

# Assignment 2, COMP4702

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## Question 4.2

```
1 % Q2
2
3 a = randn(200, 2);
4 b = a + 4;
5 c = a;
6
7 c(:, 1) = 3 * c(:, 1);
8 c = c - 4;
9
10 d = [a; b];
11 e = [a; b; c];
12
13 % hold on;
14 % plot(a(:, 1), a(:, 2), '+');
15 % plot(b(:, 1), b(:, 2), 'o');
16 % plot(c(:, 1), c(:, 2), '*');
17
18 % Use the first dataset
19 data = e;
20
21
22 figure;
23 subplot(3, 2, 1);
24 hold on;
25 % ksdensity(data, 'PlotFcn', 'contour');
26 plot(a(:, 1), a(:, 2), '+');
27 plot(b(:, 1), b(:, 2), 'o');
28 plot(c(:, 1), c(:, 2), '*');
29
30 title('Contours Overlay');
31
32 % Calculate the grid
33 [f, xi] = ksdensity(data); x = linspace(min(xi(:, 1)), max(xi(:, 1))
    ));
34 y = linspace(min(xi(:, 2)), max(xi(:, 2)));
35 [xq, yq] = meshgrid(x, y);
36 z = griddata(xi(:, 1), xi(:, 2), f, xq, yq);
37
38 % We now have x, y, z that can be used to get the gradient at any
    point
39
40 contour(x, y, z);
```

```

41 xlim([-10, 10]);
42 ylim([-10, 10]);
43 hold off;
44
45 copy = data;
46 new_points = copy;
47
48 for i = 1:5
49     new_points = step(new_points, x, y, z);
50     subplot(3, 2, i + 1);
51     hold on;
52     % ksdensity(data, 'PlotFcn', 'contour');
53     scatter(new_points(:, 1), new_points(:, 2));
54     title(sprintf('Step %d', i));
55     xlim([-10, 10]);
56     ylim([-10, 10]);
57     hold off;
58
59 end
60
61
62 function dist = euclid_distance(point1, point2)
63     dist = sqrt((point1(1) - point2(1))^2 + (point1(2) - point2(2)
64         )^2);
65
66 end
67
68 function new_points = step(points, x, y, z)
69     % Calibration factor (lambda)
70     max_distance = 1.8;
71
72     new_points = zeros(length(points), 2);
73     for i = 1:length(points)
74         point = points(i, :);
75
76         within_range = zeros(length(points), 1);
77
78         numerator = 0;
79         denominator = 0;
80
81         for j = 1:length(points)
82             other_point = points(j, :);
83             if euclid_distance(point, other_point) < max_distance
84                 within_range(j) = 1;
85                 % weight = interp2(x, y, z, other_point(1),
86                     other_point(2));

```

```

84
85         % Calculate part of sum
86         distance = euclid_distance(point, other_point);
87         numerator = numerator + (distance * other_point);
88         denominator = denominator + distance;
89     end
90 end
91
92     mx = numerator / denominator;
93     new_points(i, :) = mx(1, :);
94 end
95 end

