Does one size really fit all?

Evaluating classifiers in Bag-of-Visual-Words classification

Christian Hentschel, Harald Sack
Hasso Plattner Institute for Software Systems Engineering
Potsdam, Germany
christian.hentschel@hpi.uni-potsdam.de,
harald.sack@hpi.uni-potsdam.de

ABSTRACT

Bag-of-Visual-Words (BoVW) features that quantize and count local gradient distributions in images similar to counting words in texts have proven to be powerful image representations. In combination with supervised machine learning approaches, models for various visual concepts can be learned. While kernel-based Support Vector Machines have emerged as a de facto standard an extensive comparison of different supervised machine learning approaches has not been performed so far. In this paper we compare and discuss the performance of eight different classification models to be applied in BoVW approaches for image classification: Naïve Bayes, Logistic Regression, k-nearest neighbors, Random Forests, AdaBoost and linear Support Vector Machines (SVM) as well as generalized Gaussian kernel SVMs. Our results show that despite kernel-based SVMs performing best on the official Caltech-101 dataset, ensemble methods fall only shortly behind. In addition we present an approach for intuitive heat map-like visualization of the obtained models that help to better understand the reasons of a specific classification result.

Categories and Subject Descriptors

I.5.4 [**Pattern Recognition**]: Applications—*Computer Vision*

General Terms

Algorithms, Experimentation

Keywords

Computer Vision, Bag-of-Visual-Words, Classifier Comparison, Visualization

1. INTRODUCTION

In this paper, we consider the problem of recognizing the generic object or scene category of an image. We aim for automatic classification of an image into one or more classes describing the depicted content such as *car*, *person* or *landscape*. Within the last decade, Bag-of-Visual-Words (BoVW) features have been successfully applied in these kind of whole-image categorization tasks. The approach borrows from document representation methods in text classification and compactly summarizes images as 1D histograms of an unordered collection (i.e. *bag*) of local patch descriptors.

Part of the success of BoVW-based classification systems results from this generic image description approach. By simply counting prototypes of image characteristics and discarding any spatial information arbitrary object and scene categories have been successfully modeled in the past. In combination with supervised machine learning methods a category model is trained over the BoVW representation of a set of training images. As different local image patches may describe parts of different objects depicted in the same image the very same representation can be used to model the *car* as well as the *person* that drives the car and the *landscape* in the background by providing sufficient training examples.

In the past, Support Vector Machines (SVM) have emerged as a de facto standard to learn BoVW-based category models. Especially Radial Basis Function (RBF)-based Kernel SVMs have been widely applied. While the obtained results are very often satisfactory very few work explicitly targets the comparison of different machine learning methods for training category models. In this paper we therefore compare various approaches for image classification based on BoVW features in terms of the classification accuracy achieved on the well-known Caltech-101 benchmark dataset[1]. We analyze the performance of eight supervised machine learning methods for BoVW classification: Naïve Bayes, Logistic Regression, k-nearest neighbors, Random Forests, AdaBoost, linear Support Vector Machines and finally generalized Gaussian kernel SVM (based on standard euclidean and χ^2 distance resp.). Our intention was to evaluate whether the default choice of Kernel-based Support Vector Machines is a good choice or whether different classification scenarios demand for different classification approaches.

This paper is structured as follows: In section 2 we briefly review the Bag-of-Visual-Words approach for image classification. We describe the relevant steps for BoVW feature extraction and classification. Section 3 presents the evalu-

i-KNOW '14, September 16 – 19 2014, Graz, Austria

ACM 978-1-4503-2769-5/14/09 ...$15.00
http://dx.doi.org/10.1145/2637748.2638424

[1]The dataset is available at
`http://www.vision.caltech.edu/Image_Datasets/Caltech101`

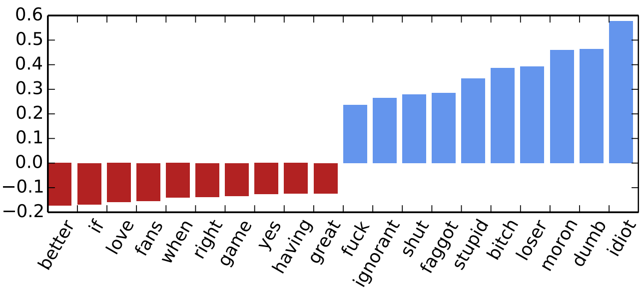


Figure 1: SVM model weights of the 10 most and least important words in classification of user comments into insults.[2]

ated classification models in more detail and discusses their relevance in the context of BoVW classification. In section 4 we present and compare the results obtained on the official Caltech-101 benchmark dataset. We discuss the individual performance obtained by each classifier with respect to the complexity of the classification task and present a novel visualization approach that helps to better understand a learned category model. Finally, section 5 concludes our paper and gives a brief outlook on future work.

