Patter Recognition
CS - 669

ASSIGNMENT 2

GMM and K-Means Clustering

Group Number 13

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1. Problem Description

Data-sets:

- Data-set 1: 2-dimensional artificial data of 3 or 4 classes: nonlinearly separable data set used in Assignment 1:
- Data-set 2: Real world data set:
  - Two dimensional speech dataset used in Assignment 1
  - 3 class scene image dataset
  - Cervical cytology (cell) image dataset

Dataset 1 and Dataset 2(a), 75% of data of a class is to be used as training data for that class, and the remaining data is to be used as test data for that class. For Dataset 2(b) and Dataset 2(c), training and test sets are given.

Classifiers:

- GMM
- K-Means Clustering

Objective:

1. Build Bayes classifier using GMM to classify data points of given data-sets on the basis of specified classifiers. Parameters of GMM are to be initialized using K-means clustering.
2. Segment the cell images by clustering the local feature vectors from cell image datasets into 3 groups using (a) K-means clustering and (b) clustering using GMM. GMM is built using the K-means clustering to initialize the parameters.
3. For each classifier and each data-set we do :
   - Classification accuracy, precision for every class, mean precision, recall for every class, mean recall, F-measure for every class and mean F-measure on test data.
   - Confusion matrix based on the performance for test data.
   - Constant density contour plot for all the classes together with the training data superposed.
   - Decision region plot with the training data superposed (only for Dataset-1 and Dataset 2(a)) superposed.
   - Result should also consist of plot of 3 clusters on training data of Dataset 2(c) and the result of cluster projected on test images.
   - Graph of iterations vs log likelihood for all the datasets with different number of components.

2. Solution Approach

1 Feature Extraction

1.1 Colour histogram feature

We extract 64 x 64 non overlapping patches on every image from the training and test sets.Extracting 8-bin colour histogram from each R, G and B from a patch, results in 3, 8-dimensional feature vectors. Concatenating them we form a 24-dimensional feature vector. Doing similar computation on all, every image is represented as a set of 24-dimensional colour histogram vectors.

When the given image is read, it will be read as 3-dimensional matrix of pixel values. Each dimension is corresponding to a colour channel. The pixel values in each colour channel are in the range 0 to 255. For a colour channel,

- Divide this range into 8 equal bins.
- Count the number of pixels falling into each bins. This results in a vector of 8 values.
- This is the 8-dimensional colour histogram (from a colour channel) feature vector. Do the same for other colour channels. Concatenate those three 8-dimensional colour histogram vectors to form 24-dimensional vector.

1.2 Bag-of-visual-words (BoVW) feature using K-means clustering

Take the 24-dimensional colour histogram feature vectors of all the training examples of all the classes. Group them into 64 clusters using K-means clustering algorithms. Now take an image, assign each 24-dimensional colour histogram feature vector to a cluster. Count the number of feature vectors assigned to each of the 64 clusters. This results in a 64-dimensional BoVW representation for that image. Repeat this for every images in training and test set.

1.3 K-Means Clustering

K-Means clustering is the simplest clustering algorithm. We have to specify the number of clusters and it gives a decent approximation of the different partitions. K-Means is mostly used as a pre-clustering algorithm to get a decent starting point for the actual clustering algorithm.

In this assignment also, we use K-Means for pre-clustering the data that is then classified using GMM.

For Dataset 1 (2-dimensional artificial data of 3 or 4 classes) , we did K-means clustering to obtain means and covariances of the k clusters. The value of k was taken as 1,2,4,8,16,32 and 64 and for each value of k taken, the points were classified into the respective clusters using minimum distance measure.The means of these clusters were updated depending upon the points that are categorised into the clusters.This was repeated several times , till convergence criteria was achieved.

Method

Using K-Means clustering, we assign data points to clusters, as well as a set of vectors μ_{k}, such that the sum of the squares of the distances of each data point to its closest vector μ_{k}, is minimum. This sum is given by,

$$J = \sum_{n=1}^{N}\sum_{k=1}^{K} r_{nk}||x_n - \mu_{\mathrm{k}}||^2 \tag{2..1}$$

The steps of K-means clustering are as follows :

First we choose some initial values for the μ_{k}. In the first phase, we minimize J with respect to the r_{nk} , keeping the μ_{k} fixed. This tells us which point belongs to which cluster .This is given by the formula,

$$r_{nk} = \begin{cases} 1, & \text{if } k = argmin_j||x_n - \mu_{\mathrm{k}}||^2 \\ 0, & \text{otherwise} \end{cases} \tag{2..2}$$

In the second phase we minimize J with respect to the μ_{k}, keeping r_{nk} fixed. This gives us the new k for each cluster. This is given by,

$$\mu_{\mathrm{k}} = \frac{\Sigma_n r_{nk} x_n}{\Sigma_n r_{nk}} \tag{2..3}$$

This two-stage optimization is then repeated until convergence criteria is satisfied.(i.e. Log likelihood is lesser than a certain threshold).

1.4 GMM (Gaussian Mixture Model)

In K-Means, we assume each point is a part of a single cluster only. In Gaussian Mixture Model, we find the responsibility that each cluster takes in generating each point.Basically, we find the probability of each point being in each cluster. Even in the GMM technique, the way of initialising means is not specified. Since we already have a decent approximation from the K-means algorithm, we use the results of the K-means clustering only. Taking the final means and variances of the different clusters from the K-means clustering results, we apply GMM to it.

For each data point x_n we define a set of binary indicator variables p_{ik} which describe which cluster the point belongs to. To find π_{k}, we need to know which data points belong to which cluster, and how many data points belong to which cluster. So, using K-means clustering, we first classify them according to minimum distance measure and calculate π_{k} for each cluster. Once we have initial values for mean, variance and π for each cluster, we find the responsibility term γ for each data point π with respect to each cluster k,using the formula,

$$\gamma(\mathrm{z_{nk}}) = \frac{\pi_k N(x_n|\mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j N(x_n|\mu_j, \Sigma_j)} \tag{2..4}$$

This is known as the expectation step of the EM algorithm. Using γ, we estimate the parameters μ_{k}, Σ_{k} and π_{k} again such that the total data likelihood is maximized.

$$\mu_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) x_n \tag{2..5}$$

$$\Sigma_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(x_n - \mu_k^{new})(x_n - \mu_k^{new})^T \tag{2..6}$$

$$\pi_k^{new} = \frac{N_k}{N} \tag{2..7}$$

where,

$$N_k = \sum_{n=1}^{N} \gamma(z_{nk}) \tag{2..8}$$

This is known as the Maximization step of the EM algorithm.

After every iteration,we have to find log likelihood value using,

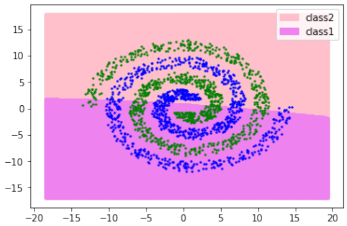
$$\ln p(X|\mu, \Sigma, \pi) = \sum_{n=1}^{N} \ln \{\sum_{k=1}^{K} \pi_k N(x_n|\mu_k, \Sigma_k)\} \tag{2..9}$$

And we repeat the process till l_{new} - l_{old} is less than a particular threshold value. This is called **Convergence Criteria.**

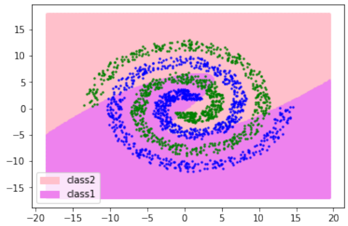
3. Results and Plots

1 Data Set 1 : Non Linearly Separable Data

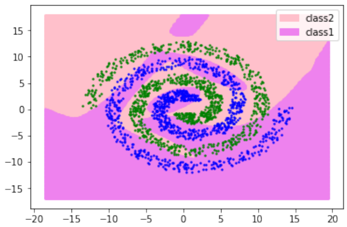
Decision boundary plots



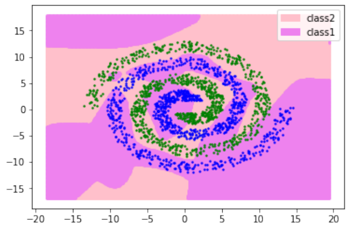
(a) Plot between class 1 and 2 for 1 cluster.



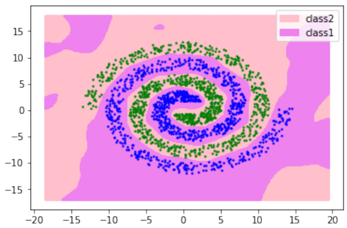
(b) Plot between class 1 and 2 for 2 clusters.



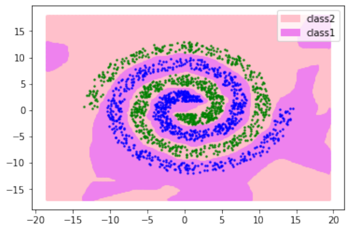
(c) Plot between class 1 and 2 for 4 clusters.



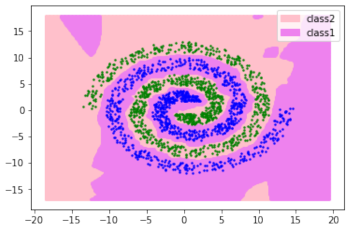
(d) Plot between class 1 and 2 for 8 clusters.



(e) Plot between class 1 and 2 for 16 clusters.



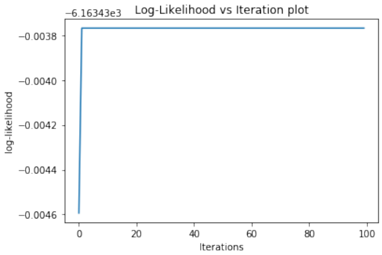
(f) Plot between class 1 and 2 for 32 clusters.



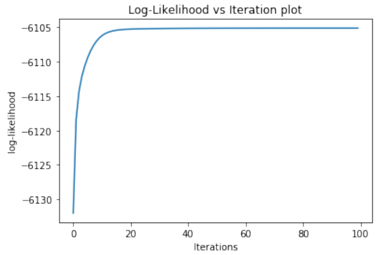
(g) Plot between class 1 and 2 for 64 clusters.

Figure 3..1. Non Linearly Separable Data Classifier Using GMM

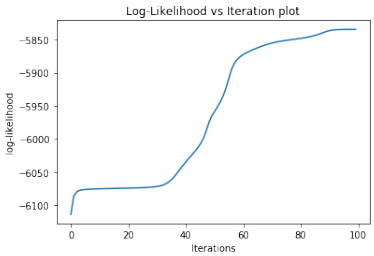
Convergence plots class1



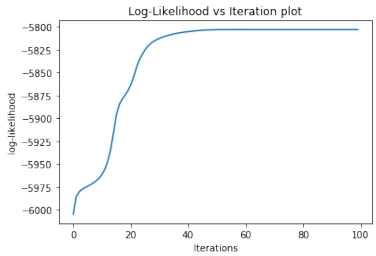
(a) convergence plot for class 1 for 1 cluster.



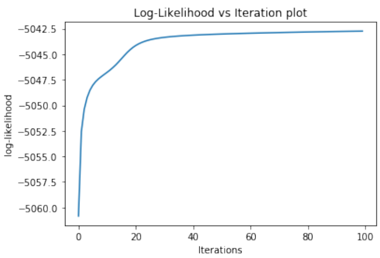
(b) Convergence plot for class 1 for 2 clusters.



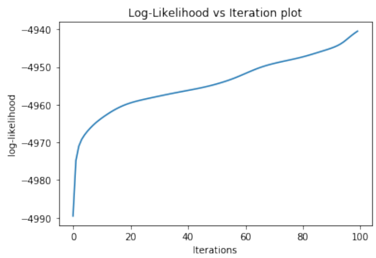
(c) Convergence plot for class 1 for 4 clusters.



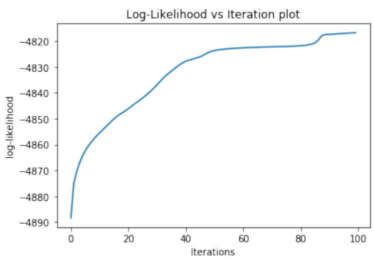
(d) Convergence plot for class 1 for 8 clusters.



