Deep Self-taught Graph Embedding Hashing with Pseudo Labels for Image Retrieval

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Outline

- **Background**
- Motivation
- Design Overview
- Methodology
- Experiment Results
- Conclusion

Background

Hashing is widely used in large-scale retrieval owing to its efficiency for storage and matching

a=[0.328, -0.112,...,0.131]

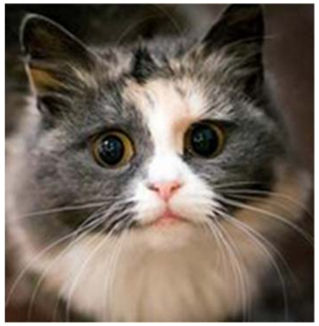
0110000110

|a-b|

$\mathrm{Exp}(a^2-b^2)^{0.5}$

ab/|a||b|

2



b=[0.187, -0.016,...,-0.547]

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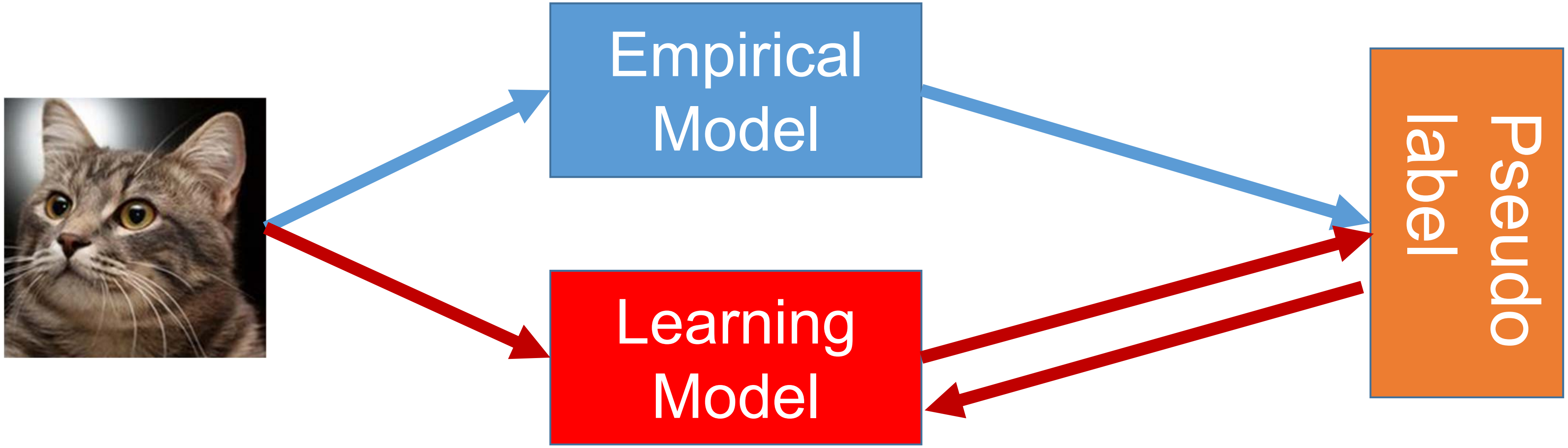
Background

However, the dependence of label information in deep learning training restricts the practicability of deep hash algorithm

