Learning Semantic Attributes via a Common Latent Space

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Abstract: Semantic attributes represent an adequate knowledge that can be easily transferred to other domains where lack of information and training samples exist. However, in the classical object recognition case, where training data is abundant, attribute-based recognition usually results in poor performance compared to methods that used image features directly. We introduce a generic framework that boosts the performance of semantic attributes considerably in traditional classification and knowledge transfer tasks, such as zero-shot learning. It incorporates the discriminative power of the visual features and the semantic meaning of the attributes by learning a common latent space that joins both spaces. We also specifically account for the presence of attribute correlations in the source dataset to generalize more efficiently across domains. Our evaluation of the proposed approach on standard public datasets shows that it is not only simple and computationally efficient but also performs remarkably better than the common direct attribute model.

1 INTRODUCTION

Visual recognition via attribute-based models has proven to be quite effective and robust especially in cases where training samples are scarce or even not available. Because they are defined by human language, semantic attributes shifted the focus of visual recognition from object naming to description, and provided a plausible way to efficiently apply the acquired knowledge from one domain to another to recognise previously unseen categories for example.

Since their introduction (Ferrari and Zisserman, 2008), semantic attributes were successfully applied in many disciplines of computer vision. They enabled new tasks in the object recognition field like unusual/missing attribute detection (Farhadi et al., 2009), detection of novel classes (Farhadi et al., 2009; Farhadi et al., 2010; Lampert et al., 2009), aiding object naming and localization (Wang and Forsyth, 2009; Wang and Mori, 2010), relative comparison of objects (Parikh and Grauman, 2011) and face verification (Kumar et al., 2011) to name a few. Recently, they were employed in action recognition showing remarkable performance both in video-based (Liu et al., 2011; Fu et al., 2012) and image-based (Yao et al., 2011) action classification.

The unique property of semantic attributes is of being both machine detectable and human understandable in comparison to raw image features. This enables them to be adequate pieces of knowledge that can be easily transferred across categories to closely related classes that can be described using the same vocabulary. Nevertheless, attribute-based models by themselves could not compete with the typical object classifiers that are built via supervised learning on image features, and they are rather used along with other models to aid the recognition performance. For example, (Farhadi et al., 2009) used both semantic and discriminative attributes for multi-class classification, where the discriminative attributes are based on random binary comparisons between sub-groups of the classes. They use random splits between groups of one to five classes and train a linear SVM classifier for each split. In their experiments, 1000 discriminative attributes are used to boost the attribute-based object recognition. (Wang and Mori, 2010), on the other hand, use a rather more sophisticated method. They jointly model object classes, global attributes, attributes-attributes interaction and attributes-object interaction. Additionally, they use a latent SVM formulation and introduce a loss function that is sensitive to the mean per class accuracy, hence, it can handle datasets with unbalanced training samples per class. They show that their discriminative latent model results in a significant improvement over state of the art in multi-class classification. In (Liu et al., 2011), the authors used data-driven attributes learned directly from image features by clustering them based on the

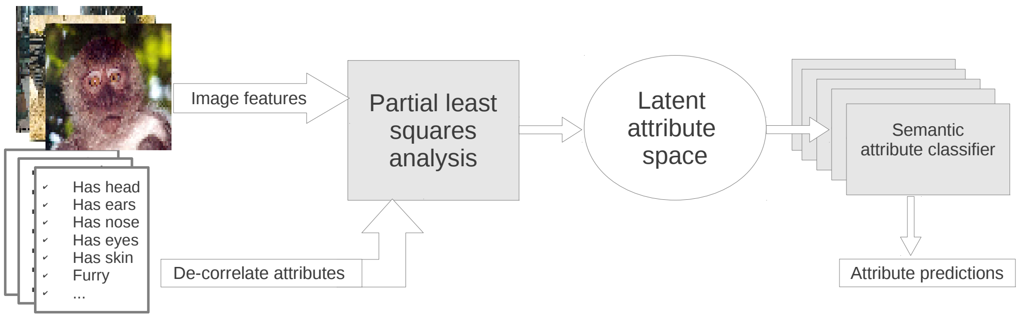


Figure 1: Summary of our approach. First, a common latent space between image features and attributes is discovered, then the semantic attribute classifiers are trained on this intermediate space to predict attributes.

mutual information loss. Then, they incorporate both attributes (semantic and data-driven) in a joint model similar in spirit to (Wang and Mori, 2010) to classify actions.

