MLIP_PA_2_ME16B001

February 20, 2020

1. Go through the datasets uploaded in the moodle and complete the following table:

Sl. No.	Name of Dataset	Image segmentation	Iris data	Letter recognition	Solar flare	Wis. breast cancer
1	Feature vector dimension	19	4	17	13	30
2	No. of classes	7	3	26	3	2
3	Prior prob. for each class	1/7	1/3	1/26	1/3	1/2
4	Mean vector dim.	19	4	17	13	30
5	Covariance matrix dim.	19×19	3×3	17×17	13×13	30×30

3. You need to perform bayesian classification for the dataset (que3.xlxs) uploaded in the moodle. Before starting, divide the data of each class into 70% data as training and 30% for testing. Text file has 1500 data points in which first 500 data points belong to 1 , next 500 to 2 and last 500 to 3. Perform Bayesian classification for following cases:

i) Same covariance matrix for all the classes. (Hint: Calculate by con- sidering all data points)
ii) Different covariance matrices. (Hint: Calculate 1 , 2 and 3 separately for each class.
iii) Diagonal covariance matrices. (Hint: Make 12 = 21 = 0 in covariance matrices generated in (ii))

Method used for multi-class bayesian classification: **One-vs-All Classification** (Build N different binary classifiers. For the ith classifier, let the positive examples be all the points in class i, and let the negative examples be all the points not in class i.)

In the given case we have 3 classes, so we have 3 ($\binom{N}{k}$) binary classifications decision boundaries. Hence using the **One-vs-All Classification** we will have to perform binary classification on two classes w1 and w2. The decision boundary can be found using

$$P(\omega_1)P(x/\omega_1) = P(\omega_2)P(x/\omega_2)$$

$$P(\omega_1)\frac{1}{\sqrt{2\pi}\sum_1^{1/2}}e^{\frac{-1}{2}(x-\mu_1)^T\Sigma_1^{-1}(x-\mu_1)} = P(\omega_2)\frac{1}{\sqrt{2\pi}\sum_2^{1/2}}e^{\frac{-1}{2}(x-\mu_2)^T\Sigma_2^{-1}(x-\mu_2)}$$

Decision rule:

$$x \in w1 \text{ if } (x-\mu_1)^T \sum_1^{-1}(x-\mu_1) - (x-\mu_2)^T \sum_2^{-1}(x-\mu_2) + \ln(\sum_1) - \ln(\sum_2) \text{ else } x \in w2$$

3 **Case i**

Class w1 mu: [0.06728701 -0.00674633] sigma: [[27.95902766 -2.73535618][-2.73535618 53.52151793]]

Class w2 mu: [9.59179143 9.43031743] sigma: [[27.95902766 -2.73535618][-2.73535618 53.52151793]]

Class w3 mu: [11.09321057 -7.98437543] sigma: [[27.95902766 -2.73535618][-2.73535618 53.52151793]]

Case 1 accuracy: 0.9977528089887641

Eigen vector 1 (w1_sigma): [-0.99444883 -0.10522129]

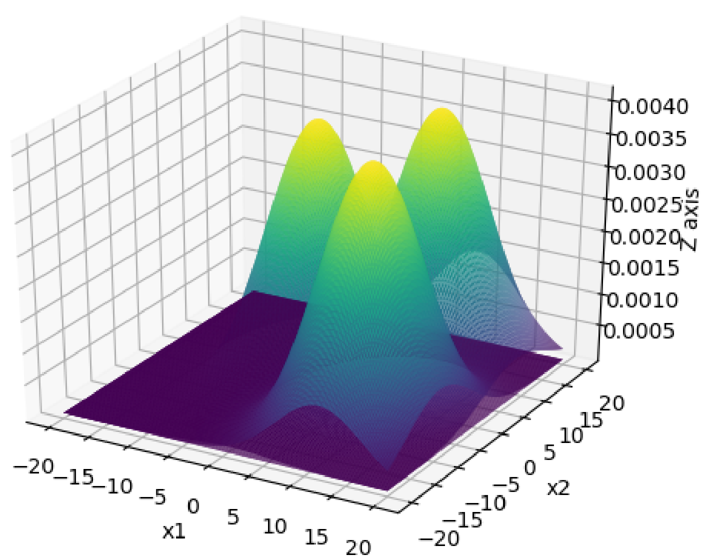
Eigen vector 2 (w1_sigma): [0.10522129 -0.99444883]

