On Trivial Solution and High Correlation Problems in Deep Supervised Hashing*

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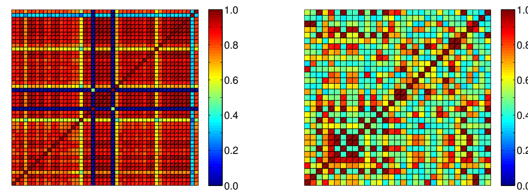
Abstract

Deep supervised hashing (DSH), which combines binary learning and convolutional neural network, has attracted considerable research interests and achieved promising performance for highly efficient image retrieval. In this paper, we show that the widely used loss functions, pair-wise loss and triplet loss, suffer from the trivial solution problem and usually lead to highly correlated bits in practice, limiting the performance of DSH. One important reason is that it is difficult to incorporate proper constraints into the loss functions under the mini-batch based optimization algorithm. To tackle these problems, we propose to adopt ensemble learning strategy for deep model training. We found out that this simple strategy is capable of effectively decorrelating different bits, making the hashcodes more informative. Moreover, it is very easy to parallelize the training and support incremental model learning, which are very useful for real-world applications but usually ignored by existing DSH approaches. Experiments on benchmarks demonstrate the proposed ensemble based DSH can improve the performance of DSH approaches significant.

Introduction

The number of images on the Internet has been growing rapidly in recent years, necessitating highly efficient indexing techniques to facilitate large-scale image retrieval. The recent works have demonstrated that hashing is a powerful technique for efficient and accurate image retrieval (Wang et al. 2016). In particular, hashing transforms real-valued image representations into binary hashcodes. Then, based on the extremely fast basic CPU operations, like bit XOR, the hamming distance between hashcodes can be obtained with little time cost. In this way, linearly scanning the the database is fast and the memory cost for storing the database is low. Suppose we have 1 billion images and each image is represented as a 128-bit binary sequence. It requires just 16GB memory to load all images' hashcodes and computing the hamming distance between a query image and all database images takes only a few seconds (Wang et al. 2015). Because of its outstanding efficiency and accuracy, hashing has been applied to many computer vision tasks, including not only image retrieval, but also large-scale clustering (Gong et al. 2015), classification (Mu et al. 2014), and re-identification (Zheng and Shao 2016).



(a) Pair-wise, mAC=0.92 (b) Triplet, mAC=0.52

Figure 1: The correlation matrix (absolute value) of hashcode bits. Different hashcode bits are highly correlated.

Inspired by the great success of convolutional neural networks (CNN) for many computer vision tasks (He et al. 2016), the researchers have made attempt to combine CNN with hashing (Lai et al. 2015; Liong et al. 2015; Liu et al. 2016; Xia et al. 2014). In particular, by slightly modifying the network structure of CNN, especially the output layer, we can train a CNN model using the similarity supervision as a very effective hashing model which takes the raw image as input and outputs the hashcodes for this image. Based on the power of CNN, the deep supervised hashing (DSH) model can effectively exploit the semantic similarity structure of images and produce better hashcodes than non-deep hashing approaches. For example, Xia et al. (2014) has shown that a simple and straightforward DSH model can improve the mean Average Precision (mAP) over the state-of-the-art non deep approaches by 15% (from about 35% to about 50%) on CIFAR10 (Krizhevsky 2009). With elaborate designs, the mAP achieves 60% and more (Liu et al. 2016).

Problem Statement

The extraordinary performance and a large number of follow-up works (Lai et al. 2015; Liong et al. 2015; Liu et al. 2016; Xia et al. 2014; Zhuang et al. 2016) motivate us to closely investigate the properties of DSH. From the literatures, we notice that the existing DSH can already yield good results with short hashcodes, e.g., 8 to 24 bits. Howev-

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er, significantly increasing the hashcode length (say, to 128 bits) can only lead to marginal performance gain while many non-deep hashing approaches can be improved a lot, which violates the intuition that longer hashcodes can encode more information such that the intrinsical similarity structure can be better preserved. In practice, we sometimes need longer hashcodes in order to improve the retrieval accuracy if larger memory or faster computing devices are available. But it seems to be difficult to obtain a better model by simply appending more output units in existing DSH approaches.