```

## Question 4.3

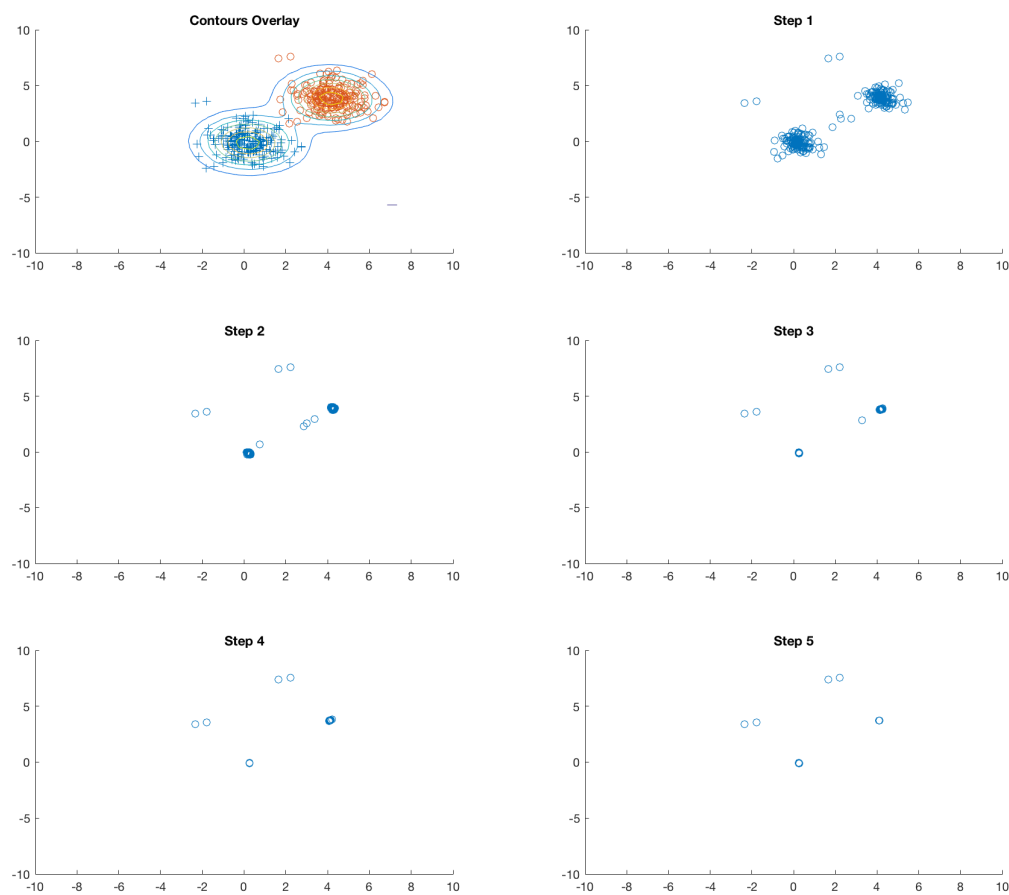


Figure 1: 2 Classes,  $\Lambda = 1.8$

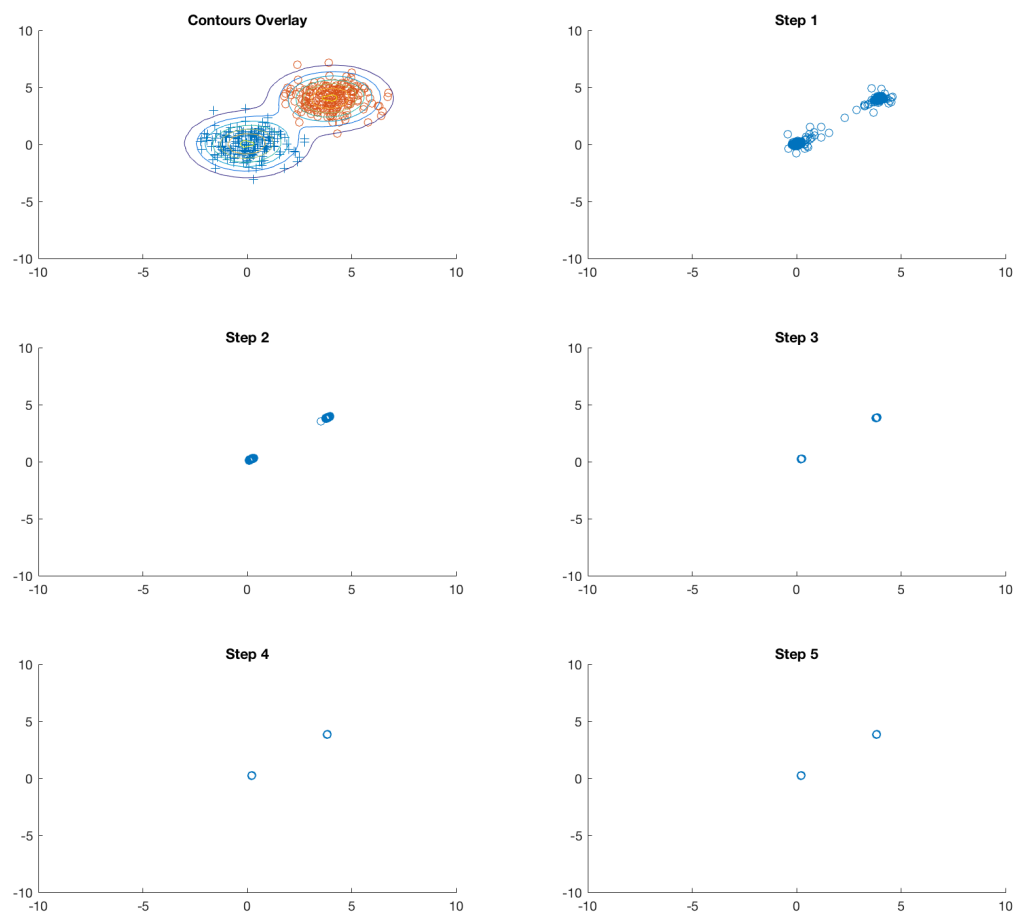


Figure 2: 2 Classes,  $\Lambda = 3$

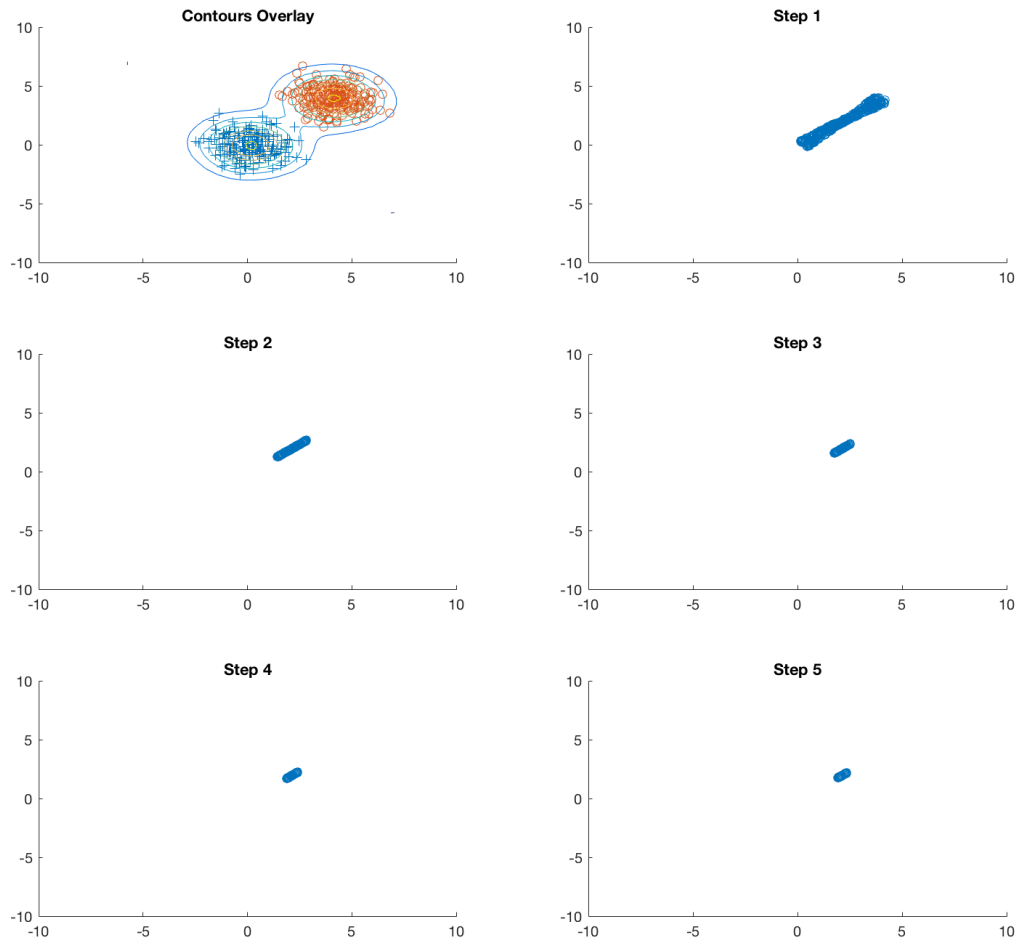


Figure 3: 2 Classes, Lambda = 5

For the 2 class problem, a lambda value set to 3 provided the best result. A lambda of 1.8 cause a few outliers not to shift towards the mean value. Whereas a lambda value of 5 caused all the points to shift towards one of the means, which is not desired. A lambda value of 3 shifted all the points to the two mean values without leaving outliers, thus is the best lambda value out of the three.