2. THE BAG-OF-VISUAL-WORDS MODEL

The Bag-of-Visual-Words (BoVW) approach extends an idea from text retrieval to visual classification [22]. In text classification systems, each text document is usually represented by a normalized histogram of word counts. Commonly, this incorporates all words from a (typically application specific) vocabulary. The vocabulary may exclude certain non-informative words (i.e. stop words) and it usually contains the words in their stemmed form. A text document is represented by a sparse term vector where each dimension corresponds to a term in the vocabulary and the value of that dimension is the number of times the term appears in the document normalized by the total number of vocabulary words in the document. The term vector is the Bag-of-Words representation – an unsorted collection of vocabulary words which coined the term *bag*. In combination with supervised machine learning methods, models for specific text categories (e.g. Spam mails) can be learned. Typically, a model captures the meaning of a category by putting higher weights to important vocabulary words and lower weights to lesser important terms based on a set of training examples from either category. An example is given in Fig. 1 where a linear Support Vector Machine (SVM) was trained on a Bag-of-Words model over a document collection of user comments. The task is to detect when a comment from a conversation would be considered insulting to another participant in the conversation. As can be seen, the model puts high weights on the insulting terms and low weights to terms usually not connotated with insults.

Similarly, an image can be described as a frequency distribution of *visual words*, independent of their spatial position in the image plane. While the notion of a word in natural languages is clear, visual words are more difficult to describe. Typically, local image features extracted at specific regions of interest are used to represent visual words. By vector quantization of these features a discrete vocabulary is created. Local features from novel images are assigned to the closest word in the vocabulary and by counting the number of local features per vocabulary word a BoVW vector is extracted per image. In [18] the authors give an extensive overview of the involved steps.

Feature representation. Similar to words being local features of a text document, local image patches are considered local features of an image. Different approaches for sampling these features have been presented in literature. The authors in [16] compared various affine region detectors and conclude that the Harris-Affine and Maximally Stable Extremal Regions (MSER) detectors performed well under different conditions. Other approaches avoid region of interest detection and simply sample local image features at dense grid points. This is mainly due to the fact that low textured image regions will be ignored by any detector. However, as shown in [22], the absence of texture must sometimes be considered as highly discriminative. A comparison of feature sampling strategies for BoVW vectors has shown that when using enough samples, dense random sampling exceeds the performance of interest point operators [17].

Feature descriptors are used to represent the local neighborhood of pixels surrounding a sampling point. Histogram of gradient based descriptors have been widely adopted in the field of BoVW models. The most popular descriptor is the Scale Invariant Feature Transform (SIFT, [14]) which aggregates 8 gradient orientations at each of 4×4 patches surrounding the sampling point to a $4*4*8 = 128$ dimensional feature vector. A comparison SIFT with other feature descriptors presented in [15] showed that SIFT-like descriptors tend to outperform the others. While SIFT was initially devised for intensity images the authors in [24] report that SIFT extracted on each channel of a color image (i.e. resulting in a 384 dimensional feature vector) improves image classification results.

Vocabulary generation. Local feature extraction over a large corpus of training images results in potentially billions of features with sometimes only minor variations. In order to obtain a discretized vocabulary that provides some invariance to small changes within the appearance of objects and to reduce the computational complexity, the number of descriptors is reduced by vector quantization approaches. Most BoVW implementations use k-means to cluster the descriptors of a training image set into k vocabulary words (e.g. [22, 6, 13]). Other approaches that have been successfully applied use Gaussian Mixtures [20].

BoVW vector generation. Once generated, the derived cluster centers are used to describe all images in the same way: By assigning all features descriptors of each image to the most similar vocabulary vector, a histogram of visual word vector frequencies is generated per image. Usually this is achieved by performing a nearest neighbor search within the vocabulary. Approximate methods have been reported to improve retrieval time. The obtained frequency distri-

[2]Adapted from A. Mueller
`https://github.com/amueller/ml-berlin-tutorial`

bution is referred to as *Bag-of-Visual-Words* and represents the global image descriptor that can be used in subsequent machine learning steps – analogous to the aforementioned Bag-of-Words descriptor on text documents. In Figure 2 the individual steps of the respective BoVW extraction process are shown.

3. BOVW CLASSIFICATION

Based on a set of training images a model for a specific visual category can be trained using the aforementioned BoVW representation. We consider the task of image categorization a binary classification problem of separating positive from negative examples from each category.

Typically, the learning stage optimizes a weight vector that emphasizes different BoVW vector dimensions (i.e. visual words) depending on the classification task – very similar to learning the importance of individual words for a specific text document class. Very early models for BoVW-based image classification have used probabilistic models such as Naïve Bayes [6], Latent Dirichlet Allocation (LDA) [9] and probabilistic Latent Semantic Analysis (pLSA) [21] that have been later replaced by discriminative models such as AdaBoost [5] and Support Vector Machines (SVM) [23]. While SVMs have become the default choice in most BoVW-based image classification approaches an extensive comparison between different machine learning methods has not yet been performed. Here, we evaluate the performance of various models in terms of the obtained average precision scores (area under the precision-recall curve).

