Assignment - IAML Fall 2011

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A

(i)

Classifier	NaiveBayes	Junction Tree	SVM
% Correct	12	37	46

(ii)
Since we have ten classes (distinct faces) it would seem reasonable to create ten clusters. Two things of note when examining the clusters are that the amount of records in the clusters is extremely imbalanced with the majority of the records being located in two separate clusters and that different faces are placed in the same cluster.

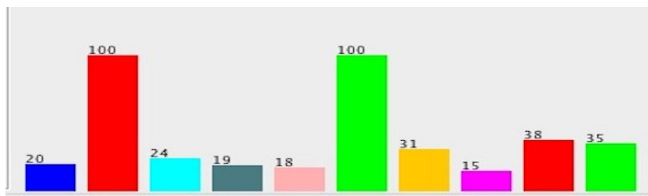


Figure 1: Number of records allocated to each cluster using 10 clusters.

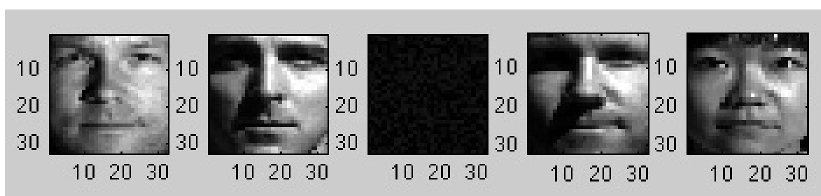


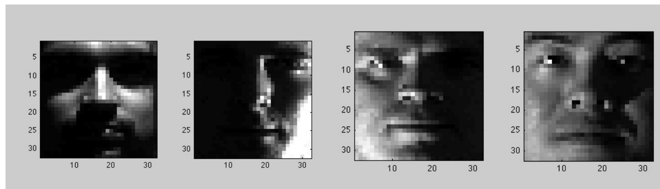
Figure 2: Sample of images from the same cluster.

The classifiers used in part (i) performed so poorly because of the noise found in the data. We can see from the sample shown in Figure 2 that the data contains blocks of all solid colors as well as faces. If we take the cluster count to 12 to account for solid black images and solid white images we can see some more reasonable results. Though the cluster shown of faces, Figure 11 in the appendix, is comprised of several different faces at least there are no solid color in this cluster anymore.
(iii)
To clean the data I used **RemoveWithValues** on values < 5.0 and > 250.0 and was left with 190 instances. I came up with these numbers by first thinking about what the problem appeared to be: images which don't contain a face but just a white or black square. Then, from examining the data in the *Edit* feature of the *Preprocess* tab, I noticed the images that had this characteristic of a single color were mostly comprised of only numbers less than 5.0 or greater than 250.0 (approximately). What I would really have liked to used would be a filter which filters out records which have a variance less than some specified variance. With this tool I could have very effectively filtered out records that were only black or white.
(iv)

Classifier	NaiveBayes	Junction Tree	SVM
% Correct	50.5	55.8	76.3

A very simple way to compare models is by the percentage of the training data they have evaluated correctly. Just this small preprocessing of the data has caused a drastic increase in the performance of the classifiers. Though it was the Naive Bayes classifier that had the most noticeable increase. This is, at least in part, because we had a number of

examples that were duplicated (e.g. all white images), or redundant, and this is known to have negative effects to the Naive Bayes learning process [4]. See Figure 4.
(v)



(a) Incorrectly classified *(b) Correctly classified*

Figure 3: Results from **SMO** *for 1(v)*

It would appear that the classifiers have the most trouble when trying to distinguish faces which contain a lot of black. Though I didn't see any specific examples I would image this is the same for images with large amounts of any single color. In the second incorrect example provided the image is nearly half completely black. This image essentially only has half the information that a more clear image might have which is going to make this harder to classify.

B

(i)
The distribution of Naive Bayes, with numeric attributes, is a normal distribution with the assumption of independence in the attributes. I do not really think this is a sensible choice for this data because the color of pixels in the same region are in fact related and are likely not distributed normally. If pixel_1 has the value 0.0 it is very unlikely that pixel_2 will have the value 250.0 while it is much more likely to have something close to 0.0.

