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Enhancing Bag-of-Words Models with Semantics-Preserving Metric Learning

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The authors present an online semantics-preserving, metric-learning technique for improving the bag-of-words model and addressing the semantic-gap issue.

Image annotation is an important technique to enable users to search massive, unlabeled images using existing text-retrieval tools. Recent years have witnessed intensive research on image annotation and object recognition. For example, some studies have employed search-based annotation methods to annotate an image with common tags of similar images retrieved from tagged image databases,[1] and some studies have formulated image annotation as a standard classification problem.[2,3] One of the key issues for existing image-annotation methods is to find an effective feature representation for images. Recently, the bag-of-words (BoW) model[4] has been actively studied for image representation. The BoW approach takes advantages of some recent advances in computer vision, such as the powerful scale invariant feature transform (SIFT) feature descriptor technique.[5]

In the SIFT method, BoW first builds a codebook by collecting SIFT descriptors and clustering them into k clusters using some existing clustering algorithm (for example, k-means[6]). With the codebook that is formed by the centroids of the resulting k clusters, BoW represents any image as a histogram of the codewords, which can be adopted for any existing classification or annotation methods. One key limitation of the existing BoW model is that semantics are lost during the codebook-generation process, which may considerably harm the discrimination capabilities of the BoW representation due to the well-known issue of the semantic gap.

To overcome the drawback of the regular BoW model, this article introduces a promising scheme of semantics-preserving metric learning (SPML), which considers the distance between the semantically identical features as a measurement of the semantic gap, and is designed to learn an optimized metric by minimizing this semantic gap to build more effective codebooks for BoW. The task can be formulated as a distance-metric learning problem with side information, which is generally a semidefinite programming problem. We first discuss a batch optimization algorithm to effectively resolve the optimization task,[7] followed by presenting a novel, online SPML algorithm (OSPML) to ensure our technique is efficient and scalable for large-scale applications.

In this article we investigate the challenge of reducing the semantic gap for building BoW models for image representation; propose a novel OSPML algorithm for enhancing BoW by minimizing the semantic loss, which is efficient and scalable for enhancing BoW models for large-scale applications; apply the proposed technique for large-scale image annotation and object recognition; and compare it to the state of the art.

Algorithm framework

We propose an SPML algorithm for improving the process of BoW's visual-words generation. Figure 1 illustrates the flowchart of the proposed framework. First of all, in the metric-learning process, objects in the images are segmented and tagged by users. SIFT features are extracted from the images to represent the objects. The SIFT features that are located at the same semantic parts of the objects are considered relevant to each other, and will be used as the similar pairwise constraints in our metric-learning task; on the other hand, any two SIFT features that are located at different semantic parts of the objects are considered irrelevant, and will be treated as the dissimilar pairwise

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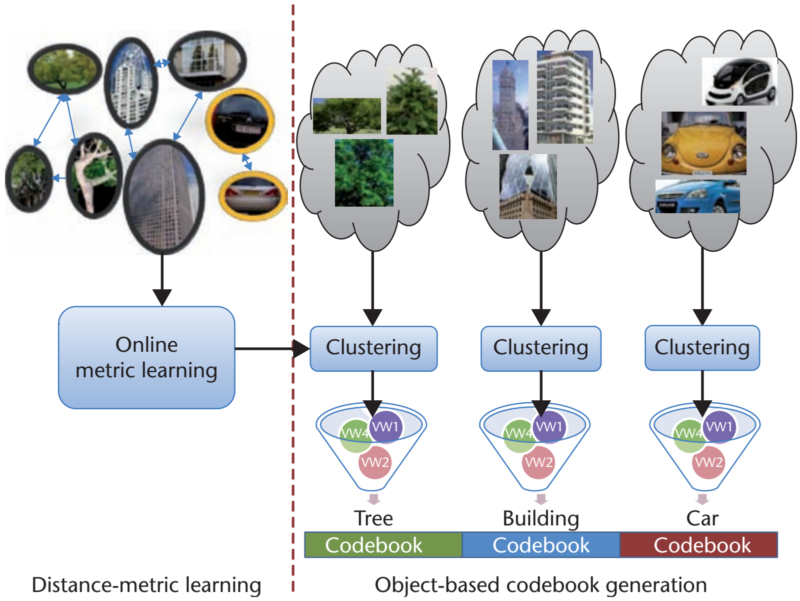


Figure 1. The key process of building the semantics-preserving, bag-of-words model. The method consists of two key steps: semantics-preserving distance metric learning, and object-based codebook generation.

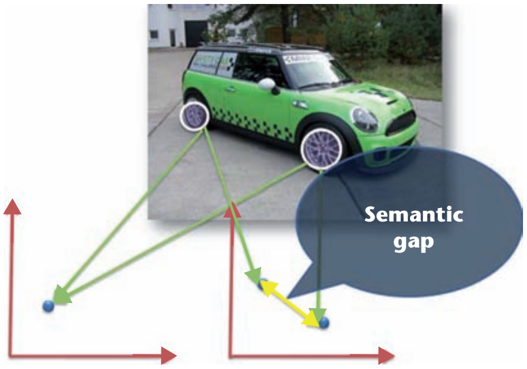


Figure 2. Illustration for the measurement of a semantic gap. For the same semantic parts of objects, the ideal way is to map them to the same place (as shown on the left side), while regular approaches often map them into different places (as shown in the right side), leading to the semantic-gap problem.

constraints in our metric-learning task. We refer to such a collection of similar and dissimilar pairwise constraints as *side information*, which is critical to the metric-learning task.

We propose a novel scheme to optimize the distance metric from the side information by minimizing the semantic loss. We define the semantic loss as the following two cases:

- two features with different semantics are mapped into the same visual word, and
- two features with the same semantics are mapped into different visual words.

The semantic loss is mainly due to the well-known semantic gap. That is, the similarity between low-level features doesn't reflect the correlation between their semantics. We propose to measure the semantic gap by computing the distance between semantically identical features, illustrated in Figure 2. In the figure, the two tires drawn on the car are semantically identical features, and their distance in feature space is defined as the measurement of the semantic gap. The idea of our work is to search for a proper distance metric so that the semantically identical features are mapped to the same (or very close) place, while the semantically different features are mapped to diverse places (far from each other). Such an optimized distance metric is used to build the semantics-preserving codebook (SPC), which is essential to the BoW representation for image annotation and object categorization.

In traditional BoW, an image is represented by the histogram of visual words from a codebook. This simple representation has some drawbacks. First of all, both the visual words extracted from the object regions and the visual words extracted from the background regions are all incorporated for generating the BoW model. Such a simple approach, however, brings the background noise into the resulting model, which is supposed to describe only the object. Moreover, this representation might be influenced if an image contains multiple objects. However, many real-world images usually contain multiple objects. As a result, all other irrelevant objects in the images will become noises when building the regular BoW model for certain objects. Although this problem may be partially resolved by some latent topic analysis, it suffers from several challenges, for example, it's often difficult to determine an appropriate number of latent topics for such approaches.