Eigen vector 1 (w2_sigma): [-0.99444883 -0.10522129]

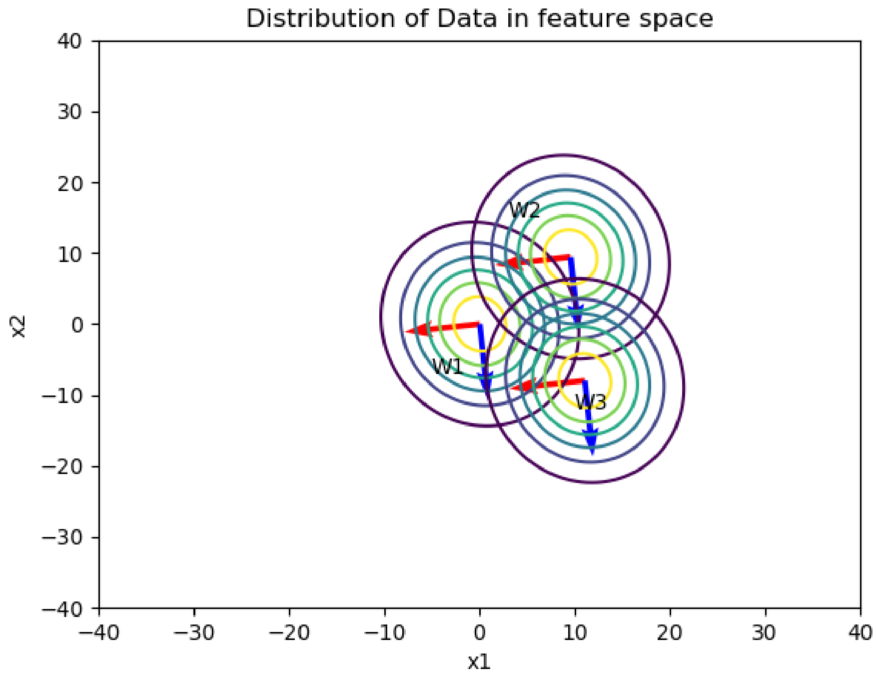
Eigen vector 2 (w2_sigma): [0.10522129 -0.99444883]

Eigen vector 1 (w3_sigma): [-0.99444883 -0.10522129]

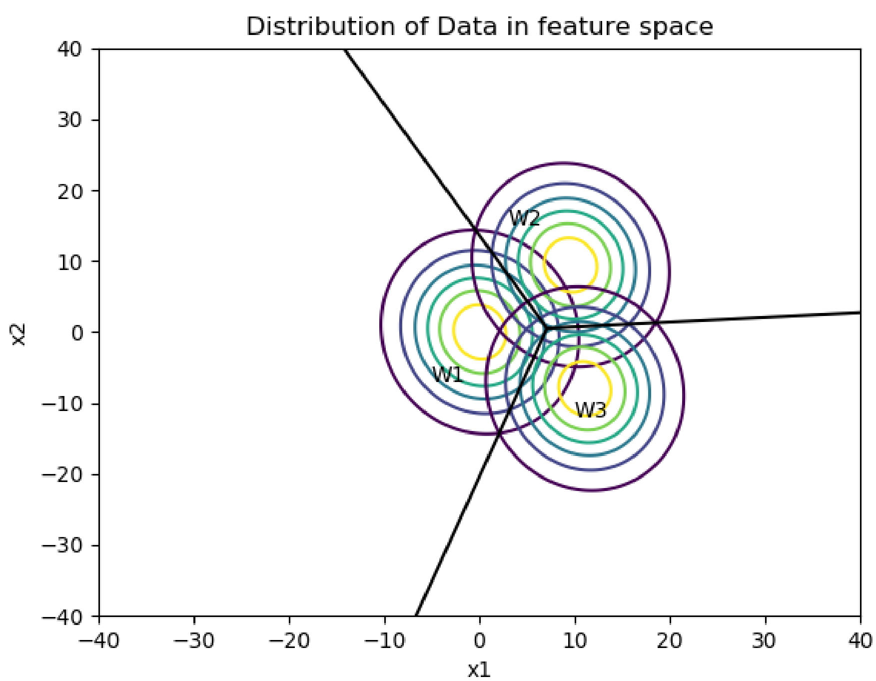
Eigen vector 2 (w3_sigma): [0.10522129 -0.99444883]



