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Object detection with Cascaded AdaBoost Classifier

The AdaBoost classifier aggregates weak classifiers to create a strong classifier which is then used to classify the images in the data set. Following are the different procedures that go into training an AdaBoost Classifier:

Extracting Haar Features

The first step to building weak classifier is to extract Haar features from all images in the training data set. Following are the steps in extracting the Haar features from an image:
1. Convert the image from RGB to gray scale.
2. Calculate the integral image. I have used OpenCV implementation (cv2integral) to calculate the integral images. The integral images are calculated using the following formula

$$\mathrm{II}(x, y) = \Sigma_{x_i \le x, y_i \le y} \mathrm{I}(x_i, y_i)$$

3. Calculate the horizontal and vertical Haar features such as [0,1] and $[1,0]^{T}$. All the horizontal features and the vertical features are calculated using filter of sizes 1x2, 1x4, 1x6 , 1x8 ….. both horizontally and vertically. Thus, we get a total of 166000 for each image in the dataset.

Build Weak Classifier

Let T be the number of weak classifier required to build one strong classifier. The following is the procedure to calculate one weak classifier:

1. Extract one feature for all images (positive and negative) in the dataset and arrange the values in ascending.

2. The error for the selected feature is calculated using the following formula given by,

$$\mathrm{e} = \min(S^{+} + (T^{-} - S^{-}), S^{-} + (T^{+} - S^{+})),$$

where T^{-} is the total sum of the negative weights, $T^{+}$is the total sum of the positive weights, S^{-} is the sum of the negative weights below the current example and S^{+} is the sum of the positive weights below the current example and.

3. The i^th weak classifier in the T weak classifiers is defined as

$$h(x, f, p, \theta) = \begin{cases} 1, if\ pf(x) < p\theta \\ 0, \quad\quad otherwise \end{cases}$$

where x is the image, F is the feature, θ is the threshold and p is the polarity. The sign of p is determined by the value of e, if $S^{+} + (T^{-} - S^{-}) < S^{-} + (T^{+} - S^{+})$), p = -1 else p = 1.

4. Once the i^th weak classifier is calculated the weights are updated using the following formula,

$$w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}, where\ \beta = \frac{\varepsilon_t}{1 - \varepsilon_t}$$

$e_i = 0$, if the sample is correctly classified and 1 if its incorrectly classified. ε_t is the weighted error.

Build a Strong Classifier

The following is the procedure to build a strong classifier:

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1. Labels the images in the training data, the positive images are given the label of one while the negative images are given a label of 0.

2. Set the weights initially for all the images in the training set. All positive images are given a weight of $\frac{1}{2\times number\ of\ positive\ images}$ and the negative images are given a weight of $\frac{1}{2\times number\ of\ negative\ images}$.

3. Normalize the weights, $w_{t\ i} = \frac{w_{t,i}}{\Sigma w_{t,i}}$

4. For all the features find the best weak feature using the steps described in the section, build a weak classifier.

5. One the best weak classifier is calculated the weights are updated using the following formula,

$$w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}, where\ \beta = \frac{\varepsilon_t}{1-\ \varepsilon_t}$$

$e_i = 0$, if the sample is correctly classified and 1 if its incorrectly classified. ε_t is the weighted error

6. Repeat steps 3-5 till you find T weak classifiers. I have set the maximum value of T to be 100 in this experiment.

7. The strong classifier is given by the formula, $C(x) = \begin{cases} 1, & \Sigma_t \alpha_t h_t(x) \geq threshold \\ & 0, otherwise \end{cases}$,

During the training procedure in order to get a 100 % true detection rate, I have set the threshold to the minimum value of $\Sigma_{t=1}^{T} \alpha_t h_t(x)$ and during training it has been set to $0.5\ \times \Sigma_{t=1}^{T} \alpha_t$.

8. The stopping criteria is for the loop is determined by the true detection and the false positive rate. In this assignment I has set the target true detection rate during training to 1 and the maximum target false positive rate to 0.5

Cascaded AdaBoost Classifier

To integrate the existing, the adaBoost Classifier with the cascade algorithm the following procedure is followed:

1. The strong classifier is calculated using T weak classifiers using the procedure described in the section build a strong classifier.

2. Once the strong classifier is identified, the training data set is updated so the that contains all the positive image and the negative images that was misclassified by the previous strong classifier. This updated dataset is then used to generate and the second strong classifier.

3. This process is repeated till the updated training data set only contains positive images. Thus, ensuring a false positive rate of 0.

Performance Analysis

The performance analysis of the AdaBoost classifier is done by calculating the false positive and false negative rates during testing.