Number of bins	**5**	**10**	**20**	**40**	**60**	**80**	**100**
% Correct	45	57	61.5	62	62.5	60.5	59

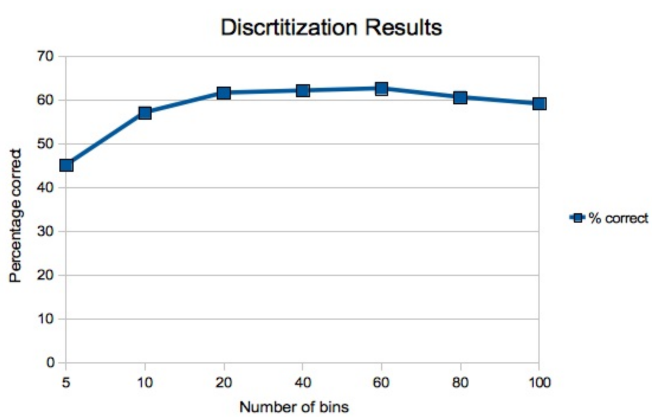


Figure 4: Results of using Naive Bayes on bins of different size

The important things to consider are what range of pixel values are significant. Too large a range will bin dissimilar values together while too small a range will bin similar values into different bins. For this case the best scenario was 60 bins which produced an accuracy rate of 62.5%. In part A we had a Naive Bayes correct percentage rate of 50.5% while with the binning we have maxed the correct percentage at 60 bins and 62.5%. As I mentioned earlier it looks like after 60 bins the range of values in each bin became too small for Naive Bayes to work as intelligently with the data. While the range of values in each bin prior to 60 bins is too large. Additionally what we have done by discretizing the

data is we have removed the assumption that this is a normal distribution.
(ii)
'Attribute evaluator' works by computing the information gain of each attribute and only selecting those with information gain higher than the specified threshold. Information gain in weka is calculated using the following equation:

$$InfoGain(Class, Attribute) = H(Class) - H(Class|Attribute)$$

As a note it is clear that $H(Class) = 1$ for **train_faces_clean.arff** because we have an equal number of each class which when plugged into our entropy equation will produce the maximum entropy:

$$H(S) = \frac{-\sum_{1}^{10} P(\frac{1}{10}) log_2(\frac{1}{10})}{log_2(10)} = 1$$

Where the $log_2(10)$ represents the number of bits of entropy in this system and is used as a normalizer. Weka computes $H(Class|Attribute)$ by first converting the attribute into a discrete value.
(iii)
The pixels with the highest information gain appear to be around the eyes and mouth mostly, with some scatterings throughout the whole face. For face recognition these locations seem to make sense as you can certainly tell a lot about a face by examining where these pixels are concentrated. One thing we couldn't do with this representation of the data is, for example, select faces with similar noses, or scars on their cheeks. This is because we've lost a lot of information about the different areas of the face.

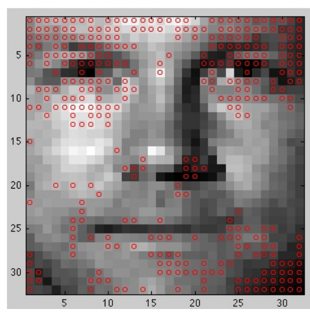


Figure 5: Pixels with the highest information gain.

(iv)

Classifier	NaiveBayes	Junction Tree	SVM
% Correct	60	63.5	91

The performance of each of the classifiers has increased but the Support Vector Machine has drastically increased (14.7%). By removing so many of the attributes, all of which weren't doing anything but confusing our classifiers, we have made the job of the classifier easier. Due to the large increase in the SVM model it is my belief that these attributes we have removed were primarily located near the decision boundary for each class. Since we have removed them the SVM will be able to construct support vectors which more accurately separate the classes.

