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Scalable Object-Class Search via Sparse Retrieval Models and Approximate Ranking

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Abstract

In this paper we address the problem of object-class retrieval in large image data sets: given a small set of training examples defining a visual category, the objective is to efficiently retrieve images of the same class from a large database. We propose two contrasting retrieval schemes achieving good accuracy and high efficiency. The first exploits sparse classification models expressed as linear combinations of a small number of features. These sparse models can be efficiently evaluated using inverted file indexing. Furthermore, we introduce a novel ranking procedure that provides a significant speedup over inverted file indexing when the goal is restricted to finding the top- k (i.e., the k highest ranked) images in the data set. We contrast these sparse retrieval models with a second scheme based on approximate ranking using vector quantization. Experimental results show that our algorithms for object-class retrieval can search a 10 million database in just a couple of seconds and produce categorization accuracy comparable to the best known class-recognition systems.

1 Introduction

Over the last decade the accuracy of object categorization systems has dramatically improved thanks to the development of sophisticated low-level features [19, 17, 3] and

to the design of powerful nonlinear classification models that can effectively combine multiple complementary descriptors [7]. However, these categorization systems do not scale well to recognition in large image collections due to their large computational costs and high storage requirements.

In a parallel line of research, the efficiency of image retrieval systems has rapidly progressed to the point of enabling real-time search in millions of images [11]. Scalability to large data sets is typically achieved by casting image search as a text retrieval problem. The analogy with text-retrieval is made possible by representing each image as a sparse histogram of quantized features, known as visual words [24]. However, this representation is best suited to implement low-level notions of visual similarity. As a result, these systems are primarily used to detect near duplicates [2] or to find images containing the same *object instance* as the one present in a given query photo [21, 22]. Hashing methods have been used to compute low-dimensional image signatures encoding the overall global structure present in an image [26]. While such representations can be used to efficiently find photos matching the global layout of a query image, they have not been shown to be able to produce good categorization accuracy.

The objective of this work is to bridge these two independent lines of research. We borrow data structures

and methods from image retrieval – such as sparse and compact descriptors, inverted files, as well as algorithms for approximate distance calculation – to develop a system for accurate and efficient *object-class* search in large image collections: given a training set of examples defining an arbitrary object class (not known before query-time), our algorithms can efficiently find images of this category in a large database. We envision such a system to be used as a tool to interactively search in collections of unlabeled images, such as community-provided pictures or albums of personal photos.

Our approach uses the binary “claseme” descriptor of Torresani et al. [27] as representation for images. The binary entries in this descriptor are the Boolean outputs of a set of nonlinear object classifiers evaluated on the image. These base classifiers are trained on an independent data set obtained using text-based image search engines. Intuitively, the claseme descriptor provides a high-level description of the image in terms of similarity to the set of base classes. The approach is analogous in spirit to image representations based on attributes [6, 16, 15], which are human-defined properties correlated to the classes to be recognized. As claseme vectors provide a rich semantic description, they have been shown to produce good categorization accuracy even with simple linear classification models, which are efficient to evaluate. Furthermore, these descriptors are compact in size (the dimensionality of the binary vector is 2625, corresponding to only 329 bytes/image) and thus allow storage of large databases in memory for efficient recognition.

In this work we investigate the benefits of using sparse classification models with attribute features, i.e. classifiers that are explicitly constrained to use only a small set of attributes for the recognition of a new query category. The sparsity of the models enables the advantageous use of inverted files [20] for efficient retrieval. Furthermore, we present a new ranking algorithm which exploits the sparsity of the classifier to find the top- k images with even lower computational cost. We show that this simple approach produces a 24-fold speedup over brute-force evaluation.

We compare these sparsity-based retrieval models with a system that uses vector quantization to efficiently approximate the ranking scores of images in the database. We demonstrate that at the cost of a small drop in accuracy, this algorithm achieves similar efficiency and supe-

rior scalability in terms of memory usage.

2 Related Work

As already pointed out above, sparse retrieval models have been extensively used in image search [24, 21, 22]. Among the methods in this genre, the min-hash technique of Chum et al. [2] bears a close resemblance to our approach. It measures similarity between two images in the form of an approximate weighted histogram intersection. This measure can be efficiently calculated using inverted lists over sketch hashes, which are tuples of randomly-selected feature subsets. However, the weights of the histogram intersection must be defined a priori, before the creation of the index, and therefore this approach can only implement static similarity measures. Our task instead requires tuning the similarity measure for every new query category. The approach in [28] also uses inverted lists defined over feature subsets, called visual phrases. The visual phrases are binary “same-class” classifiers trained to recognize whether two given images belong to the same class or to different classes, regardless of the category. In principle this model could be adapted to be used for class retrieval. However, the visual phrases output only a Boolean value and thus cannot provide a ranking.