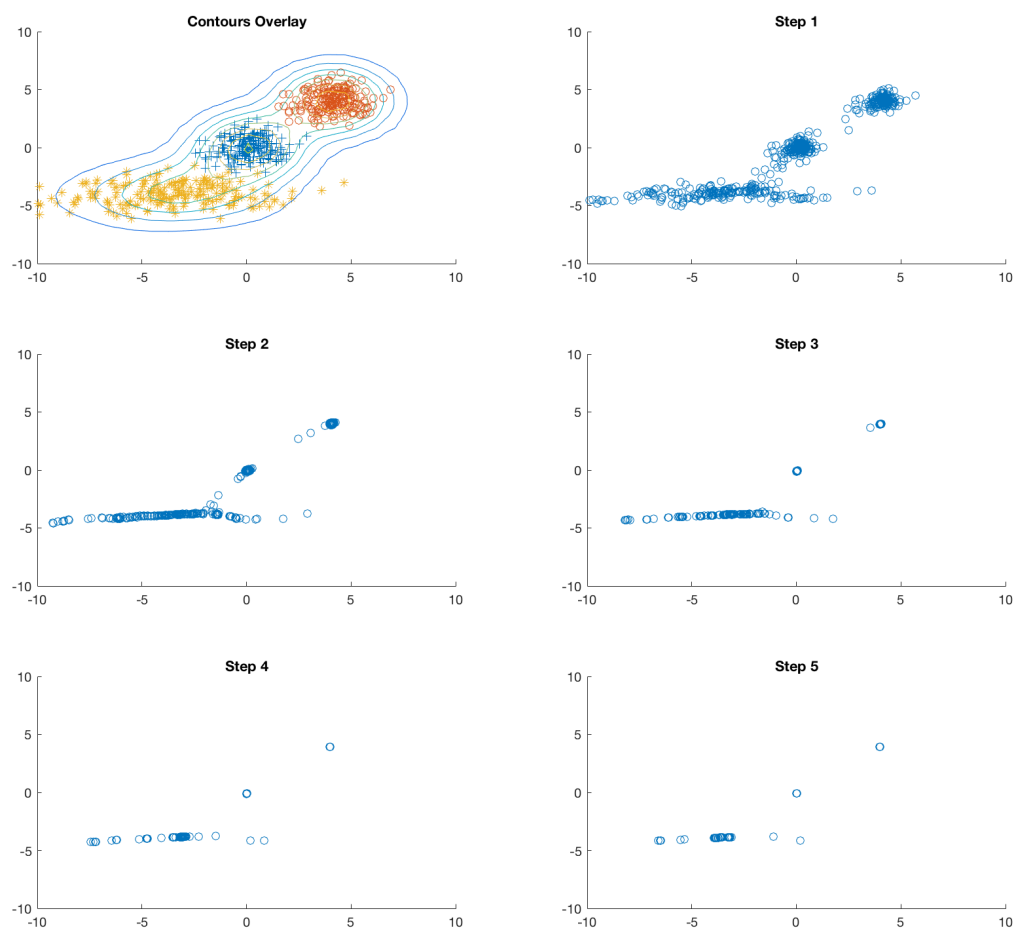


Figure 4: 3 Classes,  $\Lambda = 1.8$



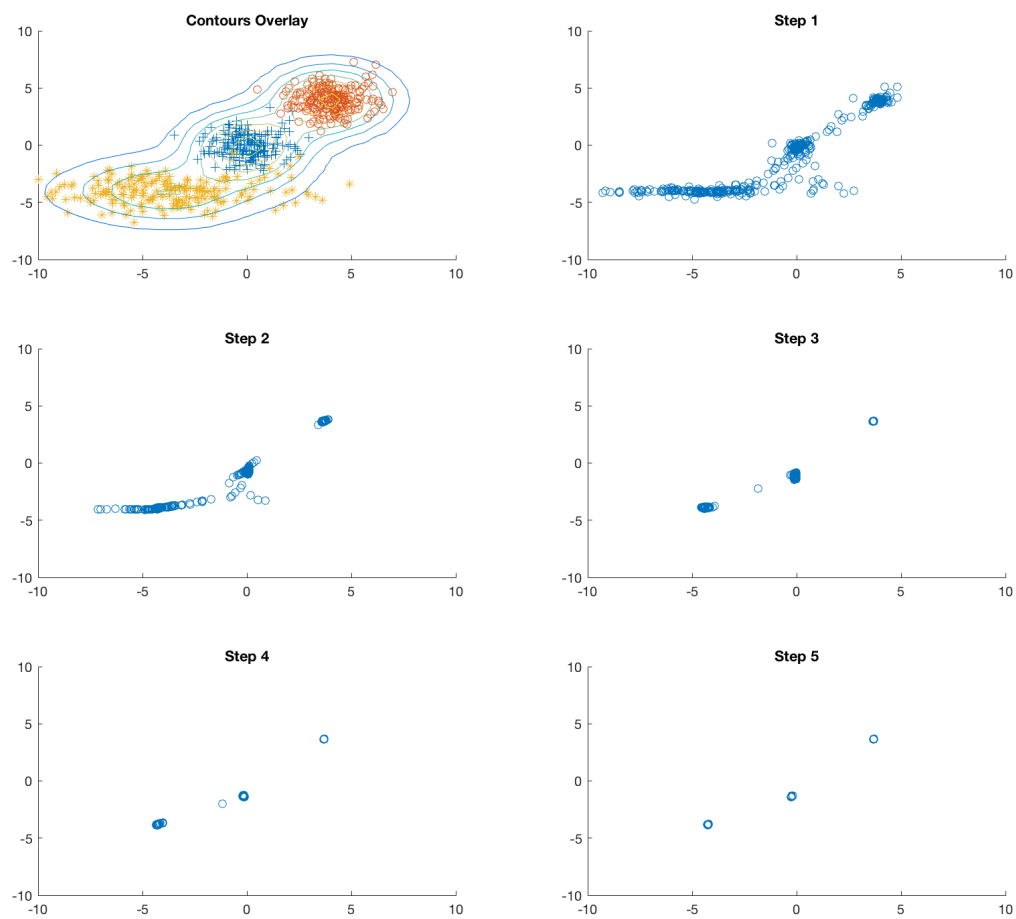


Figure 5: 3 Classes,  $\Lambda = 3$

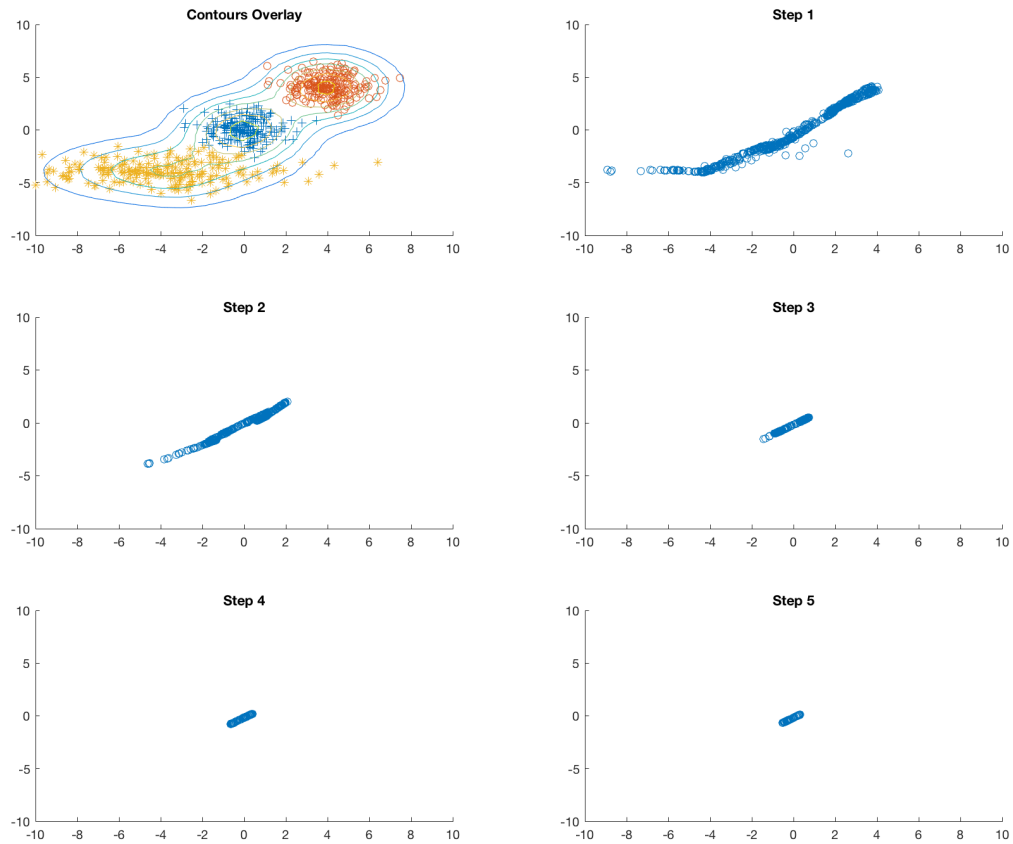


Figure 6: 3 Classes, Lambda = 5

The 3 class problem showed similar results with the same lambda values 1.8, 3 and 5. Again the 1.8 lambda value failed to shift some outliers towards the mean and the 5 lambda value shifted all of them towards a single point. The lambda value 3 correctly shifted all the points to their respective means, thus the lambda value of 3 was the best choice out of the three numbers.

## Question 5.1

```

1 %
2 % Principle Component Analysis
3 %
4
5 function result = pca(data)
6     m = mean(data);

```

```

7     S = cov(data - m);
8     [evec, eval] = eigs(S);
9
10    % Sort the eigenvalues
11    [y, i] = sort(diag(eval), 'descend');
12    % Sort the eigenvectors columns by the eigenvalue indexes
13    evec = evec(:, i);
14
15    % PCA only works if you subtract the mean
16    result = evec' * (data - m)';
17 end

