Leveraging Quadratic Spherical Mutual Information Hashing for Fast Image Retrieval

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Deep Supervised Hashing

- **Hashing** provides a way to represent images using compact codes, which allows for performing fast queries in large image databases
- **Early hashing methods,** e.g., Locality Sensitive Hashing (LSH), **focused on extracting generic codes** that could, in principle, describe **every possible image and information need**
- **Supervised hashing,** which learns hash codes that are tailored to the task at hand, c**an further improve the retrieval precision**

Deep Supervised Hashing

- Many supervised hashing methods have been proposed in recent years
- These methods **optimize various proxies for the problem at hand,** e.g, **pairwise distances** between the images, or are based on sampling **triplets that must satisfy specific relationships**

Motivation

- In this work, we **provide additional connections between an information-theoretic measure, the Mutual Information (MI), and the process of information retrieval**
- We argue that **mutual information can naturally model the process of information retrieval,** providing a solid framework to develop retrieval-oriented supervised hashing techniques
- Even though **MI provides a sound formulation for the problem of information retrieval, applying it in real scenarios is usually intractable**

Motivation

- Typically, **there is no fast way to calculate the actual probability densities,** which are involved in the calculation of MI
- **The great amount of data as well as their high dimensionality further complicate the practical application of such measures**

Proposed Method

- We proposed a **deep supervised hashing algorithm** that **optimizes** the learned codes using **a variant of an information-theoretic measure, the Quadratic Mutual Information** (QMI)

- QMI allows **for efficiently estimating MI**. However, **we further adapt QMI to the needs of supervised hashing** by employing a **similarity measure that leads to higher precision in retrieval applications**, leading to the proposed QSMI formulation **using a cosine kernel** (for two vectors $\mathbf{y}_1$ and $\mathbf{y}_2$):

$$S_{cos}(\mathbf{y}_1, \mathbf{y}_2) = \frac{1}{2}\left(\frac{\mathbf{y}_1^T \mathbf{y}_2}{\|\mathbf{y}_1\|_2 \|\mathbf{y}_2\|_2} + 1\right)$$

Proposed Method

- We also propose **using a more smooth optimization objective employing a square clamping approach**,

going from

$$I_T^{cos} = \frac{1}{N^2}\mathbf{1}_N^T\left(\mathbf{\Delta}\odot\mathbf{S} - \frac{1}{M}\mathbf{S}\right)\mathbf{1}_N,$$

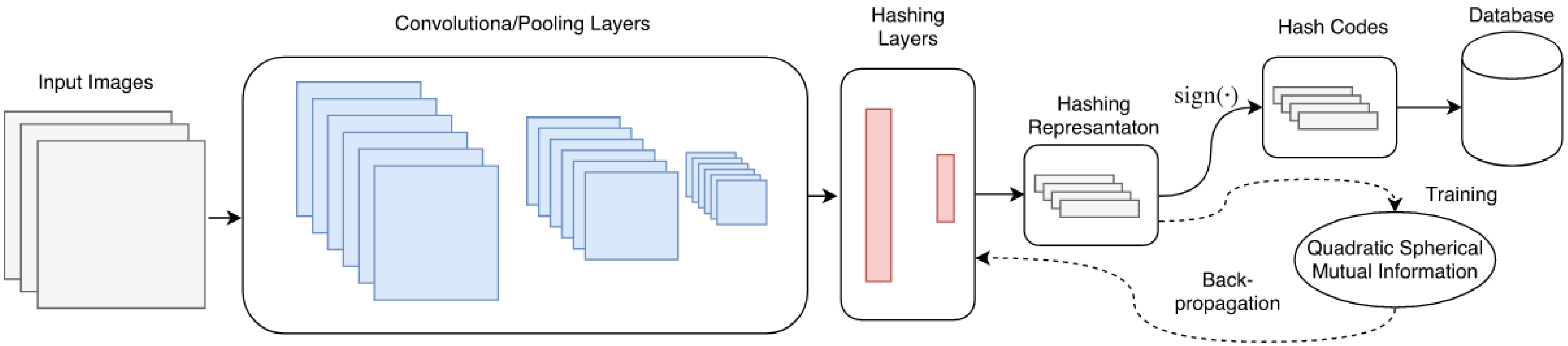
to

$$\mathcal{L}_{QSMI} = \frac{1}{N^2}\mathbf{1}_N^T\left(\mathbf{\Delta}\odot(\mathbf{S}-1)\odot(\mathbf{S}-1) - \frac{1}{M}(\mathbf{S}\odot\mathbf{S})\right)\mathbf{1}_N$$

where **S** is the similarity matrix of the data and **Δ** an appropriately defined index matrix. Note how the employed square clamp alters the optimization objective.

- This allows for significantly **improving the stability of the optimization,** while reducing the risk of converging to bad local minima.

Proposed Method



Experimental Evaluation

TABLE IV
FASHION MNIST EVALUATION (THE MAP FOR DIFFERENT HASH CODE LENGTHS IS REPORTED)

Method	12 bits	24 bits	36 bits
DSH	0.761 ± 0.018	0.792 ± 0.012	0.809 ± 0.008
DPSH	0.767 ± 0.023	0.773 ± 0.005	0.774 ± 0.008
QSMIH	$\mathbf{0.842 \pm 0.012}$	$\mathbf{0.857 \pm 0.004}$	$\mathbf{0.858 \pm 0.007}$

TABLE V
CIFAR10 EVALUATION (THE MAP FOR DIFFERENT HASH CODE LENGTHS IS REPORTED)

Method	8 bits	12 bits	24 bits	36 bits	48 bits
DSH*	0.936	0.958	0.967	0.970	0.970
DPSH*	0.776	0.933	**0.971**	**0.971**	**0.971**
QSMIH	**0.962**	**0.970**	**0.971**	**0.971**	**0.971**

CIFAR10 EVALUATION: COMPARISON WITH OTHER STATE-OF-THE-ART APPROACHES (THE MAP FOR DIFFERENT HASH CODE LENGTHS IS REPORTED)

Method	16 bits	32 bits	64 bits
DNNH	0.555	0.558	0.623
DSH	0.689	0.691	0.716
DPSH	0.646	0.661	0.686
HashNet	0.703	0.711	0.739
HashGAN	0.668	0.731	0.749
PGDH	0.736	0.741	0.762
MIHash	0.760	**0.776**	0.761
QSMIH	**0.762**	**0.776**	**0.780**

NUS-WIDE EVALUATION (THE MAP FOR DIFFERENT HASH CODE LENGTHS IS REPORTED)

Method	8 bits	12 bits	24 bits	36 bits	48 bits
DSH	0.660	0.659	0.671	0.689	0.694
DPSH	0.735	0.748	0.759	0.758	0.755
QSMIH	**0.746**	**0.753**	**0.766**	**0.764**	**0.763**

Conclusions

- We proposed **a deep supervised hashing algorithm,** adapted to the needs of large-scale hashing, which o**ptimizes the learned codes using an information-theoretic measure, the Quadratic Spherical Mutual Information**
- The proposed method **was evaluated using three datasets and evaluation setups** and compared to other state-of-the-art supervised hashing techniques
- The proposed method outperformed all the other evaluated methods regardless the size of the used dataset and the training setup

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Thank you!