

Exercise 2: Principal Component Analysis (10 + 10 P)

We consider a dataset $\mathbf{x}_1, \dots, \mathbf{x}_N \in \mathbb{R}^d$. Principal component analysis searches for a unit vector $\mathbf{u} \in \mathbb{R}^d$ such that projecting the data on that vector produces a distribution with maximum variance. Such vector can be found by solving the optimization problem:

$$\arg \max_{\mathbf{u}} \frac{1}{N} \sum_{k=1}^N \left[\mathbf{u}^\top \mathbf{x}_k - \frac{1}{N} \left(\sum_{l=1}^N \mathbf{u}^\top \mathbf{x}_l \right) \right]^2 \quad \text{with} \quad \|\mathbf{u}\|^2 = 1$$

(a) Show that the problem above can be rewritten as

$$\arg \max_{\mathbf{u}} \mathbf{u}^\top \mathbf{S} \mathbf{u} \quad \text{with} \quad \|\mathbf{u}\|^2 = 1$$

where $\mathbf{S} = \sum_{k=1}^N (\mathbf{x}_k - \mathbf{m})(\mathbf{x}_k - \mathbf{m})^\top$ is the scatter matrix, and $\mathbf{m} = \frac{1}{N} \sum_{k=1}^N \mathbf{x}_k$ is the empirical mean.

$$\begin{aligned} & \frac{1}{N} \sum_{k=1}^N \left(\mathbf{u}^\top \mathbf{x}_k - \frac{1}{N} \sum_{l=1}^N \mathbf{u}^\top \mathbf{x}_l \right)^2 = \\ &= \frac{1}{N} \sum_{k=1}^N \left(\mathbf{u}^\top \mathbf{x}_k \mathbf{u}^\top \mathbf{x}_k - \frac{1}{N} \sum_{l=1}^N \mathbf{u}^\top \mathbf{x}_k \mathbf{u}^\top \mathbf{x}_l - \frac{1}{N} \sum_{l=1}^N \mathbf{u}^\top \mathbf{x}_l \mathbf{u}^\top \mathbf{x}_k + \frac{1}{N} \sum_{l=1}^N \mathbf{u}^\top \mathbf{x}_l \cdot \sum_{l=1}^N \mathbf{u}^\top \mathbf{x}_l \right) \\ &= \frac{1}{N} \sum_{k=1}^N \left(\underbrace{\mathbf{u}^\top \mathbf{x}_k \mathbf{x}_k^\top \mathbf{u}}_{\text{this is a scalar so } \mathbf{u}^\top \mathbf{x}_k = \mathbf{x}_k^\top \mathbf{u}} - \mathbf{u}^\top \mathbf{x}_k \cdot \underbrace{\frac{1}{N} \sum_{l=1}^N \mathbf{x}_l^\top \mathbf{u}}_{\mathbf{m}^\top} - \mathbf{u} \cdot \underbrace{\frac{1}{N} \sum_{l=1}^N \mathbf{x}_l \cdot \mathbf{x}_k^\top \mathbf{u}}_{\mathbf{m}} + \mathbf{u}^\top \cdot \underbrace{\frac{1}{N} \sum_{l=1}^N \mathbf{x}_l \cdot \frac{1}{N} \sum_{l=1}^N \mathbf{x}_l^\top \mathbf{u}}_{\mathbf{m}^\top} \right) \\ &= \frac{1}{N} \sum_{k=1}^N \mathbf{u}^\top \left(\mathbf{x}_k \mathbf{x}_k^\top - \mathbf{x}_k \mathbf{m}^\top - \mathbf{m} \mathbf{x}_k^\top + \mathbf{m} \mathbf{m}^\top \right) \mathbf{u} \\ &= \frac{1}{N} \sum_{k=1}^N \mathbf{u}^\top (\mathbf{x}_k - \mathbf{m})(\mathbf{x}_k - \mathbf{m})^\top \mathbf{u} \\ &= \mathbf{u}^\top \mathbf{S} \mathbf{u} \end{aligned}$$

(b) Show using the method of Lagrange multipliers that the problem above can be reformulated as solving the eigenvalue problem

$$\mathbf{S} \mathbf{u} = \lambda \mathbf{u}$$

and retaining the eigenvector \mathbf{u} associated to the highest eigenvalue λ .