```

## Question 5.2

a

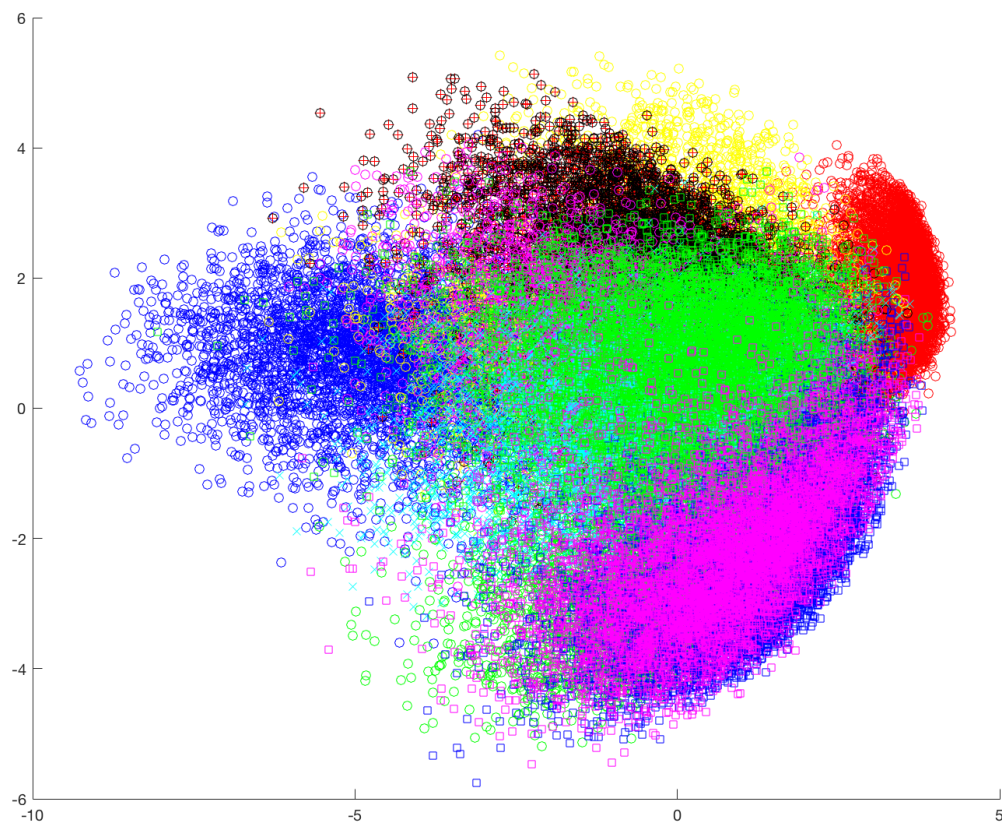


Figure 7: PCA on MNIST dataset

**b**

The first principle component accounts for 5.116% of the data, whereas the second principle component accounts for 3.7414% of the data.

