

1. Determine whether each of the following functions of vectors in \mathbb{R}^n is linear. If it is a linear function, give its inner product representation, i.e., an vector $\mathbf{a} \in \mathbb{R}^n$ for which $f(\mathbf{x}) = \langle \mathbf{a}, \mathbf{x} \rangle$ for all $\mathbf{x} \in \mathbb{R}^n$. If it is not linear, give specific $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ and $\alpha, \beta \in \mathbb{R}$ for which superposition fails, i.e., $f(\alpha\mathbf{x} + \beta\mathbf{y}) \neq \alpha f(\mathbf{x}) + \beta f(\mathbf{y})$.
 - (a) The spread of values of the vector, defined as $f(\mathbf{x}) = \max_k x_k - \min_k x_k$.
 - (b) The difference of the last element and the first, $f(\mathbf{x}) = x_n - x_1$.
 - (c) The median of a vector, where we will assume $n = 2k + 1$ is odd. The median of the vector \mathbf{x} is defined as the $(k + 1)$ -st largest number among the entries of \mathbf{x} . For example, the median of $(7.1, 3.2, 1.5)$ is 1.5.
 - (d) Vector extrapolation, defined as $x_n + (x_n - x_{n-1})$, for $n \geq 2$. (This is a simple prediction of what x_{n+1} would be, based on a straight line drawn through x_n and x_{n-1} .)

2. Let V be a Hilbert space. Let S_1 and S_2 be two hyperplanes in V defined by

$$S_1 = \{\mathbf{x} \in V \mid \langle \mathbf{a}_1, \mathbf{x} \rangle = b_1\}, \quad S_2 = \{\mathbf{x} \in V \mid \langle \mathbf{a}_2, \mathbf{x} \rangle = b_2\}.$$

Let $\mathbf{y} \in V$ be given. We consider the projection of \mathbf{y} onto $S_1 \cap S_2$, i.e., the solution of

$$\min_{\mathbf{x} \in S_1 \cap S_2} \|\mathbf{x} - \mathbf{y}\|. \quad (1)$$

- (a) Prove that $S_1 \cap S_2$ is a plane, i.e., if $\mathbf{x}, \mathbf{z} \in S_1 \cap S_2$, then $(1+t)\mathbf{z} - t\mathbf{x} \in S_1 \cap S_2$ for any $t \in \mathbb{R}$.
- (b) Prove that \mathbf{z} is a solution of (1) if and only if $\mathbf{z} \in S_1 \cap S_2$ and

$$\langle \mathbf{z} - \mathbf{y}, \mathbf{z} - \mathbf{x} \rangle = 0, \quad \forall \mathbf{x} \in S_1 \cap S_2. \quad (2)$$

- (c) Find an explicit solution of (1).
- (d) Prove the solution found in part (c) is unique.

3. Let $\{(\mathbf{x}_i, y_i)\}_{i=1}^N$ be given with $\mathbf{x}_i \in \mathbb{R}^n$ and $y_i \in \mathbb{R}$. Assume $N < n$, and $\mathbf{x}_i, i = 1, 2, \dots, N$, are linearly independent. Consider the ridge regression

$$\min_{\mathbf{a} \in \mathbb{R}^n} \sum_{i=1}^N (\langle \mathbf{a}, \mathbf{x}_i \rangle - y_i)^2 + \lambda \|\mathbf{a}\|_2^2,$$

where $\lambda \in \mathbb{R}$ is a regularization parameter, and we set the bias $b = 0$ for simplicity.

- (a) Prove that the solution must be in the form of $\mathbf{a} = \sum_{i=1}^N c_i \mathbf{x}_i$ for some $\mathbf{c} = [c_1, c_2, \dots, c_N]^T \in \mathbb{R}^N$.
(Hint: Similar to the proof of the representer theorem.)

- (b) Re-express the minimization in terms of $\mathbf{c} \in \mathbb{R}^N$, which has fewer unknowns than the original formulation.