C

Using the provided **train_faces_clean.arff** file.
(i)
Most eigenvalues are below 1 and the majority sit very close to 0 (or at 0). As we discussed in the lectures this is often the case. See Figure 6.

(ii)
Processing leaves us with 32 Eigenvectors. Compared to part A the Naive Bayes and Support Vector Machine classifiers

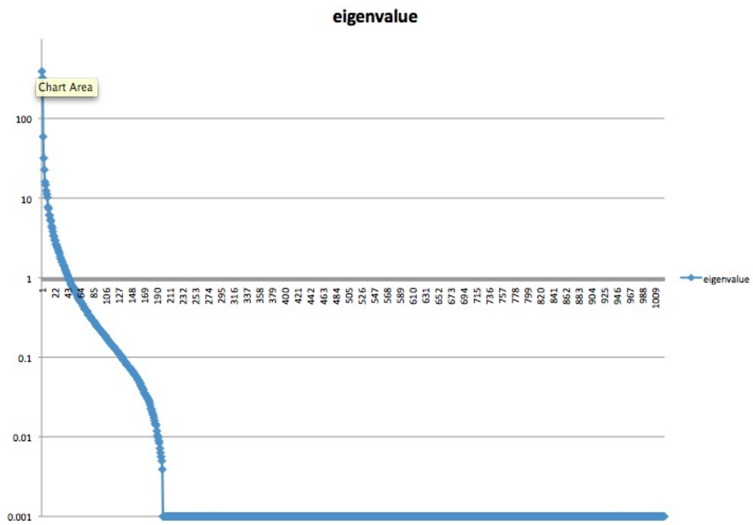


Figure 6: Eigenvalues.

improved significantly while the Junction Tree classifier improved but much less drastically. My intuition here is that the Naive Bayes and Support Vector classifiers benefit from filtering out correlated data (which is a feature of PCA) while the Junction Tree doesn't benefit quite as much (which is why Information Gain is generally used in Junction Trees).

Classifier	**NaiveBayes**	**Junction Tree**	**SVM**
% Correct	81.5	61.5	82.5

(iii)

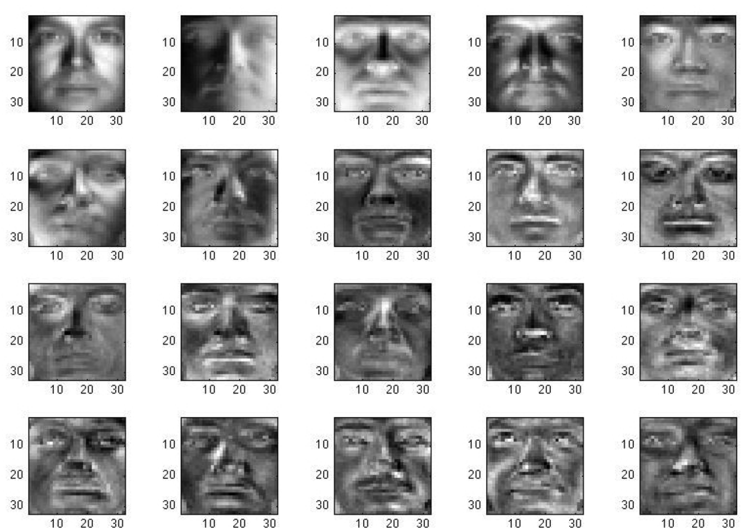
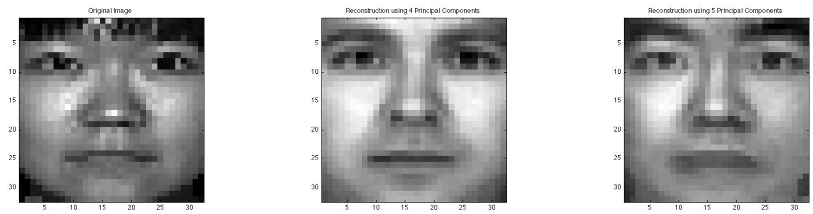


Figure 7: Top 20 Eigenfaces.