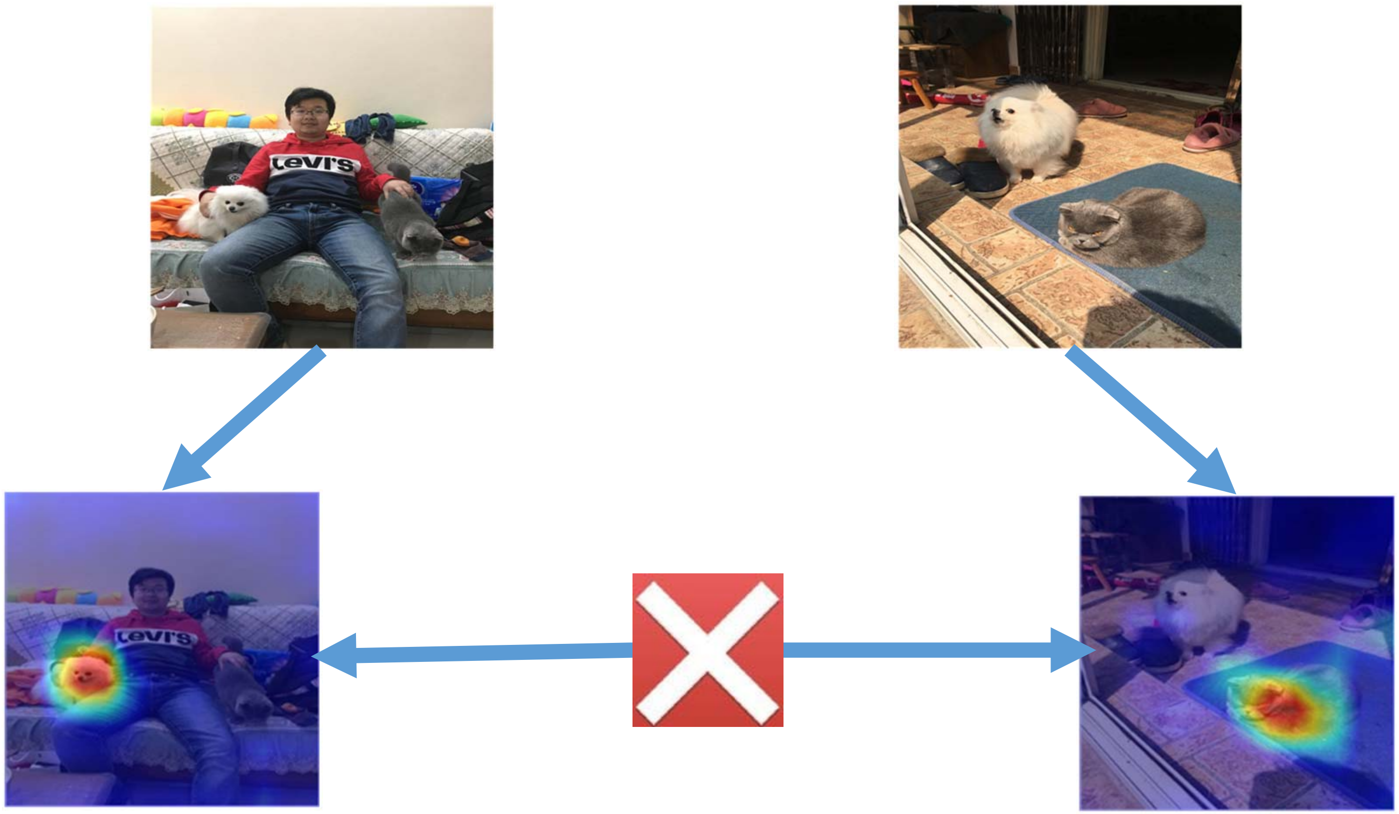
Background

Hash learning with pseudo labels



Background

Problems



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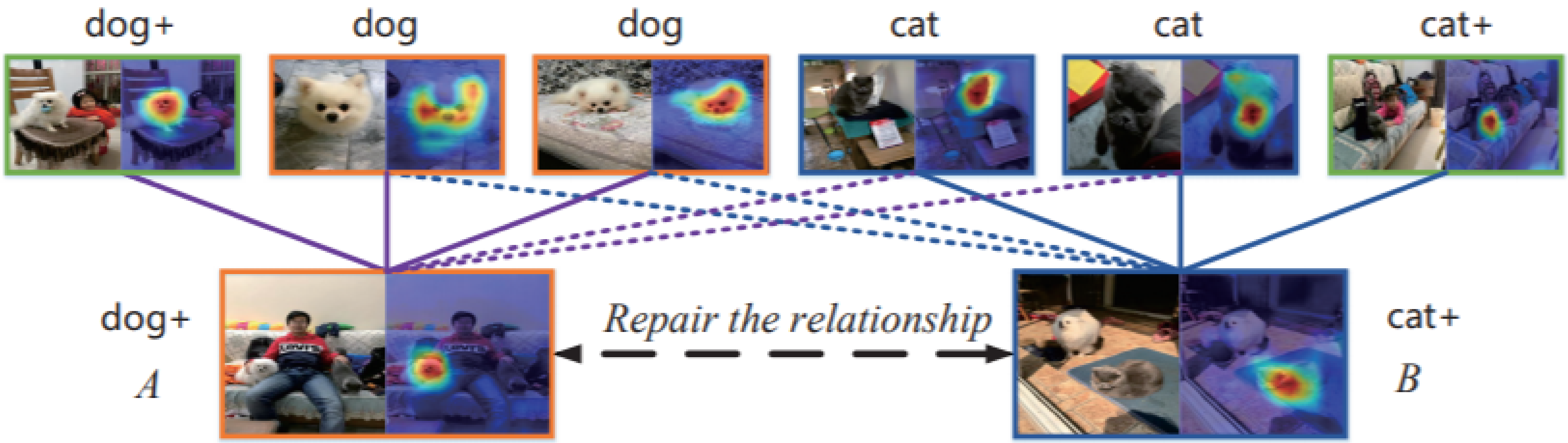
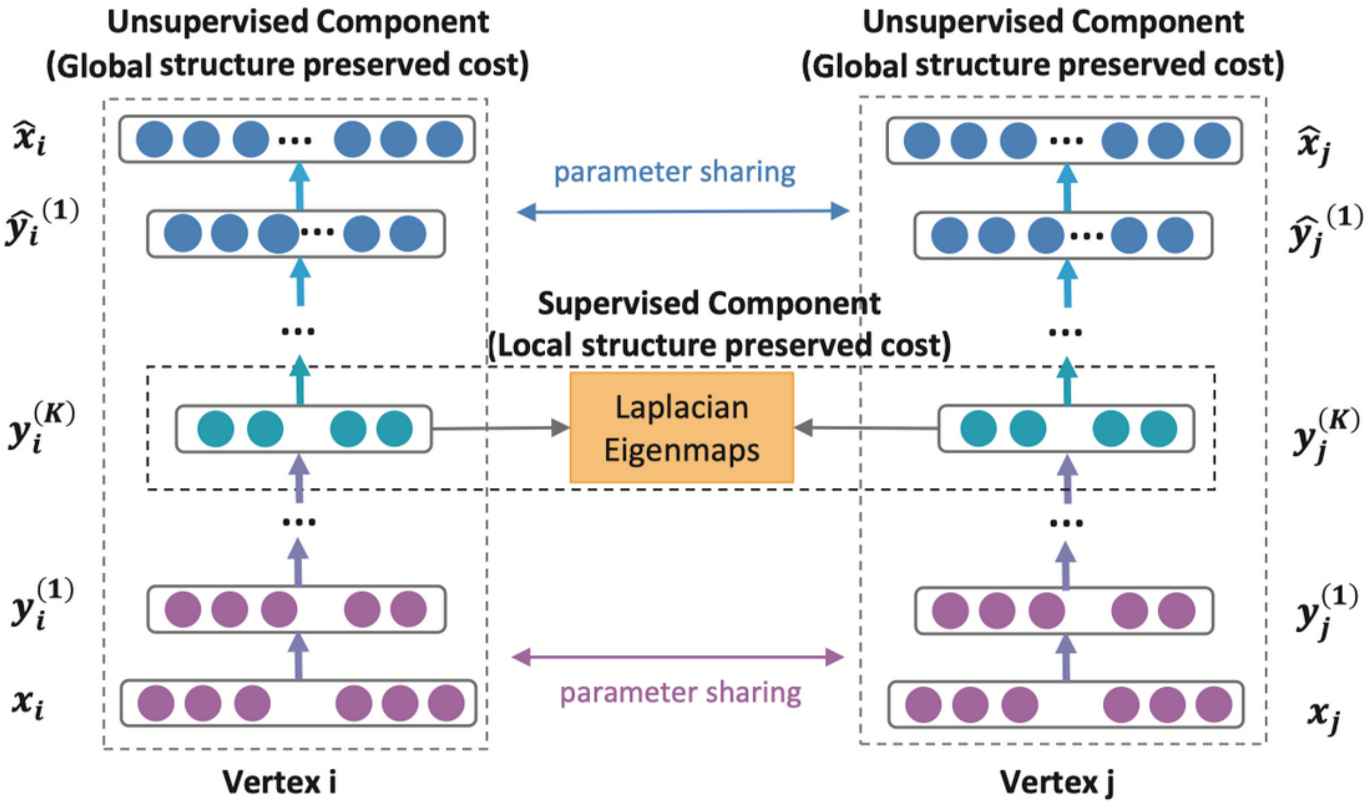
Motivation

