

# Multivariate statistics

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## Principal Component Analysis PCA

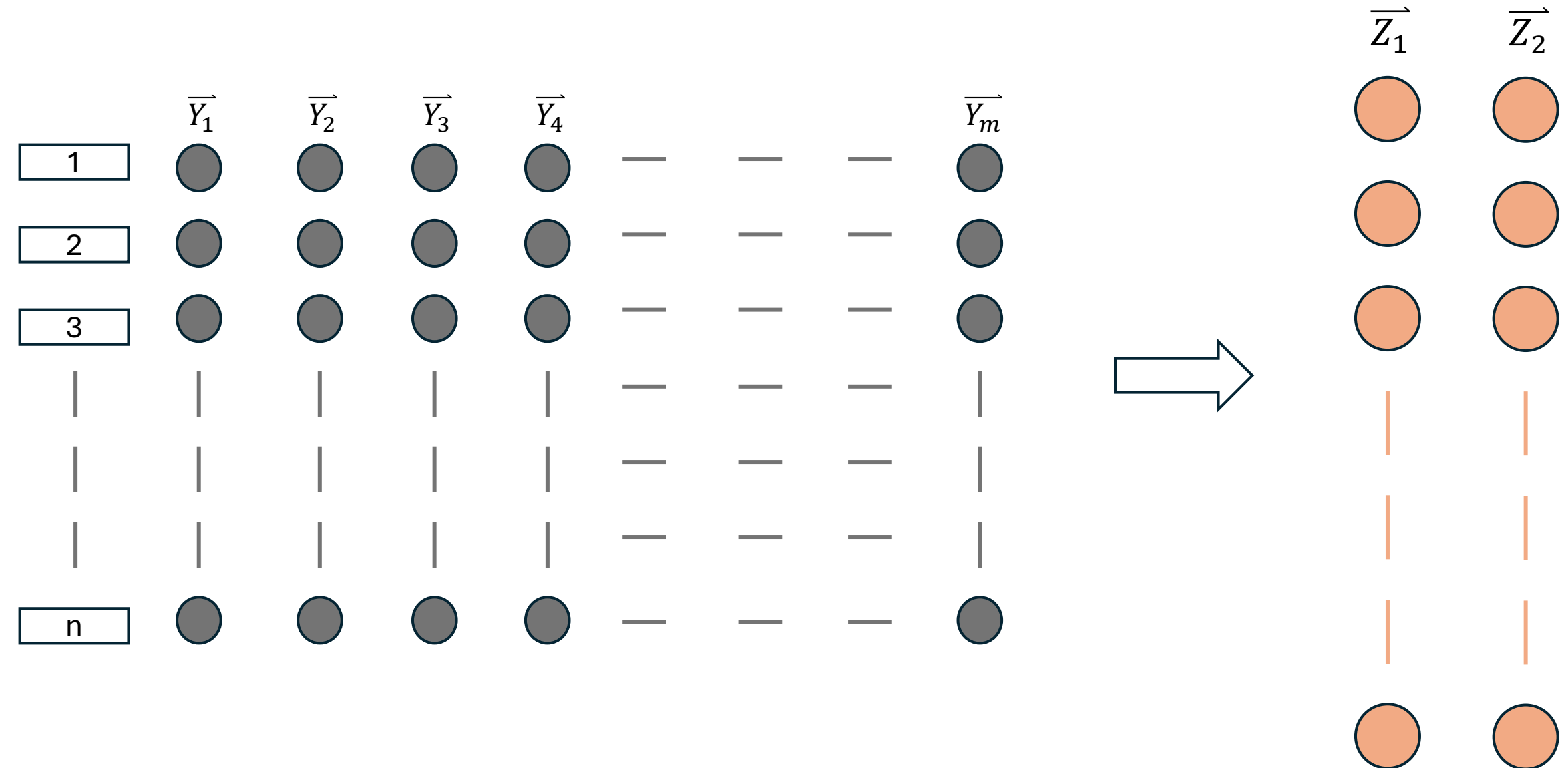
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# General idea



Do you know what a variate is?  
A linear combination?

## The variate:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_p X_p$$

$$Y_{mi} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \cdots + \beta_{pi} X_{pi}$$

*n: number of observations (individuals)*

*p: number of original variables*

*m: number of "new" variables*

*m: projections, component, factors*

# The variate:

$$Y = X\beta$$

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$$Y = X\beta$$

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ \vdots \\ Y_m \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix}$$

$$X = \begin{bmatrix} 1 & X_{11} & X_{21} & \cdots & X_{p1} \\ 1 & X_{12} & X_{22} & \cdots & X_{p2} \\ 1 & X_{13} & X_{23} & \cdots & X_{p3} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{1n} & X_{2n} & \cdots & X_{pn} \end{bmatrix}$$

# Eigenvalues and eigenvectors

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An eigenvector “ $v$ ” is non-zero vector that satisfies the following equation:

$$\longrightarrow \quad Av = \lambda v$$

If we multiply matrix “A” by vector “v”, the new vector does not change the direction after the transformation

The eigenvalue tells how much the eigenvector changes when multiplied by a matrix. It is an scaling value

Given this  
matrix:

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

Is this  
vector:  $v = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$

An  
eigenvector of  
“A”?



Given this  
matrix:

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

Is this  
vector:

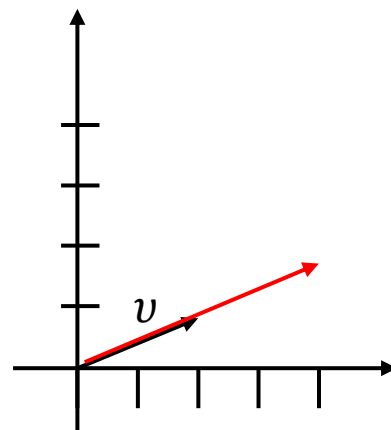
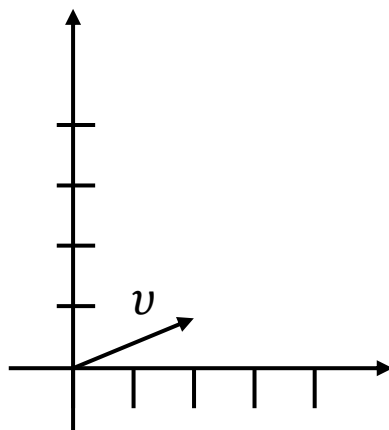
$$v = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

An  
eigenvector of  
“A”?

$$Av = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} * \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \end{bmatrix}$$

$$\lambda = 2$$

$$Av = 2 * \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$



A matrix can have multiple Eigenvectors.  
Nevertheless, eigenvalue does not change.

Given this  
matrix:

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

Is this  
vector:

$$v = \begin{bmatrix} 3 \\ 1.5 \end{bmatrix}$$

An  
eigenvector of  
“A”?

What about this:

Given this  
matrix:

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

Is this  
vector:

$$v = \begin{bmatrix} -3 \\ 3 \end{bmatrix}$$

An  
eigenvector of  
“A”?

