

# Foundations of Data Science & Machine Learning

## Tutorial 02

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**Question 1.** Rewrite the perceptron learning algorithm so that it works directly on any two sets of points  $G$  and  $B$  which are separated by a hyperplane (not necessarily passing through the origin). Give an upper bound on the number of updates in terms of parameters like  $R$  and  $\delta$  of the  $G$  and  $B$ .

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**Algorithm 1** Perceptron Learning Algorithm (General Hyperplane)

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**Input:** Two finite sets  $G, B \subset \mathbb{R}^n$  which are linearly separable by a hyperplane (not necessarily passing through the origin).

**Output:**  $a \in \mathbb{R}^n$  and  $b \in \mathbb{R}$  such that for all  $x \in G$ ,  $\langle a, x \rangle > b$  and for all  $x \in B$ ,  $\langle a, x \rangle < b$ .

$a \leftarrow 0, b \leftarrow 0$

**repeat**

**for all**  $x \in G$  **do**

**if**  $\langle a, x \rangle \leq b$  **then**

$a \leftarrow a + x$

$b \leftarrow b - 1$

**end if**

**end for**

**for all**  $x \in B$  **do**

**if**  $\langle a, x \rangle \geq b$  **then**

$a \leftarrow a - x$

$b \leftarrow b + 1$

**end if**

**end for**

**until** no updates

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The above algorithm goes through exactly the same steps as the PLA with 1 padded to each data vector and treating  $b$  as  $-a_{n+1}$ . Hence this new algorithm will terminate in at most  $4R^2/\delta^2$  steps where

$$\begin{aligned} R^2 &= \max\{\|(x_1, \dots, x_n, 1)\|^2 : (x_1, \dots, x_n) \in G \cup B\} \\ &= \max\{\|x\|^2 : x \in G \cup B\} + 1. \end{aligned}$$

and  $\delta$  is the minimum distance between the convex hulls of  $G$  and  $B$  (since it is not affected by the padding).

**Definition 1.** A function  $K : (\mathbb{R}^n \times \mathbb{R}^n) \rightarrow \mathbb{R}$  is called a *kernel* if there exists an inner product space  $V$  and a function  $\phi : \mathbb{R}^n \rightarrow V$  such that

$$\forall x, y \in \mathbb{R}^n, K(x, y) = \langle \phi(x), \phi(y) \rangle.$$

**Question 2.** Show that the function  $K : (\mathbb{R}^n \times \mathbb{R}^n) \rightarrow \mathbb{R}$  given by

$$K(x, y) = (1 + \langle x, y \rangle)^d$$

is a kernel for every degree  $d \in \mathbb{N}$ .

By considering the constant embedding  $\phi(x) = \sqrt{c}, \forall x \in \mathbb{R}^n$  to  $\mathbb{R}^1$ , we can see that the constant function  $K(x, y) = c, \forall x, y \in \mathbb{R}^n$  is a kernel. By considering the identity embedding  $\phi(x) = x$ , once can see that  $K(x, y) = \langle x, y \rangle$  is also a kernel.

Let  $K_1$  and  $K_2$  be two kernels. Since they are kernels, by definition, there exists two embeddings  $\phi_1$  and  $\phi_2$  which gives  $K_1$  and  $K_2$ . We will only prove it rigorously for the case when the co-domains of  $\phi_1$  and  $\phi_2$  are finite dimensional. Let the codomains be  $\mathbb{R}^k$  and  $\mathbb{R}^l$  respectively. Thus

$$\begin{aligned}\phi_1(x) &= (f_1(x), f_2(x), \dots, f_k(x)) \text{ and} \\ \phi_2(x) &= (g_1(x), g_2(x), \dots, g_l(x)),\end{aligned}$$

where  $f_i$ 's and  $g_i$ 's are arbitrary functions from  $\mathbb{R}^n$  to  $\mathbb{R}$ .

We will show that  $K_1 + K_2$  is a kernel. Consider the embedding  $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^{k+l}$  given by

$$\phi(x) = (f_1(x), f_2(x), \dots, f_k(x), g_1(x), g_2(x), \dots, g_l(x)).$$

It is easy to verify that  $\forall x, y \in \mathbb{R}^n$

$$\begin{aligned}\langle \phi(x), \phi(y) \rangle &= \langle \phi_1(x), \phi_1(y) \rangle + \langle \phi_2(x), \phi_2(y) \rangle \\ &= K_1(x, y) + K_2(x, y).\end{aligned}$$

and hence  $K_1 + K_2$  is a kernel.

We will show that  $K_1 K_2$  is a kernel. Consider the embedding  $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^{kl}$  given by

$$\begin{aligned}\phi(x) &= (f_1(x)g_1(x), f_1(x)g_2(x), \dots, f_1(x)g_l(x), \\ &\quad f_2(x)g_1(x), f_2(x)g_2(x), \dots, f_2(x)g_l(x), \\ &\quad \dots \\ &\quad f_k(x)g_1(x), f_k(x)g_2(x), \dots, f_k(x)g_l(x))\end{aligned}$$

One can verify by expansion that

$$\begin{aligned}K_1(x, y)K_2(x, y) &= \langle \phi_1(x), \phi_1(y) \rangle \langle \phi_2(x), \phi_2(y) \rangle \\ &= (f_1(x)f_1(y) + f_2(x)f_2(y) + \dots + f_k(x)f_k(y)) \times \\ &\quad (g_1(x)g_1(y) + g_2(x)g_2(y) + \dots + g_l(x)g_l(y)) \\ &= \langle \phi(x), \phi(y) \rangle.\end{aligned}$$

When the codomains of  $\phi_1$  and  $\phi_2$  (say  $V$  and  $W$  respectively) are infinite dimensional, we can still do the  $K_1 + K_2$  proof by considering  $\phi$  as an embedding to the *direct sum*  $V \oplus W$ . The  $K_1 K_2$  proof is more complicated to extend and we need to consider  $\phi$  as an embedding to the tensor product  $V \otimes W$ .

To complete the answer, just note that  $(1 + \langle x, y \rangle)$  is a Kernel since it is the sum of two kernels and  $(1 + \langle x, y \rangle)^d$  can be expressed as a repeated product of kernels.