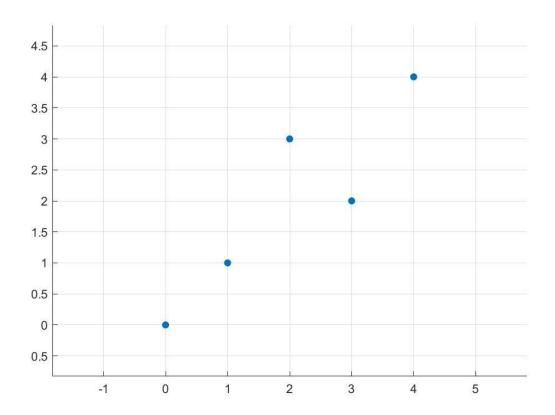
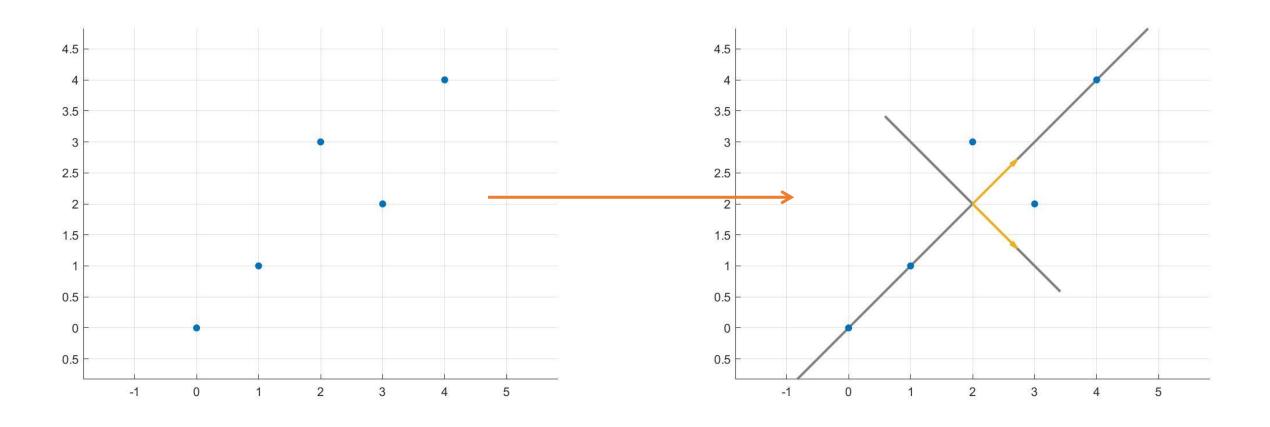
Suppose that we have a set of 2D samples:  $\left\{x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$ . Answer the following questions doing all the computations manually.

(a) Draw the data and the eigenvectors that you think that the covariance matrix of the data will have.



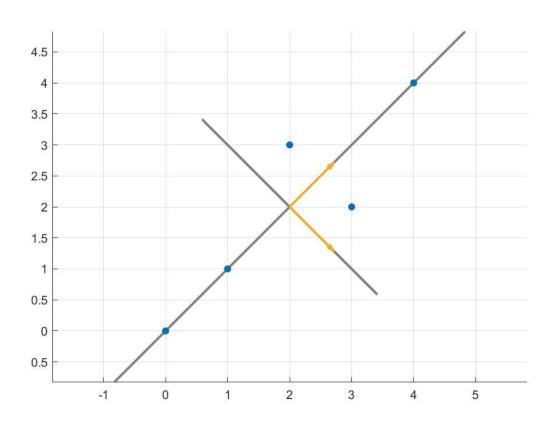
Suppose that we have a set of 2D samples:  $\left\{x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$ . Answer the following questions doing all the computations manually.

(a) Draw the data and the eigenvectors that you think that the covariance matrix of the data will have.



$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

**(b)** Without doing any computation, draw in the figure from the previous exercise the projection of the points in the component that explains more variance. Show also for every point the information loss after the projection.