First Eigenvalue: 390.78591
Second Eigenvalue: 323.30464
The Eigenfaces we have constructed represent the face similarity in the reduced space. These faces should be insensitive to factors such as lighting, expression, and orientation and are a weighted combination of all the faces in the data set. [7]. If we look at the first two we notice they are actually the same face with variations in the lighting. Where the

first Eigenface is a pretty clear picture the second is less clear.
(iv)
We can reconstruct a recognizable face with 5 components.



(a) Original face *(b) Reconstructed face (4 PCs)* *(c) Reconstructed face (5 PCs)*

Figure 8: Reconstruction of faces from PCs.

(v)
I wouldn't really expect this to matter any more than if we removed the lowest 4 Eigenvectors. With Naive Bayes we are assuming that all of the data is independent so all of the Eigenvectors should matter the same amount. I would expect the classifier accuracy to decrease just based on the fact we are removing information from our training examples. However, it would look like the accuracy improves in this case.

Classifier	**NaiveBayes**
% Correct	82.5

(vi)
Once we add in components past 40 the percent accurate starts dropping. We know from earlier that 95% of the variance is explained by the first 32 of the Eigenvectors so all we are doing by adding in these additional Eigenvectors is adding in outliers which are going to have the effect of causing the support vectors to change thus making our decision boundary less accurate.

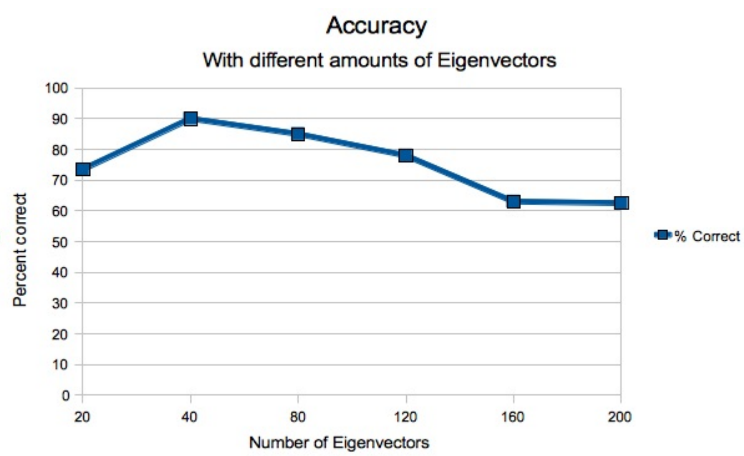


Figure 9: Shows the percentage correctly classified using an SVM.

D

(i)

	NaiveBayes	Junction Tree	SVM
train_clean	53.6(5.95)	61.90(7.19)	88.00(3.15)
train_best	63.6(6.04)	64.30(7.02)	90.10(3.19)
train_pca	79.9(5.80)	60.10(8.49)	80.90(4.89)

When comparing the results using the training sets as the baseline we get:

Confidence: 0.05			
	train_clean	**train_best**	**train_pca**
Naive Bayes	53.6(5.95)	63.60(6.04) V	79.90(5.80) V
Junction Tree	61.90(7.19)	64.30(7.02)	60.10(8.49)
SVM	88.00(3.15)	90.10(3.19)	80.90(4.89) *

Confidence: 0.01			
	train_clean	**train_best**	**train_pca**
Naive Bayes	53.6(5.95)	63.60(6.04) V	79.90(5.80) V
Junction Tree	61.90(7.19)	64.30(7.02)	60.10(8.49)
SVM	88.00(3.15)	90.10(3.19)	80.90(4.89)

From this we can see that the Naive Bayes classifier performs quite well on the **train_best** and **train_pca**. From these results I would use the train_best since at 95% confidence it has 1 win and 2 ties while the **train_pca** has 1 win, 1 loss, and 1 tie.

