

# Fast content-based image retrieval using Convolutional Neural Network and hash function

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**Abstract**—Due to the explosive increase of online images, content-based image retrieval has gained a lot of attention. The success of deep learning techniques such as convolutional neural networks have motivated us to explore its applications in our context. The main contribution of our work is a novel end-to-end supervised learning framework that learns probability-based semantic-level similarity and feature-level similarity simultaneously. The main advantage of our novel hashing scheme that it is able to reduce the computational cost of retrieval significantly at the state-of-the-art efficiency level. We report on comprehensive experiments using public available datasets such as Oxford, Holidays and ImageNet 2012 retrieval datasets.

## I. INTRODUCTION

The field of content-based image retrieval consists of a lot of different indexing structures, schemes, and methods aiding the related retrieval tasks. The goal of the indexing structures is to take an available dataset, and produce a concise and easier to handle index which can be used to search for similar content. In content-based image retrieval, both image representations and computational cost play an important and unavoidable role. Binary hashing has attracted a lot of attention due to computational and storage efficiencies of binary hash codes. It tries to map high-dimensional image data to compact binary codes in a Hamming-space while keeping several notion.

Due to the explosive increase of online images, rapid similarity search is critical for large-scale image retrieval. Benefiting from the compact binary codes, fast image search can be measured via Hamming distance and binary pattern matching, which significantly reduces the computational overhead and further optimizes the efficiency of the search. The success of deep learning techniques such as convolutional neural network (CNN) motivated us to explore its applications in providing compact binary codes directly. To address this problem, a deep semantic hashing algorithm is proposed in this paper, which based on CNN to learn semantic information and binary representations simultaneously.

The main contributions of our work are as following. An efficient end-to-end supervised learning framework is presented for fast image retrieval that learns probability-based semantic-level similarity and feature-level similarity simultaneously. Unlike previous methods [10], [11], the semantic from the last fully-connected layer is derived directly, instead of hash layer. Different from other supervised methods that learn an explicit hash function directly to map binary code features

from images, our method learns hashing codes and image representations in an implicit manner. The main advantage of our novel hashing scheme that it is able to reduce the computational cost of retrieval significantly at the state-of-the-art efficiency level.

The rest of this paper is organized as follows. In Section II, the related and previous works are reviewed. We describe the proposed fast image-retrieval architecture in Section III. Section IV shows experimental results and analysis. We draw the conclusions in Section V.

## II. RELATED WORKS

The existing hash methods can be roughly divided into two categories: data-independent and data-dependent. In this section, we will mainly focus on data-dependent hash methods which are related to our algorithm.

A typical example of data-independent methods is Locality Sensitive Hashing (LSH) [1] that uses random projection to construct hash functions. LSH hashes the input items so that similar items map to the same cluster with high probability.

Havasi et al. [2] proposed the Local Hash-indexing tree which is similar to M-index [3] where base points are chosen randomly to reduce the high-dimensional feature vectors. Unlike M-index, during random point selection a quasi-orthogonality criteria is forced.

Convolutional neural networks have achieved amazing success in modeling large-scale data recently. It have been demonstrated to be very effective in various computer vision and image processing tasks including pedestrian detection [4], face detection [5], image classification [6], image super-resolution [7], automatic image colorization [8] etc. CNN-based methods have been applied on the task of image retrieval recently.

The work of Babenko et al. [9] focuses on exploring the features of different layers, and to improve the retrieval performance with dimensional reduction. Xia et al. [10] presented an image retrieval method that uses a two-stage framework in order to accurately preserve the semantic similarities of image pairs. In the first stage, given the pairwise similarity matrix over training images a scalable coordinate descent method is proposed to decompose the similarity matrix. In the second stage, a feature representation is learned simultaneously for the input images as well as a set of hash functions. Zhao et al. [11] proposed a deep semantic ranking based method for learning

hash functions in order to preserve multilevel semantic similarity between multi-label images. CNNs were incorporated into hash functions to jointly learn feature representations and mappings from them to hash codes. A ranking list was applied to encode the multilevel similarity information. Wang et al. [12] proposed a fine-grained image similarity learning method that captures efficiently between-class and within-class image differences. A ranking loss based CNN architecture was proposed on triplet sampling to learn image similarity metric. Developing the convolutional architecture, Gong et al. [13] integrated into the CNN a warp approximate ranking algorithm.

