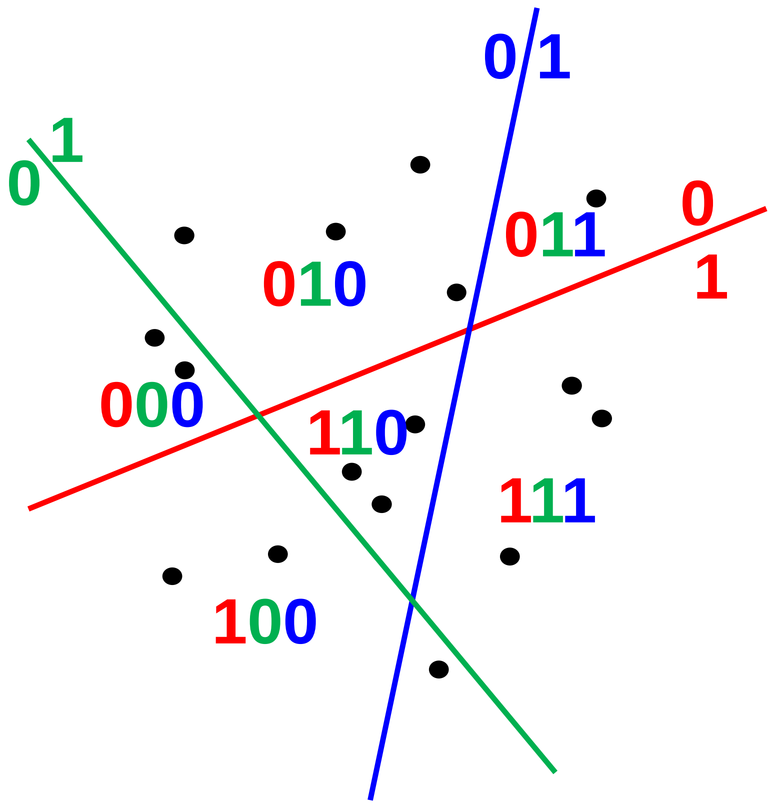


Distance between Two Points

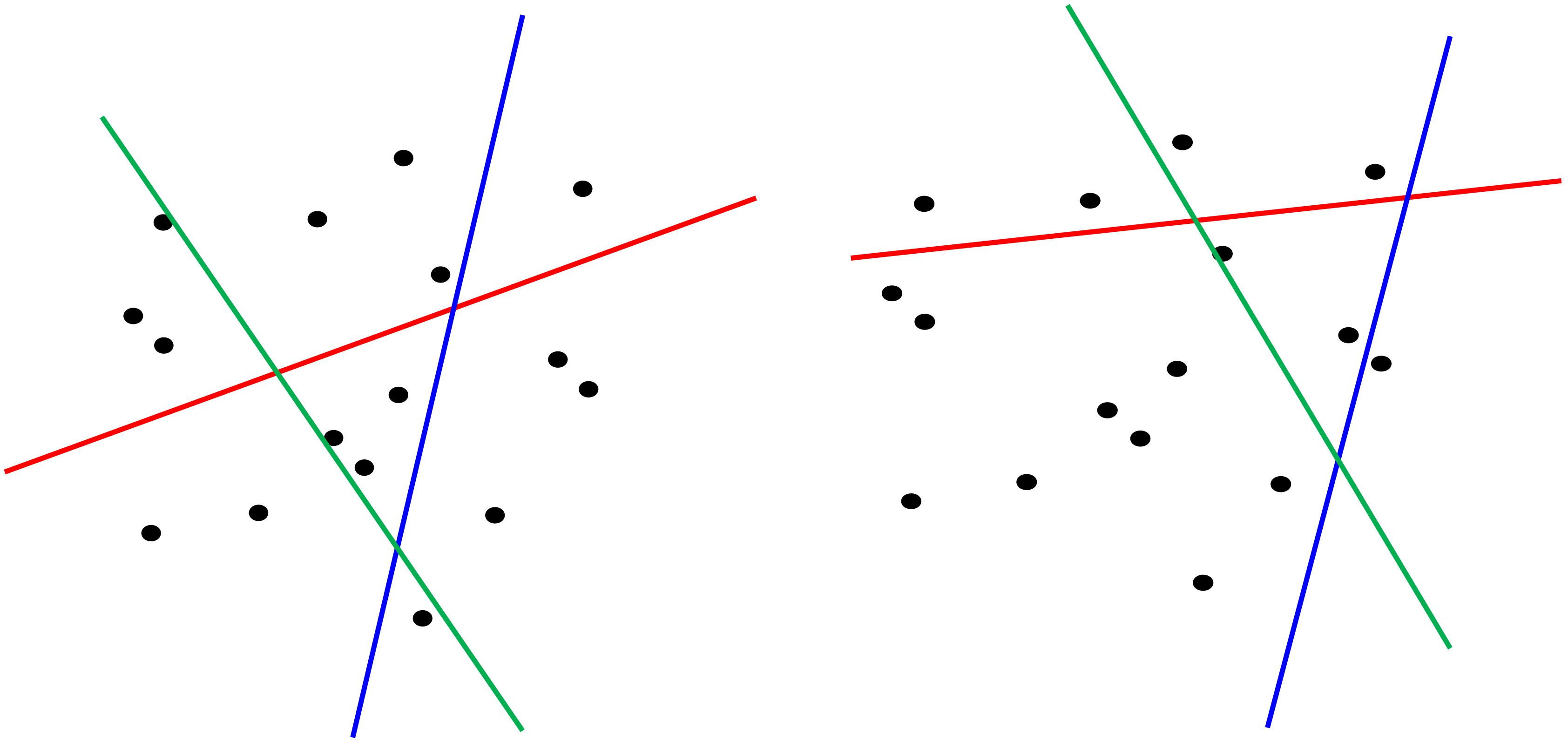
- **Measured by bit differences, known as Hamming distance**
- **Efficiently computed by XOR bit operations**

$$d_{hd}(b_i, b_j) =$$

$$|b_i \oplus b_j|$$



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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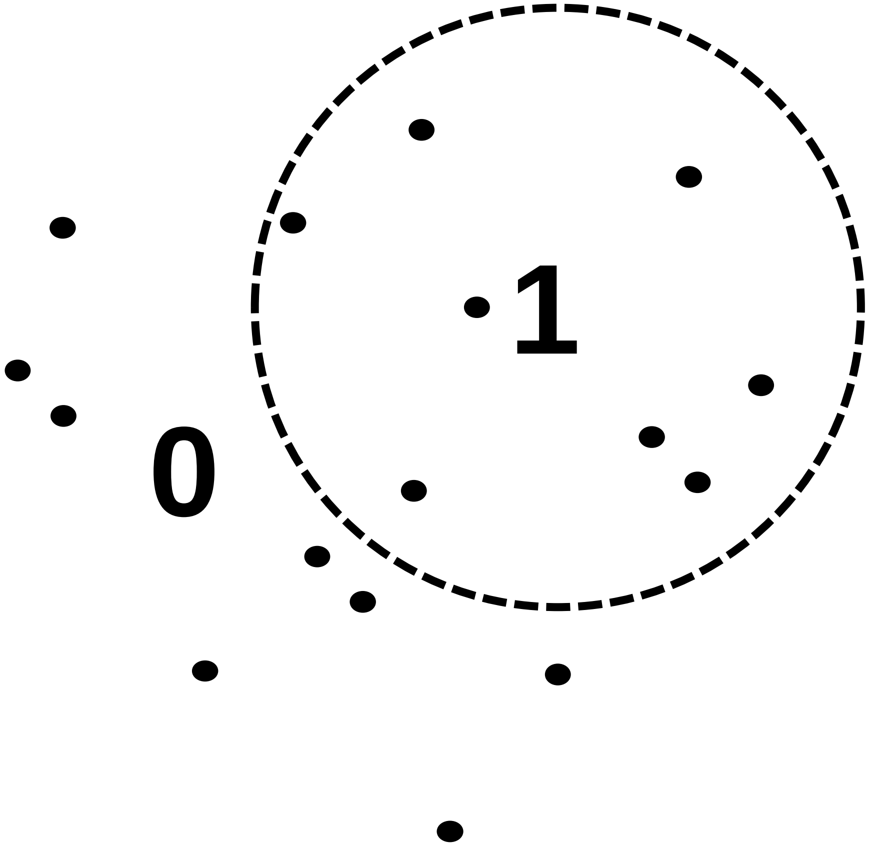
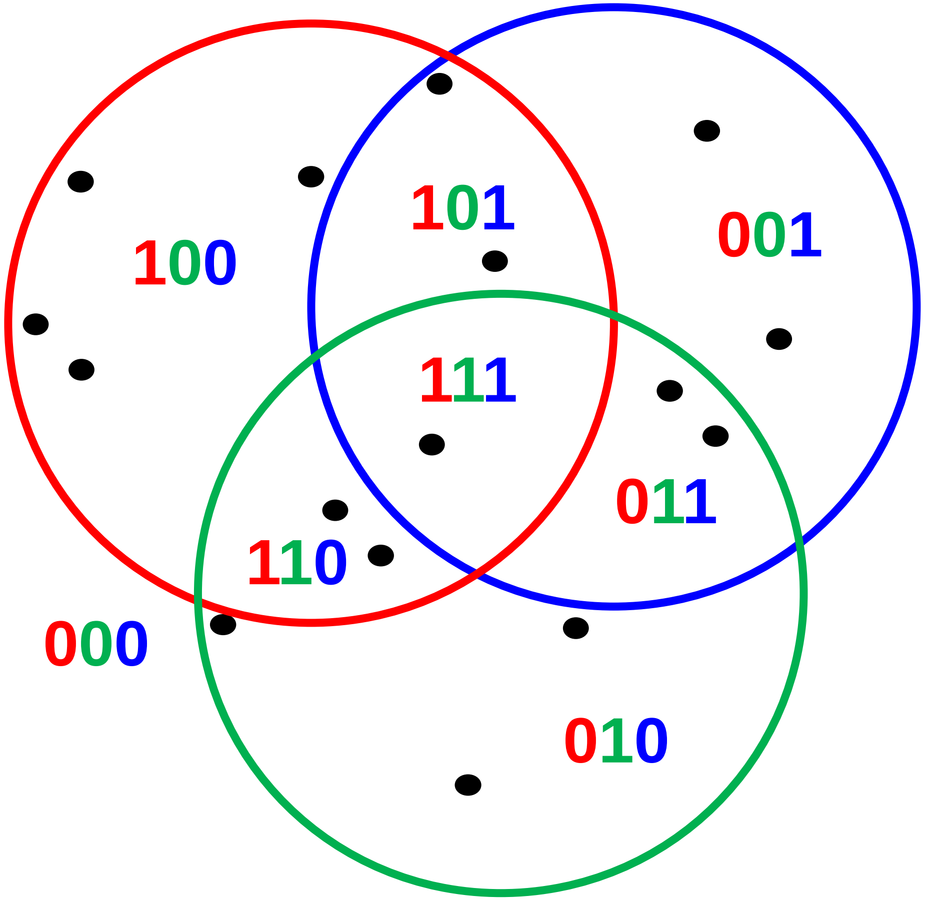
- Hyper-sphere setting strategy
- Spherical Hamming distance