All the mentioned methods tried to boost the poor performance of the semantic attribute classifiers by adding additional models like data-driven attributes, object model or/and attribute interaction model. However, these additional models, although helped in the typical multi-class classification task, they increased the complexity and computational cost of the model and they are, on the other hand, not beneficial in cases of zero- or n-shot learning, since this type of knowledge does not hold a direct semantic meaning and can not be transferred to another domain in a similar easy fashion as semantic attributes.

In (Duan et al., 2012), an iterative system is proposed to discover both discriminatively powerful and semantically meaningful attributes. In each iteration, the system finds the most confused categories based on the attributes discovered before and select a set of local candidate attributes that can best discriminate the confused categories. Then, based on a recommendation system, the model chooses the attributes that most likely have a semantic meaning to present for a human operator to name the attribute. While this system models the semantic and data-driven attributes jointly, it requires human intervention, and is intended to mine good attributes for classification and does not deal with the case of already labeled data. (Fu et al., 2012) suggested to learn a semi-latent attribute space to classify complex social activities. The latent space incorporates user defined attributes, class-conditional attributes and non-discriminative background attributes that are learned jointly from the data using an LDA framework. They leverage the use of latent attributes in zero-shot learning by using the k most confident results returned using the semantic attributes to learn a new prototype of the novel class in the full latent space, in other words an attribute-based zero-shot learning followed by a latent-attribute-based k-shot learning. Our work differs from theirs in the sense that we do not extend the attribute space to include other complementary types of attributes, rather we focus on learning a latent space that enhances the predictive power of the semantic attributes. Hence, in contrast to the previous work, we do not require additional annotations, like class labels, and the latent space is learned from the features and the defined attributes only.

We introduce a novel model to learn the semantic attributes that results in a substantially better performance in both the traditional recognition settings, like multi-class classification, and knowledge transfer-based tasks, like zero-shot learning. The model employs a multi-layer approach where a suitable latent attribute space, that combines both the semantic attribute and visual feature spaces, is first discovered and then the attribute classifiers are learned accordingly. The model is simple and robust against attribute correlations and has a low computational cost while achieving high performance. It can be easily integrated in more complex systems that make use of semantic attributes to improve the performance even further when needed.

2 APPROACH

Using separate models of data-driven and semantic attributes increases the complexity of the system and reduces its ability to generalise well across data sets. Data-driven attributes, although discriminatively powerful, are semantically meaningless, hence it's difficult to use them for across data set recognition or zero-shot learning.

In our approach, we implicitly combine both types of attributes in one model, where the data-driven attributes are extracted in a way to aid the recognition of semantic attributes. We assume that there is a common space that bridges the gap between the image features and attribute spaces and contains the best predictive "latent" attributes to estimate the semantic attributes. In other words, we introduce an intermediate layer between image features and semantic attributes (Figure 1), the latent attribute space, that improves the performance of the semantic attribute classifiers substantially over the common direct approach while at the same time reduces the computational complexity of attribute-based recognition. We also enhance the generalisability of the latent space for across-category prediction and zero-shot learning by proposing an intermediate step to decorrelate the semantic attributes in the source domain.

2.1 Latent Attribute Space

In order to enhance the generalizability of the attributes model, we suggest to learn a common latent space that learns the fundamental relations between two spaces, the visual features and the semantic attributes. In other words, a space that extracts a set of latent variables from the feature space which have the best predictive power to distinguish semantic attributes. To derive this common space we use *partial least squares analysis* (PLS).