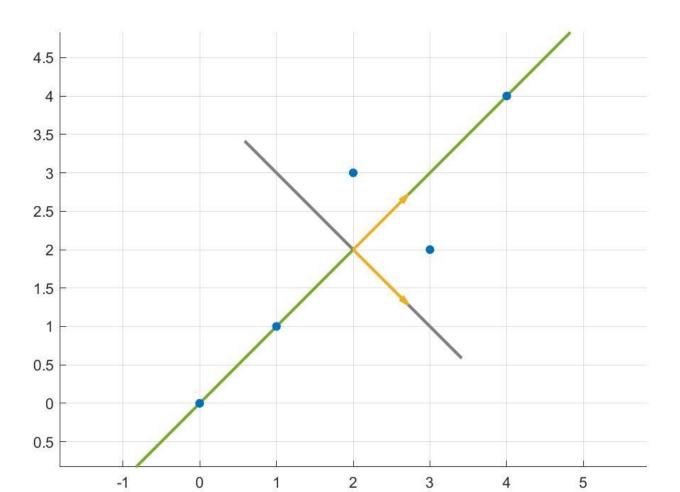


- 1) Which component explains more variance?
- **2)** What will be the projection of all the points into this component?
- 3) What information have we lost?

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

**(b)** Without doing any computation, draw in the figure from the previous exercise the projection of the points in the component that explains more variance. Show also for every point the information loss after the projection.

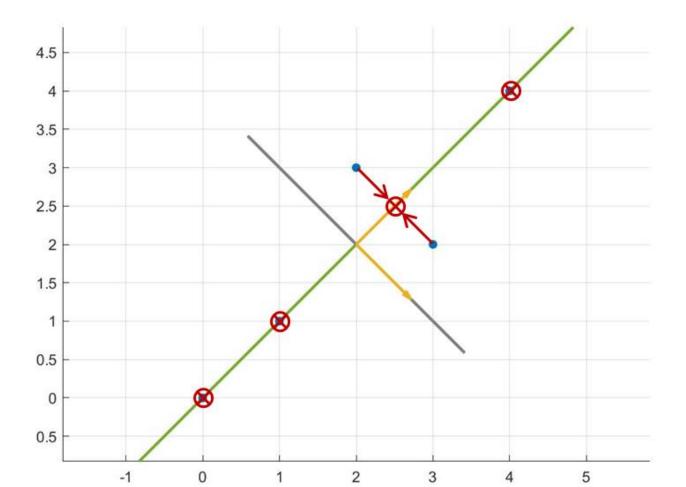
### 1) Which component explains more variance?



$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

**(b)** Without doing any computation, draw in the figure from the previous exercise the projection of the points in the component that explains more variance. Show also for every point the information loss after the projection.

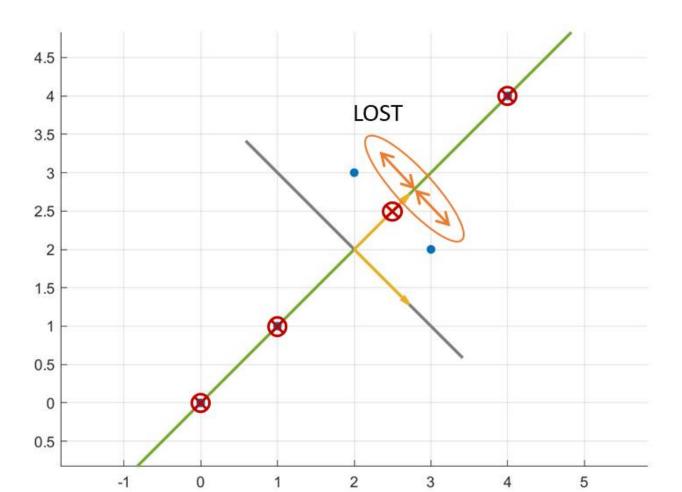
2) What will be the projection of all the points into this component?



$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

**(b)** Without doing any computation, draw in the figure from the previous exercise the projection of the points in the component that explains more variance. Show also for every point the information loss after the projection.

#### 3) What information have we lost?



$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(c) Compute the covariance matrix of the data and find the eigenvalues and eigenvectors.