To make DSH more practical, it is worth investigating this phenomenon while previous works paid little attention to it. In this paper, we argue that the widely used loss functions in DSH learning, pair-wise loss and triplet loss, are prone to achieving trivial solution, which consequently leads to highly correlated bits. Obviously, we cannot expect good performance using highly correlated hashcodes. For example, if all bits are totally (positively or negatively) correlated, the 128-bit hashcodes will perform just like the 1-bit hashcodes. This problem gets more serious for longer hashcodes. To demonstrate it, we first train a DSH model using pair-wise loss (Liu et al. 2016) or triplet loss (Lai et al. 2015). Then the hashcodes for images are extracted. Now we can compute the correlation between different bits. The correlation matrices for different loss functions are shown in Figure 1. We also compute the mean Absolute Correlation for the hashcodes:

$$\text{mAC} = \frac{2\sum_{i=1}^{k}\sum_{j>i}|C_{ij}|}{k(k-1)} \tag{1}$$

where k is the length of hashcodes and C_{ij} is the correlation coefficient between bit i and j. Obviously mAC $\in [0,1]$ and a larger mAC indicates that the hashcodes have higher correlation. From the figure we can evidently observe that hashcodes are highly correlated even with 48 bits, and the mAC values also validate the same point. Clearly, it is hard to encode more information by using the highly correlated hashcodes as presented here. In this circumstance, it seems reasonable that existing DSH approaches fail to achieve much better results by simply increasing hashcode length.

Our Contributions

The problems are clear but the solution is not that trivial. In non-deep hashing approaches, some extra constraints and regularizations can be incorporated into the learning objective such that the learned hashcodes are less correlated, like the orthogonality constraint and regularization. However, it is not straightforward to apply these constraints and regularizations to DSH because the mini-batch based optimization algorithm is adopted for deep model training and the model is not aware of the hashcodes of samples out of the mini batch. In this paper, we propose a simple yet effective learning strategy based on ensemble learning which learns different bits using different training sets and models. We found out that this simple strategy is capable of effectively decorrelating different bits such that the learned hashcodes are more informative, especially for long hashcodes. In this way, given longer hashcodes, more information about the data can be encoded such that more performance improvement can be achieved. Theoretically, we make the following contributions in this paper:

1. We show that the loss functions adopted by existing DSH approaches, pair-wise loss and triplet loss, are prone to trivial solution and produce highly correlated and redundant hashcodes. In this circumstance, increasing the hashcode length can only marginally improve the retrieval accuracy.

2. We propose a simple yet effective ensemble learning based strategy which decorrelates bits and reduces redundancy such that longer hashcodes can encode more information, leading to better performance. To our knowledge, this is the first work noticing the trivial solution and high correlation problems in DSH and systematically solve them.

3. Our approach supports incremental learning while existing DSH approaches fail to do so. In particular, when new labeled samples are given, or when longer bits are required, e.g., we change the hashcode length from 48 to 64 because better devices are given, existing DSH approaches have to totally retrain a new hashing model for 64-bit hashcodes with all training data. On the contrary, our approach only needs to learn hashing functions for the extra 16 bits.

4. It is straightforward to parallelize the training which makes the deep model training more efficient and cheap.

Related Work

By representing images as binary codes and taking advantage of fast bit operations, hashing can reduce the memory cost and accelerate the search speed with orders of magnitudes. Earlier works mostly focused on data-independent hashing, like Locality Sensitive Hashing (Gionis, Indyk, and Motwani 1999) which adopts random splits to binarize image features. Because no prior about the data is taken into account, the data-independent approaches usually requires very long hashcodes for satisfactory performance (Zhang et al. 2010). To design more effective hashcodes, the researchers turned their focus to data-dependent hashing which utilizes the data distribution information. Some widely used priors include the variance of data (Gong et al. 2013; Xu et al. 2013), manifold structure (Guo et al. 2017b; Liu et al. 2014; 2011), the cluster structure (He, Wen, and Sun 2013), and etc. For image retrieval, the users care more about the semantic similarity between images. Therefore, many supervised hashing approaches are proposed that use the semantic similarity (like the similarity matrix) as supervision to guide the hashing function learning (Ge, He, and Sun 2014; Liu et al. 2012; Shen et al. 2015; Zhang et al. 2014). Because the supervised knowledge is available, the supervised ones yield better retrieval performance, especially evaluated from the semantic perspective.

However, the retrieval accuracy of the aforementioned approaches is limited because they adopt the hand-crafted features as input which fail to capture the semantic information between them and dramatic appearance variations in real-world images. Fortunately, the recent studies have demonstrated that the convolution neural networks (CNN) (He et al. 2016) can effectively extract the semantic information from images even with large variations. Inspired by the success of CNN for some related tasks, many works combining CNN with hashing are proposed. By training CN-

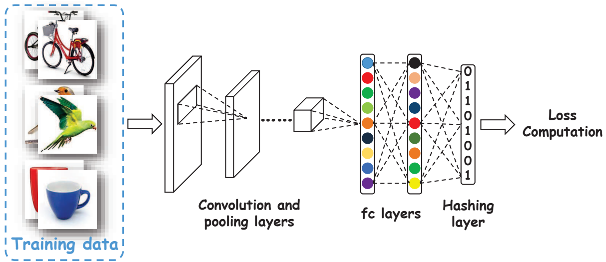


Figure 2: The basic architecture of DSH.