What about this:

Given this  
matrix:

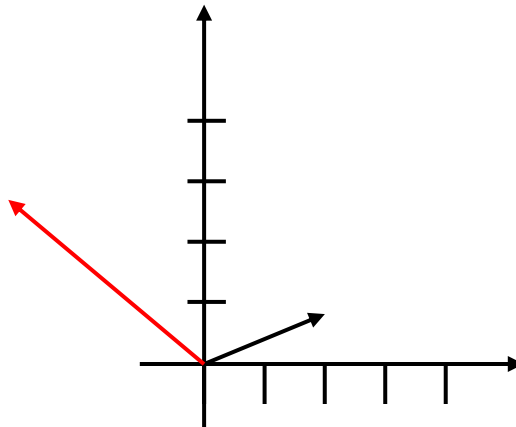
$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

Is this  
vector:

$$v = \begin{bmatrix} -3 \\ 3 \end{bmatrix}$$

An  
eigenvector of  
“A”?

$$Av = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} * \begin{bmatrix} -3 \\ 3 \end{bmatrix} = \begin{bmatrix} 3 \\ -3 \end{bmatrix} \quad \lambda = -1 \quad Av = -1 * \begin{bmatrix} -3 \\ 3 \end{bmatrix}$$



# How to calculate the “Eigens”?

$$Av = \lambda v \longrightarrow Av = \lambda Iv \quad I: \text{identity matrix, ones in the diagonal}$$

$$Av - \lambda Iv = 0 \longrightarrow (A - \lambda I)v = 0$$

$\underbrace{\hspace{1.5cm}}$

$M$

If there is a vector that, after multiplying a matrix, produces zero, the matrix is not invertible

The determinant of a non-invertible matrix is zero.

$$\det(A - \lambda I) = 0$$

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$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\det(A - \lambda I) = 0$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\det\left(\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right) = 0 \quad \longrightarrow \quad \det\left(\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix}\right) = 0$$

$$\det(A - \lambda I) = 0$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\det \left( \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right) = 0 \longrightarrow \det \left( \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \right) = 0$$

$$\det \left( \begin{bmatrix} 1 - \lambda & 2 \\ 1 & -\lambda \end{bmatrix} \right) = 0 \longrightarrow -\lambda + \lambda^2 - 2 = 0 \longrightarrow \lambda^2 - \lambda - 2 = 0$$



$$\det(A - \lambda I) = 0$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\det \left( \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right) = 0 \longrightarrow \det \left( \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \right) = 0$$

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$$\boxed{(\lambda - 2)(\lambda + 1) = 0}$$

$$\det(A - \lambda I) = 0$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

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$$\det \left( \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right) = 0 \longrightarrow \det \left( \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \right) = 0$$

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$$\boxed{(\lambda - 2)(\lambda + 1) = 0}$$

$$\lambda = 2$$

$$\lambda = -1$$

# How to get the Eigenvectors?

$$Av = \lambda v$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

$$\lambda = 2$$

$$\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = 2 \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

$$Av = \lambda v$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

$$\lambda = 2$$

$$\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = 2 \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

$$z_1 + 2z_2 = 2z_1$$

$$z_1 = 2z_2$$

$$Av = \lambda v$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix}$$

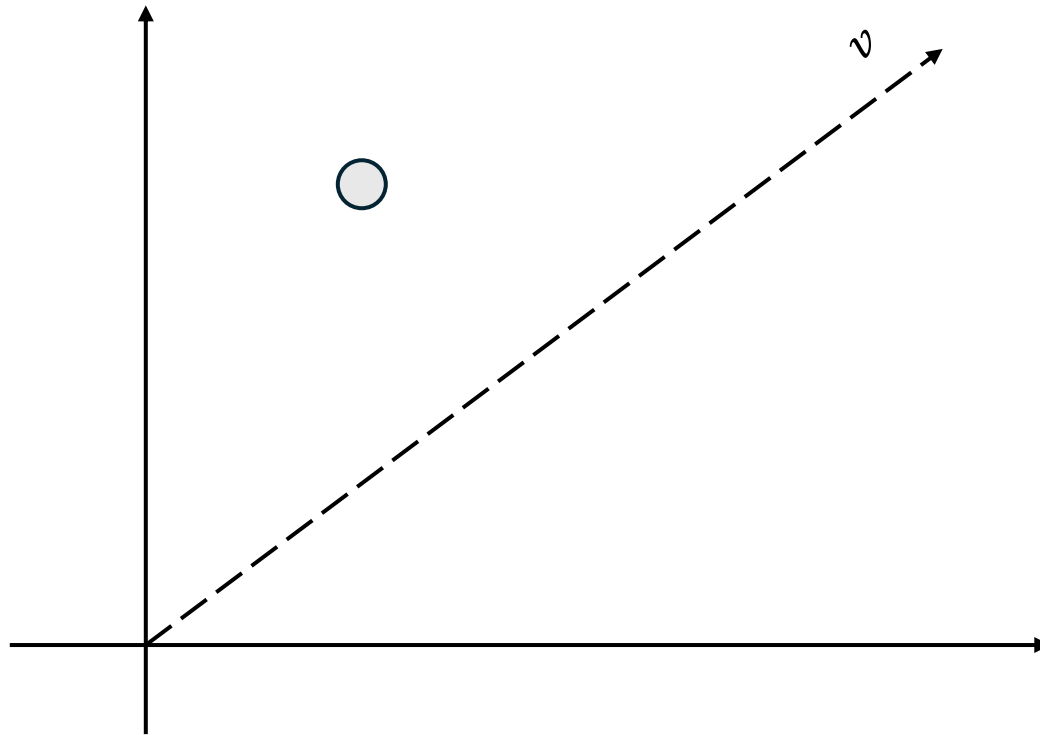
$$\lambda = 2$$

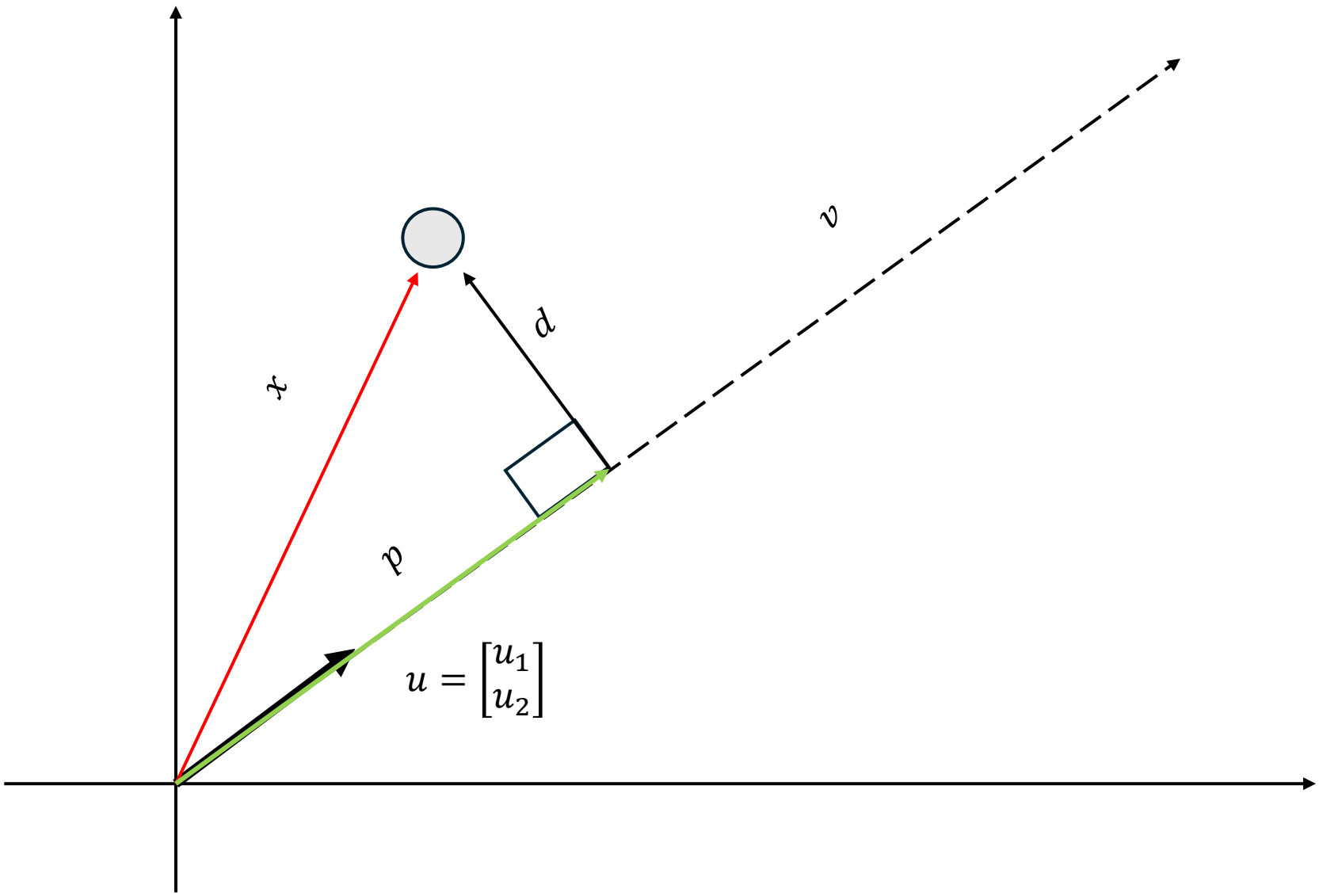
$$\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = 2 \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

