Supervised Set-to-Set Hashing in Visual Recognition

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Outline

- Introduction
- Set-to-Set Hashing
- Results
- Summary

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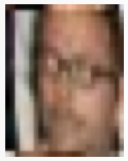
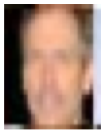
Point to Point (P2P) Hashing

Image (face) with real-valued feature vector

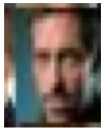


?

Similarity



0.1



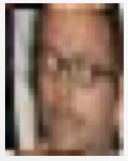
0.1

0.8 ✓

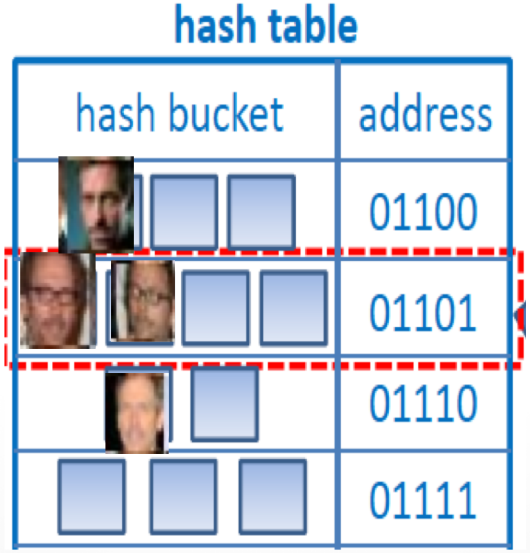
- time: O(n), increase with database size
- storage: high dimension of float number

x = [0.23, -0.2, 0.1, …, 0.8]

Feature vector to hash codes



?



✓

- time: O(1), independent of database size
- storage: low dimension of bits

x = [0 1 1 0 1]

Introduction

- P2P (ANN) search characteristics:
  - Computational time (sublinear search complexity)
  - Storage space

- What are the unsolved problems ?
  - How to measure distance between sets
    - Is there any useful information

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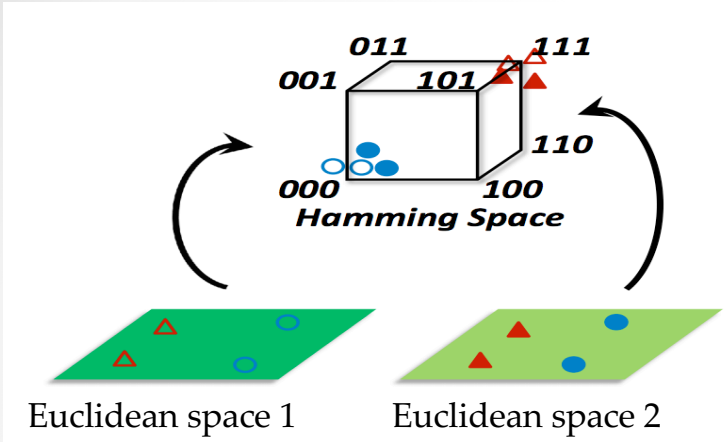
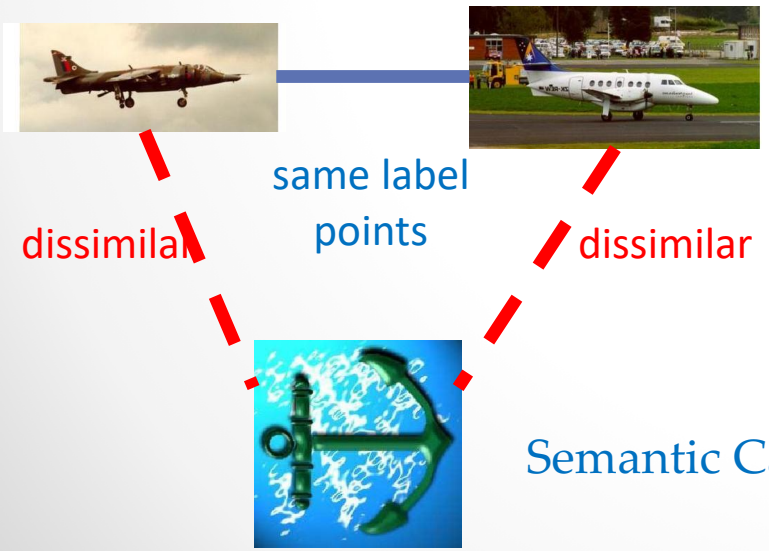
Set to Set (S2S) Hashing

