A New Ranking based Semantic Hashing Method for Deep Image Retrieval

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Abstract. Visual search in millions of samples in high-dimensional feature space is computationally expensive and challenging. A natural solution is to reduce the dimension of image representation by mapping each sample into compact binary code. In this paper, we propose a Ranking Based Semantic Hashing (RBSH) method to tackle with this problem. Observing that semantic structures carry complementary information, this paper takes advantage of semantic supervision for training high quality hashing, the semantic mapping between the high-dimensional feature space of samples and the reduced representation space of binary code, with the help of pre-trained word2vec. Specifically, the proposed method learns the mapping based on two criteria: the contrastive ranking loss and the orthogonality constraint. The former preserves the ordering of relative similarity in image pairs, while the latter makes different bit in the hash stream as orthogonal as possible. Extensive experimental study has been conducted on VOC2012 and ILSVRC2014 image sets, demonstrating that the proposed approach generally outperforms the state-of-the-art hashing techniques based methods in image search.

1. Introduction
As the increasing popularity of Internet and visual contents, there yields a huge mass of image data. Consequently, how to accurately and efficiently return user an image relevant to his query has become an interesting problem in the field of Image Retrieval (IR). Early IR systems could be classified into two categories: text-based IR approaches and content-based IR approaches[1]. Text-based IR approaches suffer from efficiency and performance problems, while content-based IR approaches have limited usage due to expensive computational cost in high-dimensional feature space[2].

With recent advance in Deep Convolutional Neural Network (DCNN) in Image Retrieval (IR), the hashing technique could significantly reduce the computation cost as well as the model complexity in image search, compared with traditional handcraft ones in CBIR systems. Most ranking based IR methods utilize inner product to approximate Hamming distance of hash codes in loss function, for convenience to model construction[3][4]. However, we find that this strategy is easy to mislead the direction of the model optimization, cause the similarity of Hamming distance of hash code describes the number of bits that need to be modified in the mutual transformation of the points in the binary hash space, there is no necessary relationship between the results calculated by their inner products[5][6]. The inner product of different points in the binary space is not necessarily related to the Hamming distance. The strategy of using the inner product of the hash code as the Hamming distance...
is not rational. Motivated by this idea, we propose a novel Ranking Based Semantic Hashing (RBSH) architecture.

The main contributions of this paper include:
- This paper proposes a new hashing method that not only learns the hashing mapping with semantic supervision, but also preserves relative similarity between images as well as semantic structures on images.
- A contrastive ranking loss with margin is utilized to learn the best Ranking Based Semantic Hashing, to make hash bit as orthogonal with each other.
- Experimental result on two well-known image datasets demonstrates the advantages of the proposed approach over recent classical hashing techniques.

2. Ranking Based Semantic Hashing (RBSH)

2.1. Approach Overview

In this section, we will present the proposed Ranking Based Semantic Hashing (RBSH) in details. Figure 1 shows the architecture of our method, which consists of three components: a weight-shared DCNN for image feature extraction, a hash function for transferring each image into hash codes and a semantic distance calculator. The hash function takes a binary mapping function with a couple-wise input, while the semantic distance calculator is used to preserve semantic information of images.

![Figure 1. Ranking Based Semantic Hashing framework.](image)

RBSH takes an image pair randomly selected from image set as input, which is feed into DCNN next. High dimensional features of samples are extracted by DCNN separately, and abstract representations of the underlying visual information of the samples could be obtained. Then features are transferred into binary hash codes by hash functions, where similarity between hash codes related to the one of features. Next, word2vec model from Google is used to get word vectors utilizing labels of input, in which distance of word vectors describes the semantic relevance of samples. In the end, a ranking loss function based on similarity of hash codes and similarity of word vectors is going to be optimized, in order to get ideal hashing model mapping features into hash codes.

2.2. Problem Formulation

Suppose that we have an image feature set \( X = \{x_i\}_{i=1}^N \) containing \( N \) samples, \( x_i \in \mathbb{R}^D \), thus feature vector \( X \) is defined as \( X \in \mathbb{R}^{D \times N} \), where the semantic similarity of sample \( x_i \) is \( c_i \). The goal of the image hashing is to project the image feature \( x_i \) into \( k \)-bit binary hash code \( h_i \in \{0,1\}^k \) by building \( K \) mappings, implementing fast approximation nearest neighbour image retrieval based on \( h_i \). The parameter matrix \( W \) consisting of \( K \) hash functions \( W = \{w_i\}_{i=1}^K \in \mathbb{R}^{D \times K} \), \( w_i \) is depended on the \( i \)-th mapping function, such that the image mapping model can be formally represented as

\[
H = f(W, X) = \text{sgn}(W^TX)
\]
Function \text{sgn} here is used to convert image features into hash space. F represents the hash function set with the matrix W as the parameters; The hash matrix H = \{h_i\}^N_{i=1} \in \mathbb{R}^{K \times N} is composed of the hash code h_i in the data set. In order to learn the parameter matrix W of the model f. Given arbitrary sample features x_i, x_j and their hash codes h_i, h_j and image categories c_i, c_j, loss function l(W, X) of RBSH could be written as

\[
\min_W \sum_{i=1}^{N} \sum_{j=1}^{N} L(h_i, h_j) \|S(c_i, c_j) + \frac{1}{2} \beta \|W\|^2
\]

s.t. \( h_i = \text{sgn}(W^T x_i) \in \{0,1\}^K \) (2)