(ii)

Seed: 42

Percent Remaining	Percent Correct
5%	21.5%
10%	31%
35%	79%
50%	80.5%
65%	91%
80%	90%
100%	92%

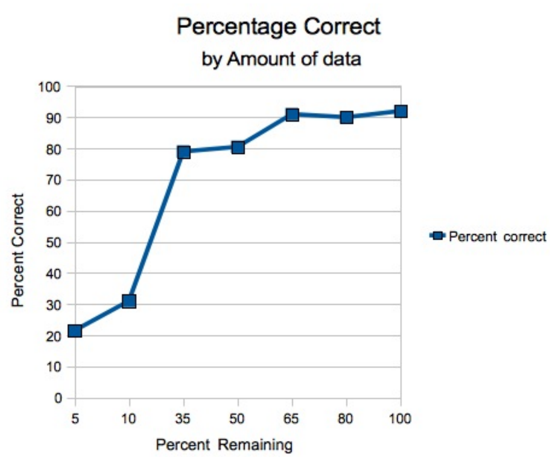


Figure 10: Percentage correct by addition of more data.

It looks at about 65% of the data the accuracy has plateaued at around 90% correct. So, it would appear that adding more data will not really bring us better performance. If we think about what the SVM is doing it is looking for an optimal decision boundary between the classes. At some point the line is going to become relatively constant where

adding more data isn't going to change the decision boundary because the new data will fall to one side of the boundary. This is known to have no effect on the classifier because it is only changing the support vectors that changes how it behaves. We can see this here at the 65% to 100% range where the percentage correct doesn't really change.
(iii)

Classifier	**Naive Bayes & PCA**	**Naive Bayes & PCA & Clustering**
% Correct	83.5%	85.6%

The performance increase from using clustering is 2.1%. By adding cluster labels to the PCA representation we have increased the accuracy of our model, but only slightly. This student's claim about adding cluster labels is not something with which I agree. For one we can see this empirically between the results just obtained (though only in a small degree). Intuitively we can imagine points when applying PCA and attempting to classify them with Naive Bayes are still not classified with a high confidence. Adding a cluster label can give us one more aspect to take into account for our decision.

E

My first objective for this portion of the assignment was to examine, very broadly, some techniques that are already in use for facial recognition and apply those to this set. What I found was that PCA is a very popular approach to this problem as well as ICA, LDA, EBGM, SVM, and HMMs (among many others) [1–3, 5, 6, 8, 9]. Having seen this research and noticing that weka doesn't appear to support ICA, LDA, EGBM, and HMMs being supported only in a downloadable module I decided to focus my efforts on trying different classifiers with PCA and in general see how different classifiers would respond to the data set.

train_faces_clean.arff	
Classifier and settings	**% Accurate**
SVM with PCA (-R=0.99 -C=3.0)	93%
SVM (-C=0.2)	93%
JT48 with clustering (-N=10 -C=0.5)	71.5%
MultilayerPerceptron	93.5%
RBFNetwork with PCA (-R=0.99)	81.5%
Simple Logistic (-P)	95.5%
Random Forest (-I=1024 -K=100 -depth=50)	96.5%

Table 1: Classifiers trained using **train_faces_clean.arff** *with* **val_faces.arff** *as the testing set. Parameters in parenthesis represent only the changed parameters.*

train_faces_clean_best.arff	
Classifier and settings	**% Accurate**
SVM with PCA (-R=0.99 -C=2.0)	94%
SVM (-C=0.7)	94%
JT48 with clustering (-N=10)	71.5%
RBFNetwork with PCA (-R=0.99 -W=0.9)	89%
Simple Logistic (-P)	93.5%
Random Forest (-I=1024 -K=150 -depth=50)	96.5%

Table 2: Classifiers trained using **train_faces_clean_best.arff** *with* **val_faces_best.arff** *as the testing set. Parameters in parenthesis represent only the changed parameters.*