(e) Convergence plot for class 1 for 16 clusters.



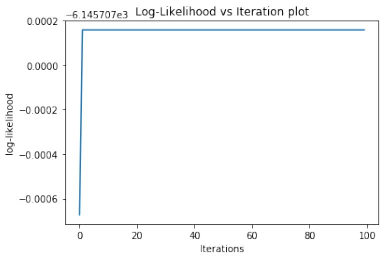
(f) Convergence plot for class 1 for 32 clusters.



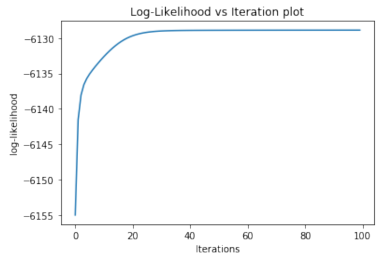
(g) Convergence plot for class 1 for 64 clusters.

Figure 3..2. Convergence plots for class1 using different number of clusters

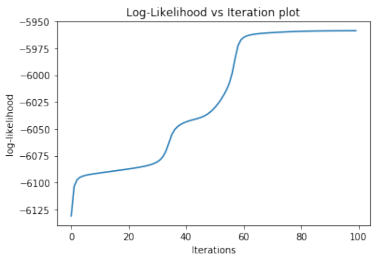
Convergence plots class2



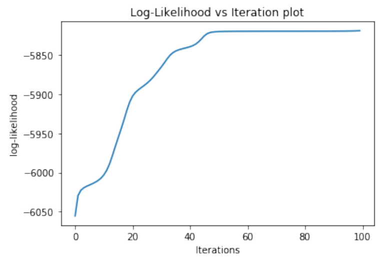
(a) Convergence plot for class 2 for 1 cluster.



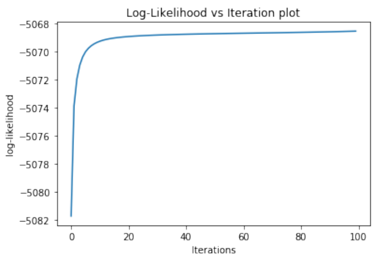
(b) Convergence plot for class 2 for 2 clusters.



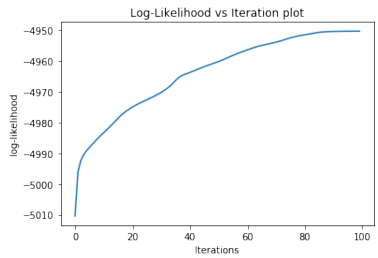
(c) Convergence plot for class 2 for 4 clusters.



(d) Convergence plot for class 2 for 8 clusters.



(e) Convergence plot for class 2 for 16 clusters.

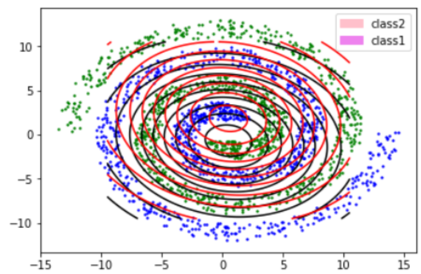


(f) Convergence plot for class 2 for 32 clusters.

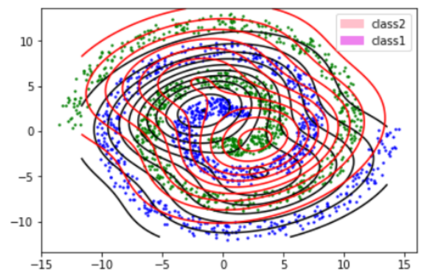
(g) Convergence plot for class 2 for 64 clusters.

Figure 3..3. Convergence plots for class2 using different number of clusters

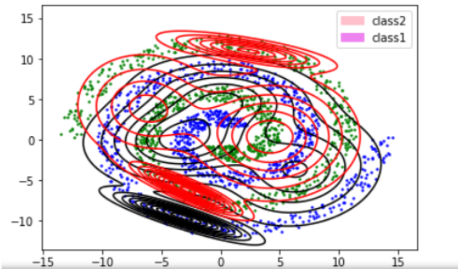
Contours



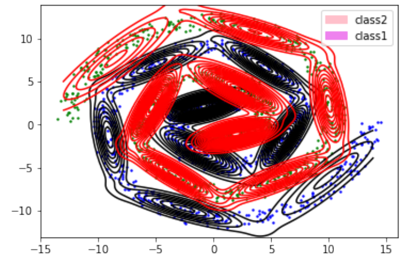
(a) Contour plot for class1 and class2 for 1 cluster.



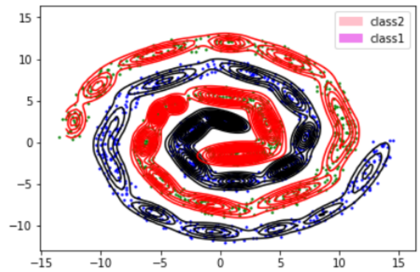
(b) Contour plot for class1 and class2 for 2 clusters.



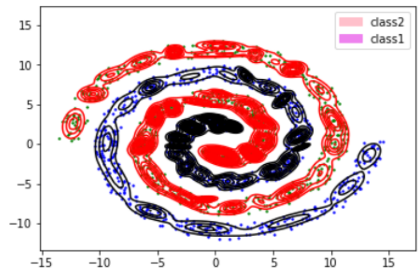
(c) Contour plot for class1 and class2 for 4 clusters.



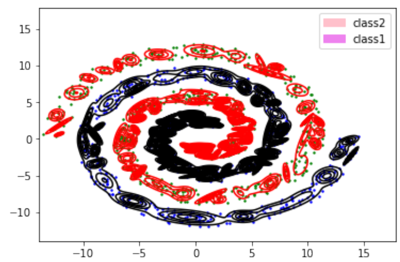
(d) Contour plot for class1 and class2 for 8 clusters.



(e) Contour plot for class1 and class2 for 16 clusters.



(f) contour plot for class1 and class2 for 32 clusters.



(g) Contour plot for class1 and class2 for 64 clusters.

Figure 3..4. Contour plots for class1 and class2 using different number of clusters

Confusion Matrix, Precision, Recall and F-measure

Accuracy=55.06%

	Class1	Class 2
Class1	189	137
Class2	156	170

(a) Confusion Matrix

	Class1	Class2
Precision	0.55	0.55
Recall	0.58	0.52
F-Measure	0.56	0.54

(b) Analysis

Table 3..1. Bayes classifier using GMM for 1 cluster

Accuracy=58.74%

	Class2	Class 3
Class2	191	135
Class3	134	192

(a) Confusion Matrix

	Class2	Class3
Precision	0.59	0.59
Recall	0.59	0.59
F-Measure	0.59	0.59

(b) Analysis

Table 3..2. Bayes classifier using GMM for 2 clusters

Accuracy=84.20%

	Class1	Class 3
Class1	264	62
Class3	41	285

(a) Confusion Matrix

	Class1	Class3
Precision	0.87	0.82
Recall	0.81	0.87
F-Measure	0.84	0.85

(b) Analysis

Table 3..3. Bayes classifier using GMM for 4 clusters

Accuracy=84.05%

	Class1	Class2
Class1	280	46
Class2	58	268

(a) Confusion Matrix

	Class1	Class2
Precision	0.83	0.85
Recall	0.86	0.82
F-Measure	0.84	0.84

(b) Analysis

Table 3..4. Bayes classifier using GMM for 8 clusters

Accuracy=100%

	Class1	Class2
Class1	326	0
Class2	0	326

(a) Confusion Matrix

	Class1	Class2
Precision	1.0	1.0
Recall	1.0	1.0
F-Measure	1.0	1.0

(b) Analysis

Table 3..5. Bayes classifier using GMM for 16 clusters

Accuracy=100%

	Class1	Class2
Class1	326	0
Class2	0	326

(a) Confusion Matrix

	Class1	Class2
Precision	1.0	1.0
Recall	1.0	1.0
F-Measure	1.0	1.0

(b) Analysis

Table 3..6. Bayes classifier using GMM for 32 clusters

Accuracy=100%

	Class1	Class2
Class1	326	0
Class2	0	326

(a) Confusion Matrix

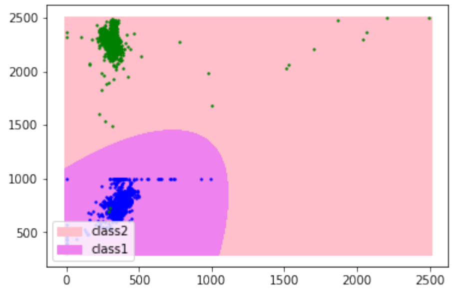
	Class1	Class2
Precision	1.0	1.0
Recall	1.0	1.0
F-Measure	1.0	1.0

(b) Analysis

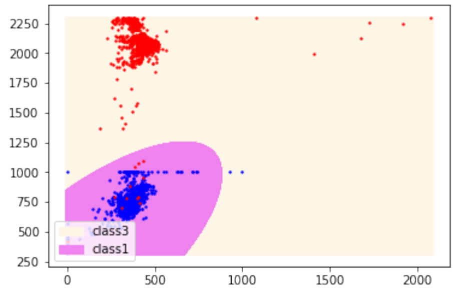
Table 3..7. Bayes classifier using GMM for 64 clusters

2 Data Set 2 : Real World Data

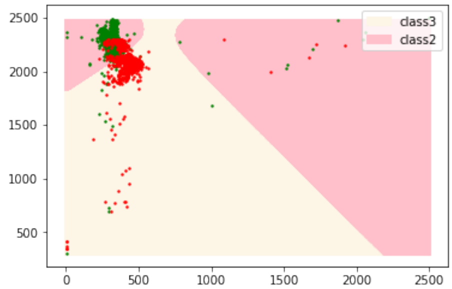
Decision boundary plots for 1 cluster



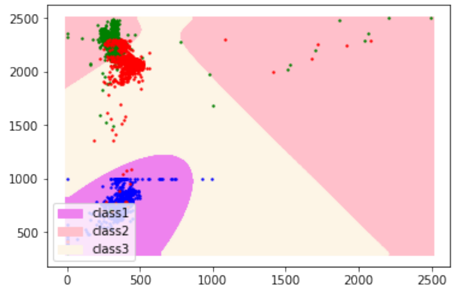
(a) Plot between class 1 and 2 for 1 cluster.



(b) Plot between class 1 and 3 for 1 cluster.



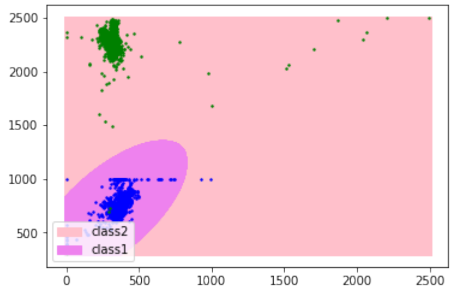
(c) Plot between class 2 and 3 for 1 cluster.



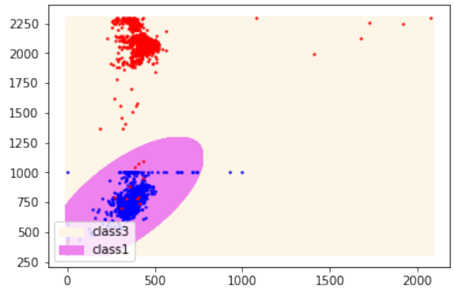
(d) Plot between class 1 and 2 and 3 for 1 cluster.

Figure 3..5. Real World Data Classifier Using GMM with 1 cluster

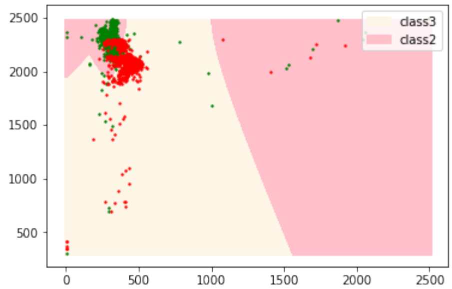
Decision boundary plots for 2 clusters



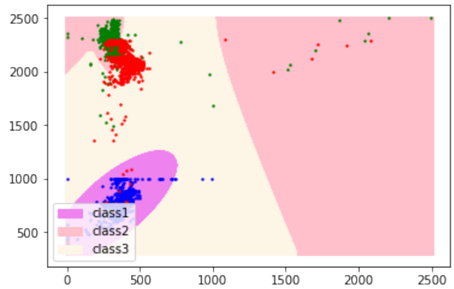
(a) Plot between class 1 and 2 for 2 clusters.



