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Supervised Hashing for Image Retrieval via Image Representation Learning

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Abstract

Hashing is a popular approximate nearest neighbor search approach for large-scale image retrieval. Supervised hashing, which incorporates similarity/dissimilarity information on entity pairs to improve the quality of hashing function learning, has recently received increasing attention. However, in the existing supervised hashing methods for images, an input image is usually encoded by a vector of hand-crafted visual features. Such hand-crafted feature vectors do not necessarily preserve the accurate semantic similarities of images pairs, which may often degrade the performance of hashing function learning. In this paper, we propose a supervised hashing method for image retrieval, in which we automatically learn a good image representation tailored to hashing as well as a set of hash functions. The proposed method has two stages. In the first stage, given the pairwise similarity matrix S over training images, we propose a scalable coordinate descent method to decompose S into a product of HH^T where H is a matrix with each of its rows being the approximate hash code associated to a training image. In the second stage, we propose to simultaneously learn a good feature representation for the input images as well as a set of hash functions, via a deep convolutional network tailored to the learned hash codes in H and optionally the discrete class labels of the images. Extensive empirical evaluations on three benchmark datasets with different kinds of images show that the proposed method has superior performance gains over several state-of-the-art supervised and unsupervised hashing methods.

Introduction

With the rapidly increasing amount of available image data on the web, *approximate nearest neighbor* (ANN) search in large-scale datasets with millions or billions images has recently received considerable attention (Jegou, Douze, and Schmid 2011; Wang, Kumar, and Chang 2010; Kulis and Grauman 2009; Liu et al. 2012). Learning-to-hash is an emerging ANN search approach which aims to learn a compact and similarity-preserving bitwise representation such that similar inputs are mapped to nearby binary hash codes. Many learning-based hashing methods have been proposed (e.g., (Kulis and Grauman 2009; Gong and Lazebnik 2011; Weiss, Torralba, and Fergus 2008; Wang, Kumar, and Chang 2010; Liu et al. 2012; Norouzi and Blei 2011; Kulis and Darrell 2009)).

Roughly speaking, the learning-based hashing methods can be divided into three main streams. The first stream is unsupervised methods (Gong and Lazebnik 2011; Kulis and Grauman 2009; Weiss, Torralba, and Fergus 2008; Salakhutdinov and Hinton 2007), in which only unlabeled data is used to learn hash functions. The other two streams are semi-supervised and supervised methods (Liu et al. 2012; Lin et al. 2013; Norouzi and Blei 2011; Kulis and Darrell 2009; Wang, Kumar, and Chang 2010), which have shown to improve the quality of hashing by incorporating supervised information (e.g., similarity/disimilarity labels over image pairs) into the hash learning process. In this paper, we focus on supervised hashing for images.

A key question in learning-based hashing for images is how to encode images into a useful feature representation so as to enhance the hashing performance. In most of the existing hashing methods for images, each input image is first encoded by a vector of some hand-crafted visual descriptors (e.g., GIST (Oliva and Torralba 2001)). However, such hand-crafted visual features, which are extracted in an unsupervised fashion, do not necessarily guarantee to accurately preserve the semantic similarities of image pairs, i.e., a pair of semantically similar/dissimilar images may not have feature vectors with relatively small/large Euclidean distance. Ideally, one would like to automatically learn such a feature representation that sufficiently preserves the semantic similarities for images during the hash learning process. Without using hand-crafted visual features, Semantic Hashing (Salakhutdinov and Hinton 2007) is a hashing method which automatically constructs binary-code feature representation for images by a multi-layer auto-encoder, with the raw pixels of images being directly used as input. However, Semantic Hashing imposes difficult optimization and its performance was surpassed by recently proposed hashing methods (e.g., (Kulis and Darrell 2009)). [0]

Recent studies have shown that incorporating supervised information can enhance the performance of hash learn-

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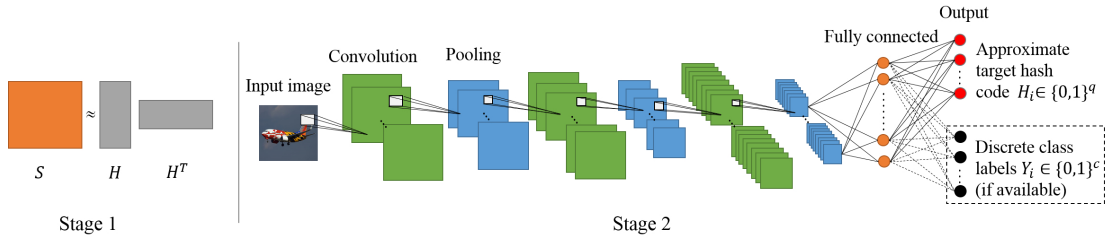


Figure 1: Overview of the proposed two-stage method. In stage 1, the pairwise similarity matrix S is decomposed into a product HH^T, where H is a matrix of approximate target hash codes. In stage 2, we use a convolutional network to learn the feature representation for the images as well as a set of hash functions. The network consists of three convolution-pooling layers, a fully connected layer and an output layer. The output layer can be simply constructed with the learned hash codes in H (the red nodes). If the image tags are available in training, one can add them in the output layer (the black nodes) so as to help to learn a better shared representation of the images. By inputting an test image to the trained network, one can obtain the desired hash code from the values of the red nodes in the output layer.

ing (Liu et al. 2012; Norouzi and Blei 2011; Kulis and Darrell 2009). In this paper, we propose a supervised hashing method for image retrieval which simultaneously learns a set of hashing functions as well as a useful image representation tailored to the hashing task. Given n images $\mathcal{I} = \{I_1, I_2, ..., I_n\}$ and a pairwise similarity matrix S in which $S_{i,j} = 1$ if I_i and I_j are semantically similar and otherwise $S_{i,j} = -1$, the task of supervised hashing is to learn a set of q hash functions based on S and I. Formulating the hash learning task as a single optimization problem usually leads to a complex and highly non-convex objective which may be difficult to optimize. To avoid this issue, one of the popular ways is decomposing the learning process into a hash code learning stage followed by a hash function learning stage (e.g., (Zhang et al. 2010; Lin et al. 2013)). As shown in Figure 1, the proposed method also adopts such a two-stage paradigm. In the first stage, we propose a scalable coordinate descent algorithm to approximately decompose S into a product form $S \approx \frac{1}{q} HH^T$, where $H \in \mathcal{R}^{n \times q}$ with each of its elements being in $\{-1, 1\}$. The k-th row in H is regarded as the approximate target hash code of the image I_k. In the second stage, we simultaneously learn a set of q hash functions and a feature representations for the images in I by deep convolutional neural networks (LeCun et al. 1998; Krizhevsky, Sutskever, and Hinton 2012).

We evaluate the proposed method on several benchmark datasets with different kinds of images. Experimental results show that the proposed method has superior performance gains over several state-of-the-art supervised and unsupervised hashing methods, and the proposed coordinate descent algorithm in stage 1 performs substantially faster than the most related competitor.

Related Work

Hashing is a widely used approach for ANN search in large-scale image retrieval, due to its encouraging efficiency in both speed and storage. Many hashing methods have been proposed (Kulis and Grauman 2009; Gong and Lazebnik 2011; Weiss, Torralba, and Fergus 2008; Wang, Kumar, and Chang 2010; Liu et al. 2012; Norouzi and Blei 2011; Kulis and Darrell 2009).

The early research of hashing focuses on data-independent methods, in which the *Locality Sensitive Hashing* (LSH) methods (Gionis, Indyk, and Motwani 1999; Charikar 2002) are the most well-known representatives. LSH methods use simple random projections as hash functions, which are independent of the data. However, LSH methods usually require long hash codes to achieve satisfactory search accuracies, resulting in large space for storage and low recall in search (Liu et al. 2012).

Compared to the data-independent methods, data-dependent hashing methods (as known as learning-based hashing) aim to generate similarity-preserving representations with shorter hash codes, by learning a set of hash functions from the training data. Such compact representations are beneficial to save space in storing large number of samples. Data-dependent methods can be divided into unsupervised, semi-supervised and supervised methods.

Unsupervised methods only use unlabeled data to generate hash functions which seek to preserve some metric distance neighbors (e.g., the ℓ_2 distance neighbors). Kernelized LSH (Kulis and Grauman 2009), ITQ (Gong and Lazebnik 2011), SH (Weiss, Torralba, and Fergus 2008) and AGH (Liu et al. 2011) are some representatives in this stream.

Semi-supervised or supervised methods try to improve the quality of hashing by leveraging supervised information (e.g., pairwise labels to indicate semantic similarities over entity pairs) into the learning process. KSH (Liu et al. 2012), BRE (Kulis and Darrell 2009), MLH (Norouzi and Blei 2011), CGHash (Li et al. 2013), ITQ-CCA (Gong and Lazebnik 2011) and SSH (Wang, Kumar, and Chang 2010) are some representatives.