### III. OUR APPROACH

In general, a hash function  $h: \mathbb{R}^D \rightarrow \{0, 1\}$  is treated as a mapping that projects a  $D$ -dimensional input onto a binary code. Let's assume that we are given a set of images and their labels  $I = \{\mathbf{x}_n, \mathcal{Y}_n\}$ , where each image  $\mathbf{x} \in \mathbb{R}^D$  is associated with a subset of possible labels  $\mathcal{Y} \subseteq \mathcal{L}$ . In previous works, the main objective was to learn a similarity function which mapped low-level image representation to a similarity value. Unlike previous methods [11], [12], [13], we obtain first the mid-level features from raw image data, then these mid-level features are used to estimate the probabilities of the semantic labels and to compute the hash codes of CNN feature vectors.

As shown in Figure 1, our algorithm consists of two main steps. In the first step, we obtain the image representations via a CNN which is supervised pre-trained on the ImageNet dataset [14] and fine-tuned on target dataset. The CNN model of Krizhevsky et al. [14] contains five convolutional layers, two fully-connected layers, and a softmax classifier. This model incorporates a huge amount of semantic information, since it was trained on more than 1 million images.

Unlike [11], the semantic from the last fully-connected layer is derived directly, instead of hash layer. The output of the last fully-connected layer is splitted into two branches. One branch leads to a  $n$ -ways softmax classifier where  $n$  stands for the number of categories of the target dataset. The other branch is a hash-like function to make the CNN features map to hash codes.

The mid-level features are extracted from the last fully-connected layer, and softmax classifiers are trained for each semantic simultaneously. We interpret the output of the classifiers as probabilities of semantic. The layers *FC6* and *FC7* are connected to the deep hash layer in order to encode a wide variety of information of visual appearance. In the following subsections we will define our feature vector and the computation of the hash function.

#### A. Probability-based Semantic-level Similarity

In case of hard assignment of semantic categories, we are given the semantic labels  $\mathcal{L} = \{1, \dots, C\}$  and the similarity between two images  $a$  and  $b$  are measured how much their indicator functions match. Let  $\delta_i(a) \in \{0, 1\}$  be the indicator function of image  $a$  has semantic  $i$ , so the semantic of image  $a$  can be denoted as  $L_i^C(a) = \{\delta_i(a) | i = (1, \dots, C)\}$ , s.t. there

must be one and only one  $\delta_i(a) = 1$ . We define the similarity between image  $a$  and  $b$  as  $\varsigma(a, b) = \sum_{(i,j)} \delta_i(a) \mathbf{S}_{ij} \delta_j(b)$ , where  $\mathbf{S} \in \mathbb{R}^{C \times C}$  and  $S_{ij}$  is a matching score between semantic  $i$  and  $j$ .

As pointed out in [15], natural semantic categories always overlap and inherently ambiguous, using hard-categories to recognize objects always leads to failure. On the other hand, perfect classification of semantic is unrealistic. In order to solve this problem and improve performance, a probability-based semantic-level similarity is proposed in this paper.

Let's assume that image  $a$  has semantic label  $i$ , we can use probability  $P(\delta_i(a) = 1 | a)$  to indicate that image  $a$  has semantic  $i$ . Obviously, the semantic label of the image will be:  $i = \max_i (P(\delta_i(a) = 1 | a))$ . As we mentioned  $\mathcal{L} = \{1, \dots, C\}$  stands for the set of semantic labels and  $I$  denotes the set of images. For each  $m \in \mathcal{L}$ ,  $a_m^+$  denotes the set of images that are relevant to the semantic  $i$ , and  $a_m^-$  stands for the set of irrelevant. The semantic relevance is defined by the matrix  $\mathbf{R}_{IL}: I \times L \rightarrow \mathbb{R}^+$ , and where  $\mathbf{R}_{IL}(a_m^+, m) > 0$  and  $\mathbf{R}_{IL}(a_m^-, m) = 0$  for all  $m \in \mathcal{L}$ . We treated images as being conditionally independent:  $P(a, b | m) = P(a | m)P(b | m)$  for any given image  $a, b$  and semantic  $m$ . The joint image-image probability can be computed as a relevance measure

$$\begin{aligned} P(a, b) &= \sum_{m \in \mathcal{L}} P(a, b | m) P(m) = \\ &= \sum_{m \in \mathcal{L}} P(a | m) P(b | m) P(m). \end{aligned} \quad (1)$$

To improve scalability, we considered two images to be related if their joint distribution exceeded a cutoff threshold  $t$ . In short, we write:

$$\mathbf{R}_{II}(a, b) = [P(a, b)]_t, \quad (2)$$

where  $t$  denotes the cutoff threshold that is  $[z]_t = z$  if  $z > t$  otherwise 0.

