ICANN19 Deep Semantic Asymmetric Hashing

Mian Zhang, Cheng Cheng and Xianzhong Long

Nanjing University of Posts and Telecommunications, Nanjing, 210023, China

Contact Author: Xianzhong Long (Ixz@njupt.edu.cn)

Problem

In image similarity retrieval and deep hashing, most existing asymmetric deep hashing methods do not sufficiently discover semantic correlation from label information, which results in reducing the discrimination of learned binary codes.

Proposed Solution

Use a label auto-encoder (LAE) and some proper constrains between LAE and the asymmetric image hashing network (ImgNet) to guide the training process of ImgNet to learn more discriminative binary codes at semantic level.

The Architecture of Deep Semantic Asymmetric Hashing



Learning Algorithm

Alternating optimization:

- Use back-propagation lacksquarealgorithm to update the parameters.
- Directly optimize the binary codes of database points.

Common Semantic Space Fig.1 The whole Hashing Network

Experiments

Dataset: CIFAR-10, MS-COCO, NUS-WIDE Comparing methods:

- Traditional methods: KSH, SDH, ITQ, FATH
- DL methods: DNNH, HashNet, DAPH, ADSH

Mean Average Precision and Top-5K Precision on CIFAR-10.



Fig.2 MAP Results

M. 41 J		CIFAR-10			
Method	12bits 2	24 bits	36bits	48bits	
KSH	0.524 (0.534	0.558	0.601	
SDH	0.461 (0.606	0.650	0.664	
ITQ	0.354 (0.371	0.414	0.423	
FATH	0.596 (0.712	0.753	0.741	

Correlation results between binary codes. mAC: mean Absolute Correlation



Fig.3 Correlation Matrix and mAC Values at 32 Bits.



DSAH	0.911	0.930	0.943	0.948
ADSH	0.890	0.924	0.932	0.934
DAPH	0.871	0.887	0.915	0.894
HashNet	0.763	0.822	0.834	0.821

The proposed method can be applied to retrieval tasks which needs long binary codes to encode more information for high retrieval accuracy if larger memory or faster computing device are available.

272