Most of the existing hashing methods for images first encode each input image by hand-crafted visual features, which may often degrade their hashing performance because hand-crafted features do not necessarily capture accurate similarity of the images. To tackle this issue, we propose a supervised hashing method to simultaneously learns a set of hash functions and a useful image feature representation which is expected to preserve the semantic similarities of image pairs. As can be seen in our experiments, such an automatically learned image representation shows its effectiveness in improving the hashing accuracies.

Without using hand-crafted features, Semantic Hashing (Salakhutdinov and Hinton 2007) learns binary-code representation for images by stacked Restricted Boltzmanne Machines (RBMs), with raw image pixels being as input. However, Semantic Hashing imposes complex and difficult optimization and its performance was surpassed by recent hashing methods (Kulis and Darrell 2009).

Similar to the two-step paradigm in TSH (Lin et al. 2013), the proposed method decomposes the learning process into a hash code learning step and a hash function learning step. However, compared to TSH, the proposed method has two advantages: (1) We propose to solve the approximate hash code learning problem by a coordinate descent method, which is empirically much faster than the corresponding decomposition method used in TSH. (2) In contrast to the hand-crafted features used in TSH, we propose to learn hash functions while simultaneously training a useful feature representation for the input images.

The Approach

Given n images $\mathcal{I} = \{I_1, I_2, ..., I_n\}$ and a pairwise similarity matrix S defined by:

$$S_{ij} = \begin{cases} +1, & I_i,\ I_j\ are\ semantically\ similar \\ -1, & I_i,\ I_j\ are\ semantically\ dissimilar. \end{cases} \quad (1)$$

The task of supervised hashing is to learn a set of q hash functions based on S and $\mathcal{I}$.

In some supervised hashing methods, the learning task is formulated as a single optimization objective which is complex and difficult to solve. While in other methods (Zhang et al. 2010; Lin et al. 2013), the learning process is decomposed into two stages: a hash code learning stage followed by a hash function learning stage, where the corresponding optimization problems in each stage is relatively simple. The proposed method follows the two-stage paradigm.

Stage 1: learning approximate hash codes

We define an n by q binary matrix H whose k-th row is $H_{k\cdot} \in \{-1, 1\}^q$. $H_{k\cdot}$ represents the target q-bit hash code for the image I_k. The goal of supervised hashing is to generate hash codes that preserve the semantic similarities over image pairs. Specifically, the Hamming distance between two hash codes $H_{i\cdot}$ and $H_{j\cdot}$ (associated to I_i and I_j, respectively) is expected to be correlated with S_{ij} which indicates the semantic similarity of I_i and I_j. Existing studies (Liu et al. 2012) have pointed out that the code inner product $H_{i\cdot}H_{j\cdot}^T$ has one-to-one correspondence to the Hamming distance between $H_{i\cdot}$ and $H_{j\cdot}$. Since $H_{i\cdot} \in \{-1, 1\}^q$, the code inner product $H_{i\cdot}H_{j\cdot}^T$ is in the range $[-q, q]$. Hence, as shown in Figure 1(Stage 1), we learn the approximate hash codes for the training images in $\mathcal{I}$ by minimizing the following reconstruction errors:

$$\min_H \sum_{i=1}^{n}\sum_{j=1}^{n}(S_{ij} - \frac{1}{q}H_{i\cdot}H_{j\cdot}^T)^2 = \min_H ||S - \frac{1}{q}HH^T||_F^2, \quad (2)$$

where $||\cdot||_F$ is the Frobenius norm and $H \in \{-1, 1\}^{n\times q}$. For the training images, H encodes the approximate hash codes which preserve the pairwise similarities in S. Note that the code inner product $H_{i\cdot}H_{j\cdot}^T$ is divided by q in order to fit $S_{ij} \in \{-1, 1\}$.

It is difficult to directly optimize (2) due to the integer constraints on H. A natural way to relaxing the objective in (2) is replacing $H \in \{-1, 1\}^{n\times q}$ by the range constraints $H \in [-1, 1]^{n\times q}$:

$$\min_H ||S - \frac{1}{q}HH^T||_F^2 \ \ s.t.\ H \in [-1, 1]^{n\times q}. \quad (3)$$

Algorithm 1 Coordinate descent algorithm for hash bit learning.

