**ECEN 649, Fall 2019**

Texas A&M University

Electrical and Computer Engineering Department

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Project Report

**Face Detection using AdaBoost and Haar Features**

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**Aggie Code of Honor**

**An Aggie does not lie, cheat or steal or tolerate those who do.**



Abstract

The main focus of the project is the implementation of the Viola-Jones Algorithm. The algorithm was a breakthrough in the field of face detection because it provided computationally feasible and accurate results. The algorithm uses a Haar features and Adaboost algorithm using a decision stamp classifier to perform the classification. In the project, we are extracting 5 different types of features types from 19 by 19 images. Then implement the Adaboost algorithm on the features to perform the classification of the image. Finally, the classifier error definition is changed to consider only the case of False negative and False positive.

Features extraction

Haar Features

Table 1 (Feature Count)

|  |  |
| --- | --- |
| Type 1 (Horizontal Edge Detection) | 7440 |
| Type 2 (Vertical Edge Detection) | 7440 |
| Type 3 (Horizontal Line Detection) | 3472 |
| Type 4 (Vertical Line Detection) | 3472 |
| Type 5 (Four Feature detection) | 3600 |
| Total | 25424 |

The feature size was limited by two constraints, one that area of the two black and white regions must be equal and the max size of the filter is 8 by 8. The computations were performed using an integral image to decrease computation time.

Type 1 Horizontal Edge Detector Sizes of m by n.

m = range[1,8], n =2\* range[1,4]

Type 2 Vertical Edge Detector Sizes of m by n.

m = 2\*range[1,4], n = range[1,8]

Type 3 Horizontal Line Detector Sizes of m by n

m = range[1,8], n = 4\*range[1,2]

The smallest size has to be 1 by 4, to insure the we have 2 white pixels for 2 black pixels.

Type 4 Vertical Line Detector Sizes of m by n

m = 4\*range[1,2], n = range[1,8]

The smallest size has to be 4 by 1, to insure the we have 2 white pixels for 2 black pixels.

Type 5 Four Feature Detector Sizes of m by n

m = 2\*range[1,4], n = 2\*range[1,4]

The smallest size has to be 2 by 2, to insure one pixel per area.

AdaBoost

Table 2 (Round Statistics)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Round | Empirical | False Positive | False negative | Feature Type | Strong Predictor accuracy |
| 1 | 0.31813 | 0.09364 | 0.22449 | Type 1 | 0.712 |
| 3 | 0.44498 | 0.07923 | 0.36575 | Type 1 | 0.604 |
| 5 | 0.47539 | 0.09124 | 0.38415 | Type 2 | 0.407 |
| 8 | 0.42497 | 0.17887 | 0.17967 | Type 1 | 0.608 |
| 10 | 0.44458 | 0.08523 | 0.35934 | Type 1 | 0.647 |

