

Homework 5

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Exercise 1

(a)

$$\begin{aligned} K(x, y) &= (\langle x, y \rangle + 1)^2 = \left(\sum_{i=1}^2 x_i y_i + 1 \right)^2 = (x_1 y_1 + x_2 y_2 + 1)^2 \\ &= (x_1 y_1 + x_2 y_2 + 1)(x_1 y_1 + x_2 y_2 + 1) \\ &= ((x_1 y_1)^2 + x_1 y_1 x_2 y_2 + x_1 y_1) + (x_2 y_2 x_1 y_1 + (x_2 y_2)^2 + x_2 y_2) + (x_1 y_1 + x_2 y_2 + 1) \\ &= (x_1 y_1)^2 + (x_2 y_2)^2 + 2(x_1 y_1 x_2 y_2) + 2(x_1 y_1) + 2(x_2 y_2) + 1 \end{aligned}$$

$$\varphi(x) = \langle x_1^2, x_2^2, \sqrt{2}x_1 x_2, \sqrt{x_1}, \sqrt{x_2}, 1 \rangle$$

Dimensionality = 6

For $c = 0$, the dimensionality scales $p + 1$

$$\begin{aligned} \text{for } p = 2: \langle x, x' \rangle^2 &= \left(\sum_{i=1}^2 x_i x'_i \right)^2 = (x_1 x'_1 + x_2 x'_2)^2 \\ &= (x_1 x'_1)^2 + 2x_1 x'_1 x_2 x'_2 + (x_2 x'_2)^2 \\ &\rightarrow \text{Dimensionality} = 3 \end{aligned}$$

(b)

No, since for SVM, we can use the kernel trick, meaning we do not have to represent the feature space specifically for non-linear kernels, since the kernel chosen can be any arbitrary kernel.

Exercise 2

(a)

$$\begin{aligned} K_{ij} &= k(x_i x_j) = \sum_{k=1}^d x_{i,k} x_{j,k} \\ \sum_{i,j} c_i c_j K_{i,j} &= \sum_{i,j} c_i c_j k(x_i x_j) = \sum_{i,j} c_i c_j \langle x_i, x_j \rangle = \sum_{i,j} \langle c_i x_i, c_j x_j \rangle \end{aligned}$$

$$\begin{aligned}
&= \sum_{i,j} \sum_k^d c_i x_{i,k} c_j x_{j,k} = \sum_i \sum_j \sum_k^d c_i x_{i,k} c_j x_{j,k} \\
&= \sum_k^d \left(\sum_i c_i x_{i,k} \right) \left(\sum_j c_j x_{j,k} \right) = \sum_k^2 \left(\sum_i c_i x_{i,k} \right)^2 \geq 0
\end{aligned}$$

(b)

$$K_{ij} = k(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle$$

$$\begin{aligned}
&\sum_{i,j} c_i c_j K_{ij} = \sum_{i,j} c_i c_j \langle \phi(x_i), \phi(x_j) \rangle \\
&= \sum_{i,j} \langle c_i \phi(x_i), c_j \phi(x_j) \rangle = \sum_i \sum_j \langle c_i \phi(x_i), c_j \phi(x_j) \rangle = \sum_i \langle c_i \phi(x_i), c_i \phi(x_i) \rangle^2 \geq 0
\end{aligned}$$

(c) (1)

$$\begin{aligned}
&k_3(x, x') = k_1(x, x') + k_2(x, x') \\
&\sum_{i,j} c_i c_j k_3(x_i, x_j) = \sum_{i,j} c_i c_j k_1(x_i, x_j) + \sum_{i,j} c_i c_j k_2(x_i, x_j) \geq 0
\end{aligned}$$

Both k_1 and k_2 are kernels and are therefore both positive semi-definite. Their sum is therefore also a kernel.

(2)

$$k_4(x, x') = \lambda k_1(x, x'), \lambda \in \mathbb{R}^+$$

$$\sum_{i,j} c_i c_j k_4(x_i, x_j) = \sum_{i,j} \lambda c_i c_j k_1(x_i, x_j) = \lambda \sum_{i,j} c_i c_j k_1(x_i, x_j) \geq 0$$

Since both λ and $K_1 \geq 0$

Exercise 3

(a)

$$k(x, x') = 3\langle x, x' \rangle^4 + 1 + x^T x' + \exp\left(-\frac{1}{2\sigma^2} \|x - x'\|^2\right)$$

$$= \lambda k_a(x, x') + k_b(x, x') + k_c(x, x')$$

– > also a kernel due to the closure properties proven in 2.c)

k_a = polynomial kernel

k_b = linear kernel

k_c = RBF kernel

(b)

$$k_{GXY}(X, X') = \begin{cases} 0, & \text{if one or both 3-mers don't start with G} \\ \text{number of perfect matches,} & \text{else} \end{cases}$$

$$= \sum_{s \in S, s' \in S'} k_{delta}(s, s')$$

$$\text{with } k_{delta} = \begin{cases} 1, & x = x' \\ 0, & \text{else} \end{cases}$$

S and S' being all possible 3-mers of X and X'

(c)

See Python program

(d)

If two sequences vary greatly in their length (for example seq1 = 3bp, seq = 99bp), our values of kGXY could potentially be extremely high, even though the sequences are obviously not similar in their length.

I don't see a problem with the lengths of the sequences not being multiples of 3, as this just increases the amount of 3-mers we get. If our sequences are of equal length, they still have the same amount of 3-mers.