$$z_1 + 2z_2 = 2z_1 \longrightarrow 2z_2 = 2z_1 - z_1 \longrightarrow 2z_2 = z_1$$

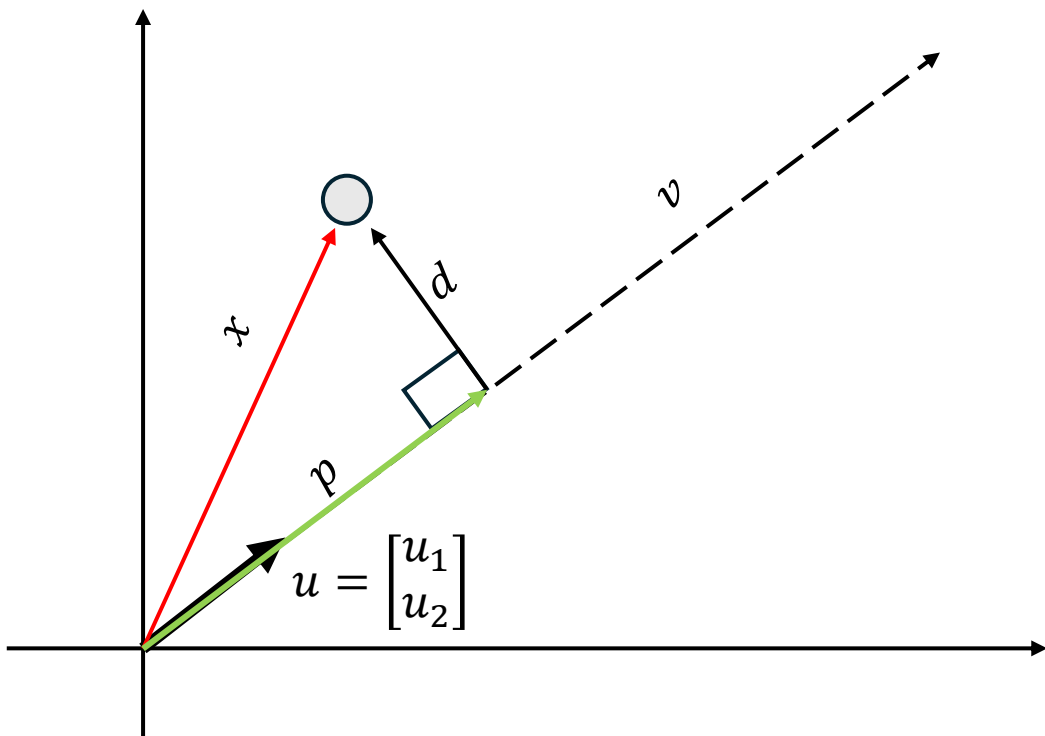
$$z_1 = 2z_2$$

# Vector projections









$u$ : Unit Vector

Dot product of a vector with itself is equal to its magnitude.

$$u = \frac{v}{||v||}$$

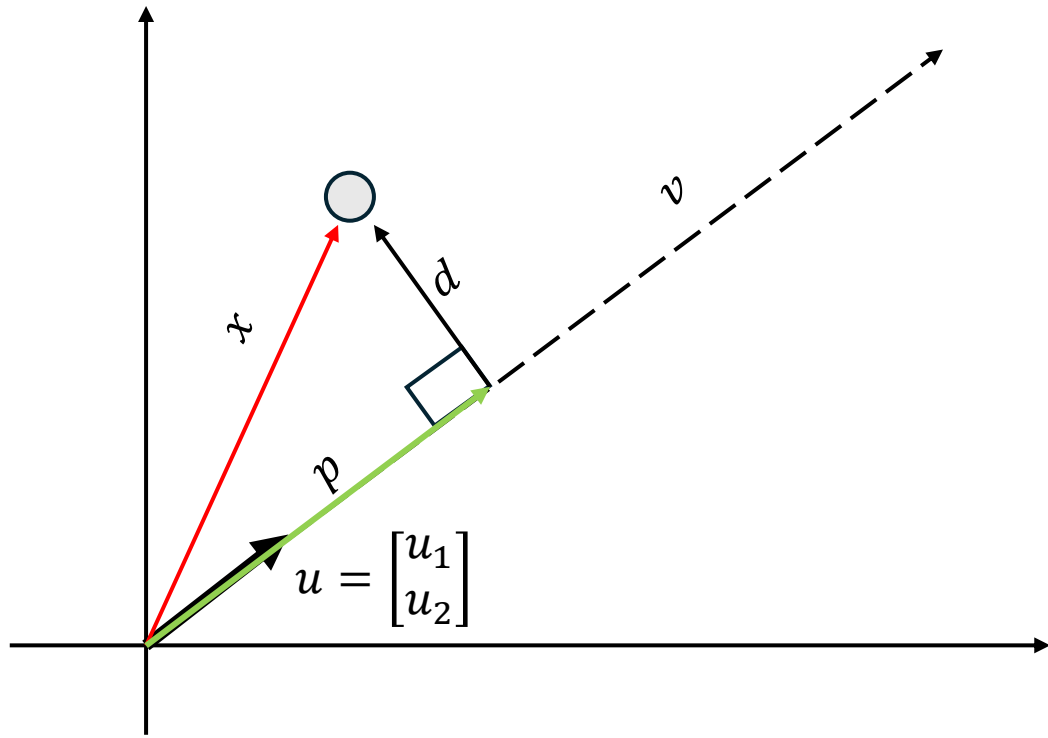
$$u \cdot u = 1$$

$$p = ku$$

$$p + d = x$$

$$d = x - p$$

$$d = x - ku$$



$u$ : Unit Vector

Dot product of a vector with itself is equal to its magnitude.

