

Adaptive Boosting (AdaBoost) FOR Face Detection

```
In [1]: %matplotlib inline
```

```
In [2]: import sys
from time import time
import numpy as np
import matplotlib.pyplot as plt
from dask import delayed
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from data_processing import data
from skimage.transform import integral_image
from skimage.feature import haar_like_feature
from skimage.feature import haar_like_feature_coord
from skimage.feature import draw_haar_like_feature
from scipy.optimize import minimize
from scipy.optimize import fminbound
from sklearn.tree import DecisionTreeClassifier
```

Draw Haar Feature

The procedure to extract the Haar-like features from an image is relatively simple. Firstly, a region of interest (ROI) is defined. Secondly, the integral image within this ROI is computed. Finally, the integral image is used to extract the features.

```
In [3]: #@delayed
def extract_feature_image(img, feature_type, feature_coord=None):
    """Extract the haar feature for the current image"""
    ii = integral_image(img)
    return haar_like_feature(ii, 0, 0, ii.shape[0], ii.shape[1],
                             feature_type=feature_type,
                             feature_coord=feature_coord)
```

We use a our project1 dataset which is composed of 1000 face images and 1000 non-face images. Each image has been resized to a ROI of 16 by 16 pixels. We select 2/3 as training set and 1/3 as testing set.

Data preparation

```

In [4]: images = data
# To speed up the example, extract the two types of features only
feature_types = ['type-2-y', 'type-3-x']

# Build a computation graph using Dask. This allows the use of multiple
# CPU cores later during the actual computation
X = delayed(extract_feature_image(img, feature_types) for img in images)
# Compute the result
t_start = time()
X = np.array(X.compute(scheduler='threads'))
time_full_feature_comp = time() - t_start

# Label images (1000 faces and 1000 non-faces)
y = np.array([1] * 500 + [0] * 500)
# Split data, 2/3 training, 1/3 testing.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
                                                    random_state=0,
                                                    stratify=None)

# Extract all possible features
feature_coord, feature_type = \
    haar_like_feature_coord(width=images.shape[2], height=images.shape[1],
                           feature_type=feature_types)

```

Before boosting, we would like to 1.compute the value of each Harr feature for each sample. Each feature corresponds to a weak learner.(This is already done by extract_feature_image function, X is the feature value)
 2.Determine the threshold between face samples and non-face samples for all the weak learners.(check the thetaLis)
 3.Calculate the classification error for each weak learner and draw the best ten features(check the errorLis)

Haar Feature before boosting

```

In [5]: thetaLis=[]
        errorLis=[]
        for k in range(0,X_train.shape[1]):
            def total(theta):
                val = np.zeros((X_train.shape[0]))
                for i in range(0, X_train.shape[0]):
                    if X_train[i,k] < theta:
                        val[i] = 0
                    else:
                        val[i] = 1
                total = 0
                for j in range (0,val.shape[0]):
                    if val[j] == y_train[j]:
                        total = total + 0
                    else:
                        total = total + 1
                total = total /val.shape[0]
                return total
            from scipy.optimize import fminbound
            xmin=fminbound(total,0,0.49,full_output=1)
            thetaLis.append(xmin[0])
            errorLis.append(xmin[1])

```

```

In [6]: np.sort(errorLis)[0:10]

```

```

Out[6]: array([0.17761194, 0.17910448, 0.17910448, 0.17910448, 0.18059701,
               0.18208955, 0.18208955, 0.18208955, 0.18358209, 0.18507463])

```

Sorted the errorLis, and pick up and plot the best ten features that with minimum classification error, we could use these features for further comparison after the boosting

```

In [7]: #check how many features we extract
        X_train.shape[1]

```

```

Out[7]: 14040

```

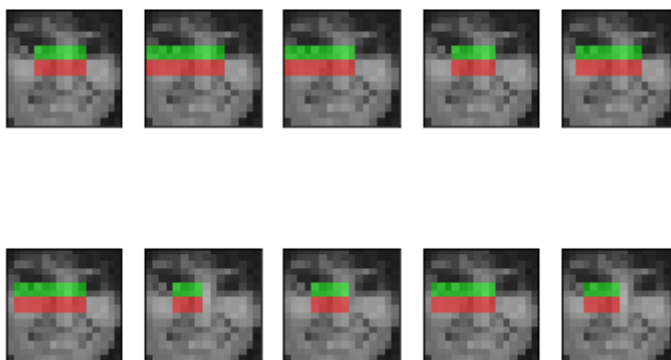
Plot 10 best features before boosting

```
In [8]: idx_sorted = np.argsort(errorLis)[0:10]
fig, axes = plt.subplots(2, 5)
for idx, ax in enumerate(axes.ravel()):
    image = images[0]
    image = draw_haar_like_feature(image, 0, 0,
                                   images.shape[2],
                                   images.shape[1],
                                   [feature_coord[idx_sorted[idx]]])

    ax.imshow(image)
    ax.set_xticks([])
    ax.set_yticks([])

_ = fig.suptitle('The most important features before boosting')
```

The most important features before boosting



Next step, we implement Adaboost classifier, get the best 10 features and compare with the one before boosting. Tune the parameters.

