

Q1

$$\frac{1}{n} \sum L(y_i, w^T x_i + b) = \frac{1}{n} \sum \log(1 + \exp(-y_i(w^T x_i + b)))$$

Let $\tilde{x}_i = \begin{bmatrix} 1 \\ x_i \end{bmatrix}$ & $\theta = \begin{bmatrix} b \\ w \end{bmatrix}$

Then $w^T x_i + b = \theta^T \tilde{x}_i$

$$\therefore = \frac{1}{n} \sum \log(1 + \exp(-y_i \theta^T \tilde{x}_i))$$

Above form is equal to the -ve log likelihood for logistic regression.

Q2

$$J(w, b) = \sum_{i=1}^n J_i(w, b) = \frac{1}{n} \sum L(y_i, w^T x_i + b) + \lambda \sum_{i=1}^n \|w\|^2$$

$$\therefore J_i(w, b) = \frac{L(y_i, w^T x_i + b)}{n} + \frac{\lambda}{n} \|w\|^2$$

& $L(y_i, w^T x_i + b) = \max\{0, 1 - y_i + \}$ $= \max\{0, 1 - y_i(w^T x_i + b)\}$

$$\therefore J_i(w, b) = \frac{\max\{0, 1 - y_i(w^T x_i + b)\}}{n} + \frac{\lambda}{n} \|w\|^2$$

~~$\frac{dJ_i(w, b)}{db}$~~

When $y_i(w^T x_i + b) < 0$

$$J_i(w, b) = \frac{\lambda}{n} \|w\|^2$$

$$\frac{dJ_i(w, b)}{db} = 0$$

$$\& \frac{dJ_i(w, b)}{dw} = \frac{2\lambda w}{n}$$

$$\therefore u_i = \begin{bmatrix} 0 \\ \frac{2\lambda w}{n} \end{bmatrix}$$

When $y_i(w^T x_i + b) > 0$

$$J_i(w, b) = \frac{1 - y_i(w^T x_i + b)}{n} + \frac{\lambda}{n} \|w\|^2$$

$$\frac{dJ_i(w, b)}{db} = \frac{-y_i}{n}$$

$$\frac{dJ_i(w, b)}{dw} = \frac{-y_i x_i}{n} + \frac{2\lambda w}{n}$$

$$\therefore u_i = \begin{bmatrix} -y_i/n \\ \frac{-y_i x_i}{n} + \frac{2\lambda w}{n} \end{bmatrix}$$

$$\therefore \text{If } y_i (\theta^T x_i) < 0$$

$$\text{If } y_i (\theta^T x_i) > 0$$

$$u_i = \begin{bmatrix} 0 \\ \frac{2\lambda}{n} \theta[2:] \end{bmatrix}$$

$$u_i = \begin{bmatrix} -y_i/n \\ \frac{-y_i}{n} x_i + \frac{2\lambda}{n} \theta[2:] \end{bmatrix}$$

d) The empirical rate of convergence is faster for stochastic sub gradient method relative to the sub gradient method because sub gradient took ~ 35 cycles to converge where stochastic sub gradient took ~ 25 cycles to converge.

Q3

$$a) \quad k(u, v) = (\langle u, v \rangle + 1)^3$$

$$= \langle u, v \rangle^3 + 1 + 3 \langle u, v \rangle^2 + 3 \langle u, v \rangle$$

$$\langle u, v \rangle = u_1 v_1 + \dots + u_d v_d$$

$$\langle u, v \rangle^2 = \left(\sum_{i=1}^d u_i v_i \right) \left(\sum_{j=1}^d u_j v_j \right)$$

$$= \sum_{j=1}^d \sum_{i=1}^d u_i v_i u_j v_j$$

$$= \underbrace{u_1^2 v_1^2 + \dots + u_d^2 v_d^2}_{d \text{ terms}} + 2 \underbrace{u_1 u_2 v_1 v_2 + \dots + u_{d-1} u_d v_{d-1} v_d}_{\frac{d(d-1)}{2}}$$

$$\langle u, v \rangle^3 = \underbrace{u_1^3 v_1^3 + \dots + u_d^3 v_d^3}_{d \text{ terms}} + 3 \underbrace{(u_1^2 u_2 v_1^2 v_2 + \dots + u_d^2 u_{d-1} v_d^2 v_{d-1})}_{d(d-1) \text{ terms}}$$

$$+ 6 \underbrace{(u_1 u_2 u_3 v_1 v_2 v_3 + \dots + u_{d-2} u_{d-1} u_d v_{d-2} v_{d-1} v_d)}_{\frac{d(d-1)(d-2)}{3!}}$$

$$\frac{d(d-1)(d-2)}{3!}$$

$$\therefore \phi(u) = \begin{bmatrix} 1 \\ \sqrt{3}u_1 \\ \vdots \\ \sqrt{3}u_d \\ \sqrt{3}u_1^2 \\ \vdots \\ \sqrt{3}u_d^2 \\ \sqrt{6}u_1u_2 \\ \vdots \\ \sqrt{6}u_{d-1}u_d \\ u_1^3 \\ \vdots \\ u_d^3 \\ \sqrt{3}u_1^2u_2 \\ \vdots \\ \sqrt{3}u_d^2u_{d-1} \\ \sqrt{6}u_1u_2u_3 \\ \vdots \\ \sqrt{6}u_{d-2}u_{d-1}u_d \end{bmatrix}$$