#### B. Feature-level Similarity

Given an image  $a$ , we first extract the output of the fully-connected layers as image representation which is denoted by a  $D$ -dimensional feature vector  $g(a)$ , where  $g(\cdot)$  is the convolution transformation over all of the previous layers. Then a  $q$ -bit binary code is obtained by a hashing function  $h(\cdot)$ . For each bit  $i = 1, \dots, q$ , the output of the binary hash codes will be:

$$H_i = \begin{cases} 1 & \text{if } \sigma(x_i) - \text{Mean}(\sigma(x_i)) > 0 \\ 0 & \text{if } \sigma(x_i) - \text{Mean}(\sigma(x_i)) \leq 0, \end{cases} \quad (3)$$

$H_i \in \{0, 1\}^q$  stands for the binary codes of each image  $I$ ,  $\text{Mean}(\mathbf{v})$  is the average value of vector  $\mathbf{v}$ . Given a query image  $x$ , we use its binary codes to identify the image from the images set  $I$ . We used the Euclidean distance to define feature-level similarity. The smaller the Euclidean distance is, the higher the similarity of the two images is, and top  $k$  ranked images are identified.

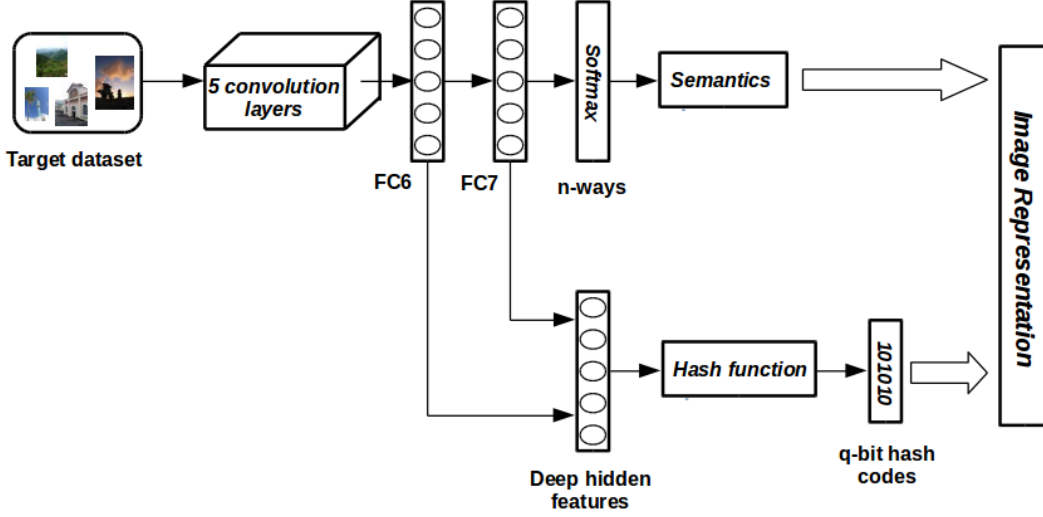


Fig. 1. The architecture of our proposed image retrieval algorithm.

TABLE II

THE DETAILED MEAN AVERAGE PRECISION (MAP) RESULTS OF EACH CATEGORIES ON OXFORD DATASET. THE BEST RESULT OF EACH CATEGORIES IS TYPED BY **BOLD**, THE SECOND BEST IS TYPED BY *italic*. OUR ALGORITHM ACHIEVED BEST RESULT IN FOUR CATEGORIES AND SECOND BEST RESULT IN TWO CATEGORIES.

Method	souls	ashm	ball	bodle	christ	corn	hert	keble	magd	pitt	red	Average
Neural Codes [9]	0.566	0.486	0.439	0.802	0.597	0.385	0.936	0.434	0.285	<b>0.68</b>	0.958	0.605
Compressed Fisher [19]	0.581	0.513	0.424	0.813	0.604	<b>0.938</b>	0.503	0.234	0.79	0.597	0.98	0.634
Compressed BoW [20]	0.667	0.621	0.225	0.506	0.537	0.084	0.704	0.143	0.617	0.112	0.713	0.448
CVLAD [21]	0.536	0.425	0.120	0.587	0.544	0.231	0.621	0.109	0.474	0.310	0.754	0.428
OASIS [22]	0.286	0.686	<i>0.615</i>	0.178	0.598	0.292	0.135	0.713	0.761	0.677	0.818	0.523
MCML [23]	0.321	0.756	<b>0.685</b>	0.143	0.563	0.327	0.096	<b>0.748</b>	0.831	0.642	0.853	0.542
LEGO [24]	0.697	0.321	0.338	0.463	0.217	0.267	0.287	<i>0.579</i>	0.734	0.112	0.180	0.381
LMNN [15]	0.845	0.7	0.324	0.727	0.832	<i>0.450</i>	0.631	0.503	0.811	0.206	0.351	0.58
Spatial Pooling [25]	<b>1.0</b>	<b>0.945</b>	0.483	<i>0.956</i>	<i>0.923</i>	0.246	<i>0.99</i>	0.425	<b>1.0</b>	0.295	<b>1.0</b>	<b>0.751</b>
CNNaug-ss [26]	0.905	0.794	0.375	<b>0.959</b>	0.913	0.245	<i>0.99</i>	0.476	0.843	<i>0.679</i>	<i>0.99</i>	0.742
MOP-CNN [27]	0.963	0.917	0.521	0.802	<b>0.833</b>	0.29	<b>1.0</b>	0.44	0.739	0.28	<b>1.0</b>	0.707
<b>Ours (t=0.2)</b>	<i>0.968</i>	<i>0.939</i>	0.496	0.907	<b>0.936</b>	0.277	<b>1.0</b>	0.439	<b>0.913</b>	0.287	<b>1.0</b>	<i>0.744</i>