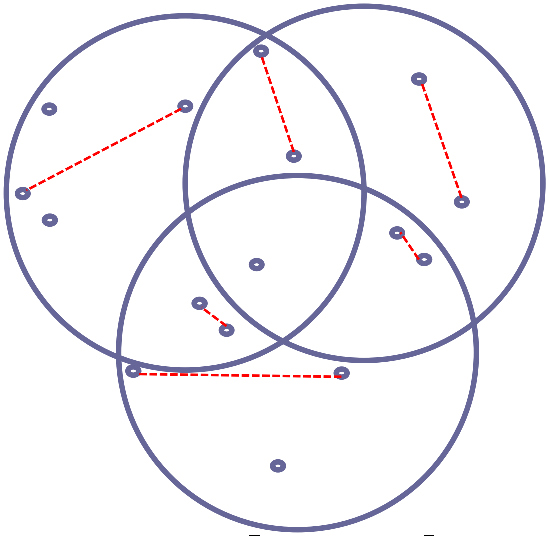
Spherical Hashing [Heo et al., CVPR 12]

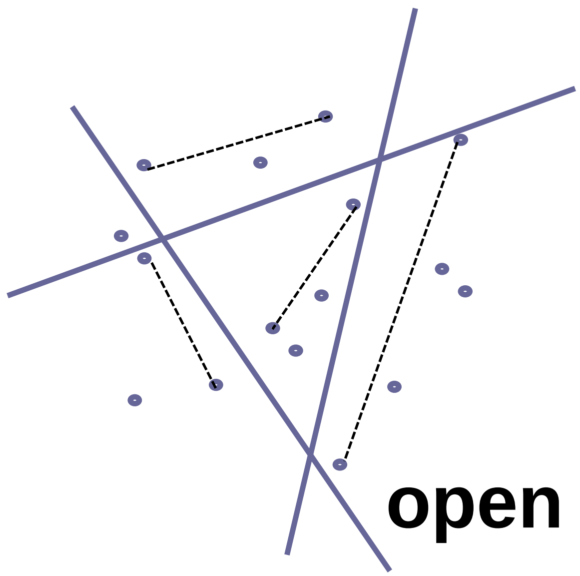


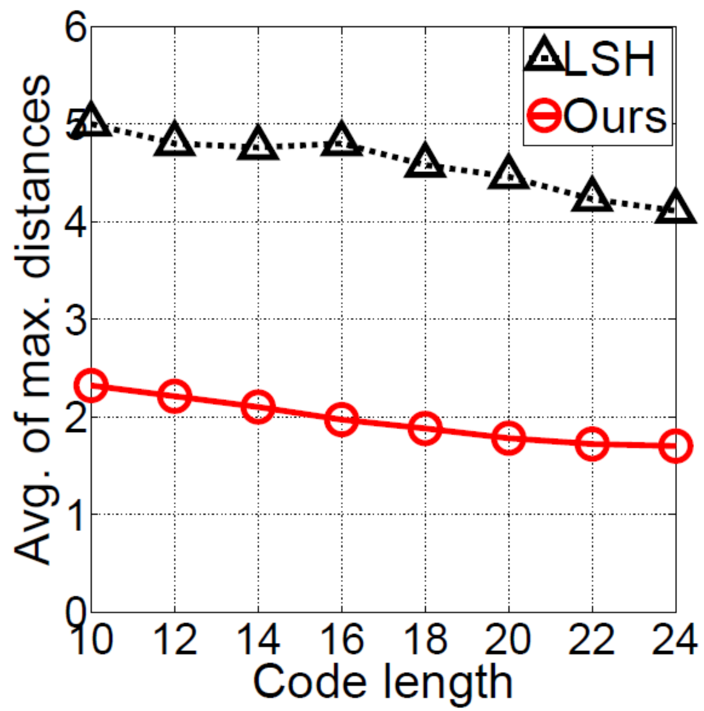
Spherical Hashing [Heo et al., CVPR 12]



Hyper-Sphere vs Hyper-Plane







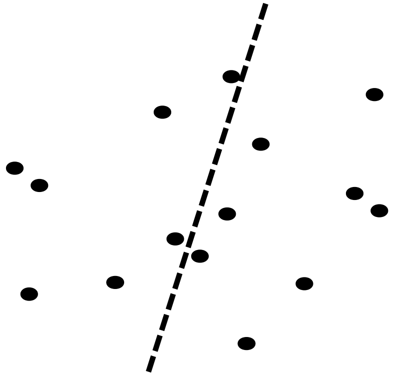
Average of maximum distances within a partition:
- Hyper-spheres gives tighter bound!

Components of Spherical Hashing

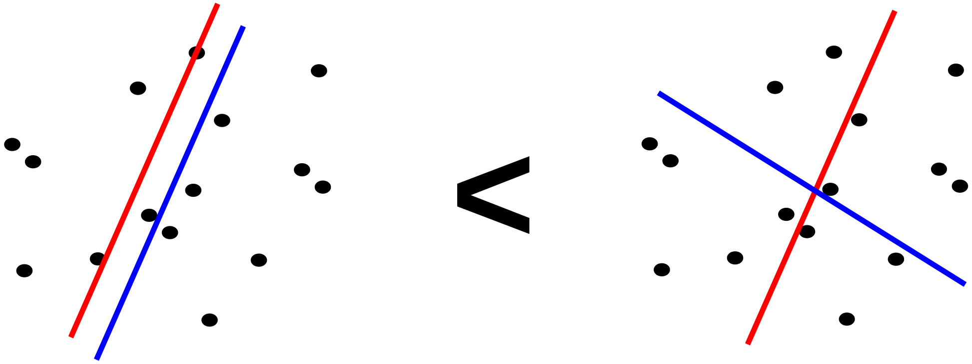
- Spherical hashing
- **Hyper-sphere setting strategy**
- Spherical Hamming distance

Good Binary Coding [Yeiss 2008, He 2011]