The idea of training sparse classification models on attribute vectors is similar in spirit to the “Object Bank” approach of Li et al. [18]. The Object Bank is a high-level image representation encoding the spatial responses of a large set of object detectors applied to the image. However, the dimensionality of these representations is too high to allow storage in memory for large collections (each descriptor contains 44,604 real values), which is the problem considered here. Li et al. have shown that the Object Bank descriptor can be compressed down to compact sizes using regularization terms enforcing feature sparsity. However, the feature selection is optimized with respect to a fixed set of classes, and the generalization performance of the selected features has not been demonstrated on novel classes. The focus of our work instead is on the design of compact models and efficient methods that can support search of arbitrary novel classes.

Our algorithm for approximate ranking shares similarities with efficient techniques for approximate nearest neighbor search. Most of these methods operate

by embedding the original feature vectors into a low-dimensional space via hashing functions or nonlinear projections such that the Hamming distance or the L2 distance in this space approximates a given metric distance in the original high-dimensional space [8, 29, 23]. In particular, Jain et al. [10] have proposed an algorithm that learns a Mahalanobis distance from similarity constraints and encodes this learned distance metric into randomized locality-sensitive hash functions. The resulting system enables efficient and accurate class recognition in large data sets. The work of Kulis and Grauman [14] has extended this approach to generate locality-sensitive hashing functions that can approximate arbitrary kernel distances. However, these methods optimize the categorization metric and the embedding space with respect to a fixed set of classes during an offline training stage, *before* the search. Instead our problem statement requires to efficiently learn *at query time* the classification model for a category that is not known in advance.

3 Object-Class Search

We now formally define our problem statement and introduce the notation that will be used in the rest of the paper. We assume we are given a database of N unlabeled images, from which binary vectors are extracted during an offline stage. We indicate with $\mathbf{x}_i \in \{0, 1\}^D$ the binary classeme descriptor computed from the i -th image in the database. These feature vectors are stored in an index for subsequent efficient retrieval. At query time we are given a set of n^+ training images belonging to an arbitrary query category as well as n^- negative examples. In a practical application the negative set could be a fixed “background” collection containing examples of many different categories (we consider such scenario in one of the experiments). We indicate with $\tilde{\mathcal{D}}$ the labeled training set obtained by merging these two sets, i.e., $\tilde{\mathcal{D}} = \{(\tilde{\mathbf{x}}_1, \tilde{y}_1), \dots, (\tilde{\mathbf{x}}_n, \tilde{y}_n)\}$ where $\tilde{\mathbf{x}}_i$ is the binary classeme vector of the i -th training example, $\tilde{y}_i \in \{0, 1\}$ indicates its binary label and $n = n^+ + n^-$ (note that we use the $\tilde{\cdot}$ symbol to differentiate training example $\tilde{\mathbf{x}}_i$ from database example \mathbf{x}_i). The objective of the system is to efficiently retrieve relevant database images and rank them according to the probability of belonging to the query category. We evaluate the accuracy of the retrieval

system in terms of precision at k . Again, we want to emphasize that the object classes provided at query time are not known in advance. Thus, the system must be able to learn the retrieval model exclusively from the set $\tilde{\mathcal{D}}$.

Since our objective is to retrieve images belonging to the query class, we employ binary classifiers as retrieval models and use their classification output as ranking score. We restrict our study to linear classifiers, since they are efficient to learn as well as to evaluate. Thus, the ranking score for database example \mathbf{x} is computed as $h_{\theta}(\mathbf{x}) = \theta \cdot \mathbf{x}$, where θ is a D -dimensional vector of parameters (we incorporate a bias term in the weight vector by adding a constant entry set to 1 for all examples). Our classifiers are learned by optimizing an objective function of the form:

$$E(\theta) = R(\theta) + \frac{C}{m} \sum_{i=1}^m L(\theta; \tilde{\mathbf{x}}_i, \tilde{y}_i) \quad (1)$$

where R is a regularization function aimed at preventing overfitting, L is the loss function penalizing misclassification, and C is a hyper-parameter trading off the two terms.