Dependency with the indirect correlation



Motivation

Second-order proximity



Wang D, Cui P, Zhu W. Structural deep network embedding[C]//Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining. 2016: 1225-1234.

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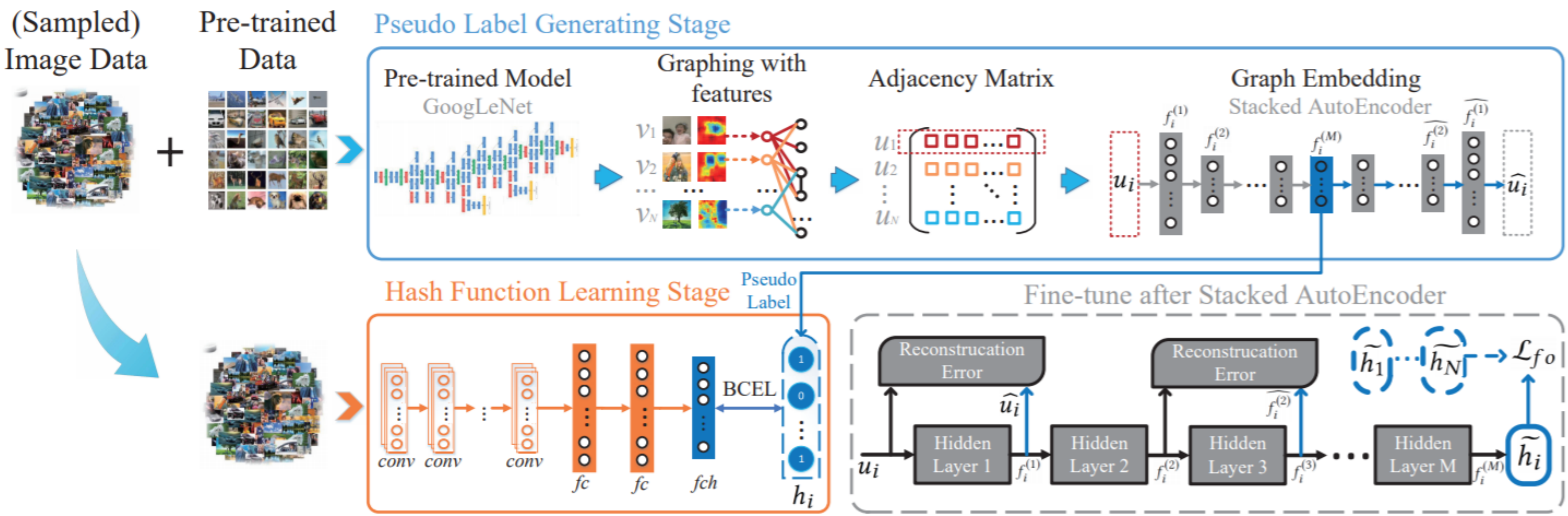
Design Overview