Input: a pairwise similarity matrix $S \in \{-1, 1\}^{n\times n}$, the number of bits q in a target hash code, the tolerance error ϵ, maximum iterations T.
Initialize: randomly initialize $H \in [-1, 1]^{n\times q}$; $L \leftarrow HH^T - qS$, $t \leftarrow 0$, $F_{(0)} \leftarrow ||L||_F^2$, $H_{(0)} \leftarrow H$, $L_{(0)} \leftarrow L$.
for t=1,...,T **do**
  Decide the order of $n \times q$ indices (i,j) by random permutation (i=1,...,n, j=1,...,q).
  for each of the $n \times q$ indices (i,j) **do**
    Select the entry h_{ij} to update.
    Calculate $g'(H_{ij})$ and $g''(H_{ij})$ by (7).
    Calculate d by (6) and update H_{ij} by $H_{ij} \leftarrow H_{ij} + d$.
    Update L by (8).
  end for
  $t \leftarrow t + 1$, $F_{(t)} \leftarrow ||L||_F^2$.
  if $F_{(t)} \le F_{(t-1)}$ **then** $H_{(t)} \leftarrow H$, $L_{(t)} \leftarrow L$,
  else $H_{(t)} \leftarrow H_{(t-1)}$, $L_{(t)} \leftarrow L_{(t-1)}$, **continue**.
  if the relatively change $\frac{F_{t-1}-F_t}{F_{t-1}} \le \epsilon$, **then break**.
end for
Output: the sign matrix of H, each of whose elements is either 1 or -1.

It is still challenging to optimize (3) due to the non-convex term HH^T. Here we propose to solve it by a coordinate descent algorithm using Newton directions. This algorithm sequentially or randomly chooses one entry in H to update while keeping other entries fixed.

Specifically, in each iteration, we update only one entry (i.e., H_{ij}) in H with other entries being fixed. Let $H = [H_{\cdot 1}, H_{\cdot 2}, \ldots, H_{\cdot q}]$, where $H_{\cdot j}$ is the j-th column in H. The objective in (3) can be rewritten as:

$$\|H_{\cdot j}H_{\cdot j}^T - (qS - \sum_{c\neq j} H_{\cdot c}H_{\cdot c}^T)\|_F^2$$

$$= ||H_{\cdot j}H_{\cdot j}^T - R||_F^2 = \sum_{l=1}^{n}\sum_{k=1}^{n}(H_{lj}H_{kj} - R_{lk})^2$$

where we set $R = qS - \sum_{c\neq j} H_{\cdot c}H_{\cdot c}^T$. Since S is symmetric, it is easy to verify that R is also symmetric. By fixing other entries in H, the objective w.r.t. H_{ij} can be rewritten as:

$$g(H_{ij}) = \sum_{l=1}^{n}\sum_{k=1}^{n}(H_{lj}H_{kj} - R_{lk})^2$$

$$= (H_{ij}^2 - R_{ii})^2 + 2\sum_{k\neq i}(H_{ij}H_{kj} - R_{ik})^2 + constant,$$

where we use the fact that R is symmetric.

Suppose we update H_{ij} to $H_{ij} + d$, the corresponding optimization problem is:

$$\min_d g(H_{ij} + d) \ \ s.t.\ -1 \le H_{ij} + d \le 1.$$

To simplify the search of d, we approximate $g(H_{ij} + d)$

Method	MNIST(MAP)				CIFAR10(MAP)				NUS-WIDE(MAP)			
	12 bits	24 bits	32 bits	48 bits	12 bits	24 bits	32 bits	48bits	12 bits	24 bits	32 bits	48 bits
CNNH+	**0.969**	**0.975**	**0.971**	**0.975**	**0.465**	**0.521**	**0.521**	**0.532**	**0.623**	**0.630**	**0.629**	**0.625**
CNNH	0.957	0.963	0.956	0.960	0.439	0.511	0.509	0.522	0.611	0.618	0.625	0.608
KSH	0.872	0.891	0.897	0.900	0.303	0.337	0.346	0.356	0.556	0.572	0.581	0.588
ITQ-CCA	0.659	0.694	0.714	0.726	0.264	0.282	0.288	0.295	0.435	0.435	0.435	0.435
MLH	0.472	0.666	0.652	0.654	0.182	0.195	0.207	0.211	0.500	0.514	0.520	0.522
BRE	0.515	0.593	0.613	0.634	0.159	0.181	0.193	0.196	0.485	0.525	0.530	0.544
SH	0.265	0.267	0.259	0.250	0.131	0.135	0.133	0.130	0.433	0.426	0.426	0.423
ITQ	0.388	0.436	0.422	0.429	0.162	0.169	0.172	0.175	0.452	0.468	0.472	0.477
LSH	0.187	0.209	0.235	0.243	0.121	0.126	0.120	0.120	0.403	0.421	0.426	0.441

