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# Project-II by Group Sydney

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Diego Antognini & Jason Racine

EPFL

diego.antognini@epfl.ch, jason.racine@epfl.ch

## Abstract

This report provides a summary of the project two of the PCML class.

## 1 Data Description

The train-data for binary classification consists of  $N = 6000$  images. As input we have 2 representations of the image : *the histogram of oriented gradients* (HOG)  $\mathbf{X}_{hog}$  and the *overFEAT ImageNet CNN features* (CNN)  $\mathbf{X}_{cnn}$ . Our input  $\mathbf{X}$  is the concatenation of  $\mathbf{X}_{hog}$  with  $\mathbf{X}_{cnn}$ .

Each input sample is a vector  $\mathbf{x}_n$  with dimension  $D = 42273$  (5408 for the HOG and 36865 for the CNN) and is the concatenation of  $\mathbf{x}_n^{hog}$  with  $\mathbf{x}_n^{cnn}$ . The output ( $\mathbf{y}$ ) represents the classification of the images. For the binary classification, the label 1 represents a car, a horse or a plane and the label 2 anything else. For the multi-class classification, the label 1 represents a car, 22 a horse, 3 a plane and 4 anything else.

We also have test-data of size  $N = XXX$  without their corresponding output. Our goal is to produce predictions for those data, as well as an approximation of the test-error using *Balanced Error Rate* (BER).

### 1.1 Histogram of Oriented Gradients

Histogram of oriented gradients is a feature used in computer vision in order to detect objects. To compute it, we first need to normalize the image, compute the gradients (of each pixel) for the different color channel and take those with the largest norm. Then we decompose the image in bins of size  $w \times h$ . For each of those bins, we compute an histogram of the orientation of the gradients using their angles and weighted by their magnitudes. The histogram has  $n$  bins from 0 to 180 degrees. We compute this histogram using 4 different normalizations.

In our case, the dimensions of this feature is  $13 \times 13 \times 32 = 5408$ , where the first 13 is the number of bins in the height, the second 13 the number of bins in the width. Finally 32 is  $4 \times 8$  where the 4 is the different normalizations for the histogram and 8 the number of bins (each bin has a size of 22.5).

### 1.2 OverFEAT ImageNet CNN features

Those features are extracted from a convolutional network-based image features extractor OverFeat. They were trained on the ImageNet dataset (tens of millions images). The size is the output of the fifth layer of the neural network which is  $1024 \times 6 \times 6 = 36864$ . In our features, we also have an extra dimension which can be ruled out.

## 2 Data visualization and analysis

We first have plot the labels distribution for the binary and multi-class cases. For the binary case, we have 60.3% for the label 1 and 39.8% for the second one. We have observed that there is a small

imbalance between the classes. For the multi-classes case, we obtain 16.07%, 19.37%, 24.87% and 39.70% for the labels 1, 2, 3 and 4. This time, the imbalance is more important, especially with the label 4 and we do have to take care about it during the training.

We also wanted to analyze the distribution of our features, and have observed that for the features HOG, each of them has a similar distribution as showed in Figure XXX. The values are essentially in the range  $[0, 0.2]$ . We are also interested about the correlation between the input and output variables. We have observed that the correlation is in the range  $[-0.24; 0.30]$ , and so can conclude that features seem not to have a direct correlation between them. However, a combination of features can have a high correlation with the output but we couldn't find such combination. Finally,  $\mathbf{X}_{hog}$  is rank-deficient with a rank of 3467 instead of 5408.

For the features CNN, first we can see that it is a sparse matrix and most of the values for each data is 0 (around 95.5%). This means that for each data, a small subset is able to describe the picture. Moreover, we can observe that we are faced to the problem of  $D > N$  and the solution we have adopted is PCA which will describe during the next sections. The values are in mainly in the range  $[0, 64.87]$ . We also wanted to see the correlation of those features with the output and have found that they are in the range  $[-0.24; 0.18]$ , which is similar to the HOG features. Finally,  $\mathbf{X}_{cnn}$  is rank-deficient with a rank of 5997 instead of 36865.

### 3 Techniques used

This section is a description of the technique we have used in the project. It describes mainly how it works, why we thought it could be useful in this project.

#### 3.1 Principal component analysis

As we have seen in the section "Data visualization and analysis", we are faced to the  $D > N$  problem mainly with the CNN features and also the HOG features depending on how we see the  $k$  for the  $k$ -fold cross validation. One way to solve this problem is to use PCA. Basically, PCA works as follow : we compute the mean and the covariance matrix  $S = \frac{1}{N} \sum_{n=1}^N (x_n - \bar{x})(x_n - \bar{x})^T$  of our data and then compute the  $M$  eigenvectors of  $S$  corresponding to the  $M$  largest eigenvalues.  $M$  is the number of features we have to take into account in order to minimize the reconstruction. Finally, the approximation of a data sample is  $\tilde{x}_n = \sum_{i=1}^M x_{ni} u_i$ . However, we couldn't compute PCA using this method, because computing the full eigenvector decomposition a matrix  $D \times D$  runs in  $O(D^3)$  and  $D$  is quite large. We have used an alternative proposed in [REF] which allows us to compute the same eigenvectors in  $O(N^3)$ , which is roughly at least 230 times faster. The trick is to express  $S = \frac{1}{N} X X^T$  and finally using  $\frac{1}{N} X X^T v_i = \lambda_i v_i$ , where  $v_i = X u_i$ , we obtain an eigenvector equation for the  $N \times N$  matrix  $S$ .