Framework for DSTGeH



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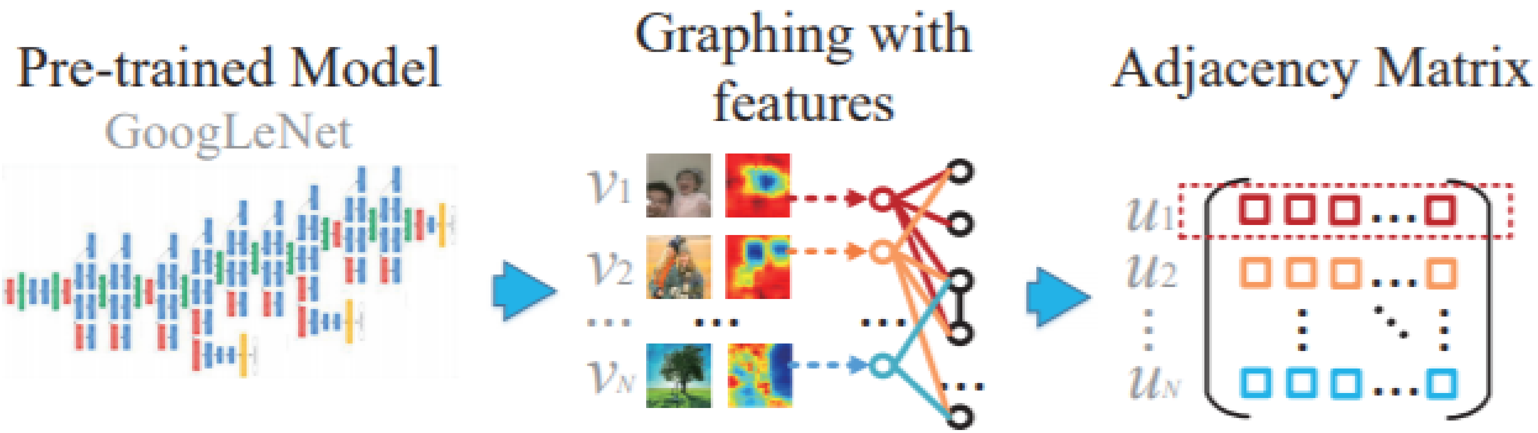
Methodology

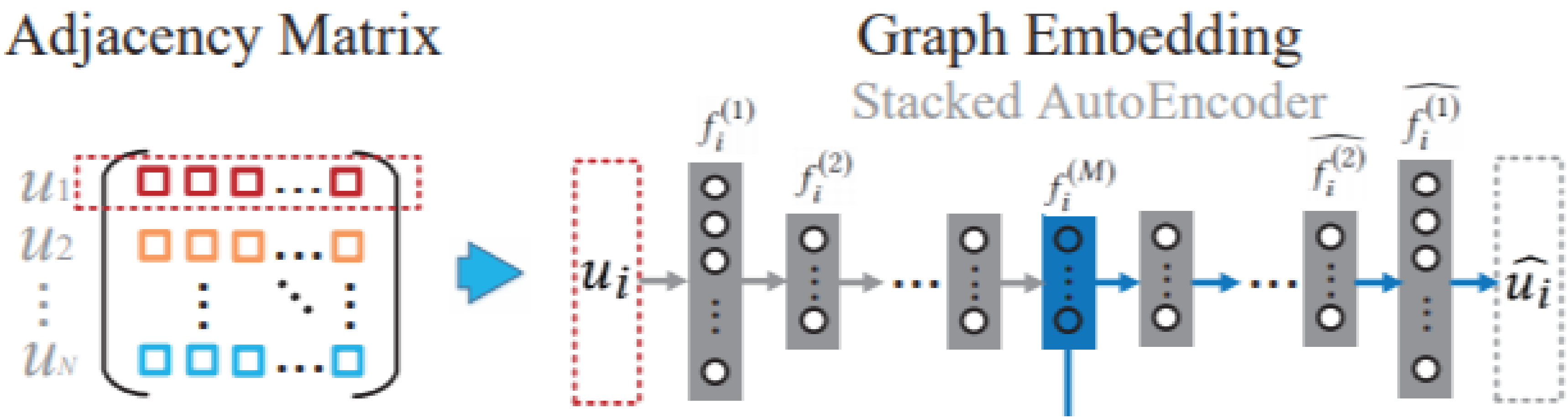
Pseudo label generating stage



cosine distance : $$u_{i,j} = \frac{\vec{v_i} \cdot \vec{v_j}}{\|v_i\| \cdot \|v_j\|}.$$

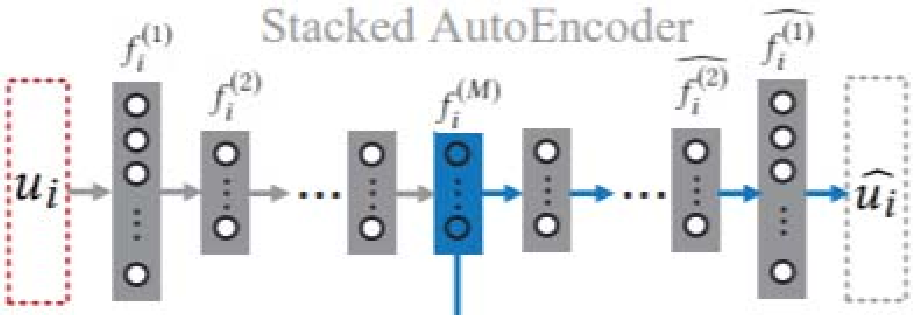
Methodology

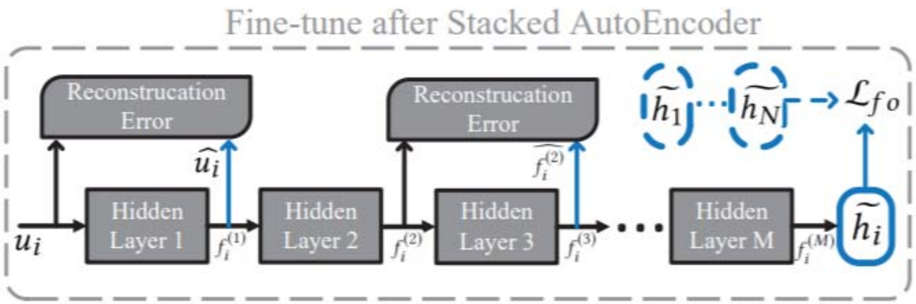
Pseudo label generating stage



Methodology

Pseudo label generating stage





Second-order Proximity of reconstruction error:

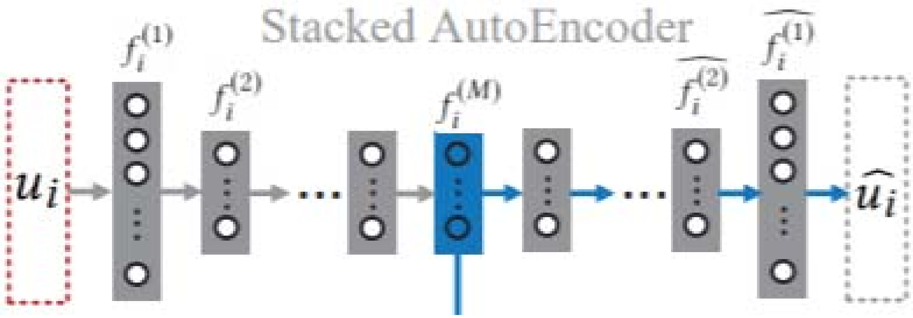
$$\mathcal{L}_{soh} = \sum_{i=1}^{N} \sum_{m=2\times t}^{M} \kappa_t \| f_i^{(m)} - \widehat{f_i^{(m)}} \|_2^2,$$

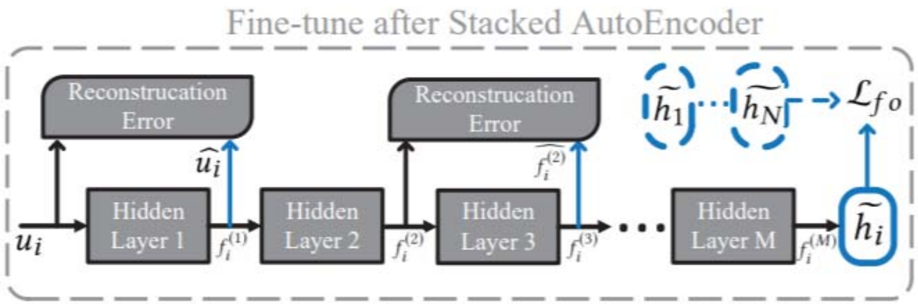
$$s.t. \quad \frac{\kappa_t}{\kappa_{t+1}} = 2, \quad \sum \kappa_t = 1,$$

$$\mathcal{L}_{so} = \mu \sum_{i=1}^{N} \| u_i - \widehat{u_i} \|_2^2 + (1-\mu)\mathcal{L}_{soh}$$

Methodology

Pseudo label generating stage





First-order Proximity of reconstruction error:

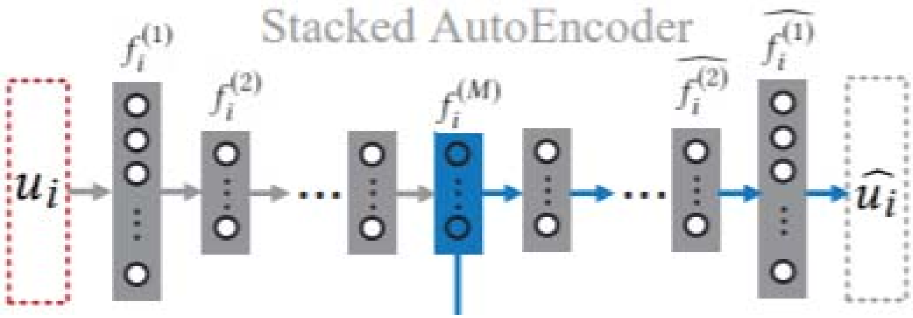
$$\mathcal{L}_{fo} = \sum_{i,j=1}^{N} u_{i,j} \| \widetilde{h_i} - \widetilde{h_j} \|_2^2$$

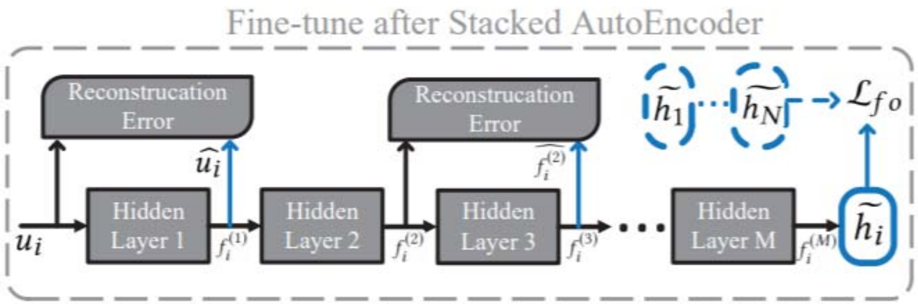
Regularize term:

$$\mathcal{L}_r = \frac{1}{2} \sum_{m=1}^{M} \| W^{(m)} \|_F^2 + \| \widehat{W^{(m)}} \|_F^2$$