Problem: $\arg \max_{\mathbf{u}} (\mathbf{u}^\top \mathbf{S} \mathbf{u}) \quad \text{s.t.} \quad \|\mathbf{u}\|^2 = 1$

Let us construct the Lagrangian: $\mathcal{L}(\mathbf{u}, \lambda) = \mathbf{u}^\top \mathbf{S} \mathbf{u} + \lambda (1 - \|\mathbf{u}\|^2)$

$$\begin{aligned} \bullet \quad & \mathbf{u}^\top \mathbf{S} \mathbf{u} = (\mathbf{u}_1 \dots \mathbf{u}_d) \begin{pmatrix} s_{11} & \dots & s_{1d} \\ \vdots & \ddots & \vdots \\ s_{d1} & \dots & s_{dd} \end{pmatrix} \begin{pmatrix} \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_d \end{pmatrix} = (\mathbf{u}_1 \dots \mathbf{u}_d) \begin{pmatrix} \sum_{i=1}^d s_{1i} u_i \\ \vdots \\ \sum_{i=1}^d s_{di} u_i \end{pmatrix} = \\ &= \sum_{j=1}^d \sum_{i=1}^d u_j s_{ji} u_i \\ \bullet \quad & \|\mathbf{u}\|^2 = \mathbf{u}^\top \mathbf{u} = \sum_{j=1}^d u_j^2 \end{aligned}$$

$$\begin{aligned}
\nabla_u \mathcal{L}(u, \lambda) &= \nabla_u \left(\sum_{j=1}^d \sum_{i=1}^d u_j s_{ji} u_i \right) + \lambda \nabla_u \left(1 - \sum_{j=1}^d u_j^2 \right) \\
&= \sum_{j=1}^d \sum_{i=1}^d \sum_{k=1}^d \frac{\partial}{\partial u_k} (u_j s_{ji} u_i) \hat{u}_k - \lambda \sum_{j=1}^d \sum_{k=1}^d \frac{\partial u_j^2}{\partial u_k} \hat{u}_k \\
&= \sum_{j=1}^d \sum_{i=1}^d \sum_{k=1}^d (\delta_{jk} s_{ji} u_i + u_j s_{ji} \delta_{ik}) \hat{u}_k - 2\lambda \underbrace{\sum_{j=1}^d u_j \hat{u}_j}_{u \text{ vector}} \\
&= \sum_{j=1}^d \sum_{i=1}^d (s_{ji} u_i \hat{u}_j + u_j s_{ji} \hat{u}_i) - 2\lambda u \\
&\quad \xrightarrow{\text{S is symmetric}} = \sum_{j=1}^d \sum_{i=1}^d (s_{ji} u_i \hat{u}_j + u_i s_{ij} \hat{u}_j) - 2\lambda u \\
&= 2 \sum_{j=1}^d \sum_{i=1}^d s_{ji} u_i \hat{u}_j - 2\lambda u \\
&= 2 \begin{pmatrix} \sum_{i=1}^d s_{1i} u_i \\ \vdots \\ \sum_{i=1}^d s_{di} u_i \end{pmatrix} - 2\lambda u = 2Su - 2\lambda u
\end{aligned}$$

Solve for $\nabla_u \mathcal{L}(u, \lambda) = 0$:

$$Su = \lambda u$$

$$\nabla_\lambda \mathcal{L}(u, \lambda) = 0 \iff \|u\|^2 = 1$$

$$\underset{\|u\|^2=1}{\operatorname{argmax}}(u^T Su) = \underset{\|u\|^2=1}{\operatorname{argmax}}(u^T \lambda u) = \underset{\|u\|^2=1}{\operatorname{argmax}}(\lambda \|u\|^2) = \lambda$$

To maximize $u^T Su$, we must take the greatest eigenvalue λ of S and its corresponding eigenvector $u \in \mathbb{R}^d$ with $\|u\|^2 = 1$