Originally proposed for the field of econometrics and widely used in the field of chemistry, PLS was applied successfully in the recent years also for computer vision problems. There, it was used to estimate a common compact intermediate space for multiple modalities, e.g in face recognition and head pose estimation (Sharma and Jacobs, 2011; Haj et al., 2012; Schwartz et al., 2010), simultaneous age, gender, and ethnicity estimation (Guo and Mu, 2011), or facial expression analysis (Gehrig and Ekenel, 2011).

In this work, we use PLS to estimate a common compact space of latent attributes which relates the visual features and the attributes. This is achieved by maximizing the covariance between the projections of features and attribute descriptions in the latent space. A PLS model will try to find the multidimensional direction in the feature space that explains the maximum multidimensional variance direction in the attribute space (Figure 2). Hence, it derives a compact representation of a dataset, that takes not only the image features into account but also the corresponding attributes and tries to find the most representative components explaining the variance of the given dataset. This allows for a very general lower dimensional space, where the information of interest, in our case the presence of specific semantic attributes, is usually present in the first few latent variables.

Other methods e.g. the principal component analysis, unlike PLS, just consider the input space to explain the variance of the data. That probably leads to the case where the first few principal components are not the most suitable candidates to discriminate the output space.

Learning a common space via PLS: Assuming that we have n samples in our training set, linear PLS models the relationship between the $n \times N$-dimensional centered image features $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_n]^T$ and the corresponding $n \times p$-dimensional latent variables $\mathbf{T} = [\mathbf{t}_1, \ldots, \mathbf{t}_p]$, respectively the $n \times M$-dimensional centered semantic attributes $\mathbf{Y} = [\mathbf{y}_1, \ldots, \mathbf{y}_n]^T$ and their latent representations $\mathbf{U} = [\mathbf{u}_1, \ldots, \mathbf{u}_p]$ as follows (Rosipal and Krämer, 2006):

$$\mathbf{X} = \mathbf{T}\mathbf{P}^T + \mathbf{E} \tag{1}$$

$$\mathbf{Y} = \mathbf{U}\mathbf{Q}^T + \mathbf{F} \tag{2}$$

where $\mathbf{P}$ and $\mathbf{Q}$ are the $N \times p$ and $M \times p$ loading matrices, respectively. $\mathbf{E}$ and $\mathbf{F}$ are the residual matrices modelling the projection error.

The relationship between the latent projections of the image features and the semantic attributes is then modelled by the inner relation:

$$\mathbf{U} = \mathbf{T}\mathbf{D} + \mathbf{H} \tag{3}$$

where $\mathbf{D}$ is a $p \times p$ diagonal matrix and $\mathbf{H}$ is again a residual matrix.

To estimate the appropriate matrices, PLS uses the following optimization criterion:

$$\begin{aligned}[cov(\mathbf{t}, \mathbf{u})]^2 &= [cov(\mathbf{X}\mathbf{w}, \mathbf{Y}\mathbf{c})]^2 \\ &= \max_{|\mathbf{r}|=|\mathbf{s}|=1} [cov(\mathbf{X}\mathbf{r}, \mathbf{Y}\mathbf{s})]^2\end{aligned} \tag{4}$$

where $cov(\mathbf{t}, \mathbf{u}) \propto \mathbf{t}^T\mathbf{u}$ represents the sample covariance between the score vectors $\mathbf{t}$ and $\mathbf{u}$. The latter are column vectors of $\mathbf{T}$ and $\mathbf{U}$, and they are the projections of $\mathbf{X}$ and $\mathbf{Y}$ using the column vectors $\mathbf{w}$ and $\mathbf{c}$ of the projection matrices $\mathbf{W}$ and $\mathbf{C}$, respectively. $\mathbf{r}$ and $\mathbf{s}$ are the candidates for $\mathbf{w}$ and $\mathbf{c}$ over which we seek to maximize the covariance, finally resulting in the best candidates $\mathbf{w}$ and $\mathbf{c}$.