Methodology

Pseudo label generating stage



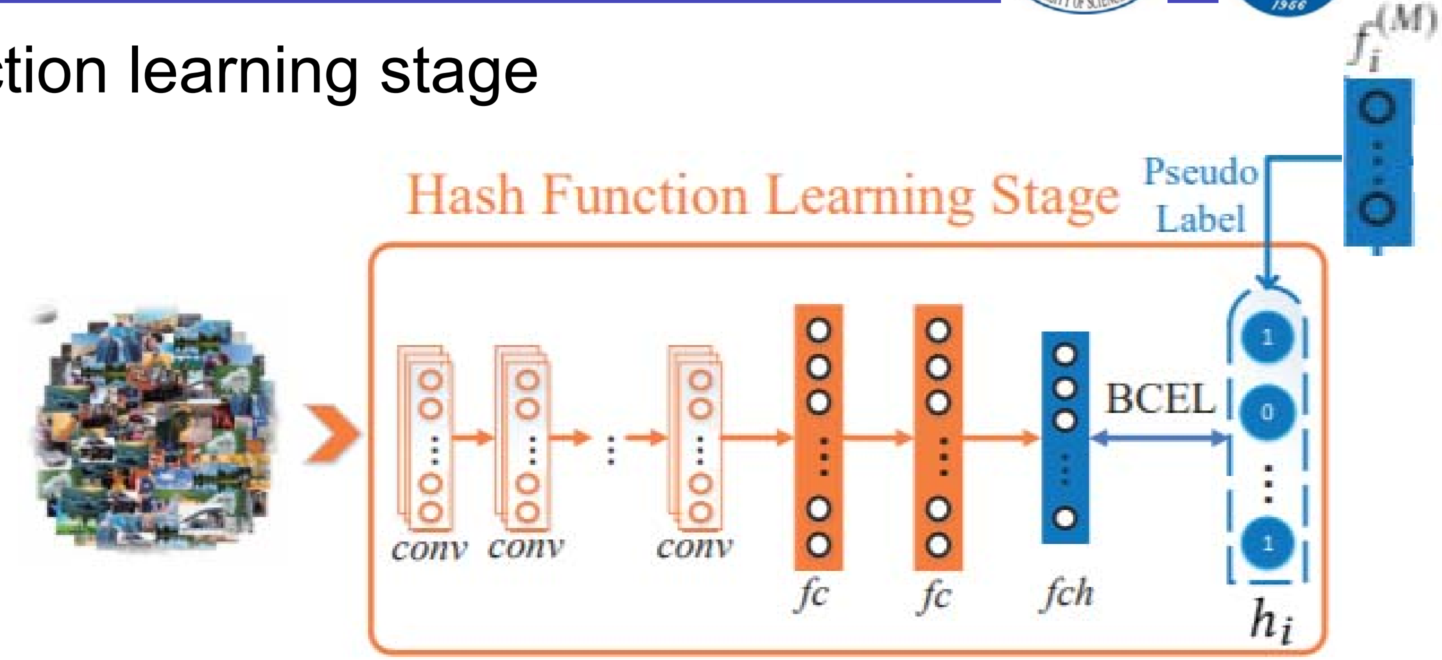


the terminal loss function:

$$\mathcal{L} = \alpha\mathcal{L}_{so} + \beta\mathcal{L}_{fo} + \gamma\mathcal{L}_{r}$$

Methodology

Hash function learning stage



BCEL: $$\mathcal{L}_h(h_i, \widetilde{H_i}) = -\sum_{p=1}^{g} h_i^p log(\widetilde{H_i^p}) + (1 - h_i^p) log(1 - \widetilde{H_i^p})$$