TABLE III

COMPARISON OF RETRIEVAL TIMES (MS) ON THREE RETRIEVAL DATASETS. THE BEST RESULT IS TYPED BY **BOLD**, THE SECOND BEST IS TYPED BY *italic*.

Method	Holidays	Oxford	ImageNet 2012
Number of Categories	500	12	1000
Neural Codes [9]	<i>0.16</i>	67.8	230.45
Compressed Fisher [19]	0.21	73.4	242.1
Compressed BoW [20]	0.2	69.3	232.7
CVLAD [21]	<b>0.15</b>	64.32	214.5
OASIS [22]	<i>0.16</i>	24.2	68.8
MCML [23]	<b>0.15</b>	30.1	75.5
LEGO [24]	0.19	<i>27.45</i>	89.5
LMNN [15]	<b>0.15</b>	27.9	55.2
Spatial Pooling [25]	2.1	145.1	390.6
CNNaug-ss [26]	1.3	122.2	370.6
MOP-CNN [27]	1.8	165.4	387.3
<b>Ours (t=0.2)</b>	<b>0.15</b>	<b>27.64</b>	<b>53.92</b>

### C. Fusion of Semantic-level and Feature-level Similarity

After defining the semantic-level and feature-level similarity, we define hierarchical similarity between image  $a$  and  $b$  by:

$$\begin{aligned} \zeta(a, b) &= (p(a), H_a)^T \mathbf{S} (p(b), H_b) = \\ &= \mathbf{R}_{II}(a, b) \times (1 - d(q, i)), \quad (4) \end{aligned}$$

where  $1 - d(q, i)$  is the feature-level similarity and  $\mathbf{R}_{II}(a, b)$  was defined by Eq. 1 and 2. First, the semantic relevance  $\mathbf{R}_{II}(a, b)$  is determined between the target and the query image, if it equals to zero the target image will be disregarded. After the semantic relevance checking, we obtain a set of candidate images. The feature-level similarity will be computed over this set.

TABLE I  
MEAN AVERAGE PRECISION (MAP) COMPARISON WITH  
STATE-OF-THE-ART METHODS ON IMAGENET 2012 DATASET MEASURED  
ON 100 CATEGORIES. THE BEST RESULT IS TYPED BY **BOLD**, THE SECOND  
BEST IS TYPED BY *italic*.

Method	MAP on ImageNet 2012
Neural Codes [9]	0.247
Compressed Fisher [19]	0.324
Compressed BoW [20]	0.305
CVLAD [21]	0.273
OASIS [22]	0.342
MCML [23]	0.315
LEGO [24]	0.142
LMNN [15]	0.183
Spatial Pooling [25]	<b>0.605</b>
CNNaug-ss [26]	0.563
MOP-CNN [27]	0.493
<b>Ours (<math>t=0.2</math>)</b>	<i>0.580</i>

#### IV. EXPERIMENTAL RESULTS

We used the *Oxford* [16] and *Holidays* datasets [17] to compare with other state-of-the-art algorithms and ImageNet 2012 [18] was used for large-scale experiments. The *Oxford* retrieval dataset contains 5062 images which were collected from Flickr by searching for particular Oxford landmarks. The collection was manually annotated to generate a comprehensive ground truth for 12 different landmarks (souls, ashm, ball, bodle, christ, corn, hert, keble, magd, pitt, red), each represented by 5 possible labels (Good, Ok, Bad, Junk).

