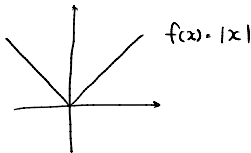


1. (Subgradient) (5 pts) Consider the L_1 norm function for $x \in \mathbb{R}^d$: $f(x) = |x|_1 = \sum_{i=1}^d |x_i|$. Show that $g = [g_1, g_2, \dots, g_d]^T$ is a subgradient of $f(x)$ at $x = 0$ if every $g_i \in [-1, 1]$. Hint: go back to the definition of subgradient: g is a subgradient of $f(x)$ at x_0 if $\forall x, f(x) \geq f(x_0) + g^T(x - x_0)$

$$f(x) = |x|_1 = \sum_{i=1}^d |x_i|$$

$$g = [g_1, g_2, \dots, g_d]^T \Rightarrow \text{subgradient of } f(x) \text{ at } x=0$$



g is a subgradient of $f(x)$ at x_0 if $\forall x, f(x) \geq f(x_0) + g^T(x - x_0)$
 when $x_0 = 0$, $f(x) \geq f(0) + g^T(x - 0)$

$$f(x) \geq g^T x$$

because the slope of $f(x)$ at $x > 0$ is 1,
 the slope of $f(x)$ at $x < 0$ is -1,

in $g \in [-1, 1]$ situation, $f(x) \geq g^T x$ is always
 True.

As a result, $g = [g_1, g_2, \dots, g_d]^T$ is a subgradient of $f(x)$
 at $x=0$

2. (Perceptron) (5 pts) Consider the following argument. We know that the number of steps for the perceptron algorithm to converge for linearly separable data is bounded by $(\frac{D}{\gamma})^2$. If we multiple the input \mathbf{x} by a small constant α , which effectively reduces the bound on $|\mathbf{x}|$ to $D' = \alpha D$, we can reduce the upper bound to $(\alpha \frac{D}{\gamma})^2$. Is this argument correct? Why?

$$\forall_i: y_i \mathbf{U}^T \mathbf{x}_i \geq \alpha r \quad \mathbf{w}_k = \mathbf{w}_{k-1} + y_k \mathbf{x}_k$$

$$① - \mathbf{U}^T \mathbf{w}_k = \mathbf{U}^T (\mathbf{w}_{k-1} + y_k \mathbf{x}_k) = \mathbf{U}^T \mathbf{w}_{k-1} + y_k \mathbf{U}^T \mathbf{x}_k \geq \mathbf{U}^T \mathbf{w}_{k-1} + \alpha r \geq k\alpha r$$

$$\begin{aligned} ② - \mathbf{w}_k^T \mathbf{w}_k &= (\mathbf{w}_{k-1} + y_k \mathbf{x}_k)^T (\mathbf{w}_{k-1} + y_k \mathbf{x}_k) \\ &= \mathbf{w}_{k-1}^T \mathbf{w}_{k-1} + 2y_k \mathbf{w}_{k-1}^T \mathbf{x}_k + \mathbf{x}_k^T \mathbf{x}_k \leq \mathbf{w}_{k-1}^T \mathbf{w}_{k-1} + \alpha^2 D^2 \\ &\leq \alpha^2 k D^2 \end{aligned}$$

According to ①, ②, $\frac{\mathbf{U}^T \mathbf{w}_k}{\|\mathbf{U}\| \|\mathbf{w}_k\|} \geq \frac{k\alpha r}{\alpha \sqrt{k} D}$

But, this cannot exceed 1

$$\therefore \frac{k\alpha r}{\alpha \sqrt{k} D} \leq 1$$

$$k\alpha r \leq \alpha \sqrt{k} D$$

$$k^2 r^2 \leq \alpha^2 k D^2$$

$$k \leq \left(\alpha \frac{D}{r} \right)^2$$

3. (Cubic Kernels.) (10 pts) In class, we showed that the quadratic kernel $K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^2$ was equivalent to mapping each $\mathbf{x} = (x_1, x_2) \in \mathbb{R}^2$ into a higher dimensional space where

$$\Phi(\mathbf{x}) = (x_1^2, x_2^2, \sqrt{2}x_1x_2, \sqrt{2}x_1, \sqrt{2}x_2, 1).$$

Now consider the cubic kernel $K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^3$. What is the corresponding Φ function?

$$(a^T b + 1)(a^T b + 1)(a^T b + 1)$$

$$((a^T b)^2 + 2(a^T b) + 1)(a^T b + 1)$$

$$(a^T b)^3 + 2(a^T b)^2 + a^T b + (a^T b)^2 + 2(a^T b) + 1$$

$$= (a^T b)^3 + 3(a^T b)^2 + 3(a^T b) + 1$$

$$\left[3 \left(\sum_{i=1}^d a_i b_i \right)^2 \right] + 6 \sum_{i=1}^d \sum_{j=2, j \neq i}^d a_i a_j b_i b_j + \frac{3 \sum_{i=1}^d a_i b_i}{+1}$$

$$\left(\sum_{i=1}^d a_i b_i \right)^3 = \sum_{i=1}^d \sum_{j=1}^d \sum_{k=1}^d a_i a_j a_k b_i b_j b_k$$

$$= a^3 b^3 + 3a^2 b + 3ab^2$$

$$[x_1^3, x_2^3, \sqrt{3}x_1^2, \sqrt{3}x_2^2, \sqrt{6}x_1x_2, \sqrt{3}x_1, \sqrt{3}x_2, 1]$$

$$\therefore \Phi(\mathbf{x}) = (x_1^3, x_2^3, \sqrt{3}x_1^2, \sqrt{3}x_2^2, \sqrt{6}x_1x_2, \sqrt{3}x_1, \sqrt{3}x_2, 1)$$

4. (Kernel or not). In the following problems, suppose that K , K_1 and K_2 are kernels with feature maps ϕ , ϕ_1 and ϕ_2 . For the following functions $K'(x, z)$, state if they are kernels or not. If they are kernels, write down the corresponding feature map, in terms of ϕ , ϕ_1 and ϕ_2 and c , c_1 , c_2 . If they are not kernels, prove that they are not.

- (5 pts) $K'(x, z) = cK(x, z)$ for $c > 0$.
- (5 pts) $K'(x, z) = cK(x, z)$ for $c < 0$.
- (5 pts) $K'(x, z) = c_1K_1(x, z) + c_2K_2(x, z)$ for $c_1, c_2 > 0$.
- (5 pts) $K'(x, z) = K_1(x, z)K_2(x, z)$.

(1) $\phi' = \sqrt{c}\phi$ $K(x, z)$ has positive values.

if $c > 0$, $K'(x, z)$ also has positive values.

(2) On the other hand, if $c < 0$, $K'(x, z)$

has negative values. Because kernel matrix is positive semi-definite, every kernel matrix should be positive values.

As a result,

$K'(x, z)$ is not kernels in equation

$$K'(x, z) = cK(x, z) \text{ for } c < 0$$

(3) $K_1(x, z)$ and $K_2(x, z)$ are kernels. so,

$c_1K_1(x, z)$, $c_2K_2(x, z)$ are also kernels

(because $c_1, c_2 > 0$ according to Q1)

As a result, $c_1K_1(x, z) + c_2K_2(x, z)$ is also kernels.

feature map $\Rightarrow \phi' = \sqrt{c_1}\phi_1 + \sqrt{c_2}\phi_2$

(4) if $K_1(x, z)$ has N_1 features
 $K_2(x, z)$ has N_2 features,

ϕ will have $N_1 \times N_2$ features,

$$\phi_{ij} = \phi_{1i} \cdot \phi_{2j}$$