

Exercise 1: Course questions

Answers can be found in class or with other students

Q3(c) $\nabla f(x) = (A + A^T)x + b$

Q7(a) `return (x[None, :] - x[:, None])**2`

Q7(b) `return np.sum((x[None, :, :] - x[:, None, :])**2, axis=-1)`

Exercise 2: Kernels

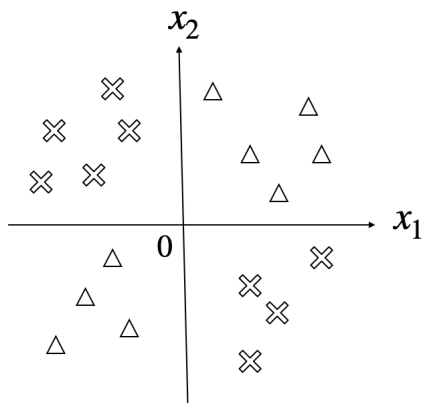
1. In course
2. Idem
3. *Bonus* Show that $\langle X, Y \rangle = \mathbb{E}[XY]$ is an inner product on the space of real-valued random variables.
 - symmetric
 - bilinear, by linearity of expectation
 - $\langle X, X \rangle = \mathbb{E}[X^2] \geq 0$. $\mathbb{E}[X^2] = 0$ implies $X = 0$ almost everywhere.
4. State whether the following functions are p.d. kernels or not. Prove your answer.
 - (a) $\mathcal{X} = \mathbb{R}^2$, $k(x, x') = x_1 x'_1 + \text{sign}(x_2) \text{sign}(x'_2)$
 Choose $\mathcal{H} = \mathbb{R}^2$, $\Phi(x) = [x_1, \text{sign}(x_2)]^T$, then $k(x, x') = \langle \Phi(x), \Phi(x') \rangle_{\mathcal{H}}$
 - (b) \mathcal{X} is an inner product space, $k(x, x') = \|x\|^2$
 k is not symmetric ! Choose $x = 0$ and x' nonzero for example
 - (c) \mathcal{X} is the space of real-valued random variables, $k(X, X') = \text{Cov}(X, X')$
 Seen in class.
 Using the scalar product from Q3, and choosing $\Phi(X) = X - \mathbb{E}[X]$, we have
 $\text{Cov}(X, X') = \langle \Phi(X), \Phi(X') \rangle$
 - (d) Let Ω be a set, $\mathcal{X} = \text{Subsets}(\Omega)$, $k(A, B) = \mathbb{P}[A \cap B]$.
 $k(A, B) = \mathbb{P}[A \cap B] = \mathbb{E}[1_{A \cap B}] = \mathbb{E}[1_A 1_B] = \langle 1_A, 1_B \rangle$
 Choose \mathcal{H} as the space of real-valued random variables, and $\Phi(A) = 1_A$
 - (e) Same as (c), with $k(A, B) = \mathbb{P}[A \cup B]$
 It is not p.d.
 From @Attou, take $A = \Omega$, $B = \emptyset$, then the Gram matrix is equal to $K = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix}$, which is not p.s.d. since $\det(K) = -1 < 0$

Exercise 3: Kernel Ridge Regression

All questions are course material.

Exercise 4: Application, XOR

In this exercise we want to classify data points $x = (x_1, x_2) \in \mathbb{R}^2$, with two labels (binary classification), as shown in the picture below. Let X_Δ and X_\times be the sets of points with respective labels Δ and \times .



1. Are the data X_Δ and X_\times linearly separable?

NO

2. (a) Find a space \mathcal{X} and a mapping $\Phi : \mathbb{R}^2 \rightarrow \mathcal{X}$ such that the projected data $\Phi(X_\Delta)$ and $\Phi(X_\times)$ are linearly separable.

There are multiple possibilities for Φ , we choose $\mathcal{X} = \mathbb{R}$ and $\Phi(x) = x_1 x_2$ here, many correctly chose $\Phi(x) = \text{sign}(x_1 x_2)$.

Ask @Najlaa for explanation and drawing.

- (b) What is the corresponding kernel function k ?

$$k(x, x') = \langle \Phi(x), \Phi(x') \rangle = x_1 x_2 x'_1 x'_2$$

- (c) *Bonus* What is the RKHS of k ?

The RKHS is the space $\mathcal{H} = \{f_\beta : (t_1, t_2) \rightarrow \beta t_1 t_2, \beta \in \mathbb{R}\}$,

with norm $\|f_\beta\|_{\mathcal{H}} = \beta^2$

Proof: Let $\mathcal{H} = \{K_x, x \in \mathbb{R}^2\}$.

Prove that \mathcal{H} is a vector space, as it is stable under linear combinations: for $a, b \in \mathbb{R}, x, x' \in \mathbb{R}^2$ there exists $z \in \mathbb{R}^2$ such that $aK_x + bK_{x'} = K_z$.

As a consequence the closure of the span of \mathcal{H} is \mathcal{H} itself.

The norm is then $\langle K_x, K_x \rangle = k(x, x) = (x_1 x_2)^2$