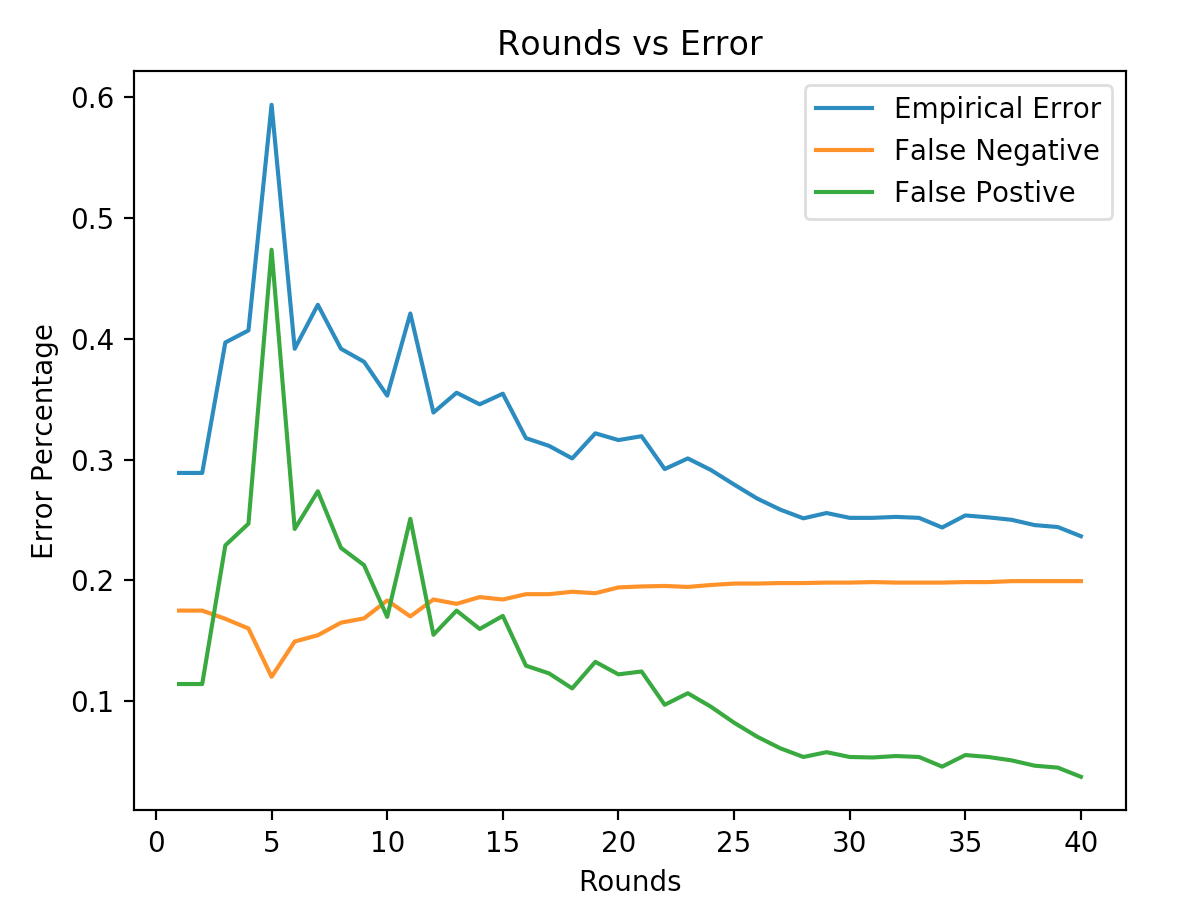


Figure 1 (Test errors over 40 rounds of ada boost)

The major focus of the classifier is on the false positive error, because the weight of the ada boost is evenly distribution amount sub population of faces and a non-faces. In the training data there are only 499 images with faces and rest are all non-faces. The weighted error of a false positive have a greater weight than false positive error. The sample size is the culprit behind the increase in false positive error.

Round 1

(Type 1) Horizontal Edge Detection

M = 6

N = 1

Position = (0, 0)