N with the supervised information, deep supervised hashing (DSH) achieves promising retrieval accuracy. Xia et al. (2014) propose a simple CNN based hashing approach that has a disjoint learning procedure and only employs CNN as a mapping model. Despite its simplicity, it outperforms state-of-the-art non-deep hashing approaches with significant margin. To make better use of the power of CNN, Lai et al. (2015) propose an end-to-end architecture that simultaneously learns the feature mapping functions and the binary codes which minimize the triplet loss. The results demonstrate that the end-to-end learning is better than disjoint learning. Liu et al. (2016) propose to consider the pair-wise loss and the quantization loss during model learning. Zhang et al. (2015) adopt the similarity regularized triplet loss and achieve state-of-the-art performance for image retrieval. Generally, the DSH approaches have dominated the leaderboard of hashing based image retrieval in recent years. Please refer to (Wang et al. 2016) for more elaborate survey.

The Proposed Model

Trivial Solution and High Correlation

To clarify the problems, we firstly briefly introduce the basic architecture of DSH, which is illustrated in Figure 2. Typically, there are three components in the network modified from some well-established architectures, like AlexNet (Krizhevsky, Sutskever, and Hinton 2012) and VGG (Szegedy et al. 2015). The first component contains the convolutional and pooling layers which adopt nonlinear transformation to extract basic image features. The second component consists of fully connected layers and hashing/quantization layers which produce (approximate) binary codes for images. The last component is the loss computation which computes the loss using the hashcodes and the supervised information. Specifically, the supervised knowledge is given as the semantic similarity matrix $\mathbf{S}$ where $s_{ij} = +1$ or -1 indicating images I_i and I_j are similar or not. The objective of DSH learning is to make similar images have similar hashcodes (small hamming distance) and dissimilar images have dissimilar hashcodes (large hamming distance). A simple loss function is pair-wise loss (Li, Wang, and Kang 2016; Liong et al. 2015; Liu et al. 2016) direct translating this objective as below:

$$\mathcal{J}^p = \sum\nolimits_{i,j} s_{ij} d(\mathbf{h}_i, \mathbf{h}_j) \tag{2}$$

where $\mathbf{h}_i, \mathbf{h}_j \in \{-1, 1\}^k$ are the hashcodes of training image I_i and I_j and k is the length of hashcodes (the number of output units in the hashing network). $d(\cdot, \cdot)$ denotes a distance measure between hashcodes, such as squared Euclidean distance $d(\mathbf{h}_i, \mathbf{h}_j) = \|\mathbf{h}_i - \mathbf{h}_j\|_2^2$ in (Liong et al. 2015; Liu et al. 2016). In addition, noticing that the retrieval cares more about the ranking than the absolute distance, ranking based loss functions are often used. The most popular one is triplet loss (Lai et al. 2015; Zhang et al. 2015) which considers the relationship of a positive sample and a negative sample to a target sample, which is defined as:

$$\mathcal{J}^t = \sum\nolimits_{i,p,n} d(\mathbf{h}_i, \mathbf{h}_i^p) - d(\mathbf{h}_i, \mathbf{h}_i^n) \tag{3}$$

where p and n denote a positive sample ($s_{ip} = 1$) and a negative sample ($s_{in} = -1$) to target image I_i respectively.

Trivial solution. Looking back to the network architecture introduced above, we can notice an important property about the hashcodes. After the final fc layer, the models to generate each hashcode bit are independent to each other. In fact, the last fc layer and the hashing layer are also fully connected. Suppose the output of the last fc layer is $\mathbf{g}_i$, the l-th bit is generated as $h_{il} = \mathcal{Q}(\mathbf{g}_i \mathbf{v}_l')$, where $\mathcal{Q}$ is a quantization function like sign function, and $\mathbf{v}_l$ are the connection weights between the l-th hashing layer unit and all units of the last fc layer. For $l_1 \neq l_2$, because $\mathbf{v}_{l_1}$ and $\mathbf{v}_{l_2}$ are free from each other, they can have totally different or identical values. It is not a critical issue for some other tasks like classification because minimizing the loss functions will assign proper values to them. However, for pair-wise loss and triplet loss, the network favors to assign identical values to them. The reason is not that clear, which is discussed below.

