

# Chapter 6

## Orthogonality and least squares

*Or how to find a  
nearly solution of  
inconsistent systems*

► Inner Product, Length and Orthogonality

► Orthogonal Sets

► Orthogonal Projections

► The Gram-Schmidt Process

► Least-Squares Problems

► Applications to Linear Models

► Inner Product Spaces

► Applications of Inner Product Spaces

## Et lille overblik so far...

Produkt

Determinant

- > Invers matrix
- > Eigenverdier og egenvektorer
  - > Skift af koordinatsystem (rotationer mm.)
  - > Diagonalisering
    - > De-kobling af dynamiske systemer
    - > Dekompositioner (ex. QR og SVD)

$$A\mathbf{x} = \lambda\mathbf{x} \Leftrightarrow (A - \lambda I)\mathbf{x} = \mathbf{0} \quad \text{have non-trivial solutions}$$

The Characteristic Equation  $\longrightarrow \det(A - \lambda I) = 0$

*The Characteristic Polynomial*  $\longrightarrow$  Polynomial of degree  $n$  in  $\lambda$   
 $\downarrow$   
 Exactly  $n$  (complex) eigenvalues (roots)  $\lambda$

For a real matrix:

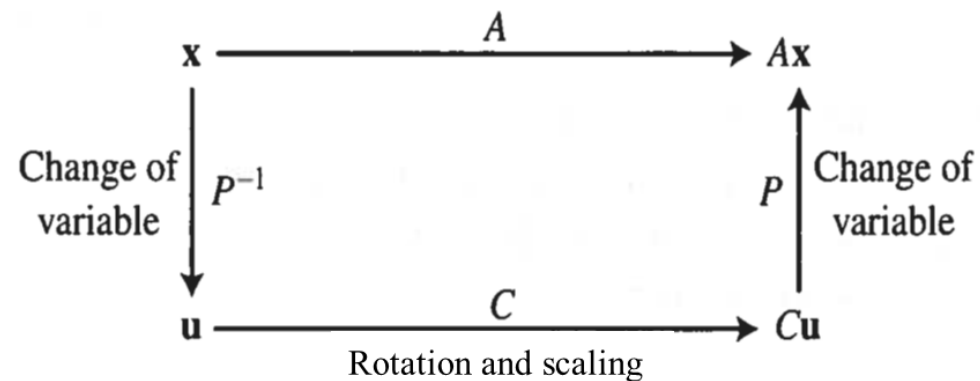
➤ Complex eigenvalues and -vectors come in pairs:  $\begin{cases} \lambda = a \pm j \cdot b \\ \mathbf{v} = Re(\mathbf{v}) \pm j \cdot Im(\mathbf{v}) \end{cases}$

## Theorem 5.9

Let  $A$  be a real  $2 \times 2$  matrix with a complex eigenvalue  $\lambda = a + j \cdot b$  ( $b \neq 0$ ) and an associated eigenvector  $\mathbf{v} = \text{Re}(\mathbf{v}) + j \cdot \text{Im}(\mathbf{v})$  in  $\mathbb{C}^2$ . Then:

$$A = PCP^{-1}$$

where  $P = [\text{Re}(\mathbf{v}_1) \quad \text{Im}(\mathbf{v}_1)]$  and  $C = \begin{bmatrix} a & b \\ -b & a \end{bmatrix} = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix} \begin{bmatrix} \cos(\varphi) & \sin(\varphi) \\ -\sin(\varphi) & \cos(\varphi) \end{bmatrix}$



↑  
rotation matrix

Note, that even though the theorem only speaks about one eigenvalue and one eigenvector we actually know two eigenvalues and two eigenvectors as  $\lambda_2 = \lambda_1^*$  and  $\mathbf{v}_2 = \mathbf{v}_1^*$

## Decoupling a dynamic system: $\mathbf{x}'(t) = A\mathbf{x}(t)$

Eigenvalues ( $\lambda_i$ ) /-vectors ( $\mathbf{v}_i$ ) /-functions for  $A$ :  $\mathbf{v}_1 e^{\lambda_1 t}, \dots, \mathbf{v}_n e^{\lambda_n t}$