1. **Balanced partitioning**

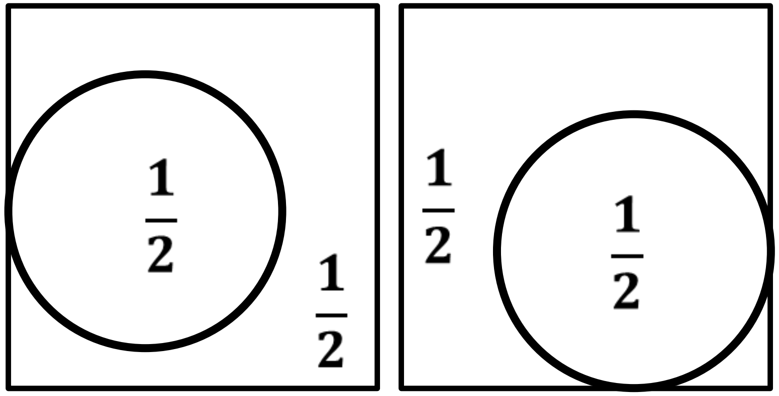


2. **Independence**

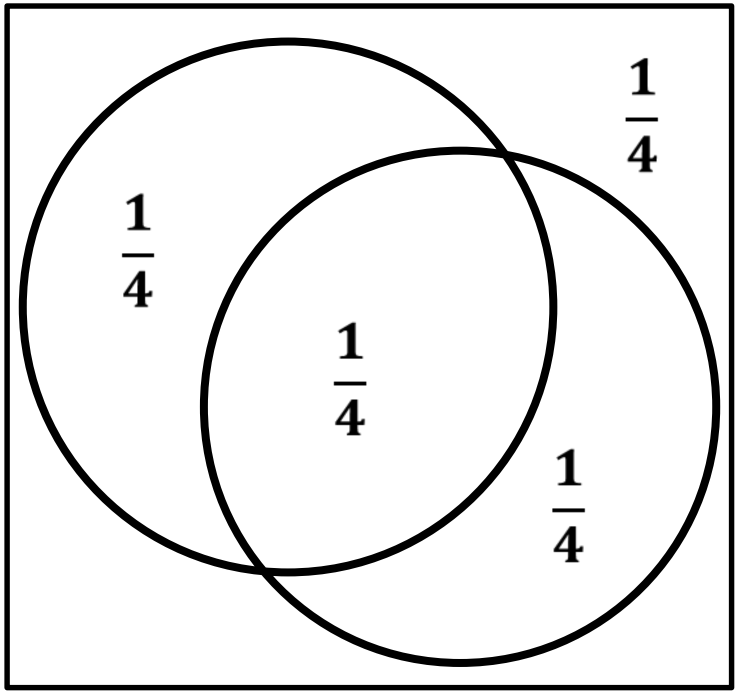


Intuition of Hyper-Sphere Setting

1. Balance

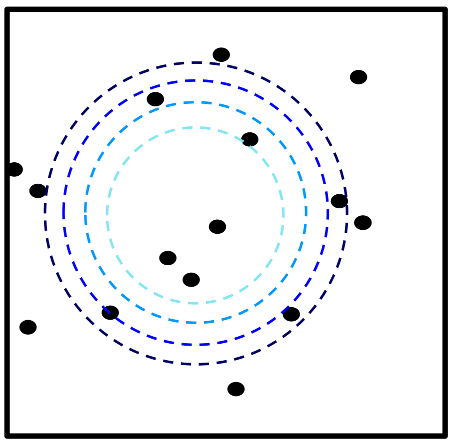


2. Independence

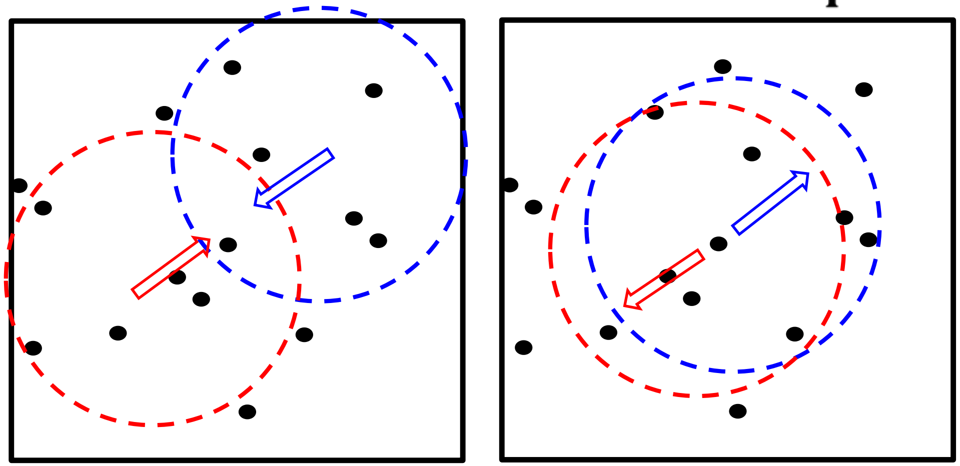


Hyper-Sphere Setting Process

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



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

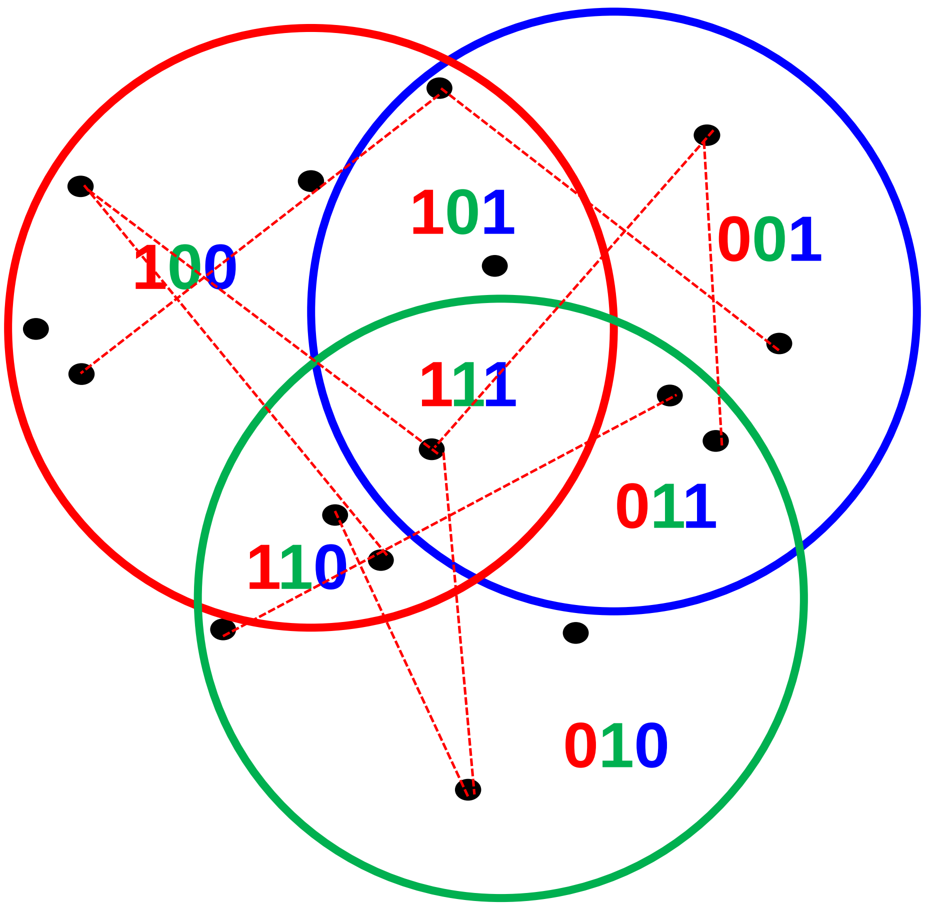


Iteratively repeat step 1, 2 until convergence.

Components of Spherical Hashing

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

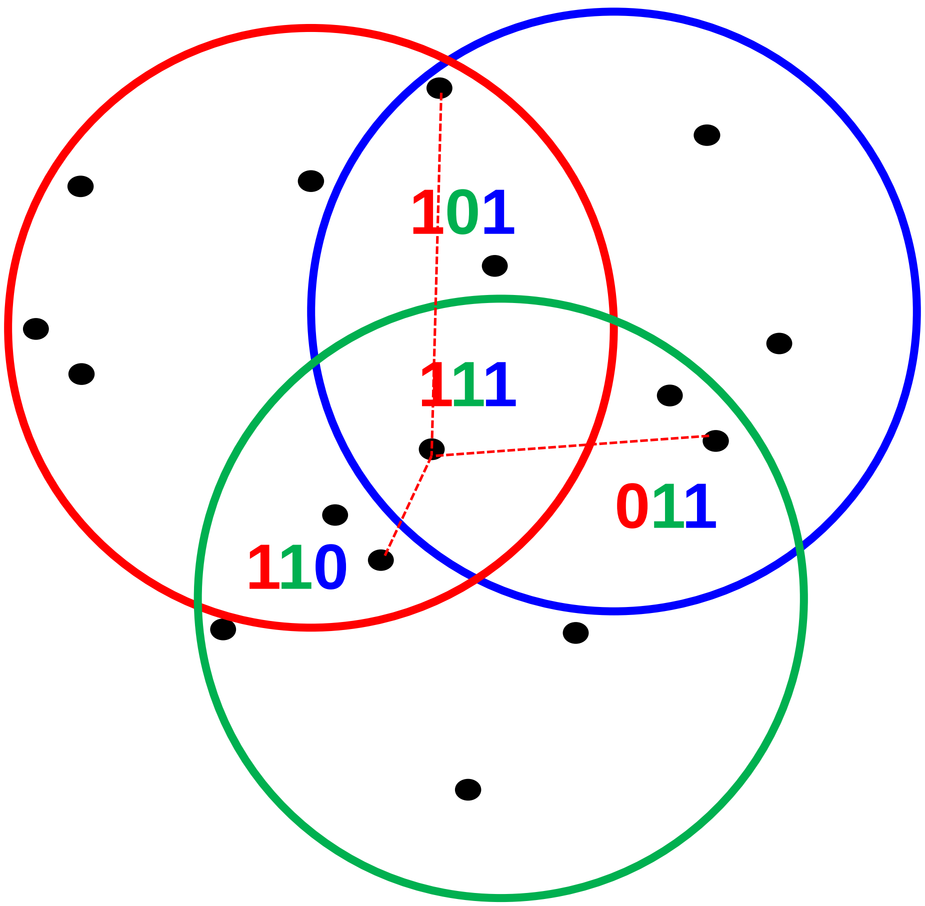
Max Distance and Common '1'



Common '1's

: 1

Max Distance and Common '1'

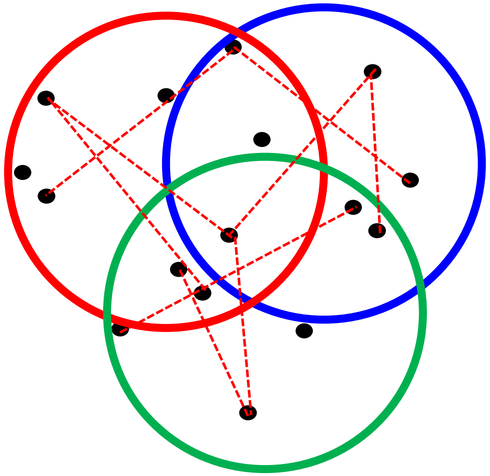


Common '1's

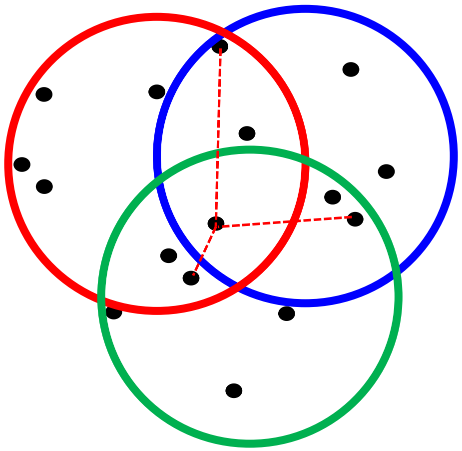
: **2**

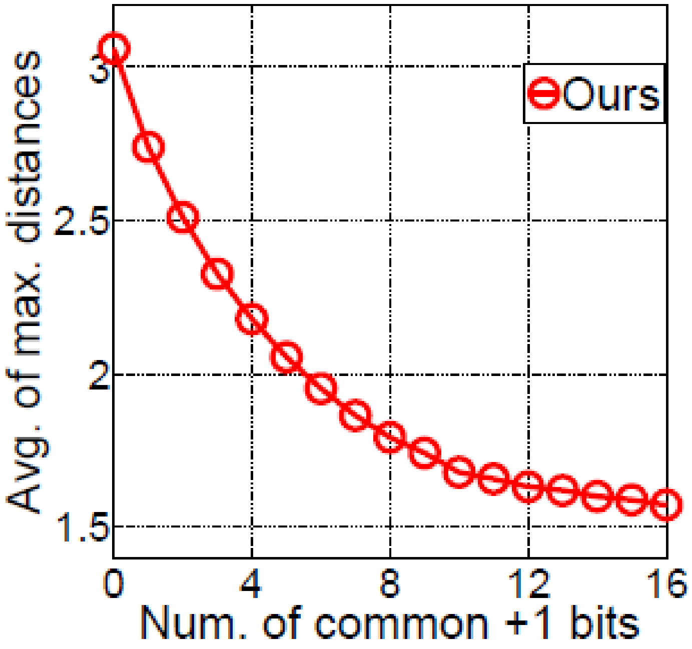
Max Distance and Common ‘1’