#### **COVARIANCE**

$$\Sigma = \frac{1}{N}(X - \mu)(X - \mu)^{\mathrm{T}} = ?$$

$$\left\{ \pmb{x}^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \pmb{x}^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \pmb{x}^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, \pmb{x}^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, \pmb{x}^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(c) Compute the covariance matrix of the data and find the eigenvalues and eigenvectors.

#### **COVARIANCE**

$$\Sigma = \frac{1}{N}(X - \mu)(X - \mu)^{\mathrm{T}} = ?$$

$$\mu = \frac{1}{N} \sum_{n=1}^{N} x^{(n)} = {2 \choose 2} \Rightarrow X - \mu = {-2 -1 \choose -2 -1 1 0 2} \Rightarrow \Sigma = \frac{1}{N} (X - \mu)(X - \mu)^{\mathrm{T}} = \frac{1}{5} {10 9 \choose 9 10}$$

$$\Sigma_{1} = \frac{1}{5} \begin{pmatrix} 10 & 9 \\ 9 & 10 \end{pmatrix} \xrightarrow{\text{SVD}} \begin{cases} \lambda_{1} = 3.8 & v^{(1)} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \\ \lambda_{2} = 0.2 & v^{(2)} = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix} \end{cases}$$

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(d) Project the data over the basis obtained with PCA. Discuss the relation existing between the covariance of the projected data and the eigenvalues computed in the previous exercise.

New coordinate system 
$$\left\{ \boldsymbol{\sigma} = \boldsymbol{\mu} = \begin{pmatrix} 2 \\ 2 \end{pmatrix}; \ \boldsymbol{v}^{(1)} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \ \boldsymbol{v}^{(2)} = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix} \right\}$$

Project the data into  $\{\mu; \ v^{(1)}, v^{(2)}\}$  = change of coordinate system

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(d) Project the data over the basis obtained with PCA. Discuss the relation existing between the covariance of the projected data and the eigenvalues computed in the previous exercise.

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$$\left\{ \boldsymbol{\sigma} = \boldsymbol{\mu} = \begin{pmatrix} 2 \\ 2 \end{pmatrix}; \ \boldsymbol{v}^{(1)} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \ \boldsymbol{v}^{(2)} = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix} \right\}$$

Project the data into  $\{\mu; \ v^{(1)}, v^{(2)}\}$  = change of coordinate system

$$x_{<\mathcal{V}>}^{(n)} = {}_{<\mathcal{E}>} \mathbf{M}_{<\mathcal{V}>} \quad \left(x_{<\mathcal{E}>}^{(n)} - \mu_{<\mathcal{E}>}\right)$$
 All the points at the same time

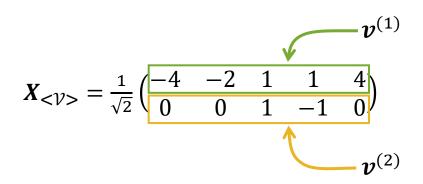
$$X_{<\nu>} = {}_{<\varepsilon>} M_{<\nu>} \quad (X_{<\varepsilon>} - \mu_{<\varepsilon>})$$

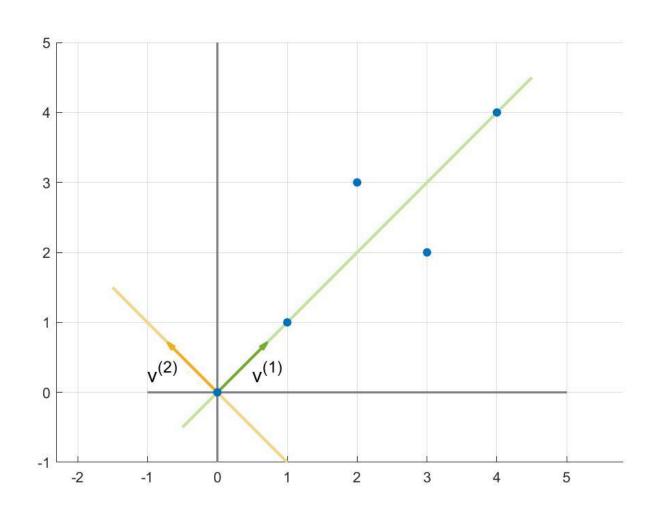
$$= \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix}^{T} \begin{pmatrix} -2 & -1 & 0 & 1 & 2 \\ -2 & -1 & 1 & 0 & 2 \end{pmatrix}$$