$$u = \frac{v}{||v||}$$

$$u \cdot u = 1$$

$$p = ku$$

$$p + d = x$$

$$d = x - p$$

$$d = x - ku$$

Remember: The dot product of two perpendicular (orthogonal) vectors is zero.

$$\longrightarrow p \cdot d = 0 \longrightarrow (ku) \cdot (x - ku) = 0 \longrightarrow kux - kuku = 0$$

$$\longrightarrow k(ux - kuu) = 0 \longrightarrow ux - kuu = 0 \longrightarrow ux - k = 0$$

$$\longrightarrow k = xu \longrightarrow p = (x \cdot u)u \longrightarrow p = \frac{x \cdot v}{||v||} u \longrightarrow \boxed{p = u^T x u}$$

# PCA: long story short

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$$SZ = \lambda Z$$

S: Covariance Matrix

Z: Eigenvectors

$\lambda$ : *Eigenvalues*

Standardize original variables  $\frac{X - \mu}{\sigma}$



Compute "S"



Calculate eigenvalues and eigenvectors

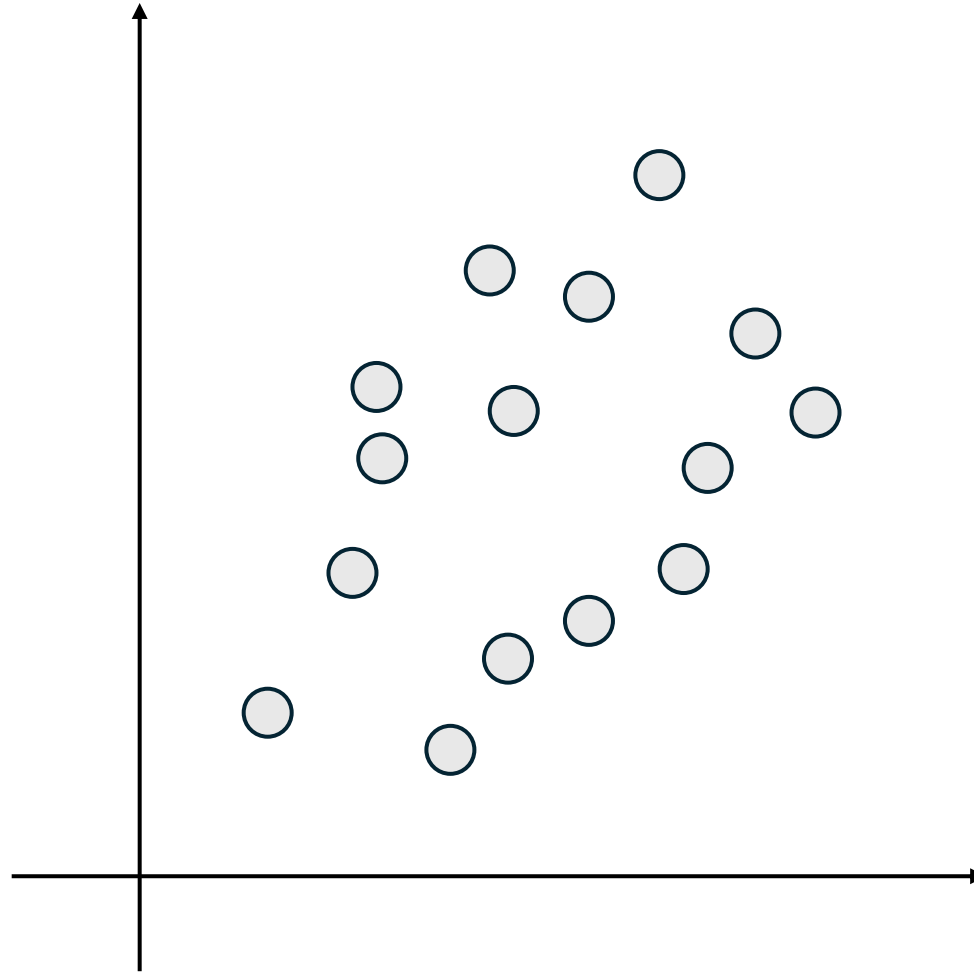


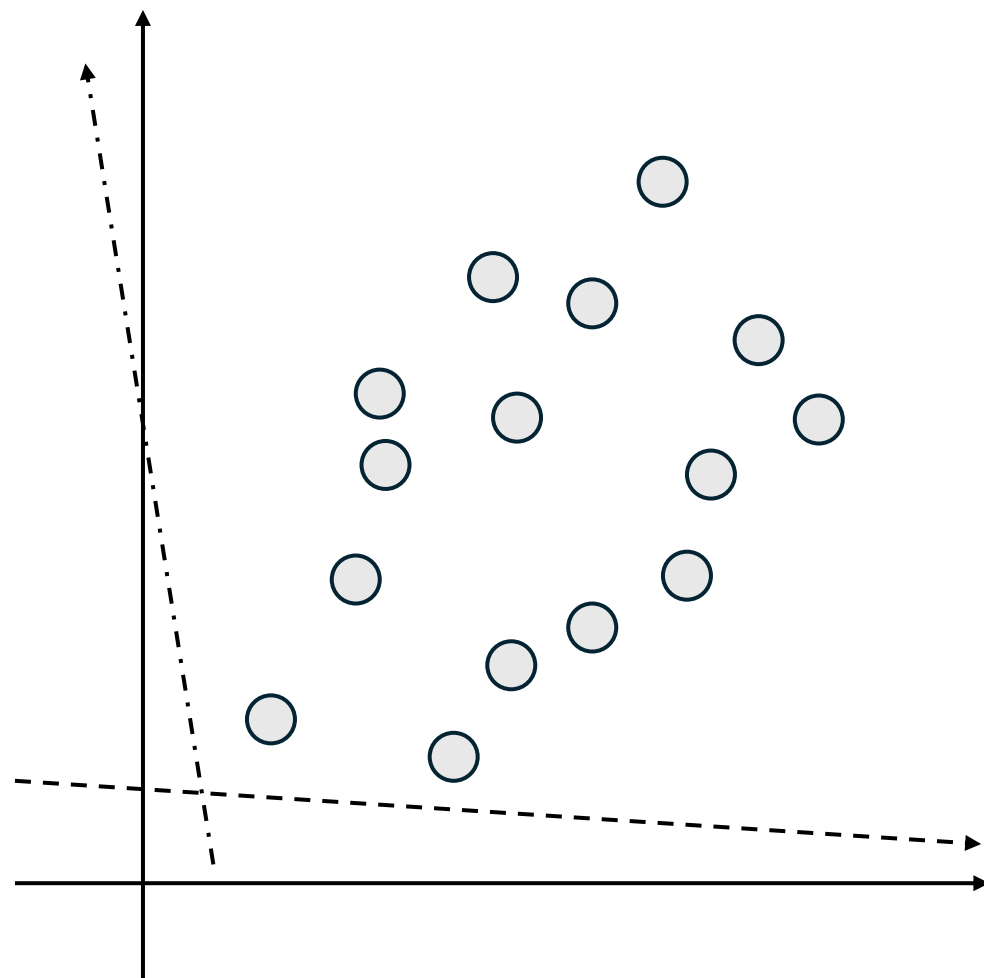
Sort by Eigenvalues: they explain variance