Firstly, we can see the loss functions in Eq. (2) and Eq. (3) are bit-wise decoupled such that they can be divided into k sub-problems. For example, the pair-wise loss with squared Euclidean distance (Liu et al. 2016) can be rewritten as:

$$\begin{aligned} \mathcal{J}^p &= \sum_{i,j} s_{ij} \|\mathbf{h}_i - \mathbf{h}_j\|_2^2 = \sum_{i,j} \sum_{l} s_{ij} (h_{il} - h_{jl})^2 \\ &= \sum_{l} \sum_{i,j} s_{ij} (h_{il} - h_{jl})^2 = \sum_{l} \mathcal{J}_l^p \end{aligned} \tag{4}$$

where $\mathcal{J}_l^p = \sum_{i,j} s_{ij} (h_{il} - h_{jl})^2$ is the l-th sub-loss. After training the DSH network by minimizing the loss $\mathcal{J}^p$, we obtain the parameters $\mathbf{v}_l$ and the sub-loss $\mathcal{J}_l^p$ can also be computed. Now let $l_m = \mathrm{argmin}_l \mathcal{J}_l^p$. If we assign the parameters $\mathbf{v}_{l_m}$ to all other bits while fixing the previous layers, we can obtain a new network. Obviously, for this network, we have $\mathcal{J}_{new}^p = k\mathcal{J}_{l_m}^p \leq \sum_l \mathcal{J}_l^p = \mathcal{J}_{old}^p$. Clearly, $\mathcal{J}_{new}^p = \mathcal{J}_{old}^p$ if and only if $\mathcal{J}_l^p = \mathcal{J}_{l_m}^p (\forall l = 1, ..., k)$. In this circumstance , if we have the optimal solution for one bit, copying its solution to other bits leads to the global optimum, which indicates the multi-bit model training problem can be solved trivially by simply learning one bit and then directly assigning its solution to all other bits. In practice, it is an undesired and bad property for multi-bit hashcodes.

The triplet loss has the same problem as the pair-wise loss. In fact, Eq. (3) can also be rewritten in the same way:

$$\mathcal{J}^t = \sum_{l} \sum_{i,p,n} (h_{il} - h_{pl})^2 - (h_{il} - h_{nl})^2 = \sum_{l} \mathcal{J}_l^t \tag{5}$$

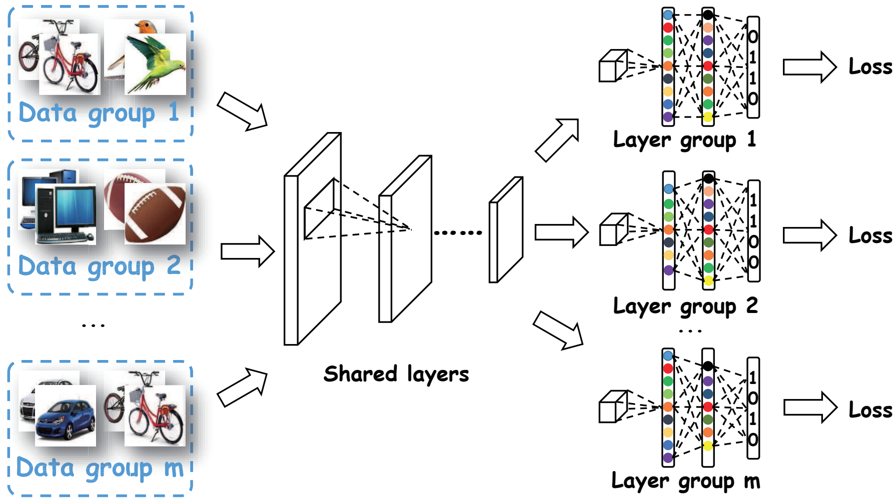


Figure 3: Ensemble based DSH. Several training subsets are sampled from the original training set (different data). Each subset is used to train a DSH sub-model producing $\frac{k}{m}$-bit hashcode(different models). To speed up the training and code generation, we freeze the first few layers and share them among all sub-models. Each sub-model only needs to optimize its specific part.

Like the case of pair-wise loss, triplet loss also suffers from trivial solution problem due to its bit-wise decoupled loss.

In non-deep hashing, it is easy to incorporate proper constraints or regularizations into the loss function, such as the orthogonality constraint $\mathbf{H}'\mathbf{H} = n\mathbf{I}_k$ or regularization $\|\mathbf{H}'\mathbf{H} - n\mathbf{I}_k\|_F^2$ on all bits to avoid the trivial solution. However, in DSH, the mini-batch based optimization algorithm is adopted such that the network can see only a small batch of data. In this way, it cannot compute the orthogonality loss which needs all data to compute or backpropagate it.

