LEVERAGING QUADRATIC SPHERICAL MUTUAL INFORMATION HASHING FOR FAST IMAGE RETRIEVAL

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Introduction

- **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, **can further improve the retrieval precision**

- 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 retrieva**l, similar to [1]

- 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**

- 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) [2]
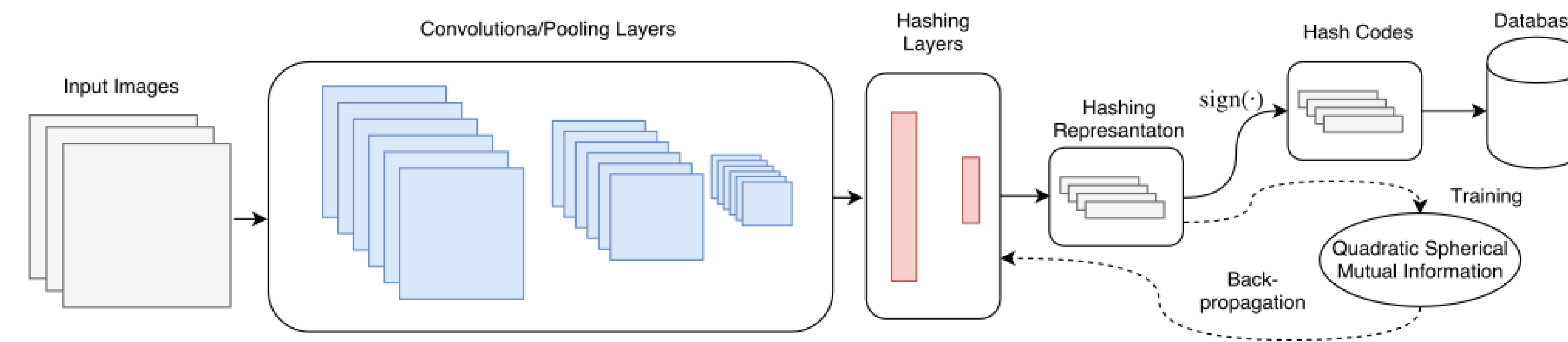
- QMI allows **for efficiently estimating MI**. However, **we further adapt QMI to the needs of supervised hashing** by employing a **similarity measure that leads to higher precision in retrieval applications**, leading to the proposed QSMI formulation **using a cosine kernel** (for two vectors $\mathbf{y}_1$ and $\mathbf{y}_2$):

$$S_{cos}(\mathbf{y_1}, \mathbf{y_2}) = \frac{1}{2}\left(\frac{\mathbf{y}_1^T\mathbf{y}_2}{\|\mathbf{y}_1\|_2\|\mathbf{y}_2\|_2} + 1\right)$$

- We 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 $\mathbf{S}$ is the similarity matrix of the data and $\mathbf{\Delta}$ 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.

Experimental Results

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**

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**

References

[1] F. Cakir, K. He, S. Adel Bargal, and S. Sclaroff, "MIHash: Online hashing with mutual information," in Proc. IEEE Int. Conf. on Computer Vision, 2017.

[2] K. Torkkola, "Feature extraction by non-parametric mutual information maximization," Journal of Machine Learning Research, vol. 3, pp. 1415 – 1438, 2003.

Acknowledgments