4 Efficient class retrieval by sparse retrieval models

Retrieval efficiency can be achieved by forcing the classifier h_{θ} to be sparse, i.e., by requiring the parameter vector θ to have very few non-zero entries so that the evaluation cost will be a small fraction of D per image. To realize this efficiency we can use an *inverted file* with D entries, each providing the list of database images containing one of the D binary features.

4.1 Sparse classifiers

The literature on sparse linear classifiers is vast and review of these methods is beyond the scope of this paper. In our work, we restrict our attention to the following sparse classification models due to their good balance of feature sparsity and accuracy:

- **L1-LR:** this is a ℓ_1 -regularized logistic regression classifier [5] obtained by defining $R(\theta) = \|\theta\|_1$ and

$L(\boldsymbol{\theta}; \tilde{\mathbf{x}}_i, \tilde{y}_i) = \log(1 + \exp(-\tilde{y}_i \boldsymbol{\theta} \cdot \tilde{\mathbf{x}}_i))$. The ℓ_1 -regularization is known to produce sparser parameter vectors than the more conventional ℓ_2 -regularization.

- **FGM:** this is the Feature Generating Machine described in Tan et al. [25]. It minimizes a convex relaxation of the constrained optimization obtained by setting $R(\boldsymbol{\theta}) = \|\boldsymbol{\theta}\|_2$, $L(\boldsymbol{\theta}, \mathbf{d}; \tilde{\mathbf{x}}_i, \tilde{y}_i) = \max(0, 1 - \tilde{y}_i(\boldsymbol{\theta} \odot \mathbf{d}) \cdot \tilde{\mathbf{x}}_i)^2$ and by enforcing constraint $\mathbf{1} \cdot \mathbf{d} \leq B$ where \odot denotes the elementwise product between vectors, $\mathbf{d} \in \{0, 1\}^D$ is a binary vector indicating the active features, and B is a hyperparameter controlling the number of nonzero weights. A cutting plane algorithm is employed to efficiently find the sparse features defined by vector \mathbf{d} . This method has been shown to produce state-of-the-art results in terms of sparsity and generalization performance.

We contrast these sparse classifiers with a traditional linear SVM using an L2 regularization term. We denote this classifier with **L2-SVM**.

4.2 Top- k pruning

In this subsection we present an algorithm that exploits sparsity to efficiently find the top-scoring k images in the database using the linear retrieval functions described above. This approach is well suited to our intended retrieval application since a user is typically interested in only the top search results. The key-idea of this ranking algorithm is to update lower and upper bounds on the scores of the images to gradually prune the candidate set without complete calculation of the classification outputs. An upper bound $u(i)$ and a lower bound $l(i)$ is defined for every image i in the database. The upper bound $u(i)$ is first initialized to score u^* , which is the highest possible score achievable given the weight vector $\boldsymbol{\theta}$. Such score is obtained when a binary feature vector contains nonzero values precisely in the positions where the weight vector $\boldsymbol{\theta}$ has positive values and it contains 0 in the entry positions where the weights are negative. Analogously, $l(i)$ is initialized to the lowest possible score l^* , which occurs when the entries of the feature vector are 0 in positions where the weights are positive and 1 where the weights are negative. Then, these bounds are updated by considering one weight entry at a time. Let p_d be the entry considered in the d -th iteration. Let us assume that $\theta(p_d)$

is positive (the case when this value is negative is analogous). Then, if the binary vector of the i -th image contains a 1 in position p_d , the lower bound $l(i)$ will be incremented by $\theta(p_d)$; if instead $x_i(p_d)$ is 0, the upper bound $u(i)$ will be decremented by $\theta(p_d)$. Thus, we see that at each iteration d the gap between the lower and the upper bound for each image i is decreased by amount $\theta(p_d)$. In order to produce the fastest reduction of this gap, we process the weights in descending order of absolute values. Furthermore, for efficiency in our implementation we only store and update the lower bound for each image, since the upper bound is trivially obtained by adding an iteration-dependent value which is constant for all images. This derives trivially from observing that at any iteration d the gap between the bounds for every image i is: $u(i) - l(i) = u^* - l^* - \sum_{d'=1}^d |\theta(d')|$. At each iteration, after updating the bounds, the algorithm identifies the set A of k images having highest lower bounds (this can be done in a linear scan over the vector l). Then, in the pruning step, the method eliminates from further consideration the images having upper bound smaller than the minimum lower bound in the set A , since such images cannot rank in the top- k . The pruning rate will obviously depend on the distribution of the weights in the vector $\boldsymbol{\theta}$ and the statistics of classemes. Intuitively, the pruning rate will be high when $\boldsymbol{\theta}$ is sparse and when the weight magnitudes decay rapidly when sorted in decreasing order. Indeed in the experiment section we empirically demonstrate that the algorithm runs faster when the weight vector has such characteristics.