3.1 Naïve Bayes

Naïve Bayes classifiers have been successfully applied for a long time. Most of their popularity comes from the fact that classification is very fast and training requires a small amount of samples to estimate the model parameters (for a more detailed analysis of why Naïve Bayes works well, see [25]). Despite the simplified assumption of feature independence they have shown good performance in many real-world situations, first of all document classification and e-mail spam filtering.

Consequently, Naïve Bayes classifiers have been among the first to be used for BoVW classification. The main intuition behind this model is that each category has a specific distribution over the vocabulary vectors. As an example, a model that represents the *car* category may emphasize vocabulary words which represent the wheels or the car body while the model of the *person* category emphasize vocabulary words for head and torso. Given a collection of training examples, the classifier learns different distributions for different categories. The distribution of a category y is parametrized by the vector $\theta_y = (\theta_{y1}, \ldots, \theta_{yn})$ where n is the number of terms in the visual vocabulary and θ_{yi} is the probability $P(x_i \mid y)$ of term i appearing in a sample belonging to category y.

Using a smoothed maximum likelihood estimator, θ_y is optimized:

$$\hat{\theta}_{yi} = \frac{N_{yi} + \alpha}{N_y + \alpha n} \tag{1}$$

where $N_{yi} = \sum_{x \in T} x_i$ is the number of times the vocabulary term i appears in a sample of category y in the training set T, and $N_y = \sum_{i=1}^{|T|} N_{yi}$ is the total count of all vocabulary terms for category y.

The smoothing parameter α prevents zero probabilities that may occur due to vocabulary terms not present at all in any of the training examples.

In [6] a Naïve Bayes classifier is compared to a linear Support Vector Machine classifier and it is shown that the latter outperforms the former. Similar results have been reported in [12]. We nevertheless decided to keep Naïve Bayes in our comparison and use it as a baseline approach.

3.2 Logistic Regression

Logistic regression is used for binary classification problems, i.e. where the task is to assign a positive y_p or negative y_n label to a novel instance. The general assumption behind logistic regression is that the probability of a category label y_p being assigned to an image represented by its BoVW vector x can be written as a logistic sigmoid acting on a linear function of x so that:

$$p(y_p|x) = \sigma(w^T x) \tag{2}$$

with $p(y_n|x) = 1 - p(y_p|x)$. Here $\sigma(\cdot)$ is the logistic sigmoid function. The model parameters w are determined using a maximum likelihood estimator [3]. Logistic Regression is a very simple classifier and therefore often used as baseline classifier.

3.3 K Nearest Neighbors

K Nearest Neighbors classification is an example of instance-based learning: instead of attempting to construct an internal model it simply stores instances of the training data (i.e. the BoVW vectors of all training images). The idea behind nearest neighbor methods is to retrieve the k training images closest in distance to a new image and predict the label from these training examples based on computation of a simple majority vote. In other words, the category of an image is set to the category that has the most representatives among the k nearest training images. The distance metric used can be any metric measure, however, standard Euclidean distance is the most common choice. The optimal choice of the value k depends on the classification task and is typically optimized by grid search and cross validation.

In order to address computational problems for large training sets approximative methods have been proposed. Most of them are based on variations of binary search trees [2]. Here, we use a KD-tree data structure.

3.4 Random Forests

The Random-Forest algorithm aggregates decisions by weak classifiers, which in this case are full decision trees [4]. The algorithm learns a total of n randomized decision trees, each built from a sample drawn with replacement (i.e., a bootstrap sample) from the training set. Instead of learning these trees on the complete set of available features, however, a random subset of these features is selected. Among the features the algorithm iteratively selects the feature that best splits the training data into positive and negative samples