High correlation. Eq. (2) and Eq. (3) are the simplest loss functions. In practice, several works attempt to perform a further nonlinear transformation on the distance. For example, a distance margin can be incorporated. For pair-wise loss, Liu *et al.*(Liu et al. 2016) reformulate Eq.(2) as below:

$$\mathcal{J}^p = \sum_{s_{ij}=1} d(\mathbf{h}_i, \mathbf{h}_j) + \sum_{s_{ij}=-1} \max(0, \lambda - d(\mathbf{h}_i, \mathbf{h}_j)) \quad (6)$$

where $\lambda \leq k$ is the margin parameter. The triplet loss can also be reformulated using the margin (Lai et al. 2015):

$$\mathcal{J}^t = \sum_{i,p,n} \max(0, \lambda + d(\mathbf{h}_i, \mathbf{h}_i^p) - d(\mathbf{h}_i, \mathbf{h}_i^n)) \quad (7)$$

The nonlinear transformation can theoretically prevent the learning from trivial solution. However, the model usually achieve a near trivial solution at last, which appears to have highly correlated hashcodes. As shown in Figure 1, the mAC of 32-bit hashcodes is 0.52 with the margin based triplet loss (Lai et al. 2015), and it gets larger for longer codes.

Ensemble based DSH

To address this issue, we propose an ensemble based strategy for DSH learning. Inspired by the classifier ensemble (Dietterich 2000), we can consider three different ways to decorrelate bits. The first is random initialization. Although the global optimum for each bit should be identical, the deep model adopts gradient descent for optimization such that different initializations are likely to result in different local optimum, which reduces the correlation between bits. In fact, the existing DSH approaches benefit from the random initialization and they perform well with short hashcodes. However, when the hashcodes are too long (say, 128 bits), the random initialization does not work well, leading to high correlation. The second is to use different training data. This is widely used for classifier ensemble, including many boosting algorithms. It is very easy to construct different sub training sets for hashing model learning as hashing is designed for large-scale problem such that there are always sufficient training data. The third is to utilize different models. In DSH, we can achieve this goal by simply changing the network architecture, like the number of fc layer units.

Based on the above discussion, we consider to use different training data and models, as illustrated in Figure 3. Given a training set, we randomly sample m groups where each group is utilized to train one model. As there are m groups, each model only needs to output $\frac{k}{m}$ bits. For example, if our target is 128-bit hashcode, we can train $m = 8$ sub-models and each sub-model outputs 16 bits. Then we can concatenate the 16-bit sub-hashcode produced by each sub-model to obtain the final 128-bit hashcode for an image.

In addition, for each sub-model, we can slightly modify its architecture. But we should notice that if we use m totally different deep networks, generating the hashcodes for an image will be computationally expensive because we need to forward this image through m networks. In fact, as suggested by Yosinski *et al.* (Yosinski et al. 2015), the first few convolutional layers of CNN mostly focus on the low-level characteristics of images, such as corners and edges. Therefore, it is reasonable to just use the pre-trained model parameters and freeze them because these low-level features should be task independent. In this way, all sub-models can share these layers to reduce computational cost. Only the last few layers, such as the fc layers and the hashing layer which are more related to the specific tasks, need further tuning by its corresponding data group. It is also simple to change the architecture of these layers. For example, we can reduce the number of hidden units in a fc layer by half, or the number of filters in the last convolutional layer by half, which can respectively lead to different models. Obviously, the models with different network architectures have different optimum such that their hashcodes have less inter-group correlation.

Parallelization and Incremental Learning

Parallelization. We can notice that training the t-th sub-model using the t-th data group has no influence on the other $m-1$ groups. So we can parallelize the model training and train each sub-model independently. As a sub-model only has $\frac{k}{m}$ output units, which are far fewer than that of one unified model as in existing approaches, and the training set is also relatively smaller because we only sample a subset from the training data, the training can converge faster. In this way, the training procedure is somehow accelerated.

Incremental Learning. Incremental learning is very important in practice. For example, when some new training samples are given, we can use it to update the hashing model. However, existing DSH approaches have to use all training data, including previous data and new data, to re-train the whole model. If only new data is utilized, the model may "forget" the previous knowledge. In the ensemble learning, we can use the new samples as a data group and only update one sub-model. In this way, the abundant knowledge from previous training data can be maintained by the other sub-models, and the new knowledge can be included by the updated sub-model. In addition, if better computing devices are available such that we can increase the hashcode length for more accurate retrieval. Existing DSH approaches have to re-train all bits from scratch while the proposed ensemble based DSH only needs to train more sub-models and reuse the previous ones. In this way, the previous knowledge and sub-models can be fully reused to save the training expense.

Experiment

Datasets and Settings

CIFAR10 (Krizhevsky 2009). CIFAR10 has 10 kinds of objects such as "bird", "ship", and "frog". For each category there are $6,000$ images belonging to it. For this dataset, we randomly sample $1,000$ images (100 images per category) as the query set, and the remaining $59,000$ images form the database. Moreover, in the database, we further randomly sample $10,000$ images as training set for model learning.