Having come up with the most accurate classifiers I could construct I then took the two different classifiers with the highest accuracy (Simple Logistic and Random Forest with **train_faces_clean.arff**) and combined the training set and validation set into one file and ran 5 fold cross-validation on the new set. The results of this test are in 3. Following this I ran each of these two classifiers (using the combined **train_faces_clean.arff** and **val_faces.arff**) on **test_faces.arff** and compared the difference in predicted values from each classifier. Given the choice between the two I am more confident in the Simple Logistic classifier because all of it's error values are drastically less than those of the Random Forest as shown in Table 3. With the two predicted results I ran a python script to examine each prediction and for each prediction that differed between the two classifiers output the prediction from the classifier that had the highest confidence in its prediction as well as which classifier the new prediction came from. Both the script used for comparison and a final table of the results generated can be found in the appendix. As specified the results have also been submitted in the file iam_assignment.res (this is the Simple Logistic run).

Classifier	% Accurate	RMS Error	Relative Absolute Error	Root Relative Squared Error
Random Forest	98.5%	0.126	35.56%	42%
Simple Logistic	98%	.06	2.57%	19.59%

Table 3: Computed from using 5 fold cross-validation on **train_faces_clean.arff** *joined with* **val_faces.arff**.

APPENDIX

.1 Python program

```
import re
def main():
    with open('iaml_assignment1.res') as f:
        rForest = f.readlines()
    with open('iaml_assignment.res') as f:
        sLog = f.readlines()
    rForest = rForest[22:222]
    sLog = sLog[417:617]
    line = count = 0
    for i,j in zip(rForest,sLog):
        i=i.split();j=j.split();
        if i[2] != j[2]:
            iGuess = float(filter(lambda x: re.search('^\*',x),i)[0].strip('*'))
            jGuess = float(filter(lambda x: re.search('^\*',x),j)[0].strip('*'))
            if iGuess > jGuess: guess = i[2] + '\tFOR'
            else: guess = j[2] + '\tLOG'
            count += 1
        else: guess = i[2]
        line += 1
        print '%s\t%s' % (line,guess)
if __name__ == '__main__':
    main()
```

.2 Results from final testing

Label	Simple Logistic	Random Forest	Combined	Winning Classifier
1	6:6	6:6	6:6	
2	8:8	8:8	8:8	
3	9:9	9:9	9:9	
4	4:4	4:4	4:4	
5	9:9	9:9	9:9	
6	7:7	7:7	7:7	
7	3:3	3:3	3:3	
8	2:2	2:2	2:2	
9	9:9	9:9	9:9	
10	1:1	1:1	1:1	
11	8:8	8:8	8:8	
12	6:6	6:6	6:6	
13	3:3	3:3	3:3	
14	1:1	1:1	1:1	

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Table 4 – continued from previous page

Label	Simple Logistic	Random Forest	Combined	Winning Classifier
15	8:8	8:8	8:8	
16	5:5	5:5	5:5	
17	4:4	4:4	4:4	
18	6:6	6:6	6:6	
19	8:8	8:8	8:8	
20	3:3	3:3	3:3	
21	3:3	3:3	3:3	
22	7:7	7:7	7:7	
23	3:3	3:3	3:3	
24	2:2	2:2	2:2	
25	4:4	4:4	4:4	
26	4:4	4:4	4:4	
27	5:5	5:5	5:5	
28	2:2	2:2	2:2	
29	10:10	10:10	10:10	
30	3:3	3:3	3:3	
31	10:10	10:10	10:10	
32	5:5	5:5	5:5	
33	7:7	7:7	7:7	
34	1:1	1:1	1:1	
35	10:10	10:10	10:10	
36	8:8	8:8	8:8	
37	7:7	7:7	7:7	
38	10:10	7:7	10:10	LOG
39	3:3	3:3	3:3	
40	7:7	4:4	7:7	LOG
41	7:7	4:4	7:7	LOG
42	6:6	6:6	6:6	
43	2:2	2:2	2:2	
44	5:5	5:5	5:5	
45	7:7	7:7	7:7	
46	9:9	9:9	9:9	
47	4:4	4:4	4:4	
48	4:4	4:4	4:4	
49	6:6	6:6	6:6	
50	9:9	9:9	9:9	
51	5:5	5:5	5:5	
52	1:1	1:1	1:1	
53	4:4	4:4	4:4	
54	8:8	8:8	8:8	
55	10:10	10:10	10:10	
56	3:3	7:7	7:7	FOR
57	9:9	9:9	9:9	
58	10:10	10:10	10:10	
59	9:9	9:9	9:9	
60	8:8	8:8	8:8	
61	5:5	5:5	5:5	
62	8:8	8:8	8:8	
63	1:1	1:1	1:1	
64	8:8	8:8	8:8	
65	10:10	10:10	10:10	

