

Assignment-3

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1 Guassian Mixture Models

1.1 a) GMM

In Gaussian Mixture Models the whole data is represented as K mixture of Gaussians.

$$p(X) = \pi_1 \mathcal{N}(\mu_1, \Sigma_1) + \pi_2 \mathcal{N}(\mu_2, \Sigma_2) + \dots + \pi_K \mathcal{N}(\mu_K, \Sigma_K) \quad (1)$$

π_k is the Probability that \mathbf{X} belongs to that gaussian. π_i is also a distribution

$$\sum_{i=1}^K \pi_i = 1 \quad (2)$$

From fact that

$$\int p(X) d\mathbf{x} = 1 \quad (3)$$

$$\int p(X) d\mathbf{x} = \int \pi_1 \mathcal{N}(x|\mu_1, \Sigma_1) d\mathbf{x} + \int \pi_2 \mathcal{N}(x|\mu_2, \Sigma_2) d\mathbf{x} \quad (4)$$

Since $\int \mathcal{N}(x|\mu_1, \Sigma_1) d\mathbf{x} = 1$

$$p(X) d\mathbf{x} = \pi_1(1) + \pi_2(1) \quad (5)$$

Substitute 1 in place of $\int p(X) d\mathbf{x}$ using equation 3. $\pi_1 + \pi_2 = 1$

1.2 b) Expectation Maximization Algorithm

1.2.1 Initialization

Apply K-means Algorithm on the given data.

Initialize μ_k , Σ_k , N_k

1.2.2 Expectation Step

$$\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)}{\sum_{n=1}^K \pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)} \quad (6)$$

1.2.3 Maximization Step

$$N_k = \sum_{n=1}^N \gamma(z_{nk}) \quad (7)$$

$$\mu_k^{new} = \frac{1}{N_k} \sum_{n=1}^N \gamma(z_{nk}) x_n \quad (8)$$

$$\Sigma_k^{new} = \frac{1}{N_k} \sum_{n=1}^N \gamma(z_{nk}) (x_n - \mu_k^{new})(x_n - \mu_k^{new})^T \quad (9)$$

$$\pi_k^{new} = \frac{N_k}{N} \quad (10)$$

1.2.4 Evaluating the log likelihood

$$\ln p(X|\mu, \Sigma, \pi) = \sum_{n=1}^N \ln \sum_{k=1}^K \pi_k \mathcal{N}(x_n | \mu_k, \Sigma) \quad (11)$$

Check for convergence , If not converged go to Expectation Step.
Check new_log.likelihood - old_log.likelihood. If it's less than 0.1 i.e difference is so low , so our algorithm is converged.

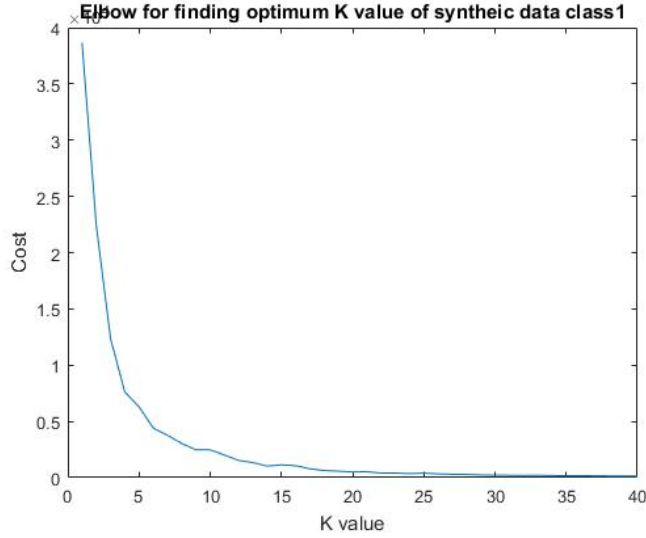
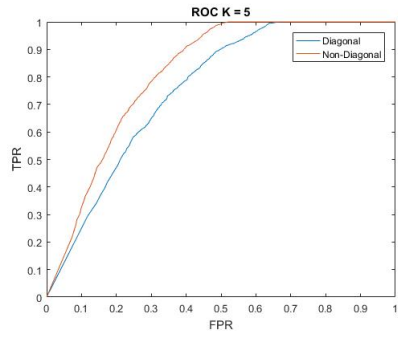


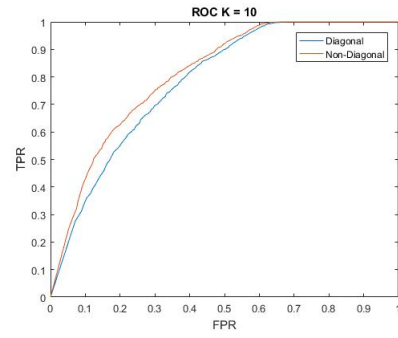
Figure 1: Cost VS K Plot For Deciding K Value