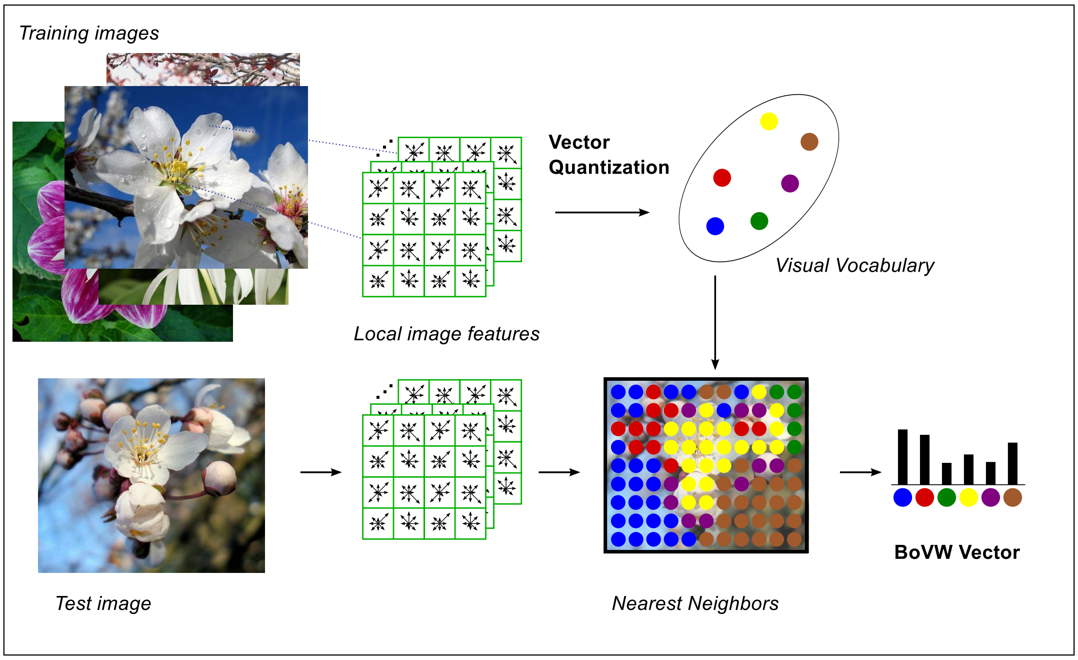


Figure 2: Steps of BoVW vector extraction with a simplified vocabulary of 6 terms.

(by minimizing the entropy within the training samples). This process is repeated until either each child node contains only examples of a single class (i.e. is pure) or all features have been considered. The number of decision trees n is usually optimized via grid search. Classification is performed by evaluating each tree separately. The prediction of a new sample is based on the majority vote over all trees.

3.5 AdaBoost

Similar to Random Forests, AdaBoost as presented in [10] is an ensemble learning method that aggregates a sequence of individual weak learners. Unlike Random Forests, AdaBoost uses a weighted sample to focus learning on the most difficult training examples. Additionally, instead of combining classifiers with equal vote (Random Forests use simple majority vote) AdaBoost uses a weighted vote.

Arbitrary classifiers can be used as weak classifiers which is one of the strength of the AdaBoost approach. However, a sequence of n decision trees with a limited size of depth d is commonly used. We use cross validation and grid-search to optimize both, the number of trees as well as their depth.

3.6 Support Vector Machines

As already mentioned, Support Vector Machines represent by far the most popular classifiers for BoVW (e.g. see [13, 26, 11]). In the presented binary case the decision function for a test sample x has the following form:

$$g(x) = \sum_i \alpha_i y_i K(x_i, x) - b \tag{3}$$

where $K(x_i, x)$ represents the Kernel function value for the training sample x_i and the test sample x, y_i being the class label of x_i ($+1$ or -1), α_i being the learned weight of the training sample x_i, and b being the learned bias parameter.

The choice of the kernel function $K(x_i, x)$ is crucial for good classification results. In the beginning of BoVW classification most authors restrained to linear Kernels:

$$K_{linear}(x, y) = x^T y \tag{4}$$

Later, more complex kernel functions have been used to model non-linear decision boundaries. Typically, these are variations of generalized forms of RBF kernels:

$$K_{d-RBF}(x, y) = exp(-\frac{1}{\gamma} d(x, y)) \tag{5}$$

where $d(x, y)$ can be chosen to be almost any distance function in the BoVW feature space. The standard Gaussian RBF kernel employs the squared euclidean distance:

$$d_{L_2}(x, y) = \|x - y\|_2^2 \tag{6}$$

Another distance that has been successfully used is the χ^2 distance that is reported to be better suited when comparing histogram structures like BoVW vectors:

$$d_{\chi^2}(x, y) = \sum_i \frac{(x_i - y_i)^2}{|x_i| + |y_i|} \tag{7}$$

The authors in [11] evaluate several factors that impact BoVW image classification using SVMs and compare several kernel functions including linear, Histogram Intersection, Gaussian RBF, Laplacian RBF, sub-linear RBF, and χ^2 RBF. On the PASCAL-2005 data set, the best mean equal error rates occurred for the latter three of the six kernels. The authors subsequently recommend the χ^2 RBF and Laplacian RBF kernels.

The kernel parameter γ (see eq. 5) is usually optimized by grid-search and cross validation. However, Zhang et al. [26] have shown, that in case of the χ^2 RBF kernel function setting this value to the mean value of the χ^2 distances between all training images gives comparable results and reduces the computational effort.

In this paper we present classification results for linear SVM as well as Gaussian RBF- and χ^2-kernel based SVMs.