The pseudocode of the algorithm is given below.

5 Efficient approximate ranking

The algorithm presented above achieves high efficiency by quickly removing from consideration images that cannot rank in the top- k . Instead, in this subsection we present an algorithm that performs fast retrieval by *approximating* the ranking score with a measure that can be computed efficiently. The exact score calculation is approximated via vector quantization. However, our descriptors are binary vectors, and as such they are not suited to be quantized. Thus, we first apply PCA to transform each binary-valued classeme vector $\mathbf{x}_i \in \{0, 1\}^D$ into a real-valued lower-dimensional vector $\hat{\mathbf{x}}_i \in \mathbb{R}^{D'}$,

Algorithm 1 Top- k pruning method

Input: Database examples $\mathbf{x}_1, \dots, \mathbf{x}_N$, weight vector θ , sorting indices p_1, \dots, p_D s.t. $|\theta(p_1)| \geq |\theta(p_2)| \geq \dots > |\theta(p_D)|$.

Output: Indices of top- k images: $A \subseteq \{1, \dots, N\}$.

```
1: Initialize candidate set:  $C := \{1, \dots, N\}$ 
2: Set  $A$  to contain the indices of  $k$  randomly chosen images.
3:  $l^* := \sum_{d \text{ s.t. } \theta(d) < 0} \theta(d)$ 
4:  $u^* := \sum_{d \text{ s.t. } \theta(d) > 0} \theta(d)$ 
5:  $\forall i : u(i) := u^*, l(i) := l^*$ 
6: for  $d = 1$  to  $D$  do
7:   for all  $i \in C$  such that  $x_i(p_d) == 1$  do
8:     if  $\theta(p_d) \geq 0$  then
9:        $l(i) := l(i) + \theta(p_d)$ 
10:    else {case  $\theta(p_d) < 0$ }
11:       $u(i) := u(i) + \theta(p_d)$ 
12:    for all  $i \in C$  such that  $x_i(p_d) == 0$  do
13:      if  $\theta(p_d) \geq 0$  then
14:         $u(i) := u(i) - \theta(p_d)$ 
15:      else {case  $\theta(p_d) < 0$ }
16:         $l(i) := l(i) - \theta(p_d)$ 
17:    Update  $A$  to contain indices of top- $k$  lower bounds
18:    Prune candidate set:
     $C = C - \{i \text{ s.t. } u(i) < \min_{j \in A} l(j)\}$ 
19:    if  $|C| == k$  then
20:      break
```

where $D' < D$ ¹. Then, we quantize each vector $\hat{\mathbf{x}}_i$ using the product quantization method of Jégou et al. [13, 12]. This approach can provide very good vector approximation at low computational cost both during the learning of the cluster centroids as well as at quantization-time. The method splits each vector $\hat{\mathbf{x}}$ into v sub-vectors $\hat{\mathbf{x}}^1, \dots, \hat{\mathbf{x}}^v$, each of length D'/v . Then, each sub-vector is quantized independently using a codebook of w cluster centroids learned from training data using k-means clustering. Thus, the complete vector $\hat{\mathbf{x}}$ is quantized as $q(\hat{\mathbf{x}})$ by the following quantizer function $q(\cdot)$:

$$q(\hat{\mathbf{x}}) = \begin{bmatrix} q_1(\hat{\mathbf{x}}^1) \\ \vdots \\ q_v(\hat{\mathbf{x}}^v) \end{bmatrix} \quad (2)$$

¹We also tried to use real-valued classeme vectors and achieved similar results. Here we prefer presenting the method based on binary classemes in order to compare the different methods in a scenario where they are all applied to the same input representation.

where $q_j(\hat{\mathbf{x}}^j) \in \mathbb{R}^{D'/v}$ is the nearest cluster centroid to sub-vector $\hat{\mathbf{x}}^j$ in the dictionary learned for the j -th sub-block of features. While quantizers are usually employed to reduce the dimensionality of the data, we use them here primarily to speed-up the calculation of the score. Given the weight vector learned in the D' -dimensional space, the idea is to approximate the exact ranking score calculation $\hat{\theta} \cdot \hat{\mathbf{x}}_i$ with $\hat{\theta} \cdot q(\hat{\mathbf{x}}_i)$. Note that this approximate score can be computed as follows:

$$\hat{\theta} \cdot q(\hat{\mathbf{x}}_i) = \sum_{j=1}^v \hat{\theta}^j \cdot q_j(\hat{\mathbf{x}}_i^j). \quad (3)$$