Implement AdaBoost Classifier and draw the best 10 features

```
In [25]: # Train a AdaBoost classifier and assess its performance, assuming we stop
         # with 40 weak-classifier
         clf = AdaBoostClassifier(DecisionTreeClassifier(max_depth=1),
                                n_estimators=40, learning_rate=0.55, algorithm='SAMME', random_state=None)
         clf.fit(X_train, y_train)
         time_full_train = time() - t_start
         auc_full_features = roc_auc_score(y_test, clf.predict_proba(X_test)[:, 1])

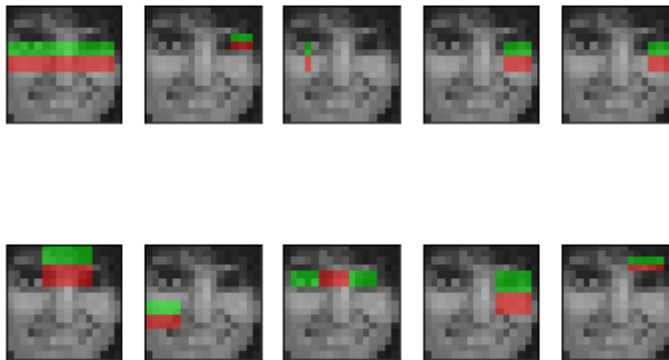
         # Sort features in order of importance and plot the six most significant
         idx_sorted_new = np.argsort(clf.feature_importances_)[::-1]

         fig, axes = plt.subplots(2, 5)
         for idx, ax in enumerate(axes.ravel()):
             image = images[0]
             image = draw_haar_like_feature(image, 0, 0,
                                           images.shape[2],
                                           images.shape[1],
                                           [feature_coord[idx_sorted_new[idx]]])

             ax.imshow(image)
             ax.set_xticks([])
             ax.set_yticks([])

         _ = fig.suptitle('The most important features')
```

The most important features



check the predict probability and predict label, conclude the confusion matrix.

```
In [26]: from sklearn.metrics import confusion_matrix
         from sklearn.metrics import roc_curve
         from sklearn.metrics import auc
         predict_prob = clf.predict_proba(X_test)[:, 1]
         predict_label = clf.predict(X_test)
         fpr,tpr,threshold = roc_curve(y_test,predict_prob)
         confusion_matrix(y_test, predict_label)
```

```
Out[26]: array([[165,   2],
                [  2, 161]], dtype=int64)
```

Define ROC function and plot ROC curve for final results

Plot ROC

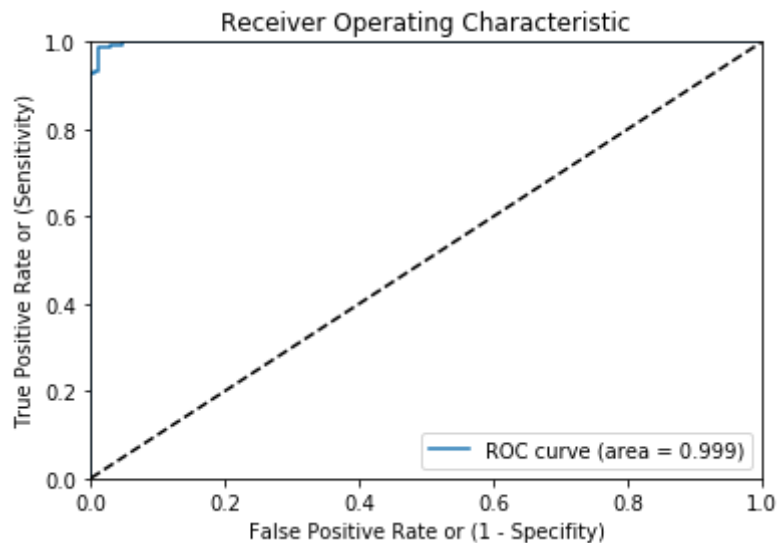
```
In [27]: def ROCcurve(test_data,predict_score):
    print(test_data.shape)
    print(predict_score.shape)
    fpr,tpr,threshold = roc_curve(test_data,predict_score)
    roc_auc = auc(fpr,tpr)

    # Plot ROC curve
    plt.plot(fpr, tpr, label='ROC curve (area = %0.3f)' % roc_auc)
    plt.plot([0, 1], [0, 1], 'k--') # random predictions curve
    plt.xlabel('False Positive Rate or (1 - Specificity)')
    plt.ylabel('True Positive Rate or (Sensitivity)')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.title('Receiver Operating Characteristic')
    plt.legend(loc="lower right")
```

```
In [28]: ROCcurve(y_test,predict_prob)
```

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(330,)
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(330,)
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```
In [29]: auc_full_features
```

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Out[29]: 0.9988244370155395
```

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In [ ]:
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