Change-of-variable matrix:  $P = [\mathbf{v}_1 \ \dots \ \mathbf{v}_n]$

Diagonal matrix:  $D = \begin{bmatrix} \lambda_1 & \dots & 0 \\ \vdots & \dots & \vdots \\ 0 & \dots & \lambda_n \end{bmatrix}$ ;  $A = PDP^{-1} \Rightarrow \mathbf{y}' = D\mathbf{y}$  where  $\mathbf{y}(t) = P^{-1}\mathbf{x}(t)$

*Decoupled system* (points to  $\mathbf{y}' = D\mathbf{y}$ )

*Solution in eigen-function basis* (points to  $\mathbf{y}(t)$ )

Initial value:  $\mathbf{x}(0) = \mathbf{x}_0 \Rightarrow \mathbf{y}(0) = P^{-1}\mathbf{x}(0) = P^{-1}\mathbf{x}_0 = \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix}$

Solution in the original system:

$$\mathbf{x}(t) = P\mathbf{y}(t) = [\mathbf{v}_1 \ \dots \ \mathbf{v}_n] \begin{bmatrix} c_1 e^{\lambda_1 t} \\ \vdots \\ c_n e^{\lambda_n t} \end{bmatrix} = c_1 \mathbf{v}_1 e^{\lambda_1 t} + \dots + c_n \mathbf{v}_n e^{\lambda_n t} = \sum_{i=1}^n c_i \mathbf{v}_i e^{\lambda_i t}$$

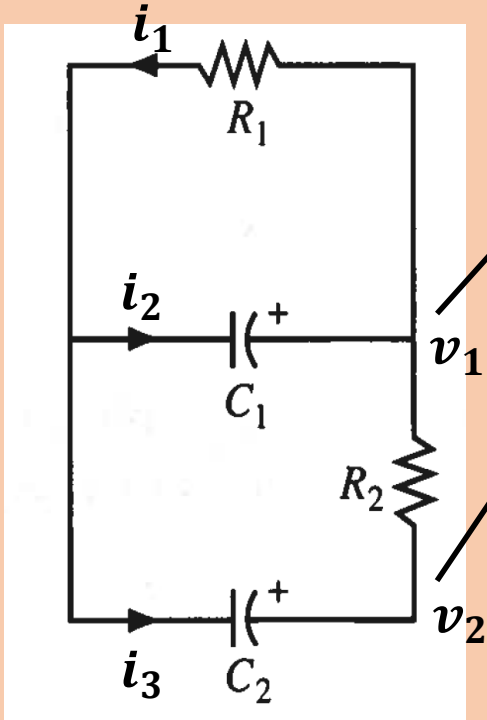
*Solution in eigen-function basis* (points to the vector of exponentials)

*eigenvalue* (points to  $\lambda_i$ )

*eigenvector* (points to  $\mathbf{v}_i$ )

# Dynamic systems *Time developing*

Ex fra L9



*KCL*

$$\left. \begin{aligned} -C_1 \frac{dv_1}{dt} &= \frac{v_1 - v_2}{R_2} + \frac{v_1}{R_1} \\ -C_2 \frac{dv_2}{dt} &= \frac{v_2 - v_1}{R_2} \end{aligned} \right\}$$