The efficiency stems from the fact that the terms $\hat{\theta}^j \cdot q_j(\hat{\mathbf{x}}_i^j)$ can be read from a lookup table computed in a preprocessing stage for all v centroids of each sub-block j . The creation of this table for all sub-blocks will have cost of $\mathcal{O}(wD')$. But then computing the approximate score in eq. 3 will amount to simply adding together v values read from the look-up table. Thus, the overall complexity of calculating the ranking scores for all images in the databases, including the preprocessing, will be $\mathcal{O}(wD' + vN)$.

As discussed in full detail in [13], choosing the number of PCA dimensions D' poses a challenging dilemma. When D' is large, the PCA projection error is small, but there is a subsequent large quantization error. In principle this quantization error can be fought off by increasing v and w at the expense of a larger code size and a higher computational cost for quantization and learning. On the other hand, choosing a small D' , leads to a large projection error followed by a small quantization error. In our problem the choice of D' has an even greater importance: since we are training our linear classifier in the PCA subspace, the choice of D' will dictate the Vapnik-Chervonenkis (VC) dimension, i.e., the capacity of our classification model [9]. A linear classifier defined in a D' -dimensional space has VC dimension $D' + 1$. Thus, using a large D' will allow us to obtain more powerful classifiers. In the experiment section we analyze empirically how D', w, v affect the accuracy, the speed, as well as the memory usage.

Another practical issue to consider is that the PCA components, by construction, have different variance, with the first few entries typically capturing most of the

energy in the signal. A naïve application of product quantization would subdivide a vector according to the order of components so that the j -th sub-block would consist of the consecutive feature entries from position $(1 + (j - 1)D'/v)$ to (jD'/v) . However, such strategy would blindly allocate the same number of centroids for the most informative components (the ones in the first sub-block) as well as for the least informative. We address this problem using the solution proposed in [13]: we apply a random orthogonal transformation after PCA so that the variances of the resulting components will be more even. We then quantize the examples and train our retrieval models in this space.

6 Experiments

In this section we empirically evaluate the proposed algorithms and the several possible parameter options on challenging data sets under the performance measures of retrieval accuracy, speed and memory usage. We denote the top- k pruning method with **TkP** and the approximate ranking technique with **AR**.

Retrieval evaluation on ILSVRC2010 (150K images).

We first evaluate our methods using the data set of the Large Scale Visual Recognition Challenge 2010 (ILSVRC2010) [1], which includes images of 1000 different categories. We use a subset of the ILSVRC2010 training set to learn the classifiers: for each of the 1000 classes, we train a classifier using $n^+ = 50$ positive examples (i.e., images belonging to the query category) and $n^- = 999$ negative examples obtained by sampling one image from each of the other classes. To cope with the largely unequal number of positive and negative examples ($n^- \gg n^+$) we normalize the loss term for each example in eq. 1 by the size of its class. We evaluate the learned retrieval models on the ILSVRC2010 test set, which includes 150,000 images, with 150 examples per category. Thus, the database contains $n_{test}^+ = 150$ true positives and $n_{test}^- = 149,850$ distractors for each query. Figure 1 shows precision versus search time for AR and TkP in combination with different classification models. Since AR does not use sparsity to achieve efficiency, we only paired it with the L2-SVM model. The x -axis shows average retrieval time per query, measured on a single-

