

1.a.

$$X = UV^T = [6 \ 0 \ 2 \ 6]^T [4 \ 2 \ 1 \ 1]$$

$$= \begin{bmatrix} 24 & 12 & 6 \\ 0 & 0 & 0 \\ 12 & 6 & 3 \\ 24 & 12 & 6 \end{bmatrix}$$

b.

$$\begin{aligned} \text{Given } (X) &= \frac{1}{2} \sum (X_{ij} - y_{ij})^2 \\ &= \frac{1}{2} [(24-5)^2 + (7-6)^2 + 2 + (12-4)^2 + (12-3)^2 + 6] \\ &= \frac{1}{2} \cdot 25 \cdot 5 = 25 \cdot 5 \end{aligned}$$

c.

$$\text{Let } U = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \quad UV^T = \begin{bmatrix} 4u_1 & 2u_1 & u_1 \\ 4u_2 & 2u_2 & u_2 \\ 4u_3 & 2u_3 & u_3 \\ 4u_4 & 2u_4 & u_4 \end{bmatrix}$$

$$\begin{aligned} J(u_1) &= \frac{1}{2} [(5-u_1)^2 + (7-2u_1)^2] + \frac{\lambda}{2} u_1^2 \\ \frac{\partial J(u_1)}{\partial u_1} &= (5-u_1) \cdot (-1) + (7-2u_1) \cdot (-2) + \lambda \cdot u_1 \end{aligned}$$

$$\text{For } \frac{\partial J(u_1)}{\partial u_1} = 0;$$

$$\begin{aligned} -u_1 + 14u_1 - 14 + 4u_1 + u_1 &= 0 \\ -5 &= -34 \end{aligned}$$

d. The value of  $u_1$  will decrease to very low value.

1. c.

$$U = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix}$$

$$UV^T = \begin{bmatrix} 4u_1 & 2u_1 & u_1 \\ 4u_2 & 2u_2 & u_2 \\ 4u_3 & 2u_3 & u_3 \\ 4u_4 & 2u_4 & u_4 \end{bmatrix}$$

$$J(u_1) = \frac{1}{2} [(5-4u_1)^2 + (7-u_1)^2] + \frac{1}{2} u_1^2$$

$$\begin{aligned} \frac{\partial J(u_1)}{\partial u_1} &= (5-4u_1)(-4) + (7-u_1)(-1) + u_1 \\ &= -20 + 16u_1 - 7 + u_1 + u_1 \end{aligned}$$

$$\begin{aligned} 16u_1 &= 27 \\ \Rightarrow u_1 &= \frac{27}{16} \end{aligned}$$

$$\begin{aligned} J(u_2) &= \frac{1}{2} [(2u_2-2)^2] + \frac{u_2^2}{2} \\ &= (2u_2-2) \cdot 2 + u_2 \end{aligned}$$

$$\begin{aligned} 0 &= 5u_2 - 4 \\ \Rightarrow u_2 &= \frac{4}{5} \end{aligned}$$

$$J(u_3) = \frac{1}{2} [(4u_3-4)^2] + \frac{u_3^2}{2}$$

$$\begin{aligned} \frac{\partial J(u_3)}{\partial u_3} &= (4u_3-4) \cdot 4 + u_3 \\ \Rightarrow u_3 &= \frac{16}{17} \end{aligned}$$

$$\begin{aligned} J(u_4) &= \frac{1}{2} (2u_4-3)^2 + \frac{u_4^2}{2} \\ &+ \frac{1}{2} (u_4-6)^2 \end{aligned}$$