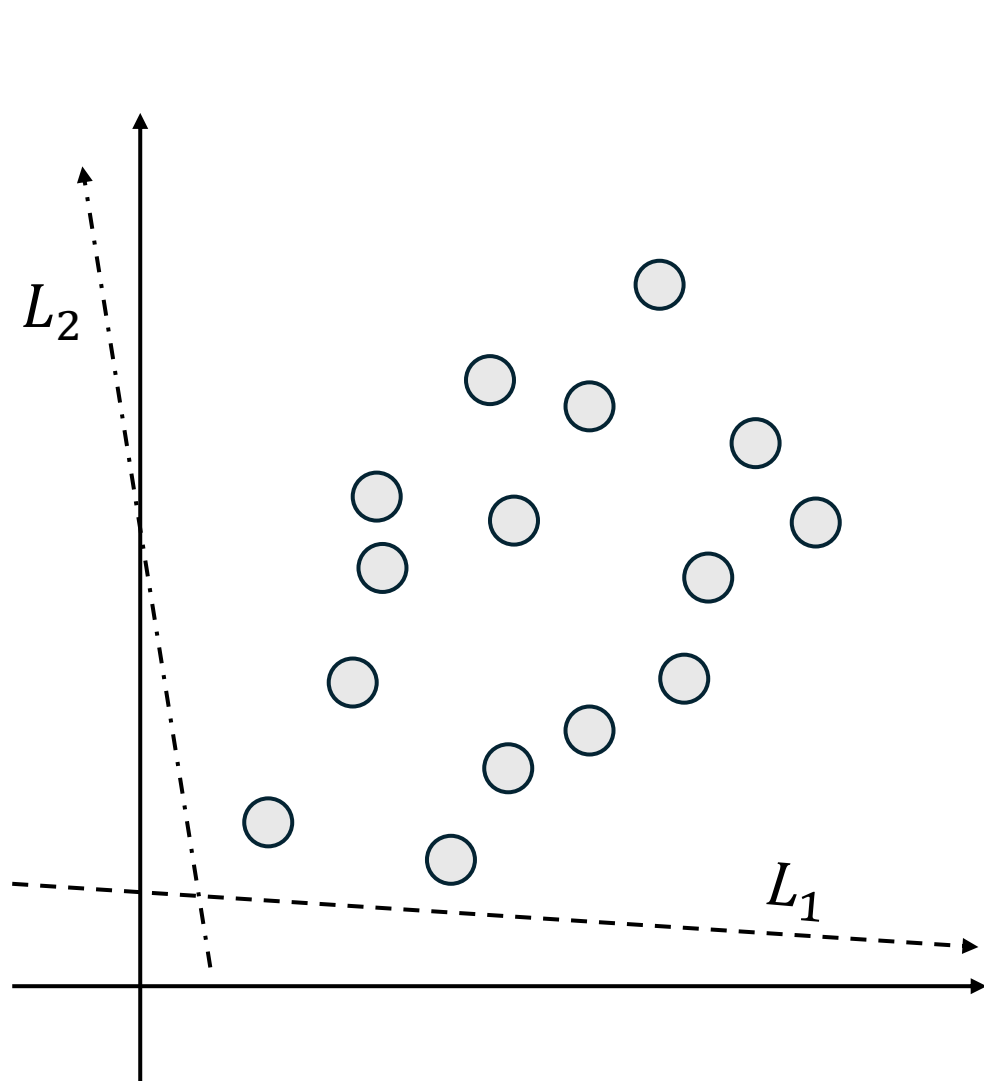


Transform (reproject) and interpret

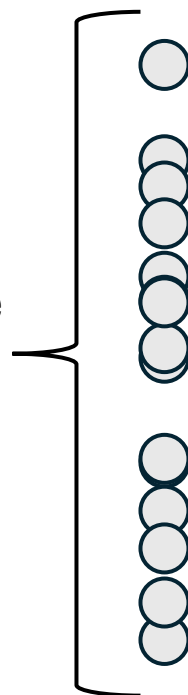
Where and how would you project this data?  
(you want to preserve as much as the original variability)



