

# Exercise Sheet 6

### Exercise 1: Convolution Kernel (20 P)

Let  $x, x'$  be two univariate real-valued discrete signals, that we consider in the following to be infinite-dimensional. We consider a discrete convolution over these two signals

$$[x * x']_t = \sum_{\tau=-\infty}^{\infty} x(\tau) \cdot x'(t - \tau)$$

which also produces an infinite-dimensional output signal. We then define the ‘convolution kernel’ as:

$$k(x, x') = \|x * x'\|^2 = \sum_{t=-\infty}^{\infty} ([x * x']_t)^2.$$

- (a) Show that the convolution kernel is positive semi-definite, that is, show that

$$\sum_{i=1}^N \sum_{j=1}^N c_i c_j k(x_i, x_j) \geq 0$$

for all inputs  $x_1, \dots, x_N$  and choice of real numbers  $c_1, \dots, c_N$ .

- (b) Give an explicit feature map for this kernel.

### Exercise 2: Weighted Degree Kernels (20 P)

The weighted degree kernel has been proposed to represent DNA sequences ( $\mathcal{A} = \{\text{G, A, T, C}\}$ ), and is defined for pairs of sequences of length  $L$  as:

$$k(x, z) = \sum_{m=1}^M \beta_m \sum_{l=1}^{L+1-m} I(u_{l,m}(x) = u_{l,m}(z)).$$

where  $\beta_1, \dots, \beta_M \geq 0$  are weighting coefficients, and where  $u_{l,m}(x)$  is a substring of  $x$  which starts at position  $l$  and of length  $m$ . The function  $I(\cdot)$  is an indicator function which returns 1 if the input argument is true and 0 otherwise.

[illegible]

- (a) Show that  $k$  is a positive semi-definite kernel. That is, show that

$$\sum_{i=1}^N \sum_{j=1}^N c_i c_j k(x_i, x_j) \geq 0$$

for all inputs  $x_1, \dots, x_N$  and choice of real numbers  $c_1, \dots, c_N$ .

- (b) Give a feature map associated to this kernel for the special case  $M = 1$ .

- (c) Give a feature map associated to this kernel for the special case  $M = 2$  with  $\beta_1 = 0$  and  $\beta_2 = 1$ .

**Exercise 3: Fisher Kernel (20 P)**

The Fisher kernel is a structured kernel induced by a probability model  $p_\theta(x)$ . While it is mainly used to extract a feature map of fixed dimensions from structured data on which a structured probability model readily exists (e.g. a hidden Markov model), the Fisher kernel can in principle also be derived for simpler distributions such as the multivariate Gaussian distribution.

The probability density function of the Gaussian distribution in  $\mathbb{R}^d$  of mean  $\mu$  and covariance  $\Sigma$  is given by:

$$p(x) = \frac{1}{\sqrt{(2\pi)^d \det(\Sigma)}} \exp\left(-\frac{1}{2}(x - \mu)^\top \Sigma^{-1}(x - \mu)\right)$$

In this exercise, we consider the covariance matrix  $\Sigma$  to be fixed, and therefore, the only effective parameter of the model (on which the Fisher kernel is based) is the mean  $\mu$ .

- (a) *Show* that the Fisher kernel associated to this probability model is given by:

$$k(x, x') = (x - \mu)^\top \Sigma^{-1}(x' - \mu)$$

- (b) *Give* a feature map associated to this kernel.

**Exercise 4: Programming (40 P)**

Download the programming files on ISIS and follow the instructions.