In our experiment, we adopt the SIMPLS algorithm for partial square analysis (de Jong, 1993). This also restricts the score vectors $\mathbf{t}$ to be orthogonal, i.e. $\mathbf{t}_j^T\mathbf{t}_i = 0$ for $i > j$. Thus, the resulting score matrix $\mathbf{T}$ is orthonormal and will be in the further process used as the latent attributes representation.

To project image features into this latent attribute space, SIMPLS estimates the projection or weighting matrix $\mathbf{W}$, so that:

$$\mathbf{T} = \mathbf{X}\mathbf{W} \tag{5}$$

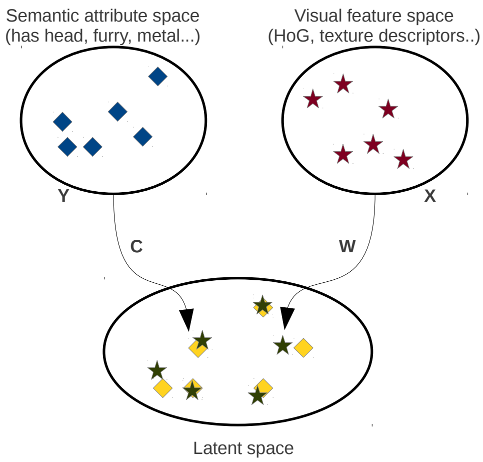


Figure 2: A latent space between image features and attributes is learned by maximizing the covariance between the projections of features and attributes into the latent space using partial least squares analysis.

2.2 Correlated Attributes

In general, the attribute description will have some correlation, which might be either due to the composition of the database or a general correlation between these attributes. To make the classifier generalize better to unknown data, e.g. other categories or in the case of zero-shot learning, and improve convergence, we want to remove that correlation. Additionally, we want to give each decorrelated attribute equal importance by normalizing it to have unit variance. To achieve this, we propose to whiten the semantic attributes description matrix $\mathbf{Y}$.

Whitening is a linear transformation, which multiplies a whitening matrix Ψ to the attribute description matrix $\mathbf{Y}$ (Hyvärinen and Oja, 2000; Comon, 1994) resulting in the whitened semantic attributes description matrix:

$$\tilde{\mathbf{Y}} = \mathbf{Y}\Psi \tag{6}$$

such that the covariance matrix $cov(\mathbf{Y}) = E(\mathbf{y}\mathbf{y}^T)$ for the zero-mean normalized semantic attributes is transformed into the identity matrix:

$$cov(\tilde{\mathbf{Y}}) = E(\tilde{\mathbf{y}}\tilde{\mathbf{y}}^T) = \Psi^T E(\mathbf{y}\mathbf{y}^T)\Psi = \mathbf{I} \tag{7}$$

We can see from Eq. (7) that Ψ should be the inverse of the square root of $cov(\mathbf{Y})$. This problem can be solved by means of an eigen-value decomposition (EVD) or more numerically reliable using a singular value decomposition (SVD):

$$E(\mathbf{y}\mathbf{y}^T) = \mathbf{V}\Sigma\mathbf{V}^T \tag{8}$$

where $\mathbf{V}$ and Σ are the matrix of eigenvectors and eigenvalues, respectively. The whitening matrix thus is estimated by:

$$\Psi = \mathbf{V}\Sigma^{-\frac{1}{2}} \tag{9}$$

so that

$$\begin{aligned} cov(\tilde{\mathbf{Y}}) &= \Sigma^{-\frac{1}{2}T}\mathbf{V}^T E(\mathbf{y}\mathbf{y}^T)\mathbf{V}\Sigma^{-\frac{1}{2}} \\ &= \Sigma^{-\frac{1}{2}T}\mathbf{V}^T\mathbf{V}\Sigma\mathbf{V}^T\mathbf{V}\Sigma^{-\frac{1}{2}} \\ &= \mathbf{I} \end{aligned} \tag{10}$$