PDF: same covariance matrix



Eignevectors: same covariance matrix



Decision boundary: same covariance matrix

3 **Case ii**

Class w1 mu: [0.06728701 -0.00674633] sigma: [[3.84966996 2.64627645][2.64627645 3.67725503]]

Class w2 mu: [9.59179143 9.43031743] sigma: [[4.00356409 -2.84888395][-2.84888395 3.82907431]]

Class w3 mu: [11.09321057 -7.98437543] sigma: [[4.51003748 0.07124775][0.07124775 1.0674692]]

Case 2 accuracy: 1.0

Eigen vector 1 (w1_sigma): [0.71852614 0.69549996]

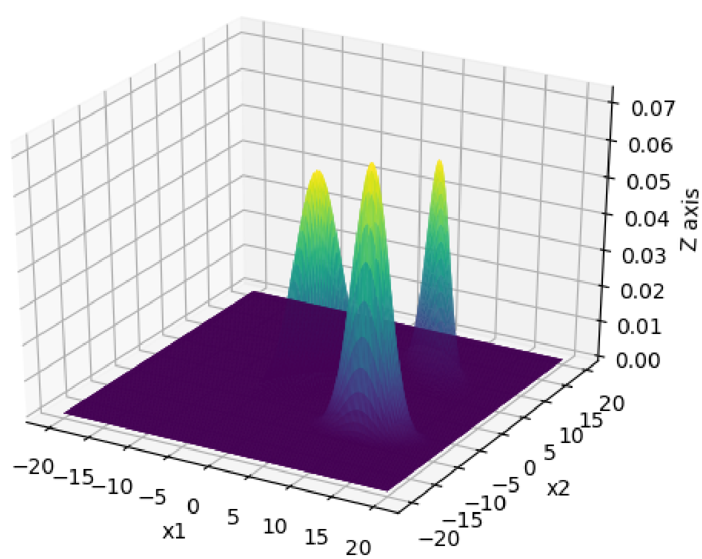
Eigen vector 2 (w1_sigma): [-0.69549996 0.71852614]

Eigen vector 1 (w2_sigma): [0.71784744 -0.69620044]

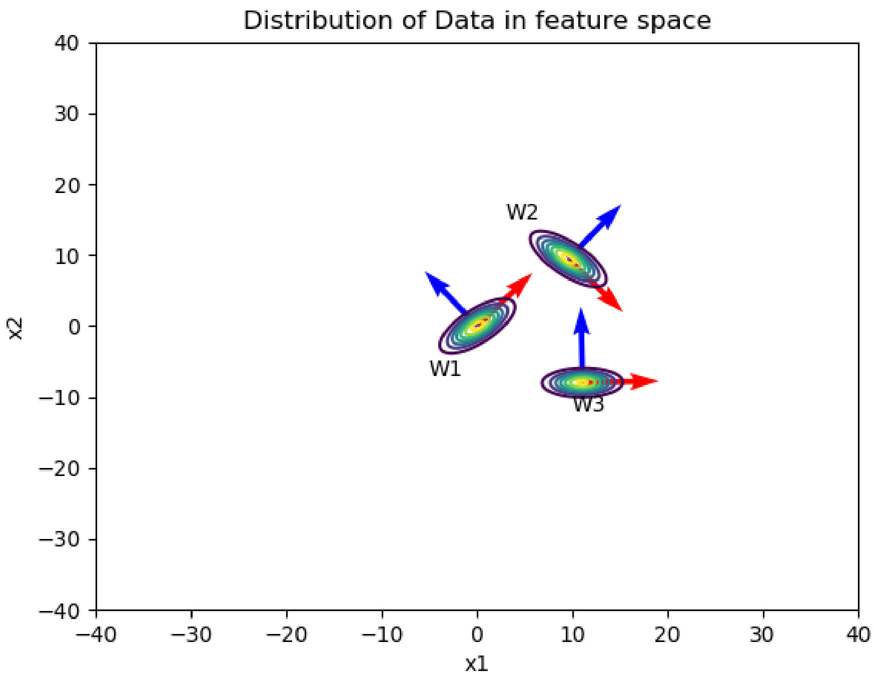
Eigen vector 2 (w2_sigma): [0.69620044 0.71784744]