2 Question 1 Real Data

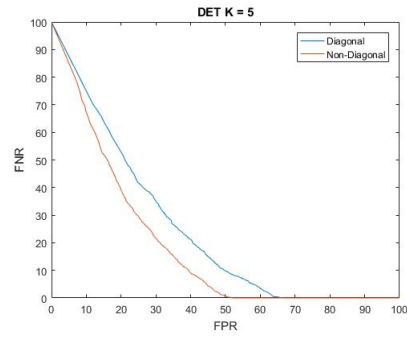
2.1 ROC and DET Plots for both Diagonal and Non Diagonal Covariance Matrices



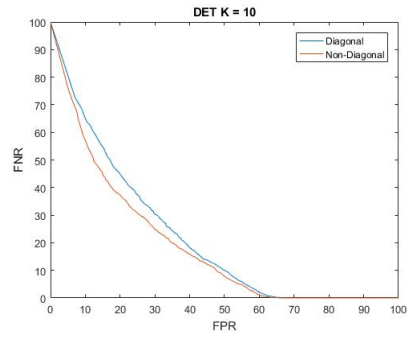
(a) ROC for K=5



(b) ROC for K=10



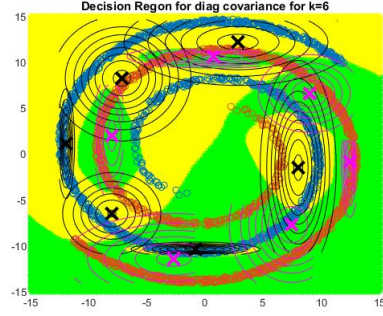
(c) DET for K=5



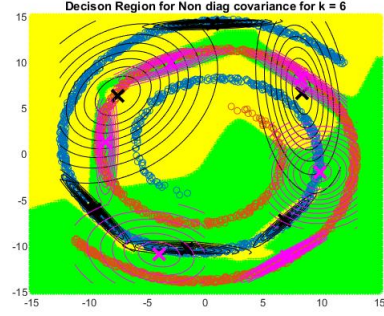
(d) DET for K=10

Figure 2: Plots for Real Data

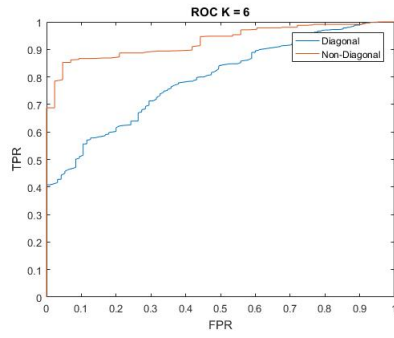
3 Synthetic Data



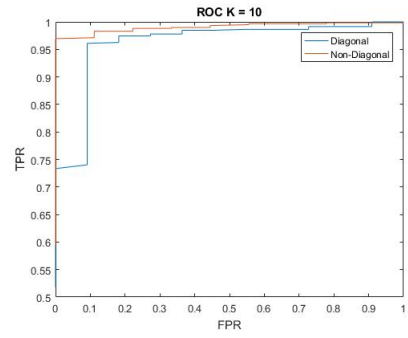
(a) Decision Boundary For Diagonal Covariance $K=6$



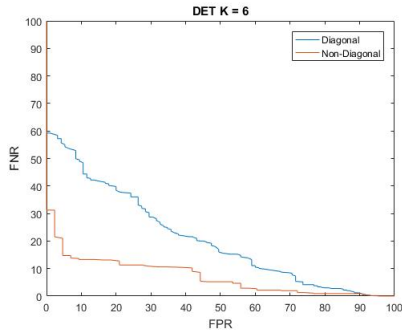
(b) Decision Boundary For Non-Diagonal Covariance $k=6$



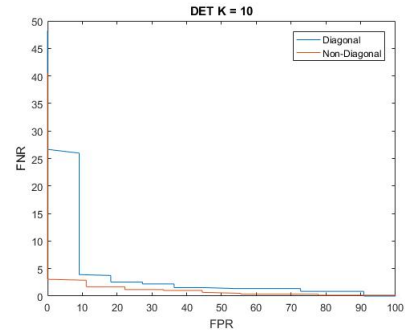
(c) ROC for $K=6$



(d) ROC for $k=10$



(e) DET for $K=6$



(f) DET for $K=10$

Figure 3: Plots for Synthetic Data

Table 1: Accuracy Values for Different K Values Real Data

K	Diagonal	Non-Diagonal
6	73.7%	76.3%
10	75.9%	78.9%

Table 2: Accuracy Values for Different K Values Synthetic Data

K	Diagonal	Non-Diagonal
6	93.5%	95.7%
10	98.8%	99.2%

3.1 Confusion Matrices

		1	2	3
Output	1	37.7%	7.1%	16.5%
	2	0%	23.7 %	0%
	3	0%	0%	14.9%

Accuracy is 76.3 %

Table 3:Confusion Matrix for Real World Data

		1	2
Output	1	50%	4.3%
	2	0%	45.7%

Accuracy is 95.7% Table 4 Confusion Matrix for Synthetic Data