Table 1: MAP of Hamming ranking w.r.t different number of bits on three datasets. For NUS-WIDE, we calculate the MAP values within the top 5000 returned neighbors. The results of CNNH / CNNH+ are the average of 5 trials.

by a quadratic function via Taylor expansion:

$$\hat{g}(H_{ij}+d) = g(H_{ij}) + g'(H_{ij})d + \frac{1}{2}g''(H_{ij})d^2, \quad (4)$$

where $g'(H_{ij})$ ($g''(H_{ij})$) is the first (second) order derivative of g at H_{ij}:

$$g'(H_{ij}) = 4\sum_{k=1}^{n}(H_{ij}H_{kj} - R_{ik})H_{kj}$$

$$g''(H_{ij}) = 12H_{ij}^2 - 4R_{ii} + 4\sum_{k\neq i} H_{kj}^2$$

By setting the derivative of (4) w.r.t. d to be zero, we have $d = -\frac{g'(H_{ij})}{g''(H_{ij})}$. Hence, the solution to the objective

$$\min_d \hat{g}(H_{ij}+d) \ \ s.t. \ -1 \leq H_{ij}+d \leq 1. \quad (5)$$

is

$$d = \max(-1-H_{ij}, \min(-\frac{g'(H_{ij})}{g''(H_{ij})}, 1-H_{ij})), \quad (6)$$

which can be used in the update rule $H_{ij} \leftarrow H_{ij} + d$.

Note that directly calculating the matrix $R = qS - \sum_{c\neq i} H_{\cdot c}H_{\cdot c}^T \in \mathcal{R}^{n\times n}$ needs $O(n^2)$ time, which is time-consuming with large number n of training images. To tackle this issue, we do not calculate R explicitly. Specifically, we maintain a matrix $L = HH^T - qS$. Given L, $g'(H_{ij})$ and $g''(H_{ij})$ can be calculated by:

$$g'(H_{ij}) = 4L_{i\cdot}H_{\cdot j},\ g''(H_{ij}) = 4(H_{\cdot j}^T H_{\cdot j} + H_{ij}^2 + L_{ii}), \quad (7)$$

where $L_{i\cdot}$ is the i-th row of L. Hence, we can calculate $g'(H_{ij})$ and $g''(H_{ij})$ in $O(n)$ time. After H_{ij} is updated, it is easy to verify that only the i-th row and i-th column of L are affected. For example, given $H_{ij} \leftarrow H_{ij} + d$, we update L by:

$$L_{i\cdot} \leftarrow L_{i\cdot} + dH_{\cdot j}^T,\ L_{\cdot i} \leftarrow L_{\cdot i} + dH_{\cdot j},\ L_{ii} \leftarrow L_{ii} + d^2. \quad (8)$$

Hence, the time complexity of updating L is also $O(n)$.

The sketch of the proposed coordinate descent algorithm is shown in Algorithm 1[1] . In each iteration of the inner loop, the overall time complexity is $O(n)$. The time complexity of the whole algorithm is $O(Tqn^2)$ with small T and q (e.g., $T = 5$ and $q \leq 64$ in our experiments), making the algorithm scale well with relatively large n.

[1]Since the objective (3) is non-convex w.r.t. H, Algorithm 1 is a greedy algorithm and it cannot guarantee to decrease (3) in each iteration. Hence, similar to existing methods (Liu et al. 2012; Lin et al. 2013; Kulis and Darrell 2009), if in some iteration (of the outer loop) increases the value of (3), Algorithm 1 does not update H and L and continues the loop (see the IF-ELSE block in the outer loop of Algorithm 1). Note that in our experiments, we found that Algorithm 1 decreases (3) in every iteration.

Stage 2: learning image feature representation and hash functions

In contrast to the existing supervised hashing methods which use hand-crafted visual features for images, in the second stage, we simultaneously learn a feature representation for the training images as well as a set of hash functions.