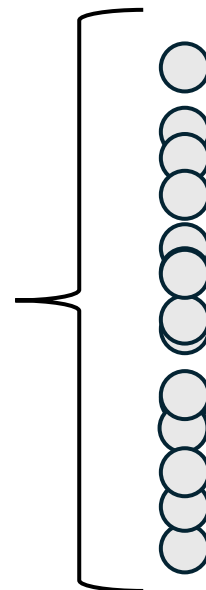




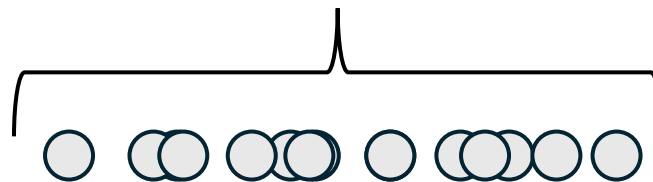
Projection into the  
vertical axis



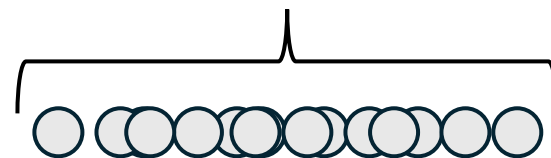
Projection  
into  $L_2$

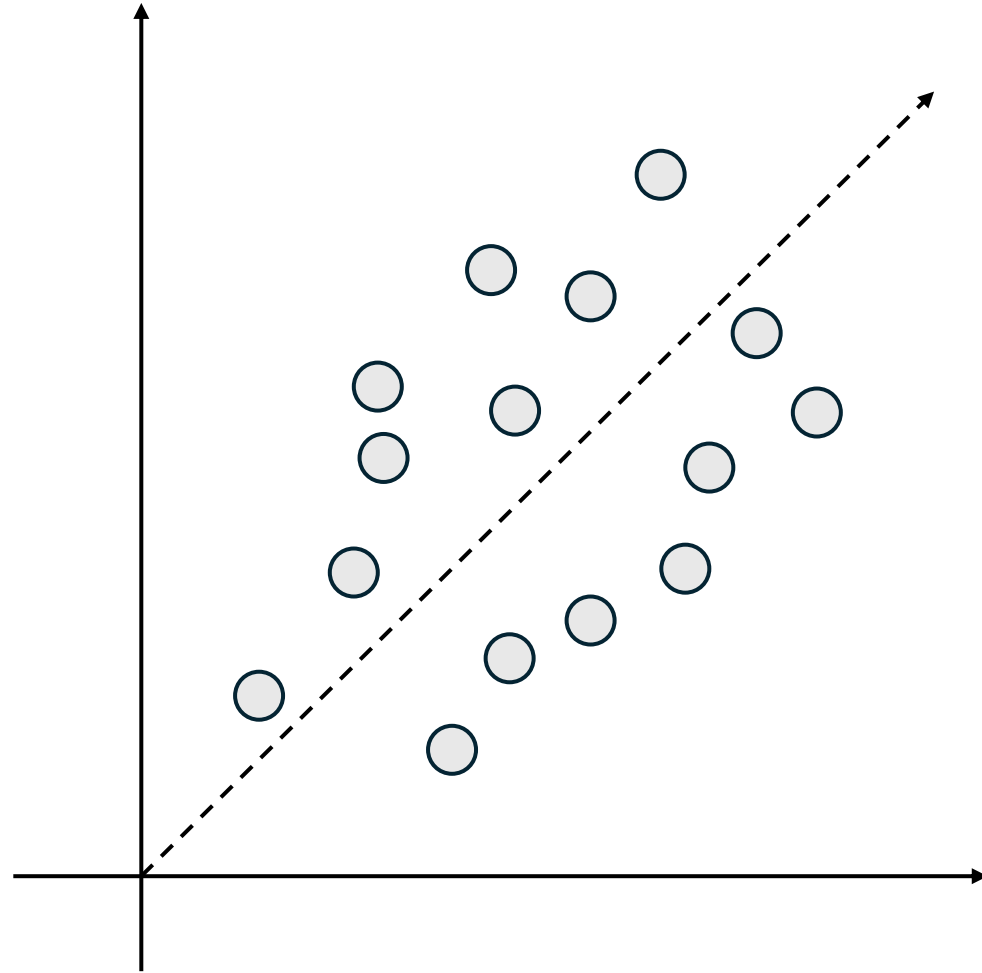


Projection into the  
horizontal axis

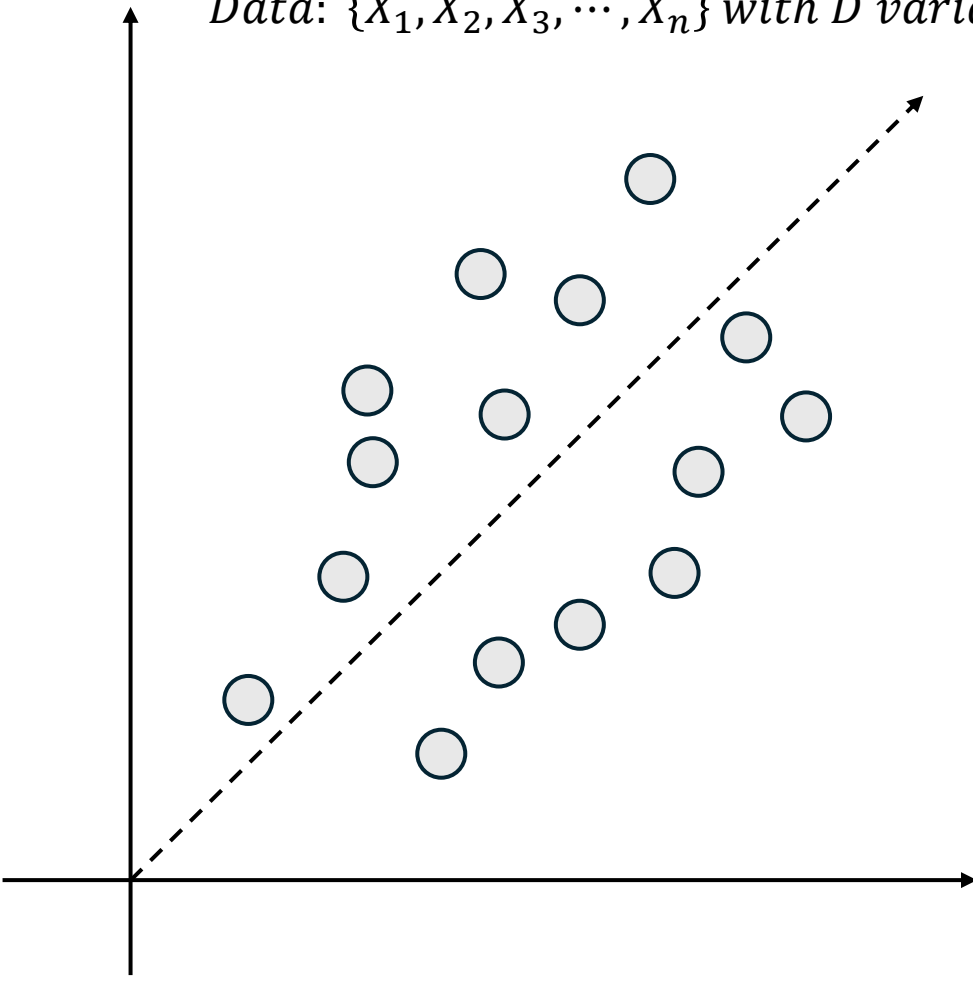


Projection into  $L_1$





Data:  $\{X_1, X_2, X_3, \dots, X_n\}$  with  $D$  variables



$$PROJE_{u_1}(x_i) = u_1^T x_i u$$

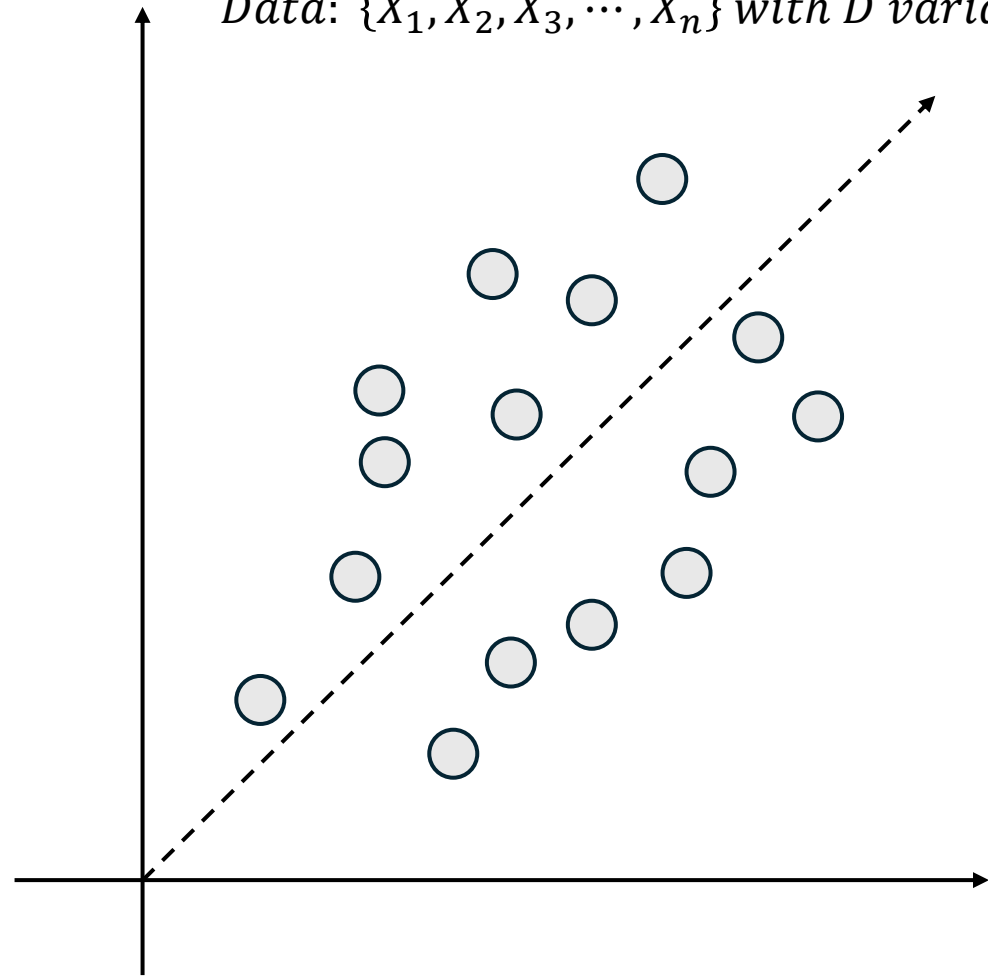
$$PROJE_{u_1}(\bar{x}) = u_1^T \bar{x} u$$

$u$ : Unit Vector

How to get a variance  
of the projections?