For the reasons discussed previously, our new SPML approach aims to preserve the semantics by modeling each individual object rather than simply modeling a whole image. In particular, we adopt some training images labeled by human beings, for example, MIT's Labelme testbed[8] where the objects are all well-segmented and labeled by real users.

By the proposed SPML framework, we first apply SIFT to extract local features from each image. The SIFT features that are located at the regions of the same semantics (labels) in all the images are collected to represent the semantics. To preserve the semantics in the BoW model, all the collected features related to the same semantics are clustered into one or several discriminative visual words for representing the object, where the clustering process adopts an optimized distance metric designed to minimize the overall semantic loss.

It's worth noting that the metric is learned on the basis of a sample of features, and will be fixed and used for the whole feature set. The visual words used for representing an object might describe different semantic parts or different views of the object. Finally, the set of visual words used for one object is often different from the set used for another different object. This process is different from the regular BoW model where all objects share the same set of visual words. Next, we present a novel learning technique designed to find an optimal distance metric to overcome the limitation of semantic loss during the codebook-generation process.

Learning to optimize metrics for enhancing BoW

Codebook generation is a critical step in building the BoW model. Instead of generating the codebook by applying simple *k*-means clustering in Euclidean space, which often leads to much semantic loss, we suggest a novel metric-learning scheme that exploits side information for minimizing the semantic loss in the codebook-generation process.

Problem formulation

We first introduce the concept of side information. Consider a set of pairwise feature instances $\{(x_{i1}, x_{i2})\}_{i=1}^{N}$ and a set of corresponding instance constraints $\{(z_{i1},z_{i2},y_i)\}_{i=1}^{N}$, where $x_{i1} \in \mathbb{R}^d$ and $x_{i2} \in \mathbb{R}^d$ are two *d*-dimensional feature instances, for example, SIFT feature vectors. Here, x_{i1} indicates the first feature vector in the pair, and x_{i2} is the second feature vector in the pair; z_{i1} and z_{i2} are binary indicators to indicate whether a feature instance is located at the object region or the background region in the image. The variable y_i indicates whether the feature instances in pair (x_{i1}, x_{i2}) are of the same semantics. If both x_{i1} and x_{i2} are on the same semantic part, then $y_i = +1$; otherwise, $y_i = -1$.

In general, side information can be generated automatically from locations of feature points in well-segmented images. For example, in Labelme, objects and background regions are manually separated for each image, and different parts of the objects are also manually segmented by users. Hence, if two feature vectors are located at the same region or at the regions of the same semantic label, they will be considered as having the same semantic meaning, that is, $y_i = 1$. Similarly, in the Pascal visual object classes (VOC) 2006 datasets (see http://www.pascal-network.org/challenges/VOC/voc2006/results.pdf), objects in each image are separated from the background by a bounding box. Thus, two features that are in the same bounding box or in the bounding boxes with the same label are treated as having the same semantic meanings.

Given the side information, the goal of our task is to learn a distance metric A to measure distance between any two visual features x_{i1} and x_{i2} represented in the following framework:

$$d(x_{i1}, x_{i2}) = \sqrt{(x_{i1} - x_{i2})^{\top} A (x_{i1} - x_{i2})}$$

where matrix $A \in \mathbb{R}^{dxd}$ is the target distance metric that must be positive and semidefinite with respect to the properties of a valid metric, that is, $A \succeq 0$. To find an optimal metric A, the basic principle of our metric-learning task is that distances between visual feature vectors of the same semantics should be minimized, and distances between feature vectors of different semantics should be maximized. On the basis of this principle, we can search for the optimal metric that facilitates clustering the feature vectors of the same semantics into the same visual words, so each visual word has a certain specific semantic meaning. To this end, we formulate our distance-metric learning problem into the following optimization:

$$\min_{A \succeq 0, b} \sum_{i} z_{i1} z_{i2} \xi_i + \frac{\lambda}{2} tr(AA^{\top})$$

$$s.t. y_i(\| x_{i1} - x_{i2} \|_A - b) \leq \xi_i, \xi_i \geq 0, i = 1, \ldots, n$$

where $\|\cdot\|_A$ is the Mahanalobis distance between two features under metric A, $tr(\cdot)$ is a trace operator, and λ is a regularization parameter. The first term of the objective function consists of the slack variables that account for the semantic loss with respect to the side information of n pairwise constraints $\{(x_{i1}, x_{i2}, z_{i1}, z_{i2}, y_i)\}_{i=1}^{N}$. With the first inequality constraint, minimizing this term makes the distance between two semantically identical features closer, and thus more likely to be mapped into the same visual word. The second term of the objective function is a regularization term, which is designed to prevent overfitting by minimizing the model complexity. By solving the optimization problem, we can obtain the optimized distance metric A and the threshold variable b that could be used to determine whether two features are similar or dissimilar. In general, this optimization belongs to a general semidefinite program, which is often hard to solve with global optima for large applications.

Batch algorithm

We first introduce a batch gradient descent algorithm by combining with an active constraint selection scheme to solve the optimization efficiently. To simplify the notation, we denote the feature matrix as $X \in \mathbb{R}^{N_{tr} \times d}$, where N_{tr} is the number of SIFT features in the training set, and d is the feature dimension. We also represent all the feature pairs (x_{i1}, x_{i2}) in the training data by two feature matrices $X_1 = [x_{11}, x_{21}, \cdots, x_{n1}]^\top$ and $X_2 = [x_{12}, x_{22}, \cdots, x_{n2}]^\top$, and similarly their constraints by three matrices $Z_1 = \mathrm{diag}(z_{11}, z_{21}, \cdots, z_{n1}), Z_2 = \mathrm{diag}(z_{12}, z_{22}, \cdots, z_{n2})$, and $Y = \mathrm{diag}[y_1, \cdots, y_n]$. The proposed iterative optimization algorithm is described as follows.

Firstly, we choose an active subset of informative side information from the training data as the training instances. We denote S_t as the active set at the t-th iteration. The informative training instances in S_t satisfy either one of the two conditions: features are of the same semantics but with large distance in the current metric space; or features are of different semantics but with small distance in the current metric space. Specifically, S_t is found by combining the following two subsets:

$$S_t^+ = \left\{(x_{i1}, x_{i2}, y_i) | (1 + y_i) \| x_{i1} - x_{i2} \|_A^2 \ > 1\right\},$$

$$S_t^- = \{(x_{i1}, x_{i2}, y_i) | (1 - y_i) \ \| x_{i1} - x_{i2} \|_A^2 \ < 1\}$$

Secondly, on the basis of the active set S_t at the t-th iteration, we then apply the gradient descent technique to search for the optimal metric A and threshold b as follows: $A_{t+1} \leftarrow A_t - \frac{\gamma}{t}\nabla_A L, b_{t+1} \leftarrow b_t - \frac{\gamma}{t}\nabla_b L$, where $\nabla_A L \leftarrow \left(\lambda A + D_X Z_1 Z_2 Y^\top D_X\right), D_X = X_1 - X_2$, $\nabla_b L \leftarrow tr(Z_1 Z_2 Y)$, and γ is a learning rate.