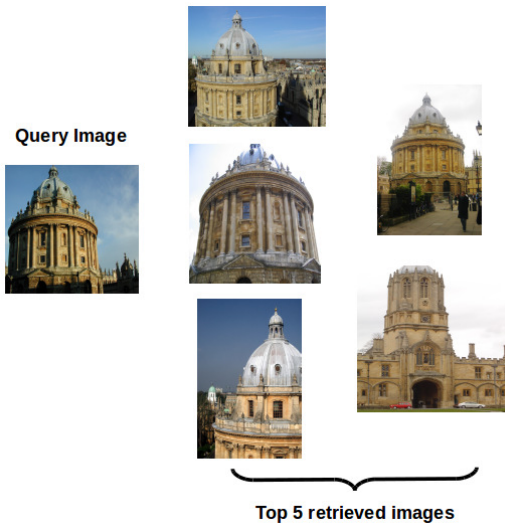


Fig. 2. Images retrieved by the proposed architecture.

We have used 1670 images as our validation dataset and the other 3392 images as training dataset. The amount of training images is very important for training a CNN. That is why we were forced to extend the number of images of each category to 1000 using among others horizontal flipping, rotation, and brightness transformations.

Figure 2 and Figure 3 illustrate some query results. In these figures, the query image can be seen on the left and we give the top 5 retrieved images to each query image on the right. In the

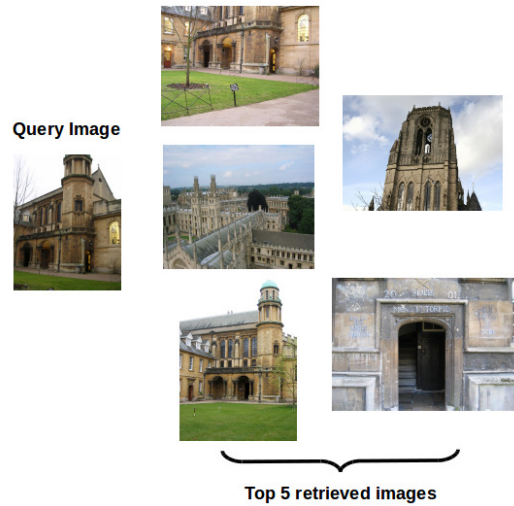


Fig. 3. Images retrieved by the proposed architecture.

following, we give qualitative results in order to prove that our architecture is good for preserving the semantics which makes the target images similar to the query image.

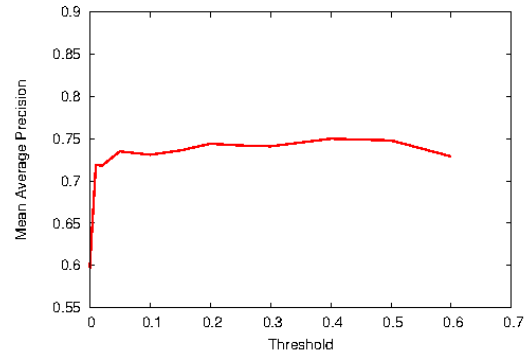


Fig. 4. Combining Probability-based Semantic-level Similarity with different thresholds. Measured on *Oxford* dataset.

Figure 4 shows the mean average precision curves on *Oxford* dataset with different threshold  $t$ . As we described above, higher thresholds will filter out more semantic dissimilarities, but it may exclude similar categories, especially for complex scenes. The published curve shows that  $t = 0.2$  is a good choice. That is why we used everywhere  $t = 0.2$  threshold during the evaluation of our algorithm.

Table II summarizes the comparison with other state-of-the-art methods with respect to Mean Average Precision measured on *Oxford* dataset. It can be seen that our method produces competitive results in comparison to other CNN-based approaches (Spatial Pooling, CNNaug-ss, MOP-CNN) and significantly outperforms most of the SIFT-based approaches (Compressed Fisher, Compressed BoW, CVLAD, OASIS, LEGO). Due to the proposed architecture and special localization of hash function, we outperform in retrieval times the other state-of-the-art algorithms (Table III).

Finally, we measured the precision on ImageNet 2012

dataset in order to demonstrate the efficiency and scalability of our algorithm. Table I summarizes the obtained results. It can be seen that our method gives competitive results in comparison to other CNN-based approaches (Spatial Pooling, CNNaug-ss, MOP-CNN).

## V. CONCLUSION

We have introduced a novel end-to-end supervised learning framework that learns probability-based semantic-level similarity and feature-level similarity simultaneously. We reported on competitive results using public available datasets including Oxford, Holidays and ImageNet 2012 retrieval datasets. Semantic-level similarity and feature-level similarity were combined in the retrieval process and this layout provided strong priors to determine similarity distance effectively. We showed if efficiency and speed considered together our method outperforms the state-of-the-art results.

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