

# CSE512 Fall 2018 Machine Learning - Homework 6

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# 1 PCA via Successive Deflation

1.  $\mathbf{A}$  and  $\mathbf{B}$  are symmetric,  $(\mathbf{AB})^T = \mathbf{B}^T \mathbf{A}^T = \mathbf{BA} \Rightarrow \mathbf{v}_1 \mathbf{v}_1^T \mathbf{X} \mathbf{X}^T = \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T$   
 $\mathbf{v}_1 \mathbf{v}_1^T \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T = \mathbf{v}_1 \mathbf{v}_1^T n \lambda_1 \mathbf{v}_1 \mathbf{v}_1^T = n \lambda_1 \mathbf{v}_1 \mathbf{v}_1^T = \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T$

$$\begin{aligned}\tilde{\mathbf{C}} &= \frac{1}{n} \tilde{\mathbf{X}} \tilde{\mathbf{X}}^T \\ &= \frac{1}{n} (\mathbf{I} - \mathbf{v}_1 \mathbf{v}_1^T) \mathbf{X} \mathbf{X}^T (\mathbf{I} - \mathbf{v}_1 \mathbf{v}_1^T) \\ &= \frac{1}{n} (\mathbf{X} \mathbf{X}^T - \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T - \mathbf{v}_1 \mathbf{v}_1^T \mathbf{X} \mathbf{X}^T + \mathbf{v}_1 \mathbf{v}_1^T \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T) \\ &= \frac{1}{n} (\mathbf{X} \mathbf{X}^T - \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T - \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T + \mathbf{X} \mathbf{X}^T \mathbf{v}_1 \mathbf{v}_1^T) \\ &= \frac{1}{n} (\mathbf{X} \mathbf{X}^T - n \lambda_1 \mathbf{v}_1 \mathbf{v}_1^T) \\ &= \frac{1}{n} \mathbf{X} \mathbf{X}^T - \lambda_1 \mathbf{v}_1 \mathbf{v}_1^T\end{aligned}$$

2.

$$\begin{aligned}\mathbf{C} \mathbf{v}_j &= \lambda_j \mathbf{v}_j \\ \Rightarrow \frac{1}{n} \mathbf{X} \mathbf{X}^T \mathbf{v}_j &= \lambda_j \mathbf{v}_j \\ \Rightarrow \frac{1}{n} \mathbf{X} \mathbf{X}^T \mathbf{v}_j - \lambda_1 \mathbf{v}_1 \mathbf{v}_1^T \mathbf{v}_j &= \lambda_j \mathbf{v}_j \\ \Rightarrow \left( \frac{1}{n} \mathbf{X} \mathbf{X}^T - \lambda_1 \mathbf{v}_1 \mathbf{v}_1^T \right) \mathbf{v}_j &= \lambda_j \mathbf{v}_j \\ \Rightarrow \tilde{\mathbf{C}} \mathbf{v}_j &= \lambda_j \mathbf{v}_j\end{aligned}$$

Therefore,  $\mathbf{v}_j$  is also a principal eigenvector of  $\tilde{\mathbf{C}}$  with the same eigenvalue  $\lambda_j$

3. Let the eigenvalues of  $\mathbf{C}$  rank in decreasing order

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_{d-1} \geq \lambda_d > 0 \quad (1)$$

Let the eigenvalues of  $\tilde{\mathbf{C}}$  rank in decreasing order

$$\lambda'_1 \geq \lambda'_2 \geq \dots \geq \lambda'_{d-1} > 0 \quad (2)$$

$\mathbf{u}$  is the principal eigenvector of  $\tilde{\mathbf{C}}$ , so

$$\tilde{\mathbf{C}} \mathbf{u} = \lambda'_1 \mathbf{u} \quad (3)$$

From the above question 1.2, we have the conclusion that for  $j \neq 1$ ,  $\mathbf{v}_j$  is also a principal eigenvector of  $\tilde{\mathbf{C}}$  with the same eigenvalue  $\lambda_j$ .

Let  $j = 2$ , then  $\mathbf{v}_2$  is a eigenvector with eigenvalue  $\lambda_2$ , so

$$\tilde{\mathbf{C}} \mathbf{v}_2 = \lambda_2 \mathbf{v}_2 \quad (4)$$

From formulas (1), (2), (3), (4), we can conclude that  $\lambda'_1 = \lambda_2$  and  $\mathbf{u} = \mathbf{v}_2$

4. I wrote a piece of python code to represent psuedo code.

```
def first_k_vector(C, k, f):  
    lambdas, principal_basis = [], []  
    for _ in range(k):  
        lamb, u = f(C)  
        lambdas.append(lamb)  
        principal_basis.append(u)  
        C = C - lamb * numpy.matmul(u, u.T)  
    return lambdas, principal_basis
```

## 2 Action recognition with CNN