(b) Plot between class 1 and 3 for 2 clusters.



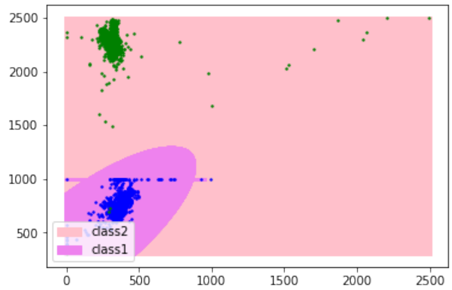
(c) Plot between class 2 and 3 for 2 clusters.



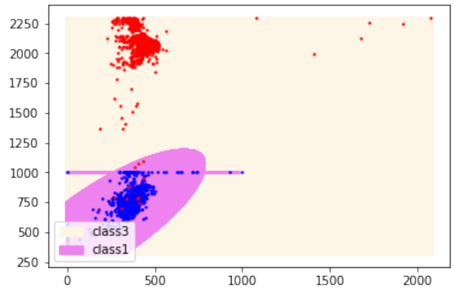
(d) Plot between class 1 and 2 and 3 for 2 clusters.

Figure 3..6. Real World Data Classifier Using GMM with 2 clusters

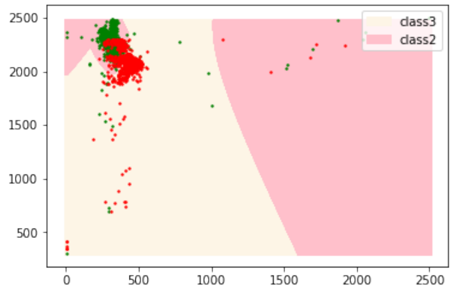
Decision boundary plots for 4 clusters



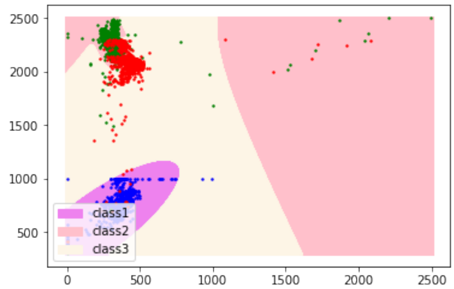
(a) Plot between class 1 and 2 for 4 clusters.



(b) Plot between class 1 and 3 for 4 clusters.



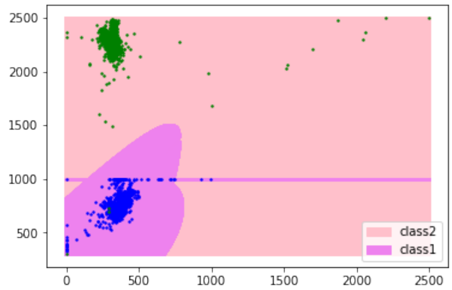
(c) Plot between class 2 and 3 for 4 clusters.



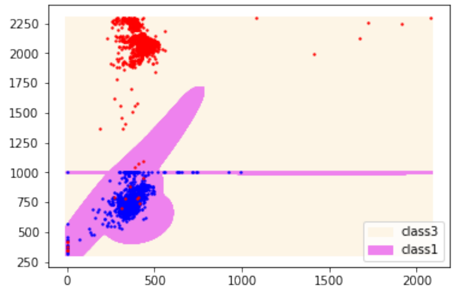
(d) Plot between class 1 and 2 and 3 for 4 clusters.

Figure 3..7. Real World Data Classifier Using GMM with 4 clusters

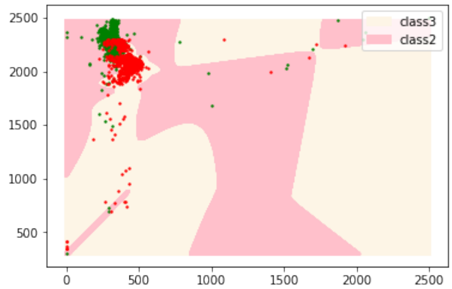
Decision boundary plots for 8 clusters



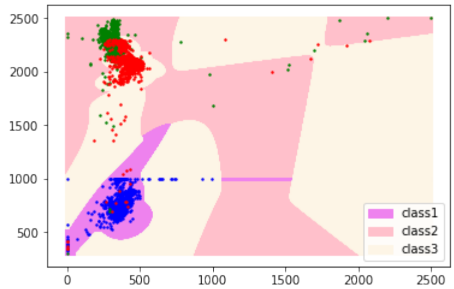
(a) Plot between class 1 and 2 for 8 clusters.



(b) Plot between class 1 and 3 for 8 clusters.



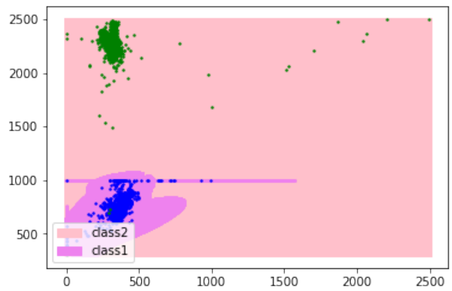
(c) Plot between class 2 and 3 for 8 clusters.



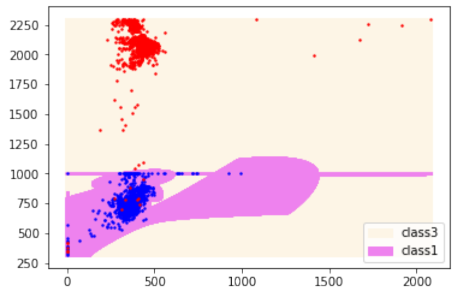
(d) Plot between class 1 and 2 and 3 for 8 clusters.

Figure 3..8. Real World Data Classifier Using GMM with 8 clusters

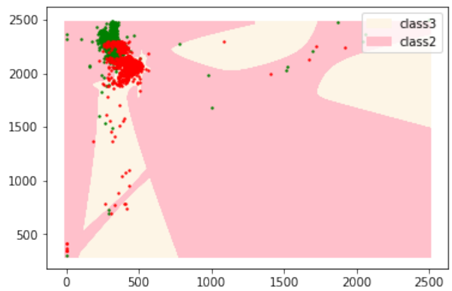
Decision boundary plots for 16clusters



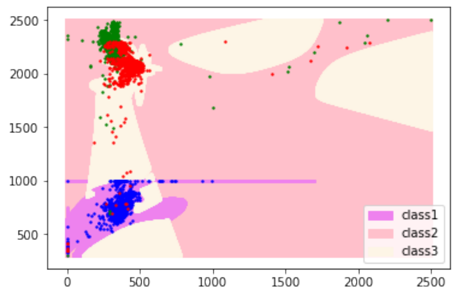
(a) Plot between class 1 and 2 for 16 clusters.



(b) Plot between class 1 and 3 for 16 clusters.



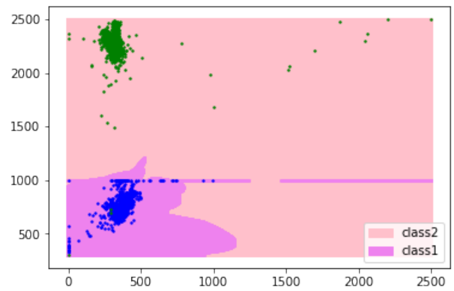
(c) Plot between class 2 and 3 for 16 clusters.



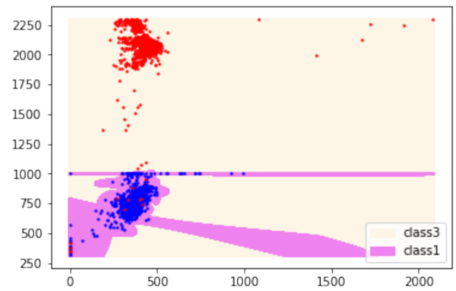
(d) Plot between class 1 and 2 and 3 for 16 clusters.

Figure 3..9. Real World Data Classifier Using GMM with 16 clusters

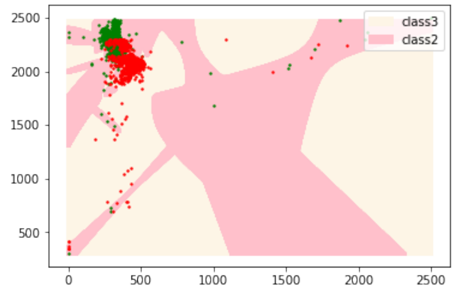
Decision boundary plots for 32 clusters



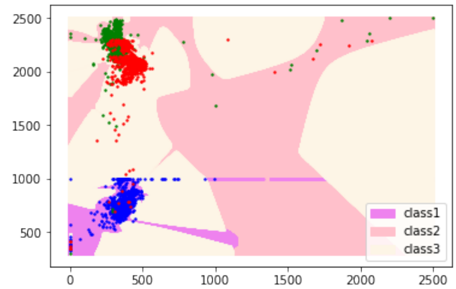
(a) Plot between class 1 and 2 for 32 clusters.



(b) Plot between class 1 and 3 for 32 clusters.



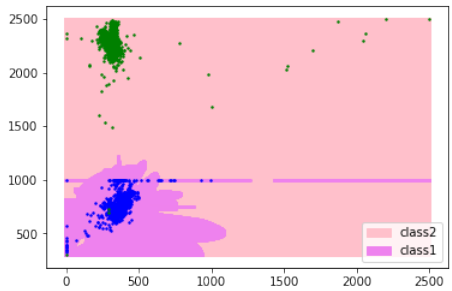
(c) Plot between class 2 and 3 for 32 clusters.



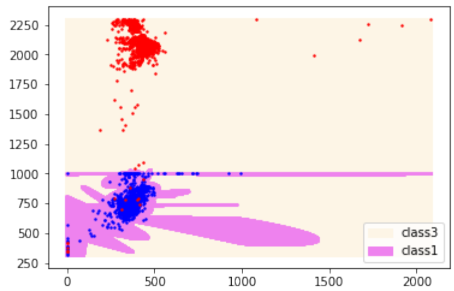
(d) Plot between class 1 and 2 and 3 for 32 clusters.

Figure 3..10. Real World Data Classifier Using GMM with 32 clusters

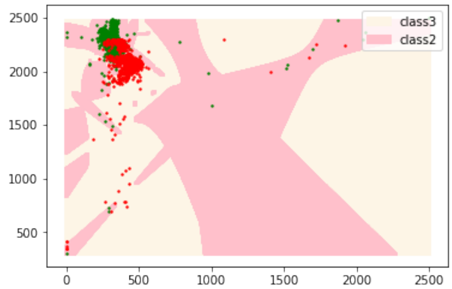
Decision boundary plots for 64 clusters



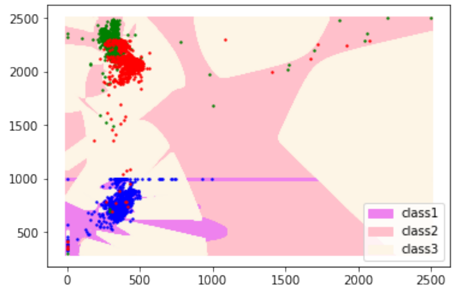
(a) Plot between class 1 and 2 for 64 clusters.



(b) Plot between class 1 and 3 for 64 clusters.



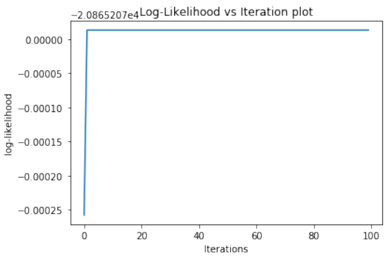
(c) Plot between class 2 and 3 for 64 clusters.