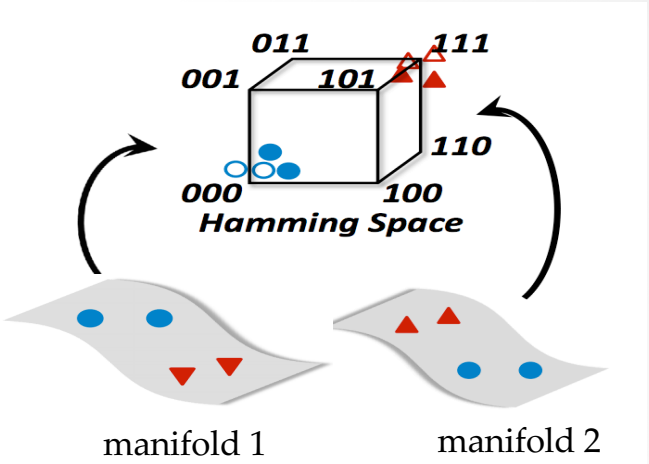
Supervised Information



Traditional hash learning methods

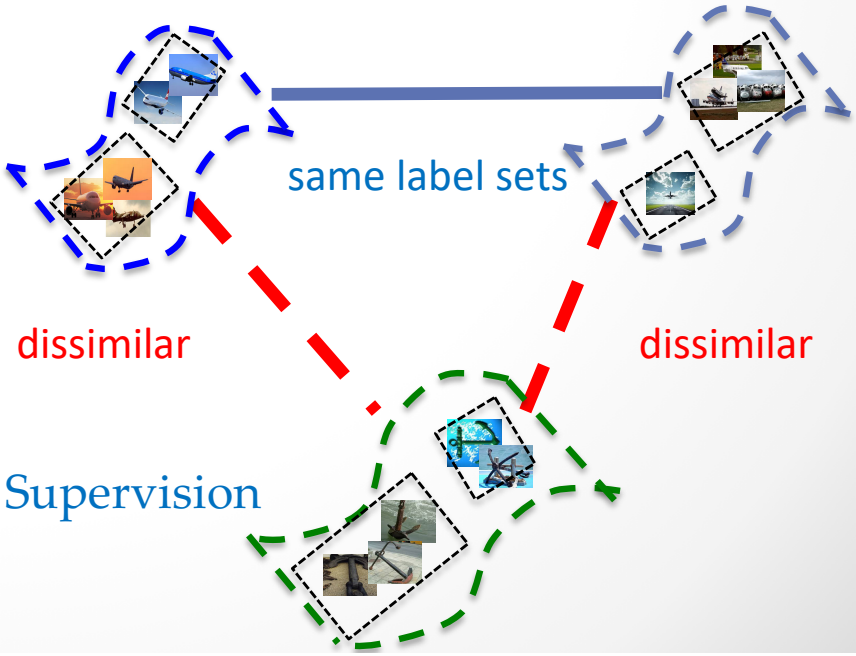
Point-to-point setting





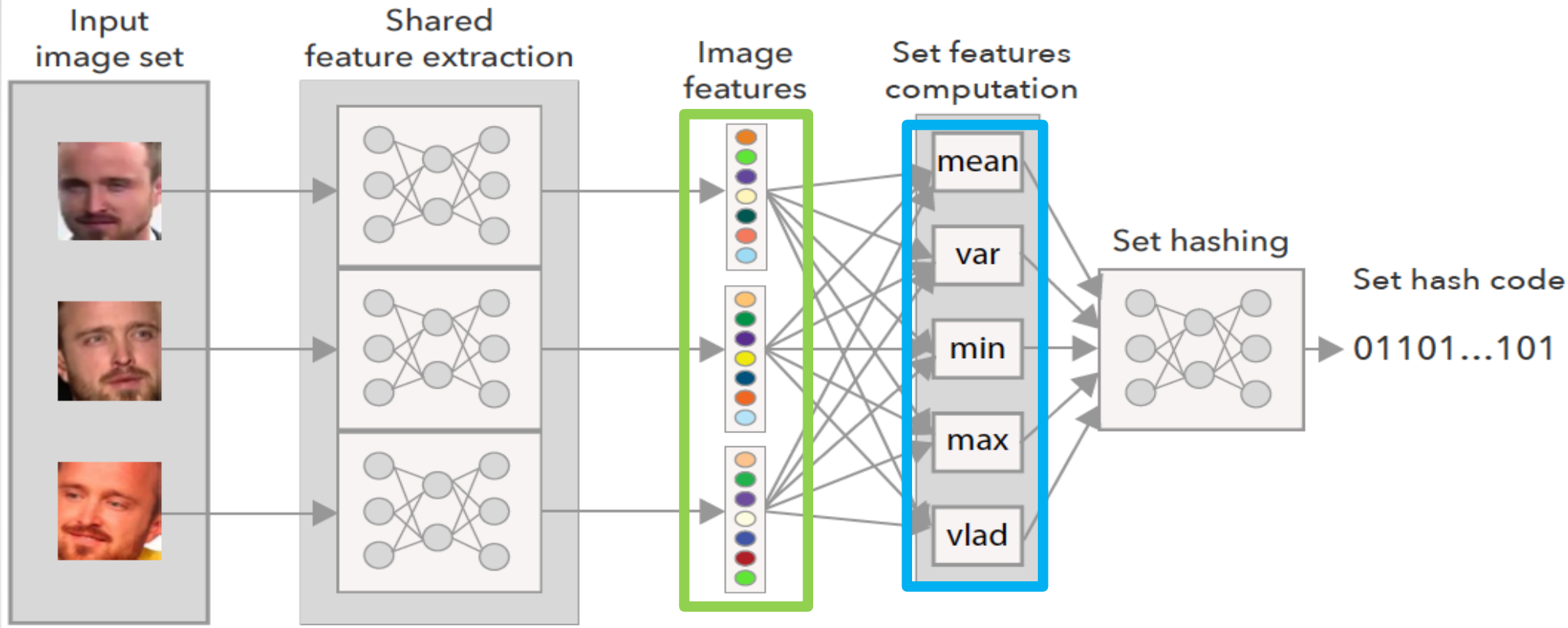
Proposed image set hash learning method

Set-to-set setting



Semantic Category Supervision

Image Set Hashing



Reference:

- Deep Image Set Hashing, [arXiv:1606.05381v2, 2016]
- End-to-End image Set hashing, but **No** structural Information

Introduction

- **What are we proposing?**

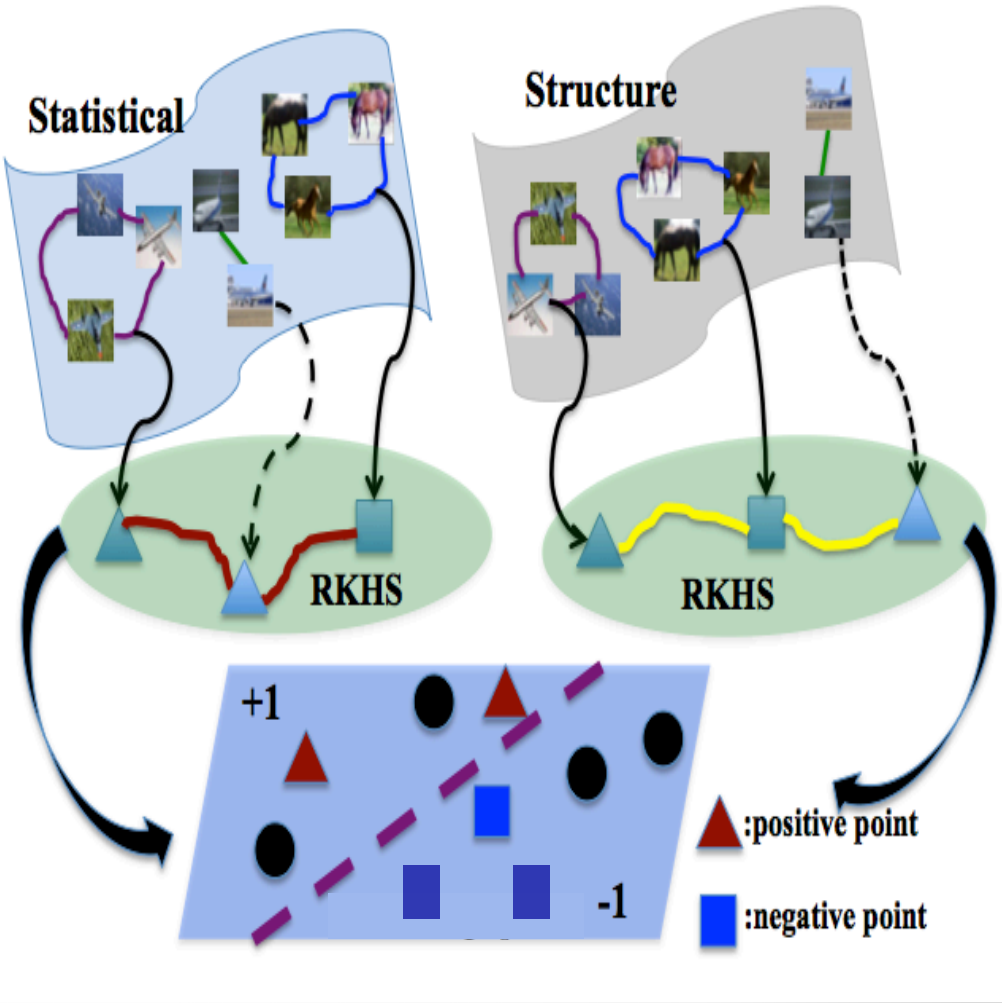
  - Set-to-Set Hashing => binary codes for a set

  - Multiple information => statistical & structural information to improve the retrieval performance