Common ‘1’s: **1**



Common ‘1’s: **2**





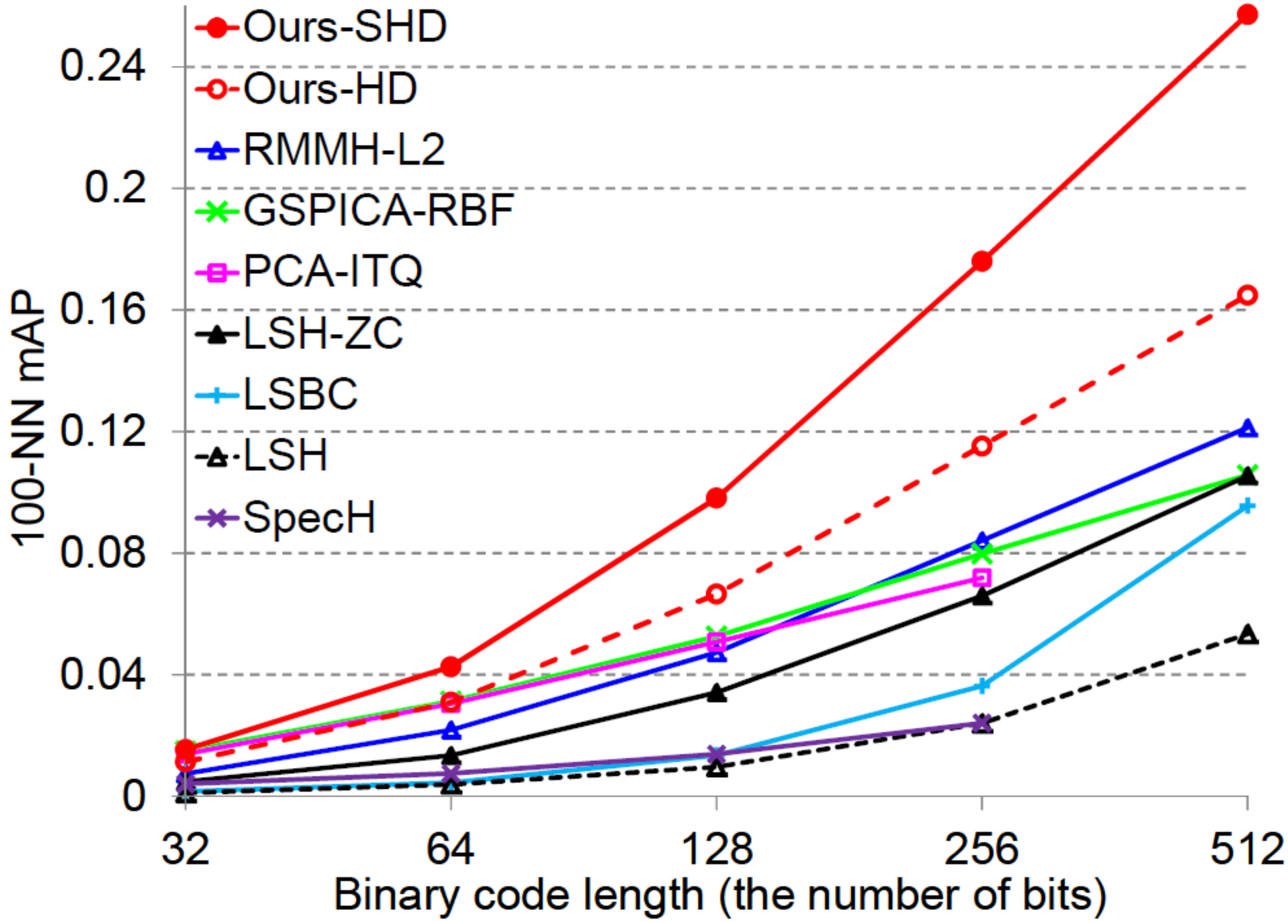
Average of maximum distances between two partitions: decreases as number of common ‘1’

Spherical Hamming Distance (SHD)

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

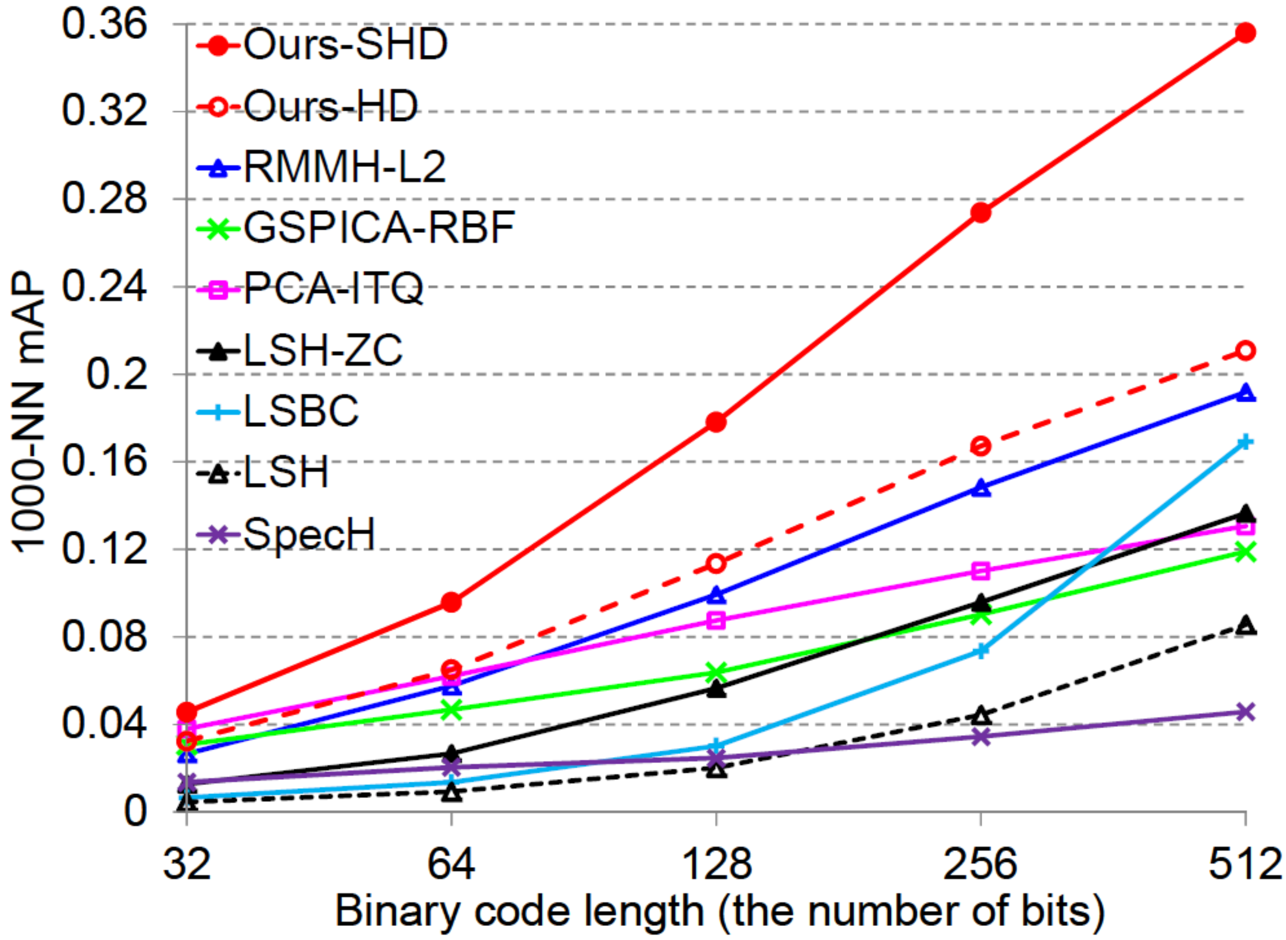
SHD: Hamming Distance divided by the number of common '1's.