So if we apply whitening to the semantic attribute descriptions, Eq. (2) changes to:

$$\tilde{\mathbf{Y}} = \mathbf{U}\mathbf{Q}^T + \mathbf{F} \tag{11}$$

2.3 Semantic Attributes

Once the latent space is determined, the attribute classifiers can then be learned using linear support vector machines over the latent attributes (Figure 1) by minimizing the objective function:

$$\begin{aligned} &\frac{1}{2}\|w\prime\|^2 + C\sum_i \max(0, 1 - y_i.f(x_i)) \\ &where\ f(x_i) = w\prime\varphi(x_i) \\ &\qquad\qquad = w\prime(x_i^T\mathbf{W}) \end{aligned} \tag{12}$$

The dimensionality of the latent attribute space is usually much lower than the image feature space. This allows to train the numerous attribute classifiers very fast compared to direct approaches.

3 EVALUATION

We evaluate our approach on the common attribute-based recognition settings, namely the attribute prediction for within and across category, multi-class classification and zero-shot learning. We test on the a-Pascal / a-Yahoo datasets, introduced by (Farhadi et al., 2009).

The a-Pascal dataset is based on the Pascal VOC 2008 dataset (Everingham et al., 2008), it contains various types of object classes from three main categories (animals, vehicles, and artefacts). The dataset has 6340 training images and 6355 test images for 20 object classes. The a-Yahoo dataset has 2644 samples collected from Yahoo images for 12 object classes. The classes in a-Yahoo are selected to have some similarity with the categories in a-Pascal in order to evaluate the attributes generalization properties in across category recognition. The images in these two datasets are annotated with 64 semantic binary attributes. They describe the shape (2D boxy, round,

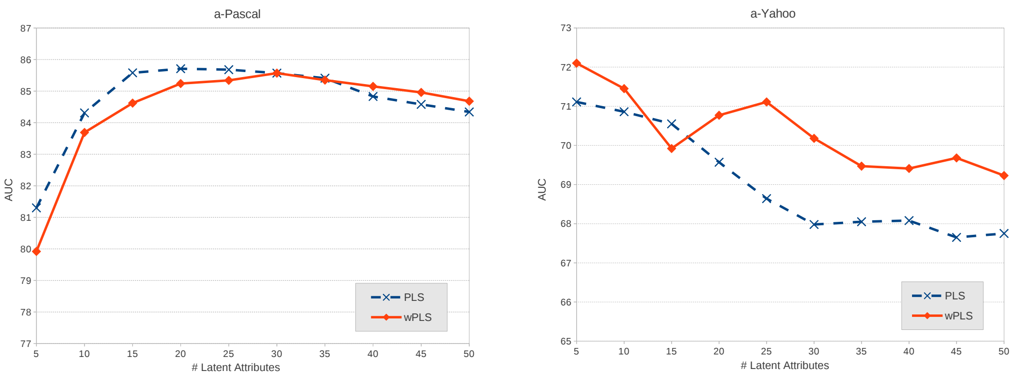


Figure 3: The performance of our model with and without the attribute *whitening* step in relation to the number of latent attributes (*w*PLS and PLS, respectively). The average AUC over all attribute classifiers is reported for within (left) and across (right) category prediction.

...), parts (tail, head, wheel, ...), and material (metal, plastic, ...) of the object.

In the following experiments, we follow the setup suggested by the authors for training and testing. We also use the image features (or base features) provided with the datasets to have a fair comparison with (Farhadi et al., 2009). The base features are made up of histograms of HOG, color, edge and local texture descriptors that are joined together in a 9751 dimensional feature vector.