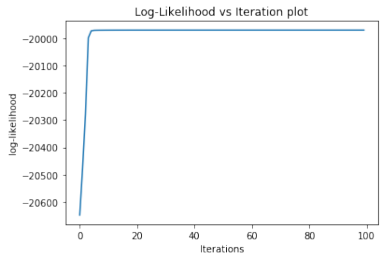
(d) Plot between class 1 and 2 and 3 for 64 clusters.

Figure 3..11. Real World Data Classifier Using GMM with 64 clusters

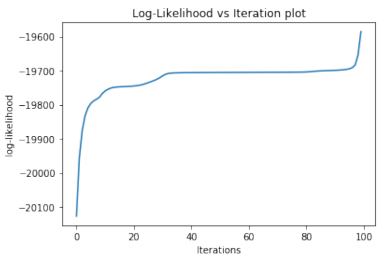
Convergence plots for class1



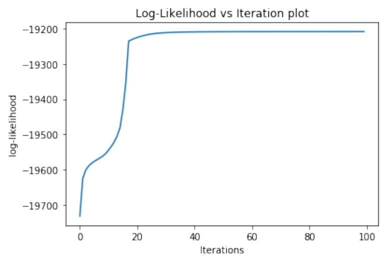
(a) convergence plot for class 1 for 1 cluster.



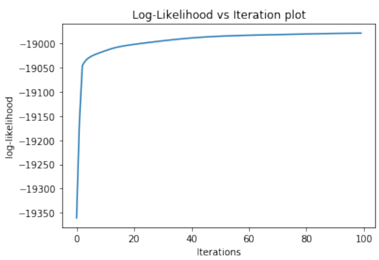
(b) Convergence plot for class 1 for 2 clusters.



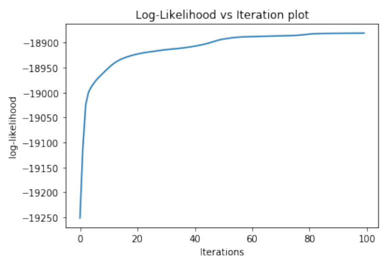
(c) Convergence plot for class 1 for 4 clusters.



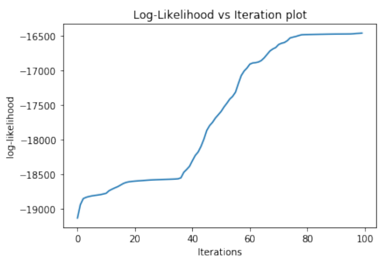
(d) Convergence plot for class 1 for 8 clusters.



(e) Convergence plot for class 1 for 16 clusters.



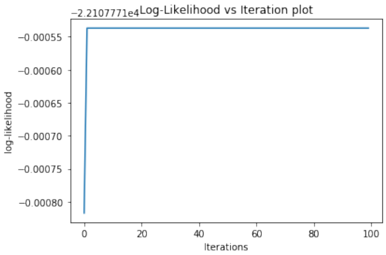
(f) Convergence plot for class 1 for 32 clusters.



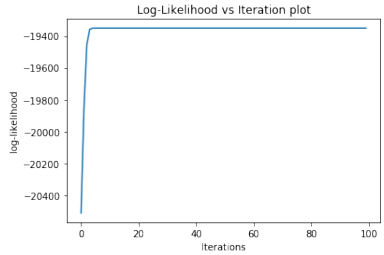
(g) Convergence plot for class 1 for 64 clusters.

Figure 3..12. Convergence plots for class1 using different number of clusters

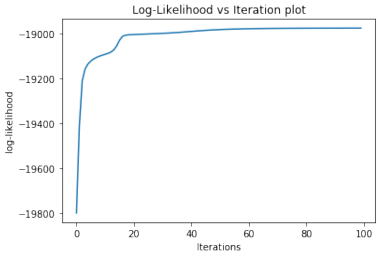
Convergence plots for class2



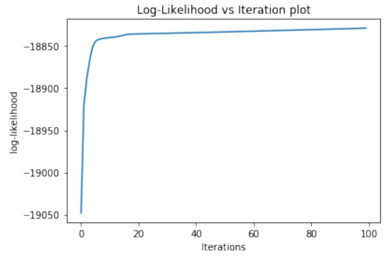
(a) convergence plot for class 2 for 1 cluster.



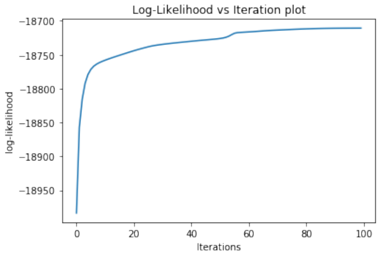
(b) Convergence plot for class 2 for 2 clusters.



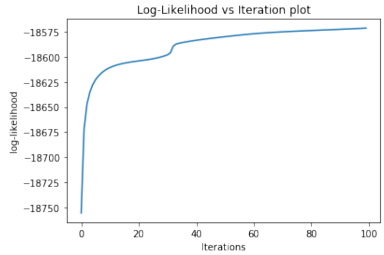
(c) Convergence plot for class 2 for 4 clusters.



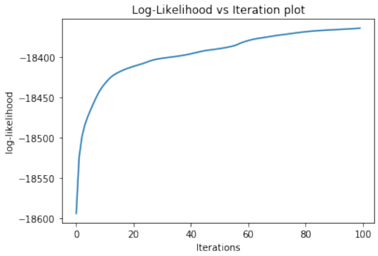
(d) Convergence plot for class 2 for 8 clusters.



(e) Convergence plot for class 2 for 16 clusters.



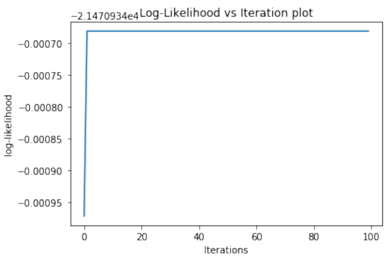
(f) Convergence plot for class 2 for 32 clusters.



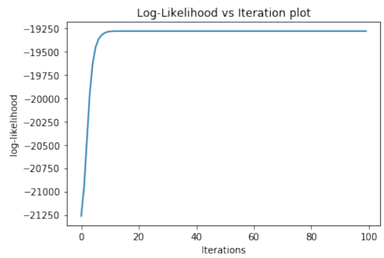
(g) Convergence plot for class 2 for 64 clusters.

Figure 3..13. Convergence plots for class2 using different number of clusters

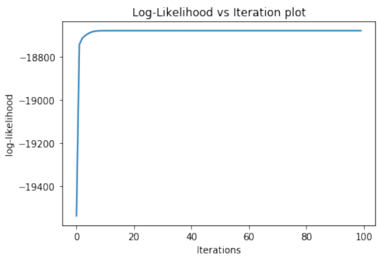
Convergence plots for class3



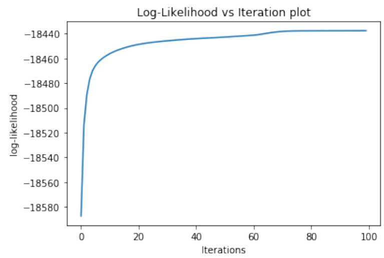
(a) convergence plot for class 3 for 1 cluster.



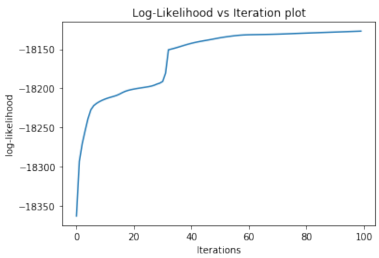
(b) Convergence plot for class 3 for 2 clusters.



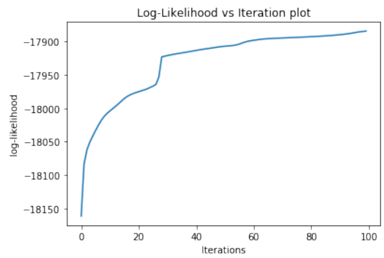
(c) Convergence plot for class 3 for 4 clusters.



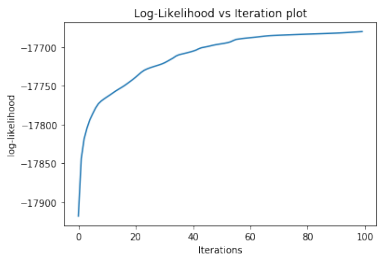
(d) Convergence plot for class 3 for 8 clusters.



(e) Convergence plot for class 3 for 16 clusters.



(f) Convergence plot for class 3 for 32 clusters.



(g) Convergence plot for class 3 for 64 clusters.

Figure 3..14. Convergence plots for class3 using different number of clusters

Real World data classifier for 1 cluster

Accuracy=100%

	Class1	Class 2
Class1	622	0
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..8. Real World data classifier for 1 cluster : Class1 and Class2

Accuracy=99.75%

	Class1	Class 3
Class1	621	1
Class3	2	571

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..9. Real World data classifier for 1 cluster : Class1 and Class3

Accuracy=88.20%

	Class2	Class 3
Class2	581	16
Class3	122	451

(a) Confusion Matrix

	Class2	Class3
Precision	0.83	0.88
Recall	0.97	0.79
F-Measure	0.89	0.87

(b) Analysis

Table 3..10. Real World data classifier for 1 cluster : Class2 and Class3

	Class1	Class2	Class 3
Class1	621	0	1
Class2	0	581	16
Class3	2	122	449

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.83	92.30	92.13
Precision	1.00	0.83	0.96
Recall	1.00	0.97	0.78
F-Measure	1.00	0.89	0.86

(b) Analysis

Table 3..11. Real World data classifier for 1 cluster: Class1 a nd Class2 and Class3

Real World data classifier for 2 clusters

Accuracy=99.92%

	Class1	Class 2
Class1	621	1
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..12. Real World data classifier for 2 clusters :
Class1 and Class2

Accuracy=99.75%

	Class1	Class 3
Class1	621	1
Class3	2	571

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..13. Real World data classifier for 2 clusters :
Class1 and Class3

Accuracy=94.19%

	Class2	Class 3
Class2	570	27
Class3	41	532

(a) Confusion Matrix

	Class2	Class3
Precision	0.93	0.95
Recall	0.95	0.92
F-Measure	0.94	0.94

(b) Analysis

Table 3..14. Real World data classifier for 2 clusters :
Class2 and Class3

	Class1	Class2	Class 3
Class1	621	0	1
Class2	0	570	27
Class3	2	41	530

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.83	96.21	96.04
Precision	1.00	0.93	0.95
Recall	1.00	0.95	0.92
F-Measure	1.00	0.94	0.94

(b) Analysis

Table 3..15. Real World data classifier for 2 clusters :
Class1 and Class2 and Class3

Real World data classifier for 4 clusters

Accuracy=100%

	Class1	Class 2
Class1	622	0
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..16. Real World data classifier for 4 clusters :
Class1 and Class2

Accuracy=99.83%

	Class1	Class 3
Class1	622	10
Class3	2	571

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..17. Real World data classifier for 4 clusters :
Class1 and Class3

Accuracy=94.96%

	Class2	Class 3
Class2	575	22
Class3	37	536

(a) Confusion Matrix

	Class2	Class3
Precision	0.94	0.96
Recall	0.96	0.94
F-Measure	0.95	0.95

(b) Analysis

Table 3..18. Real World data classifier for 4 clusters :
Class2 and Class3

	Class1	Class2	Class 3
Class1	622	0	0
Class2	0	575	22
Class3	2	37	534

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.89	96.71	96.60
Precision	1.00	0.94	0.96
Recall	1.00	0.96	0.93
F-Measure	1.00	0.95	0.95

(b) Analysis

Table 3..19. Real World data classifier for 4 clusters :
Class1 and Class2 and Class3

Real World data classifier for 8 clusters

Accuracy=100%

	Class1	Class 2
Class1	622	0
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..20. Real World data classifier for 8 clusters : Class1 and Class2

Accuracy=99.83%

	Class1	Class 3
Class1	622	0
Class3	2	571

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..21. Real World data classifier for 8 clusters : Class1 and Class3

