

Theodore Kim

CS-UY 4563 – Introduction to Machine Learning

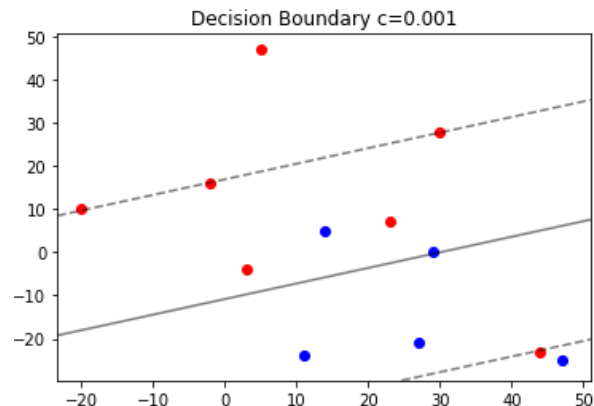
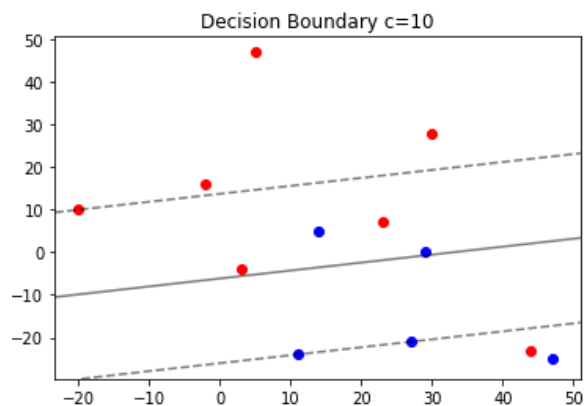
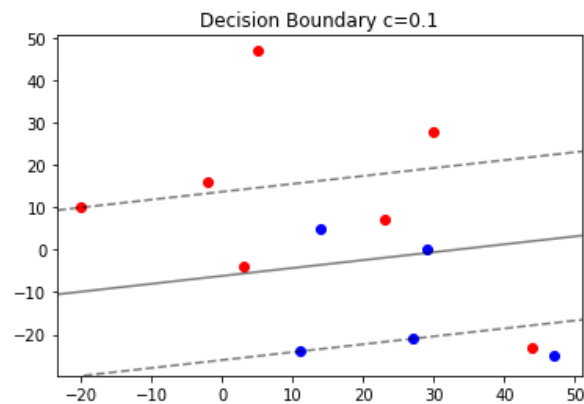
HW #5b

### 1. Using soft-margin SVM:

- (a) If the cost ( $\xi_i$ ) of a point  $x_i$  is 0, the point is located on the outside of the margin and is correctly classified.
- (b) If the cost ( $\xi_i$ ) of a point  $x_i$  is greater than 0 and less than 1, the point is located within the margin but on the "correct" side of classifier line, therefore the classification was "correct" but there is a chance that, the relaxation of the margin misclassified the point.
- (c) If the cost ( $\xi_i$ ) of a point  $x_i$  is greater than 1, the point is located on the wrong side of the classifier line and the margin and is therefore incorrectly classified.

### 2. Plot the decision boundary when $C=0.1$ and $C=10$

$x_1$	$x_2$	$y$
5	47	-1
14	5	1
47	-25	1
3	-4	-1
-2	16	-1
30	28	-1
27	-21	1
11	-24	1
29	0	1
23	7	-1
-20	10	-1
44	-23	-1

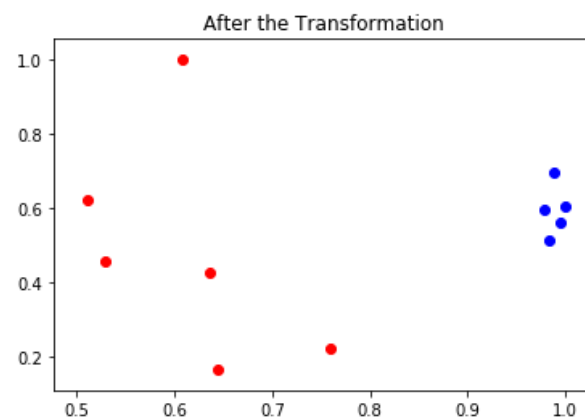
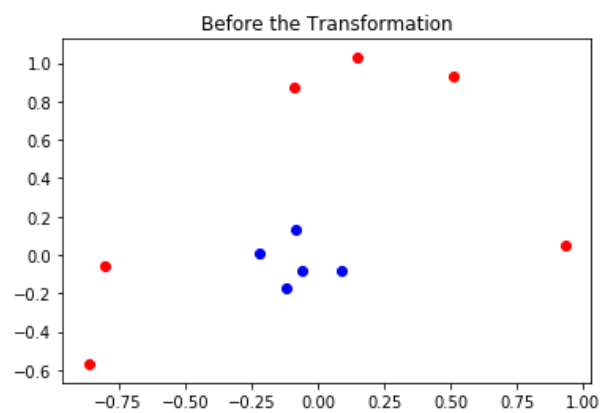