Animals with Attributes (Lampert, Nickisch, and Harmeling 2014). AwA dataset is collected from Web which consists of 50 animal species. There are $30,475$ images in AwA. We randomly sample $1,000$ images (20 images per category) as the query set, and the remaining $29,475$ images as database where $10,000$ images are used for training.

ImageNet (Russakovsky et al. 2015). ImageNet is a well-known benchmark dataset for the Large Scale Visual Recognition Challenge (ILSVRC). It has $1,000$ object categories with about 1.2 million training images and 50 thousand validation images. Following (Guo et al. 2017a), we randomly select 100 categories which leads to a database with about 120 thousand images and a query set with about $5,000$ images. In this dataset, $10,000$ images (100 per category) are randomly selected from the database for training models.

We adopt the widely used mean Average Precision (mAP) as the numeric evaluation metric. We also report the precision-recall curve to compare the retrieval performance. Following the widely used setting in previous works (Guo, Ding, and Han 2017; Liong et al. 2015; Liu et al. 2016; Xia et al. 2014; Zhuang et al. 2016; Zheng, Tang, and Shao 2016; Zheng and Shao 2016), a database image is considered as a true positive of a query image if they share the same label.

Implementation Details

Our ensemble based DSH can be regarded as a general framework such that it can be combined with previous DSH approaches. In the experiment, we basically consider the pair-wise loss (Liu et al. 2016) and the triplet loss (Lai et al. 2015). To construct different data groups for training, we adopt a random complementary sampling strategy. In particular, we randomly sample half of training data ($5,000$ images in our experiment) for the first data group and then we use the other half for the second group. Next, we again randomly sample half of training data for the third group and the other half for the fourth group. We continue the procedure until m groups are obtained. In this way, we can guarantee that all data are equally used for training for $m/2$ times and each group can be as different from the others as possible.

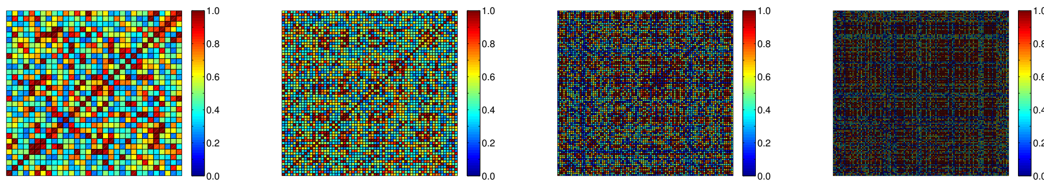
In the experiment, we utilize the Caffe (Jia et al. 2014) tool and we adopt AlexNet (Krizhevsky, Sutskever, and Hinton 2012) pre-trained on ImageNet classification task as the base network which has 5 convolutional layers (with ReLU layers and pooling layers) and 2 fully connected layers. We further add another hashing layer at the end of the network to produce k-bit hashcodes. In fact, we can surely adopt more complicated network such as ResNet (He et al. 2016). But it is unclear whether the performance gain over the other approaches is given by our method or a powerful network. Hence, we adopt a relatively simple but effective network.

How Many Layers to Share?

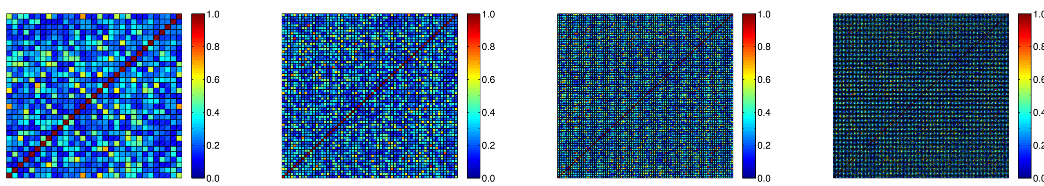
As introduced before, the ensemble learning based DSH needs to train m different sub-models where each produces $\frac{k}{m}$ bits. If all sub-models are totally different, the training will be slow and generating hashcode for image is inefficient because we need to forward this image for m times. One solution is to share some layers, especially the first few layers between each sub-model. In this way, there will be less parameters to learn such that the training can be accelerated, and the computation in the first few layers can be shared to improve generation speed. Clearly, there is a trade-off between efficiency and accuracy. So we first investigate the influence of the number of shared layers on the performance. Here, we use the ImageNet for experiment and we train 6 sub-models where each model produce 16-bit hashcodes which leads to 96 bits in total. We present the results

Table 1: mAP Comparison on benchmark datasets.