Results



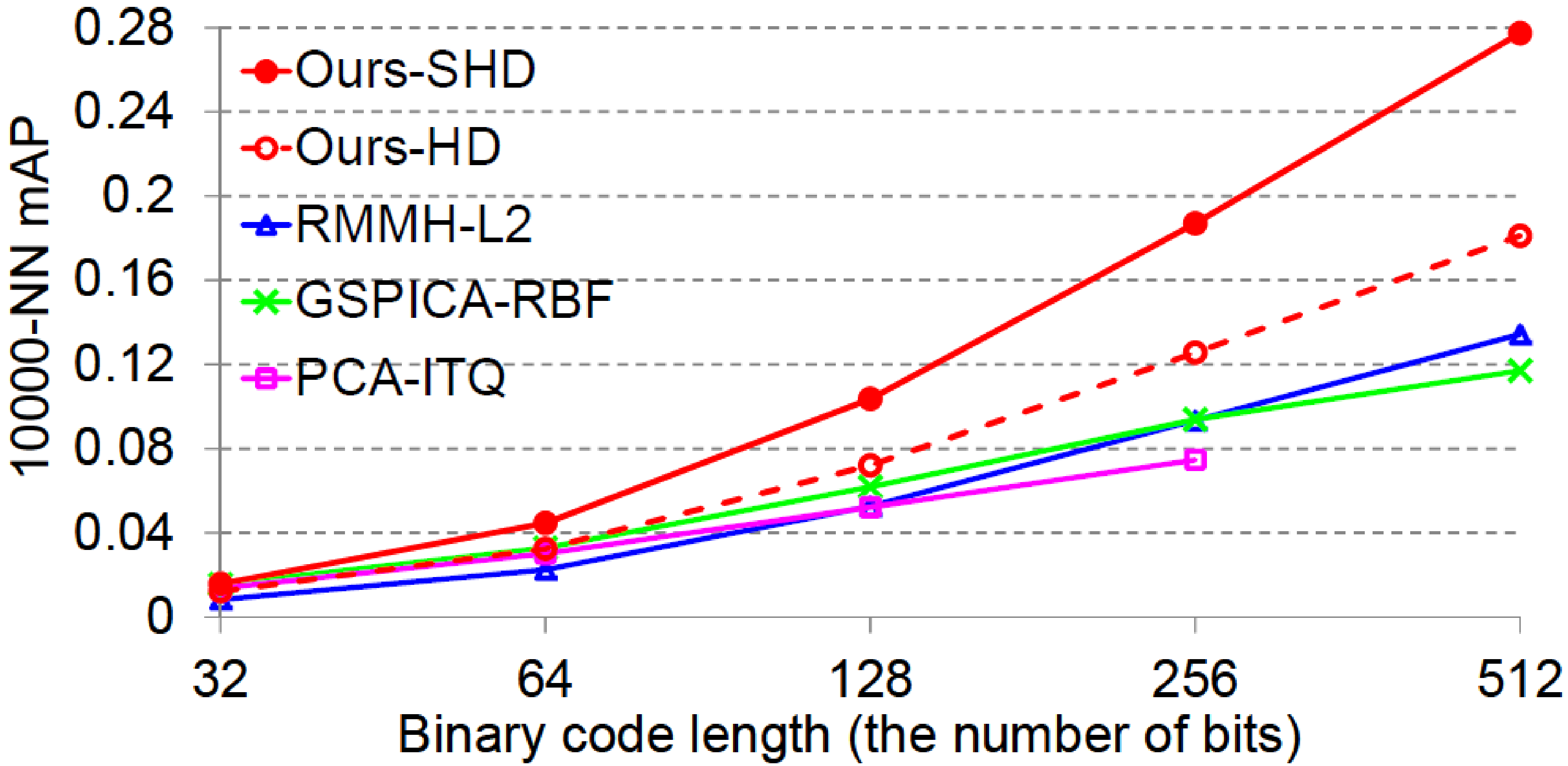
384 dimensional 1 million GIST descriptors

Results



960 dimensional 1 million GIST descriptors

Results



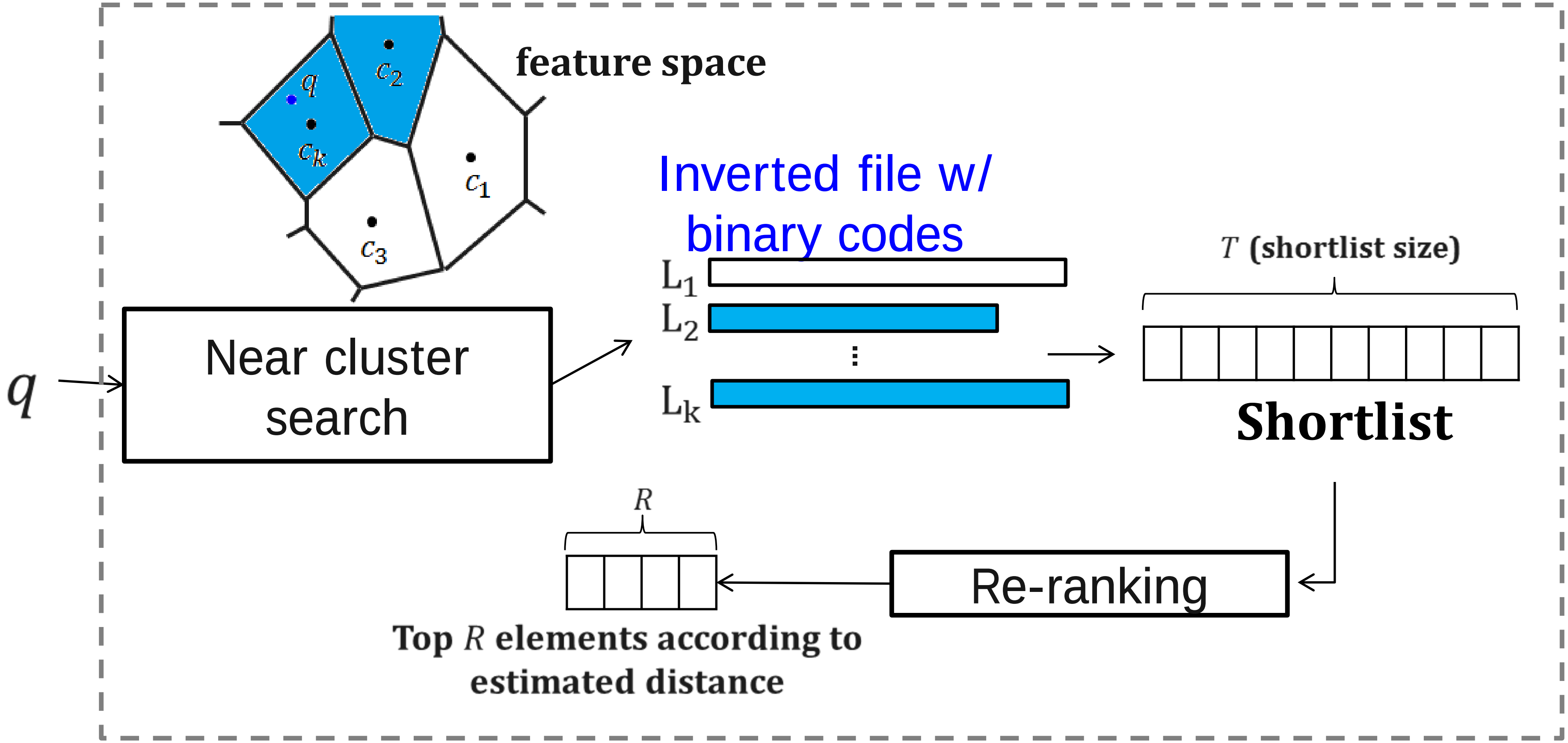
384 dimensional 75 million GIST descriptors

Summary

- The need of binary code embedding

- Spherical binary code embedding
  - Uses spherical hashing for tighter bounds
  - Iterative process to achieve balance and independence
  - Spherical Hamming distance