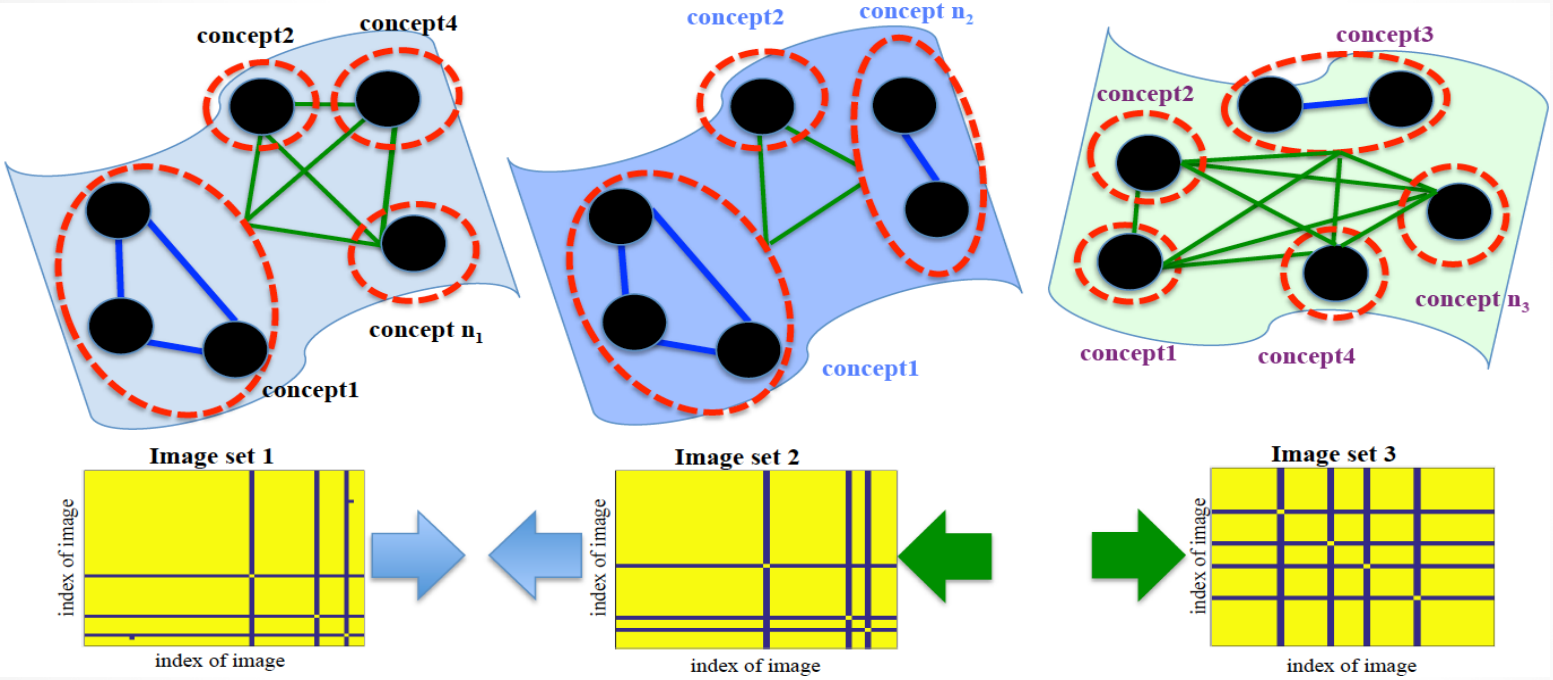
  - State-of-the-art results

Multiple Information for Image Set Hashing

- Statistical information:
  - Gaussian-logarithm kernel
- Structural information:
  - Graph kernel to capture topological (clique decomposition) similarity



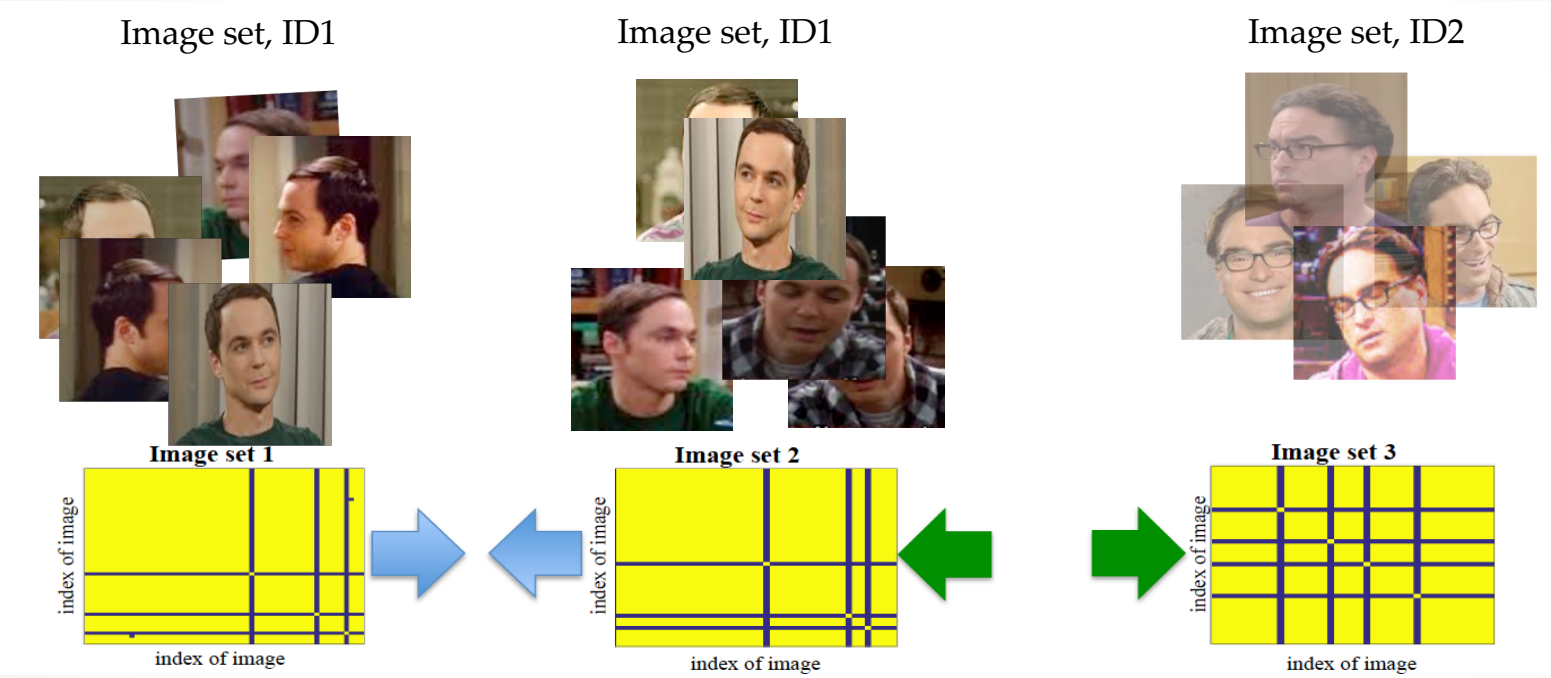
Structural Information and Similarity Measure