$$= \frac{1}{\sqrt{2}} \begin{pmatrix} -4 & -2 & 1 & 1 & 4 \\ 0 & 0 & 1 & -1 & 0 \end{pmatrix}$$

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(d) Project the data over the basis obtained with PCA. Discuss the relation existing between the covariance of the projected data and the eigenvalues computed in the previous exercise.



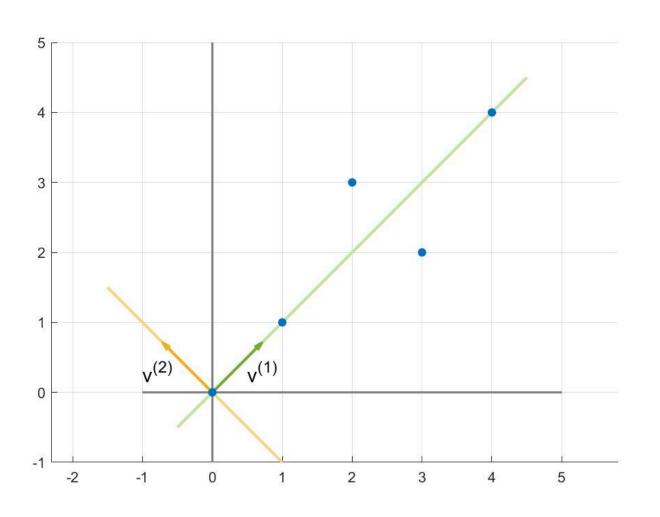


$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(d) Project the data over the basis obtained with PCA. Discuss the relation existing between the covariance of the projected data and the eigenvalues computed in the previous exercise.

What if we computed the covariance of the data in the new basis?

$$\Sigma_{<\mathcal{V}>} = \frac{1}{N} (X_{<\mathcal{V}>} - \mu_{<\mathcal{V}>}) (X_{<\mathcal{V}>} - \mu_{<\mathcal{V}>})^{\mathrm{T}} = ?$$

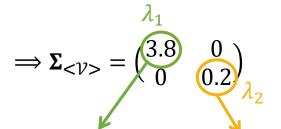


$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(d) Project the data over the basis obtained with PCA. Discuss the relation existing between the covariance of the projected data and the eigenvalues computed in the previous exercise.

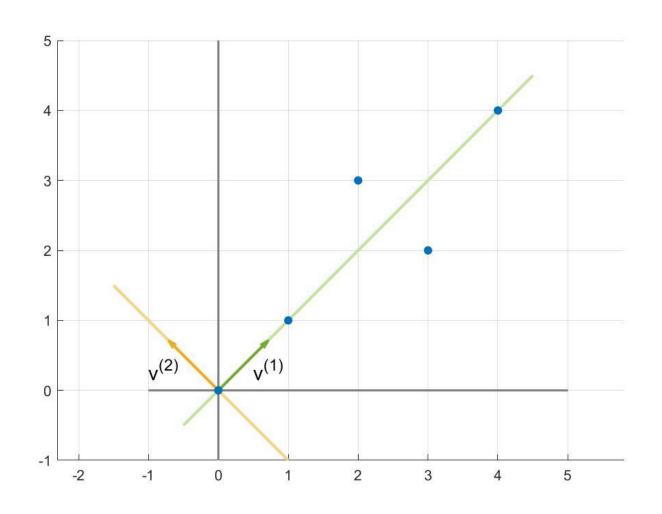
What if we computed the covariance of the data in the new basis?

$$\Sigma_{<\nu>} = \frac{1}{N} (X_{<\nu>} - \mu_{<\nu>}) (X_{<\nu>} - \mu_{<\nu>})^{\mathrm{T}} = ?$$