Recently, deep learning has become a hot topic in machine learning research. In contrast to other deep architectures (e.g., (Hinton and Salakhutdinov 2006; Salakhutdinov and Hinton 2009)), deep convolutional neural networks (CNNs) (LeCun et al. 1998) are designed to take advantage of the 2D structure of images and able to learn translation invariant features. CNNs have shown encouraging results in various visual tasks such as object recognition (Krizhevsky, Sutskever, and Hinton 2012). Here we focus on leveraging convolutional networks in hash learning. We adopt the well-known architecture in (Krizhevsky, Sutskever, and Hinton 2012) as our basic framework. As shown in Figure 1(Stage 2), our network has three convolution-pooling layers with rectified linear activation, max pooling and local contrast normalization, a standard fully connected layer and an output layer with softmax activation. We use 32, 64, 128 filters (with the size 5×5) in the 1st, 2nd and 3rd convolutional layers. We use dropout (Hinton et al. 2012) in the fully connected layer with a rate of 0.5. Here we mainly focus on the design of the output layer, so as to explore how to train a network tailored to the hashing task.

In many scenarios of supervised hashing for images, the similarity/dissimilarity labels on image pairs are derived from the discrete class labels of the individual images. That is, in hash learning, the discrete class labels of the training images are usually available. Here we can design the output layer of our network in two ways, depending on whether the discrete class labels of the training images are available.

In the first way, given only the learned hash code matrix H with each of its rows being a q-bit hash code for a training image, we define an output layer with q output units (the red nodes in the output layer in Figure 1(Stage 2)), each of which corresponds to one bit in the target hash code for an image. We denote the proposed hashing method using a CNN with such an output layer (with only the red nodes, ignoring the black nodes and the associated lines) as CNNH.

In the second way, we assume the discrete class labels of the training images are available. Specifically, for n training images in c classes (an image may belong to multiple classes), we define a n by c discrete label matrix $Y \in \{0,1\}^{n\times c}$, where $Y_{ij} = 1$ if the i-th training image belongs to the j-th class, otherwise $Y_{ij} = 0$. For the output layer in our network, in addition to defining the q output units (the red nodes in the output layer) corresponding to the hash bits as in the first way, we add c output units (the black nodes in the output layer in Figure 1(Stage 2)) which correspond to the class labels of a training images. By incorporating the image class labels as a part in the output layer, we enforce the network to learn a shared image representation which matches both the approximate hash codes and the image class labels. It can be regarded as a transfer learning case in which the incorporated image class labels are expected to be helpful for learning a more accurate image representation (i.e. the hidden units in the fully connected layer). Such a better image representation may be advantageous for hash functions learning. We denote the proposed method using a CNN with the output layer having both the red nodes and the black nodes as CNNH+.

The convolutional networks automatically learn an image representation (represented by the orange nodes in the fully connected layer) as well as a set of hash functions (represented by the solid lines between the orange nodes and the red nodes within the last two layers). In prediction, one can input a test image to the trained networks and obtain the hash code from the values of the red nodes in the output layer.

Experiments

Results on image search

We evaluate the proposed method on three benchmark datasets with different kinds of images. (1) The **MNIST**[2] dataset consists of 70K 28×28 greyscale images of handwritten digits from '0' to '9'. (2) The **CIFAR-10**[3] consists of 60K 32×32 color tinny images which are categorized into 10 classes (6K images per class). (3) The **NUS-WIDE**[4] dataset has nearly 270K images collected from the web. It is a multi-label dataset in which each image is annotated with one or multiple semantic tags (class labels) from 81 concept tags. Following (Liu et al. 2011), we only use the images associated with the 21 most frequent concept tags (classes), where the number of images associated with each tag is at least 5K. For simplicity, we resize each image to 64×64.

We compare the performance of the proposed CNNH and CNNH+ against seven state-of-the-art hashing methods, including three unsupervised methods LSH (Gionis, Indyk, and Motwani 1999), SH (Weiss, Torralba, and Fergus 2008) and ITQ (Gong and Lazebnik 2011), and four supervised methods KSH (Liu et al. 2012), MLH (Norouzi and Blei 2011), BRE (Kulis and Darrell 2009) and ITQ-CCA (Gong and Lazebnik 2011). The results of LSH are obtained by our implementation. The results of the other six baseline methods are obtained by the open-source implementations provided by their respective authors.

In MNIST and CIFAR-10, we randomly select 1K images (100 images per class) as the test query set. For the unsupervised methods, we use the rest images as training samples. For the supervised methods, we randomly select 5K images (500 images per class) from the rest images as the training set. The pairwise similarity matrix S is constructed based on the image class labels.

In NUS-WIDE, we randomly sample 100 images from each of the selected 21 classes to form a test query set of 2,100 images. For the unsupervised methods, the rest images in the selected 21 classes are used as the training set. For supervised methods, we uniformly sample 500 images from each of the selected 21 classes to form a training set. We construct the pairwise similarity matrix S based on whether two images share at least one common tag.

