

# Principal Component Analysis

Grant McNaughton

23 February 2024

## 1 Problem

Informally put, the problem is to find a “natural” coordinate system for a given collection of points. The following makes it precise.

**Problem 1.**

$$\begin{aligned}
 \text{In:} \quad X &= \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \in \mathbb{R}^{m \times d} && \text{where } x_i \text{ is a point in the } d\text{-dim space} \\
 \text{Out:} \quad c &= [c_1 \cdots c_d] \in \mathbb{R}^d && \text{where } c_j \text{ is the mean of the } j\text{-th coordinate of the } m \text{ points} \\
 B &= [b_1 \cdots b_d] \in \mathbb{R}^{d \times d} && \text{where } b_k = \arg \max_{\substack{u \in \mathbb{R}^d \\ \|u\|=1 \\ b_1 \cdot u = \cdots = b_{k-1} \cdot u = 0}} \sum_{1 \leq i \leq m} (x_{ci} \cdot u)^2
 \end{aligned}$$

$$\text{where again } \begin{bmatrix} x_{c1} \\ \vdots \\ x_{cm} \end{bmatrix} = \begin{bmatrix} x_1 - c \\ \vdots \\ x_m - c \end{bmatrix}$$

**Remark 2.**

1.  $c$  is the center of the “natural” coordinate system.
2.  $B$  is the orthonormal basis defining the “natural” coordinate system.

## 2 Theory

$$\text{Notation 3. Let } Xc = \begin{bmatrix} x_{c1} \\ \vdots \\ x_{cm} \end{bmatrix}.$$

**Theorem 4.** Let  $S = X_c^t X_c \in \mathbb{R}^{d \times d}$ . Let  $V = [v_1 \cdots v_d]$ ,  $\Lambda = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_d \end{bmatrix} = ED(S)$ . Assume that  $\lambda_1 \geq \cdots \geq \lambda_d$  and that  $\|v_1\| = \cdots = \|v_d\| = 1$ . Then  $B = V$ .

*Proof.* We will prove by induction that  $B = V$ . First, we will prove that  $B_1, B_2 = v_1, v_2$ .

Consider the following set of equations:

$$\begin{aligned}\sum_{i=1}^m (x_{ci} \cdot u)^2 &= \|X_c u\|^2 \\ &= (X_c u)^\top (X_c u) \\ &= u^\top X_c^\top X_c u \\ &= u^\top S u\end{aligned}$$

Because  $V$  is orthonormal,  $u$  can be expressed as  $a_1 v_1 + \dots + a_d v_d$  for some set of constants  $a_1, \dots, a_d$ . We can continue our computation as follows:

$$\begin{aligned}\sum_{i=1}^m (x_{ci} \cdot u)^2 &= u^\top S u \\ &= u^\top S (a_1 v_1 + \dots + a_d v_d) \\ &= u^\top (a_1 \lambda_1 v_1 + \dots + a_d \lambda_d v_d) \\ &= (a_1 v_1^\top + \dots + a_d v_d^\top) (a_1 \lambda_1 v_1 + \dots + a_d \lambda_d v_d)\end{aligned}$$

Because all vectors  $v_i$  are orthogonal,  $v_i^\top v_i = 1$  and  $v_i^\top v_j = 0$  for all  $i, j \in [1, n], i \neq j$ . Therefore,

$$\begin{aligned}\sum_{i=1}^m (x_{ci} \cdot u)^2 &= (a_1 v_1^\top + \dots + a_d v_d^\top) (a_1 \lambda_1 v_1 + \dots + a_d \lambda_d v_d) \\ &= a_1^2 \lambda_1 + \dots + a_d^2 \lambda_d\end{aligned}$$

From this, we can rewrite our problem as

$$\operatorname{argmax}_{\|u=1\|} \left( \sum_{i=1}^m (x_{ci} \cdot u)^2 \right) = \operatorname{argmax}_{\sum_{i=1}^d a_i^2 = 1} (a_1^2 \lambda_1 + \dots + a_d^2 \lambda_d)$$

Without loss of generality, assume the eigendecomposition of  $S$  is sorted such that  $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_d$ . When this is the case,  $a_1 = 1, a_n = 0$  for all  $n \in [2, d]$  and  $a_1^2 \lambda_1 + \dots + a_d^2 \lambda_d = \lambda_1$ . Thus  $b_1 = \operatorname{argmax}_{\|u=1\|} (x_{c1} \cdot u)^2 = u = v_1$ .

