TU MÜNCHEN FAKULTÄT FÜR INFORMATIK PD DR. RUDOLPH TRIEBEL JOHN CHIOTELLIS

# Machine Learning for Robotics and Computer Vision Winter term 2015

# Solution Sheet 4

Topic: Boosting and Kernels December 18th, 2015

## Exercise 1: Adaboost

See code

#### Exercise 2: Kernels

Remember that for a function to be a valid kernel, it must correspond to a scalar product in some (perhaps infinite dimensional) feature space. First let us write down the kernel constructing rules that we will use: Let  $K_1$  and  $K_2$  be kernels on  $\mathfrak{X} \subseteq \mathbb{R}^n$  and  $K_3$  be kernel on  $f: \mathfrak{X} \to \mathbb{R}^m$ .

## Rules

1. 
$$K(x,y) = K_1(x,y) + K_2(x,y)$$

2. 
$$K(x,y) = cK_1(x,y)$$
 ,  $c > 0$ 

3. 
$$K(x,y) = K_1(x,y)K_2(x,y)$$

4. 
$$K(x,y) = K_3(f(x), f(y))$$

5. 
$$K(x,y) = x^T B y$$
 , for B square, symmetric and positive semi-definite

6. 
$$K(x,y) = c$$
 ,  $c > 0$ 

#### **Proofs**

1.

$$K_1(x,y) + K_2(x,y) = \phi_1(x)^T \phi_1(y) + \phi_2(x)^T \phi_2(y)$$
  
=  $(\phi_1(x) \quad \phi_2(x))^T (\phi_1(y) \quad \phi_2(y))$   
=  $\phi(x)^T \phi(y)$ 

with 
$$\phi(x) = (\phi_1(x) \quad \phi_2(x))^T$$
.

2.

$$cK_1(x, y) = c\phi_1(x)^T \phi_1(y)$$

$$= \sqrt{c}\sqrt{c}\phi_1(x)^T \phi_1(y)$$

$$= (\sqrt{c}\phi_1(x))^T (\sqrt{c}\phi_1(y))$$

$$= \phi(x)^T \phi(y)$$

with 
$$\phi(x) = (\frac{\sqrt{c}}{\sqrt{n_1}}\phi_1(x)_1, \dots, \frac{\sqrt{c}}{\sqrt{n_1}}\phi_1(x)_{n_1})^T$$

and 
$$\phi_1(x) \in \mathbb{R}^{n_1}$$
,  $\phi_2(x) \in \mathbb{R}^{n_2}$ ,  $\phi(x) \in \mathbb{R}^{n_1+n_2}$ .

3.

$$K_{1}(x,y)K_{2}(x,y) = \phi_{1}(x)^{T}\phi_{1}(y)\phi_{2}(x)^{T}\phi_{2}(y)$$

$$= (\sum_{i} \phi_{1}(x)_{i}\phi_{1}(y)_{i})(\sum_{j} \phi_{2}(x)_{j}\phi_{2}(y)_{j})$$

$$= \sum_{i} \sum_{j} \phi_{1}(x)_{i}\phi_{1}(y)_{i}\phi_{2}(x)_{j}\phi_{2}(y)_{j}$$

$$= \sum_{i} \sum_{j} \phi_{1}(x)_{i}\phi_{2}(x)_{j}\phi_{1}(y)_{i}\phi_{2}(y)_{j}$$

$$= \sum_{k} \phi_{k}(x)\phi_{k}(y)$$

$$= \phi(x)^{T}\phi(y)$$

with 
$$\phi(x) = \begin{pmatrix} \phi_1(x)_1 \phi_2(x)_1 \\ \vdots \\ \phi_1(x)_1 \phi_2(x)_{n_2} \\ \phi_1(x)_2 \phi_2(x)_1 \\ \vdots \\ \phi_1(x)_n, \phi_2(x)_n \end{pmatrix} \in \mathbb{R}^{n_1 \cdot n_2}.$$

4. Since  $K_3$  is a valid kernel in  $\mathbb{R}^m$  there is a feature space  $\psi$  for which it holds

$$K_3(f(x), f(y)) = \psi(f(x))^T \psi(f(y))$$

Therefore it is also a valid kernel in  $\mathbb{R}^n$  with with  $\phi(x) = \psi(f(x))$ .

5. Since B is symmetric and positive definite we can use its Cholesky decomposition:

$$x^T B y = x^T L L^T y = (L^T x)^T (L^T y) = \phi(x)^T \phi(y)$$

with 
$$\phi(x) = L^T x$$
.

6. c is a kernel (Rule 5 with B = I and Rule 4 with  $\phi(x) = \phi(y) = (\frac{\sqrt{c}}{\sqrt{m}}, \dots, \frac{\sqrt{c}}{\sqrt{m}})^T$  if  $\phi(x) \in \mathbb{R}^m$ .

Gaussian Kernel First let us prove that the exponential of a kernel is also a kernel. Using the Taylor expansion of the exponential, we have:

$$exp(K_1(x,y)) = 1 + \sum_{n=1}^{\infty} \frac{1}{n!} K_1(x,y)^n$$

Using the rules we defined, we see that

- $K_1(x,y)^n$  is a kernel (iteratively Rule 3)
- $(\frac{1}{n!})K_1(x,y)^n$  is a kernel (Rule 2)
- $\sum_{n=1}^{\infty} (\frac{1}{n!}) K_1(x,y)^n$  is a kernel (iteratively Rule 1)
- 1 is a kernel (Rule 6)
- the whole expression is a kernel because of Rule 1.

Now we can rewrite the Gaussian kernel as follows:

$$\begin{split} \exp(-\frac{|x-y|^2}{2\sigma^2}) &= \exp(-\frac{(x-y)^T(x-y)}{2\sigma^2}) = \exp(-\frac{x^Tx - 2x^Ty + y^Ty}{2\sigma^2}) \\ &= \exp(-\frac{x^Tx}{2\sigma^2}) \exp(-\frac{y^Ty}{2\sigma^2}) \exp(\frac{x^Ty}{2\sigma^2}) \end{split}$$

The expression  $\frac{x^T y}{2\sigma^2}$  is a kernel because of Rule 5 (B = I) and Rule 2  $(c = \frac{1}{2\sigma^2})$  and as we showed its exponential is also a kernel.

The remaining expression is a kernel because of Rule 4 with  $\phi(x) = (\frac{\exp(-\frac{x^Tx}{2\sigma^2})}{\sqrt{m}}, \dots, \frac{\exp(-\frac{x^Tx}{2\sigma^2})}{\sqrt{m}})$  and  $\phi(y) = (\frac{\exp(-\frac{y^Ty}{2\sigma^2})}{\sqrt{m}}, \dots, \frac{\exp(-\frac{y^Ty}{2\sigma^2})}{\sqrt{m}})$ .

Polynomial Kernel The polynomial kernel is defined as

$$K(x,y) = (x^T y + c)^d$$
 ,  $c > 0, d \in \mathbb{N}$ 

Using the rules we defined we see that:

- $x^T y$  is a kernel (Rule 5 with B = I)
- c is a kernel (Rule 6)
- $x^Ty + c$  is a kernel (Rule 1)
- $(x^Ty + c)^d$  is a kernel (Rule 3)