**c**

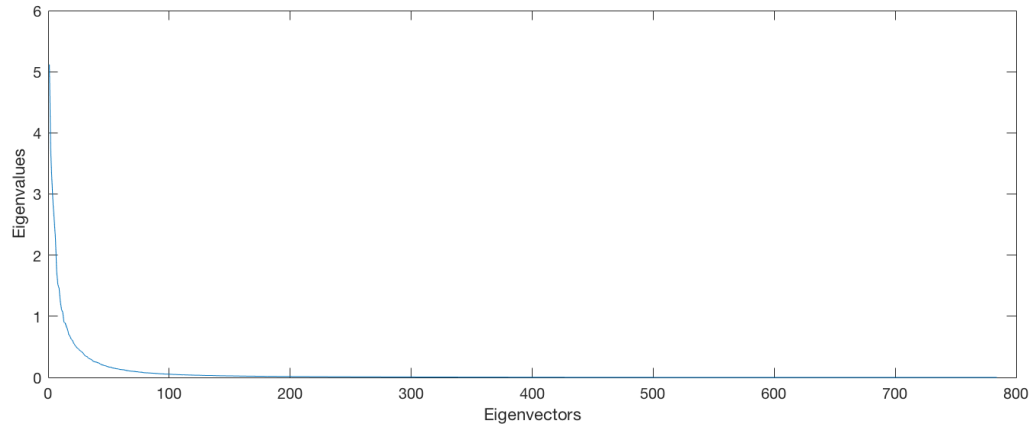


Figure 8: Scree Graph

## Question 5.6

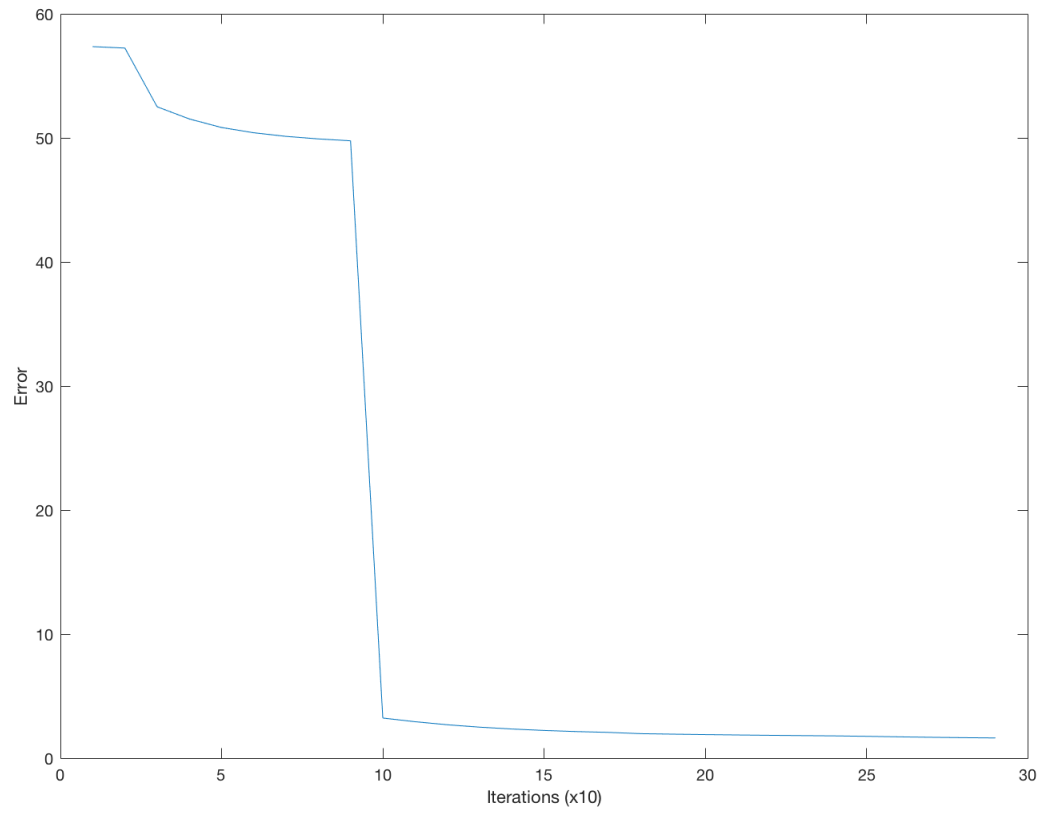