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Experimental Results

- Datasets: CIFAR-10 dataset

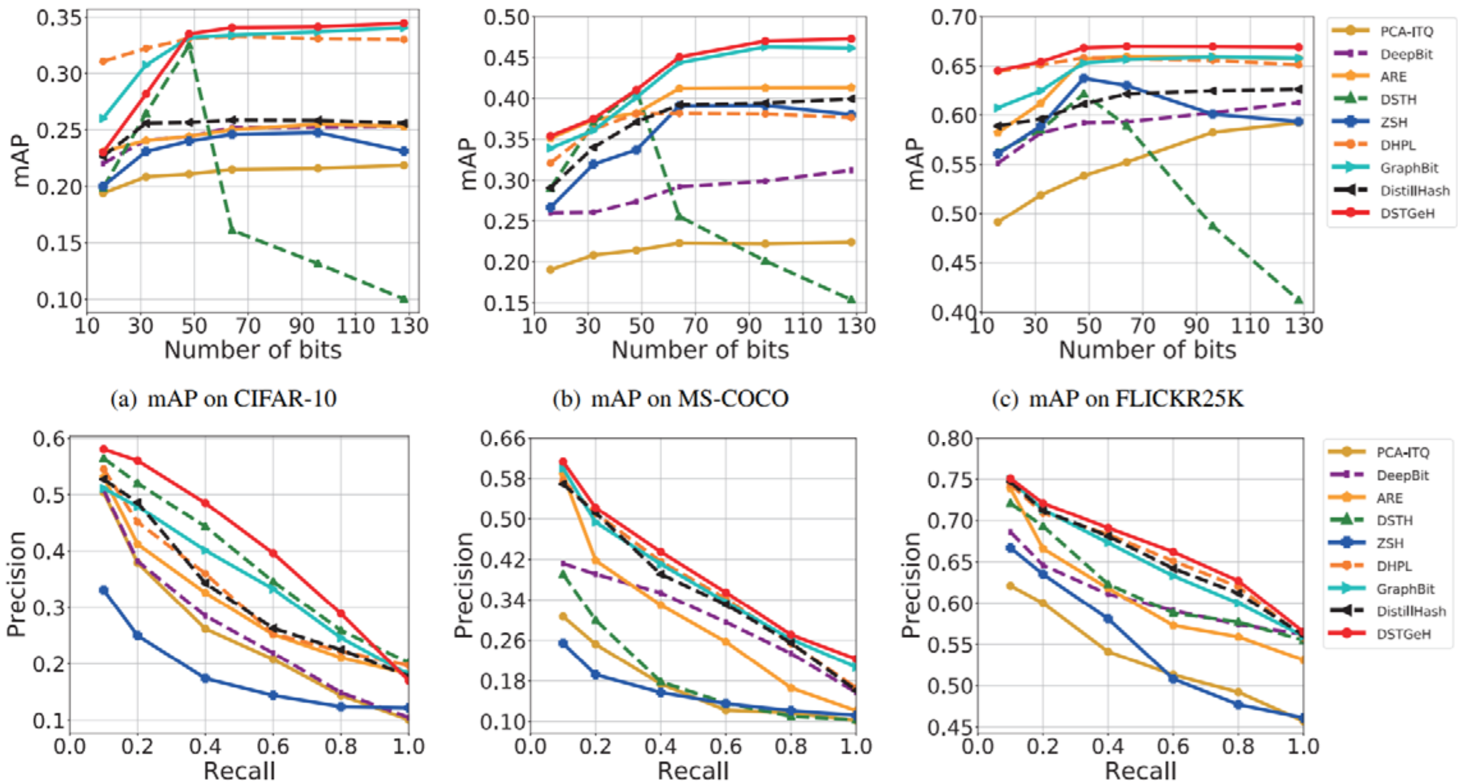
  MS-COCO dataset

  FLICKR25K dataset

- Experimental Procedures:
  - Comparison with the State-of-the-art Methods
  - Ablation Studies

Experimental Results

Comparison with the State-of-the-art Methods



(a) mAP on CIFAR-10 (b) mAP on MS-COCO (c) mAP on FLICKR25K

(d) PR on CIFAR-10 (e) PR on MS-COCO (f) PR on FLICKR25K

Fig. 5: mAP with different code lengths and 48-bits PR curve on CIFAR-10, MS-COCO and FLICKR25K.

Experimental Results

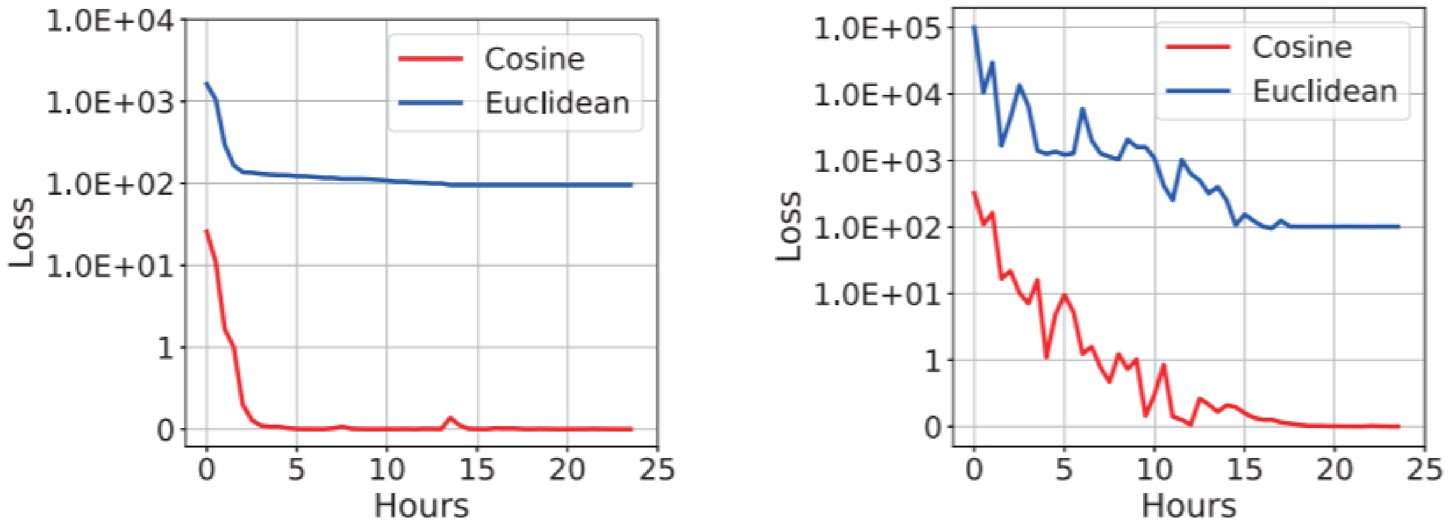
Ablation Studies: Influence of hash length and distance metric

Table 1: Performance (mAP) variances varying code length L and distance metric.

Dataset	Distance Metric	mAP@Hash Code Length L					
		16-bits	32-bits	48-bits	64-bits	96-bits	128-bits
CIFAR-10	Cosine	**0.2303**	**0.2818**	**0.3352**	**0.3408**	**0.3415**	**0.3447**
	Euclidean	0.2223	0.2702	0.3165	0.3252	0.3247	0.3269
MS-COCO	Cosine	0.3540	**0.3750**	**0.4102**	**0.4508**	**0.4703**	**0.4731**
	Euclidean	**0.3543**	0.3552	0.4008	0.4388	0.4607	0.4621

Experimental Results

Ablation Studies: Influence of distance metric



(a) CIFAR-10 (b) MS-COCO

Fig. 3: GE convergence on CIFAR-10 and MS-COCO with different distance metrics in the first stage.