\( \| \cdot \|_H \) and \( \| \cdot \| \) is Hamming distance and Euclidean distance respectively here, \( S(c_i, c_j) \) is semantic similarity of \( x_i \) and \( x_j \), where the more similar between \( x_i \) and \( x_j \) in semantic space, the smaller \( S(x_i, x_j) \) will be. \( L(x, y) \) is a logistic function \( L(x, y) = \ln(1 + \exp(-xy)) \), to measure the loss between Hamming distance \( \| h_i, h_j \|_H \) and semantic similarity \( S(c_i, c_j) \). Regularization item \( \frac{1}{2} \beta \|W\|^2 \) limits the complexity of W and avoids over-fitting, \( \beta \) is the regularization coefficient. RBSH uses the square of Euclidean distance of hash code as the estimation of Hamming similarity. The square of the Euclidean distance equals the Hamming distance of the binary hash code. Based on the conclusion, the Hamming distance between RBSH \( x_i \) and \( x_j \) is

\[
\| h_i, h_j \|_H = \| [k \mid h_i^k \neq h_j^k], 1 \leq k \leq K \| = \| h_i - h_j \|^2
\]

(3)

Stand on previous definitions, the loss function is constructed as

\[
l(W, X) \approx \sum_{i=1}^{N} \sum_{j=1}^{N} L(\|\text{sgn}(W^T x_i) - \text{sgn}(W^T x_j)\|^2, S(c_i, c_j)) + \frac{1}{2} \beta \|W\|^2
\]

(4)

Because of constraint in hash space \{0,1\}, it's NP-Hard to optimize \( l(W, X) \) directly. For ease of optimization, natural relaxation tricks are utilized, we release the constraint \( h_i = \text{sgn}(W^T x) \approx \text{Sigmoid}(W^T x) \) and rewritten the loss function as:

\[
l(W, X) \approx \sum_{i=1}^{N} \sum_{j=1}^{N} L(\|\text{Sigmoid}(W^T x_i) - \text{Sigmoid}(W^T x_j)\|^2, S(c_i, c_j)) + \frac{1}{2} \beta \|W\|^2
\]

(5)

It's still a complex problem to solve \( l(W, X) \). Adopting the optimization policy in [4][5], we obtain a new version of loss function by further constraint release:

\[
l(W, X) \approx \sum_{i=1}^{N} \sum_{j=1}^{N} L(\|W^T x_i - W^T x_j\|^2, S(c_i, c_j)) + \frac{1}{2} \beta \|W\|^2
\]

\[
= \sum_{i=1}^{N} \sum_{j=1}^{N} L(\|(x_i - x_j)^T WW^T (x_i - x_j), S(c_i, c_j)) + \frac{1}{2} \beta \|W\|^2
\]

(6)

2.3. Semantic Ranking of Label

Different from In a word, categories are not completely independent, and binary similarity is not able to measure the inherent semantic relations between them. In order to fully learn the potential semantic association between categories, RBSH chooses to calculate semantic distance with the natural language processing technology Word2Vec[6], one of the most widely used tools in the field of NLP proposed by Google. Suppose the word vector of \( c_i \) and \( c_j \) is \( v_i \) and \( v_j \), the semantic similarity is calculated by the following equation:

\[
S(c_i, c_j) = \|v_i - v_j\|
\]

(7)

Typical semantic similarities is better than category similarity. It's shown that distance of word vector from Word2Vec describes semantic similarity well, the distance between related categories tends to be close[7]. RBSH amplifies \( S(c_i, c_j) \) by an enhancement factor to increase the semantic difference between categories during experiment phrase, to speed up model training.
2.4. Optimization

Given loss function $l(W, X)$, RBSH selects Batch Gradient Descent to find optional parameters $W$. Arbitrarily selecting two samples $x_q$ and $x_i$, the gradient of the parameter $W$ is calculated as:

$$\frac{\partial l(W, X)}{\partial W} = \frac{-\mathbf{(x_q-x_i)^T(x_q-x_i)W*}\mathbf{s(c_i,c_q)}}{1+\exp((\mathbf{x_q-x_i)^TW(x_q-x_i)*}\mathbf{s(c_i,c_q))}} + \beta W$$  \hspace{1cm} (8)