For the proposed CNNH and CNNH+, we directly use the image pixels as input. For all of the baseline methods, we follow (Norouzi and Blei 2011; Wang, Kumar, and Chang 2010) to represent each image in MNIST by a 784-dimensional greyscale vector; we follow (Liu et al. 2012) to represent each image in CIFAR-10 by a 512-dimensional GIST vector; we represent each image in NUS-WIDE by a 500-dimensional bag-of-words vector (which is included in the NUS-WIDE dataset).

To evaluate the quality of hashing, we use four evaluation metrics: Mean Average Precision (MAP), Precision-Recall curves, Precision curves within Hamming distance 2, and Precision curves w.r.t. different number of top returned samples. For fair comparisons, all of the methods use identical training and test sets.

Since CNNH and CNNH+ use random initialization of H in stage 1, in all of the experiments, the results of CNNH and CNNH+ are the average of 5 trials.

As shown in Table 1 and Figure 2$\sim$4, two observations can be made from the results:

(1) On all of the three datasets, CNNH+ and CNNH achieve substantially better search accuracies (w.r.t. MAP, precision within Hamming distance 2, precision-recall, and precision with varying size of top returned samples) than the baseline methods. For example, compared to the second best competitor (except for CNNH), the MAP results of CNNH+ indicate a relative increase of **8.2**% $\sim$ **11.1**% **/ 49.4**% $\sim$ **54.6**% **/ 6.3**% $\sim$ **12.1**% on MNIST / CIFAR-10 / NUS-WIDE, respectively. The substantial superior performance of CNNH+ verifies that automatically learning a good image representation as well as a set of hash functions is beneficial to enhance the hashing quality for images.

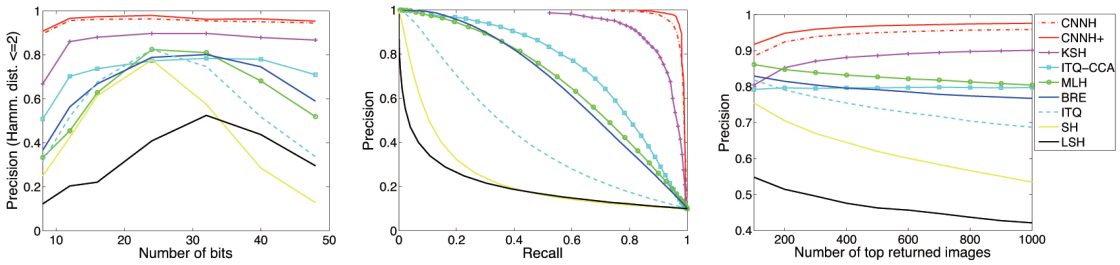
(2) CNNH+ shows slightly but consistently better search accuracies than CNNH, which verifies that incorporating both the approximate hash codes and image tags in training helps to learn a better shared image representation and enhance the hashing performance.

Note that various hand-crafted features can be used in the baseline methods. We conduct experiments to observe the effects on hashing with different features. We only evaluate KSH because it performs the best among the baselines. As shown in Figure 6, on MNIST and CIFAR-10, the search

[2] http://yann.lecun.com/exdb/mnist/

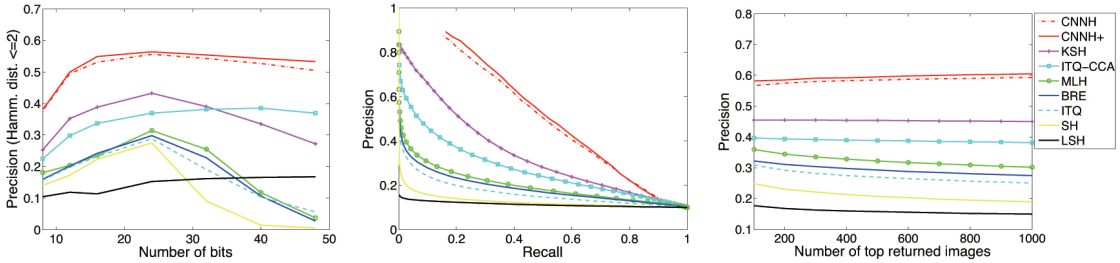
[3] http://www.cs.toronto.edu/ kriz/cifar.html