*Knudepunktsligninger*

*Husk strømmen  
gennem en kondensator*

$$I_C = C \cdot dv_C / dt$$

*Two coupled linear 1. order differential equations*

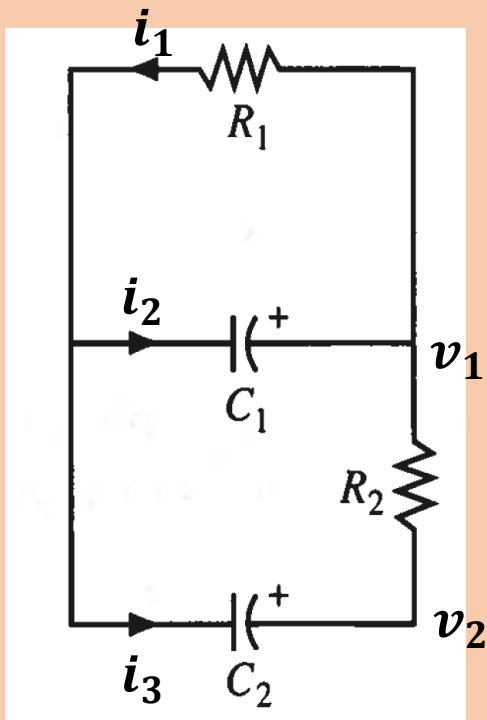
$$\Rightarrow \left. \begin{aligned} \frac{dv_1}{dt} &= -\frac{1}{C_1} \left( \frac{1}{R_1} + \frac{1}{R_2} \right) v_1 + \frac{1}{R_2 C_1} v_2 \\ \frac{dv_2}{dt} &= \frac{1}{R_2 C_2} v_1 - \frac{1}{R_2 C_2} v_2 \end{aligned} \right\}$$

$$\Rightarrow \begin{bmatrix} \frac{dv_1}{dt} \\ \frac{dv_2}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{1}{C_1} \left( \frac{1}{R_1} + \frac{1}{R_2} \right) & \frac{1}{R_2 C_1} \\ \frac{1}{R_2 C_2} & -\frac{1}{R_2 C_2} \end{bmatrix} \cdot \begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix}$$

$$\Rightarrow \mathbf{x}'(t) = \mathbf{A}\mathbf{x}(t)$$

*System of coupled  
linear 1. order  
differential equations*

## Ex fra L9



$$R_1 = 1\Omega \quad R_2 = 2\Omega \quad C_1 = 1F \quad C_2 = 0.5F \quad v_1(0) = 5V \quad v_2(0) = 4V$$

$$\begin{bmatrix} \frac{dv_1}{dt} \\ \frac{dv_2}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{1}{C_1} \left( \frac{1}{R_1} + \frac{1}{R_2} \right) & \frac{1}{R_2 C_1} \\ \frac{1}{R_2 C_2} & -\frac{1}{R_2 C_2} \end{bmatrix} \cdot \begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix} = \begin{bmatrix} -\frac{3}{2} & \frac{1}{2} \\ 1 & -1 \end{bmatrix} \cdot \begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix}$$

$$\det(A - \lambda I) = \begin{vmatrix} -\frac{3}{2} - \lambda & \frac{1}{2} \\ 1 & -1 - \lambda \end{vmatrix} = \lambda^2 + \frac{5}{2}\lambda + 1 = 0 \Rightarrow \lambda = \begin{cases} -\frac{1}{2} \\ -2 \end{cases}$$

$$\text{Eigenvectors: } \lambda_1 = -\frac{1}{2} \Rightarrow \mathbf{u}_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \text{and} \quad \lambda_2 = -2 \Rightarrow \mathbf{u}_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$P = [\mathbf{u}_1 \ \mathbf{u}_2] = \begin{bmatrix} 1 & -1 \\ 2 & 1 \end{bmatrix}$$

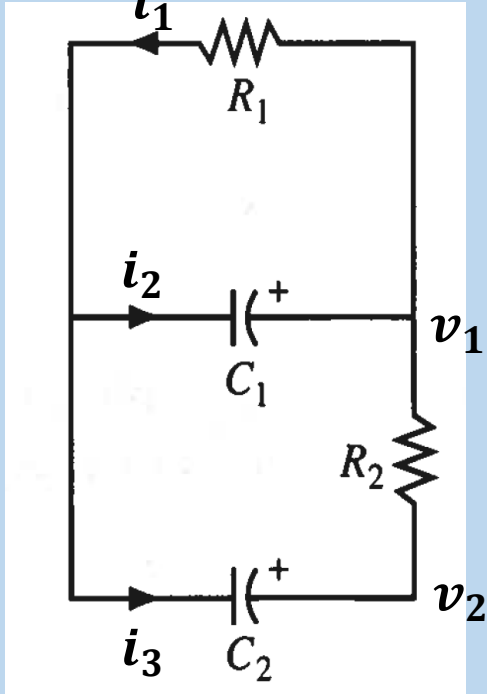
$$D = \begin{bmatrix} -\frac{1}{2} & 0 \\ 0 & -2 \end{bmatrix}$$