### 3. Transform the below dataset in order to make it linearly separable.

a) For the below data, I used an RBF kernel transformation using the landmark set:

$l = \{(-0.06, 0.08), (0.93, 0.05)\}$  These points were chosen for their relatively central position to the two class clusters.

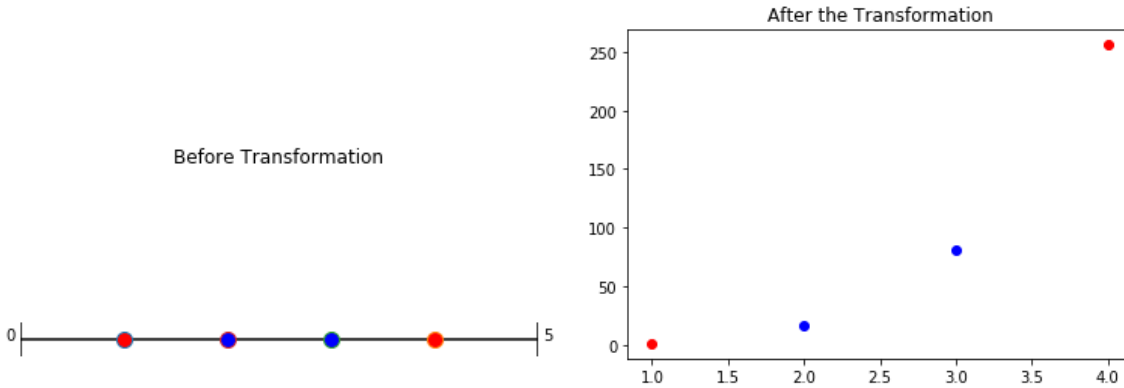
$x_1$	$x_2$	$z_1$	$z_2$	$y$
0.15	1.03	0.5283	0.4564	-1
-0.08	0.13	0.9780	0.5985	1
-0.8	-0.06	0.7603	0.2226	-1
-0.22	0.01	0.9833	0.5158	1
0.51	0.93	0.5104	0.6216	-1
-0.09	0.87	0.6365	0.4247	-1
0.09	-0.08	0.9888	0.6968	1
-0.12	-0.17	0.9942	0.5625	1
0.93	0.05	0.6074	1.0000	-1
-0.06	-0.08	1.0000	0.6074	1
-0.86	-0.57	0.6440	0.1663	-1



b) For the below data

$x_1$	$y$
1	-1
2	1
3	1
4	-1

I made it linearly separable using a polynomial kernel transformation with degree = 4. I transformed the data into two features:  $\phi(x) = [x, x^2]$



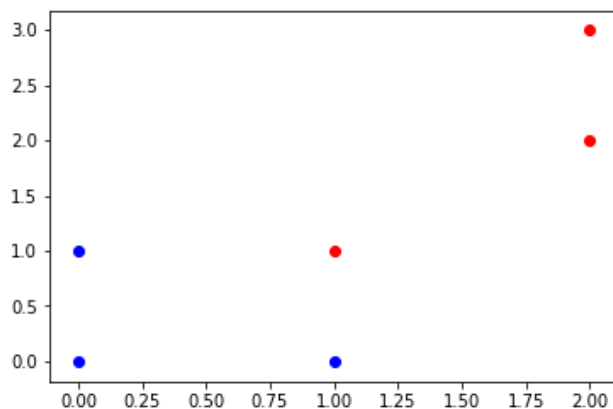
4. If in question (3A), if the point  $(-0.08, 0.13)$  is removed, does the margin stay the same? Which points, if removed, will change the margin?