3.1 Attributes Prediction

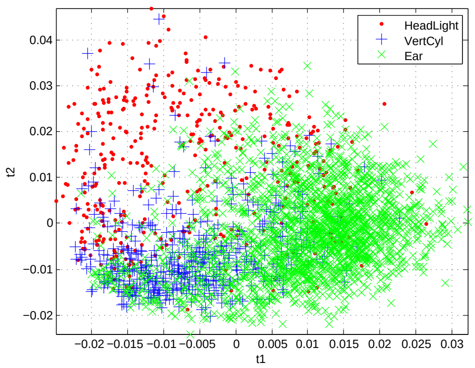
We check the effectiveness of our model in learning uncorrelated attributes in two protocols. The within category prediction, where attributes are learned and tested on the same dataset (a-Pascal[train], a-Pascal[test]) and the across category prediction, where attributes are learned and tested on two different datasets (a-Pascal[train], a-Yahoo), hence they have different correlation statistics. We report the average area under the receiver operating characteristic (ROC) curve of the binary attribute classifiers in relation to different number of latent attributes.

Attribute generalization: Figure 3 shows the performance of our model with and without the attribute decorrelation step explained in Section 2.2. When considering within category prediction, both models have similar performance with a slight edge to the model with the correlated attributes. This is due to the fact that both train and test datasets have similar correlation statistics, hence it's beneficial to incorporate this information in the latent space. However, the performance of the model deteriorates much more when moving to across category prediction compared to the one with the decorrelation components.

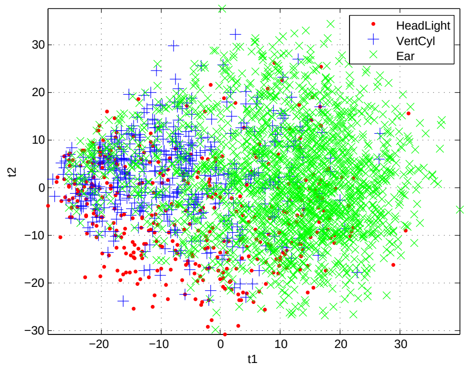
Figure 3 *right* presents the performance of the model on a-Yahoo, where using the *decorrelation* successfully improves performance up to 3% on average which gives the model a clear advantage over the basic one regarding generalization across datasets. We also observe that when the number of latent attributes increases, the performance of both methods have the tendency to decline for across category prediction with a clear advantage of the whitened over the correlated-attributes model. We speculate that this may be the result of unnecessary information from the source dataset (a-Pascal) being incorporated in the latent space, showing that the few first latent attributes represent the most appropriate knowledge to transfer across datasets.

Number of latent attributes: One of the main parameters of our approach is the dimensionality of the attribute latent space. The method for choosing the optimal number of latent attributes is depending on the targeted task of the system. For example, if the focus is on the performance for within category tasks, the number of attributes can be determined by simply doing n-fold cross validation on the training set, and if the across category performance is favoured, then a leave N class out technique would be more suitable to get the number of latent attributes. For our experiments, we choose the number of latent attributes by splitting the a-Pascal training set into a development and validation set (50/50) and picking the number of latent space dimensions that results in the best semantic attribute classifiers when tested on the validation set. The validation results in selecting 35 latent attributes which we use in the rest of our experiments and report the performance accordingly.