Figure 9: Error vs Iteration

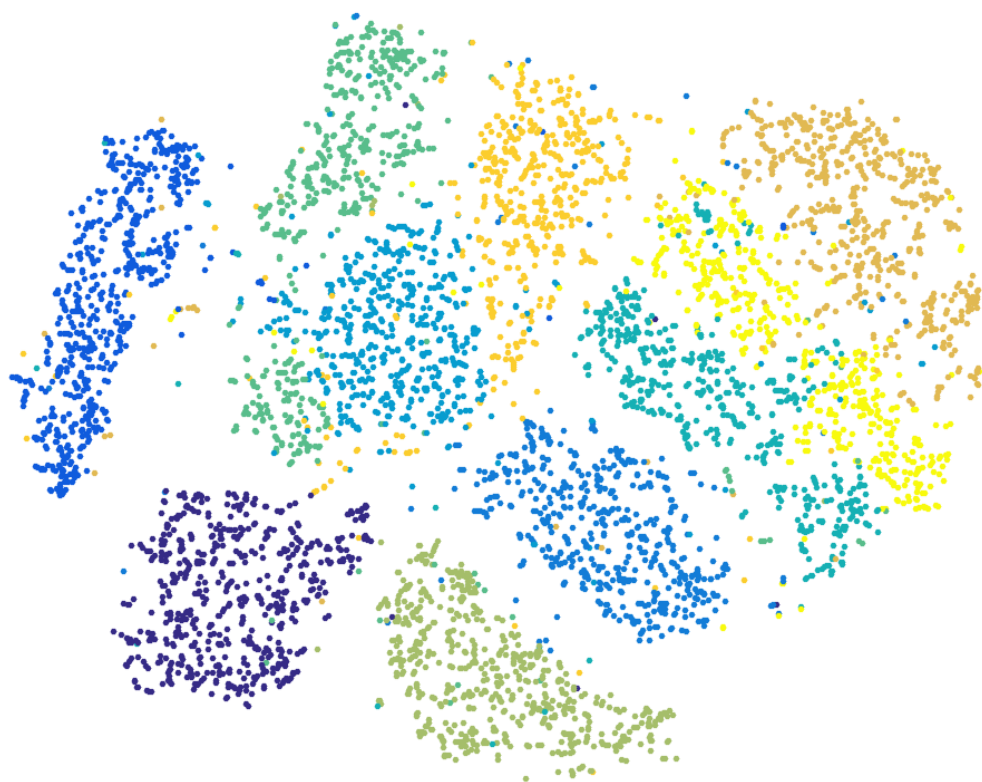


Figure 10: Iteration 300

## Question 5.8