Project 2 - Adaptive Boosting (AdaBoost) for Face Detection

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Dataset: coming from project02 provided data. We pick up 500 face and 500 nonface images as our whole dataset. Split data into 2/3 training set and 1/3 testing set.

Language: python3

Setp1: Draw Haar Features

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.

Each Haar Feature itself is a rectangular filter, feature output is the difference between adjacent regions. Efficiently computable with integral image: any sum can be computed in constant time.

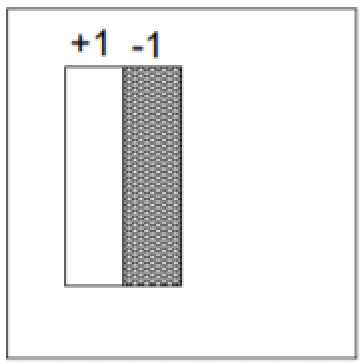
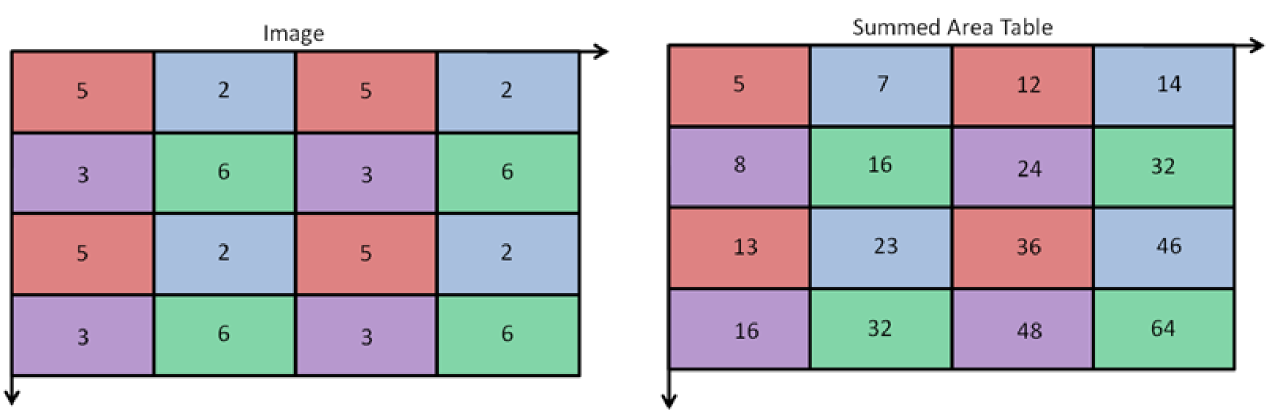


Figure1. Haar Feature example

The trick is to compute an “integral image.” Every pixel is the sum of its neighbors to the upper left.



Solution is found using: A + D – B – C.

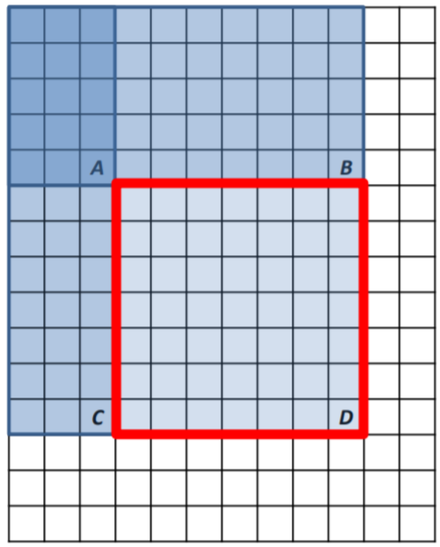


Figure2. Solution Method

Step2: Determine the threshold between face samples and non-face samples for all the weak learners before boosting

After getting each feature output, we could prepare out training data and testing data. Each feature represents a weak classifier, each weak classifier has a related optimal classification threshold and classification error. The tuition behind it is that each image for this specific classifier has a corresponding output value, we have to determine a threshold that best separates positive (faces) and negative (non-faces) training examples, in terms of weighted error.

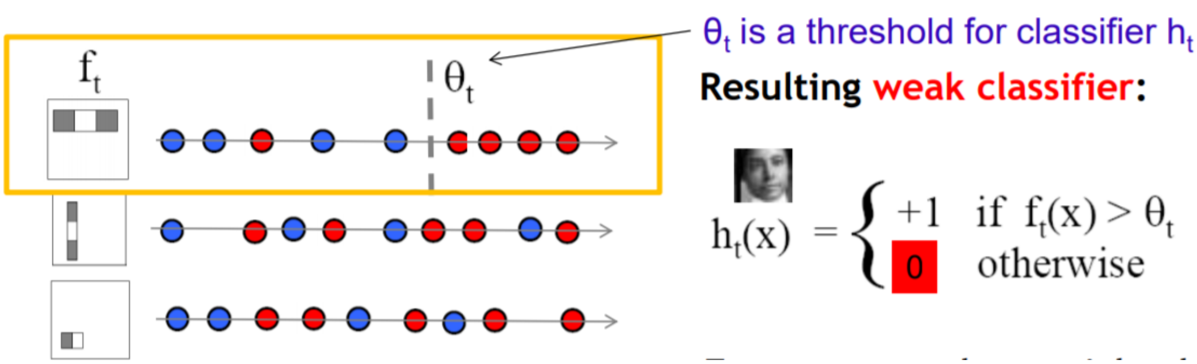


Figure3. Tuition of each wear classifier.