- Structural information: $K_g(\mathbf{x}_i, \mathbf{x}_j) = \frac{\sum_{p=1}^{n_i}\sum_{q=1}^{n_j} A_{ip}A_{jq}g(x_{ip}, x_{jq})}{\sum_{p=1}^{n_i} A_{ip}\sum_{q=1}^{n_j} A_{jq}}$

- Statistical information: $K_s(\mathbf{x}_i, \mathbf{x}_j) = \phi(C_i)^\top \phi(C_j)$
$= exp(-||log(C_i) - log(C_j)||_F^2 / 2\gamma_s^2)$

Structural Information and Similarity Measure



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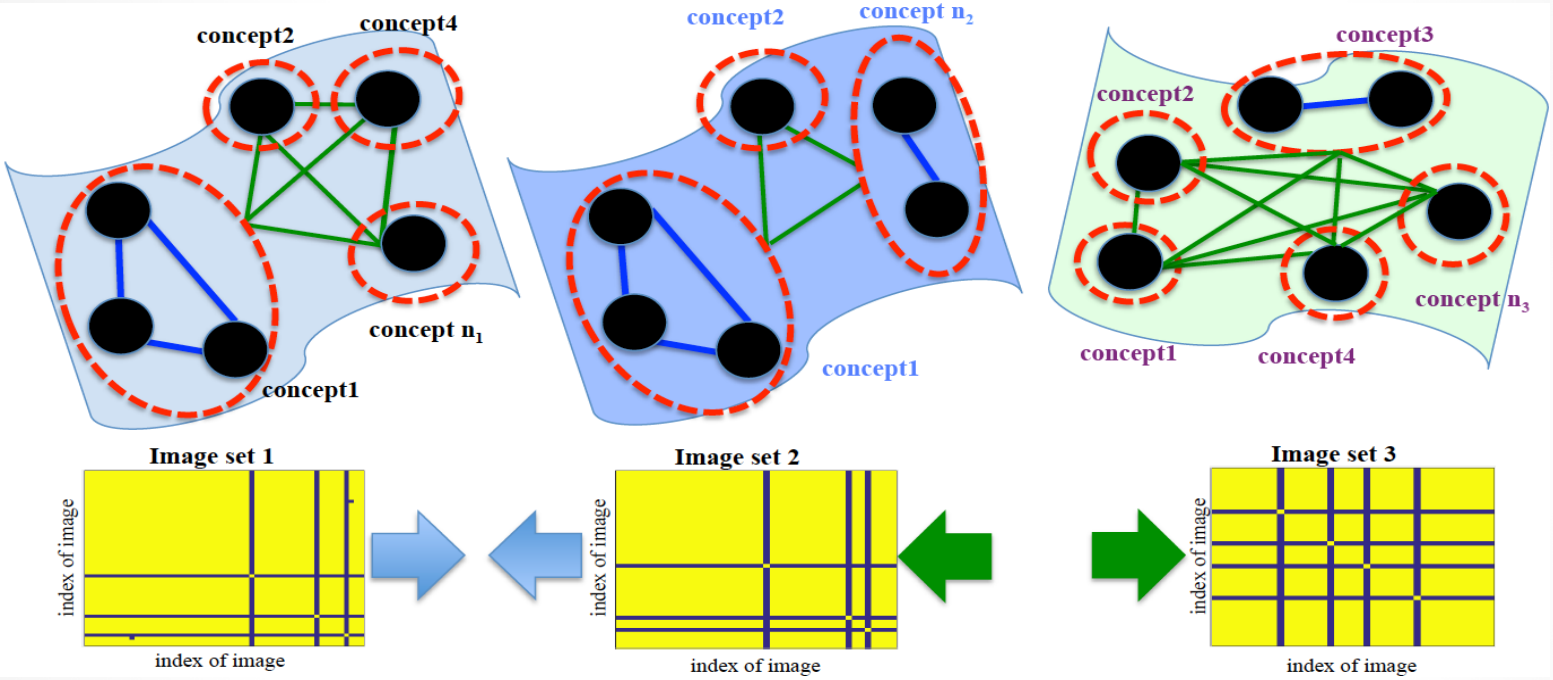