4. EMPIRICAL EVALUATION

In our experiments we have computed BoVW models for the 101 classes of the Caltech-101 benchmark dataset [8]. We extract SIFT features at equidistantly sampled regions (every 6 pixels) on each channel of an image in RGB color space[3]. By concatenating these features we obtain a 384-dimensional feature vector at each grid point. These features are used to compute the visual vocabulary by running a k-means clustering with $k = 100$ on a random subset of 800.000 RGB-SIFT features taken from the training images set. Finally, BoVW histograms are computed by assigning each of the extracted RGB-SIFT feature of an image to its most similar vocabulary word using an approximate nearest neighbor classifier. BoVW histograms are further L_1 normalized in order to account for varying images sizes.

It should be stated that a vocabulary size of $k = 100$ is most likely not optimal. In [6] the impact of the vocabulary size on the overall classification performance is discussed. The authors state that larger vocabulary sizes perform better, within the tested range of 100-2500. However, for the sake of computational efficiency, we limit the vocabulary size to $k = 100$. Since evaluation of different classifiers is based on identical setups, this does not prevent from comparing relative accuracy scores. However, it should be stated that absolute classifier accuracy will probably increase with increasing vocabulary sizes.

4.1 Evaluation Dataset

The Caltech-101 dataset [8] was generated by using Google Image Search to collect images for the 101 categories and performing a manual post filtering to get rid of irrelevant images. An additional background clutter category with arbitrary images not falling into any of the categories was added (The keyword *things* was used to obtain random images, a total of 467 images were collected). The number of images per category vary largely – from 31 (*inline skate*) to 800 (*airplanes*). The authors denote, that some preprocessing has been performed: Categories with a predominant vertical structure were rotated to an arbitrary angle. Categories where two mirror image views were present, were manually flipped, so all instances are facing the same direction. Finally, all images were scaled to 300 pixels width.

[3]We use the OpenCV 2.4.3 SIFT descriptor implementation: `http://opencv.org/`

Table 1: Experimental results of different classifiers obtained on BoVW features extracted from the Caltech-101 dataset. Reported score is mean Average Precision over all categories. Additionally, hyperparameters optimized via cross validation are reported.

Classifier	Hyperparameters	mAP
Naïve Bayes	α (smoothing parameter)	0,480
k nearest neighbors	k (no. of nearest neighbors)	0,524
Logistic Regression	C (regularization)	0,548
linear SVM	C (regularization)	0,554
RBF kernel SVM	C (regularization), γ (kernel coefficient)	0,593
Random Forest	n (no. of decision trees)	0,612
AdaBoost	n (no. of decision trees), d (depth of each decision tree)	0,632
χ^2-kernel SVM	C (regularization)[5]	0,674

4.2 Experimental Setup

Each category model was trained under identical conditions. We first have split the set of images of any category (including the background class) into 50% training and 50% testing data. Subsequently, we have trained models for each category using the machine learning approaches presented in Section 3. Each model was trained in a binary setting taking the training images of the respective class as positive and the training images from the background class as negative examples. Hyperparameters for each model were optimized in a 3-fold nested cross validation (if applicable). We have used implementations for the various algorithms as provided by the scikit-learn[4] machine learning library [19]. Finally, all models were tested on the aforementioned testing data. Results as well as the particular parameters that were optimized are reported in Table 1.

We compute the Average Precision (AP) for all categories based on the aforementioned evaluation set using the respective models that have been trained with the hyperparameters that showed best results during cross validation. Finally, we averaged the AP scores of a classifier over all categories to obtain the mean Average Precision (mAP) score that is reported in Table 1. The mAP score is used as a single number to evaluate the overall performance of a single classifier and compare different classifiers.

4.3 Discussion

The mAP scores reported in Table 1 indicate a superior performance for χ^2-kernel SVMs. These findings are in line with the results reported by the authors of [11] who recommend χ^2-kernel SVMs for use with BoVW-based models. Likewise, the comparatively poor performance of the Naïve Bayes classifier follows prior experimental results. Therefore, Naïve Bayes is recommended to be used for obtaining baseline results only or whenever strong requirements for retrieval time need to be met, e.g. for very large datasets.

[4]scikit-learn: `http://scikit-learn.org`

The performance of the k nearest neighbor classifier performs only slightly better than the Naïve Bayes model. We assume this is mainly due to the fact of KNN being a low bias/high variance approach, which easily overfits on most of the categories due to the small number of training examples. While both models do not achieve competitive performance, their strong advantage is the relatively low training effort required. Linear SVM and Logistic regression show similar performance which can be attributed to both computing a very similar linear model. The advantage of a Logistic regression model over Support Vector machines is that the former provides an intuitive probabilistic interpretation. Moreover, extensions have been presented that make it easy to iteratively update a Logistic Regression model by adding more training images (using online gradient descent methods).