$(-0.18, 0.13)$  would not change the margin as its transformed feature  $(0.9780, 0.5985)$  does not lie on the support vector. On the other hand, the point  $(-0.22, 0.01)$  would change the margin as its transformed feature,  $(0.9833, 0.5158)$ , does lie on the support vector. Finally, the points  $(-0.8, -0.06)$  and  $(0.93, 0.05)$  lie on opposite support vector, and removing them would also alter the margin.

5. Given the data:

$x_1$	$x_2$	$y$
1	1	-1
2	3	-1
2	2	-1
0	0	1
1	0	1
0	1	1

a) Plot the points and determine if they are separable.



**They do seem linearly separable.**

b) Write the constraints for the constrained optimization problem:

$$\min w_1^2 + w_2^2$$

$$\text{subject to } -1(w_0 + w_1 + w_2) \geq 1$$

$$-1(w_0 + 2w_1 + 3w_2) \geq 1$$

$$-1(w_0 + 2w_1 + 2w_2) \geq 1$$

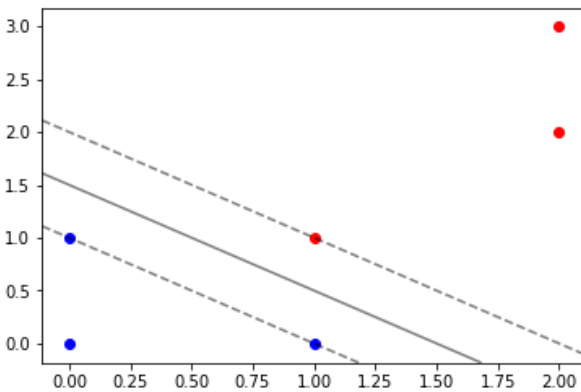
$$1(w_0) \geq 1$$

$$1(w_0 + w_1) \geq 1$$

$$1(w_0 + w_2) \geq 1$$

c) Find the hyperplane that separates the points and has the maximal margin

$$w = \begin{bmatrix} -1.99921875 \\ -1.99921875 \end{bmatrix} \quad w_0 = 2.99895833$$



d) Identify the support vectors

**The support vectors are:**

**(0, 1) and (1,0)**

**(1,1)**

6. Demonstrate if  $\phi(x) = \phi([x_{i1}, x_{i2}]) = (1, \sqrt{2}x_{i1}, \sqrt{2}x_{i2}, x_{i1}^2, x_{i2}^2, \sqrt{2}x_{i1}x_{i2})$ , then  $\phi(x)^T \phi(x') = (1 + x^T x)^2$

$$\phi(x)^T = \phi([x_{i1}, x_{i2}])^T = \begin{bmatrix} 1 \\ \sqrt{2}x_{i1} \\ \sqrt{2}x_{i2} \\ x_1^2 \\ x_2^2 \\ \sqrt{2}x_{i1}x_{i2} \end{bmatrix}$$

$$\phi(x') = \phi([x_{i1}, x_{i2}]) = [1 \quad \sqrt{2}x_{1i} \quad \sqrt{2}x_{2i} \quad x_i^2 \quad x_{i+1}^2 \quad \sqrt{2}x_{1i}x_{2i}]$$

$$\phi(x)^T \cdot \phi(x') = \begin{bmatrix} 1 \\ \sqrt{2}x_{i1} \\ \sqrt{2}x_{i2} \\ x_1^2 \\ x_2^2 \\ \sqrt{2}x_{i1}x_{i2} \end{bmatrix} \cdot [1 \quad \sqrt{2}x_{1i} \quad \sqrt{2}x_{2i} \quad x_i^2 \quad x_{i+1}^2 \quad \sqrt{2}x_{1i}x_{2i}]$$

$$\begin{aligned} \phi(x)^T \cdot \phi(x') &= \left( 1 + (\sqrt{2}x_{i1} \cdot \sqrt{2}x_{1i}) + (\sqrt{2}x_{i2} \cdot \sqrt{2}x_{2i}) + (x_1^2 \cdot x_i^2) + (x_2^2 \cdot x_{i+1}^2) \right. \\ &\quad \left. + (\sqrt{2}x_{i1}x_{i2} \cdot \sqrt{2}x_{1i}x_{2i}) \right) \end{aligned}$$

$$\phi(x)^T \cdot \phi(x') = (1 + x^T x)^2$$