



[\(Optional\) Unit 8 Principal](#)
[Course](#) > [component analysis](#)

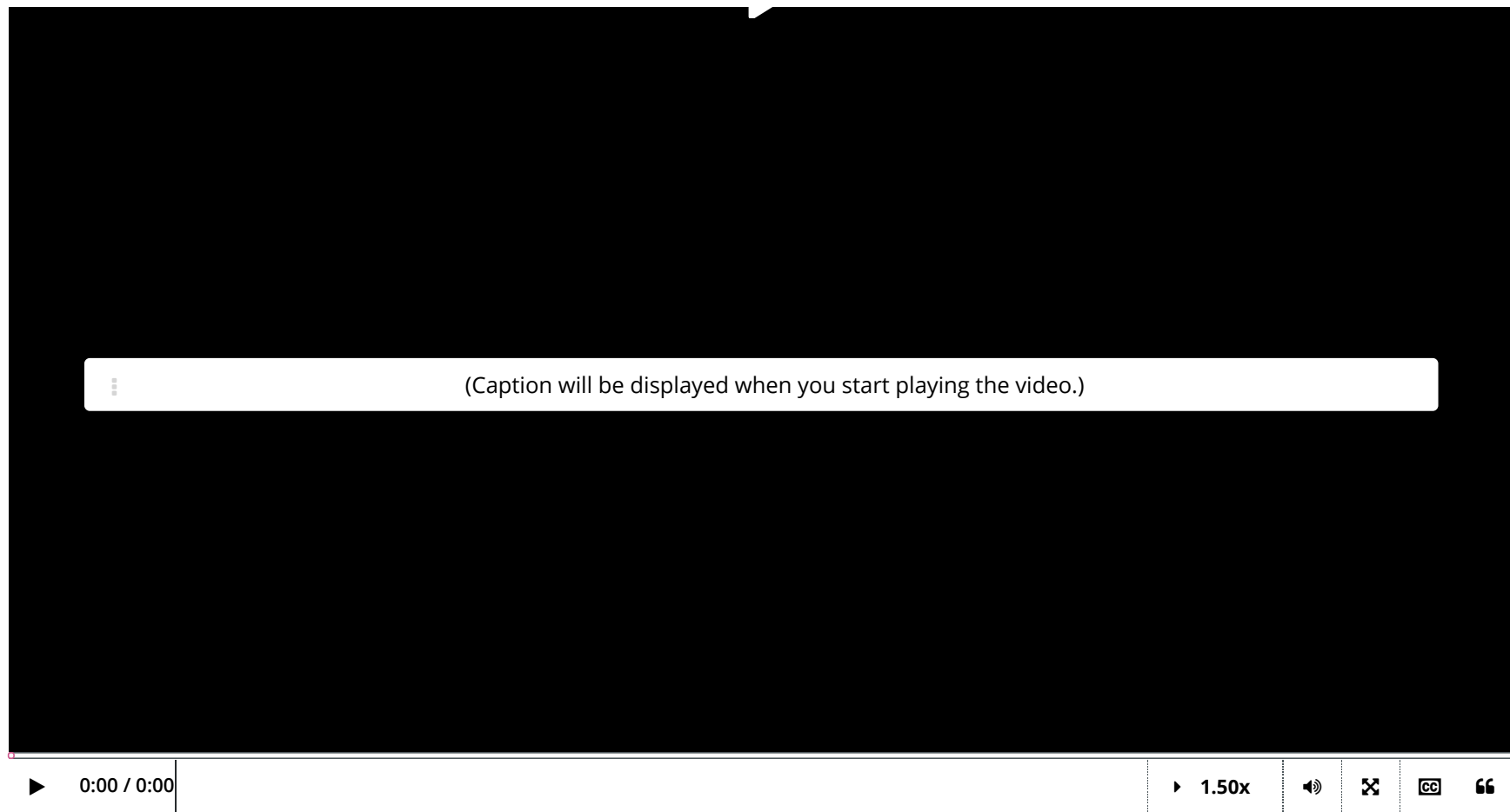
[\(Optional\) Lecture 23: Principal](#)
> [Component Analysis](#)

7. Largest Eigenvalue and Principal
> Directions

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PCA of Covariance Matrix: The Largest Eigenvalues and the Principal Directions





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Empirical Variance in the Direction of the Top Eigenvector

1/1 point (ungraded)

Let $\mathbf{X}_1, \dots, \mathbf{X}_n \in \mathbb{R}^d$ denote a data set. Let S denote the empirical covariance for this data set, and apply the decomposition theorem to write

$$S = PDP^T$$

where D is a diagonal matrix and $PP^T = I_d$. Further let's suppose that

$$D = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_d \end{pmatrix}, \quad P = \begin{pmatrix} \uparrow & \uparrow & \cdots & \uparrow \\ \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_d \\ \downarrow & \downarrow & \cdots & \downarrow \end{pmatrix}$$

where $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d \geq 0$ and $\mathbf{v}_1, \dots, \mathbf{v}_d \in \mathbb{R}^d$.

What is

$$\mathbf{v}_1^T S \mathbf{v}_1?$$

☒ λ_1

☐ λ_d

☐ λ_1^2

☐ None of the above.



Solution:

Observe that

$$\begin{aligned}
\mathbf{v}_1^T S \mathbf{v}_1 &= \mathbf{v}_1^T P D P^T \mathbf{v}_1 \\
&= (1, 0, \dots, 0) \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_d \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \\
&= \lambda_1
\end{aligned}$$

where we used that $PP^T = P^T P = I_d$.

Remark 1: The direction \mathbf{v}_1 (recall that $\|\mathbf{v}_1\|^2 = 1$) is the direction \mathbf{w} that maximizes the empirical variance of the (one-dimensional) projected data set

$$\mathbf{w}^T \mathbf{X}_1, \mathbf{w}^T \mathbf{X}_2, \dots, \mathbf{w}^T \mathbf{X}_n.$$

Remark 2: Similarly, we also have for $1 \leq i \leq d$

$$\mathbf{v}_i^T S \mathbf{v}_i = \lambda_i.$$

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You have used 2 of 3 attempts

 Answers are displayed within the problem

Is the Direction of Largest Empirical Variance Unique?

1/1 point (ungraded)

Consider the statistical set-up of the previous problem. In particular, recall that S denotes the empirical covariance matrix of the data set $\mathbf{X}_1, \dots, \mathbf{X}_n$ and that S has eigenvalues $\lambda_1, \dots, \lambda_d$ and corresponding eigenvectors $\mathbf{v}_1, \dots, \mathbf{v}_d$.

Unlike the previous problem, let's assume that we have **strict** inequalities

$$\lambda_1 > \lambda_2 > \cdots > \lambda_{d-1} > \lambda_d > 0.$$

We showed in the previous problem that $\mathbf{v}_1^T S \mathbf{v}_1 = \lambda_1$.

Does there exist a unit vector $\mathbf{w} \neq \mathbf{v}_1, \mathbf{w} \neq -\mathbf{v}_1$ such that

$$\mathbf{w}^T S \mathbf{w} \geq \lambda_1?$$

(Refer to the slides.)

☐ Yes

☒ No



Solution:

The correct answer is **"No"**. First observe that if \mathbf{w} is a unit vector, then $P^T \mathbf{w}$ is also a unit vector. This is because

$$\mathbf{w}^T P P^T \mathbf{w} = (P^T \mathbf{w})^T P^T \mathbf{w}$$

$$= \mathbf{w}^T P P^T \mathbf{w}$$

$$= \mathbf{w}^T \mathbf{w}$$

$$= 1.$$

To go from the second to third line, we used that $PP^T = I_d$ and associativity of matrix multiplication.

$$PP^T = I_d$$

Next, note that by the given decomposition

$$\mathbf{w}^T S \mathbf{w} = \mathbf{w}^T P D P^T \mathbf{w} = (P^T \mathbf{w})^T D (P^T \mathbf{w}).$$

But as \mathbf{w} ranges over all unit vectors, we know that $P^T \mathbf{w}$ also ranges over all unit vectors. So if there exists $\mathbf{b} \neq \mathbf{v}_1$ such that $\mathbf{b}^T D \mathbf{b} = \lambda_1$, there must exist $\mathbf{w} \neq \mathbf{v}_1$ such that $\mathbf{w}^T S \mathbf{w} = \lambda_1$.

Observe that by matrix multiplication, $\mathbf{b} \neq P^T \mathbf{v}_1 = \mathbf{e}_1 = (1, 0, \dots, 0)^T$

$$\mathbf{b}^T D \mathbf{b} = \sum_{i=1}^n \lambda_i (\mathbf{b}^i)^2 \leq \lambda_1 (\mathbf{b}^1)^2 + \lambda_2 (1 - \mathbf{b}_1^2).$$

We also used that $\lambda_1 > \lambda_2$ and for all \mathbf{b} . Suppose (so that $\mathbf{b}^1 \neq 1$ and $\mathbf{b}^2 > 0$), then we have

$$\lambda_1 > \lambda_2 \mathbf{b}_1^2 < 1 - \lambda_2 \mathbf{b}_1^2 \leq 1 - \lambda_1 \mathbf{b}_1^2 \leq \lambda_1 \mathbf{b}_1^2 > 0$$

$$\mathbf{b}^T D \mathbf{b} \leq \lambda_1 (\mathbf{b}^1)^2 + \lambda_2 (1 - \mathbf{b}_1^2) < \lambda_1 (\mathbf{b}^1)^2 + \lambda_1 (1 - \mathbf{b}_1^2) = \lambda_1,$$

where we used the strict inequality. Therefore, the equality case is **only** possible if $\mathbf{b} = (1, 0, \dots, 0)^T$. Hence, we must also have $\mathbf{w} = \mathbf{v}_1$ if equality holds.

$$\lambda_1 > \lambda_2$$

$$\mathbf{b} = (1, 0, \dots, 0)^T$$

$$\mathbf{w} = \mathbf{v}_1$$

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