Accuracy=94.70%

	Class2	Class 3
Class2	567	30
Class3	32	541

(a) Confusion Matrix

	Class2	Class3
Precision	0.95	0.95
Recall	0.95	0.94
F-Measure	0.95	0.95

(b) Analysis

Table 3..22. Real World data classifier for 8 clusters : Class2 and Class3

	Class1	Class2	Class 3
Class1	623	0	0
Class2	0	567	30
Class3	2	32	539

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.89	96.54	96.43
Precision	1.00	0.95	0.95
Recall	1.00	0.95	0.94
F-Measure	1.00	0.95	0.94

(b) Analysis

Table 3..23. Real World data classifier for 8 clusters : Class1 and Class2 and Class3

Real World data classifier for 16 clusters

Accuracy=100%

	Class1	Class 2
Class1	622	0
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..24. Real World data classifier for 16 clusters : Class1 and Class2

Accuracy=99.67%

	Class1	Class 3
Class1	619	3
Class3	1	572

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	0.99
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..25. Real World data classifier for 16 clusters : Class1 and Class3

Accuracy=94.87%

	Class2	Class 3
Class2	575	22
Class3	38	535

(a) Confusion Matrix

	Class2	Class3
Precision	0.94	0.96
Recall	0.96	0.93
F-Measure	0.95	0.95

(b) Analysis

Table 3..26. Real World data classifier for 16 clusters : Class2 and Class3

	Class1	Class2	Class 3
Class1	622	0	0
Class2	0	575	22
Class3	1	38	534

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.94	96.65	96.60
Precision	1.00	0.94	0.96
Recall	1.00	0.96	0.93
F-Measure	1.00	0.95	0.95

(b) Analysis

Table 3..27. Real World data classifier for 16 clusters : Class1 and Class2 and Class3

Real World data classifier for 32 clusters

Accuracy=100%

	Class1	Class 2
Class1	622	0
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..28. Real World data classifier for 32 clusters : Class1 and Class2

Accuracy=99.33%

	Class1	Class 3
Class1	615	7
Class3	1	572

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..29. Real World data classifier for 32 clusters : Class1 and Class3

Accuracy=95.56%

	Class2	Class 3
Class2	571	26
Class3	26	547

(a) Confusion Matrix

	Class2	Class3
Precision	0.96	0.95
Recall	0.96	0.95
F-Measure	0.96	0.95

(b) Analysis

Table 3..30. Real World data classifier for 32 clusters : Class2 and Class3

	Class1	Class2	Class 3
Class1	615	0	7
Class2	0	571	26
Class3	1	26	546

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.55	97.10	96.65
Precision	1.00	0.96	0.94
Recall	1.00	0.96	0.95
F-Measure	0.99	0.96	0.95

(b) Analysis

Table 3..31. Real World data classifier for 32 clusters : Class1 and Class2 and Class3

Real World data classifier for 64 clusters

Accuracy=100%

	Class1	Class 2
Class1	622	0
Class2	0	597

(a) Confusion Matrix

	Class1	Class2
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	1.00	1.00

(b) Analysis

Table 3..32. Real World data classifier for 64 clusters : Class1 and Class2

Accuracy=99.33%

	Class1	Class 3
Class1	615	7
Class3	1	572

(a) Confusion Matrix

	Class1	Class3
Precision	1.00	1.00
Recall	1.00	1.00
F-Measure	0.99	0.99

(b) Analysis

Table 3..33. Real World data classifier for 64 clusters : Class1 and Class3

Accuracy=95.04%

	Class2	Class 3
Class2	572	25
Class3	33	540

(a) Confusion Matrix

	Class2	Class3
Precision	0.95	0.96
Recall	0.96	0.94
F-Measure	0.95	0.95

(b) Analysis

Table 3..34. Real World data classifier for 64 clusters : Class2 and Class3

	Class1	Class2	Class 3
Class1	615	0	7
Class2	0	572	25
Class3	1	33	539

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	99.55	96.76	96.32
Precision	1.00	0.95	0.94
Recall	0.99	0.96	0.94
F-Measure	0.99	0.95	0.94

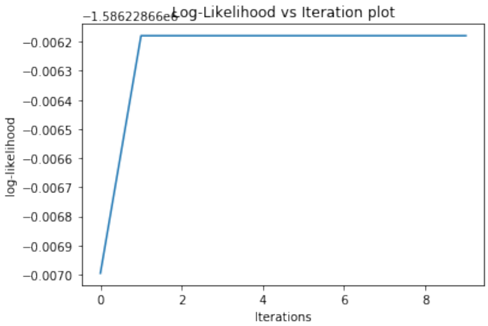
(b) Analysis

Table 3..35. Real World data classifier for 64 clusters : Class1 and Class2 and Class3

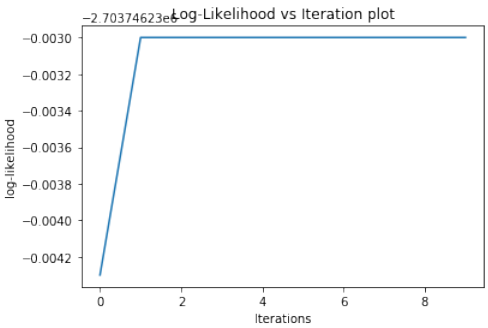
3 Data Set 3 : Three class scene image data set

3.1 Classifier 1 : Histogram feature vector based

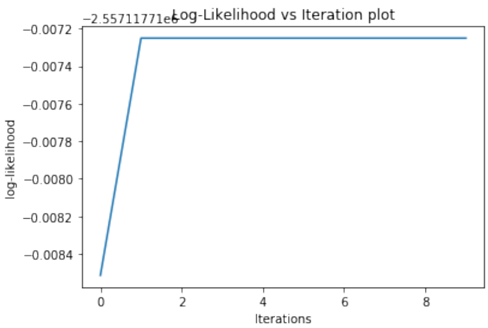
Convergence plots for 1 cluster



(a) Convergence plot for Class1 for 1 cluster.



(b) Convergence plot for Class2 for 1 cluster.



(c) Convergence plot for Class3 for 1 cluster.

Figure 3..15. Histogram feature based classifier for 1 cluster.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=62.31%

	Class1	Class 2
Class1	15793	39571
Class2	13975	72747

(a) Confusion Matrix

	Class1	Class2
Precision	0.53	0.65
Recall	0.29	0.84
F-Measure	0.37	0.73

(b) Analysis

Table 3..36. Histogram feature based classifier: Class1 and Class2

Accuracy=63.41%

	Class1	Class 3
Class1	0	55364
Class3	0	95956

(a) Confusion Matrix

	Class1	Class3
Precision	0.50	0.63
Recall	0	1
F-Measure	0	0.78

(b) Analysis

Table 3..37. Histogram feature based classifier: Class1 and Class3

Accuracy=58.18%

	Class2	Class 3
Class2	73229	13493
Class3	62896	33060

(a) Confusion Matrix

	Class2	Class3
Precision	0.54	0.71
Recall	0.84	0.34
F-Measure	0.66	0.46

(b) Analysis

Table 3..38. Histogram feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	22423	28552	4389
Class2	19519	6258	4622
Class3	31782	53828	10346

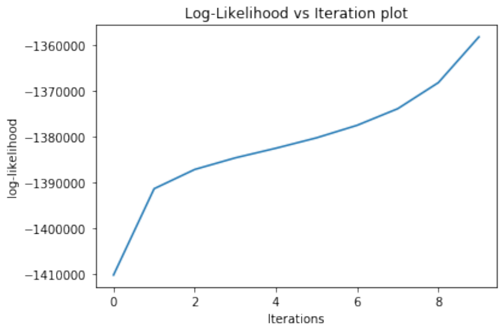
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	64.61	55.25	60.25
Precision	0.30	0.43	0.53
Recall	0.41	0.72	0.12
F-Measure	0.35	0.54	0.18

(b) Analysis

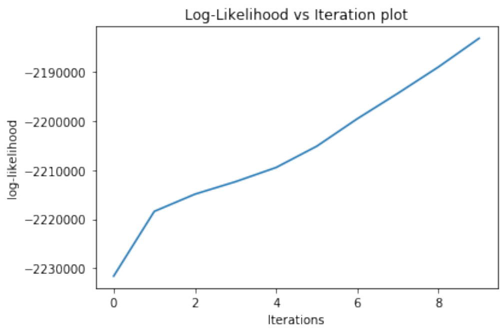
Table 3..39. Histogram feature based classifier: Class1 and Class2 and Class3

Convergence plots for 2 clusters



(a) Convergence plot for Class1 for 2 clusters.

(b) Convergence plot for Class2 for 2 clusters.



(c) Convergence plot for Class3 for 2 clusters.

Figure 3..16. Histogram feature based classifier for 2 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=43.68%

	Class1	Class 2
Class1	31540	23824
Class2	56196	30526

(a) Confusion Matrix

	Class1	Class2
Precision	0.36	0.56
Recall	0.57	0.35
F-Measure	0.44	0.43

(b) Analysis

Table 3..40. Histogram feature based classifier: Class1 and Class2

Accuracy=63.10%

	Class1	Class 3
Class1	78	55286
Class3	544	95412

(a) Confusion Matrix

	Class1	Class3
Precision	0.13	0.63
Recall	0.00	0.99
F-Measure	0.00	0.77

(b) Analysis

Table 3..41. Histogram feature based classifier: Class1 and Class3

Accuracy=40.55%

	Class2	Class 3
Class2	31855	54867
Class3	53722	42234

(a) Confusion Matrix

	Class2	Class3
Precision	0.37	0.43
Recall	0.37	0.44
F-Measure	0.37	0.44

(b) Analysis

Table 3..42. Histogram feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	13162	22660	19542
Class2	14714	28711	43297
Class3	12269	50676	33011

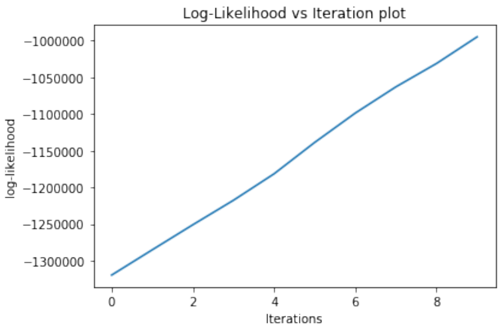
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	70.94	44.82	47.16
Precision	0.33	0.28	0.34
Recall	0.23	0.33	0.34
F-Measure	0.28	0.30	0.34

(b) Analysis

Table 3..43. Histogram feature based classifier: Class1 and Class2 and Class3

Convergence plots for 4 clusters



(a) Convergence plot for Class1 for 4 clusters.

(b) Convergence plot for Class2 for 4 clusters.

(c) Convergence plot for Class3 for 4 clusters.

Figure 3..17. Histogram feature based classifier for 4 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=58.05%

	Class1	Class 2
Class1	18851	36513
Class2	23088	63634

(a) Confusion Matrix

	Class1	Class2
Precision	0.45	0.64
Recall	0.34	0.73
F-Measure	0.39	0.68

(b) Analysis

Table 3..44. Histogram feature based classifier: Class1 and Class2

Accuracy=63.26%

	Class1	Class 3
Class1	49	55315
Class3	275	95681

(a) Confusion Matrix

	Class1	Class3
Precision	0.15	0.63
Recall	0.00	1.00
F-Measure	0.00	0.77

(b) Analysis

Table 3..45. Histogram feature based classifier: Class1 and Class3

Accuracy=57.62%

	Class2	Class 3
Class2	61046	25676
Class3	51736	44220

(a) Confusion Matrix

	Class2	Class3
Precision	0.54	0.63
Recall	0.70	0.46
F-Measure	0.61	0.53

(b) Analysis

Table 3..46. Histogram feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	17616	28120	9628
Class2	19805	53861	13056
Class3	32053	45317	18586

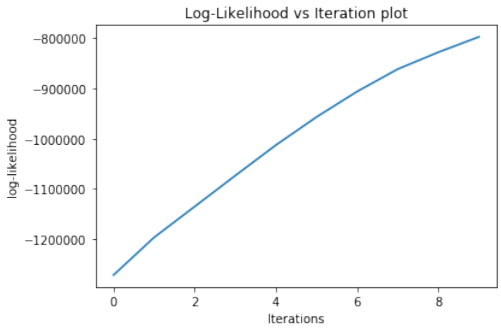
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	62.36	55.34	57.97
Precision	0.25	0.42	0.45
Recall	0.32	0.62	0.19
F-Measure	0.28	0.50	0.27

(b) Analysis

Table 3..47. Histogram feature based classifier: Class1 and Class2 and Class3

Convergence plots for 8 clusters



(a) Convergence plot for Class1 for 8 clusters.