RBSH takes the mean error of the top T samples closest to the $x_q$ in Hamming space as the gradient of the parameter for target image sample $x_q$. Specifically, the image sample $x_q$ is randomly picked up during each iteration from image set $X$, then $X$ will be sorted by Hamming distance of each sample to $x_q$:

$$r(x_q, W, X) = \{r_1, ..., r_i, ..., r_N\}$$  \hspace{1cm} (9)

If $\|h_q, h_i\|_H \leq \|h_q, h_j\|_H$, we have $r_i \leq r_j$. As for sample $x_q$, RBSH ensures the Top-T samples $\{r_1, ..., r_T\}$ in sorted set $r(x_q, W, X)$ hold high semantic similarity with $x_q$. As a result, the goal of RBSH is to minimize the mean predictive loss of T samples by updating gradient:

$$\frac{\partial l(W, X)}{\partial W} = \frac{1}{T} \sum_{t=1}^{T} \frac{-\mathbf{(x_q-x_i)^T(x_q-x_i)W*}\mathbf{s(c_i,c_q)}}{1+\exp((\mathbf{x_q-x_i)^TW(x_q-x_i)*}\mathbf{s(c_i,c_q))}} + \beta W$$  \hspace{1cm} (10)

Update $W$ using gradient:

$$W = W - \gamma \frac{\partial l(W, X)}{\partial W}$$  \hspace{1cm} (11)

Where $\gamma$ is learning rate.

3. Experiment

In order to evaluate the performance of RBSH, we conducted extensive evaluations to compare RBSH and recent related works on two widely used image sets. And this paper selects metrics for evaluating the performance of algorithm retrieval with precision, recall, and Mean Average Precision (MAP).

This paper selects two widely-ussed image data sets as experimental objects for model performance evaluation, ILSVRC2014 and VOC2012. ILSVRC2014 is provided by ImageNet Large Scale Visual Recognition Challenge 2014 [8]. Experiments approves the advance of RBSH proposed in this paper. Figure 2 compares the MAP of six approaches in TOP-1000 of test set, and Recall-Precision of training set. Table 1 records MAP of six methods on ILSVRC2014 with various hash code lengths.
Table 1. MAP on ILSVRC2014

| Method | SKLSH | SGH | DSH | SpH | SDH | RBSH |
|--------|-------|-----|-----|-----|-----|------|
| 16 bits| 0.244 | 0.532 | 0.104 | 0.423 | 0.550 | 0.709 |
| 24 bits| 0.273 | 0.628 | 0.123 | 0.493 | 0.568 | 0.737 |
| 32 bits| 0.369 | 0.678 | 0.162 | 0.499 | 0.559 | 0.741 |
| 48 bits| 0.363 | 0.691 | 0.303 | 0.533 | 0.591 | 0.742 |
| 64 bits| 0.424 | 0.697 | 0.426 | 0.559 | 0.585 | 0.744 |

Table 2. MAP on VOC2012

| Method | SKLSH | SGH | DSH | SpH | SDH | RBSH |
|--------|-------|-----|-----|-----|-----|------|
| 16 bits| 0.291 | 0.363 | 0.372 | 0.337 | 0.337 | 0.421 |
| 24 bits| 0.298 | 0.364 | 0.373 | 0.366 | 0.371 | 0.427 |
| 32 bits| 0.292 | 0.356 | 0.375 | 0.353 | 0.393 | 0.431 |
| 48 bits| 0.304 | 0.351 | 0.369 | 0.358 | 0.404 | 0.454 |
| 64 bits| 0.309 | 0.350 | 0.364 | 0.365 | 0.423 | 0.478 |

Figure 3 and Table 2 presents experimental evaluations of six methods on the VOC2012. It's concluded that RBSH has more satisfactory performance than others. Compared to ILSVRC2014, VOC2012 has more objects in single image, which leads to worse performance than the one on latter.

4. Conclusions and Discussion

In this paper, we present Ranking-Based Semantic Hashing framework for image retrieval, which takes advantage of both visual similarity and semantic distance between images. By learning hash function using semantic information, further improvements are consistently conducted in the experiments phase comparing to existing classical work. Our future works are paying attention to potential improvements in proposed work. First, as our architecture is a co-training process with contrastive loss, how the architecture performs utilizing more complex loss like Triplet loss with batch hard mining (TriHard loss) or Margin sample mining loss (MSML) will be further investigated and
evaluated. Next, more in-depth studies of how to fuse the two components into an end-to-end way could be explored. Furthermore, how to apply our proposed architecture to video retrieval seems attractive.

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