Surprisingly, both ensemble methods (Random Forests as well as AdaBoost) outperform the standard Gaussian RBF by $2-3\%$ which again performs only slightly better (app. 4%) than the linear SVM model and significantly worse (8%) than the χ^2-based counter part. These findings emphasize the fact that the decision for the right kernel is crucial to good classification results. Kernel-based SVMs on the other hand come with a couple of disadvantages most of all an increased evaluation time during classification due to the fact that an possibly complex kernel function needs to be computed between each support vector and a given testing example. In these cases, the use of either ensemble method will reduce classification time with only minor loss in accuracy. Finally, the mAP scores between the worst (Naïve Bayes) and the best (χ^2-kernel SVM) differ only by 19% which should be attributed to the fact that the Caltech-101 dataset is a comparatively easy dataset. The covered categories all represent objects (rather than complex scenes) and most images depict the respective object centered and at a similar scale. More testing with other, more difficult datasets is required here.

Figure 3 presents the mean average precision obtained by the best and the worst performing model computed over different training set sizes as they occur for the various categories in the Caltech-101 dataset. The scores indicate a correlation between training set size and the obtained classification accuracy with more training data resulting in higher performance. This correlation has been asserted in previous work (e.g. see [1]) and is especially true for high variance data such as BoVW models. While in general the classification performance based on comparatively few training data points varies strongly a few outliers featuring considerably high mAP scores for both classifiers are visible (categories: *minaret*, *car_side* and *leopards*). A closer look into these categories reveals that all training images taken from the *minaret* category have been rotated by an arbitrary angle (cf. Sec. 4.1), which presumably imposes a strong bias on both models. A very similar observation can be made for the category *leopards*: most images are surrounded by a more or less prominent black border.

4.4 Model Visualization

By visualizing the learned influence of individual vocabulary terms similar to the visualization of the most and least important words of the Bag-of-Words model presented in Fig.

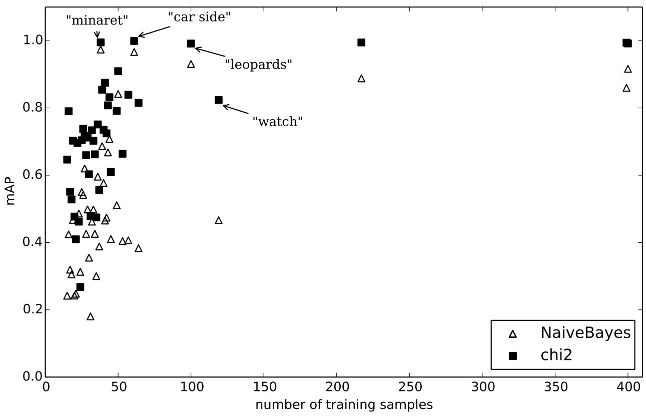
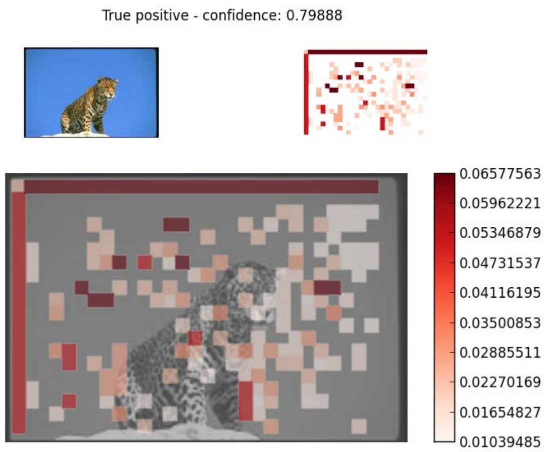


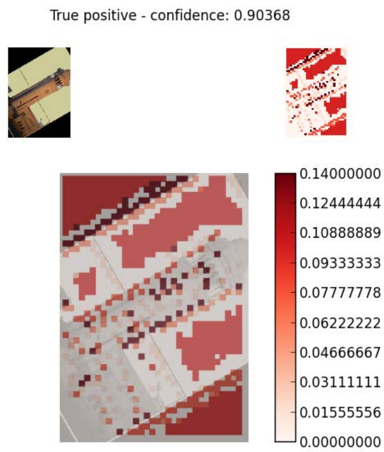
Figure 3: MAP scores of Naïve Bayes and χ^2-kernel SVM classifiers computed over different training data sizes.

1 we were able to validate our assumption of dataset artifacts (black border and rotation) having a strong impact on the overall classification outcome. Since each feature of a BoVW-vector corresponds to a visual word in the vocabulary and the value of each feature is generated by binning local SIFT descriptors to the most similar visual word we can extend the learned importance scores (i.e. BoVW feature weights) of a model to the respective SIFT descriptors. By highlighting the support regions of SIFT descriptors assigned to important visual words using a heat map like representation we are able to visualize the influence each individual pixel has on the overall classification result. Kernel-based SVMs, however, such as the best-performing χ^2-based solution prevent deducing individual feature weights due to the implicit mapping into higher dimensional kernel spaces. AdaBoost on the other hand allows for immediate extraction of features weights as it selects features based on their capability of solving the classification problem by computing the decrease in entropy of the obtained class separation. We use this mean decrease in impurity over all decision trees in an ensemble as direct indicator for feature importance.

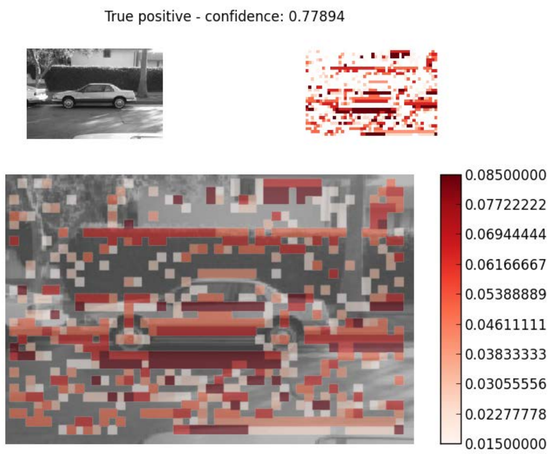
Figure 4 shows examples of heat maps generated for correctly classified test samples of the categories *minaret* and *leopards*. For reasons of clarity we limit the visualized pixel contributions to the most important visual words, i.e. only the upper quartile of the importance scores obtained per visual word are shown. Darker areas mark more important regions and white pixels have least impact on the classification result. Considering Fig. 4b the model has picked up the textureless black background induced by the rotation of the original picture as highly relevant (hence, the original intention of the dataset authors to reduce the impact of dominant vertical structures by rotation caused new artifacts and dominant edges). Similarly, in Fig. 4a the upper end leftermost black border surrounding the picture of the *leopards* category has been learned as important characteristic. Since negative training images taken from the background class possess neither black borders nor rotation artifacts, these properties are represented by a very specific distribution over the vocabulary vectors and therefore easily learned even by comparatively simple models such as Naïve Bayes (χ^2-kernel SVM performs only slighty better than Naïve Bayes, see Fig. 3). The essential properties of



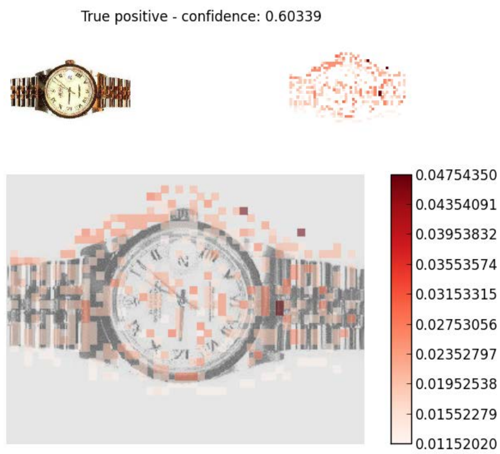
(a) Category: *leopards*



(b) Category: *minaret*



(c) Category: *car_side*



(d) Category: *watch*

Figure 4: Visualizations of feature importances of the AdaBoost classifier. Top left: original image. Top right: heat map of the upper quartile of the learned feature importances. Bottom: Desaturated original image with the superposed heat map (best viewed in color and magnification).

the objects behind each category, however, have not been learned.

In Fig. 4c and 4d exemplary visualizations of the AdaBoost models for *car_side* and *watch* are shown. While the model for the *car* category shows many dominant features (e.g. prominent horizontal lines), features of the category *watch* are much less evident as hardly any visual word has been assigned a high importance score. Consequently, the category is much more difficult to be captured (which may explain the poor performance of Naïve Bayes when compared to χ^2-kernel SVM, see Fig. 3) and requires more sophisticated approaches to be correctly modeled.

5. CONCLUSION AND FUTURE WORK

In this paper we have evaluated different classification approaches for BoVW based image classification. Our tests have shown that Support Vector Machines using χ^2-distance metric perform best on the Caltech-101 dataset. Moreover, our results indicate that ensemble methods such as AdaBoost provide a reasonable alternative whenever a kernel-based approach is not practicable, e.g. due to high demands on computation time. In addition, we have presented an approach for intuitive verification of a classification model using a heat-map like representation. Based on this visualization, a closely coupled human and machine analysis enables visual analytics to reveal deficiencies in the trained models.

Future work will focus on extending our tests to more diverse datasets. As discussed, the Caltech-101 dataset is very object centric and comparatively easy to learn. We intend to evaluate the presented classifiers on larger and more complex datasets such as ImageNet [7]. Moreover, we plan to conduct tests with varying vocabulary sizes as we assume that the increased sparsity in the BoVW vectors may favor simpler models such as linear SVMs.

6. REFERENCES

[1] M. Banko and E. Brill. Scaling to very very large corpora for natural language disambiguation. In *Proceedings of the 39th Annual Meeting on Association for Computational Linguistics - ACL '01*, pages 26–33, Morristown, NJ, USA, 2001. Association for Computational Linguistics.

[2] J. L. Bentley. Multidimensional binary search trees used for associative searching, 1975.

[3] C. M. Bishop. *Pattern recognition and machine learning*. Springer New York:, 2006.

[4] L. Breiman. Random Forests. *Machine Learning*, 45:5–32, 2001.

[5] S. Chen, J. Wang, Y. Liu, C. Xu, and H. Lu. Fast feature selection and training for AdaBoost-based concept detection with large scale datasets. In *Proceedings of the international conference on Multimedia - MM '10*, page 1179, New York, New York, USA, 2010. ACM Press.

[6] G. Csurka, C. R. Dance, L. Fan, J. Willamowski, C. Bray, and D. Maupertuis. Visual Categorization with Bags of Keypoints. In *Workshop on Statistical Learning in Computer Vision, ECCV*, pages 1–22, 2004.

[7] J. Deng, W. Dong, R. Socher, L.-j. Li, K. Li, and L. Fei-Fei. ImageNet: A large-scale hierarchical image database. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 248–255. IEEE, June 2009.

[8] L. Fei-Fei, R. Fergus, and P. Perona. Learning generative visual models from few training examples: An incremental Bayesian approach tested on 101 object categories. *Computer Vision and Image Understanding*, 106(1):59–70, Apr. 2007.

[9] L. Fei-Fei and P. Perona. A Bayesian hierarchical model for learning natural scene categories. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 2, pages 524—-531 vol. 2, 2005.

[10] Y. Freund and R. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. In *Computational Learning Theory*, volume 904, pages 23–37. 1995.

[11] Y.-G. Jiang, C.-W. Ngo, and J. Yang. Towards optimal bag-of-features for object categorization and semantic video retrieval. *Proceedings of the 6th ACM international conference on Image and video retrieval - CIVR '07*, pages 494–501, 2007.

[12] F. Jurie and B. Triggs. Creating efficient codebooks for visual recognition. *Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1*, pages 604–610 Vol. 1, 2005.

[13] S. Lazebnik, C. Schmid, and J. Ponce. Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories. In *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Volume 2 (CVPR'06)*, pages 2169–2178. IEEE, 2006.

[14] D. G. Lowe. Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*, 60(2):91–110, Nov. 2004.

[15] K. Mikolajczyk and C. Schmid. Performance evaluation of local descriptors. *IEEE transactions on pattern analysis and machine intelligence*, 27(10):1615–30, Oct. 2005.

[16] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. V. Gool. A Comparison of Affine Region Detectors. *International Journal of Computer Vision*, 65(1-2):43–72, 2005.

[17] E. Nowak, F. Jurie, and B. Triggs. Sampling strategies for bag-of-features image classification. *Computer VisionâĂŞECCV 2006*, pages 490–503, 2006.

[18] S. O'Hara and B. Draper. Introduction to the bag of features paradigm for image classification and retrieval. *arXiv preprint arXiv:1101.3354*, (July):1–25, 2011.

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2012.

[20] F. Perronnin and C. Dance. Fisher Kernels on Visual Vocabularies for Image Categorization. *2007 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8, June 2007.

[21] J. Sivic, B. C. Russell, A. A. Efros, A. Zisserman, and W. T. Freeman. Discovering objects and their location in images. In *Proceedings of the IEEE International Conference on Computer Vision*, volume I, pages 370–377, 2005.

[22] J. Sivic and A. Zisserman. Video Google: a text retrieval approach to object matching in videos. In *Proceedings Ninth IEEE International Conference on Computer Vision*, number Iccv, pages 1470–1477. IEEE, 2003.

[23] C. G. M. Snoek and M. Worring. Concept-Based Video Retrieval. *Foundations and TrendsÂő in Information Retrieval*, 2(4):215–322, 2009.

[24] K. E. A. van de Sande, T. Gevers, and C. G. M. Snoek. Evaluating color descriptors for object and scene recognition. *IEEE transactions on pattern analysis and machine intelligence*, 32(9):1582–96, Sept. 2010.

[25] H. Zhang. The Optimality of Naive Bayes. *Machine Learning*, 1:3, 2004.

[26] J. Zhang, M. Marszałek, S. Lazebnik, and C. Schmid. Local Features and Kernels for Classification of Texture and Object Categories: A Comprehensive Study. *International Journal of Computer Vision*, 73(2):213–238, Sept. 2006.