The last parameter to set, is the parameter  $M$  which defines the  $M$  largest eigenvectors to take into consideration for our feature selection. We introduce a distortion measure  $J = \frac{1}{N} \sum_{n=1}^N \|x_n - \tilde{x}_n\|^2$  which represents the mean squared distance between the original data sample and our approximation. Without going into the steps, the solution to the minimization of  $J$  is  $J = \sum_{i=M+1}^D \lambda_i$ .

The Figure XX shows the plot of  $J$  for the HOG features and the CNN features. For the CNN, we have tried several values for  $M$  and have conclude that  $M_{CNN} = 150$  was a good value allowing us to compute faster results without losing too much accuracy. The corresponding distortion might be very high compared to the HOG features, but the range of the values are not the same, CNN has values going larger than 0.2. We tried some bigger values but we didn't get major improvements in terms of error. For the HOG features, the distortion measure seems more nice, we did the same experiments and finally set  $M_{HOG} = 500$ .

#### 3.2 Neural Networks

This is the multi-layer perceptron (MLP) we have seen in class. The neural networks used in this project comes from the given DeepLearning matlab toolbox. It uses batch sizes in order to use less memory (take the first  $n$  data samples and works on them, then the next  $n$  etc). We have let the default parameter (100). The number of epochs is simply the number of time where all the training

data do a forward and a backward pass. We have put this value to 20, in order to have a little more accuracy without loosing a lot of time, it was a good compromise because larger epochs don't mean especially better accuracy. the number of input is  $M$  and output is either 2 or 4, depending of the type of classification (binary or multi-class). For the number of hidden layer, we have let 1 because we didn't see improvement by adding some more. However, the number of neurons in the hidden layer has been tested and have found 1000 for the binary classification and 700 for the multi-class case. We also have to set up the learning rate : the optimal value we have found is 3 for the binary case and 2 for the multi-class one. By default, the activation function used is the *tanh* one. We didn't see so much different using the *sigmoid*. Finally, the algorithm uses stochastic gradient descent using a momentum of 0.5, which might help to converge faster.

Neural networks are suitable for problems which might be difficult to describe in a mathematically manner and is robust to the noise, which is very useful in our case. However, we have to be careful with the weights initialization because neural networks are very sensitive to them, and especially with overfitting and computing the generalization error, this task is harder with neural networks.

### 3.3 Support Vector Machine

The normal support vector machine is a technique used for binary classification. The goal is to divide the space using an hyperplan in a way to maximize the margin, which represents the distance between closest members of the two classes. It is an interesting method because it has a regularization parameter which help to avoid overfitting. Another advantages is we can easily change the kernel function in order to try to find better boundaries. However, what is difficult is to find good parameters ( $C$ ,  $\gamma$ ).  $\gamma$  is the kernel scale parameter which is related to how the data are scattered. We might have many support vectors and overfit if we set the  $C$  too large and on the contrary if it is small, we might have not enough support vector and underfit. However, the best results we can obtain with support vector machine need to have a small imbalance between the positive and negative examples. As seen in the section "Data visualization and analysis", there classes are not very well balanced as much for the binary classification as the multi-class classification. We have use the same algorithm we have seen in the lab *SMO*.

We have used the method *fitcecoc* in matlab. We have used k-fold cross valiation to find  $C$  and  $\gamma$  and have set the margin  $C = 1$ , and  $\gamma = 1$ . Only the linear kernel function was available in this mode, and so, gaussian kernel might give better results.

To adapt support vector machine to a multi-class classifier, we have used *One Versus All* method, which divides the problem in 4 binary classifications. We train the data with all the classifiers and at the end, each classifier says if the data is positive to its class. If there are more than one classifier with the data sample considered as positive, we use the highest confidence to associate the class. Another possible method would have been to use *One Versus One* which needs 6 classifiers in our case, and is less sensitive to the imbalance but needs more computational resource, but it didn't give better results.

### 3.4 Bootstrap Aggregation

As we have seen in the lecture, decision trees are good because the training and the prediction is quite fast, even with many features or large dataset but have a high variance. The idea of decision trees, is to have a several questions where to answer yes/no and to move in the tree. At the end, the leaves give the corresponding class. To construct this list of questions, we divide recursively the space in a way to minimize the cost of impurity (depending of the threshold to find and the current feature). The depth of the tree is a parameter.

The idea of bootstrap aggregation is to average several decision trees. It will help to reduce the variance and avoid overfitting. It generates  $m$  new training sets of the same size, by sampling uniformly and with replacement the original training set. Then we have  $m$  decision trees which will grows independently with their own generated training sets. Finally, to predict the class it takes the average over all the trees. In order to find those parameters  $m$  and the maximum depth of the tree, we have also used k-fold cross validation and the best values are  $m = 200$  and maximum depth of 512 for the binary classification and for the multi-class case  $m = 500$  and maximum depth also of 512.

### 3.5 Random Forests

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## 4 Evaluation methods

In order to evaluate our different models, we have split our data in two sets of 80% and 20% for the training and the test sets. We choose this percentage in order to have still enough data for the training set and also enough to estimate correctly our models on the testing set. We learn only on the training set and then use the test set in order to estimate the error using the *Balanced Error Rate*. This error compute the average percentage of misclassification per class. It allows us to avoid the case of the 90%/10% and having a good error. We have also used k-fold cross validation to tune the parameters up of our different models. We set  $k = 10$  because we have a lot of data, splitting them into 10 folds seems reasonable (4320 data samples for the training set and 480 for the testing set). We repeated the experiment 30 times with different seeds in order to split the data in a unique random way for each trial and so try to have an unbiased estimation error.

## 5 Model comparison

### 5.1 Binary classification

### 5.2 Multi-class classification

## 6 Feature transformation

## 7 Conclusion

## 8 References

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