Threshold = -85.5

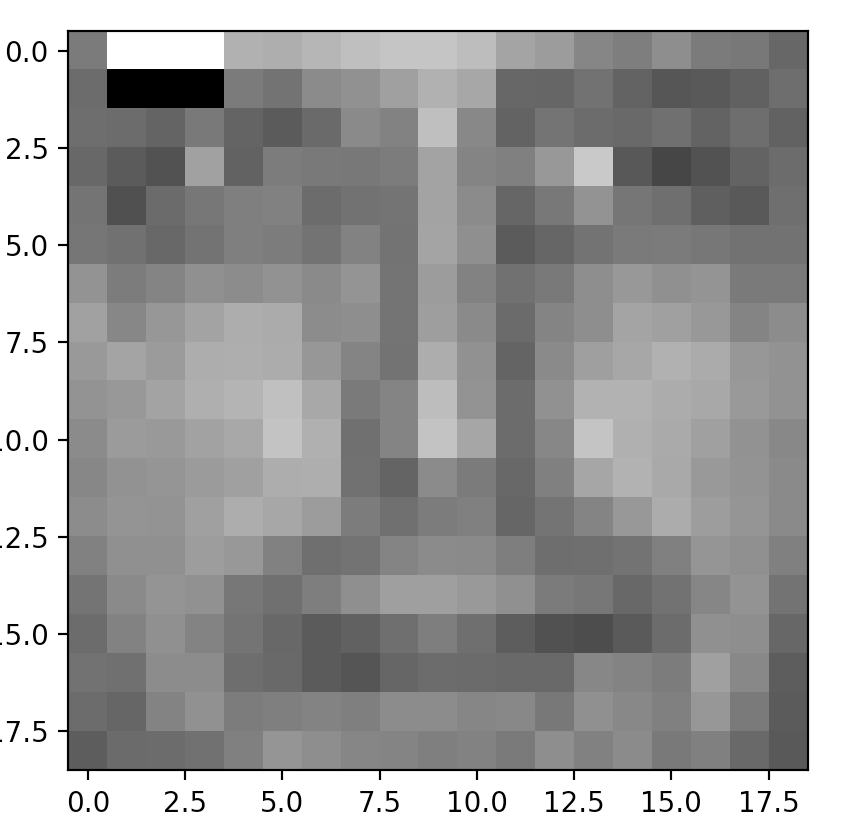


Figure 2(Round 1 features)

The feature is using the fact that a person’s head is lighter than their eyebrows portion in the image. The alone was able to have an accuracy of 68.18%

Round 3

(Type 2) Vertical Edge Detection

M = 4

N = 1

Position = (9, 16)

Threshold = -18.5]

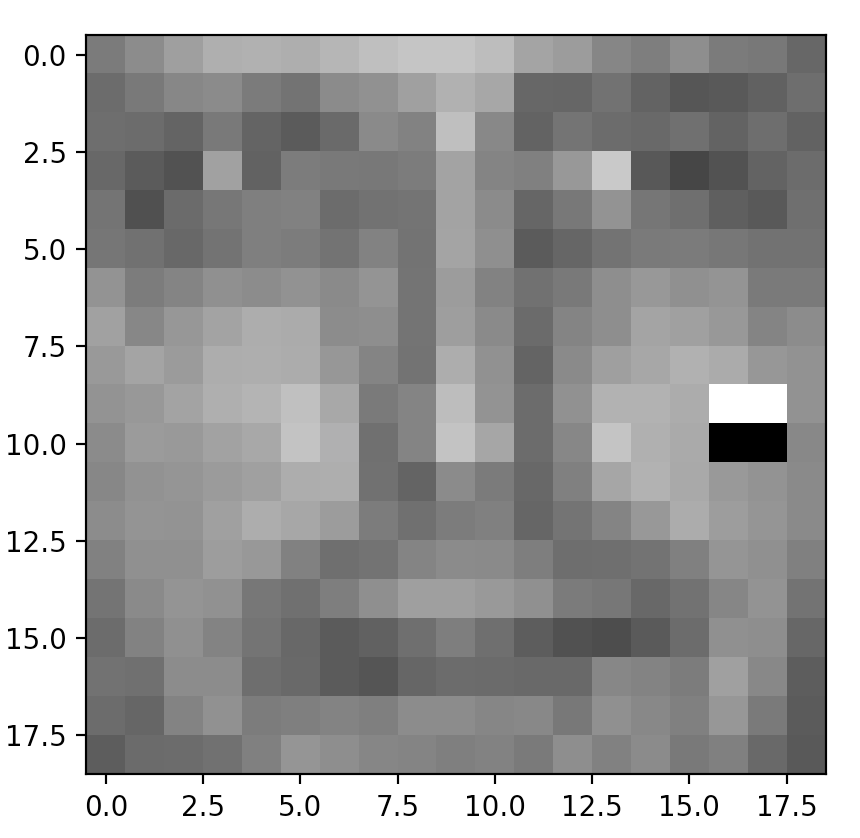


Figure 3(Round 3 features)

The feature may be good for classifying to determining a face, it is really good in determining non-faces and decrease the false positive error.