$$\mathbf{y}(t) = P^{-1} \mathbf{v}(t) = \frac{1}{3} \begin{bmatrix} 1 & 1 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix} = \begin{bmatrix} \frac{1}{3}v_1(t) + \frac{1}{3}v_2(t) \\ -\frac{2}{3}v_1(t) + \frac{1}{3}v_2(t) \end{bmatrix}$$

$$\mathbf{y}' = \begin{bmatrix} -\frac{1}{2} & 0 \\ 0 & -2 \end{bmatrix} \mathbf{y} \Rightarrow \begin{cases} y_1' = -\frac{1}{2}y_1 \\ y_2' = -2y_2 \end{cases} \Rightarrow \mathbf{y}(t) = \begin{bmatrix} c_1 e^{-\frac{1}{2}t} \\ c_2 e^{-2t} \end{bmatrix} = \begin{bmatrix} 3e^{-\frac{1}{2}t} \\ -2e^{-2t} \end{bmatrix} \quad \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} = \mathbf{y}(0) = P^{-1} \mathbf{v}(0) = \frac{1}{3} \begin{bmatrix} 1 & 1 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} 5 \\ 4 \end{bmatrix} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$$

$$\Rightarrow \mathbf{v}(t) = \begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix} = P \mathbf{y}(t) = \begin{bmatrix} 1 & -1 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 3e^{-\frac{1}{2}t} \\ -2e^{-2t} \end{bmatrix} = \begin{bmatrix} 3e^{-\frac{1}{2}t} + 2e^{-2t} \\ 6e^{-\frac{1}{2}t} - 2e^{-2t} \end{bmatrix}$$

# OPGAVE 1



”rigtige” værdier

$$R_1 = 4.7k\Omega$$

$$R_2 = 22k\Omega$$

$$C_1 = 1\mu F$$

$$C_2 = 47nF$$

- Bestem talværdierne i koefficientmatricen A
  - Find determinanten for A
  - Løs  $\lambda$ -polynomiet og find derved egenværdierne
  - Bestem de to tilhørende egenvektorer
  - Opstil matricerne P og D, og find den inverse af P
  - Bestem den transformerende spændingsvektor  $\mathbf{v}(t)$
  - Find transformerende begyndelsesbetingelser  $\mathbf{v}(0)$
  - Indsæt  $\mathbf{v}(0)$  samt  $\lambda_1$  og  $\lambda_2$  i egenfunktionerne
  - Transformer  $\mathbf{v}(t)$  tilbage til  $\mathbf{v}(t)$  vha. P
- 
- Plot  $v_1$  og  $v_2$  som funktion af tiden

Begyndelsesbetingelser:

$$v_1(0) = 10V \quad v_2(0) = 12V$$



## 6.1 Inner Product, Length and Orthogonality

$$\boldsymbol{u} \cdot \boldsymbol{v} = \boldsymbol{u}^T \boldsymbol{v}$$

Prik-produkt

$$\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$$

$$\mathbf{u} \cdot \mathbf{v} = \mathbf{u}^T \mathbf{v} = [u_1 \ u_2 \ \cdots \ u_n] \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = u_1 v_1 + u_2 v_2 + \cdots + u_n v_n = \sum_{i=1}^n u_i v_i \in \mathbb{R}$$