Summary



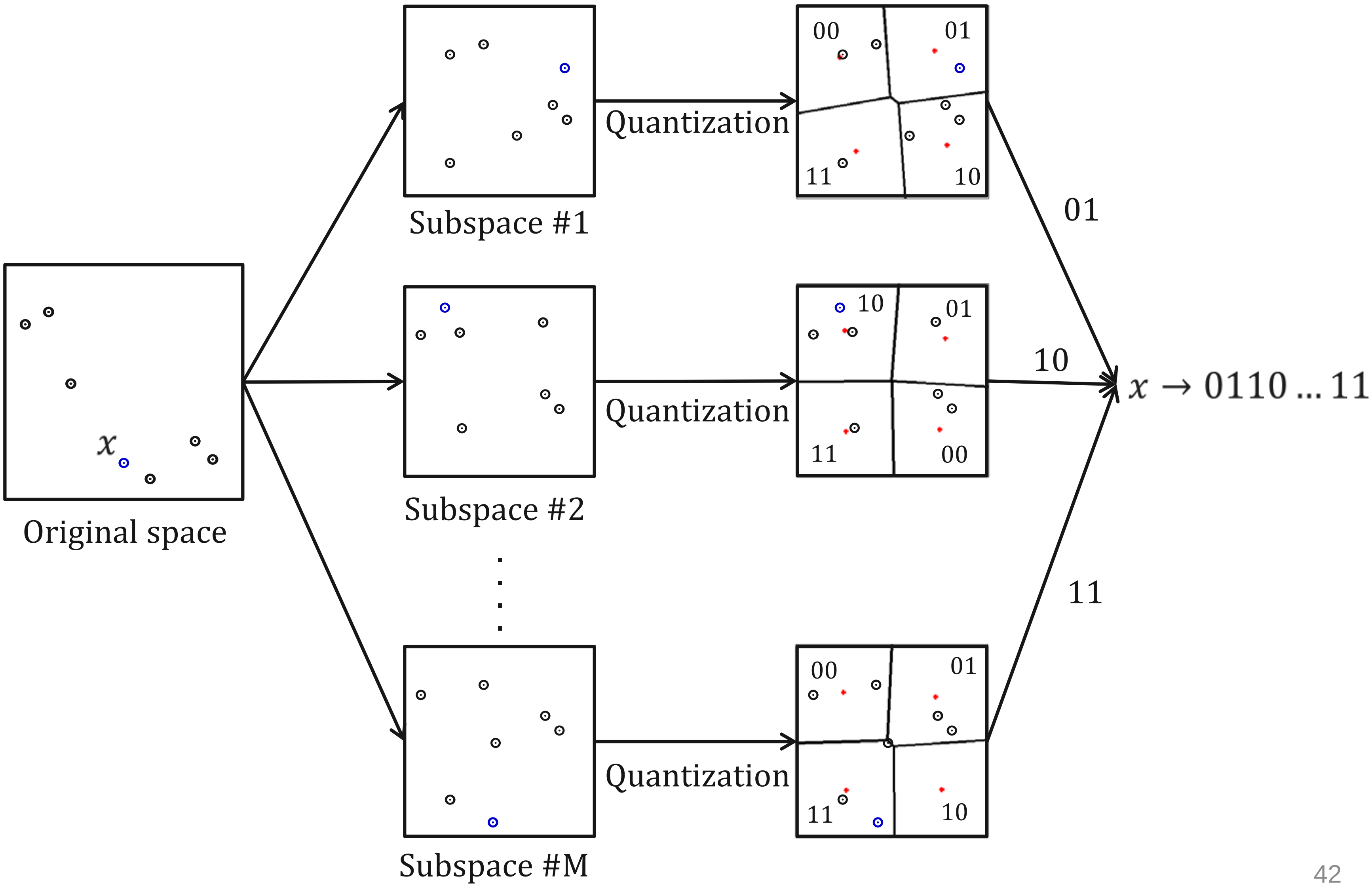
Ack.: Dr. Heo

Distance Encoded Product Quantization

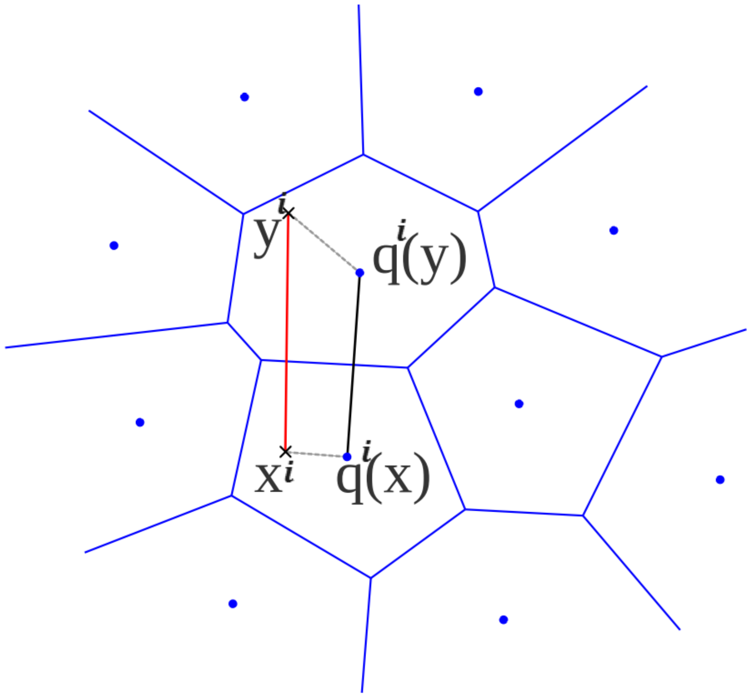
Jae-Pil Heo, Zhe Lin, and Sung-Eui Yoon

CVPR 2014

PQ: Product Quantization [Jegou et al., TPAMI 2011]

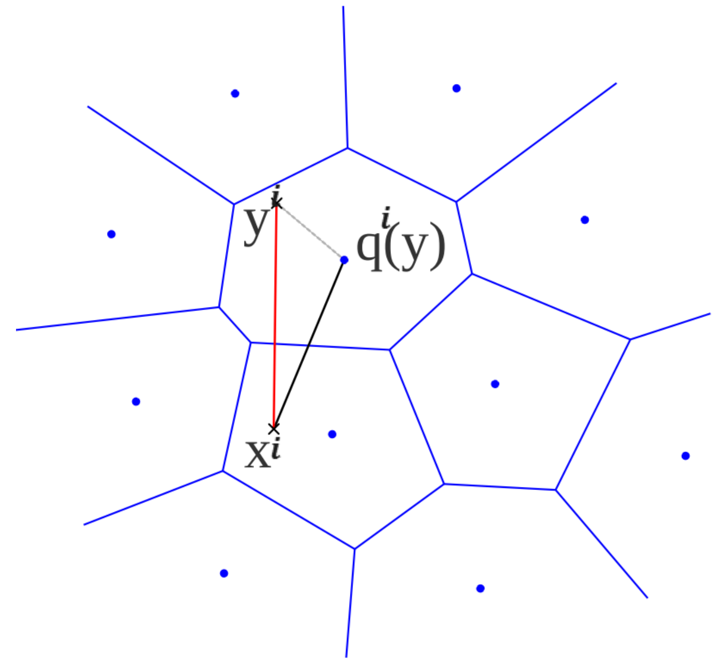


Distance Computation in PQ



Symmetric Distance

$$d_{SD}^{PQ}(x,y)^2 = \sum_{i=1}^{M} \left\| q^i(x^i) - q^i(y^i) \right\|^2$$



Asymmetric Distance

$$d_{AD}^{PQ}(x,y)^2 = \sum_{i=1}^{M} \left\| x^i - q^i(y^i) \right\|^2$$

Terms

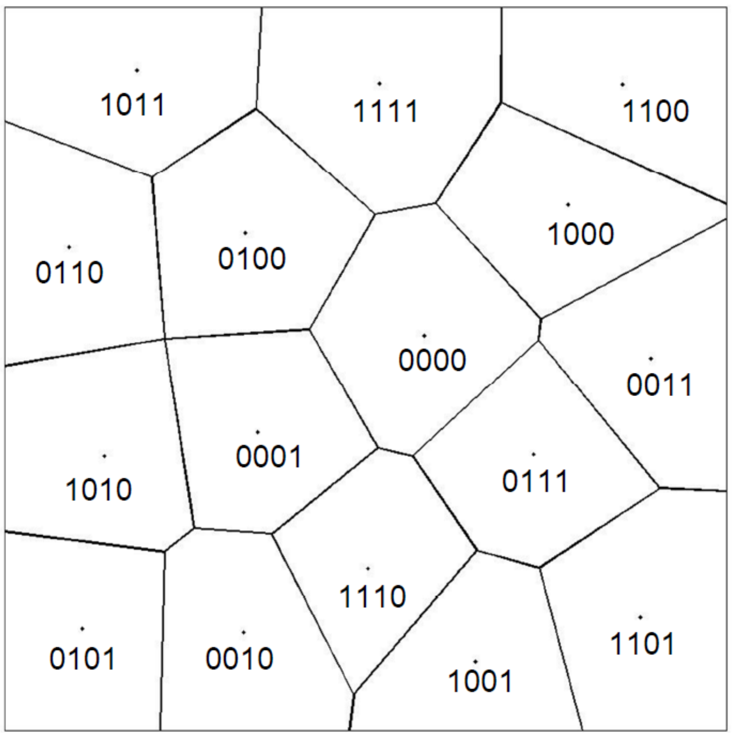
x: query, y: data, M: # of Subspaces,

q^i: quantizer in i^{th} subspace, x^i: sub-vector of x in i^{th} subspace

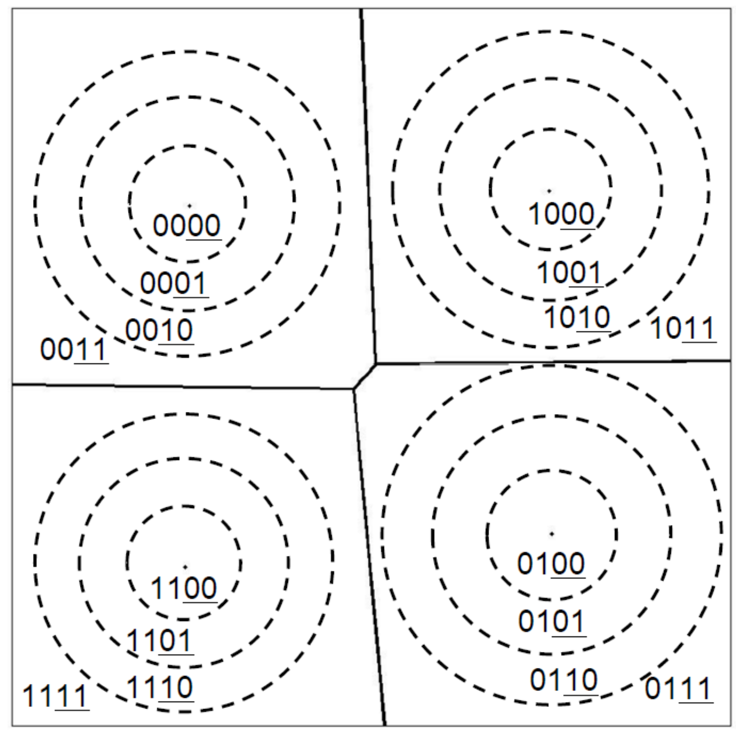
Figures are from [Jegou et al., TPAMI 2011]

DPQ: Distance Encoded PQ

- DPQ encodes quantized distance from the center as well as the cluster index in each subspace.