Finally, to enforce the valid metric constraint, at the end of each iteration, we project the current solution of metric A back to a positive semidefinite cone by an eigen decomposition approach.

Online algorithm

We now present a more efficient and scalable algorithm to solve the metric-learning problem with an online-learning approach. We denote by A_t and b_t the solution at the t-th step. For online learning, we assume the pairwise constraints are given sequentially. For each received pairwise constraint $(x_{i1}, x_{i2}, z_{i1}, z_{i2}, y_i)$, we use current solution A_t and b_t to make predictions on the constraint, and then measure the incurred loss. Whenever the loss is nonzero, that is, $z_{i1} z_{i2} \xi_i > 0$, we update the solution with the following optimization:

$$\min_{A \succeq 0, \mathrm{b}} \xi_i + \frac{\lambda}{2} tr\left(AA^\top\right) - \eta\left(tr\left(AA_t^\top\right) - \frac{1}{2} \| b - b_t \|^2\right) \quad (1)$$

$$s.t. y_i(\| x_{i1} - x_{i2} \|_A - b) \leq \xi_i, \quad \xi_i \geq 0$$

where both λ and η are regularization parameters. In Equation 1, we add the last regularization term to prevent the new solution from deviating too much from the previous solution, and simplify $z_{i1} z_{i2} \xi i$ into ξi since $z_{i1} z_{i2}$ will be1 for any nonzero loss.

The following theorem gives the optimal solution for each step of the proposed OSPML algorithm:

$$A_{t+1} = \frac{\eta}{\lambda} A_t - \frac{\tau}{\lambda} G_t, \quad \text{and} \quad b_{t+1} = b_t + \frac{\tau}{\eta}$$

where $G_t = y_i (x_{i1} - x_{i2})(x_{i1} - x_{i2})^\top$ and the optimal τ is

$$\tau = min\left(1, \frac{\lambda}{tr\left(G_t G_t^\top\right)} y_i(\| x_{i1} - x_{i2} \| A_t - b_t)\right)$$

The details of the proof to the above theorem can be found in the "Proof of Theorem 1" sidebar (next page). Finally, Algorithm1, shown in Figure 3, illustrates the process of the OSPML algorithm.

Proof of Theorem 1

Proof: To solve the optimization problem, we define the Lagrangian:

$$L(A,b,\xi_i,\tau,\gamma) = \xi_i + \frac{\lambda}{2} tr\left(AA^\top\right) - \eta tr\left(AA_t^\top\right) + \frac{\eta}{2} \| b - b_t \|^2 \\ + \tau(y_i(\| x_{i1} - x_{i2} \|_A - b) - \xi_i) - \gamma\xi_i$$

where $\tau \geq 0$ and $\gamma \geq 0$ are Lagrangian multipliers. The optimal solution can be found by setting the gradients of the Lagrangian with respect to A and b to zeros respectively, that is,

$$\frac{\partial L(A,b,\xi_i,\tau,\gamma)}{\partial A} = \lambda A - \eta A_t + \tau G_t = 0$$

and

$$\frac{\partial L(A,b,\xi_i,\tau,\gamma)}{\partial b} = \eta(b - b_t) - \tau = 0$$

where $G_t = y_i(x_{i1} - x_{i2})(x_{i1} - x_{i2})^\top$. As a result, we have the optimal solution as follows:

$$A_{t+1} = \frac{\eta}{\lambda} A_t - \frac{\tau}{\lambda} G_t \quad \text{and} \quad b_{t+1} = b_t + \frac{\tau}{\eta}$$

where τ is an unknown variable to be determined. To find the optimal τ value, we differentiate the Lagrangian with respect to ξ_i and setting it to 0, that is,

$$\frac{\partial L(A,b,\xi_i,\tau,\gamma)}{\partial \xi_i} = 1 - \tau - \gamma = 0 \qquad \text{(A)}$$

Equation A indicates that $\tau \leq 1$ given the fact that $\gamma \geq 0$. Plugging the Equations (A) and (B) back into the original Lagrangian, we have:

$$L(\tau) = -\frac{\eta^2}{2\lambda} tr(A_t A_t^T) + \frac{\tau^2}{2\lambda} tr(G_t G_t^\top) \\ + \tau y_i(\| x_{i1} - x_{i2} \|_A - b) - \xi_i \qquad \text{(B)}$$

By differentiating the above with respect to τ and then setting it to 0, we can find the solution for τ:

$$\tau = \frac{\lambda}{tr(G_t G_t^T)} y_i(\| x_{i1} - x_{i2} \|_{A_t} - b_t)$$

Finally, combining the previous result that $\tau \leq 1$, we thus prove the conclusion of the theorem.

```
INPUT:
SIFT feature matrix: $X \in R^{N \times d}$, and pairwise constraints: $(x_{i1}, x_{i2}, z_{i1}, z_{i2}, y_i)$,
and parameters $\lambda$ and $\eta$
PROCEDURE:
initialize metric and threshold: $A = I, b = 1$
set iteration step $t = 0$;
repeat
    (1) sample one constraint $(x_{i1}, x_{i2}, z_{i1}, z_{i2}, y_i)$ and calculate
        $l_t = z_{i1} z_{i2} y_i ||x_{i1} - x_{i2}||_{A_t} - b_t$
    if $(l_t > 0)$ then
        (2) calculate the optimal $\tau$ value: $\tau = \min(1, \frac{\lambda}{tr(G_t G_t^\top)} y_i ||x_{i1} - x_{i2}||_{A_t} - b_t)$
        (3) update the metric and threshold: $A_t + 1 = \frac{\eta}{\lambda} A_t - \frac{\tau}{\lambda} G_t$, and, $b_t + 1 = b_t + \frac{\tau}{\eta}$
    end if
    $t = t + 1$
until convergence
OUTPUT: feature metric $A = PSD(A_t + 1)$, threshold variable $b_t + 1$
```

Figure 3. The online semantics-preserving metric learning (OSPML) algorithm.

Application to codebook generation

The codebook for BoW can be generated by clustering SIFT features into visual words (or codewords) under the optimized metric. Different visual words can represent different views or different parts of an object. We propose to generate the codebook for each object category so that the linkage between the codewords in the codebook and the high-level semantics of object category can be effectively established, which is essential to bridge the gap between low-level features and high-level semantics. Specifically, for each object category, we first collect all the related features from the same object regions, and then perform the k-means clustering[6] on the basis of the optimized distance metric A that is obtained from the proposed SPML scheme. The k-means clustering produces a set of k clusters (whose centroids are used as visual words or codewords) for this object category. Finally, we form the SPC by gathering all the codewords from every object category.

In general, there are two important issues for building the SPC: codebook size assignment and visual word generation.