Eigen vector 1 (w3_sigma): [0.99978609 0.02068282]

Eigen vector 2 (w3_sigma): [-0.02068282 0.99978609]



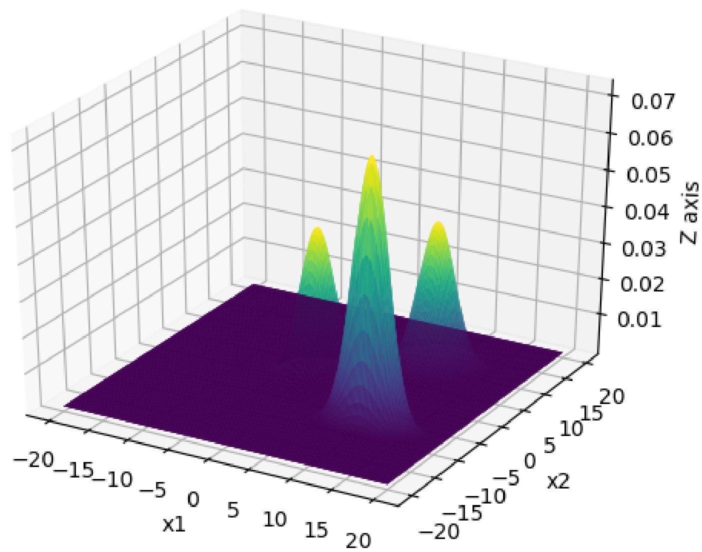
PDF: different covariance matrix



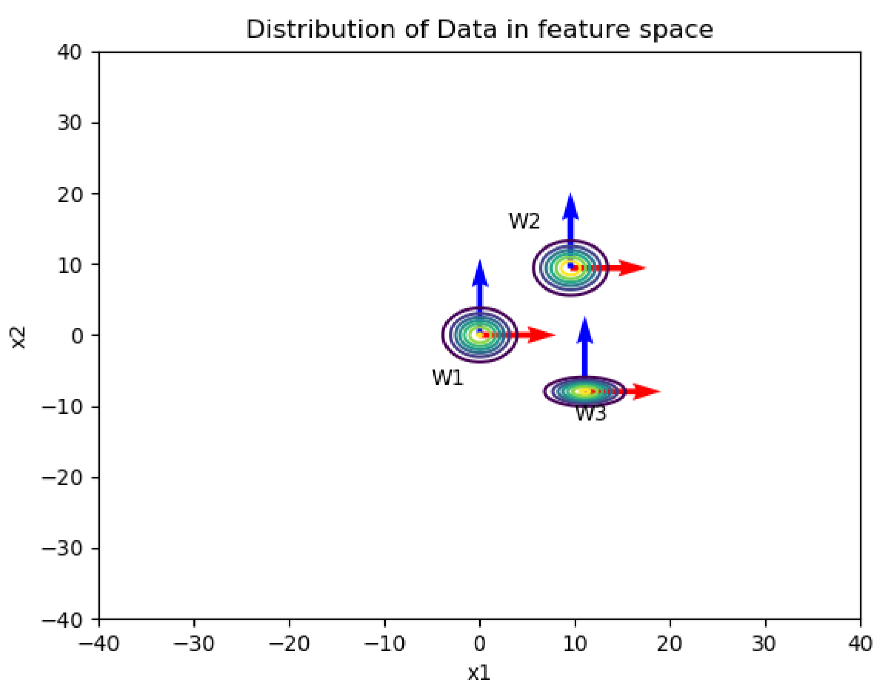
Eignevectors: different covariance matrix