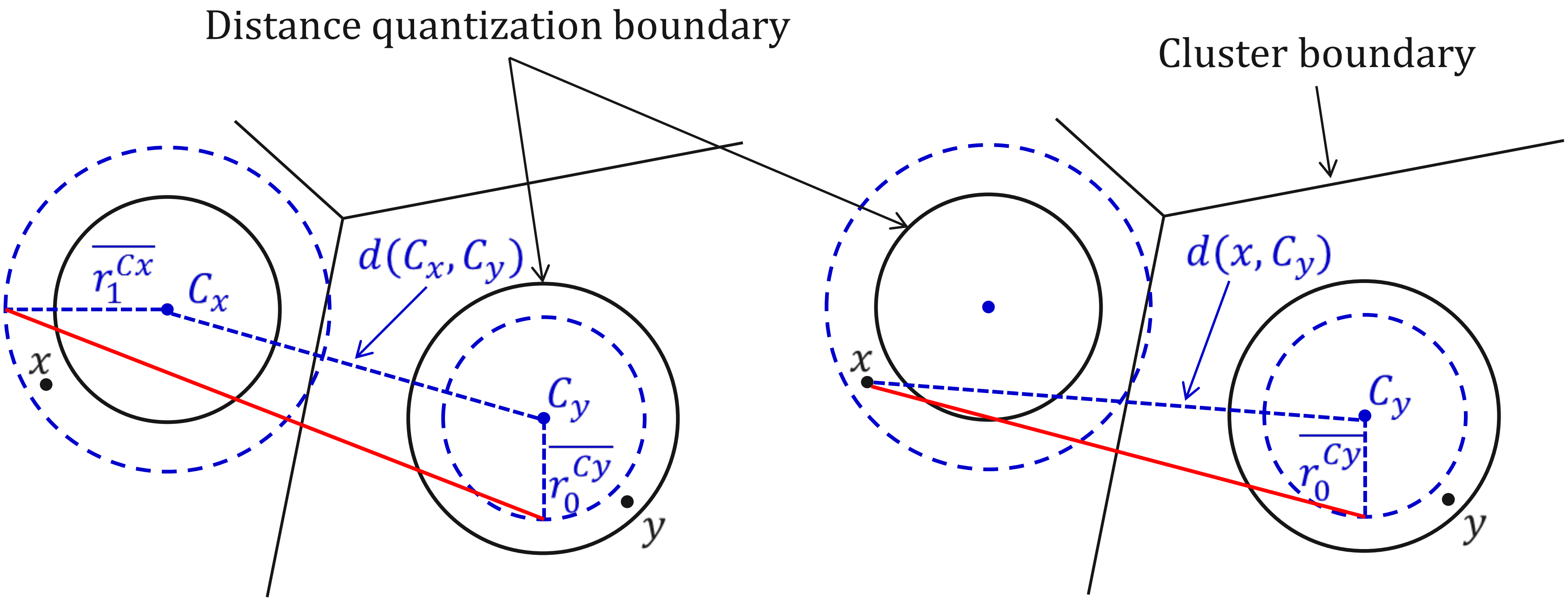


PQ example



DPQ example

Distance Computation in DPQ



Symmetric Distance

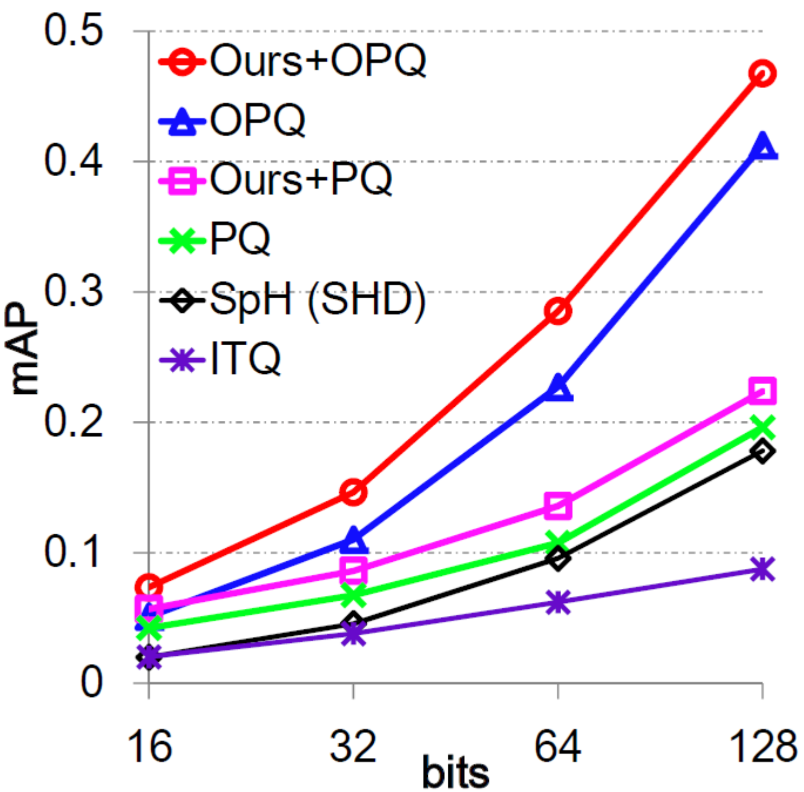
Asymmetric Distance

$$d_{SD}^{DPQ}(x,y)^2 = d(C_x, C_y)^2 + \overline{r_1^{Cx}}^2 + \overline{r_0^{Cy}}^2$$

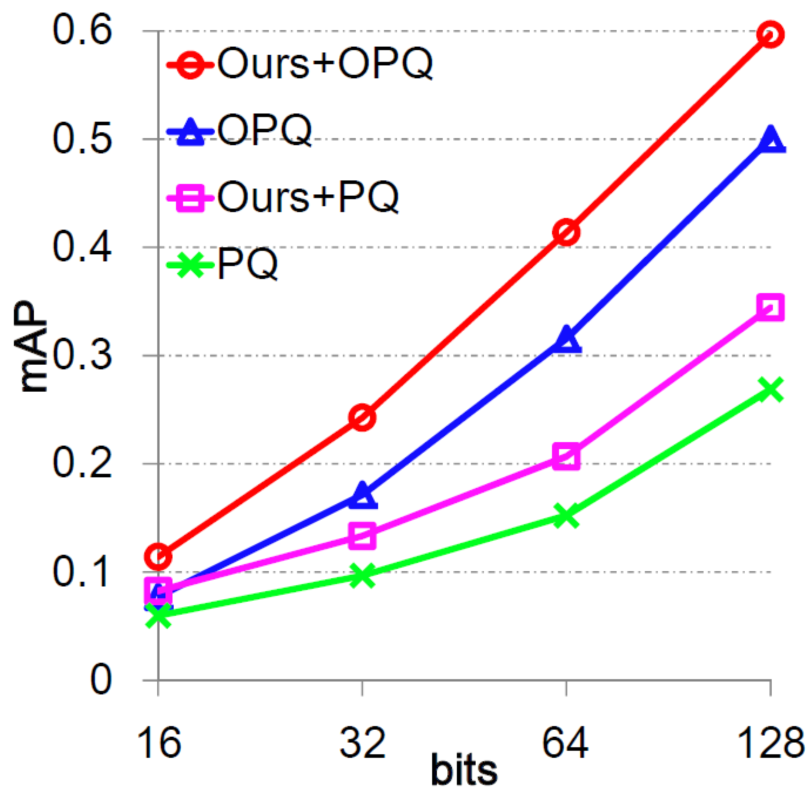
$$d_{SD}^{DPQ}(x,y)^2 = d(x, C_y)^2 + \overline{r_0^{Cy}}^2$$

$\overline{r_j^{C}}$: average distance from the center to points whose cluster center is C and quantized distance index is j

Results on GIST-1M-960D



Symmetric distance



Asymmetric distance

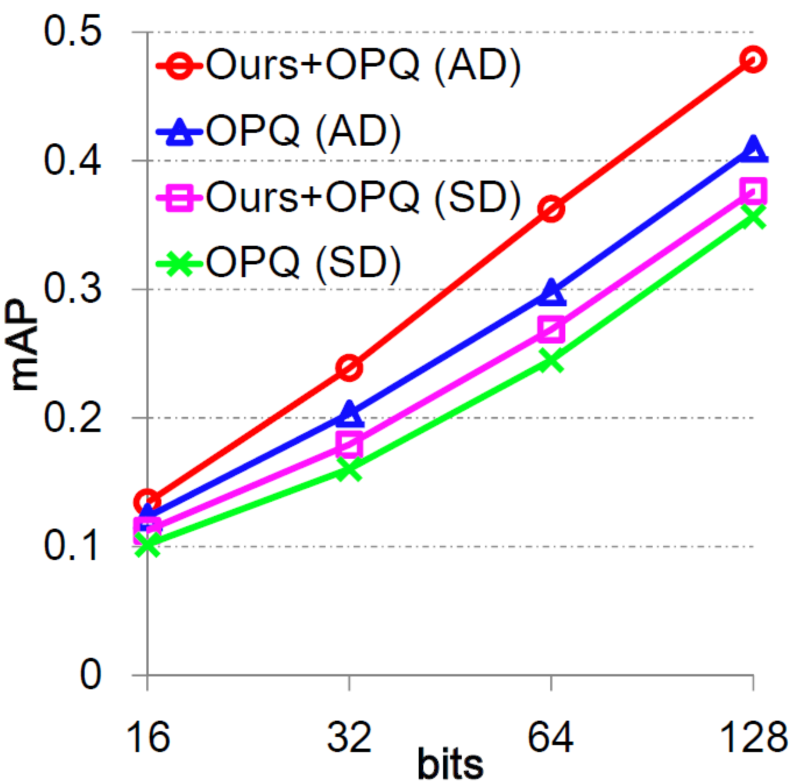
1000-nearest neighbor search mAP

OPQ: Optimized PQ [Ge et al., CVPR 2013]

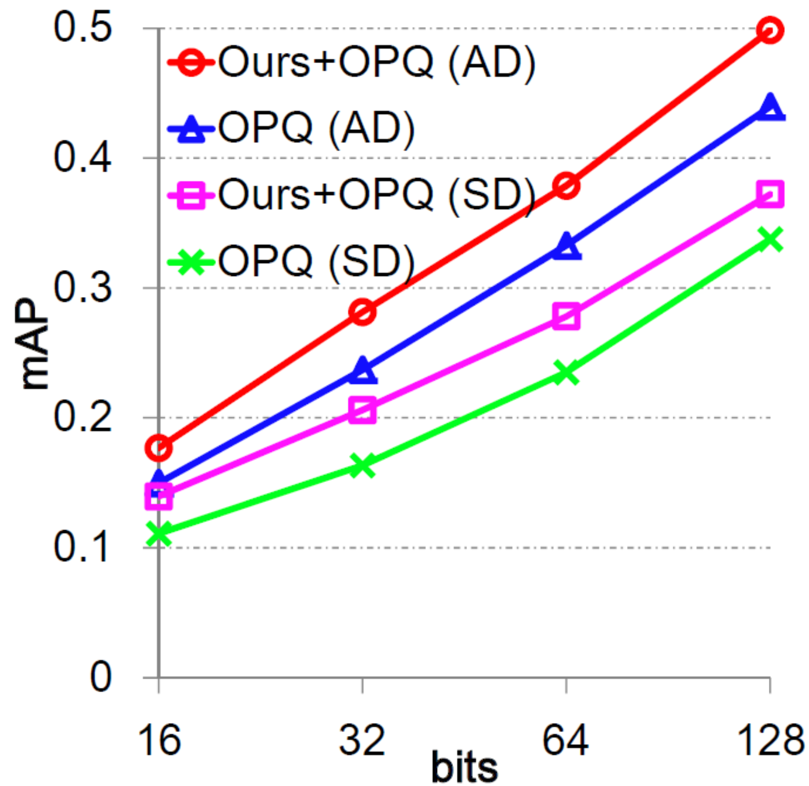
SpH: Sperical Hashing [Heo et al., CVPR 2012]

ITQ: Iterative Quantization [Gong and Lazebnik, CVPR 2011]