$$\therefore \phi(u) = \begin{bmatrix} 1 \\ \sqrt{3}u_1 \\ \vdots \\ \sqrt{3}u_d \\ \sqrt{3}u_1^2 \\ \vdots \\ \sqrt{3}u_d^2 \\ \sqrt{6}u_1u_2 \\ \vdots \\ \sqrt{6}u_{d-1}u_d \\ u_1^3 \\ \vdots \\ u_d^3 \\ \sqrt{3}u_1^2u_2 \\ \vdots \\ \sqrt{3}u_d^2u_{d-1} \\ \sqrt{6}u_1u_2u_3 \\ \vdots \\ \sqrt{6}u_{d-2}u_{d-1}u_d \end{bmatrix}$$

b) k_1 is IP kernel & k_2 is IP kernel

Let's prove $\underbrace{a_1k_1 + a_2k_2}_{k_3}$ is symmetric & PSD kernel.

$$k_3(u, v) = a_1k_1(u, v) + a_2k_2(u, v)$$

We know k_1 & k_2 are IP kernels $\therefore k_1(u, v) = k_1(v, u)$
& $k_2(u, v) = k_2(v, u)$

$$\therefore k_3(u, v) = a_1k_1(v, u) + a_2k_2(v, u) \\ = k_3(v, u)$$

$\therefore k_3$ is symmetric.

Now, to prove ~~PSD~~ PSD,

$$\begin{bmatrix} a_1 k_1(x_1, x_1) + a_2 k_2(x_1, x_1) & \dots & a_1 k_1(x_1, x_n) + a_2 k_2(x_1, x_n) \\ \vdots & & \vdots \\ a_1 k_1(x_n, x_1) + a_2 k_2(x_n, x_1) & \dots & a_1 k_1(x_n, x_n) + a_2 k_2(x_n, x_n) \end{bmatrix}$$

K_3

Above can be rewritten as summation of two matrices

$$\text{ie } \begin{bmatrix} a_1 k_1(x_1, x_1) & \dots & a_1 k_1(x_1, x_n) \\ \vdots & & \vdots \\ a_1 k_1(x_n, x_1) & \dots & a_1 k_1(x_n, x_n) \end{bmatrix} + \begin{bmatrix} a_2 k_2(x_1, x_1) & \dots & a_2 k_2(x_1, x_n) \\ \vdots & & \vdots \\ a_2 k_2(x_n, x_1) & \dots & a_2 k_2(x_n, x_n) \end{bmatrix}$$

$$= a_1 \begin{bmatrix} k_1(x_1, x_1) & \dots & k_1(x_1, x_n) \\ \vdots & & \vdots \\ k_1(x_n, x_1) & \dots & k_1(x_n, x_n) \end{bmatrix} + a_2 \begin{bmatrix} k_2(x_1, x_1) & \dots & k_2(x_1, x_n) \\ \vdots & & \vdots \\ k_2(x_n, x_1) & \dots & k_2(x_n, x_n) \end{bmatrix}$$

$$= \underbrace{\quad}_{K_1} \quad \underbrace{\quad}_{K_2}$$

$$= a_1 K_1 + a_2 K_2$$

$$K_3 = a_1 K_1 + a_2 K_2.$$

To prove K_3 is PSD,

$$x^T K_3 x = a_1 \underbrace{x^T K_1 x}_{\geq 0} + a_2 \underbrace{x^T K_2 x}_{\geq 0}$$

$$\geq 0 \text{ given } \geq 0 \text{ as } K_1 \text{ is PSD } \geq 0 \text{ given } \geq 0 \text{ as } K_2 \text{ is PSD}$$

$$\therefore x^T K_3 x \geq 0$$

or K_3 is PSD

$\therefore K_3$ is symmetric & PSD $\Rightarrow K_3$ is an IP kernel

c) k is inner product kernel.

$$\therefore \langle u, v \rangle = \langle v, u \rangle \quad - (1)$$

$$\& \langle u, u \rangle \geq 0 \quad - (2)$$

To prove: Symmetric.

$$\begin{bmatrix} \langle x_1, x_1 \rangle & \langle x_1, x_2 \rangle & \dots & \langle x_1, x_n \rangle \\ \langle x_2, x_1 \rangle & & & \\ \vdots & & & \\ \langle x_n, x_1 \rangle & & & \langle x_n, x_n \rangle \end{bmatrix}$$

$$\because \langle x_2, x_1 \rangle = \langle x_1, x_2 \rangle \quad (\text{from property (1)})$$

$\therefore K$ is symmetric.

To prove PSD

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}^T \begin{bmatrix} \langle x_1, x_1 \rangle & \dots & \langle x_1, x_n \rangle \\ \vdots & & \vdots \\ \langle x_n, x_1 \rangle & \dots & \langle x_n, x_n \rangle \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

$$= \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}^T \left[y_1 \begin{bmatrix} \langle x_1, x_1 \rangle \\ \vdots \\ \langle x_n, x_1 \rangle \end{bmatrix} + \dots + y_n \begin{bmatrix} \langle x_1, x_n \rangle \\ \vdots \\ \langle x_n, x_n \rangle \end{bmatrix} \right]$$