Codebook size assignment

One key challenge of our codebook generation is to assign varied numbers of codes for diverse objects of different complexity. In our codebook size assignment approach, we follow two principles: the number of codes increases linearly with respect to the visual complexity of an object category; and the visual complexity of an object category can be measured by the diversity of its associated features.

In our solution, we apply information theory to measure the visual complexity of an object category. Given an object category that contains a bag of features from their associated images, we assume that each feature in the category can be generated from the bag in some probability. Specifically, we denote by C_i an object category and by x_j some feature. The generative probability $p(x_j|C_i)$ can be estimated as follows:

$$p(x_j|C_i) = \frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{\|x_j-\hat{x}\|_A^2}{2\sigma^2}}$$

where

$$\hat{x} = \frac{1}{n_{C_i}}\sum_{x_j \in C_i} x_j$$

and n_{C_i} is the total number of features related to the objects from C_i. On the basis of this probability, we calculate the entropy of the bag as a measurement of the object's visual complexity

$$H(C_i) = -\sum_{x_j \in C_i} p(x_j|C_i)\log p(x_j|C_i)$$

Finally, we assign object C_i the number of codes L_{C_i} that are proportional to its visual complexity, that is,

$$L_{C_i} = \left\lfloor L_{max} \times \frac{H(C_i)}{\log n_{C_i}} \right\rfloor$$

where L_{max} is the maximum size of the SPC for each category. The total number of visual words for all categories is $L_{max} \times M$, where M is the number of categories.

Visual word generation

Visual word generation is a key step of codebook generation for producing a set of L_{C_i} visual words for each object category C_i by applying k-means clustering on the associated features. Specifically, we denote by X_i a collection of features belonging to object category C_i, that is, $X_i = \{(x,y)|x \in X, y = C_i, C_i \in \mathbb{C}$, where y denotes the object category label of feature x, X is the feature space, and $\mathbb{C}$ is the label space. The algorithm first applies the k-means clustering on X_i with the optimized metric A to generate a set of K clusters, denoted by $\{c_{ij}, r_{ij}|j = 1 \cdots, K\}$, where K is set to be larger than $max_i L_{C_i}$, c_{ij} denotes the center of the j-th cluster, and r_{ij} denotes the range radius of the cluster, which is defined as the largest distance from the features to the cluster center.

Moreover, to reduce noisy clusters, we sort the K clusters by their sizes S_{ij} computed as follows:

$$S_{ij} = \sum_x \delta(\| x - c_{ij} \|_A, r_{ij})$$

where $\delta(a,b) = \begin{cases} 1 & a \le b \\ 0 & \text{otherwise} \end{cases}$

The algorithm then chooses top L_{C_i} largest clusters as the set of visual words to form the codebook for category C_i. Finally, the algorithm combines all the visual words from every object category and outputs the set of visual words along with their ranges, that is, $\{w_k, r_k\}_{k=1}^{Lmax}$, as the final SPC.

Visual word histogram

To apply SPC during the test phase, the key is to generate a visual word histogram for each novel test image. We first extract SIFT features from a novel image, and map each of the extracted SIFT features $x \in \mathbb{R}^d$ to a visual word ID k in the cookbook. Each visual feature can be assigned to multiple visual words among different object categories because the ranges of visual words may overlap each other and the same semantics may appear in different objects. In our approach, we assign a feature to a visual word when the distance between them is smaller than some range radius.

Specifically, we define some mapping function $\pi(x,k)$ between feature x and visual word w_k as follows:

$$\pi(x,k) = \begin{cases} 1 & ||x - w_k||_A < r_k \\ 0 & \text{otherwise} \end{cases}$$

We apply this mapping function to compute the frequency of a visual word w_k appearing in image I as

$$f_I(k) = \sum\nolimits_{x \in I} \pi(x,k)$$

Finally, we can obtain the visual word histogram by normalizing the visual word frequencies as follows:

$$h_I(w_k) = \frac{f_I(k)}{\sum_{v=1}^{Lmax} f_I(v)}$$

With this representation, we can annotate an image simply by adopting a Bayes classifier similar to the approach used in Wu et al.[3]

Experiments

This section presents our extensive experiments to empirically evaluate the performance

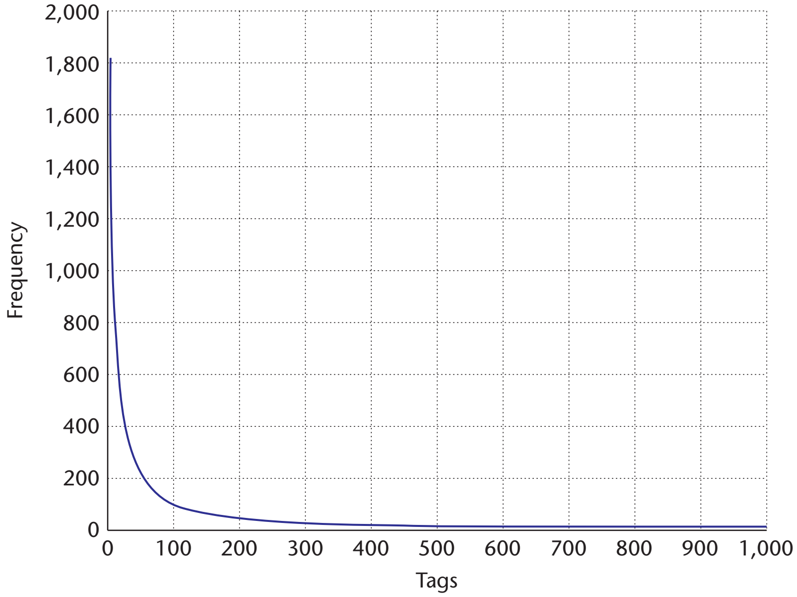


Figure 4. The distribution of the tags and their frequency values in our image data collection.

of the proposed SPML method and the existing BoW model for image annotation and object categorization. In addition to testing the proposed metric-learning algorithm, we show that the proposed semantics-preserving BoW framework can be integrated with other existing distance metric learning (DML) techniques. We evaluate different implementations by adapting other existing DML algorithms to our framework.

Experimental testbed

We formed a large and diverse image testbed consisting of 1,073 different object categories and 10,000 images, of which 6,964 images were from Labelme and the rest were from Flickr. The objects in our testbed included cars, trees, buildings, persons, lights, ladders, sidewalks, air conditioners, mailboxes, signs, bicycles, umbrellas, and so on. For feature extraction, we adopted the SIFT descriptor to extract local visual features from the images. Each image contained about 1,000 SIFT features represented in 128-dimensional space. In total, the entire data set consisted of about 13,570,000 SIFT features, which presented a great challenge for applying machine learning techniques.