Results on BoW-1M-1024D



Original Data



L_2 Normalized data

1000-nearest neighbor search mAP

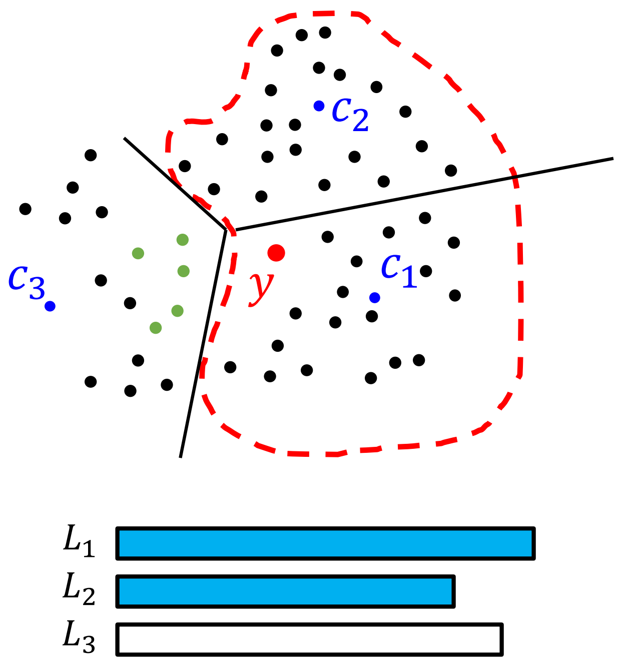
SD: Symmetric distance

AD: Asymmetric distance

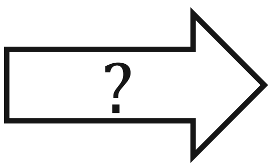
Residual-Aware Shortlist Retrieval

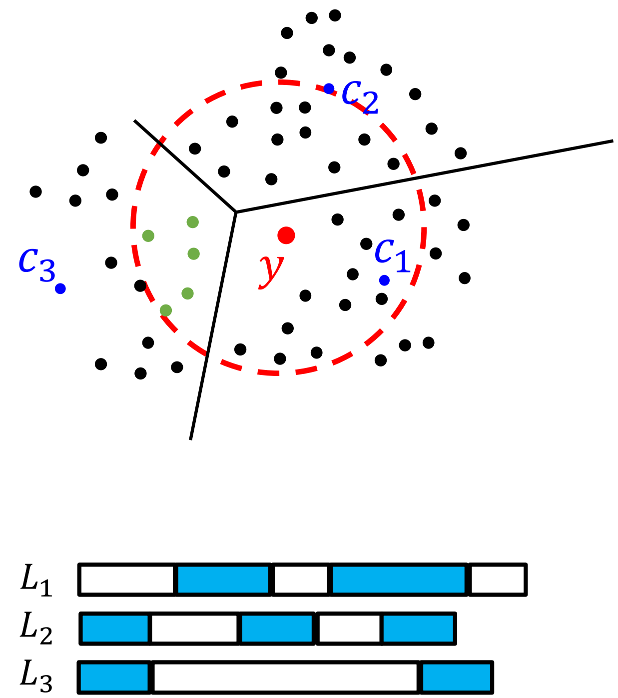
[Jaepil et al., CVPR 2016]

Limitation of prev. methods



Neighbors could be missed due to the quantization error

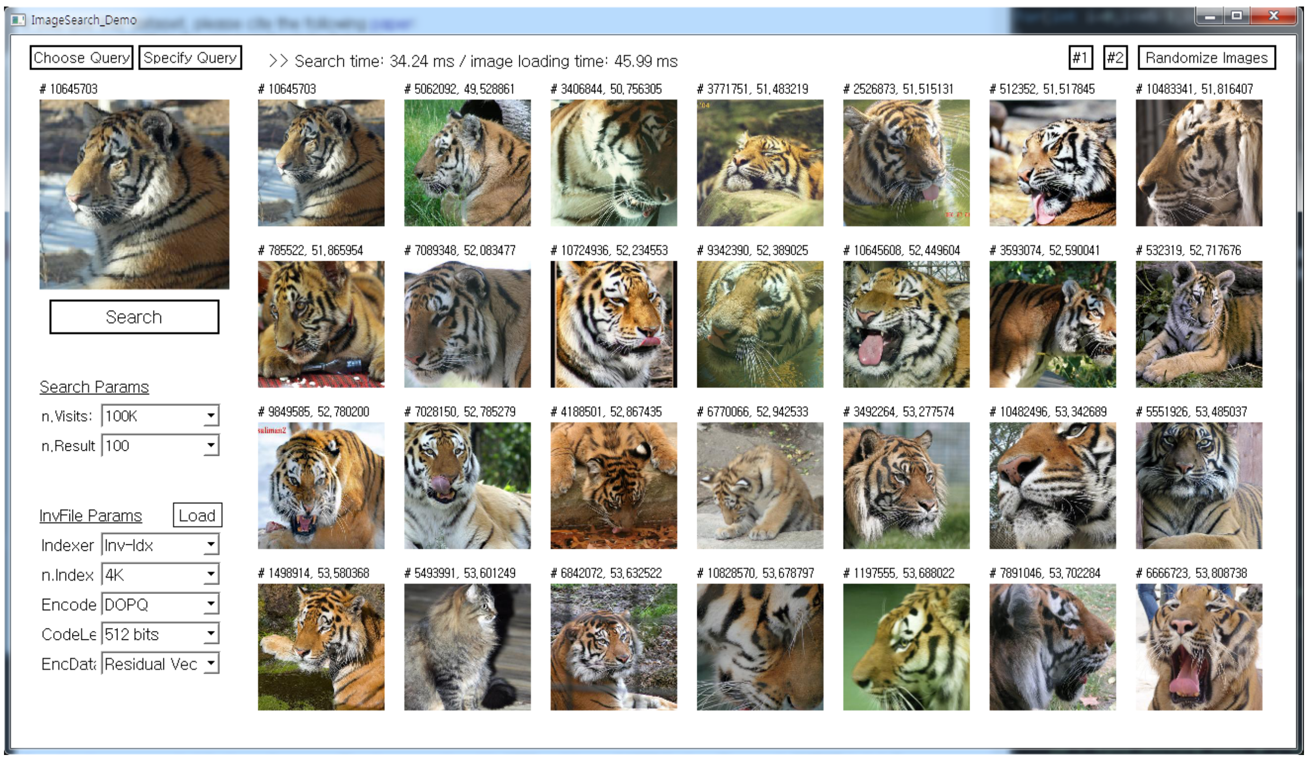




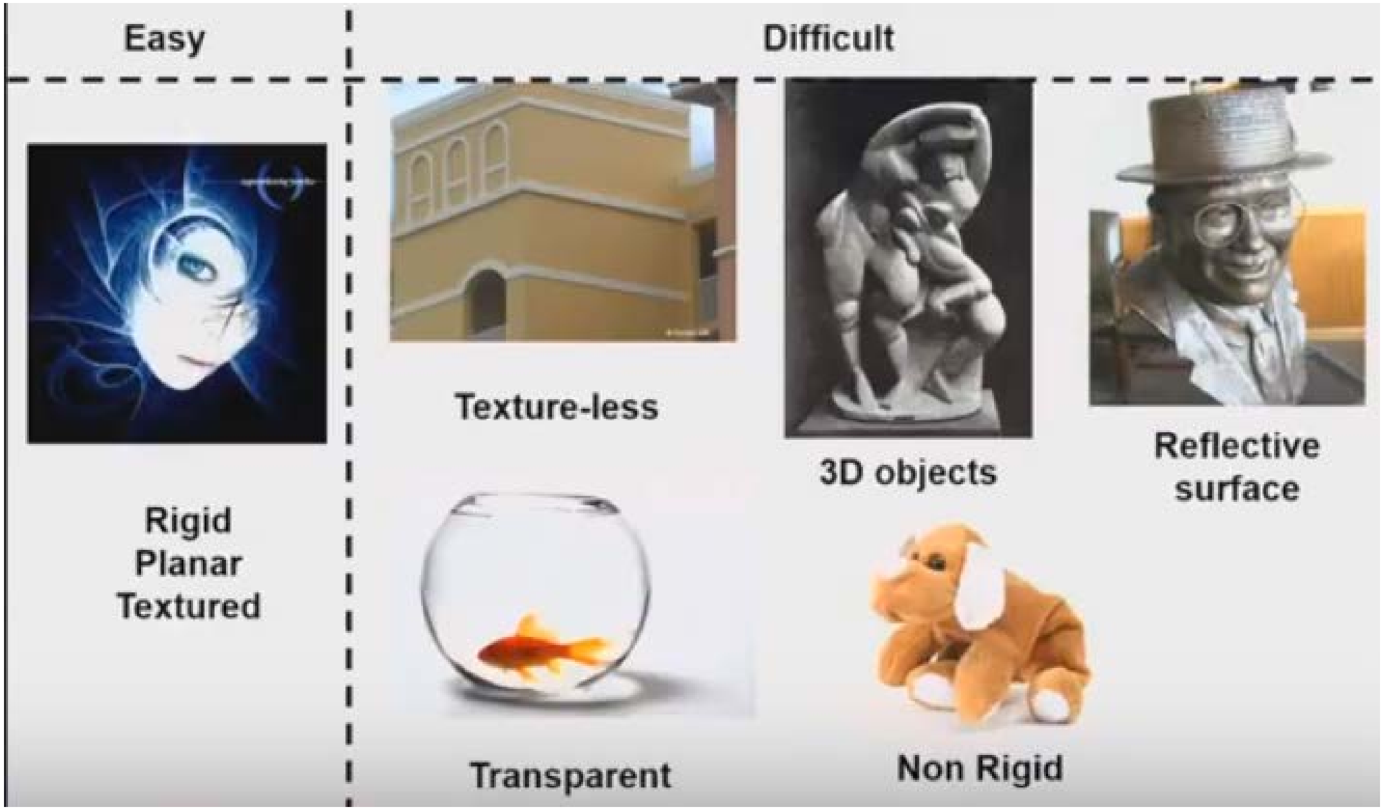
Select promising subset in parallel from all the lists

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**



Limitations of Image Search



Ack: Vijay Chandrasekhar

- **Large-scale video retrieval**
  - **30 frames per sec., 5 billion shared video at youtube**

Class Objectives were:

- **Understand the basic hashing techniques based on hyperplanes**
- **Get to know a recent one based on hyperspheres**
- **Codes are available**

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

Next Time…

- **Novel applications**