Round 5

(Type 2) Horizontal Edge Detection

M = 2

N = 2

Position = (9, 14)

Threshold = -16.5

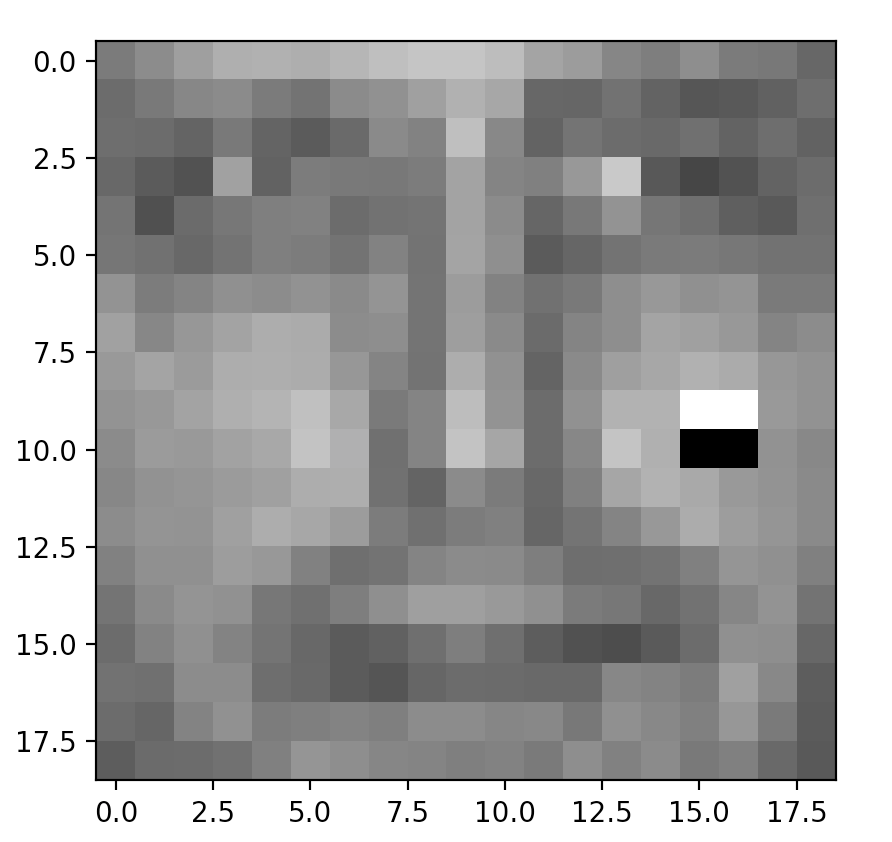


Figure 4(Round 5 features)

The feature may be good for classifying to determining a face, it is really good in determining non-faces. By the addition of this feature the strong classifier will low false positive error but increase in the total error of the classifier.

Round 8

(Type 1) Horizontal Edge Detection

M = 4

N = 1

Position = (7, 16)

Threshold = -48.5

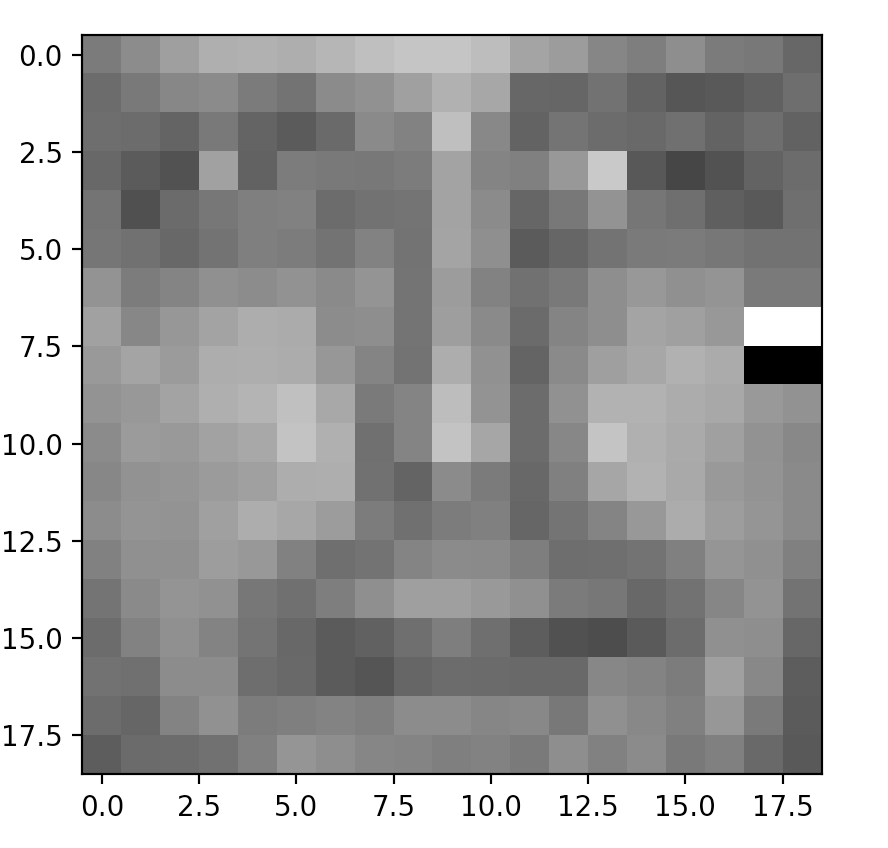


Figure 5(Round 8 features)

In round 8 of the algorithm is there is a trend that start to in error statistics. The features is utilizing the fact that the eyes are darker than the cheeks. This clearly a feature present in must human faces and can help detect them.

Round 10

(Type 1) Horizontal Edge Detection

M = 4

N = 1

Position = (8, 16)

Threshold = -22.5

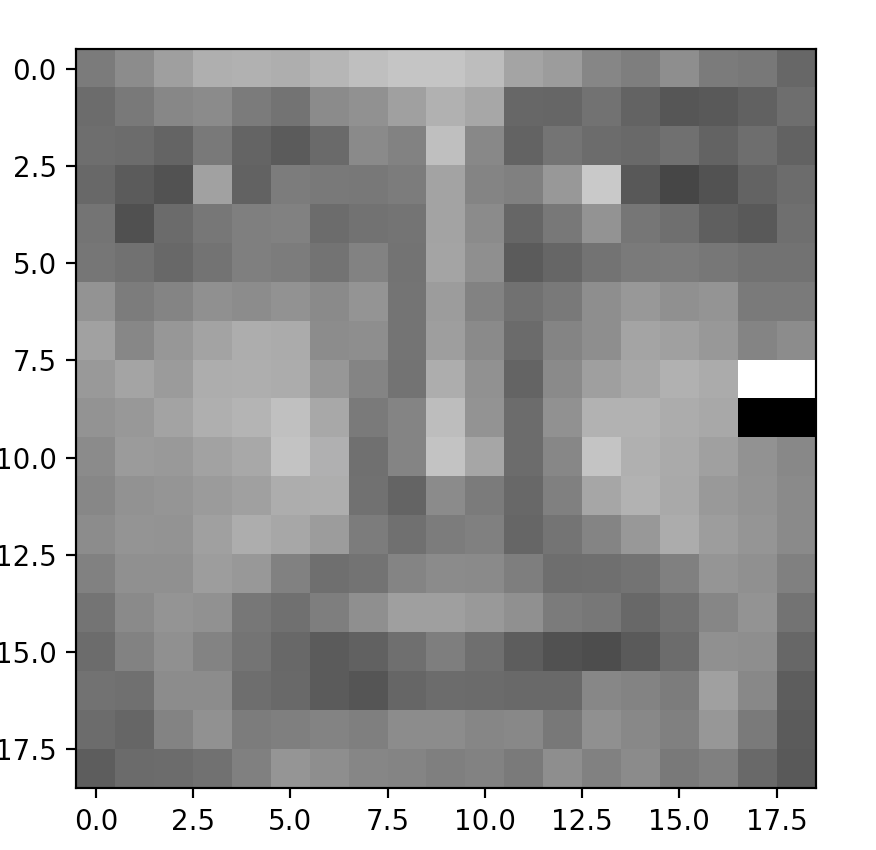


Figure 6(Round 10 features)

In round 10 of the algorithm is saturating in the value of the false negative, while the false positive error continuous to decrease. The features are utilizing the fact that the eyes are darker than the cheeks. This is the same feature type and size of the feature found in round 8. This redundancy may be attributed to size limitation placed on the Haar features.

Ada Boost Medication

Table 2 (Result from different criteria after 5 rounds)

|  |  |  |  |
| --- | --- | --- | --- |
| **Criterion** | **Empirical Error** | **False Positive** | **False Negative** |
| **Empirical Error** | 0.59384 | 0.12005 | 0.47379 |
| **(FN) Gama = 0.1** | 0.44098 | 0.08964 | 0.35134 |
| **(FP) Gama = 0.9** | 0.73990 | 0.05442 | 0.68547 |

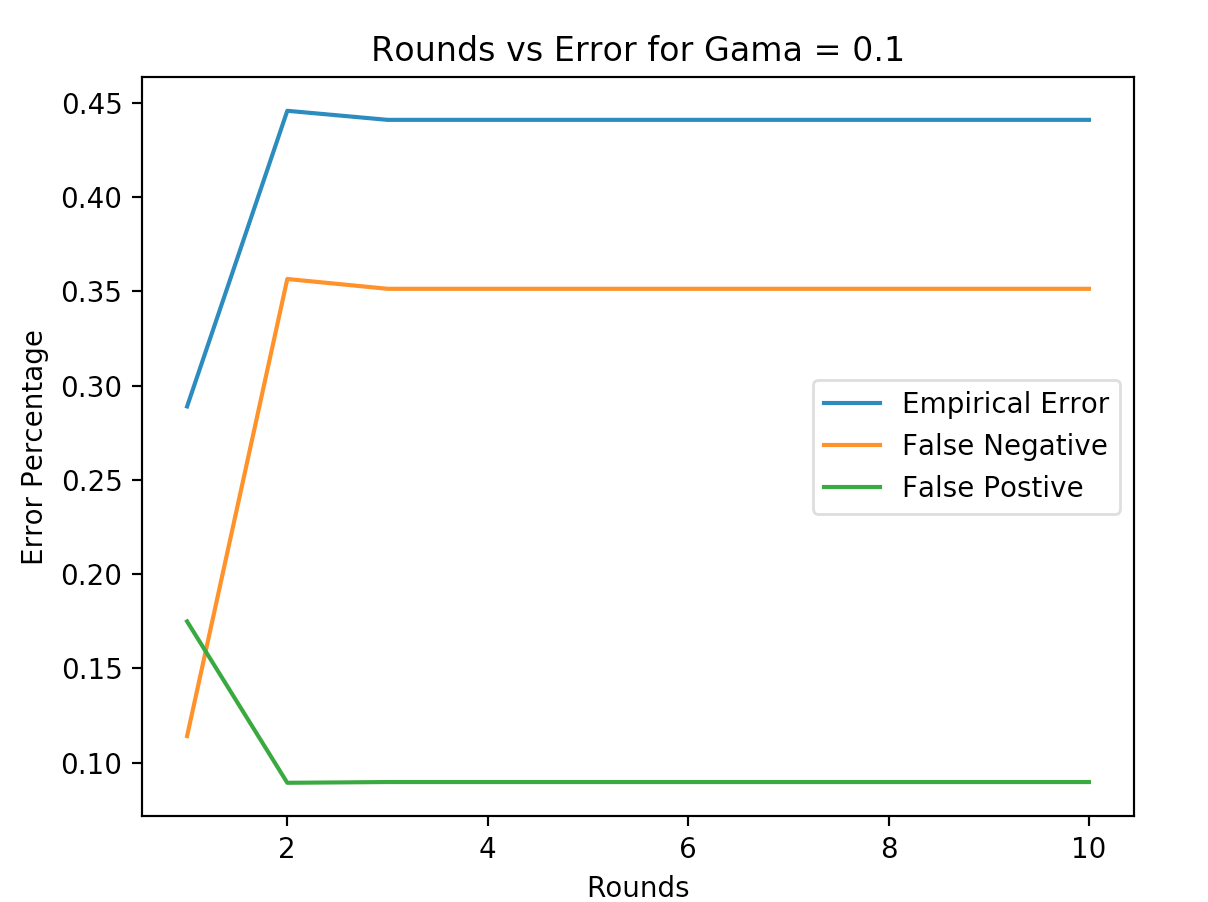


Figure 7(Test errors over 5 rounds of Ada boost with Gama = 0.1)

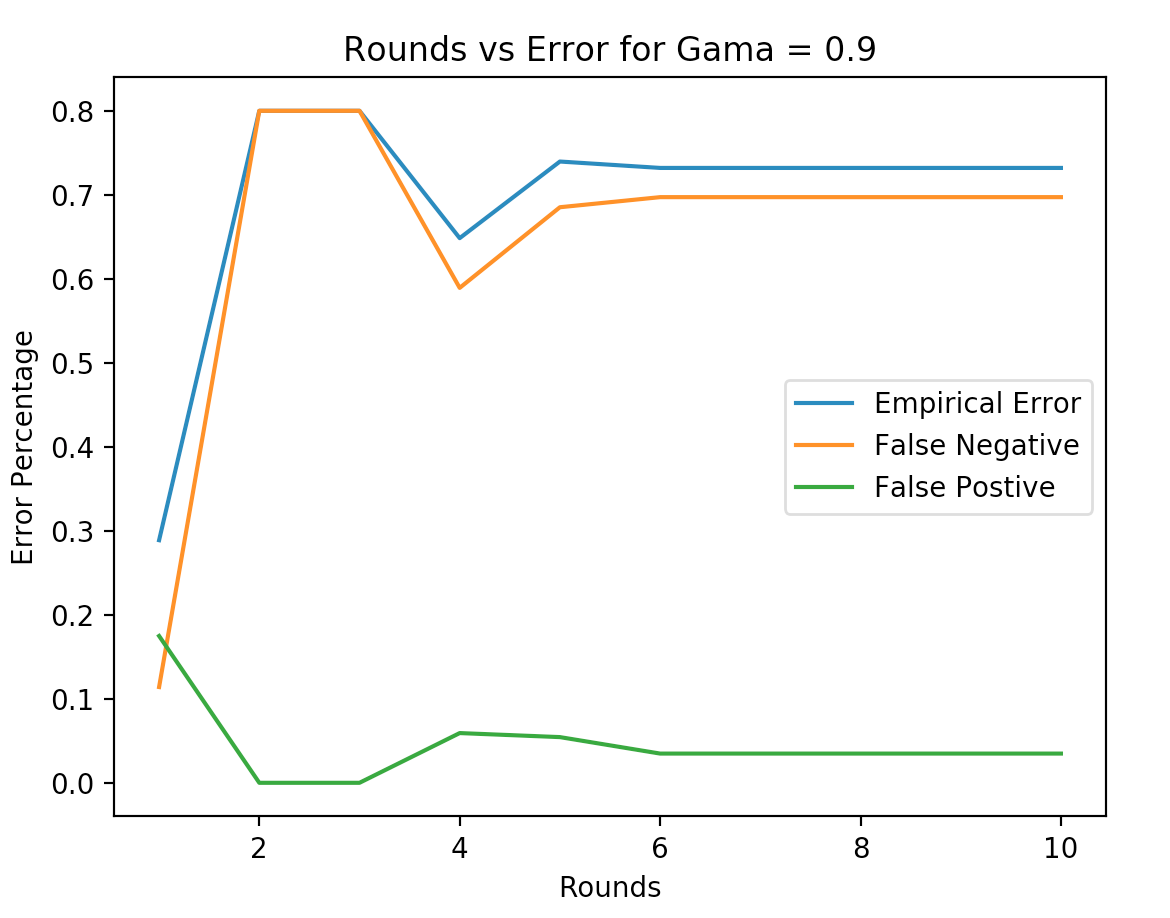


Figure 7(Test errors over 5 rounds of Ada boost with Gama = 0.9)