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$$False\ Positive\ rate = \frac{No\ of\ misclassified\ negative\ test\ images}{Total\ number\ of\ negative\ test\ images}$$

$$False\ Negative\ rate = \frac{No\ of\ misclassified\ positive\ test\ images}{Total\ number\ of\ positive\ test\ images}$$

Results from Task 2

Training results:

Table showing false positive rates during training

Stage	1	2	3	4	5	6	7
No. of Classifiers	9	11	8	7	8	6	5
Accumulate False positive rates	0.45278	0.226394	0.080205	0.031286	0.010808	0.000568	0

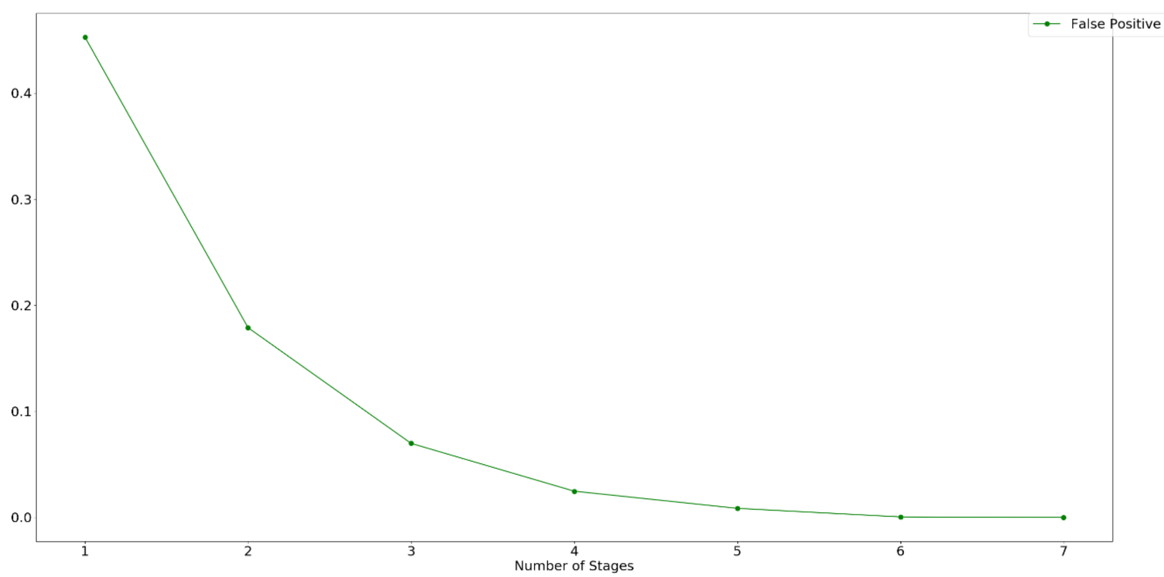

Figure 2: Accumulated false positive rates vs number of stages during training

Training results:

Table showing accumulates false positive and false negative rates during testing

No of stages	Accumulated False Positive Rates	Accumulates False Negative Rates
1	0.1	0.12921348

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2	0.00386364	0.2808671
3	0.000333678	0.34550845
4	5.081e-05	0.41536991
5	1.20096e-05	0.46792093
6	4.66738e-06	0.49781301
7	4.65677e-06	0.50063429

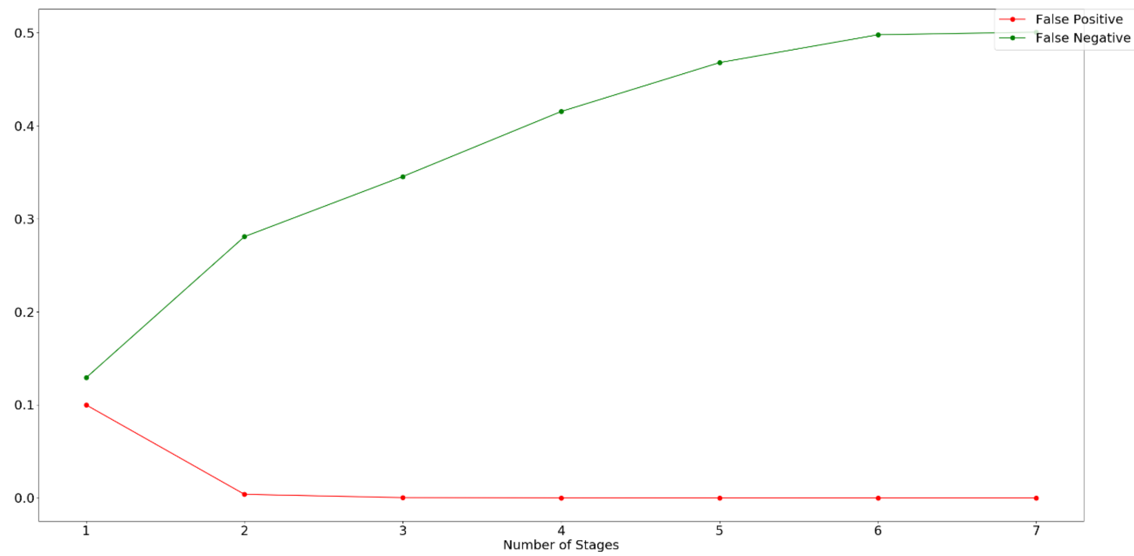

Figure 3: Accumulated false positive and false negative rates vs number of stages during testing

Conclusions:

From the graphs it is seen that the false positive rates decrease as the number of stages increase. The false negative rate is however seen to increase as the number of stages increase as the number of stages increase. This is because the false negative rate is equal to 1 - True Positive Rate, as the number of stages increase true positive rate decreases and thus false negative rate increases.