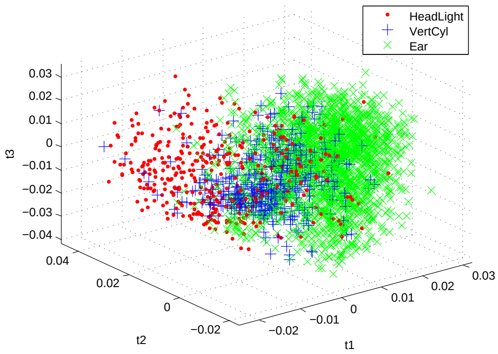
Attribute prediction vs. baseline: We compare the attribute prediction performance of our model



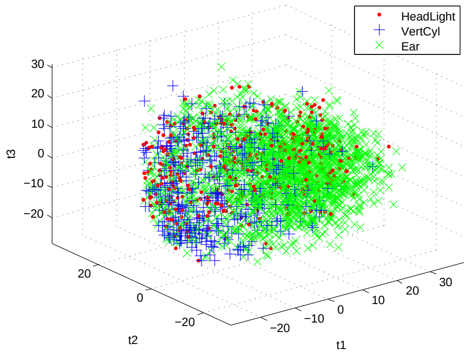
(a) First two dimensions for *w*PLS.



(b) First two dimensions for PCA.



(c) First three dimensions for *w*PLS.



(d) First three dimensions for PCA.

Figure 4: (a) and (b) visualize the first two, and (c) and (d) the first three learned dimensions in the latent space and PCA, respectively. The points are labelled according to three of the semantic attributes for a better view of the sample distributions after projection to the latent space. (Best viewed in color.)

against the baseline model (Farhadi et al., 2009). In the attribute-baseline model, the attribute classifiers are trained directly on the base features. We train both models on the a-Pascal training set and evaluate on the a-Pascal test set. In Figure 5 left, we see that most of the attribute classifiers (49 out of 64) benefit from our model with up to 6.6% increase in terms of area under curve of ROC. On average, our model achieves 85.35% area under the ROC curve compared to 83.54% of the baseline (our implementation of the baseline system is slightly better than the one reported in (Farhadi et al., 2009) with 83.4% average AUC). When testing using across category protocol (test on a-Yahoo which has 10 different classes). We can see in Figure 5 right, that our model has on average a better prediction performance than the baseline (58% of the classifiers have better performance with an increase up to 23% in terms of AUC compared to the baseline) although we have selected the number of latent attributes that favour within category prediction. Hence, our semantic attribute classifiers outperform the model that learns directly from image feature space in both within category and across category prediction.

To have a closer look at the learned latent space, we visualize the directions learned by the model. In Figure 4a and Figure 4c, the first two and three latent variables projected from the visual feature space are displayed. The projections are labelled with three semantic attributes (*Headlight*, *VerticalCylindrical* and *Ear*). The figure shows intuitively that the model learns meaningful discriminant directions in the latent space that bring distinct semantic attributes into compact clusters. In contrast, the unsupervised PCA learns a latent space that best explains the variance in the feature space which is usually not suitable enough to learn the semantic attributes as seen in Figure 4b and Figure 4d.

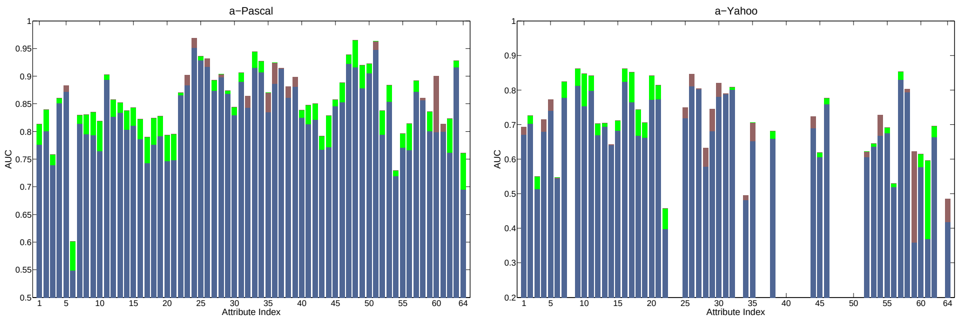


Figure 5: Comparison between the direct approach and ours for attribute classifiers prediction performance on the datasets a-Pascal(left) and a-Yahoo(right). The green bars indicate an improvement of our model over the baseline while the red bars indicate a reduction in performance (best viewed in color).