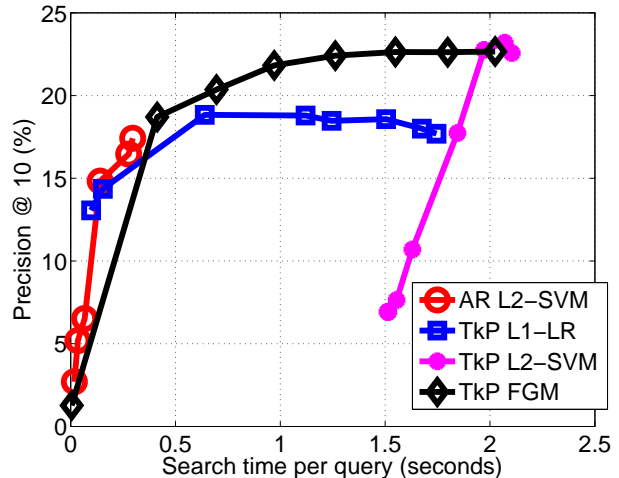


Figure 1: Class-retrieval precision versus search time for the ILSVRC2010 data set: x -axis is search time; y -axis shows percentage of true positives ranked in the top 10 using a database of 150,000 images (with $n_{test}^- = 149,850$ distractors and $n_{test}^+ = 150$ true positives for each query class). The curve for each method is obtained by varying parameters controlling the accuracy-speed tradeoff (see details in the text).

core computer with 16GB of RAM and an Intel Core i7-930 CPU @ 2.80GHz. The y -axis reports precision at 10 which measures the proportion of true positives in the top 10. The times reported for TkP were obtained using $k = 10$. The curve for AR was generated by varying the parameter choices for v and w , as discussed in further detail later. The performance curves for “TkP L1-LR” and “TkP L2-SVM” were produced by varying the regularization hyperparameter C in eq. 1. While C is traditionally viewed as controlling the bias-variance tradeoff, in our context it can be interpreted as a parameter balancing generalization accuracy versus sparsity, and thus retrieval speed. In the case of “TkP FGM” we have kept a constant C (tuned by cross-validation), and instead varied the sparsity of this classifier by acting on the separate parameter B . From this figure we see that AR is overall the fastest method at the expense of search accuracy: a peak precision of 22.6% is obtained by TkP using L2-SVM but AR with the same classification model achieves only a top precision of 17.5% due to a combination of fewer learn-

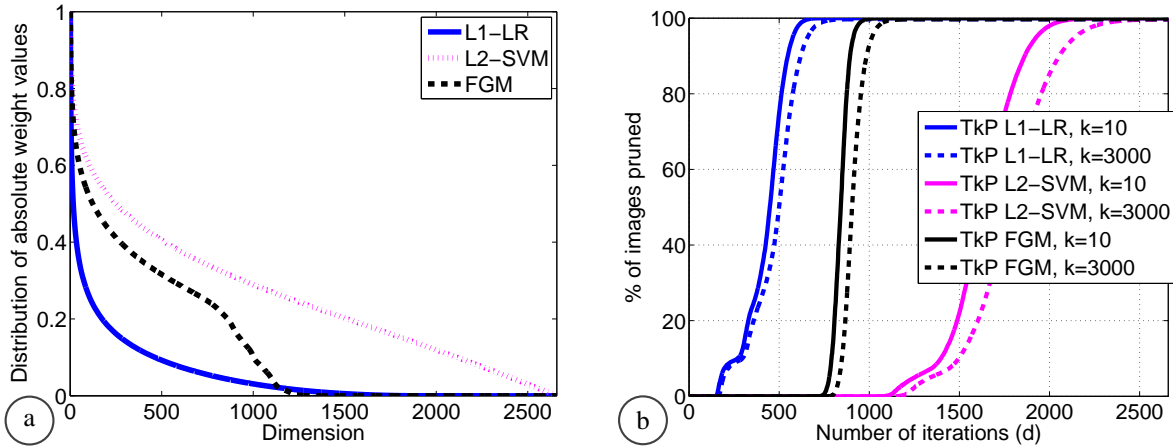


Figure 2: (a) Distribution of weight absolute values for different classifiers (after sorting the weight magnitudes). TkP runs faster with sparse, highly skewed weight values. (b) Pruning rate of TkP for various classification model and different values of k ($k = 10, 3000$).

ing parameters (in this experiment we used $D' = 512$), PCA projection error and quantization error. As expected, we note that TkP runs faster when used in combination with L1-LR or FGM rather than L2-SVM, since it benefits from sparsity in the parameter vectors to eliminate images from consideration. However, we see that sparsity negatively affects accuracy, with L2-SVM providing clearly much better precision compared to L1-LR.

In our experiments we found that TkP typically exhibits faster retrieval in conjunction with L1-LR rather than FGM. We can gain an intuition on the reasons by inspecting the average distribution of weight absolute values in figure 2(a). The average distribution for each classification model was obtained by first sorting the weight absolute values for each query in descending order and then normalizing by the largest absolute value. For this experiment we chose $B = 1000$ for the FGM model. We can see that although for this setting the weight vectors learned by FGM are on average more sparse than those produced by L1-LR, the normalized magnitude of the L1-LR weights decays much faster. TkP benefits from the presence of these highly skewed weight magnitudes to produce more aggressive pruning. Figure 2(b) shows the average proportion of database pruned by the top- k method as a function of iteration number (d) for $k = 10$ and $k = 3000$.