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The Mapping Function

Weak Learners:

$$f(\mathbf{x}) = \text{sign}(K_m(\mathbf{x}_a, \mathbf{x}) - K_m(\mathbf{x}_b, \mathbf{x}) + \varepsilon)$$

positive — The m_{th} kernel — negative

A strong split (bit):

$$F(\mathbf{x}) = \text{sign}(\sum_{t=1}^{T} \lambda^t f^t(\mathbf{x}))$$

The best weak learner
at iteration t

Image Set Hashing via Multiple Information

- Problem Formulation

$$\min_{H_q, H_r} \underbrace{\alpha D_s}_{\text{Discriminative property}} + \underbrace{\beta D_c}_{\text{Refining hash code}} + \underbrace{\nu_1 \sum_{\substack{r' \in \{1:R\} \\ i \in \{1:N\}}} \Omega}_{\text{MKL}}$$

$$s.t. \quad H_q^{r'i} = sgn\left(\sum_{t=1}^{T} \lambda_t f_q^{tr'}(\mathbf{x}_i)\right), \forall i \in \{1:N\}, \forall r' \in \{1:R\}$$

$$H_r^{r'i} = sgn\left(\sum_{t=1}^{T} \lambda_t f_r^{tr'}(\mathbf{x}_i)\right), \forall i \in \{1:N\}, \forall r' \in \{1:R\}$$

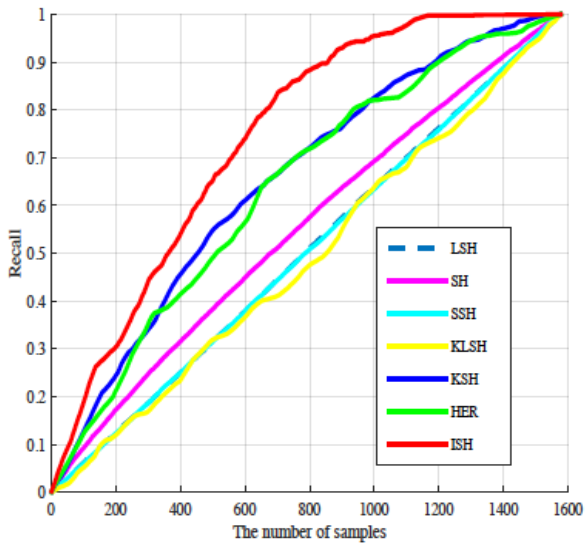
Experiment Settings

- Dataset:
  - CIFAR-10: 60, 000 images are randomly selected to 195 image sets for training process; 100 image sets for test query, the left images are around 50,000 for test database (around 1700 image sets)
  - Big Bang Theory video (image set) benchmark (BBT): 3,341 videos with 12 characters, 100 image sets for training, 100 image sets for test query, 3041 image sets for test database

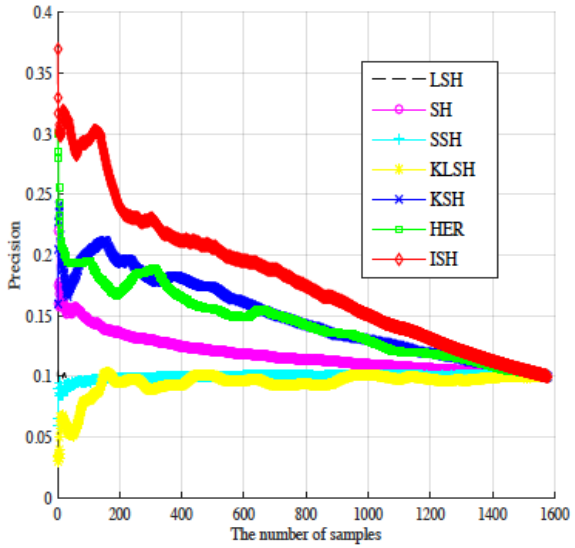
Retrieval Performance on CIFAR-10

	Compared Methods						Our Method
bits	LSH [13]	SH [49]	SSH [41]	KLSH [16]	KSH [21]	HER [18]	ISH
8bits	0.1063	0.1279	0.1165	0.1067	0.2363	0.2284	**0.2822**
12bits	0.1073	0.1330	0.1416	0.1210	0.2486	0.2672	**0.3069**
24bits	0.1086	0.1317	0.1512	0.1420	0.2680	0.2772	**0.3159**
32bits	0.1194	0.1322	0.1574	0.1501	0.2818	0.2937	**0.3292**
48bits	0.1105	0.1352	0.1629	0.1622	0.3003	0.3154	**0.3334**

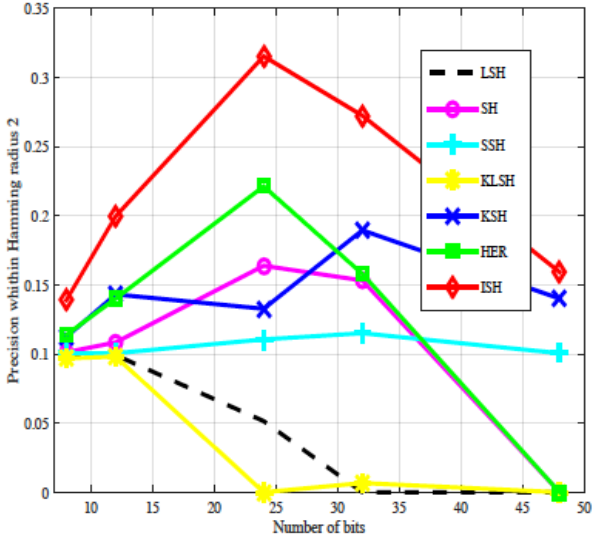
Performance on CIFAR-10. KLSH, KSH, HER, ISH use image sets as input