Data:  $\{X_1, X_2, X_3, \dots, X_n\}$  with  $D$  variables



$$PROJE_{u_1}(x_i) = u_1^T x_i u$$

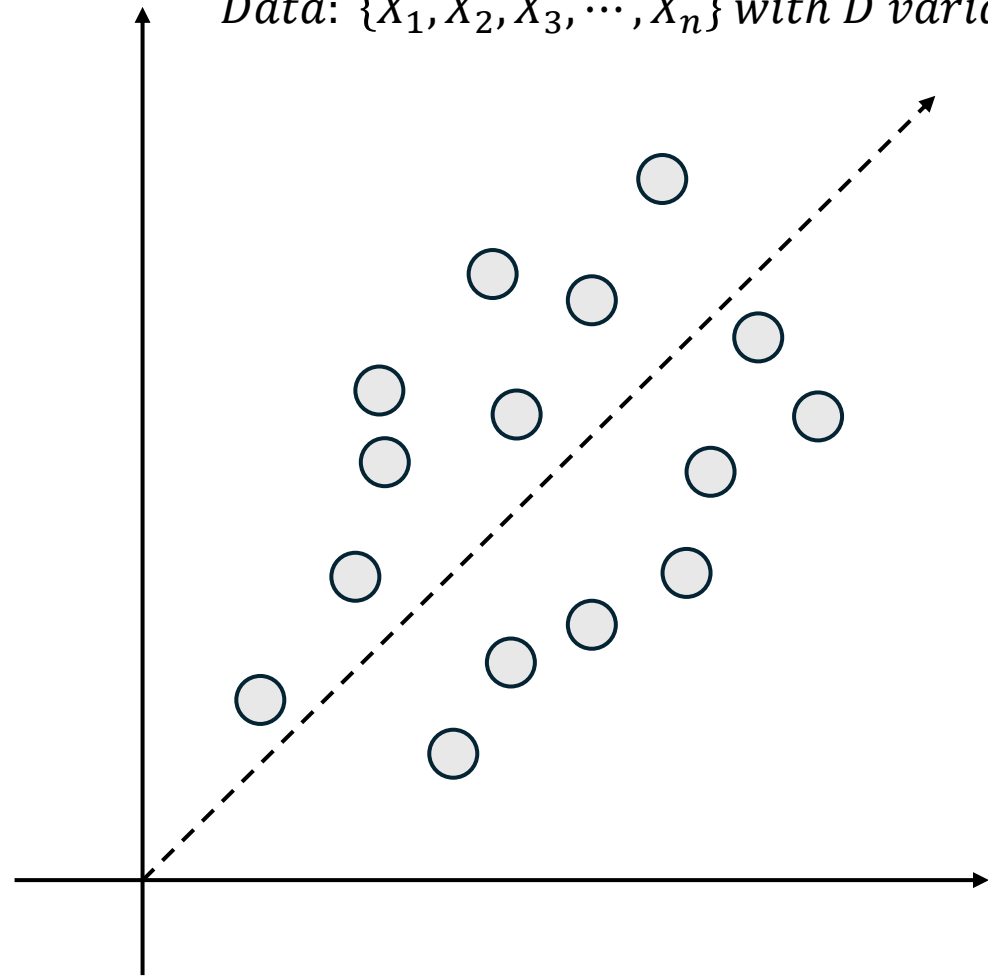
$$PROJE_{u_1}(\bar{x}) = u_1^T \bar{x} u$$

$u$ : Unit Vector

How to get a variance  
of the projections?

$$\frac{1}{n} \sum_{i=1}^n (u_1^T x_i - u_1^T \bar{x})^2$$

Data:  $\{X_1, X_2, X_3, \dots, X_n\}$  with  $D$  variables



$$PROJE_{u_1}(x_i) = u_1^T x_i u$$

$$PROJE_{u_1}(\bar{x}) = u_1^T \bar{x} u$$

$u$ : Unit Vector

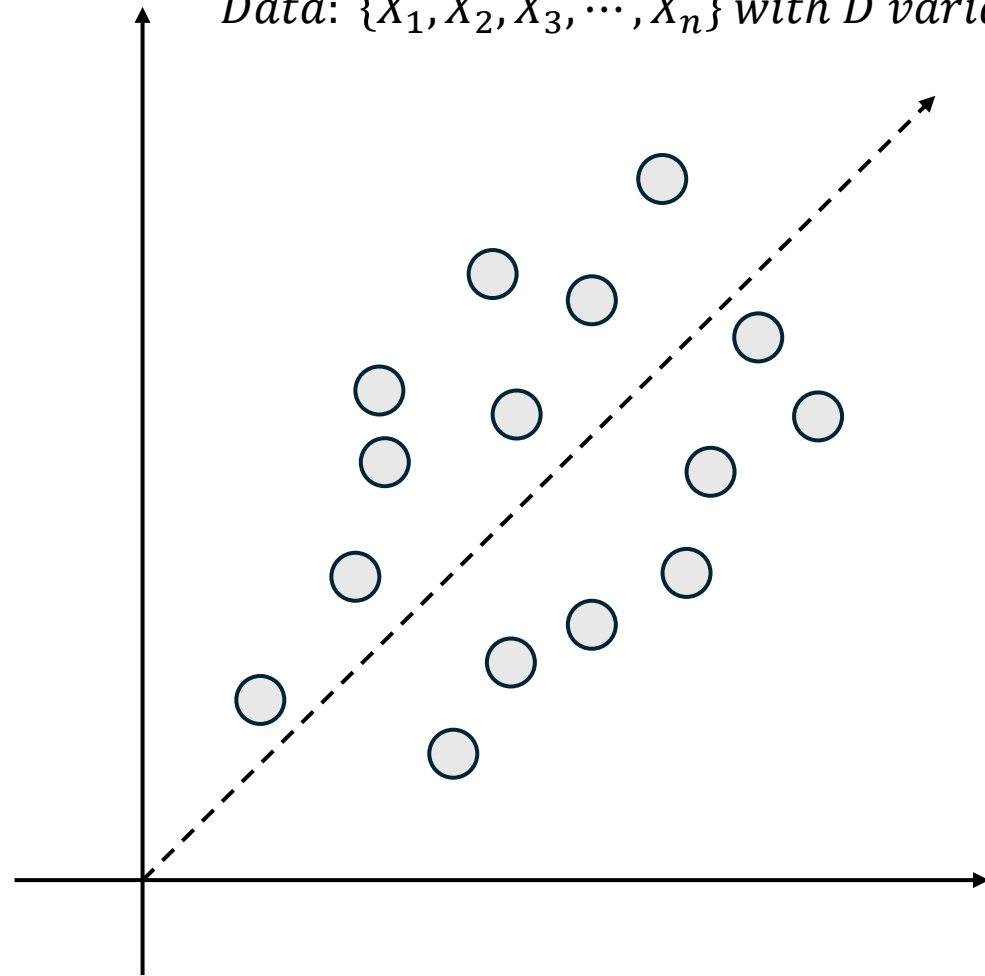
How to get a variance  
of the projections?

$$\frac{1}{n} \sum_{i=1}^n (u_1^T x_i - u_1^T \bar{x})^2$$

$$\frac{1}{n} \sum_{i=1}^n \left( u_1^T (x_i - \bar{x}) \right)^2$$

$$\frac{1}{n} \sum_{i=1}^n u_1^T (x_i - \bar{x}) (x_i - \bar{x})^T u_1 \longrightarrow u_1^T \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}) (x_i - \bar{x})^T u_1$$

Data:  $\{X_1, X_2, X_3, \dots, X_n\}$  with  $D$  variables



$$PROJE_{u_1}(x_i) = u_1^T x_i u$$

$$PROJE_{u_1}(\bar{x}) = u_1^T \bar{x} u$$

$u$ : Unit Vector

How to get a variance  
of the projections?