Assume the induction hypothesis  $b_n = v_n$ .

Then  $b_{n+1}$  is given by 
$$\operatorname{argmax}_{\substack{\|u=1\| \\ b_1 \cdot u = \dots = b_n \cdot u = 0}} (x_{ci} \cdot u)^2 = \operatorname{argmax}_{\substack{\sum_{i=1}^d a_i^2 = 1 \\ b_1 \cdot a = \dots = b_n \cdot a = 0}} (a_1^2 \lambda_1 + \dots + a_d^2 \lambda_d).$$

Because setting  $a_x$  as any nonzero value for any  $x \in [1, n]$  will make  $b_x \cdot a = 0a_1 + \dots + 0a_{x-1} + 1a_x + 0a_{x+1} + \dots + 0a_d = a_x \neq 0$ , we know that  $a_x = 0$  and our new problem can be expressed as

$$\operatorname{argmax}_{\substack{\sum_{i=1}^d a_i^2 = 1 \\ b_1 \cdot a = \dots = b_n \cdot a = 0}} (a_{n+1}^2 \lambda_{n+1} + \dots + a_d^2 \lambda_d).$$

Once again, this is maximized when  $a_{n+1} = 1, a_x = 0$  for all  $x \in [n+2, d]$  and  $a_{n+1}^2 \lambda_{n+1} + \dots + a_d^2 \lambda_d = \lambda_{n+1}$ . Thus  $b_{n+1} = \operatorname{argmax}_{\substack{\|u=1\| \\ b_1 \cdot u = \dots = b_n \cdot u = 0}} (x_{ci} \cdot u)^2 = v_{n+1}$ .

By the principle of mathematical induction, we can say that  $b_n = v_n$  for all  $n \in [1, d]$ .  $\square$

**Corollary 5.** Let  $U, \Sigma, V = SVD(X_c)$ . Then  $B = V$ .

*Proof.* Immediate from the fact that the normalized eigenvector matrix of  $S = X_c^t X_c$  is the same as the right singular vector matrix of  $X_c$ .  $\square$

**Algorithm 6.**  $c, V \leftarrow PCA(X)$

1.  $c \leftarrow \text{column mean of } X$

$$2. X_c \leftarrow \begin{bmatrix} x_1 - c \\ \vdots \\ x_m - c \end{bmatrix}$$

3.  $U, \Sigma, V \leftarrow SVD(X_c)$

4. return  $c, V$ .

**Theorem 7.** Let  $X' = \begin{bmatrix} x'_1 \\ \vdots \\ x'_d \end{bmatrix} \in \mathbb{R}^{m \times d}$  be such that  $x_i - c = x'_{i1}v_1^t + \cdots + x'_{id}v_d^t$ . Then  $X' = X_c V$ .

*Proof.* Note that because  $V$  is an orthogonal matrix,  $V^T = V^{-1}$  and  $v_i v_i^T = 1, v_i v_j^T = 0$  for all  $i, j \in \mathbb{N}, i \neq j$ . Additionally, we have already defined  $X_c = X - c$ , so we can say that  $x_i - c = x_{ci} = x'_{i1}v_1^T + \cdots + x'_{id}v_d^T$ .

$x_{ci} \in \mathbb{R}^{1 \times d}$  and  $V \in \mathbb{R}^{d \times d}$ , so  $x_{ci}V = (x'_{i1}v_1^T + \cdots + x'_{id}v_d^T)V \in \mathbb{R}^{1 \times d}$ . From this, we can show the following:

$$\begin{aligned} x_{ci}V &= (x'_{i1}v_1^T + \cdots + x'_{id}v_d^T)V \\ &= x'_{i1}v_1^T v_1 + x'_{i1}v_1^T v_2 + \cdots + x'_{i1}v_1^T v_d + x'_{i2}v_2^T v_1 + \cdots + x'_{id}v_d^T v_1 + \cdots + x'_{id}v_d^T v_d \\ &= x'_{i1} + x'_{i2} + \cdots + x'_{id} \\ &= x'_i \end{aligned}$$

We can then generalize  $x_{ci}V = x'_i$  to say that  $X_c V = X'$ .  $\square$