(b) Convergence plot for Class2 for 8 clusters.

(c) Convergence plot for Class3 for 8 clusters.

Figure 3..18. Histogram feature based classifier for 8 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=57.86%

	Class1	Class 2
Class1	19965	35399
Class2	24462	62260

(a) Confusion Matrix

	Class1	Class2
Precision	0.45	0.64
Recall	0.36	0.72
F-Measure	0.40	0.68

(b) Analysis

Table 3..48. Histogram feature based classifier: Class1 and Class2

Accuracy=62.91%

	Class1	Class 3
Class1	85	55279
Class3	850	95106

(a) Confusion Matrix

	Class1	Class3
Precision	0.09	0.63
Recall	0.00	0.99
F-Measure	0.00	0.77

(b) Analysis

Table 3..49. Histogram feature based classifier: Class1 and Class3

Accuracy=57.34%

	Class2	Class 3
Class2	62584	24138
Class3	53791	42165

(a) Confusion Matrix

	Class2	Class3
Precision	0.54	0.64
Recall	0.72	0.44
F-Measure	0.62	0.52

(b) Analysis

Table 3..50. Histogram feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	21812	25639	7913
Class2	26432	49633	10657
Class3	33428	43340	19188

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	60.76	55.44	59.95
Precision	0.27	0.42	0.51
Recall	0.39	0.57	0.20
F-Measure	0.32	0.48	0.29

(b) Analysis

Table 3..51. Histogram feature based classifier: Class1 and Class2 and Class3

Convergence plots for 16 clusters

(a) Convergence plot for Class1 for 16 clusters.

(b) Convergence plot for Class2 for 16 clusters.

(c) Convergence plot for Class3 for 16 clusters.

Figure 3..19. Histogram feature based classifier for 16 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=59.90%

	Class1	Class 2
Class1	21091	34273
Class2	22702	64020

(a) Confusion Matrix

	Class1	Class2
Precision	0.48	0.65
Recall	0.38	0.74
F-Measure	0.43	0.69

(b) Analysis

Table 3..52. Histogram feature based classifier: Class1 and Class2

Accuracy=63.35%

	Class1	Class 3
Class1	18	55346
Class3	112	95844

(a) Confusion Matrix

	Class1	Class3
Precision	0.14	0.63
Recall	0.00	1.00
F-Measure	0.00	0.78

(b) Analysis

Table 3..53. Histogram feature based classifier: Class1 and Class3

Accuracy=57.71%

	Class2	Class 3
Class2	60945	25777
Class3	51478	44478

(a) Confusion Matrix

	Class2	Class3
Precision	0.54	0.63
Recall	0.70	0.46
F-Measure	0.61	0.54

(b) Analysis

Table 3..54. Histogram feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	15257	19323	20784
Class2	15779	42255	28688
Class3	22477	33631	39848

(a) Confusion Matrix

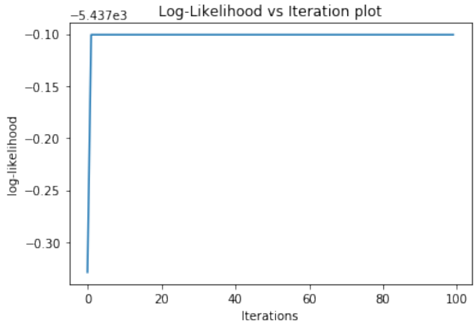
	Class1	Class2	Class3
Accuracy	67.08	59.07	55.65
Precision	0.29	0.44	0.45
Recall	0.28	0.49	0.42
F-Measure	0.28	0.46	0.43

(b) Analysis

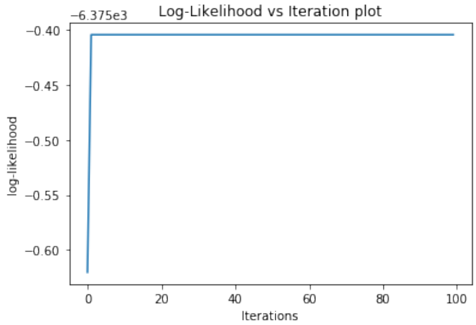
Table 3..55. Histogram feature based classifier: Class1 and Class2 and Class3

3.2 Classifier 2 : BoVW feature vector based

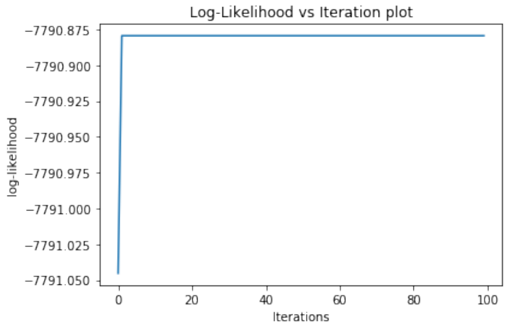
Convergence plots for 1 cluster



(a) Convergence plot for Class1 for 1 cluster.



(b) Convergence plot for Class2 for 1 cluster.



(c) Convergence plot for Class3 for 1 cluster.

Figure 3..20. BoVW feature based classifier for 1 cluster.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=52%

	Class1	Class 2
Class1	35	15
Class2	33	17

(a) Confusion Matrix

	Class1	Class2
Precision	0.51	0.53
Recall	0.7	0.34
F-Measure	0.59	0.41

(b) Analysis

Table 3..56. BoVW feature based classifier: Class1 and Class2

Accuracy=48%

	Class1	Class 3
Class1	20	30
Class3	22	28

(a) Confusion Matrix

	Class1	Class3
Precision	0.48	0.48
Recall	0.4	0.56
F-Measure	0.43	0.52

(b) Analysis

Table 3..57. BoVW feature based classifier: Class1 and Class3

Accuracy=49%

	Class2	Class 3
Class2	24	26
Class3	25	25

(a) Confusion Matrix

	Class2	Class3
Precision	0.49	0.49
Recall	0.48	0.5
F-Measure	0.48	0.50

(b) Analysis

Table 3..58. BoVW feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	18	8	24
Class2	19	7	24
Class3	21	6	23

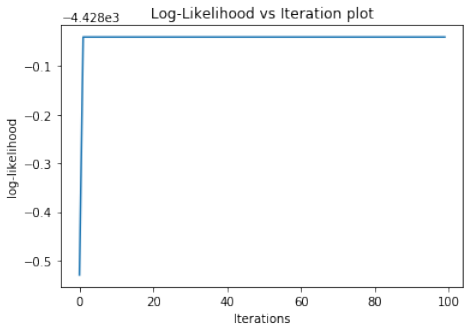
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	52	62	50
Precision	0.31	0.33	0.33
Recall	0.36	0.14	0.46
F-Measure	0.33	0.20	0.38

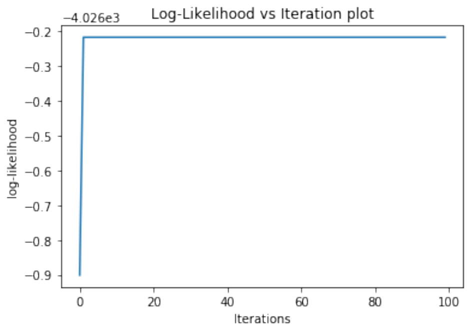
(b) Analysis

Table 3..59. BoVW feature based classifier: Class1 and Class2 and Class3

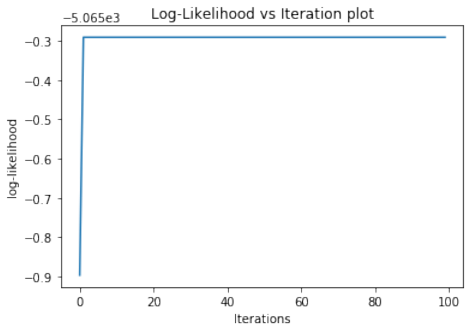
Convergence plots for 2 clusters



(a) Convergence plot for Class1 for 2 clusters.



(b) Convergence plot for Class2 for 2 clusters.



(c) Convergence plot for Class3 for 2 clusters.

Figure 3..21. BoVW feature based classifier for 2 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=52%

	Class1	Class 2
Class1	40	10
Class2	38	12

(a) Confusion Matrix

	Class1	Class2
Precision	0.51	0.55
Recall	0.8	0.24
F-Measure	0.63	0.33

(b) Analysis

Table 3..60. BoVW feature based classifier: Class1 and Class2

Accuracy=52%

	Class1	Class 3
Class1	45	5
Class3	43	7

(a) Confusion Matrix

	Class1	Class3
Precision	0.51	0.58
Recall	0.9	0.14
F-Measure	0.65	0.23

(b) Analysis

Table 3..61. BoVW feature based classifier: Class1 and Class3

Accuracy=52%

	Class2	Class 3
Class2	43	7
Class3	41	9

(a) Confusion Matrix

	Class2	Class3
Precision	0.51	0.56
Recall	0.86	0.18
F-Measure	0.64	0.27

(b) Analysis

Table 3..62. BoVW feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	38	8	4
Class2	36	12	2
Class3	41	5	4

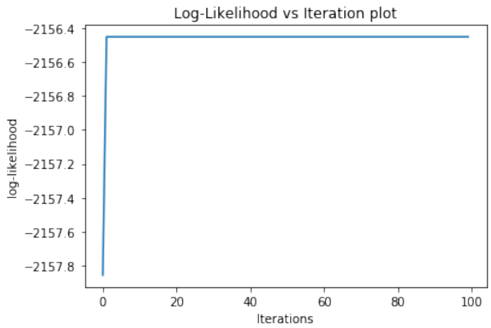
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	40.67	66	65.33
Precision	0.33	0.48	0.4
Recall	0.76	0.24	0.08
F-Measure	0.46	0.32	0.13

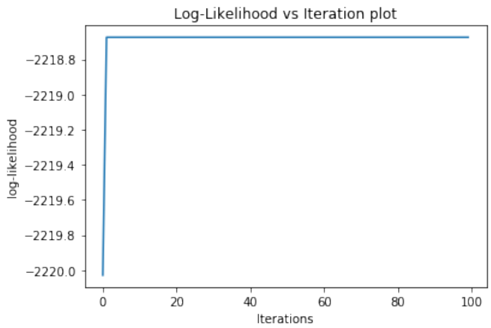
(b) Analysis

Table 3..63. BoVW feature based classifier: Class1 and Class2 and Class3

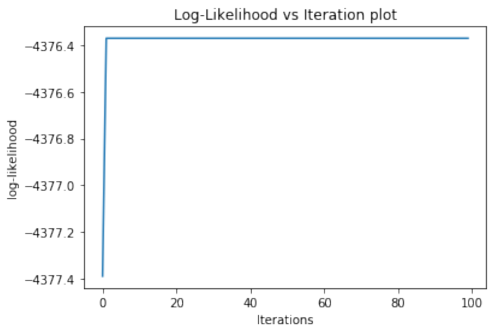
Convergence plots for 4 clusters



(a) Convergence plot for Class1 for 4 clusters.



(b) Convergence plot for Class2 for 4 clusters.



(c) Convergence plot for Class3 for 4 clusters.

Figure 3..22. BoVW feature based classifier for 4 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=49%

	Class1	Class 2
Class1	41	9
Class2	42	8

(a) Confusion Matrix

	Class1	Class2
Precision	0.49	0.47
Recall	0.82	0.16
F-Measure	0.62	0.24

(b) Analysis

Table 3..64. BoVW feature based classifier: Class1 and Class2

Accuracy=45%

	Class1	Class 3
Class1	33	17
Class3	38	12

(a) Confusion Matrix

	Class1	Class3
Precision	0.46	0.41
Recall	0.66	0.24
F-Measure	0.55	0.30

(b) Analysis

Table 3..65. BoVW feature based classifier: Class1 and Class3

Accuracy=52%

	Class2	Class 3
Class2	38	12
Class3	36	14

(a) Confusion Matrix

	Class2	Class3
Precision	0.52	0.54
Recall	0.76	0.37
F-Measure	0.61	0.37

(b) Analysis

Table 3..66. BoVW feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	27	6	17
Class2	36	8	6
Class3	37	2	11

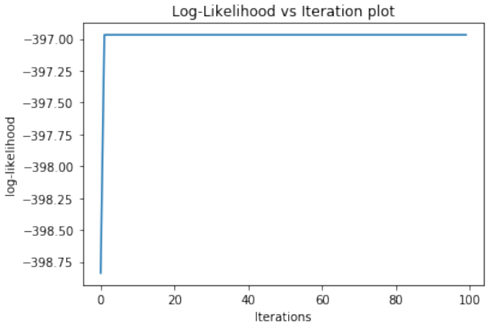
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	36	66.67	58.67
Precision	0.27	0.5	0.32
Recall	0.54	0.16	0.22
F-Measure	0.36	0.24	0.26

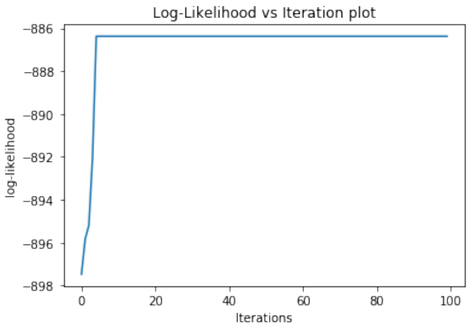
(b) Analysis

Table 3..67. BoVW feature based classifier: Class1 and Class2 and Class3

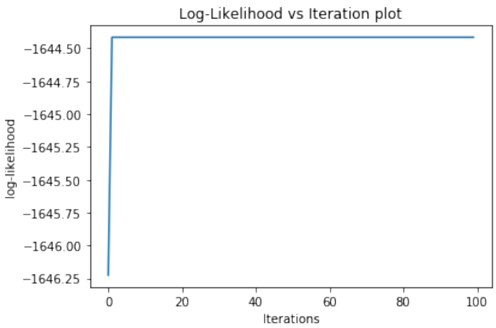
Convergence plots for 8 clusters



(a) Convergence plot for Class1 for 8 clusters.



(b) Convergence plot for Class2 for 8 clusters.



(c) Convergence plot for Class3 for 8 clusters.

Figure 3..23. BoVW feature based classifier for 8 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=59%

	Class1	Class 2
Class1	44	6
Class2	35	15

(a) Confusion Matrix

	Class1	Class2
Precision	0.56	0.72
Recall	0.88	0.3
F-Measure	0.68	0.42

(b) Analysis

Table 3..68. BoVW feature based classifier: Class1 and Class2

Accuracy=53%

	Class1	Class 3
Class1	49	1
Class3	46	4

(a) Confusion Matrix

	Class1	Class3
Precision	0.52	0.8
Recall	0.98	0.08
F-Measure	0.68	0.15

(b) Analysis

Table 3..69. BoVW feature based classifier: Class1 and Class3

Accuracy=54%

	Class2	Class 3
Class2	46	4
Class3	42	8

(a) Confusion Matrix

	Class2	Class3
Precision	0.52	0.67
Recall	0.92	0.16
F-Measure	0.67	0.26

(b) Analysis

Table 3..70. BoVW feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	35	10	5
Class2	32	14	4
Class3	36	6	8

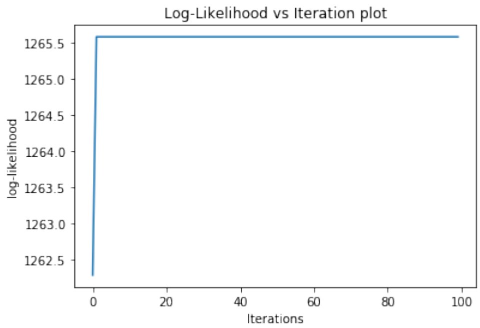
(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	44.67	65.33	66
Precision	0.34	0.47	0.47
Recall	0.7	0.28	0.16
F-Measure	0.46	0.35	0.23

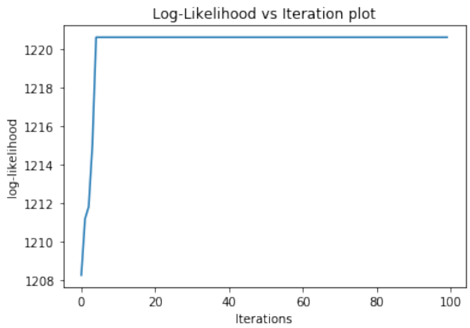
(b) Analysis

Table 3..71. BoVW feature based classifier: Class1 and Class2 and Class3

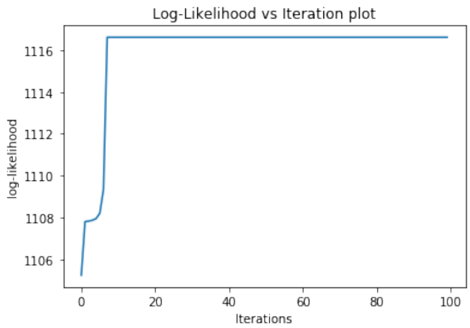
Convergence plots for 16 clusters



(a) Convergence plot for Class1 for 16 clusters.



(b) Convergence plot for Class2 for 16 clusters.



(c) Convergence plot for Class3 for 16 clusters.

Figure 3..24. BoVW feature based classifier for 16 clusters.

Confusion Matrix, Precision, Recall and F-measure

Accuracy=50%

	Class1	Class 2
Class1	50	0
Class2	50	0

(a) Confusion Matrix

	Class1	Class2
Precision	0.5	0.5
Recall	1.00	0.00
F-Measure	0.67	0.00

(b) Analysis

Table 3..72. BoVW feature based classifier: Class1 and Class2

Accuracy=50%

	Class1	Class 3
Class1	50	0
Class3	50	0

(a) Confusion Matrix

	Class1	Class3
Precision	0.5	0.5
Recall	1.00	0.00
F-Measure	0.67	0.00

(b) Analysis

Table 3..73. BoVW feature based classifier: Class1 and Class3

Accuracy=50%

	Class2	Class 3
Class2	50	0
Class3	50	0

(a) Confusion Matrix

	Class2	Class3
Precision	0.5	0.5
Recall	1.00	0.00
F-Measure	0.67	0.00

(b) Analysis

Table 3..74. BoVW feature based classifier: Class2 and Class3

	Class1	Class2	Class 3
Class1	50	0	0
Class2	47	1	2
Class3	46	1	3

(a) Confusion Matrix

	Class1	Class2	Class3
Accuracy	38	66.67	67.33
Precision	0.35	0.5	0.6
Recall	1.00	0.02	0.06
F-Measure	0.52	0.04	0.11

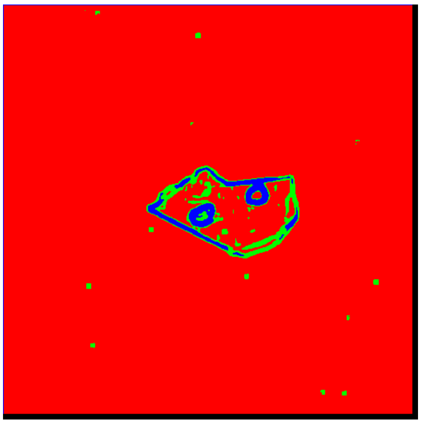
(b) Analysis

Table 3..75. BoVW feature based classifier: Class1 and Class2 and Class3

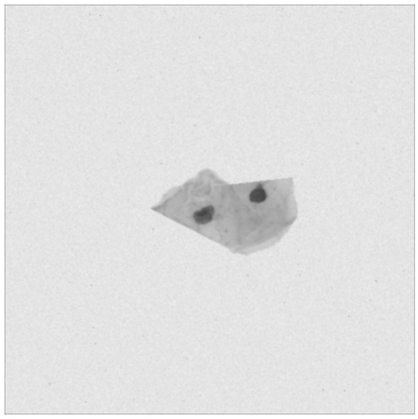
4 Data Set 4 : Cell Data Segmentation

4.1 Segmentation 1 : K-means based segmentation

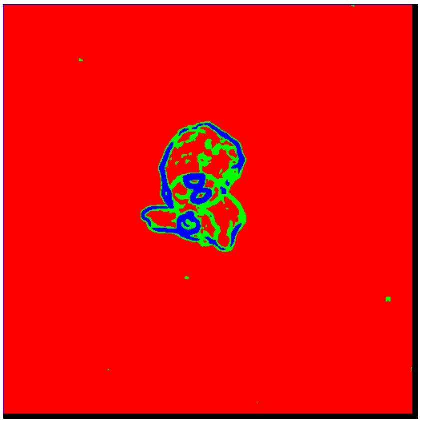
Images formed by K-means clustering with normalized features



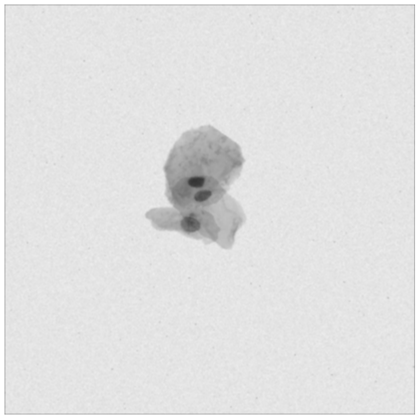
(a)



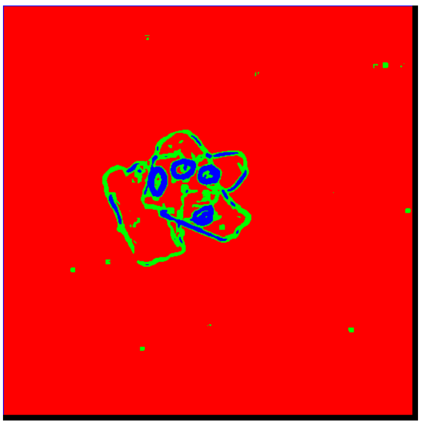
(b)



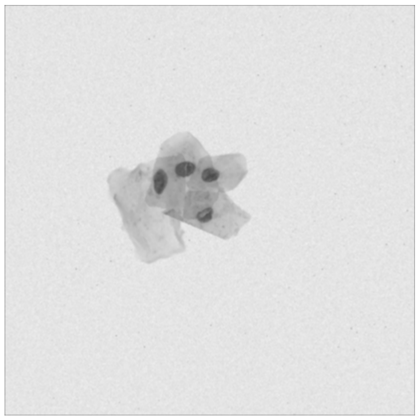
(c)



(d)



(e)



(f)

Figure 3..25. Segmentation using K-means clustering

Images formed by K-means clustering without normalization

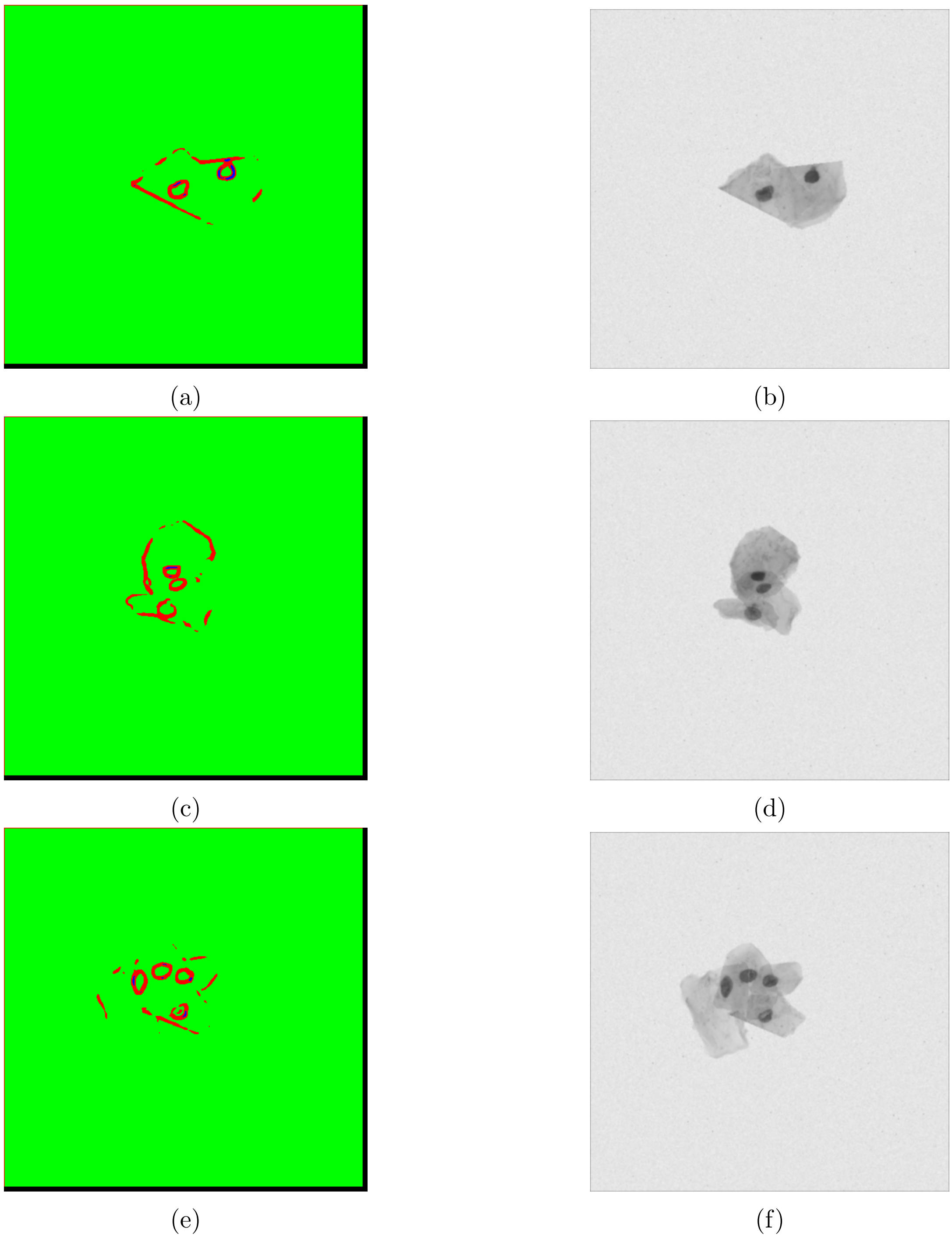


Figure 3..26. Segmentation using K-means clustering without normalization.

4.2 Segmentation 2 : GMM based segmentation

Images formed by GMM with normalized features

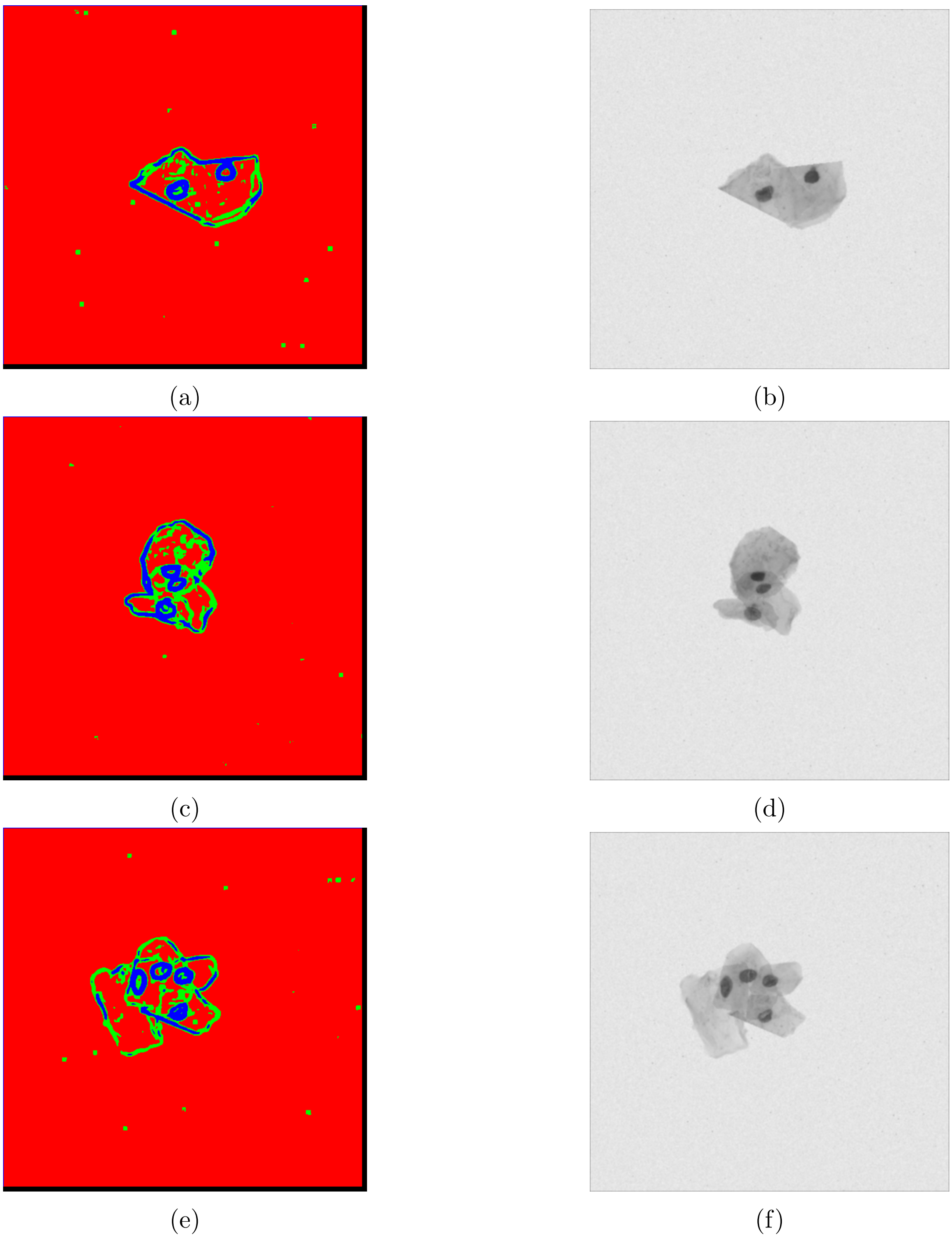
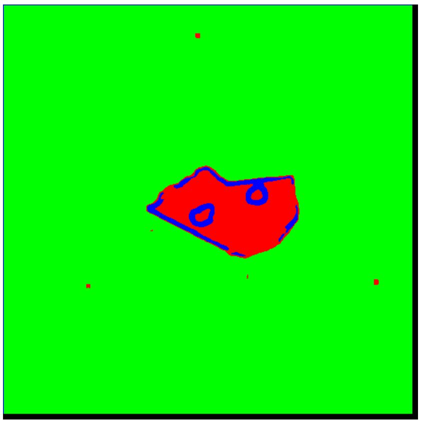
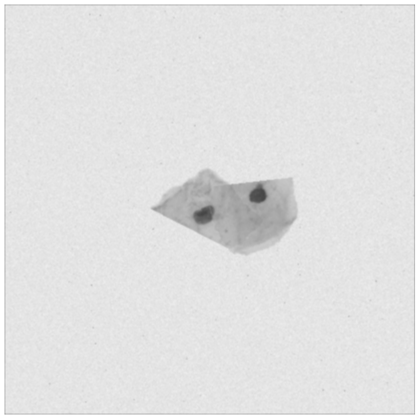


Figure 3..27. Segmentation using GMM with normalized features

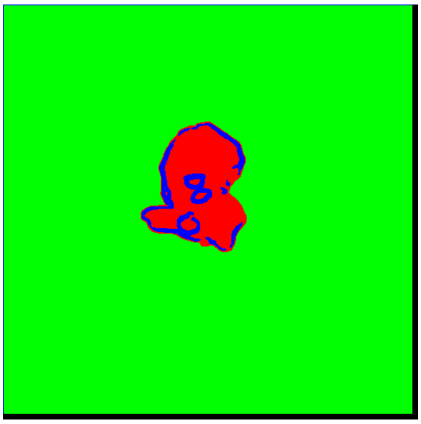
Images formed by GMM without normalization



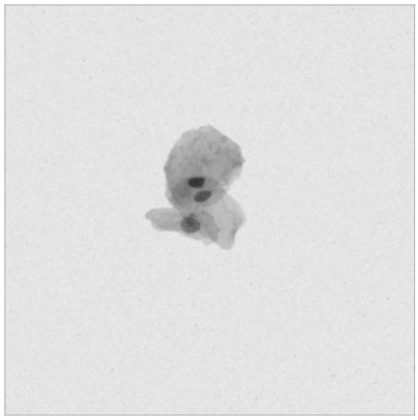
(a)



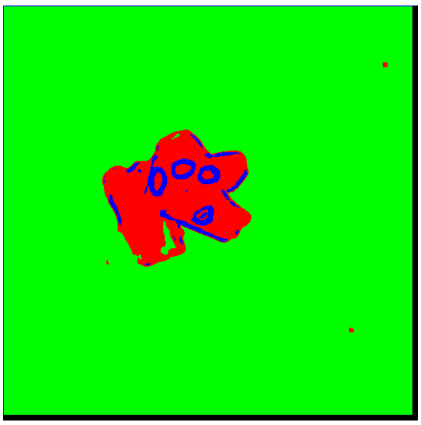
(b)



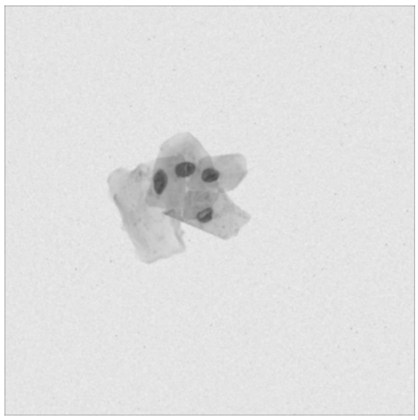
(c)



(d)



(e)



(f)

Figure 3..28. Segmentation using GMM without normalization

4. Observations and Inferences

1. As the Number of cluster increases the accuracy of Bayes Classifier using GMM also increases.

2. Number of Iterations for Convergence increases with the increase in number of Clusters.

3. A contour plot is a graphical technique for representing a 3-dimensional surface by plotting constant z slices, called contours, on a 2-dimensional format.The three dimesional surface formed in our case is gaussian surface, so the 2d format of this surface will either be circle or ellipse depending on the covariance matrix.Since the convariance matrix is not diagonal, so the 2d shapes formed are ellipses with there centres at the peak of different gaussians. For each cluster, a seperate gaussian is formed and therefore a seperate group of concentric ellipses will be formed for each cluster.The orientation of the ellipse will be determined by the covariance matrix and the spread of the data. The major axis of the ellipse also tell us about the direction in which the variance will be more.

4. The reason behind the low accuracy in Histogram representation is as follows

   1.) We assumed the covariance matrix as diagonal (to counter the overflow error).Also,while doing the iterations, if our determinant was coming out to as zero, we used to tweak the covariance matrix a bit in order to make it non zero.Due to this, the originality of the distributions was lost to a certain extent which gave rise to misclassification.

   2.) The data distribution was assumed to be coming from two normal distributions (as a mixture of them).This might not be the case. So this may also adds to error generation.

5. In case of BoVW representation the classification accuracy is low. This is because many approximation techniques were used to counter the overflow error and the division by zero error. We considered the covariance matrix as diagonal instead of full covariance matrix. Moreover, the no of training examples were quite few and thus GMM wasn't able to estimate the parameters efficiently.

6. We have normalized the features and tried to cluster the data as we are getting boundaries as one cluster because very high variance at boundaries which is very different from the other data points. We have observed that K-means clustering with normalized features is giving better results than original one where as in GMM the original one is giving better results than that of with normalized features.

5. Conclusions

1. We came to know that K-Means is really a computationally expensive algorithm because it took nearly 40 minutes for the computation of 300000x32 sized array to get clustered.

2. As the variance is considered as one of the feature, the model is considering the boundary as one cluster as it has high variance features which is very different from the other points such as in cytoplasm and nucleus which have very low variance because of which they might be considered as same cluster.

3. We came to know that GMM with using K-Means provides the better segmentation results because of the factor of the responsibility term.