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Table 4 – continued from previous page

Label	Simple Logistic	Random Forest	Combined	Winning Classifier
66	8:8	8:8	8:8	
67	9:9	7:7	9:9	LOG
68	8:8	6:6	8:8	LOG
69	7:7	7:7	7:7	
70	4:4	4:4	4:4	
71	5:5	5:5	5:5	
72	7:7	7:7	7:7	
73	6:6	6:6	6:6	
74	5:5	5:5	5:5	
75	1:1	1:1	1:1	
76	8:8	8:8	8:8	
77	4:4	4:4	4:4	
78	3:3	3:3	3:3	
79	9:9	9:9	9:9	
80	2:2	2:2	2:2	
81	1:1	1:1	1:1	
82	7:7	7:7	7:7	
83	10:10	10:10	10:10	
84	5:5	8:8	5:5	LOG
85	2:2	2:2	2:2	
86	4:4	4:4	4:4	
87	2:2	2:2	2:2	
88	10:10	10:10	10:10	
89	10:10	10:10	10:10	
90	6:6	6:6	6:6	
91	5:5	5:5	5:5	
92	6:6	6:6	6:6	
93	4:4	7:7	4:4	LOG
94	7:7	7:7	7:7	
95	8:8	8:8	8:8	
96	2:2	2:2	2:2	
97	9:9	9:9	9:9	
98	10:10	10:10	10:10	
99	6:6	6:6	6:6	
100	5:5	5:5	5:5	
101	10:10	10:10	10:10	
102	7:7	7:7	7:7	
103	10:10	10:10	10:10	
104	5:5	5:5	5:5	
105	8:8	8:8	8:8	
106	9:9	9:9	9:9	
107	5:5	5:5	5:5	
108	8:8	8:8	8:8	
109	6:6	6:6	6:6	
110	9:9	9:9	9:9	
111	1:1	1:1	1:1	
112	9:9	9:9	9:9	
113	7:7	7:7	7:7	
114	6:6	6:6	6:6	
115	5:5	5:5	5:5	
116	5:5	5:5	5:5	

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Table 4 – continued from previous page

Label	Simple Logistic	Random Forest	Combined	Winning Classifier
117	4:4	4:4	4:4	
118	1:1	1:1	1:1	
119	1:1	1:1	1:1	
120	2:2	2:2	2:2	
121	7:7	7:7	7:7	
122	2:2	2:2	2:2	
123	3:3	3:3	3:3	
124	2:2	2:2	2:2	
125	9:9	9:9	9:9	
126	5:5	5:5	5:5	
127	4:4	4:4	4:4	
128	3:3	3:3	3:3	
129	1:1	1:1	1:1	
130	3:3	10:10	3:3	LOG
131	10:10	10:10	10:10	
132	1:1	1:1	1:1	
133	3:3	3:3	3:3	
134	2:2	2:2	2:2	
135	3:3	3:3	3:3	
136	5:5	5:5	5:5	
137	8:8	8:8	8:8	
138	6:6	6:6	6:6	
139	6:6	6:6	6:6	
140	1:1	1:1	1:1	
141	4:4	4:4	4:4	
142	4:4	4:4	4:4	
143	6:6	6:6	6:6	
144	6:6	6:6	6:6	
145	1:1	1:1	1:1	
146	2:2	2:2	2:2	
147	3:3	3:3	3:3	
148	7:7	7:7	7:7	
149	2:2	2:2	2:2	
150	1:1	1:1	1:1	
151	8:8	8:8	8:8	
152	5:5	5:5	5:5	
153	9:9	9:9	9:9	
154	7:7	7:7	7:7	
155	5:5	5:5	5:5	
156	3:3	3:3	3:3	
157	3:3	7:7	3:3	LOG
158	1:1	1:1	1:1	
159	10:10	10:10	10:10	
160	2:2	2:2	2:2	
161	9:9	9:9	9:9	
162	8:8	8:8	8:8	
163	10:10	10:10	10:10	
164	2:2	2:2	2:2	
165	2:2	2:2	2:2	
166	8:8	8:8	8:8	
167	4:4	4:4	4:4	