[4] http://lms.comp.nus.edu.sg/research/NUS-WIDE.htm



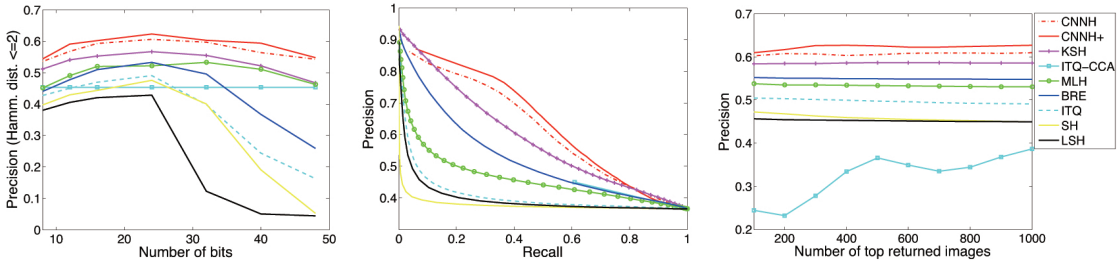
(a) (b) (c)

Figure 2: The results on MNIST. (a) precision curves within Hamming radius 2; (b) precision-recall curves of Hamming ranking with 48 bits; (c) precision curves with 48 bits w.r.t. different number of top returned samples.



(a) (b) (c)

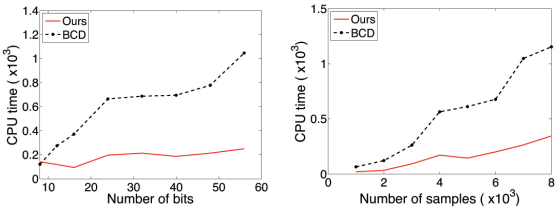
Figure 3: The results on CIFAR10. (a) precision curves within Hamming radius 2; (b) precision-recall curves of Hamming ranking with 48 bits; (c) precision curves with 48 bits w.r.t. different number of top returned samples



(a) (b) (c)

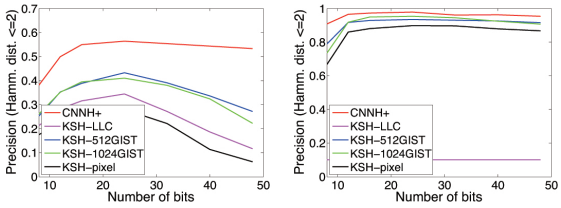
Figure 4: The results on NUS-WIDE. (a) precision curves within Hamming radius 2; (b) precision-recall curves of Hamming ranking with 48 bits; (c) precision curves with 48 bits w.r.t. different number of top returned samples

accuracies of KSH with raw pixels, 512-dim GIST, 1024-dim GIST and 21504-dim sparse-coding features (extracted by LLC (Wang et al. 2010)) are inferior to those of CNNH+. Automatically learning features in CNNH+ makes it easy to be applied to image retrieval in new domains.



(a) (b)

Figure 5: CPU time of stage 1 on CIFAR10.



(a) (b)

Figure 6: Comparison results of KSH with different features on (a) CIFAR-10, and (b) MNIST.

Efficiency of approximate hash code learning

In stage 1 of CNNH/CNNH+, we proposed a coordinate descent algorithm to factorize S into HH^T, whose time complexity is $O(Tqn^2)$. Note that there exist other algorithms to

factorize S into HH^T, such as the block coordinate descent (BCD) algorithm in (Lin et al. 2013). Hence, we empirically compare the efficiency of the propose coordinate descent algorithm to the most related BCD algorithm in (Lin et al. 2013)[5] on CIFAR-10. For fair comparisons, we use the same stopping criterion (as shown in Algorithm 1) in the two algorithms. As can be seen in Figure 5, the proposed coordinate descent algorithm is much faster to converge than the BCD algorithm. For either the number n of training samples or the number q of bits increasing, the CPU time of the baseline increases more rapidly than the proposed algorithm, which indicates the proposed algorithm's superior scalability in the scenarios with large number of training samples.

Conclusions

In this paper, we developed a supervised hashing method for image retrieval, which simultaneously learns a good representation of images as well as a set of hash functions. The proposed method firstly factorizes the pairwise semantic similarity matrix into approximate hash codes for the training images, and then trains a deep convolutional network with the approximate hash codes as well as the image tags (if available). Empirical evaluations in image search show that the proposed method has encouraging performance gains over state-of-the-arts.

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[5]We carefully implemented the BCD algorithm in (Lin et al. 2013), in which we used the LBFGS-B solver at http://users.eecs.northwestern.edu/ nocedal/lbfgsb.html.

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