	ImageNet				CIFAR10				AwA			
	32 bits	64 bits	96 bits	128 bits	32 bits	64 bits	96 bits	128 bits	32 bits	64 bits	96 bits	128 bits
LSH	0.2350	0.3596	0.4172	0.4584	0.2553	0.2940	0.3224	0.3380	0.1870	0.2249	0.2617	0.2889
KSH	0.2976	0.3943	0.4472	0.4851	0.5080	0.5572	0.5666	0.5798	0.3279	0.3751	0.4089	0.4262
SDH	0.2804	0.3897	0.4592	0.5016	0.5140	0.5520	0.5644	0.5879	0.3279	0.3751	0.4089	0.4262
LFH	0.2349	0.3417	0.4105	0.4484	0.2665	0.3519	0.4128	0.4493	0.2420	0.2977	0.3472	0.3689
CNNH	0.4498	0.5038	0.5294	0.5380	0.4720	0.4990	0.5133	0.5370	0.4498	0.4831	0.4942	0.5099
DeSH	0.4651	0.5132	0.5287	0.5472	0.6390	0.6441	0.6473	0.6520	0.5174	0.5300	0.5347	0.5380
DNNH	0.4931	0.5343	0.5431	0.5576	0.6199	0.6317	0.6489	0.6531	0.5285	0.5484	0.5577	0.5607
DRSCH	0.4752	0.5277	0.5301	0.5399	0.6287	0.6326	0.6338	0.6390	0.5010	0.5075	0.5159	0.5190
Ours	0.4946	**0.5631**	**0.5831**	**0.6156**	0.6421	**0.6622**	**0.6989**	**0.7051**	**0.5494**	**0.5804**	**0.5960**	**0.6078**



(a) 32 bits, mAC $= 0.38$ (b) 64 bits, mAC $= 0.52$ (c) 96 bits, mAC $= 0.64$ (d) 32 bits, mAC $= 0.73$



(e) 32 bits, mAC $= 0.17$ (f) 64 bits, mAC $= 0.21$ (g) 96 bits, mAC $= 0.23$ (h) 128 bits, mAC $= 0.25$

Figure 4: The correlation matrix and mAC values of (Lai et al. 2015) (the first row) and ours (the second row).

in Table 2. Generally, we can observe that the results change a little if we only fix the first 3 layers, which is consistent with our intuition because the first few layers focus on the low-level features, like edges and corners of images. Moreover, if some layers like $\mathrm{conv5}$ are fixed, the retrieval performance drops significantly because these layers are more task-specific. From the results we can see that fixing $\mathrm{conv1}$ to $\mathrm{conv3}$ is a good balance between efficiency and accuracy. In the following experiments, we keep $\mathrm{conv1}$ to $\mathrm{conv3}$ fixed for each sub-model if no more statement is given.

Table 2: The influence of fixed layers. This table shows the mAP when fixing layers between the first to the target layer.

layers	pair-wise	triplet	layers	pair-wise	triplet
none	0.5871	0.6022	conv1	0.5852	0.5991
conv2	0.5793	0.5942	conv3	0.5717	0.5831
conv4	0.5434	0.5668	conv5	0.5173	0.5412
fc6	0.4647	0.5082	fc7	0.4190	0.4378

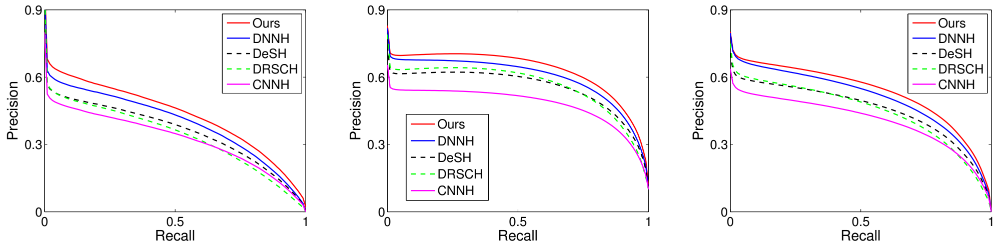
The Correlation of Hashcodes

The reason why existing DSH approaches fail to achieve significant gain using longer hashcode is because their hashcodes are highly correlated such that longer codes cannot encode more information. To address this issue, we adopt an ensemble based strategy for DSH. In this part we investigate the ability of ensemble based DSH to decorrelate bits. We use AwA dataset and triplet loss (Lai et al. 2015).

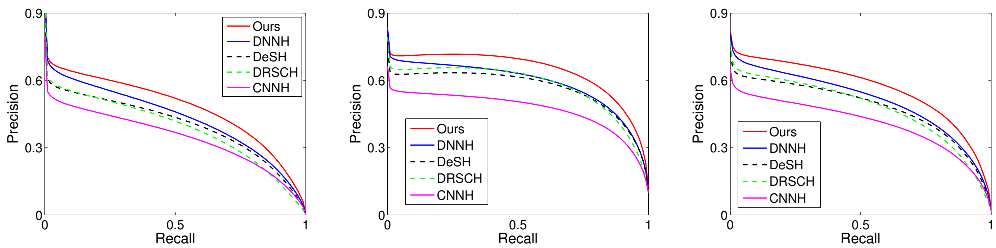
We also use 16 bits for each sub-model. The correlation matrices and the corresponding mAC values by Eq. (1) are shown in Figure 4. Benefiting from the random initialization and the margin in the loss function, (Lai et al. 2015) can achieve about 0.20 mAC with 16 bits and 0.38 mAC with 32 bits. However, when we increase the hashcode length to 64 and more, the correlation increases very fast and reaches 0.73 mAC with 128 bits. On the contrary, with the ensemble based strategy, we can significantly suppress the correlation and the mAC only reaches 0.25 with 128 bits, indicating our approach can encode more information in the hashcodes.