Experimental Results

Ablation Studies: Influence of GE component

Table 2: Performance (PR) variance on 48-bits varying GE method, recall and loss function.

Dataset	GE Method (Loss Function)	Precision@Recall 10%	20%	40%	60%	80%	F_1
CIFAR-10	LE (BCEL)	0.3944	0.3302	0.2835	0.2397	0.2086	0.2828
	Word2Vec (BCEL)	0.5623	0.5037	0.4193	0.3025	0.2343	0.3260
	SDNE (BCEL)	**0.5919**	0.5578	0.4573	0.3604	0.2673	0.3487
	SDNE+SAE (BCEL)	0.5804	**0.5601**	**0.4848**	**0.3962**	**0.2885**	**0.3610**
	SDNE+SAE (MLML)	0.4311	0.3534	0.2942	0.2599	0.2217	0.2933
	SDNE+SAE (MLSML)	0.2319	0.2206	0.2032	0.1623	0.1303	0.1197
MS-COCO	LE (BCEL)	0.3120	0.2402	0.2001	0.1657	0.1304	0.2241
	Word2Vec (BCEL)	0.5509	0.5050	0.4001	0.3075	0.2265	0.3231
	SDNE (BCEL)	0.5932	0.5215	0.4188	0.3070	0.2173	0.3235
	SDNE+SAE (BCEL)	**0.6136**	**0.5223**	**0.4347**	**0.3552**	**0.2709**	**0.3458**
	SDNE+SAE (MLML)	0.3561	0.2437	0.2074	0.1763	0.1410	0.2322
	SDNE+SAE (MLSML)	0.2019	0.1882	0.1724	0.1592	0.1333	0.2098

Experimental Results

Ablation Studies: Influence of loss function

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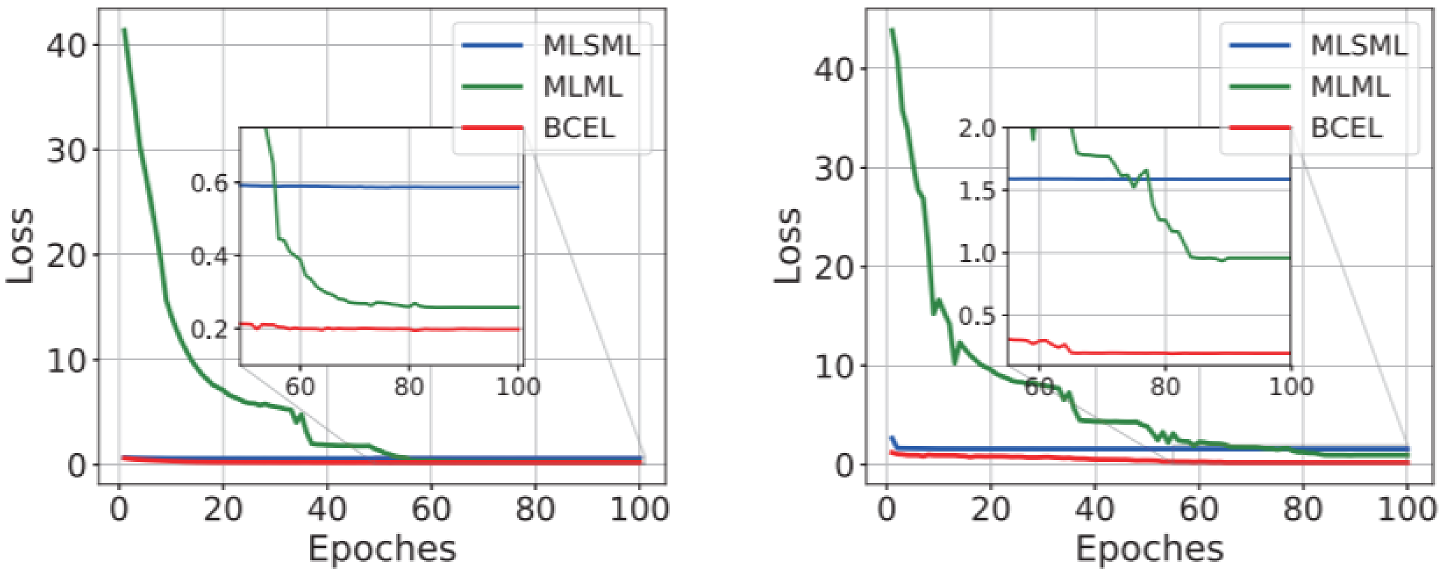
Experimental Results

Ablation Studies: Influence of loss function



(a) CIFAR-10 (b) MS-COCO

Fig. 4: Hash function convergence on CIFAR-10 and MS-COCO with different loss functions in the second stage.

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Conclusion

- We propose a deep self-taught graph embedding hashing (DSTGeH) framework for image retrieval.
- We introduce the second-order proximity into the hash learning, which improves the precision of hash code in the self-taught framework with pseudo labels.
- DSTGeH achieves the best performances on most evaluation metrics and produce an overwhelming advantage on multi-label datasets.

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Thank You!

Yu Liu

Yangtao Wang

Chan Guo

Ke Zhou

Jingkuan Song

Zhili Xiao