	Ours	Base features	Semantic attr.	Semantic + Discriminative attr.
# Dimensions	**64**	9751	64	1064
Mean overall accuracy	**59.6**	58.5	56.1	59.4
Mean per class accuracy	**40.9**	35.5	34.3	37.7

Table 1: The multi-class classification accuracies of our approach compared to the models proposed by (Farhadi et al., 2009) on the a-Pascal dataset.

3.2 Multi-Class Classification

Most of the systems that use attributes in multi-class classification use them as a sub-model of a more complicated system since using just the semantic attributes didn't result in comparable performance to the baseline-models that learn the classes directly from image features. We show here that our model outperforms both the baseline-model of objects and attributes. Using our approach presented in Section 2, we train the semantic attribute classifiers based on the latent attribute space using linear SVMs. We use the predicted semantic attributes afterwards to train a linear multi-class SVM (Chang and Lin, 2011). For all SVM classifiers, the parameters are selected using a 5-fold cross validation on the training data set of a-Pascal. We report the overall and the mean per class accuracies, because the dataset is heavily biased towards the "person" class (with 2500 out of 6340 train samples).

Table 1 shows the performance of our approach compared to (Farhadi et al., 2009). It outperforms the class-based (base features) and attribute-based (semantic attr.) models with up to 3.5% in terms of overall accuracy, 5.4% and 6.6% with regard to the per class accuracy. The best result reported in (Farhadi et al., 2009) uses, in addition to semantic attributes, 1000 discriminative attributes along with a feature selection method. Our method still performs better with a 3.2% absolute increase in per class accuracy.

Due to the high dimensionality reduction when learning semantic attributes via latent attribute space, our model is computationally very efficient. Using a computer with core i7 @ 3.20 GHz, we trained our model in 20.2 minutes, which includes the validation time to get the proper latent attributes number (15.8 min.), getting the latent attribute space and learning the semantic attributes with linear SVMs and 5-folds cross validation for parameter selection (4.4 min.). In comparison, the baseline model, that learns attributes directly from the raw features space, trained in 13.77 hours (826.65 min.). The computational efficiency, simplicity and the higher performance of our model make it a good candidate for large scale visual recognition.

3.3 Zero-Shot Learning

One of the important properties of the attribute-based recognition is the ability to generalize across domains. It enables zero-shot learning of novel categories based on the semantic description of the category. We test our approach on zero-shot learning by performing multi-class classification on a-Yahoo based on category-level attribute descriptions of the 10 classes in a-Yahoo and using attribute classifiers trained on a-Pascal.

In (Farhadi et al., 2009) category-level attributes are not provided, in order to test for zero-shot learning we get the attribute description for each of the classes in a-Yahoo by calculating the attribute-class frequency matrix over all classes in the dataset and thresholding using the average frequency.

For classification, we use the first nearest neighbour (1NN) classifier to find out the nearest class description to the predicted attributes. Table 2 shows that our model outperforms the baseline model, that uses the base feature space to learn the semantic attributes, with an absolute accuracy increase of 1.51% and 2.03% in overall and per class accuracy, respectively.

	Ours	Semantic attr. on base features (baseline)
Mean overall accuracy	**25.53**	24.02
Mean per class accuracy	**23.94**	21.91

Table 2: Results of zero-shot learning on the a-Yahoo dataset, comparing our approach to a baseline model that learns the semantic attributes directly from image features.

4 CONCLUSION

We have introduced a combined model of latent and semantic attributes. The layered approach uses partial least squares to find a suitable latent attribute space to learn the semantic attributes. The experiment results show that different tasks based on attribute recognition benefit clearly from our model. The model outperforms the direct approach model in within and across category attribute prediction, multi-class classification and zero-shot learning. In addition, our model is simple and computationally more efficient than methods that use the base feature space.

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