As anticipated, a smaller value of k allows the method to eliminate more images from consideration at a very early stage.

We now turn to study the effect of parameters D', v, w on the efficiency and accuracy of AR. Figure 3 shows retrieval speed and precision obtained by varying v and w for $D' \in \{128, 256, 512\}$. Increasing the dictionary size (w) reduces the quantization error while raising the quantization time: note the slightly better accuracy but higher search time when we move from parameter setting ($D' = 512, v = 256, w = 2^6$) to ($D' = 512, v = 256, w = 2^8$). The number of sub-blocks (v) critically affects the retrieval time: reducing v lowers a lot the search time but causes a drop in accuracy. Finally, note how D' impacts the accuracy since it affects both the number of parameters in the classifier as well as the projection error: using a large D' is beneficial for accuracy when v and w are large; however, when there are few cluster centroids or the number of sub-blocks is small, lowering D' improves precision since this mitigates the quantization error.

Finally, we also ran an experiment simulating real-world usage of an object-class retrieval system where a user may provide a positive training set but no negative set. In such cases one could use a “background” set for the negative examples. Thus, here we used as negative

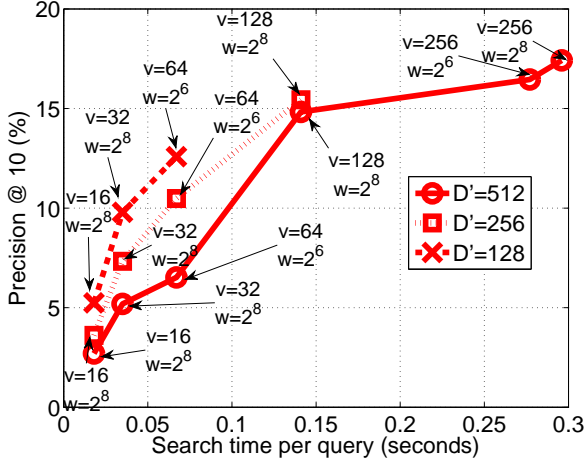


Figure 3: Effects of parameters D' , v , w on the accuracy and search time of AR for the ILSVRC2010 data set. A small v implies faster retrieval at the expense of accuracy. Using a larger value for w reduces the quantization error at a small increase in search time. Lowering D' decreases the power of the classifier (VC-dimension) and increases the PCA projection error, thus negatively impacting precision.

examples for each query, $n^- = 999$ randomly chosen images from all 1000 categories, thus possibly containing also some true positives (i.e., images of the query class). As expected, we found the precisions of the L1-LR and L2-SVM classifiers to be nearly unchanged by the few incorrectly labeled examples: precisions at 10 in this case are 18.75% and 22.55%, respectively.

Retrieval results on ImageNet (10M images). We now present results on the 10-million ImageNet dataset [4] which encompasses over 15,000 categories (in our experiment we used 15203 classes). We used a subset of 950 categories as query classes. For each of these classes we capped the number of true positives in the database to be $n_{test}^+ = 450$. The total number of distractors for each query is $n_{test}^- = 9,671,611$. We trained classifiers for each query category using a training set consisting of $n^+ = 10$ positive examples and $n^- = 15,202$ negative images obtained by sampling one training image for each

of the negative classes. We omit from this experiment the FGM model as its training time is over 300 times longer than the time needed to learn the L1-LR or L2-SVM classifier and thus its use on such a large scale benchmark is difficult (as a reference, learning a L1-LR or an L2-SVM classifier for a query category in this experiment takes around 2 seconds). The results are summarized in figure 4, once again in the form of retrieval time versus precision at 10. We can see that on this data set, TkP provides clearly the best accuracy-speed tradeoff with near peak-precision achieved for an average retrieval time of just a couple of seconds. The plot reports time for $k = 10$, but we found that when setting $k = 3000$ the retrieval time of TkP increases by only roughly 35% compared to the case $k = 10$. AR is once again very fast but it provided lower precision due to the issues pointed out above. In this figure we are also including the retrieval times obtained with a simple architecture of inverted lists, with each list enumerating the images containing one particular classeme. Retrieval with inverted files obviously yields the same accuracy as TkP but it is more than 7 times slower. Overall, TkP with L1-LR provides a 24-fold speed-up compared to brute-force evaluation.