3 **Case iii**

Class w1 mu: [0.06728701 -0.00674633] sigma: [[3.84966996 0.][0. 3.67725503]]
Class w2 mu: [9.59179143 9.43031743] sigma: [[4.00356409 0.][0. 3.82907431]]
Class w3 mu: [11.09321057 -7.98437543] sigma: [[4.51003748 0.][0. 1.0674692]]
Case 3 accuracy: 0.9977528089887641
Eigen vector 1 (w1_sigma): [1. 0.]
Eigen vector 2 (w1_sigma): [0. 1.]
Eigen vector 1 (w2_sigma): [1. 0.]
Eigen vector 2 (w2_sigma): [0. 1.]
Eigen vector 1 (w3_sigma): [1. 0.]
Eigen vector 2 (w3_sigma): [0. 1.]



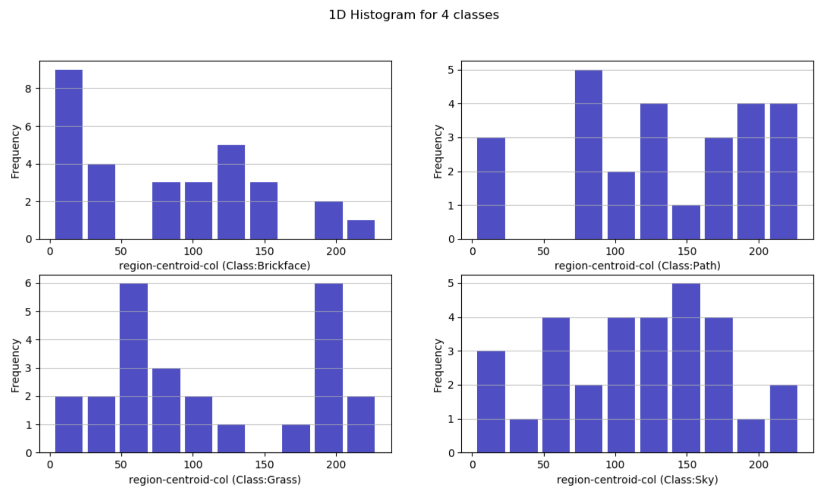
PDF: different covariance matrix (diagonal)



Eignevectors: different covariance matrix (diagonal)

2. Select any one dataset. Then for each class select one feature and plot 1D histogram i.e. $p(x_k/_i)$ for at least 3 classes, where x_k is the k^{th} feature of datset and $_i$ represents the i^{th} class. Now apply bayesian classification using the above likelihoods, you can experiment with different values of k. Repeat the same by selecting 2 features for at least 3 classes and plot 2D histogram (you can use inbuilt command for this).