Var of the data in the direction of  $v^{(1)}$ 

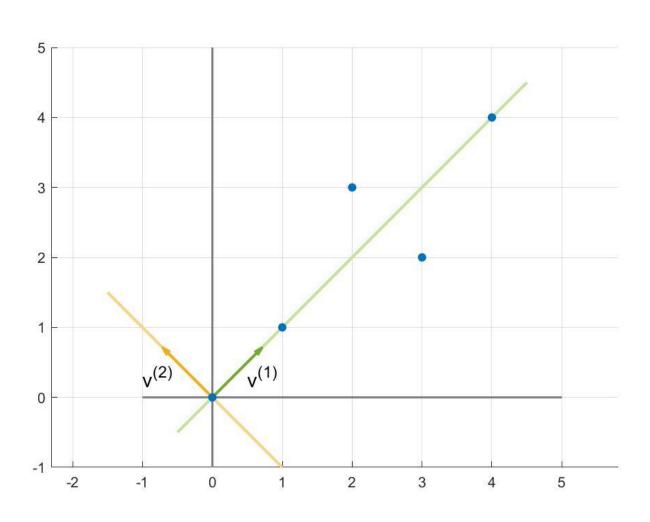
Var of the data in the direction of  $v^{(2)}$ 



$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

Which component maximizes the variance of the data?



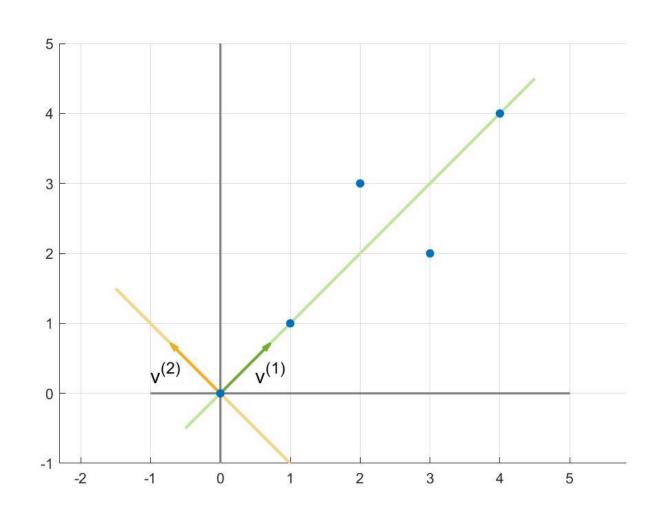
$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

Which component maximizes the variance of the data?

$$\lambda_1$$
 = variance in  $v^{(1)} \Longrightarrow \frac{\lambda_1}{\lambda_1 + \lambda_2} = \frac{3.8}{3.8 + 0.2} = 95\%$  of var

$$\lambda_2$$
 = variance in  $v^{(2)} \Longrightarrow \frac{\lambda_2}{\lambda_1 + \lambda_2} = \frac{0.2}{3.8 + 0.2} = 5\%$  of var



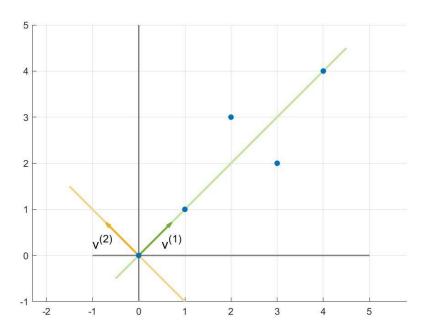
$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

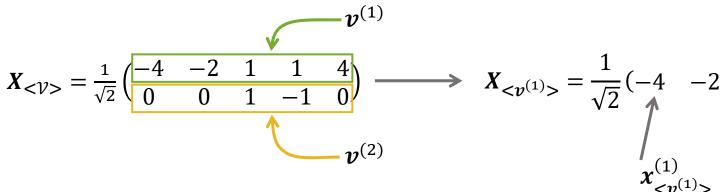
(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

#### **REMINDER**

Project the data into  $\{ \mu; \ v^{(1)}, v^{(2)} \}$  = change of coordinate system

Project the data into  $\{ \pmb{v}^{(1)} \}$  = taking only the component corresponding to  $\pmb{v}^{(1)}$ 





How do we do this without changing of basis?