In our case, for the purpose of computational efficiency, we only select the “type-2-y”, “type-3-x” features which have the shape shown below:

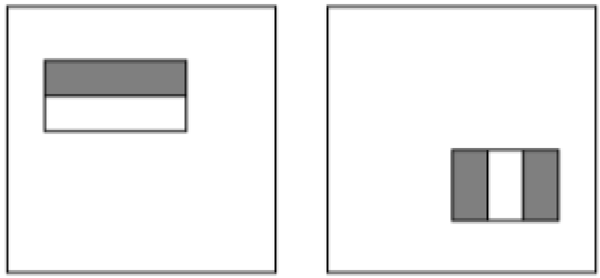
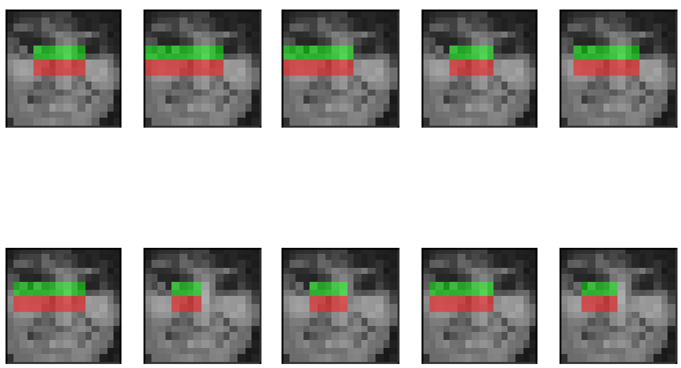


Figure4. “type-2-y”, “type-3-x” filters

Totally we could extract 14040 features for 16 by 16 pixel pictures. We implement scipy.optimize. fminbound to determine each feature’s threshold and calculate the error rate. Important to point out, all of this threshold will be updated for further Adaboost algorithm. Error rate is calculate by:

Number of Misclassification / Total Image Number

We draw the 10 best feature before boosting, print out their related error as well. The results are shown below:



```
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])
```

Figure5. 10 best features before boosting

From above, it seems Haar features itself does not work pretty well, most of the features will cluster in the central part of the face. Next step, we are trying to implement the Adaboost to pick up the 10 most valuable features and we could compare with this result.

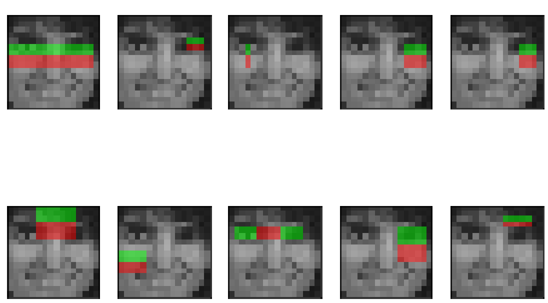
Step3: Adboosting

The details mathematical algorithm has been elaborated in the project description, we could conclude the algorithm logic by turning to table1

- Given example images $(x_1, y_1), \dots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \dots, T$:
  1. Normalize the weights,
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i \, |h_j(x_i) - y_i|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
  $$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$
  where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
where $\alpha_t = \log \frac{1}{\beta_t}$

Table1[1]. Adaboost logic

We assume our algorithm stops when there are 40 weak classifier added to the model in order to avoid overfitting issues. After getting the results ,we could evaluate the model performance based on ROC score etc. The best 10 features after implementing Adaboost algorithm are showing below:



Figures6. 10 best features with Adaboost

From above results, we could find out that the model works for picking up some face features compared with the one before boosting.

Step4: Evaluation on test set

After training the model, we could apply this strong classifier on the data set. From 330 testing data, we could achieve ROC score with 0.9988, which is almost equal to 1. From 330 testing data, the confusion matrix return with [165, 2, 2, 161] which means TN, FP, FN, TP is equal to 165, 2, 2, 161 separately. Plot ROC curve.