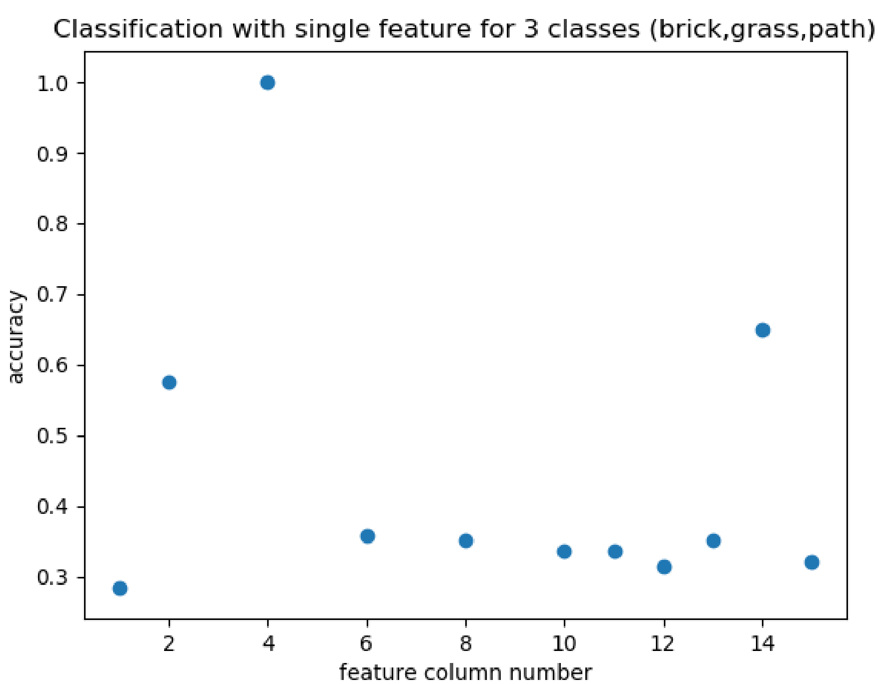
1D histogram i.e. $p(x_k/_i)$ for four classes. (**Dataset used: ImageSegData.xls**)



Eignevectors: different covariance matrix (diagonal)

Class w1 mu: 83.4 sigma: 3924.84
Class w2 mu: 130.7 sigma: 6282.41
Class w3 mu: 150.166666667 sigma: 5304.27222222
Accuracy (feature col 1): 0.2846715328467153 Class w1 mu: 109.333333333 sigma: 815.155555556
Class w2 mu: 203.5 sigma: 688.85
Class w3 mu: 187.233333333 sigma: 128.445555556
Accuracy (feature col 2): 0.5766423357664233 Class w1 mu: 0.00370370366667 sigma: 0.000397805204664
Class w2 mu: 0.0259259256667 sigma: 0.00220850475693
Class w3 mu: 0.011111111 sigma: 0.00111111108889
Accuracy (feature col 4): 1.0 Class w1 mu: 1.03703704833 sigma: 0.363031532388
Class w2 mu: 1.50740746533 sigma: 0.523813440071
Class w3 mu: 2.40000015667 sigma: 1.07251031475
Accuracy (feature col 6): 0.35766423357664234 Class w1 mu: 1.337036999 sigma: 0.624883411346
Class w2 mu: 2.142592569 sigma: 0.864543941427
Class w3 mu: 4.62037006333 sigma: 12.6934314975
Accuracy (feature col 8): 0.35036496350364965 Class w1 mu: 13.16543213 sigma: 64.1186774656
Class w2 mu: 14.9777777333 sigma: 24.8360869291
Class w3 mu: 49.4913578 sigma: 82.115853565

Accuracy (feature col 10): 0.3357664233576642 Class w1 mu: 13.6111110133 sigma: 50.5528781667
Class w2 mu: 11.91111109 sigma: 15.5838676692
Class w3 mu: 43.9925927 sigma: 64.3061116331
Accuracy (feature col 11): 0.3357664233576642 Class w1 mu: 16.5777778267 sigma: 110.07687324
Class w2 mu: 13.6148150733 sigma: 30.3043086951
Class w3 mu: 61.2259271 sigma: 132.745270642
Accuracy (feature col 12): 0.31386861313868614 Class w1 mu: 9.30740752667 sigma: 42.1059142203
Class w2 mu: 19.4074074333 sigma: 33.049657901
Class w3 mu: 43.2555558 sigma: 59.433863508
Accuracy (feature col 13): 0.35036496350364965 Class w1 mu: 1.33703700867 sigma: 12.9724143557
Class w2 mu: -9.20000004 sigma: 16.8151442585
Class w3 mu: -16.4962962333 sigma: 13.3520429467
Accuracy (feature col 14): 0.6496350364963503 Class w1 mu: 10.2370370373 sigma: 59.3273529908
Class w2 mu: -4.08888889467 sigma: 10.6324280558
Class w3 mu: 35.2037038 sigma: 56.8716688746
Accuracy (feature col 15): 0.32116788321167883



Variation of accuraty with features (single)

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