Recall curve @24 bits



Precision curves @24 bits

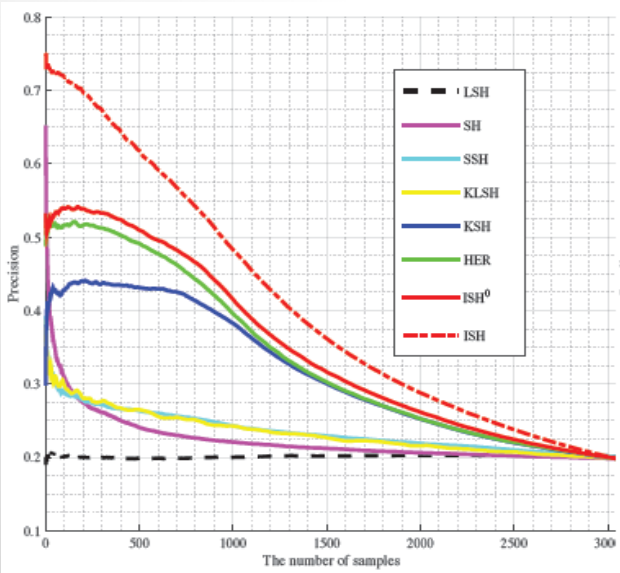


Hamming radius 2

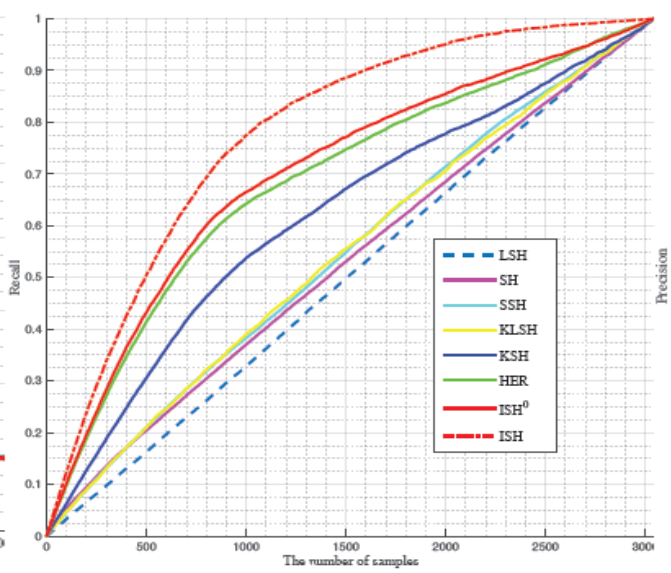
Performance on BBT TV-series

	TV drama: the Big Bang Theory				
Method	8 bits	16 bits	32 bits	64 bits	128 bits
LSH [13]	0.2109	0.2086	0.2092	0.1963	0.1994
ITQ [10]	0.2935	0.3025	0.2989	0.3029	0.3060
SH [49]	0.2377	0.2652	0.2665	0.2623	0.2673
DBC [30]	0.4489	0.4495	0.4235	0.4005	0.3867
SSH [42]	0.2716	0.2855	0.2662	0.2584	0.3003
MM-NN [25]	0.3752	0.3955	0.4664	0.5124	0.4922
KLSH [16]	0.2450	0.2498	0.2381	0.2256	0.2325
KSH (point)	0.4090	0.4366	0.4454	0.4567	0.4604
KSH [21] (set)	0.4590	0.4619	0.4534	0.4685	0.4631
HER [18]	0.4606	0.5049	0.5227	0.5490	0.5539
ISH^0	0.4833	0.5279	0.5359	0.5501	0.5712
ISH	**0.5018**	**0.5592**	**0.5864**	**0.6007**	**0.6280**

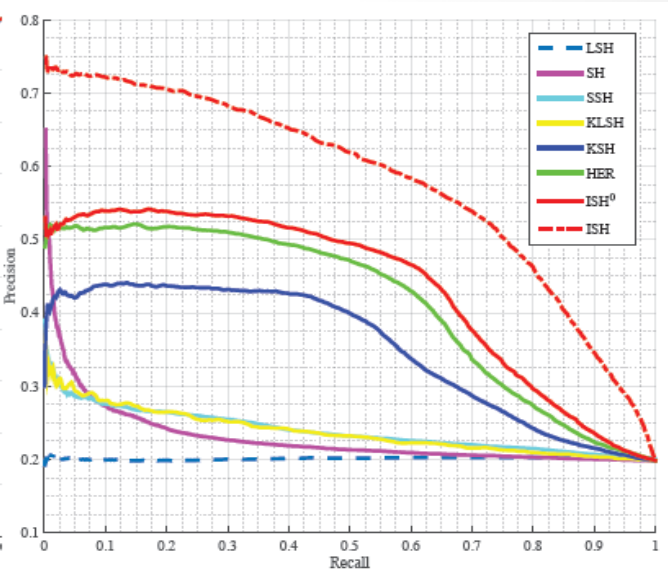
Performance on BBT. KLSH, KSH, HER, ISH^0, ISH use image sets as input



Mean recall curves for Hamming ranking using 128 bits



Mean precision curves for Hamming ranking using 128 bits



Mean precision-recall curves for Hamming ranking using 128 bits

Summary

- S2S provides the promising applications/results comparing to the traditional hashing methods (P2P)

- S2S hashing improves the retrieval performance by utilizing multiple (structural and statistical) information

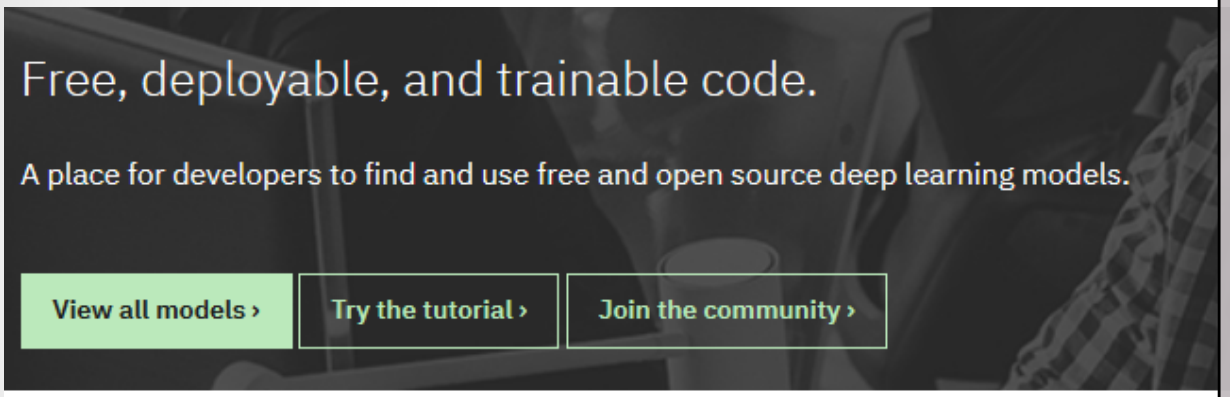
- State-of-the-art results in retrieval datasets

- No complex deep learning frameworks

MAX for Developers

Find model asset → Deploy pre-trained model asset → Use model asset

- Audio classification
- Image classification
- Text classification
- Object detection
- Facial recognition
- Image-to-image translation
- Image-to-text translation
- …



Deployable | Facial Recognition

Facial Emotion Classifier

Detect faces in an image and predict the emotional state of each person

View model »

Artificial intelligence | Deep learning +

Deployable | Object Detection In Images

Image Segmenter

Identify objects in an image, additionally assigning each pixel of the image to a particular object.

View model »

Deployable | Object Detection In Images

Object Detector

Localize and identify multiple objects in a single image.

View model »

Artificial intelligence | Deep learning +

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IBM Data Asset eXchange (DAX)

- Curated free and open datasets under open data licenses
- Standardized dataset formats and metadata
- Ready for use in enterprise AI applications
- Complement to the **M**odel **A**sset e**X**change (**MAX**)

Data **A**sset e**X**change

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Model **A**sset e**X**change

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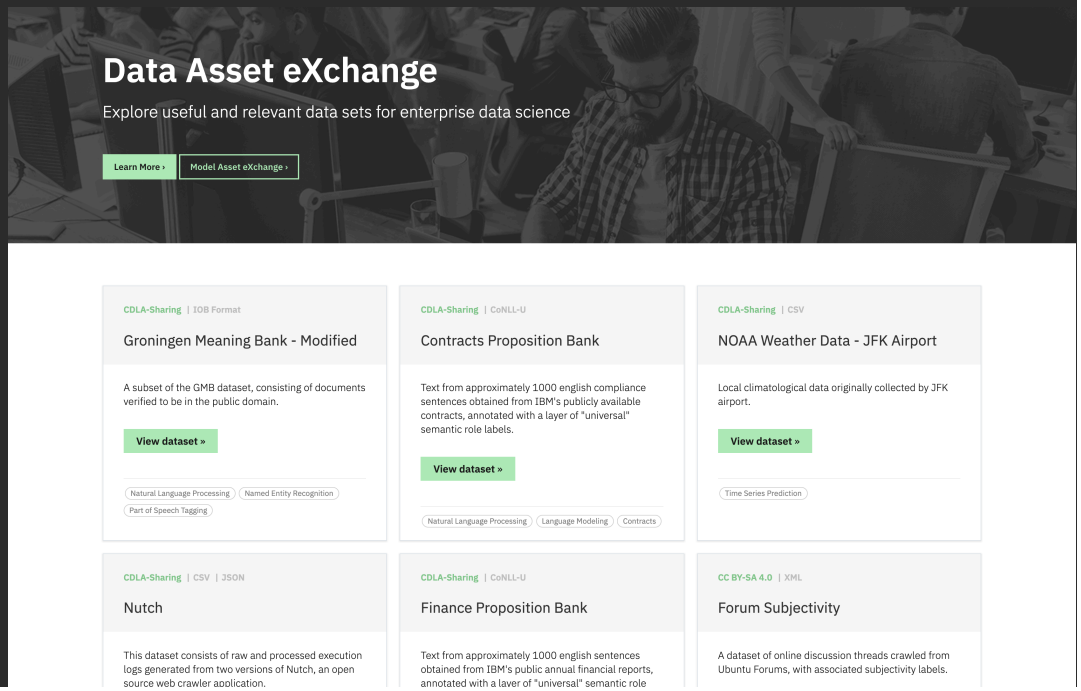


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YAQHANYELAY
SUKSAMA
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