$$\begin{aligned} &= 2(2u_4-3) + u_4 \\ &= u_4 - 6 \end{aligned}$$

$$\Rightarrow u_4 = 2$$

$$U = \begin{bmatrix} 27/16 \\ 4/5 \\ 16/17 \\ 2 \end{bmatrix}$$

$$K(x, q) = (x^T q + 1)^2$$

$$= \left( \sum x_i q_i + 1 \right)^2$$

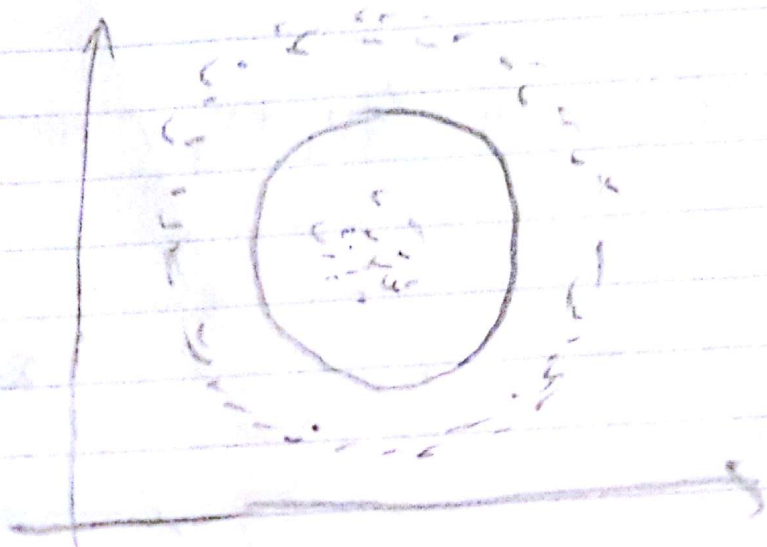
$$= (x_1 q_1 + x_2 q_2 + 1)^2$$

$$= x_1^2 q_1^2 + x_2^2 q_2^2 + 2x_1 x_2 q_1 q_2 + 2x_1 q_1 + 2x_2 q_2 + 1$$

$$\phi(x) = [x_1^2, x_2^2, \sqrt{2}x_1 x_2, \sqrt{2}x_1, \sqrt{2}x_2, 1]$$

$\sqrt{2}x_1 x_2$  represents the measure when both  $x_1, x_2$  appear simultaneously in bag of words vectors.  
 ie if  $x_1, x_2$  represents 2 words,  $\sqrt{2}x_1 x_2 \neq 0$  when both are present.

$\phi(x)_3 = x_1^2 + x_2^2$  could have been used  
 find  $x_3$ .



2.  
(1)  
(a) Quadratic kernel.  $\rightarrow$  hyperbolic

(b) Gaussian kernel  $\rightarrow$  over fitted

(c) Linear kernel  $\rightarrow$  straight line

(d) 3<sup>rd</sup> order kernel.  $\rightarrow$  3 turns in  
classifies

For value of  $\lambda$ , increasing the value of  $\lambda$  starts  
to underfit the data. Since (b) is overfitted  
(b) will increase it's performance on test data.

### 3. Linear Regression

(a) (i) looks like an exponential dataset.  $\phi(x) = e^x$   
Exponential kernel will be best model.

(ii) piecewise function. if  $x > 0$ ,  $\phi(x) = x - 1$   
if  $x < 0$ ,  $\phi(x) = x + 1$

(b) (i)  $L(\theta, \theta_0) = \sum_{t=1}^n (y^{(t)} - \theta \cdot x^{(t)} - \theta_0)^2 + \lambda \theta^2$

$$\frac{\partial L}{\partial \theta} = -x^{(t)} \sum_{t=1}^n (y^{(t)} - \theta \cdot x^{(t)} - \theta_0) + 2\lambda \theta$$

$$\frac{\partial L}{\partial \theta_0} = -2 \sum_{t=1}^n (y^{(t)} - \theta x^{(t)} - \theta_0)$$

(ii) For,  $\frac{\partial L}{\partial \theta_0} = 0$

$$-2 \left( \sum_{t=1}^n y^{(t)} - \theta \cdot x^{(t)} \right) + 2n\theta_0 = 0$$

$$\Rightarrow \theta_0 = \frac{1}{n} \sum_{t=1}^n (y^{(t)} - \theta \cdot x^{(t)})$$



$$\frac{\partial L}{\partial \theta} = 2\lambda\theta - 2 \sum_{t=1}^n (y^{(t)} - \theta x^{(t)} - \theta_0) x^{(t)}$$

$$= 2\lambda\theta - 2 \sum_{t=1}^n \left( y^{(t)} - \theta x^{(t)} - \left[ \frac{1}{n} \sum_{i=1}^n (y^{(i)} - \theta x^{(i)}) \right] x^{(t)} \right)$$

$$= 0$$

$$= \lambda\theta - \sum_{t=1}^n y^{(t)} x^{(t)} - \sum_{t=1}^n \theta x^{(t)} x^{(t)}$$

$$+ \sum_{t=1}^n \frac{1}{n} \left( \sum_{i=1}^n (y^{(i)} - \theta x^{(i)}) \right) x^{(t)} = 0$$

$$\lambda\theta - \frac{1}{n} \sum_{t=1}^n \sum_{i=1}^n \theta x^{(i)} x^{(t)} + \frac{1}{n} \sum_{t=1}^n \sum_{i=1}^n y^{(i)} x^{(t)}$$

$$\rightarrow \sum_{t=1}^n y^{(t)} x^{(t)} + \theta \sum_{t=1}^n (x^{(t)})^2 = 0$$

$$\Rightarrow \theta = \frac{\sum_{t=1}^n y^{(t)} x^{(t)}}{\sum_{t=1}^n (x^{(t)})^2} = \frac{\frac{1}{n} \sum_{t=1}^n \sum_{i=1}^n y^{(i)} x^{(t)}}{\frac{1}{n} \sum_{t=1}^n \sum_{i=1}^n \theta x^{(i)} x^{(t)} + \sum_{t=1}^n (x^{(t)})^2}$$