

## Question 5 - kernel PCA

1. The kernel matrix is defined as  $K_{i,j} = \langle \phi(x_i), \phi(x_j) \rangle$   
In order to center the data we need to subtract  
the mean of the vector points in the feature space:

$$\text{mean} = \frac{1}{n} \sum_{t=1}^n \phi(x_t) = \bar{\phi}$$
$$\Downarrow$$

$$v_i = \phi(x_i) - \bar{\phi} = \phi(x_i) - \frac{1}{n} \sum_{t=1}^n \phi(x_t)$$

And so we can see that the centered  $K'_{i,j} = \langle v_i, v_j \rangle$  matrix  
can be expressed as :

$$K'_{i,j} = \langle \phi(x_i) - \bar{\phi}, \phi(x_j) - \bar{\phi} \rangle$$
$$\Downarrow$$

$$K'_{i,j} = \langle \phi(x_i), \phi(x_j) \rangle - \langle \phi(x_i), \bar{\phi} \rangle - \langle \bar{\phi}, \phi(x_j) \rangle + \langle \bar{\phi}, \bar{\phi} \rangle$$
$$\Downarrow$$

$$K'_{i,j} = \langle \phi(x_i), \phi(x_j) \rangle - \frac{1}{n} \sum_{t=1}^n \langle \phi(x_i), \phi(x_t) \rangle - \frac{1}{n} \sum_{t=1}^n \langle \phi(x_t), \phi(x_j) \rangle + \frac{1}{n^2} \sum_{t=1}^n \sum_{s=1}^n \langle \phi(x_t), \phi(x_s) \rangle$$

The original  $K$  matrix is  $K_{i,j} = \langle \phi(x_i), \phi(x_j) \rangle$  substituting  
that in the expression above gives us the following expression:

$$K'_{i,j} = K_{i,j} - \frac{1}{n} \sum_{t=1}^n K_{i,t} - \frac{1}{n} \sum_{t=1}^n K_{t,j} + \frac{1}{n^2} \sum_{t=1}^n \sum_{s=1}^n K_{t,s}$$

in the above expression we can see that  $K'_{i,j}$  is calculated  
using  $K_{i,j}$

2.

$$\frac{1}{n} \sum_{i=1}^n \phi(x_i) = 0$$

$$S = \sum_{i=1}^n \phi(x_i) \phi(x_i)^T$$

The eigen vectors of  $S$  satisfy the following equation:

$$S u_j = \lambda_j u_j$$

To prove that  $u_j$  is a linear combination of  $\phi(x_i)$  we assume

$$u_j = \sum_{i=1}^n a_{j,i} \phi(x_i)$$

↓

$$\begin{aligned} S u_j &= S \left( \sum_{i=1}^n a_{j,i} \phi(x_i) \right) = \lambda_j \left( \sum_{i=1}^n a_{j,i} \phi(x_i) \right) \\ &= \sum_{i=1}^n a_{j,i} \sum_{t=1}^n \phi(x_t) \langle \phi(x_t), \phi(x_i) \rangle \end{aligned}$$

$$= \sum_{t=1}^n \phi(x_t) \sum_{i=1}^n a_{j,i} k_{t,i}$$

we know that  $k_{t,i} = \langle \phi(x_t), \phi(x_i) \rangle$  so we use that to simplify the expression

$$\sum_{t=1}^n \phi(x_t) \left( \sum_{i=1}^n a_{j,i} k_{t,i} \right) = \sum_{t=1}^n \phi(x_t) \lambda_j a_{j,t}$$

if we match the coefficients we find that

$$\sum_{i=1}^n a_{j,i} k_{t,i} = \lambda_j a_{j,t} \Rightarrow k_{a,j} = \lambda_j a_j$$

So we can see that  $a_j$  is in the vector of coefficients

### 3. Algorithm :

1. Calculate and center the kernel matrix  $K$

2 solve the following equation  $KA_j = \lambda_j A_j$  so that we find the eigenvalues and eigenvectors (use 2.)

3. Choose the top  $k$  eigenvectors that we found in the previous

4. normalize the chosen  $k$  eigenvalues and return them

4.  $z_j = \langle a_j, \varphi(x) \rangle = \left\langle \sum_{i=1}^n \alpha_{j,i} \varphi(x_i), \varphi(x) \right\rangle$

$$\omega_j \cdot \sum_{i=1}^n 2_{j,i} \varphi(x_i) = \sum_{i=1}^n \omega_{j,i} \langle \varphi(x_i), \varphi(x) \rangle$$

$$= \sum_{i=1}^n \lambda_{j,i} k(x_i, x)$$

↑  
eigenvector  
coefficients
↑  
kernel function

5 code in collab, yes it did better than PCA