We would like also to comment on the memory usage. The inverted file architecture requires the most space. We represented the image IDs in inverted files using one byte per image: we achieve this by storing only ID displacements (which in our experiment happened to be always smaller than 255) between consecutive images in the list. Despite this clever encoding the total storage requirement for the 10M data set was roughly 9GB. TkP was implemented using a bit map of all classemes for all images which takes a space of $(2659/8) \times N$ bytes for a database containing N images, which in this case amounts to about 3GB. AR is the most space-efficient: it requires only $v \log_2 w$ bits to represent each image using vector quantization and the cluster centroids are stored in only $D'w$ real values. Thus on the 10M data set, the memory usage of AR was only 1.8GB. This is clearly the most scalable approach in term of memory usage.

Object-class retrieval accuracy on Caltech256. Our choice of retrieval models and features was primarily motivated by computational complexity constraints. Thus, a natural, legitimate question is: how much accuracy have

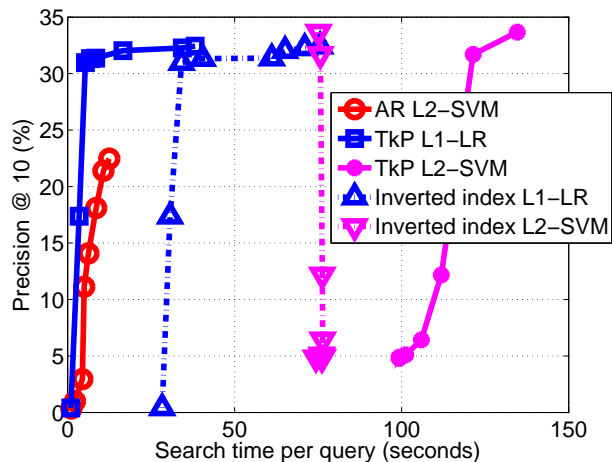


Figure 4: Search time versus retrieval precision at 10 for the 10-million ImageNet dataset. For each query class, there exist $n_{test}^+ = 450$ positive images and $n_{test}^- = 9,671,611$ distractors in the database.

we sacrificed for the sake of this efficiency? We answer this question by comparing the retrieval accuracy of our approaches with the state-of-the-art class-recognition system of Gehler and Nowozin [7], which has been shown to produce the best categorization results to date on several recognition benchmarks. This classifier combines non-linear kernel distances computed from multiple feature descriptors. Its high computational complexity and large feature storage requirements makes it impossible to use in large image databases such as those considered in this paper. Thus, we carry out our this accuracy comparison on the small Caltech256 data set. We use as low-level features for LP- β the same 13 descriptors that were used to learn the classems [27], so as to have a comparison between methods on common ground. We train the retrieval models on each Caltech256 class separately by choosing $n^+ = 50$ positive examples of the query category and $n^- = 255$ negative examples obtained by sampling one image from each of the other categories. We report the precision on ranking a database of 6,400 images including $n_{test}^+ = 25$ true positives and $n_{test}^- = 6,375$ distractors obtained by choosing 25 examples from each of the other 255 classes. Table 1 shows that our simple retrieval models applied to binary classeme vectors achieve accu-

	L1-LR	L2-SVM	FGM	LP- β
precision@25	28.2%	30.2%	29.6%	32.8%
training time (seconds)	0.044	0.028	11.04	253.7

Table 1: Caltech256 evaluation: precision at 25 and training time for the state-of-the-art LP- β classifier as well as for linear classifiers trained on binary classems. The training set sizes are $n^+ = 50$ and $n^- = 255$. The number of true positives in the database is $n_{test}^+ = 25$ and the number of distractors are $n^- = 6400$. The precisions of these simple linear models approach the accuracy of the LP- β classifier which is recognized as one of the best object classification systems to date.

racy comparable to that of the much more computationally expensive LP- β classifier and are several orders of magnitude more efficient to train as well as test.

7 Discussion

We have presented models and algorithms that enable near-instantaneous novel class recognition and search in databases containing several million images with accuracy approaching that of the best known categorization systems. Such scalability is achieved by borrowing tools from information retrieval such as small (but highly-informative) binary codes to represent documents, sparse retrieval models, and algorithms for approximate distance calculation. While such tools had already been exploited for near-duplicate image detection and for search of object instances we believe we are the first to adapt them to the problem of object class recognition in large collections.

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