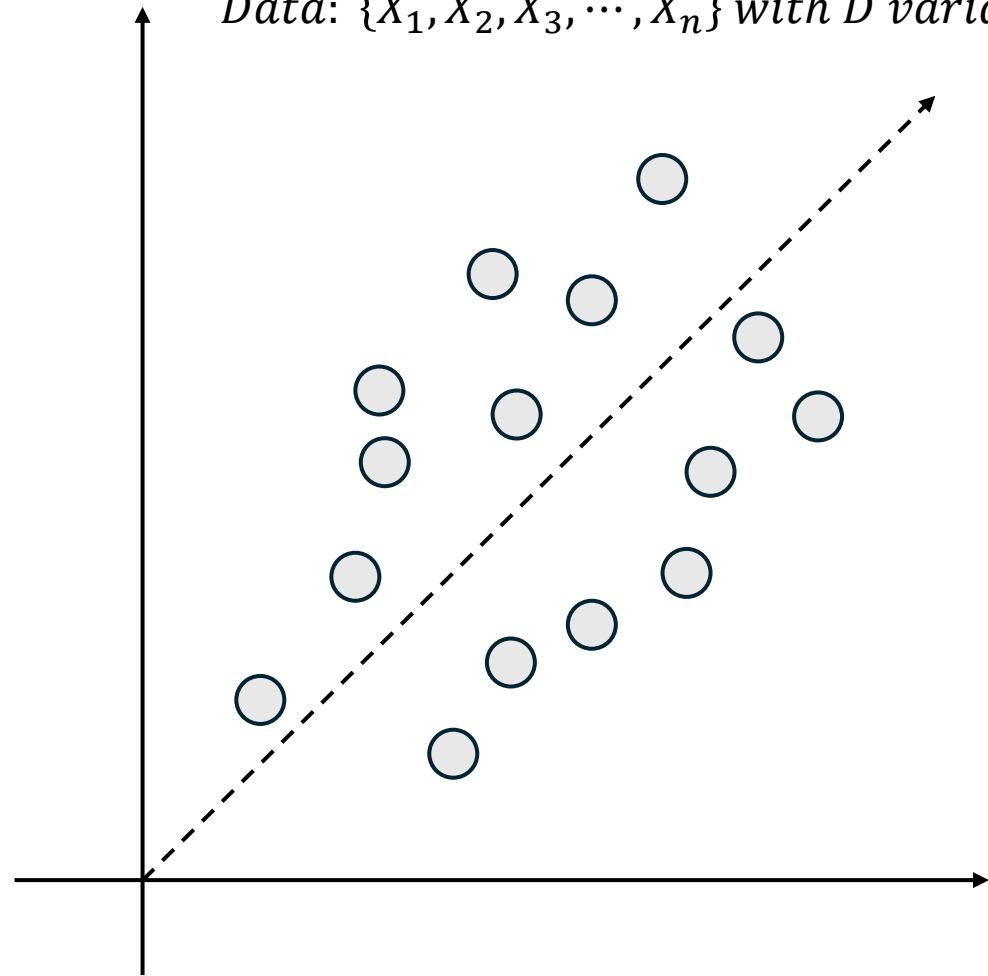
$$\frac{1}{n} \sum_{i=1}^n (u_1^T x_i - u_1^T \bar{x})^2$$

$$\frac{1}{n} \sum_{i=1}^n \left( u_1^T (x_i - \bar{x}) \right)^2$$

$$\frac{1}{n} \sum_{i=1}^n u_1^T (x_i - \bar{x}) (x_i - \bar{x})^T u_1 \longrightarrow u_1^T \left[ \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}) (x_i - \bar{x})^T \right] u_1$$

What is this? Does it ring a bell?

Data:  $\{X_1, X_2, X_3, \dots, X_n\}$  with  $D$  variables



$$PROJE_{u_1}(x_i) = u_1^T x_i u$$

$$PROJE_{u_1}(\bar{x}) = u_1^T \bar{x} u$$

$u$ : Unit Vector

How to get a variance  
of the projections?

$$\frac{1}{n} \sum_{i=1}^n (u_1^T x_i - u_1^T \bar{x})^2$$

$$\frac{1}{n} \sum_{i=1}^n \left( u_1^T (x_i - \bar{x}) \right)^2$$

$$\frac{1}{n} \sum_{i=1}^n u_1^T (x_i - \bar{x}) (x_i - \bar{x})^T u_1 \longrightarrow u_1^T \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}) (x_i - \bar{x})^T u_1 \longrightarrow \boxed{u_1^T S u_1}$$

We want to maximize this

So...

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$

This is the difficult part. How would you solve it?

So...

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$

This is the difficult part. How would you solve it?

Hint: Lagrange Multipliers

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$

---

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$



To optimize, you take the derivative and equalize to zero.

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$


---

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$

$$\frac{d}{du_i} \left( u_1^T S u_1 - \lambda (1 - u_1^T u_1) \right) = 0$$



$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$


---

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$

$$\frac{d}{du_i} \left( u_1^T S u_1 - \lambda (1 - u_1^T u_1) \right) = 0$$

$$2S u_i - \lambda 2u_i = 0$$

$$\boxed{S u_i = \lambda u_i}$$

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$


---

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$

$$\frac{d}{du_i} \left( u_1^T S u_1 - \lambda (1 - u_1^T u_1) \right) = 0$$

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What is this? Does it ring a bell?

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$


---

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$

$$\frac{d}{du_i} \left( u_1^T S u_1 - \lambda (1 - u_1^T u_1) \right) = 0$$

$$2S u_1 - \lambda 2u_1 = 0$$

$$\boxed{S u_1 = \lambda u_1}$$

$$u_1^T S u_1 = \lambda u_1^T u_1 \longrightarrow u_1^T S u_1 = \lambda$$

Which eigenvalue to use?

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$

$$\frac{d}{du_i} (u_1^T S u_1 - \lambda (1 - u_1^T u_1)) = 0$$

$$2S u_1 - \lambda 2u_1 = 0$$

$$\boxed{S u_1 = \lambda u_1}$$

$$u_1^T S u_1 = \lambda u_1^T u_1 \longrightarrow u_1^T S u_1 = \lambda$$

Which eigenvalue to use?  
The highest, because it is  
the one that maximizes  
the variance of the  
projection.

---

$$\text{Max. } u_1^T S u_1$$

$$\text{s.t: } u_1^T u_1 = 1$$

$$u_1^T S u_1 - \lambda (1 - u_1^T u_1)$$

$$\frac{d}{du_i} (u_1^T S u_1 - \lambda (1 - u_1^T u_1)) = 0$$

$$2S u_1 - \lambda 2u_1 = 0$$

$$\boxed{S u_1 = \lambda u_1}$$

$$u_1^T S u_1 = \lambda u_1^T u_1 \longrightarrow u_1^T S u_1 = \lambda$$



<https://quantitupod.org/s3e03-principal-components-analysis-is-your-pal/>

# Go to the tutorial!

# Thank you!

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