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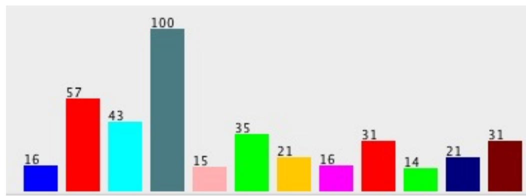
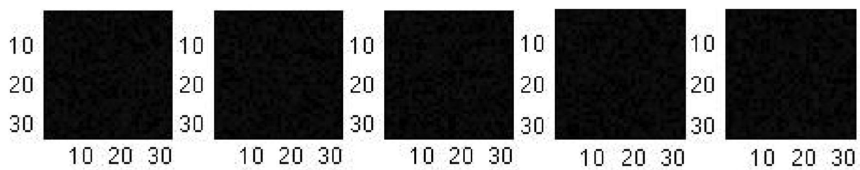
Table 4 – continued from previous page

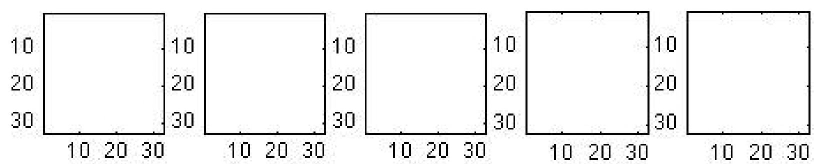
Label	Simple Logistic	Random Forest	Combined	Winning Classifier
168	10:10	10:10	10:10	
169	3:3	3:3	3:3	
170	1:1	1:1	1:1	
171	3:3	3:3	3:3	
172	6:6	6:6	6:6	
173	1:1	1:1	1:1	
174	2:2	2:2	2:2	
175	6:6	6:6	6:6	
176	10:10	10:10	10:10	
177	3:3	3:3	3:3	
178	9:9	9:9	9:9	
179	7:7	7:7	7:7	
180	2:2	2:2	2:2	
181	7:7	7:7	7:7	
182	4:4	4:4	4:4	
183	1:1	1:1	1:1	
184	6:6	6:6	6:6	
185	8:8	8:8	8:8	
186	10:10	10:10	10:10	
187	6:6	6:6	6:6	
188	5:5	5:5	5:5	
189	4:4	4:4	4:4	
190	9:9	9:9	9:9	
191	8:8	8:8	8:8	
192	9:9	9:9	9:9	
193	8:8	8:8	8:8	
194	9:9	9:9	9:9	
195	10:10	10:10	10:10	
196	3:3	3:3	3:3	
197	1:1	1:1	1:1	
198	5:5	5:5	5:5	
199	2:2	2:2	2:2	
200	3:3	3:3	3:3	



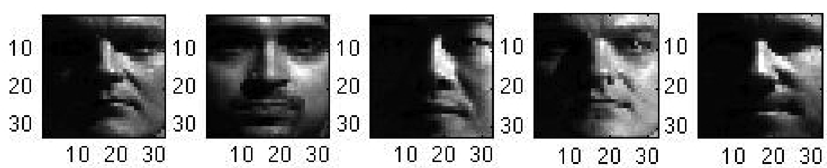
(a) Distribution of 12 clusters



(b) Sample from cluster 4



(c) Sample from cluster 2



(d) Sample from cluster 1

Figure 11: Results from A(ii) using 12 clusters.

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