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

Project the data into  $\{ m{v}^{(1)} \}$  = taking only the component corresponding to  $m{v}^{(1)}$ 

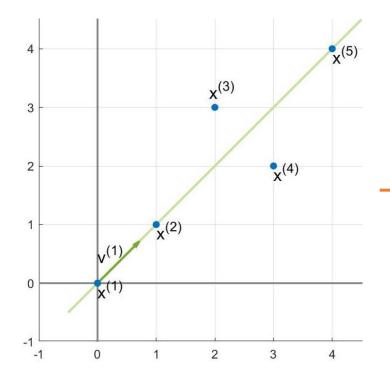
$$X_{<\mathcal{V}>} = \frac{1}{\sqrt{2}} \begin{pmatrix} -4 & -2 & 1 & 1 & 4 \\ \hline 0 & 0 & 1 & -1 & 0 \\ \hline v^{(2)} \end{pmatrix} \longrightarrow X_{<\mathbf{v}^{(1)}>} = \frac{1}{\sqrt{2}} (-4 & -2 & 1 & 1 & 4)$$

$$\begin{split} X_{<\mathcal{V}>} &= {}_{<\mathcal{E}>} \mathsf{M}_{<\mathcal{V}>} \ \, (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) = \begin{pmatrix} | & | \\ v^{(1)} & v^{(2)} \\ | & | \end{pmatrix}^{\mathsf{T}} (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) = \begin{pmatrix} - & v^{(1)^{\mathsf{T}}} & - \\ - & v^{(2)^{\mathsf{T}}} & - \end{pmatrix} (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) \\ &= \begin{pmatrix} v^{(1)^{\mathsf{T}}} (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) \\ v^{(2)^{\mathsf{T}}} (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) \end{pmatrix} = \begin{pmatrix} X_{<\nu^{(1)}>} \\ X_{<\nu^{(2)}>} \end{pmatrix} \end{split}$$

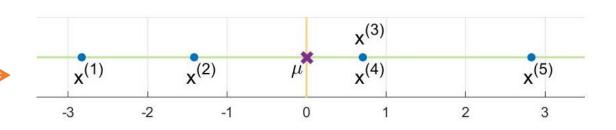
$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

$$X_{< v^{(1)}>} = v^{(1)^{\mathrm{T}}} (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) = \frac{1}{\sqrt{2}} (1 \quad 1) \begin{pmatrix} -2 & -1 & 0 & 1 & 2 \\ -2 & -1 & 1 & 0 & 2 \end{pmatrix} = \frac{1}{\sqrt{2}} (-4 \quad -2 \quad 1 \quad 1 \quad 4)$$

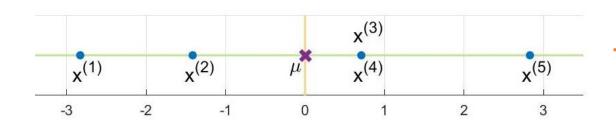


Project the data into  $\{oldsymbol{v}^{(1)}\}$ 



$$\left\{ \boldsymbol{x}^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \boldsymbol{x}^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \boldsymbol{x}^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, \boldsymbol{x}^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, \boldsymbol{x}^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.



Re-project the data

x(4) x(4) x(4) x(1) x(1) x(1) x(1) 1 2 3 4

**Re-project** the data = **undo** change of coordinate system

From 
$$\{\mathbf{0}; \ \mathbf{e}^{(1)}, \mathbf{e}^{(2)}\}$$
 to  $\{\mu; \ \mathbf{v}^{(1)}, \mathbf{v}^{(2)}\} \rightarrow X_{<\mathcal{V}>} = {}_{<\mathcal{E}>} M_{<\mathcal{V}>} (X_{<\mathcal{E}>} - \mu_{<\mathcal{E}>})$ 

From 
$$\{\mu; \ v^{(1)}, v^{(2)}\}$$
 to  $\{0; \ e^{(1)}, e^{(2)}\} \longrightarrow_{<\mathcal{V}>} M_{<\mathcal{E}>} X_{<\mathcal{V}>} + \mu_{<\mathcal{E}>} = X_{<\mathcal{E}>}$ 

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

**(e)** Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

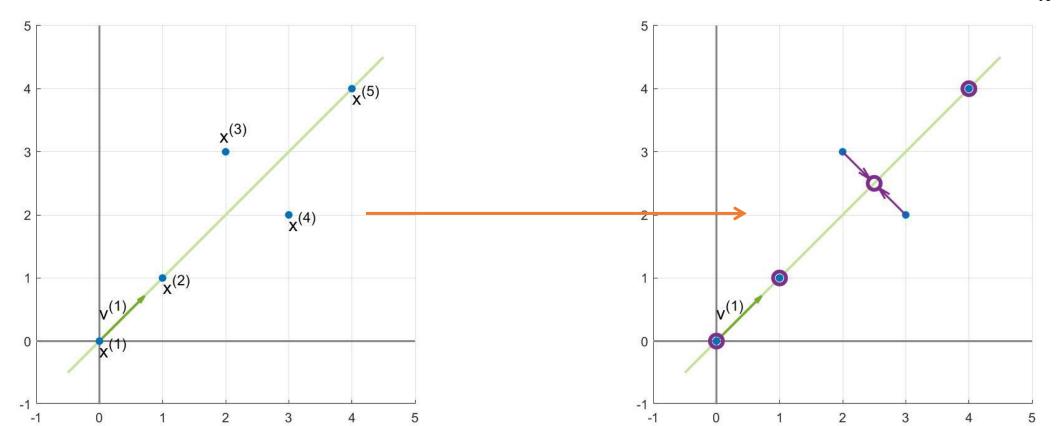
**Re-project** the data

$$X_{\text{reproj}} = v^{(1)} \cdot X_{< v^{(1)} >} + \mu_{<\mathcal{E}>} = ?$$

$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

(e) Choose the component that maximizes the variance of the data. Project and re-project the data using the chosen component. Draw the results.

**Re-project**: 
$$X_{\text{reproj}} = v^{(1)} \cdot X_{< v^{(1)}>} + \mu_{<\mathcal{E}>} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \cdot \frac{1}{\sqrt{2}} \begin{pmatrix} -4 & -2 & 1 & 1 & 4 \end{pmatrix} + \begin{pmatrix} 2 \\ 2 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 2.5 & 2.5 & 4 \\ 0 & 1 & 2.5 & 2.5 & 4 \end{pmatrix}$$



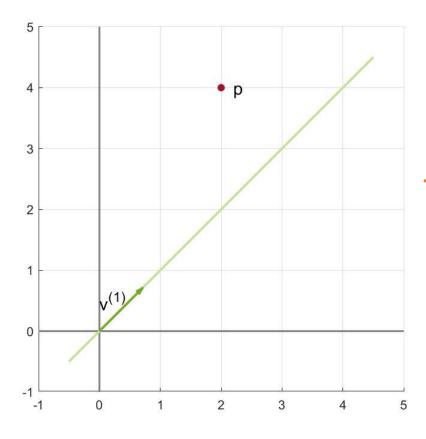
$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

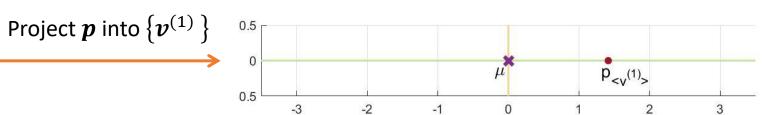
Project: 
$$p_{< v^{(1)}>} = v^{(1)^{T}} (p_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) = ?$$

**Re-project**: 
$$p_{\text{reproj}} = v^{(1)} \cdot p_{< v^{(1)}>} + \mu_{<\mathcal{E}>} = ?$$

$$\left\{ x^{(1)} = \binom{0}{0}, x^{(2)} = \binom{1}{1}, x^{(3)} = \binom{2}{3}, x^{(4)} = \binom{3}{2}, x^{(5)} = \binom{4}{4} \right\} \subset \mathbb{R}^2$$

Project: 
$$p_{< v^{(1)}>} = v^{(1)^{\mathrm{T}}} (p_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) = \frac{1}{\sqrt{2}} (1 \quad 1) \cdot \left( \binom{2}{4} - \binom{2}{2} \right) = \frac{2}{\sqrt{2}}$$

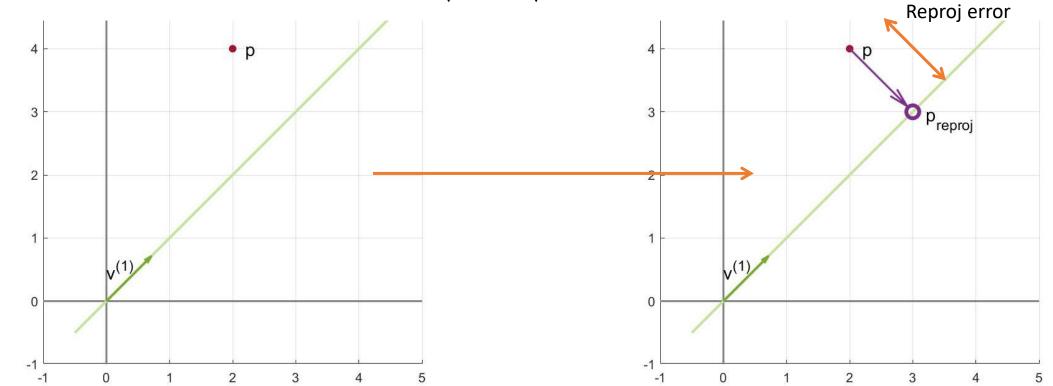




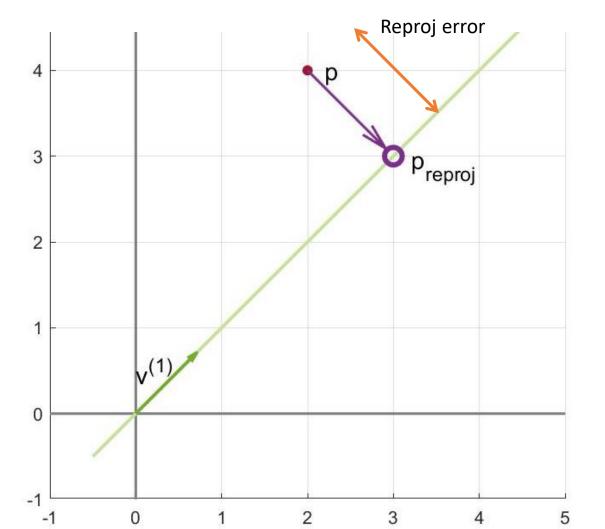
$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$

Project: 
$$p_{< v^{(1)}>} = v^{(1)^{T}} (p_{<\mathcal{E}>} - \mu_{<\mathcal{E}>}) = \frac{1}{\sqrt{2}} (1 \quad 1) \cdot (\binom{2}{4} - \binom{2}{2}) = \frac{2}{\sqrt{2}}$$

Re-project: 
$$p_{\text{reproj}} = v^{(1)} \cdot p_{< v^{(1)}>} + \mu_{<\mathcal{E}>} = \frac{1}{\sqrt{2}} {1 \choose 1} \cdot \frac{2}{\sqrt{2}} + {2 \choose 2} = {3 \choose 3}$$



$$\left\{ x^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, x^{(2)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 2 \\ 3 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 3 \\ 2 \end{pmatrix}, x^{(5)} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} \right\} \subset \mathbb{R}^2$$



**Reproj error** = 
$$d(\boldsymbol{p}, \boldsymbol{p}_{\text{reproj}}) = d\left(\binom{2}{4}, \binom{3}{3}\right) = \sqrt{2}$$