

## Exercise 1

①

1a) Polynomial Kernel:  $k(x, x') = (\langle x, x' \rangle + c)^p$

Given:  $c=1$ ;  $p=2$ ;  $x=(x_1, x_2)$ ;  $x'=(x'_1, x'_2)$

What is  $\phi(x)$ ?



$$k(x, x') = (\langle x, x' \rangle + 1)^2 = \left( \sum_{i=1}^2 x_i x'_i + 1 \right)^2 = (x_1 x'_1 + x_2 x'_2 + 1)^2 \quad \left| \text{write it out} \right.$$

$$= \left( (x_1 x'_1)^2 + x_1 x'_1 x_2 x'_2 + x_1 x'_1 \right) + \left( x_2 x'_2 x_1 x'_1 + (x_2 x'_2)^2 + x_2 x'_2 \right) + (x_1 x'_1 + x_2 x'_2 + 1) \quad \left| \text{simplify} \right.$$

$$= (x_1 x'_1)^2 + (x_2 x'_2)^2 + 2(x_1 x'_1 x_2 x'_2) + 2(x_1 x'_1) + 2(x_2 x'_2) + 1$$

$$\phi(x) = (x_1^2, x_2^2, \sqrt{2} x_1 x_2, \sqrt{2} x_1, \sqrt{2} x_2, 1)$$

The feature space has dimensionality 6.

The feature space of the Gaussian RBF kernel with  $\sigma=1$  has infinite dimensionality.

The RBF kernel can be broken down to an infinite sum over polynomial kernels by applying a Taylor expansion of  $e^x$ . This results in a projection into a vector space with infinite dimensions.

1b) No, we don't need to represent the feature space explicitly for non-linear kernels when using an SVM classifier. We can use the kernel trick as a shortcut around this.

## Exercise 2

(2)

2a)  $\mathbf{x} \in \mathbb{R}^d$ ; linear kernel:  $k(\mathbf{x}, \mathbf{x}') = \langle \mathbf{x}, \mathbf{x}' \rangle = \sum_i^d x_i x'_i$

$$\sum_{i,j} c_i c_j k(\mathbf{x}_i, \mathbf{x}_j) = \sum_{i,j} c_i c_j \langle \mathbf{x}_i, \mathbf{x}_j \rangle = \sum_{i,j} \langle c_i \mathbf{x}_i, c_j \mathbf{x}_j \rangle, \text{ for } c_i, c_j \in \mathbb{R}$$

$$= \sum_{i,j} \sum_k c_i x_{i,k} c_j x_{j,k} = \sum_k \left( \sum_i c_i x_{i,k} \right) \left( \sum_j c_j x_{j,k} \right)$$

$$= \sum_k \left( \sum_i c_i x_{i,k} \right)^2 \geq 0 \quad \rightarrow \text{Condition for positive semi-definiteness is fulfilled.}$$

2b)  $k(\mathbf{x}, \mathbf{x}') = \langle \phi(\mathbf{x}), \phi(\mathbf{x}') \rangle$

$$\sum_{i,j} c_i c_j k(\mathbf{x}_i, \mathbf{x}_j) = \sum_{i,j} c_i c_j \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}_j) \rangle = \sum_{i,j} \langle c_i \phi(\mathbf{x}_i), c_j \phi(\mathbf{x}_j) \rangle$$

$$= \sum_{i,j} \sum_k c_i \phi(x_{i,k}) c_j \phi(x_{j,k}) = \sum_k \left( \sum_i c_i \phi(x_{i,k}) \right) \left( \sum_j c_j \phi(x_{j,k}) \right)$$

$$= \sum_k \left( \sum_i c_i \phi(x_{i,k}) \right)^2 \geq 0$$

2c)  $k_3(\mathbf{x}, \mathbf{x}') = k_1(\mathbf{x}, \mathbf{x}') + k_2(\mathbf{x}, \mathbf{x}')$

$$\sum_{i,j} c_i c_j k_3(\mathbf{x}_i, \mathbf{x}_j) = \sum_{i,j} c_i c_j k_1(\mathbf{x}_i, \mathbf{x}_j) + \sum_{i,j} c_i c_j k_2(\mathbf{x}_i, \mathbf{x}_j) \geq 0$$

Since  $k_1$  &  $k_2$  are kernels and therefore positive semi-definit (psd), their sum is also psd and therefore a kernel.

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

$$\sum_{i,j} c_i c_j k_4(\mathbf{x}_i, \mathbf{x}_j) = \lambda \sum_{i,j} c_i c_j k_1(\mathbf{x}_i, \mathbf{x}_j) \geq 0$$

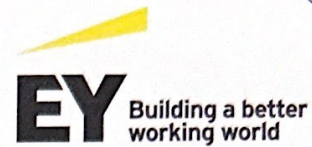
Since  $k_1$  is psd, any multiplication with  $\lambda \in \mathbb{R}^+$  will turn out psd.



### Exercise 3

③

$$\begin{aligned} 3a) \quad k(x, x') &= 6 \langle x, x' \rangle^4 + 3 + x^T x' + \exp\left(-\frac{1}{2\sigma^2} \|x - x'\|^2\right) \\ &= \lambda_1 k_1 \langle x, x' \rangle + \lambda_2 k_2 \langle x, x' \rangle + k_3 \langle x, x' \rangle + k_4 \langle x, x' \rangle \end{aligned}$$



Where:  $\lambda_1 = 6$

$k_1$  = polynomial kernel with  $c=0$  and  $p=4$

$\lambda_2 = 3$

$k_2$  = "all-ones" kernel

$k_3$  = linear kernel

$k_4$  = Gaussian RBF kernel

→ According to proof in 2c) we can sum all of these up and receive a kernel.

3b)

$$k_{\text{base}}(s, s') = \begin{cases} 0, & \text{if } s \text{ or } s' \text{ don't start with a 'G'} \\ 1, & \text{if } s \text{ and } s' \text{ start with a 'G' and the values in} \\ & \text{positions 2 \& 3 of } s \& s' \text{ differ} \\ 2, & \text{if } s \text{ and } s' \text{ start with a 'G' and} \\ & \text{there is only one match for values in positions 2 \& 3 of } s \& s'. \\ 3, & \text{if } s \text{ and } s' \text{ start with a 'G' and the values in} \\ & \text{positions 2 \& 3 of } s \& s' \text{ match.} \end{cases}$$

The substructures of  $S$  and  $S'$  are all possible 3-mers of the strings  $S$  and  $S'$ .

Formal mathematical description of  $k_{\text{base}}(s, s')$ , with python indexing.

$$\hookrightarrow k_{\text{base}}(s, s') = \begin{cases} 0, & \text{if } s[0] \neq G \vee s'[0] \neq G \\ 1, & \text{if } s[0] == s'[0] == G \wedge s[1] \neq s'[1] \wedge s[2] \neq s'[2] \\ 2, & \text{if } s[0] == s'[0] == G \wedge (s[1] == s'[1] \oplus s[2] == s'[2]) \\ 3, & \text{if } s[0] == s'[0] == G \wedge s[1] == s'[1] \wedge s[2] == s'[2] \end{cases}$$

3d)

If we compare sequences of unequal length, where one is much longer than the other, it is hard to tell significance of the result, or will be misleading. It seems to be a similar problem like with Jaccard measures on finite sets.

An attempt to fix this would be to normalize the score.

I do not see a problem if the sequence lengths aren't multiples of 3, it is irrelevant to the task at hand.