

MSBD 5004 Mathematical Methods for Data Analysis

Homework 2

Due date: October 14, Friday

1. Let $(V, \|\cdot\|)$ be a normed vector space.

(a) Prove that, for all $\mathbf{x}, \mathbf{y} \in V$,

$$|\|\mathbf{x}\| - \|\mathbf{y}\|| \leq \|\mathbf{x} - \mathbf{y}\|.$$

(b) Let $\{\mathbf{x}_k\}_{k \in \mathbb{N}}$ be a convergent sequence in V with limit $\mathbf{x} \in V$. Prove that

$$\lim_{k \rightarrow \infty} \|\mathbf{x}_k\| = \|\mathbf{x}\|.$$

(Hint: Use part (a).)

(c) Let $\{\mathbf{x}^{(k)}\}_{k \in \mathbb{N}}$ be a sequence in V and $\mathbf{x}, \mathbf{y} \in V$. Prove that, if

$$\mathbf{x}^{(k)} \rightarrow \mathbf{x}, \quad \text{and} \quad \mathbf{x}^{(k)} \rightarrow \mathbf{y},$$

then $\mathbf{x} = \mathbf{y}$. (In other words, the limit of the same sequence in a normed vector space is unique.)

2. Let V be a vector space, and $\langle \cdot, \cdot \rangle$ be an inner product on V . Use the definition of inner product to prove the following.

(a) Prove that $\langle \mathbf{0}, \mathbf{x} \rangle = \langle \mathbf{x}, \mathbf{0} \rangle = 0$ for any $\mathbf{x} \in V$. Here $\mathbf{0}$ is the zero vector in V .

(b) Prove that the second condition

$$\langle \alpha \mathbf{x}_1 + \beta \mathbf{x}_2, \mathbf{y} \rangle = \alpha \langle \mathbf{x}_1, \mathbf{y} \rangle + \beta \langle \mathbf{x}_2, \mathbf{y} \rangle, \quad \forall \mathbf{x}_1, \mathbf{x}_2, \mathbf{y} \in V, \alpha, \beta \in \mathbb{R}$$

is equivalent to

$$\langle \mathbf{x}_1 + \mathbf{x}_2, \mathbf{y} \rangle = \langle \mathbf{x}_1, \mathbf{y} \rangle + \langle \mathbf{x}_2, \mathbf{y} \rangle \quad \text{and} \quad \langle \alpha \mathbf{x}, \mathbf{y} \rangle = \alpha \langle \mathbf{x}, \mathbf{y} \rangle, \quad \forall \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}, \mathbf{y} \in V, \alpha \in \mathbb{R}.$$

3. $\mathbb{R}^{m \times n}$ is a vector space over \mathbb{R} . Show that $\langle \mathbf{A}, \mathbf{B} \rangle = \text{trace}(\mathbf{A}^T \mathbf{B})$ for $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{m \times n}$ is indeed an inner product on $\mathbb{R}^{m \times n}$. Here $\text{trace}(\cdot)$ is the trace of a matrix, i.e., the sum of all diagonal entries.

4. Let V be a vector space with a norm $\|\cdot\|$ that satisfies the parallelogram identity

$$\|\mathbf{x} + \mathbf{y}\|^2 + \|\mathbf{x} - \mathbf{y}\|^2 = 2\|\mathbf{x}\|^2 + 2\|\mathbf{y}\|^2, \quad \forall \mathbf{x}, \mathbf{y} \in V.$$

Note that we don't have an inner product on V so far. For any $\mathbf{x}, \mathbf{y} \in V$, define

$$f(\mathbf{x}, \mathbf{y}) := \frac{1}{2} (\|\mathbf{x} + \mathbf{y}\|^2 - \|\mathbf{x}\|^2 - \|\mathbf{y}\|^2)$$

(a) Prove $f(\mathbf{x}, \mathbf{x}) \geq 0$ for any $\mathbf{x} \in V$, and $f(\mathbf{x}, \mathbf{x}) = 0$ if and only if $\mathbf{x} = \mathbf{0}$.

(b) Prove $f(\mathbf{x}, \mathbf{y}) = f(\mathbf{y}, \mathbf{x})$ for all $\mathbf{x}, \mathbf{y} \in V$.

- (c) Prove $f(\mathbf{x} + \mathbf{y}, \mathbf{z}) = f(\mathbf{x}, \mathbf{z}) + f(\mathbf{y}, \mathbf{z})$ for all $\mathbf{x}, \mathbf{y}, \mathbf{z} \in V$.
- (d) Prove $f(-\mathbf{x}, \mathbf{y}) = -f(\mathbf{x}, \mathbf{y})$ for all $\mathbf{x}, \mathbf{y} \in V$.
- (e) Prove $(f(\mathbf{x}, \mathbf{y}))^2 \leq f(\mathbf{x}, \mathbf{x})f(\mathbf{y}, \mathbf{y})$ for all $\mathbf{x}, \mathbf{y} \in V$.

(c)(d)(e) together with some other technique can show that $f(\alpha\mathbf{x} + \beta\mathbf{y}, \mathbf{z}) = \alpha f(\mathbf{x}, \mathbf{z}) + \beta f(\mathbf{y}, \mathbf{z})$. Therefore, we can finally prove f defines an inner product. This question showed that the parallelogram identity is also a sufficient condition for a norm to be induced by an inner product. Combined with the parallelogram law on inner product spaces, we see that the parallelogram identity is a necessary and sufficient condition for a norm to be induced by an inner product.

5. Suppose that K_1 and K_2 are two kernel functions, and suppose that $a > 0$ is a constant. Prove that the following functions are also kernel functions:

- (a) $K(\mathbf{x}, \mathbf{y}) = K_1(\mathbf{x}, \mathbf{y}) + K_2(\mathbf{x}, \mathbf{y})$;
- (b) $K(\mathbf{x}, \mathbf{y}) = a \cdot K_1(\mathbf{x}, \mathbf{y})$.

6. Consider the polynomial kernel function $K : (\mathbb{R}^2, \mathbb{R}^2) \rightarrow \mathbb{R}$ defined by $K(\mathbf{x}, \mathbf{y}) = (\mathbf{x}^T \mathbf{y} + 1)^2$. The associated feature map ϕ and the feature space H are given explicitly as in the following

$$\phi : \mathbf{x} = (x_1, x_2) \rightarrow \phi(\mathbf{x}) = (\sqrt{2}x_1, \sqrt{2}x_2, x_1^2, x_2^2, \sqrt{2}x_1x_2, 1) \in \mathbb{R}^6 := H.$$

This feature map takes the data from a two-dimensional to a six-dimensional space in a way that linear relations in the feature space correspond to quadratic relations in the input space. Prove that indeed ϕ and H satisfies

$$K(\mathbf{x}, \mathbf{y}) = \langle \phi(\mathbf{x}), \phi(\mathbf{y}) \rangle,$$

and prove K is symmetric positive semi-definite (SPSD).

7. If \mathbf{A} is a $d \times d$ symmetric positive semi-definite (SPSD) matrix, then the function $K : (\mathbb{R}^d, \mathbb{R}^d) \rightarrow \mathbb{R}$ given by $K(\mathbf{x}, \mathbf{y}) = \mathbf{y}^T \mathbf{A} \mathbf{x}$ is a kernel function.