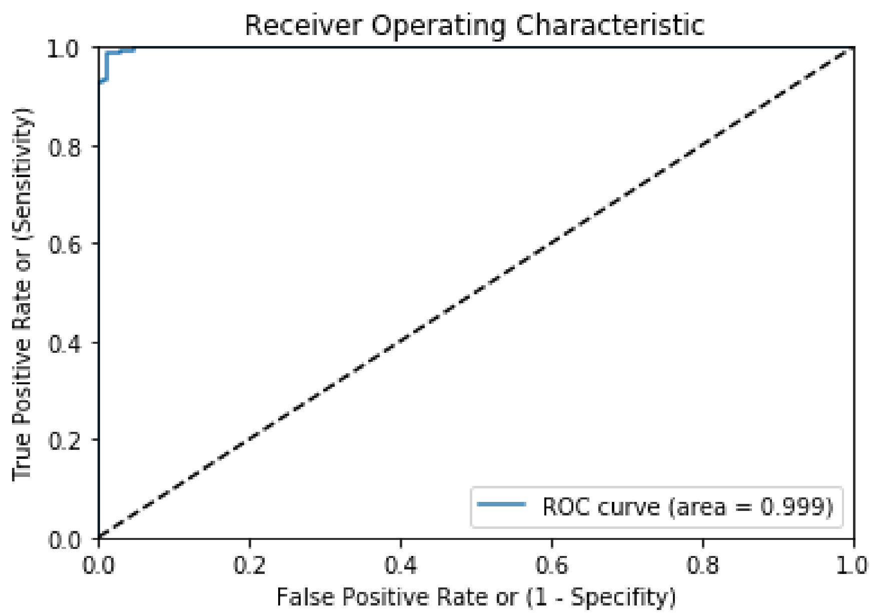


Figure7. ROC with Adaboost

The full code we attach in the end

Reference

[1] V. Paul and J. Michael, “Rapid Object Detection using a Boosted Cascade of Simple Features,” *Accept. Conf. Comput. Vis. PATTERN Recognit.*, pp. 1193–1197, 2001.

Appendix: Jupyter Notebook

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

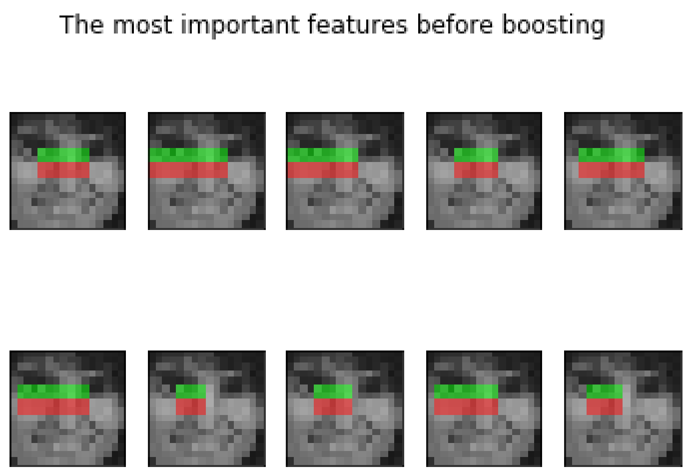
In [7]:
```
#check how many features we extract
X_train.shape[1]
```

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')
```



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

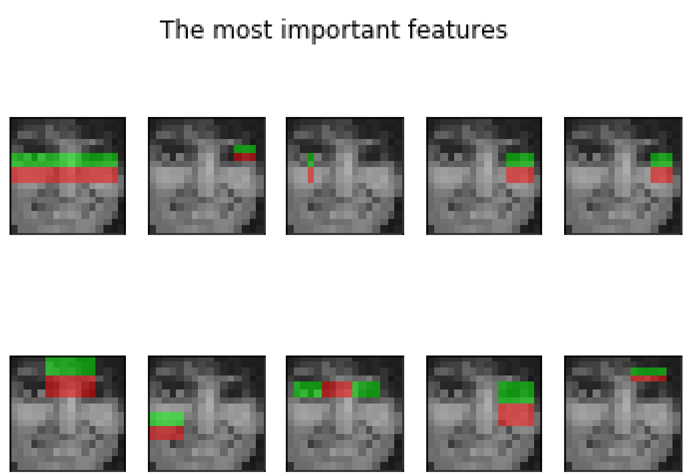
Implement AdaBoost Classfier and draw the best 10 features

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')
```



check the prdict 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

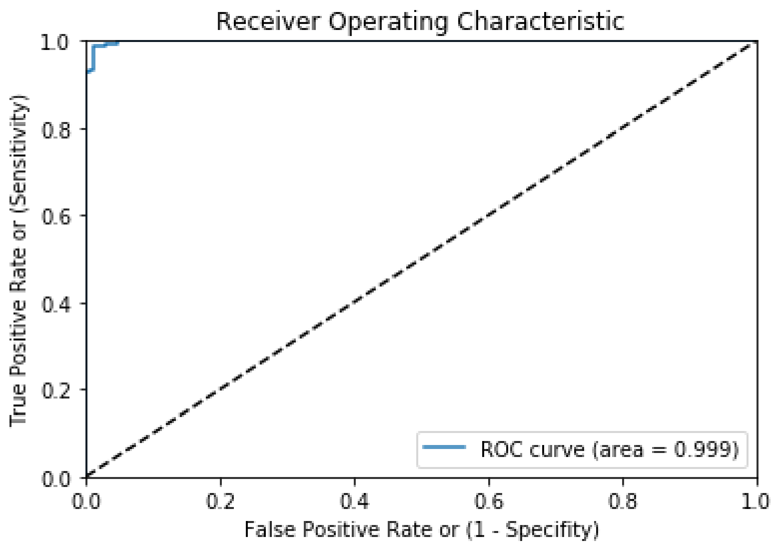
Plot ROC

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 - Specifity)')
    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)
```

```
(330,)
(330,)
```



In [29]:
```
auc_full_features
```

Out[29]:
```
0.9988244370155395
```

In [ ]: