Researcher’s Name: Sean Pavlak Date Performed: 04/05/16

Gender Detection based on Facial Feature Ratios

Abstract:

In my investigation, I applied learning techniques to data collected by Apple’s CoreImage facial detection. CoreImage was able to detect 3 facial feature coordinates, and I translated those coordinates into distances after performing appropriate triangulation methods. Then these distances were able to yield their appropriate ratios. These ratios were then compared to the training set. The machine learning algorithm that I applied was the Naive Bayes Classifier, and I was able to successfully predict the gender of a user with an accuracy of 62% from only 4 ratios.

Methods and Data:

In order to use the Naive Bayes Classifier, it is first necessary to have a large training set so that the program can determine what traits are more significant and which class contains this data more often. So to develope my training set, I first started with 100 head on images of random human faces, 50% male and 50% female.

I then was able to place points on these locations and apply Delaunay Triangulation, as shown in figure 1, to this set of points. The triangulation is named after Boris Delaunay for his work on this topic from 1934. In mathematics and computational geometry, a Delaunay triangulation for a set P of points in a plane is a triangulation DT(P) such that no point in P is inside the circumcircle of any triangle in DT(P).

Delaunay triangulations maximize the minimum angle of all the angles of the triangles in the triangulation; they tend to avoid skinny triangles. This is important when mapping from 2D images to 3D images, because a 3D image tends to not produce this kind of triangles.

After I was able to apply Delaunay Triangulation to each of the 100 faces I then calculated the distances between these points, as shown in table 1.

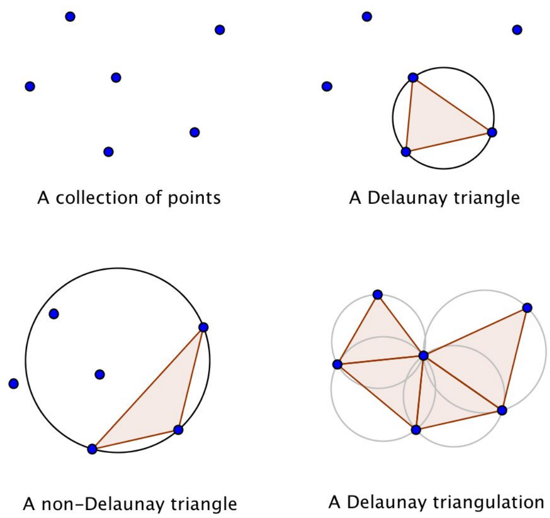

Figure 1: Example of proper Delaunay Triangulation.

Count	Gender	LE-RE	LE-M	RE-M	ME-M
1	Female	178.01	224.80	226.93	200.64
2	Female	110.00	133.02	135.57	121.00
3	Female	183.07	217.00	217.57	196.09
4	Female	123.26	147.26	146.29	136.18
5	Female	55.04	66.64	68.15	58.03
6	Female	67.07	79.16	80.23	71.01
7	Female	91.24	118.77	127.75	114.35
8	Female	134.36	159.56	157.34	144.83
9	Female	129.02	151.64	150.79	137.03
10	Female	68.18	82.87	83.24	74.03
11	Female	165.03	200.63	199.52	181.60
12	Female	90.01	103.79	104.65	98.02
13	Female	38.11	48.79	48.17	44.46
14	Female	35.47	37.95	40.21	35.65
15	Female	78.24	95.40	98.75	88.50
51	Male	169.52	213.35	221.03	204.87
52	Male	54.41	64.12	64.61	60.82
53	Male	101.49	128.50	132.70	118.29
54	Male	94.28	106.26	110.53	101.22
55	Male	200.01	228.08	228.12	202.09
56	Male	280.34	369.80	349.40	344.89
57	Male	185.69	231.86	229.14	210.99
58	Male	45.84	59.05	56.40	52.37
59	Male	190.79	239.43	229.87	217.58
60	Male	89.00	110.49	109.38	101.08
61	Male	67.38	77.05	77.35	69.73
62	Male	79.24	93.17	92.14	86.86
63	Male	113.09	136.23	140.28	127.44
64	Male	63.97	85.66	85.87	77.78
65	Male	80.96	103.04	103.56	94.09

Table 1: Distance data for the first 15 male and female faces.

I was able to calculate the four distinct distance fields: distance from left eye to right eye, distance from left eye to the center of the mouth, the distance from the right eye to the mouth, and the distance from the midpoint between the eye to the center of the mouth. Once all 100 distances were calculated I needed to establish the ratios between these distances. I found the ratios between all the distances, this gave 6 ratio fields. For the sake of efficiency I reduced that set down to the best 4.

I was able to determine the better and worse ratios by first calculating the female, male, and total average value for each ratio field. I then calculated the difference between the male and female average, and then divided that range by the average. As shown in equation 1 and table 2.

$$f_{Range:Average}(x) = \frac{(\bar{x}_F - \bar{x}_M)}{\bar{x}_{Total}} \tag{1}$$

LE-RE:ME-M	LE-M:RE-M	LE-M:ME-M	RE-M:ME-M
Female Average	Female Average	Female Average	Female Average
0.8923390839	0.9956995748	1.08713524	1.092074563
Male Average	Male Average	Male Average	Male Average
0.8724406121	0.997995136	1.069103613	1.071314105
Total Average	Total Average	Total Average	Total Average
0.882389848	0.9968473554	1.078119427	1.081694334
Range	Range	Range	Range
0.01989847179	0.002295561223	0.01803162718	0.02076045781
Range:Average	Range:Average	Range:Average	Range:Average
0.02255065812	0.002302821199	0.01672507399	0.01919253634

Table 2: Significance chart showing the best of the 6 measured ratios.

Even after selecting the optimal ratios, the available ratios only support a 1.7 % - 2.3 % change between male and female. However when all four are applied to a learning algorithm we are able to achieve a much higher percent range between our two classes.

From the total average we were able to construct a chart that plotted each range and whether each face scored above or below average, table 3 and 4 show the first 20 females and last 20 males data chart respectively.

Count	Gender	LE-RE:ME-M	LE-M:RE-M	LE-M:ME-M	RE-M:ME-M
1	Female	Above	Below	Above	Above
2	Female	Above	Below	Above	Above
3	Female	Above	Above	Above	Above
4	Female	Above	Above	Above	Below
5	Female	Above	Below	Above	Above
6	Female	Above	Below	Above	Above
7	Female	Below	Below	Below	Above
8	Female	Above	Above	Above	Above
9	Female	Above	Above	Above	Above
10	Female	Above	Below	Above	Above
11	Female	Above	Above	Above	Above
12	Female	Above	Below	Below	Below
13	Female	Below	Above	Above	Above
14	Female	Above	Below	Below	Above
15	Female	Above	Below	Below	Above
16	Female	Above	Above	Above	Below
17	Female	Above	Above	Above	Above
18	Female	Below	Above	Below	Below
19	Female	Below	Above	Below	Below
20	Female	Below	Below	Below	Above
21	Female	Above	Below	Above	Above

Table 3: Naive Bayes Classifier chart for females

80	Male	Below	Above	Above	Below
81	Male	Above	Below	Above	Above
82	Male	Below	Above	Above	Below
83	Male	Below	Above	Above	Above
84	Male	Below	Above	Below	Below
85	Male	Above	Above	Above	Below
86	Male	Below	Below	Below	Below
87	Male	Below	Above	Below	Below
88	Male	Above	Above	Above	Above
89	Male	Above	Below	Above	Above
90	Male	Below	Above	Below	Below
91	Male	Above	Above	Above	Below
92	Male	Above	Above	Above	Above
93	Male	Below	Below	Below	Above
94	Male	Below	Below	Above	Above
95	Male	Below	Below	Below	Below
96	Male	Above	Below	Above	Above
97	Male	Below	Below	Below	Below
98	Male	Above	Below	Above	Above
99	Male	Below	Below	Below	Below
100	Male	Above	Below	Below	Above

Table 4: Naive Bayes Classifier chart for males

Based on the data collected the best algorithm to implement would be the Naive Bayes Classifier, which in other reports showed to have an 84.7475%. This algorithm seemed optimal because it is able to perform with very little execution time and can achieve a high accuracy.

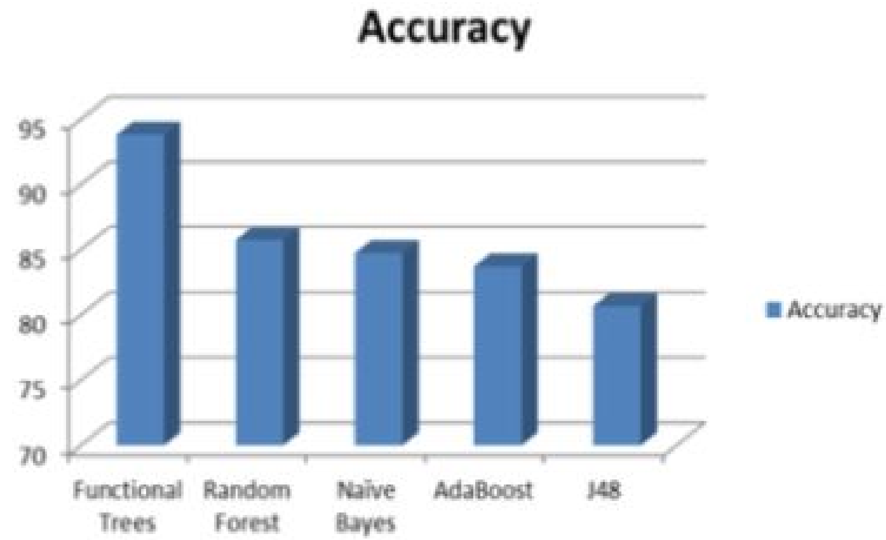

Figure 2: Machine learning accuracies for gender detection found by the International Journal of Applications Vol 124 No. 6

$$p(C_k|x) = p(C_k)\ p(x|C_k)\ p(x)^{-1} \tag{2}$$

From equation 2 we can make some reductions to simplify our calculations. $p(C_k)$ in both female and male classes is 0.5, so this can be removed. Also p(x) in both cases is equal, and we intend to compare male to female so this scalar multiple will inevitably be canceled. So our formula is as follows

$$p(C_k|x) = p(x|C_k) \tag{3}$$

Once I had all 100 subjects ratio data charts build I was able to determine the values to input into equation 3 for the male and female class. Whichever value is higher determines which class the face most likely belongs.

LE-RE:ME-M	Above Count	Below Count
Female	0.6	0.4
Male	0.38	0.62
LE-M:RE-M	Above Count	Below Count
Female	0.52	0.48
Male	0.44	0.56
LE-M:ME-M	Above Count	Below Count
Female	0.58	0.42
Male	0.52	0.48
RE-M:ME-M	Above Count	Below Count
Female	0.64	0.36
Male	0.56	0.44

Table 5: Naive Bayes Classifier value chart for male and female

The program I developed to implement this method is in the form of an iPhone application. The application on startup presents a front camera stream and a face detection indicator. If the application finds a face in the stream the indicator's opacity is set to 1.0. As shown in figure 3.
On tap the stream stops and the image pulled is analyzed by Apple's CoreImage framework and the eyes and mouth locations are recorded. These points then undergo the same Delaunay Triangulation and distance collection as I performed in designing the training set.

Once the distances are collected, the application finds the necessary 4 ratios, compares them the the ratio averages, and runs equation 3 with the data from table 5. This then produces two values, belonging to the male class and female class.

On completion of the machine learning algorithm, the application compares the male and female class values and selects the larger value, displaying a male or female indicator in the top left over the face indicator. This data is then passed to the second view in the application where all the collected data is displayed. As shown in figures 3 and 4.

This algorithm's runtime is negligible, and the whole process is very organic and smooth. This showed me that we were able to perform a gender detection within milliseconds with decent results.

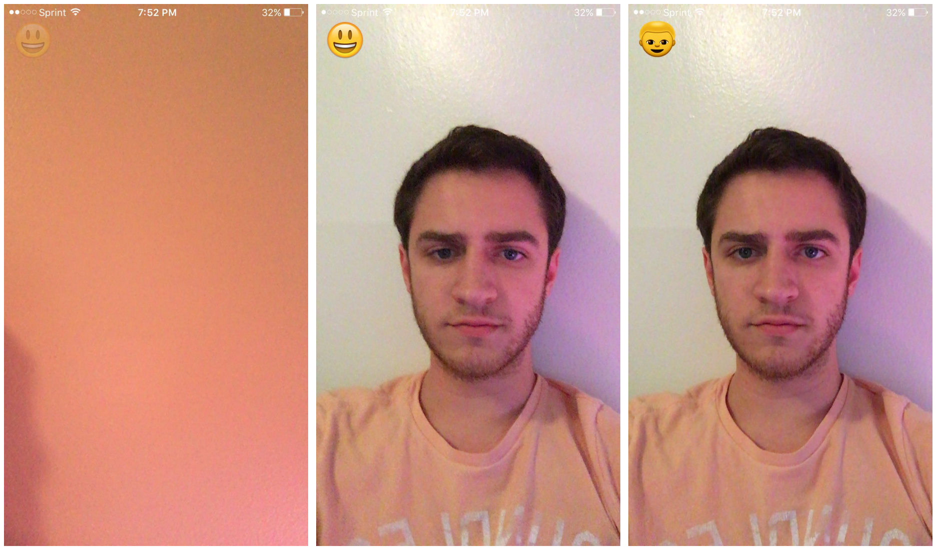

Figure 3: Example of face indicator opacity change and gender recognition.

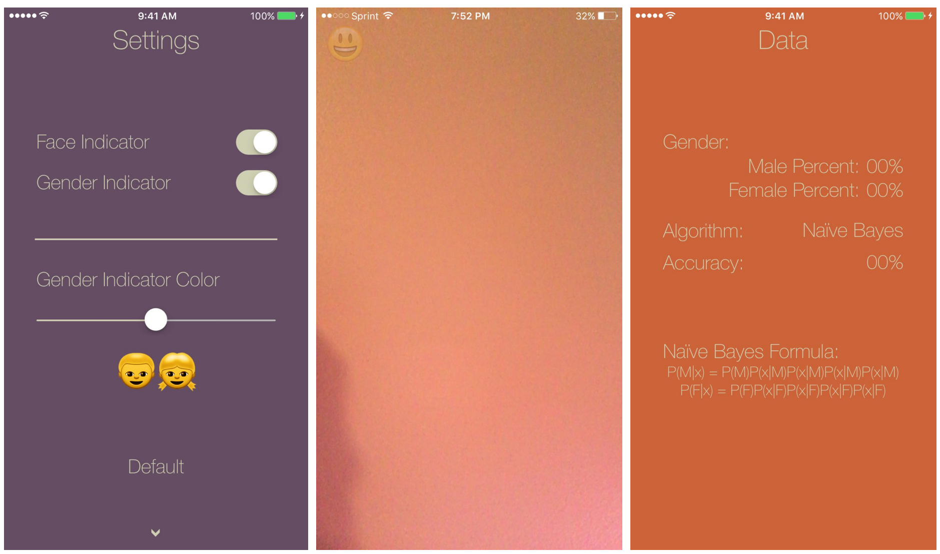

Figure 3: Example of gender detection application's multiple screens.

Conclusion:

Upon analysis of the training set, we were able to achieve a male success rate of 64% and a female success rate of 58%. This gave an average success rate of 62% which is much lower than the theoretical 85%, but this algorithm only took 4 points and all of the ratios had at best a 2% change.

If we also used the face height and width, there are 3 additional ratios with a percent difference greater than 4.5%. This means that I would be able to increase my success rate by about 10 - 15%, this would bring our average success rate to about 75%. Which is impressive given the speed of the algorithm.