We chose this data set for several reasons. First of all, images from the Labelme data set have high-quality, user-generated object segmentation and labeling information. The segmentation and labeling information can be as detailed as parts of the objects, such as the front light of a car, the door of a building, and so on. Such detailed labeling information can help generate high-quality side information for learning distance metrics. Secondly, this data set is large in that it has over 1,000 common categories and 10,000 images with 13 million SIFT features. Third, these object categories commonly appear in daily life. Specifically, for each image, there are on average 20 objects positioned and occluded as they exist in the real world. And for each category, there are on average 20 instances. The distribution of the categories and tags and their frequency values are shown in Figure 4. It's a great challenge for any model to detect and annotate these objects in such a complex situation. Finally, the data set consisting of images from both Labelme and Flickr enables us to examine if the learned distance metric from one data set could also be applied or generalized to another data set.

Experimental settings

We compare the proposed SPML method with state-of-the-art DML methods. In particular, we implemented two SPML algorithms: a batch algorithm (SPML)[7] and an online algorithm (OSPML). We compare these against other metric-learning algorithms, including relevant component analysis (RCA),[9] information theoretic metric learning (ITML),[10] large margin nearest neighbor (LMNN),[11] and neighborhood components analysis (NCA).[12] We implemented these under the same settings.

RCA is parameter-free. For ITML, we set the algorithm convergence threshold to 10^{-4}, and the slack variable to 1. For LMNN, we set the step size 10^{-9}, the multiplicative factor to 1.1, and the cut-off threshold to 10^{-22}. For NCA, we set the length to 5, the Wolfe-Powell parameters RHO and SIG to 0.01 and 0.5, and the slope ratio to 100.

Experiment 1: annotation performance

The ground truth of annotation was generated by Web users from the Labelme project. We adopted standard performance metrics, that is, average precision and average recall, to evaluate the annotation performance at the top *N* annotations.

In our experiment, we performed distance metric learning by five-fold cross validation on Labelme data, in which four folds are used for building the codebook and one fold is

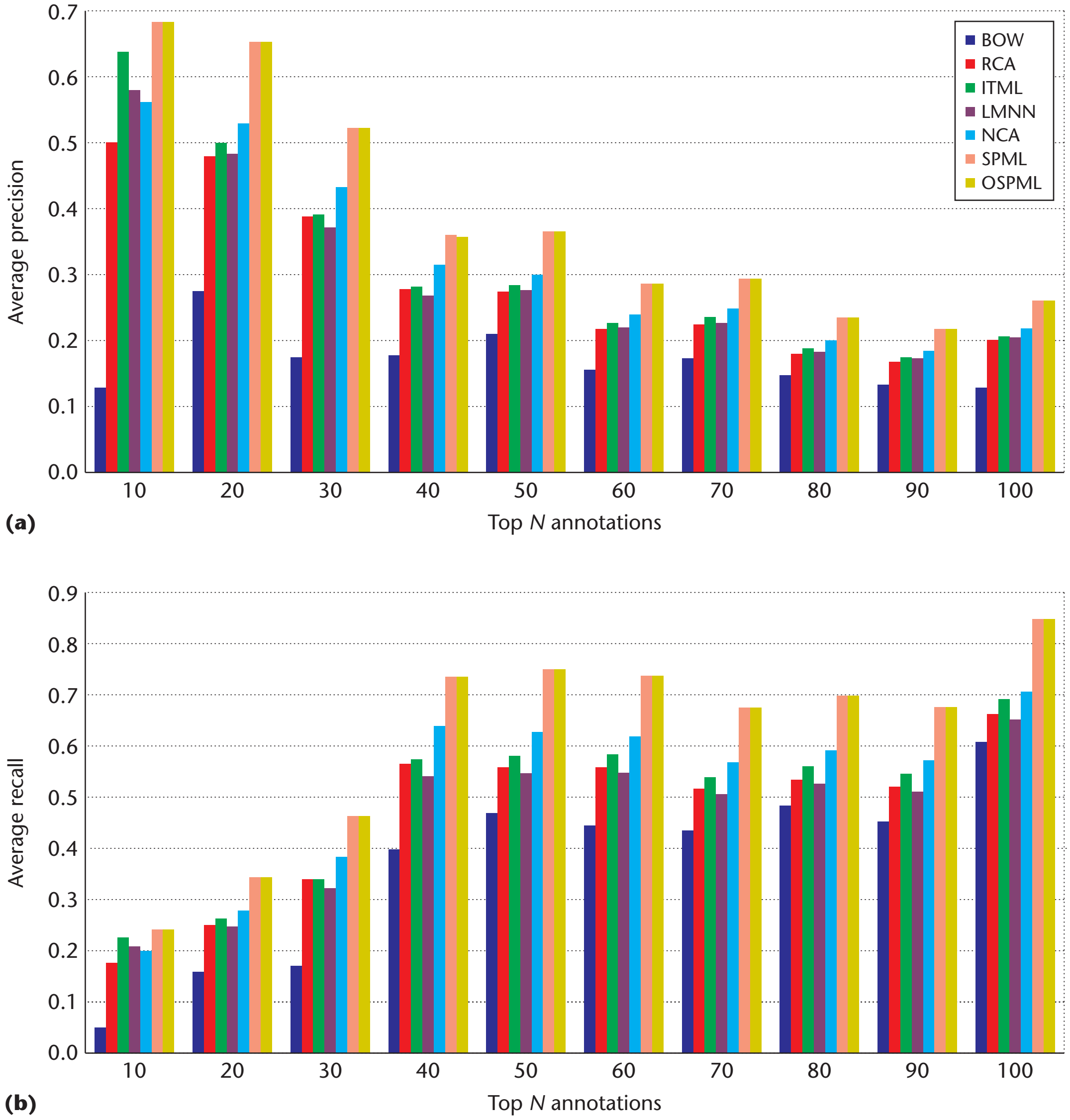


Figure 5. Performance comparison of different approaches for image annotation: (a) average precision and (b) average recall.

used for testing the annotation performance. Then we applied the learned metric on the Flickr data. In our methods, there are two key parameters: the constraint size (that is, the number of sampled pairwise constraints) and the codebook size. In this experiment, we simply fixed the constraint's size to 10,000 and the codebook size to 2,500. Figure 5 shows the comparison results of different approaches, including a regular BoW method and several implementations of our semantics-preserving BoW scheme using different DML algorithms.

As Figure 5 shows, we found that most DML-based algorithms significantly improve the annotation performance of the regular BoW in terms of both precision and recall. Compared to the other existing DML algorithms, the proposed SPML and OSPML algorithms also have clear advantages. These results show that the codebook generated with our SPML technique is more discriminative than the regular BoW, and that SPML is effective in reducing the semantic loss during codebook generation.

Experiment 2: object vs. general codebook

Our SPML scheme in general adopts an object-based codebook, which is denoted as *object codebook*. Unlike the regular BoW that adopts a general codebook without considering specific objects, our object codebook enjoys several advantages, such as high efficiency and excellent scalability. In addition, as with regular BoW, we can generate a general codebook by applying the similar metric-learning technique as used in the SPML scheme. This experiment is designed to compare the

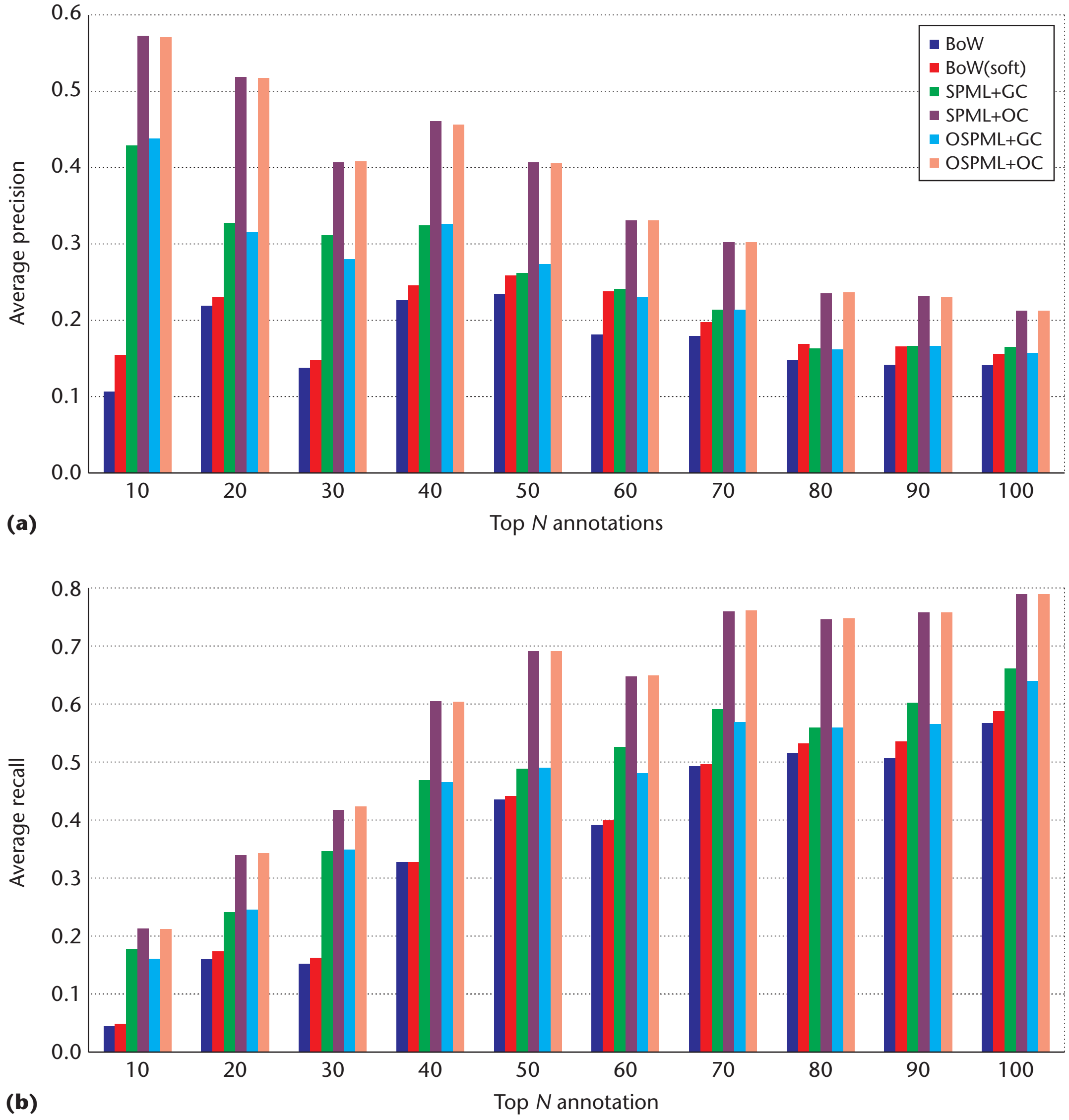


Figure 6. Comparison between general codebook and object codebook: (a) average precision and (b) average recall.

performance between object codebook and general codebook.

We have implemented two kinds of semantics-preserving codebooks. One is an object codebook similar to the previous experiment, and the other is a global semantics-preserving codebook similar to the regular BoW except for the usage of the optimized metric. Finally, we compared a regular BoW codebook, denoted as *BoW*, and an improved BoW model with a soft codeword assignment,[13] denoted as *BoW(soft)*.

Figure 6 summarizes the comparison results. Both SPC approaches performed considerably better than the regular BoW codebook. Further, by comparing object-based and global codebooks, we found that both of the two object codebooks consistently surpassed their corresponding global codebooks in all top annotation results. These results again validate the effectiveness of the SPML technique.

Experiment 3: annotation performance of varied codebook sizes

This experiment evaluates the performance under different codebook sizes. We fixed the size of the tag corpus at 1,000 and gradually increased the size of the codebook to evaluate the average precision and average recall of the top 50 annotations under each codebook. The performance evaluation results are shown in Figure 7.

As shown in Figure 7, we found that the codebook size could influence the performance. If the codebook size is too small, it might not be discriminative enough. If the

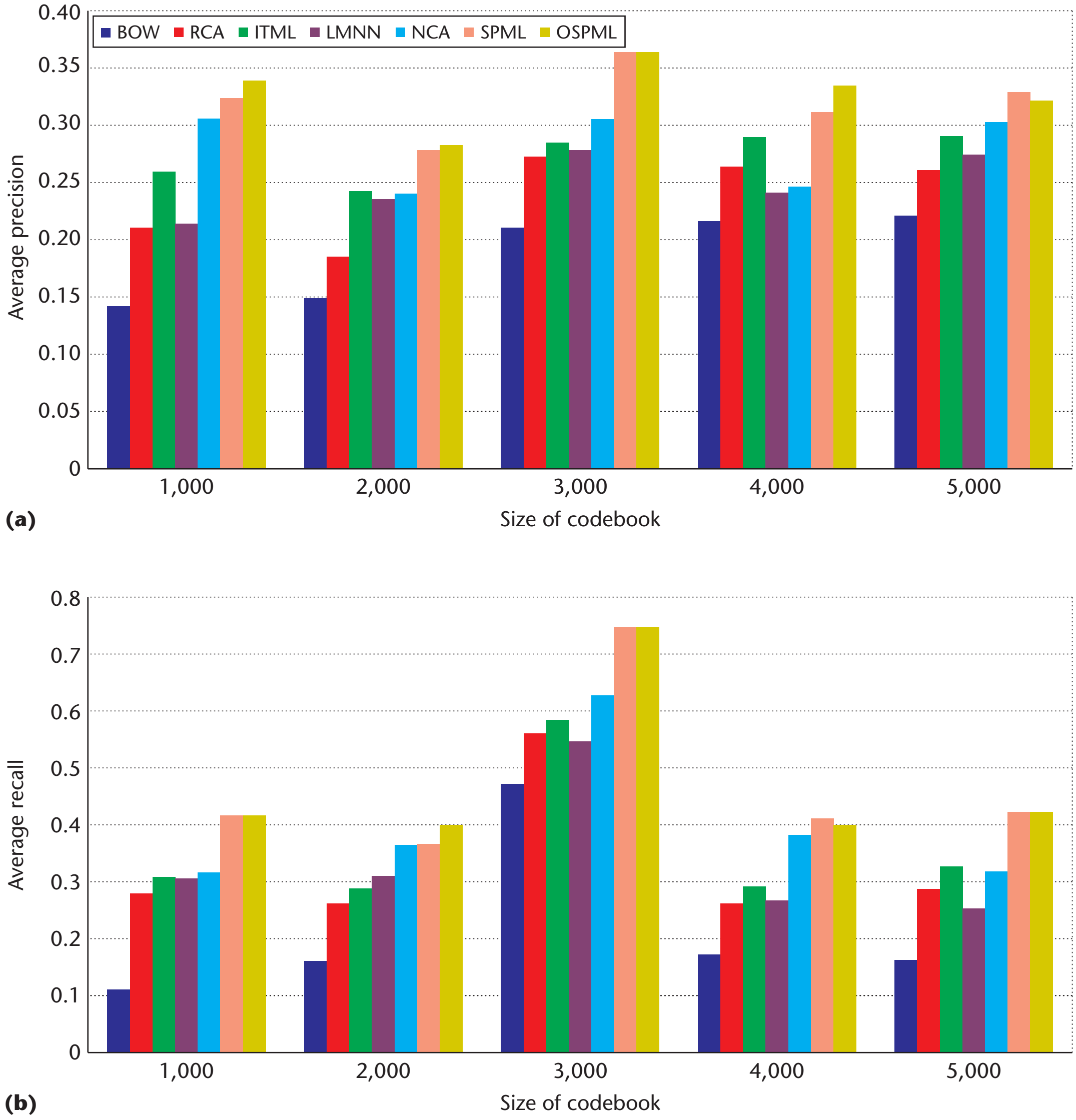


Figure 7. Performance evaluation of varied codebook sizes: (a) average precision and (b) average recall.

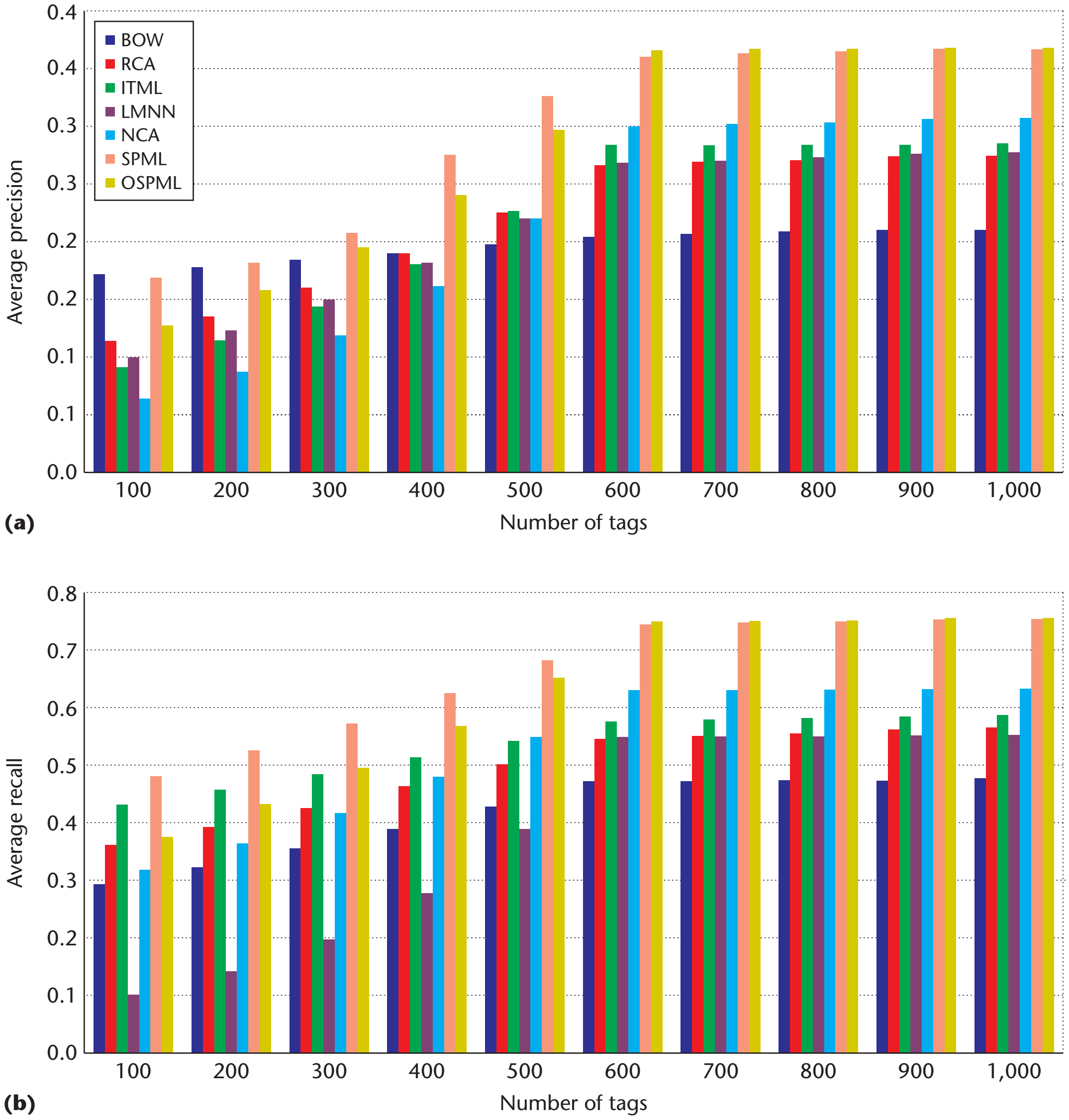
codebook size is too large, it may bring noise. Typically, the optimal size of the codebook may depend on the data set, which could be chosen by cross validation in practice.

Also we found that the number of codes for each category is small. It seems the discriminative of visual words is not on the number, but whether these visual words exactly describe the specific object. Even for the global codebook, we might find for some objects, the high frequent visual word is not much. Another fact is the number of codes also determined by the visual complexity of the object. In Labelme data, most of the objects, such as a window, road, lake, sky, cloud, railing, and so on, are not complex. For those visually simple objects, we found that one code is enough. For the global codebook, we found that not all visual words are useful. In the Bayes classifier, we might use just a few high-frequency codes that can determine the objects. Besides, we found that other irrelevant codes might even decrease the performance. We often see that when the number of categories increase, the performance of the global codebook might decrease.

Experiment 4: annotation performance of varied number of tags

This experiment is to discover the relation between the number of tags and the annotation performance. We fixed the codebook size to 3,000, randomly chose the first 100 tags, and then gradually increased the tag corpus size. We then evaluated the annotation performance within each chosen tag corpus. Our goal

Figure 8. Performance evaluation of varied numbers of tags: (a) average precision and (b) average recall.



was to examine how the tag corpus size influences the performance. Figure 8 shows the evaluation results.

We found that the performance is improved when the number of tags increases. This is because each image usually contains multiple objects, some of which might not appear in a small tag corpus. When increasing the tag corpus size, objects find their proper tags more easily from the tag corpus, leading to a boost in the annotation performance. When the number of tags is too small, it's less likely to find an image with proper tags that describe the same object as the target image. Therefore, increasing the size of tag corpus generally improves the annotation performance of the target image.

Experiment 5: application to object recognition

To further examine the performance of the proposed online SPML technique for object recognition, we applied the technique on the Pascal VOC 2006 object-recognition challenge. Unlike the Labelme data set where objects are manually well segmented, the objects in the VOC 2006 data set are only marked in the images with a rough bounding box. The number of object categories is only 10 for the VOC 2006 data set, which is much smaller than the Labelme data set. Although this data set seems less challenging, we believe both of them could help to examine the robustness of our techniques as they generally have different data distributions.

Table 1. Comparison of area under the (receiver operating characteristic) curve results on the Pascal visual object classes 2006 data set.

Category	BoW	AP06-Lee	LSPCH	XRCE	RCA	ITML	LMNN	NCA	SPML	OSPML
Bicycle	56.91	79.10	94.80	94.30	93.45	96.98	94.12	95.34	99.89	99.82
Bus	56.61	63.70	98.10	97.80	97.57	98.17	97.79	95.98	97.15	97.16
Car	60.31	83.30	97.50	96.70	94.42	93.17	93.13	93.13	94.54	94.31
Cat	61.08	73.30	93.70	93.30	92.19	94.15	92.97	93.32	93.33	93.12
Cow	68.53	75.60	93.80	94.00	93.91	92.18	92.77	92.75	94.18	93.97
Dog	73.22	64.40	87.60	86.60	87.77	92.11	90.06	89.97	94.42	94.32
Horse	28.83	60.70	92.60	92.50	93.22	95.58	96.18	93.85	95.18	95.19
Motorbike	36.01	67.20	96.90	95.70	92.19	94.37	94.75	94.19	96.97	97.01
Person	60.78	55.00	85.50	86.30	92.18	93.33	94.18	91.31	92.68	93.17
Sheep	60.74	79.20	95.60	95.10	97.19	97.15	92.39	95.67	97.44	97.28
Average	56.30	70.15	93.61	93.23	93.41	94.72	93.83	93.55	95.58	95.54

For object recognition, we adopted discriminative classification models, that is, support vector machines (SVMs). In particular, all the VOC 2006 training data is used to train the codebook as well as a set of binary SVM classifiers in which each of the SVM classifiers would be employed to detect one object category. Once the classifiers were trained, we tested the performance of the SVM classifiers on the VOC 2006 test set, and compared the results with the existing BoW model as well as some other state-of-the-art object-recognition methods, including XRCE,[14] AP06-Lee,[15] and QMUL-LSPCH.[15] Because there are only 10 object categories, we fixed the codebook size to 500 during the codebook-learning process. For the parameters in SVM training, we adopted the default settings ($C = 1$) with the radial-basis-function kernel of $\gamma = 0.07$. Finally, we measured the detection performance by the area under the (receiver operating characteristic, or ROC) curve (AUC).

Table 1 shows the AUC results. First of all, we found that most DML-based approaches significantly outperformed the regular BoW without metric learning. Second, by examining different DML algorithms, we found that the SPML and OSPML algorithms achieved the best performance. Moreover, compared to the other state-of-the-art object-recognition approaches, the proposed algorithms often obtained the best results for most cases. Finally, we found that the proposed online SPML algorithm is mostly comparable to the batch SPML algorithm for most cases.

Experiment 6: evaluation of computational cost

As indicated, we adopted the five-fold cross validation approach in which four folds of the data are used to learn the metric and generate the codebook, and one fold is used for object annotation. In the experiment, we focused on comparing the computational time costs of the OSPML algorithm, which can efficiently learn the metrics in a scalable manner. We have extensively evaluated the performance of our technique on a large data set of millions of features with various DML algorithms to learn metrics for codebook generation.

By computing the average time costs of all the compared DML algorithms in the object-annotation experiments, we found RCA, an extremely simple algorithm, is most efficient, taking about 1.58 seconds. We found LMNN to be the least efficient algorithm, taking about 1,545.35 seconds for optimizing the metric. Among the rest, NCA, the second least-efficient algorithm, took about 391.13 seconds, and ITML took about 80.37 seconds. For the two semantics-preserving metric-learning algorithms, the batch SPML algorithm took about 8.28 seconds, while the proposed online algorithm OSPML took about 5.85 seconds, ranking the second most-efficient algorithm among all the compared algorithms.

Conclusion

Encouraging results indicated that our technique is effective and promising for large-scale multimedia applications. In our future work,

Related Work

Our work is generally related to the bag-of-words studies,[1,2] for which we refer readers to a comprehensive survey on BoW.[1] On the other hand, from a machine-learning viewpoint, our work is related to supervised distance metric learning (DML). This work mainly follows our recent study.[3] This article differs in that we propose a novel online semantics-preserving, metric-learning algorithm, which is more efficient and scalable for large-scale applications. Here, we briefly discuss some related work on distance metric learning.

In the literature, DML has been actively studied. Existing DML studies can be roughly grouped into two major categories. One category is to learn metrics with class labels, such as neighborhood components analysis (NCA),[4] which are often studied for classification.[5] NCA learns a distance metric by extending the nearest-neighbor classifier. The maximum-margin nearest neighbor (LMNN) classifier[6] extends NCA through a maximum margin framework. Information-theoretic metric learning (ITML)[7] presented the metric-learning problem from the information-theory approach, and achieved the optimal metric by minimizing the differential relative entropy between two multivariate Gaussians under constraints on the distance function.

The other category of DML is to learn metrics from pairwise constraints that are mainly used for clustering and retrieval. Examples include relevant components analysis (RCA)[8] and discriminative component analysis (DCA),[9] among others. RCA learns a global linear transformation from the equivalence constraints. The learned linear transformation can be used directly to compute distance between any two examples. DCA and kernel DCA[9] improve RCA by exploring negative constraints and capturing nonlinear relationships using contextual information. Essentially, RCA and DCA can be viewed as extensions of linear discriminant analysis by exploiting the must-link constraints and cannot-link constraints.

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we plan to develop more effective algorithms to solve the optimization task of the distance metric learning problem to further improve the efficiency and scalability of the proposed BoW models. In addition, we plan to work on mining probabilistic constraints from noisy data of user-contributed photo collections, discovering the relation between visual words to reduce their redundancy, and applying our technique to other real large-scale multimedia applications. **MM**

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