Benchmark Comparison

Now we compare our approach against existing hashing approaches on benchmark datasets. Based on the results shown in Table 2, we use triplet loss and freeze $\mathrm{conv1}$ to $\mathrm{conv3}$ layers in the comparison. For each sub-model, 16 output units are used, which means 16-bit hashcodes are generated.



(a) ImageNet, 64 bits (b) CIFAR10, 64 bits (c) AwA, 64 bits



(d) ImageNet, 128 bits (e) CIFAR10, 128 bits (f) AwA, 128 bits

Figure 5: The precision-recall curves of DSH approaches.

As our approach supports incremental learning, we train our model in an incremental way. For example, we train 2 sub-models for 32-bit experiment. Then for 64-bit experiment, we reuse these 2 sub-models and only train 2 new sub-models. On the other hand, for other approaches, we totally train a new model for each hashcode length.

We select the following hashing approaches as baselines. Locality Sensitive Hashing (LSH) (Gionis, Indyk, and Motwani 1999), and three state-of-the-art supervised hashing approaches, Kernelized Supervised Hashing (KSH) (Liu et al. 2012), Supervised Discrete Hashing (SDH) (Shen et al. 2015), and Latent Factor Hashing (LSH) (Zhang et al. 2014). For these non-deep approaches, we use the output of $\mathrm{fc7}$ layer of pre-trained AlexNet as input features. More importantly, we select four state-of-the-art deep supervised hashing approaches, CNNH (Xia et al. 2014), DeSH (Liu et al. 2016), DNNH (Lai et al. 2015), and DRSCH (Zhang et al. 2015). For all approaches, including all baselines and ours, we use the same query-database-train split for fairness.

The mAP comparison are summarized in Table 1 and the precision-recall curves of all DSH approaches are shown in Figure 5. Clearly, the deep approaches significantly outperform non-deep approaches, especially with short hashcode length, like 32 bits, which is consistent with the results in previous literatures (Lai et al. 2015; Liu et al. 2016; Xia et al. 2014; Zhang et al. 2015). However, there is one important observation we need to highlight, which is not fully discussed in previous works, that the DSH approaches' performance increases very slowly. From 32 bits to 128 bits, the end-to-end DSH approaches, DeSH, DNNH, and DRSCH increase mAP by $\mathbf{3.86}\%$, $\mathbf{4.33}\%$, and $\mathbf{3.10}\%$ respectively in average. The reason is that they obtain highly correlated bits in long hashcodes such that they fail to encode more information, which has been discussed heavily in this paper. Our approach is comparable to the baselines with 32 bits, which is much better than non-deep approaches. But we can observe that our approach is able to further improve its performance with longer hashcodes. In particular, our approach increases mAP from 32 bits to 128 bits by $\mathbf{8.07}\%$, which is far larger than the other DSH approaches. Moreover, the average performance gap between our approach and best DSH approach is $\mathbf{2.63}\%$, $\mathbf{4.28}\%$, and $\mathbf{5.24}\%$ with 64 bits, 96 bits, and 128 bits respectively, getting larger with longer codes. Both observations, together with the results in Figure 4, demonstrate that our approach can effectively decorrelate bits and prevent the triplet loss and from trivial solution and high correlation problems, making the hashcodes more informative. Moreover, the results also show our approach works well in the incremental learning, which is very useful for real-world applications.

Conclusion

In this paper, we show that existing state-of-the-art DSH approaches, which adopt pair-wise loss and triplet loss, suffer from trivial solution and high correlation problems such that they fail to achieve significant performance gain using longer codes because it is difficult to incorporate proper constraints or regularizations into the loss function under the mini-batch based optimization algorithm. To address these problems, we propose a simple training strategy based on ensemble. We decompose the k-bit problem into m $\frac{k}{m}$-bit sub-problems and use different training data and different models for each sub-problem. The simple strategy is capable of effectively decorrelating bits, making the hashcodes more informative. Comprehensive experiments on three benchmark datasets demonstrate that the ensemble based DSH can indeed achieve significant gain using longer hashcodes and clearly defeat existing DSH approaches.

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