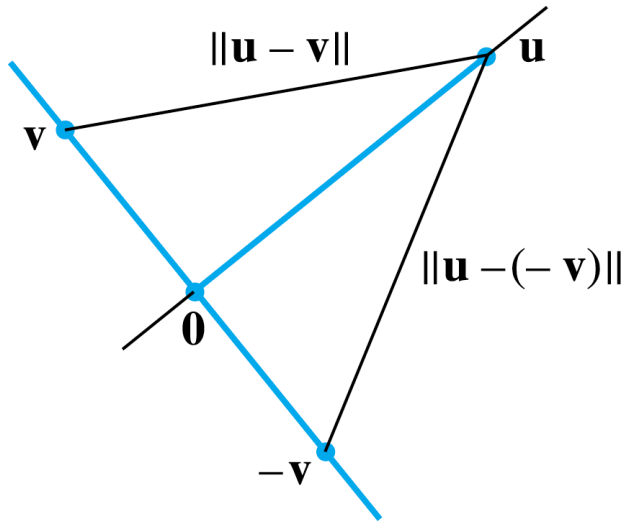
## Rules calculating :

1.  $\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u}$
2.  $(\mathbf{u} + \mathbf{v}) \cdot \mathbf{w} = \mathbf{u} \cdot \mathbf{w} + \mathbf{v} \cdot \mathbf{w}$
3.  $(c\mathbf{u}) \cdot \mathbf{v} = \mathbf{u} \cdot (c\mathbf{v})$
4.  $\mathbf{u} \cdot \mathbf{u} \geq 0$  and  $\mathbf{u} \cdot \mathbf{u} = 0 \Leftrightarrow \mathbf{u} = \mathbf{0}$

- The (or length) of a vector is defined as:  $\|\mathbf{v}\| = \sqrt{\mathbf{v} \cdot \mathbf{v}} = \sqrt{v_1^2 + \cdots + v_n^2}$
- A vector  $\mathbf{v}$  is (unit vector) if:  $\|\mathbf{v}\| = 1$
- The between two vectors is defined as:  
$$\text{dist}(\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\| = \sqrt{(u_1 - v_1)^2 + \cdots + (u_n - v_n)^2}$$
- The  $\theta$  between two vectors is given by:  $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| \|\mathbf{v}\| \cos(\theta)$

# Definition

Two vectors  $\mathbf{u}$  and  $\mathbf{v}$  in  $\mathbb{R}^n$  are orthogonal if  $\mathbf{u} \cdot \mathbf{v} = 0$ .



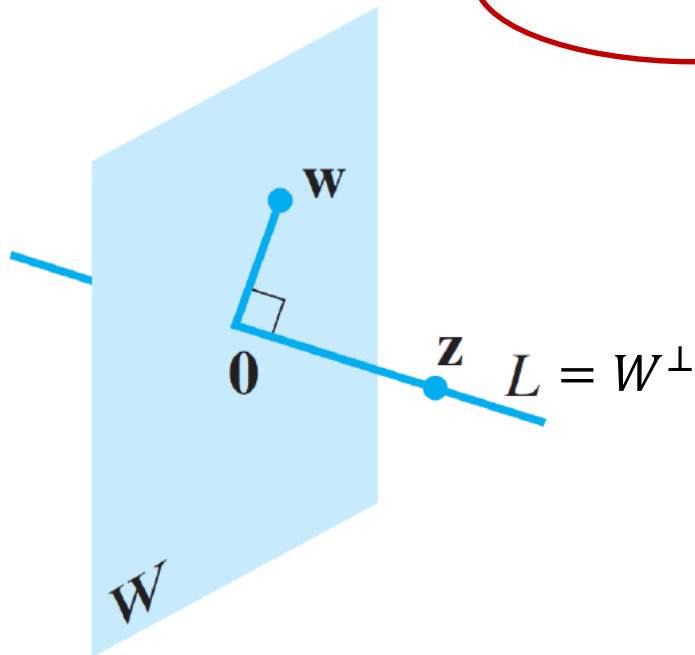
Pythagoras:  $\mathbf{u}$  and  $\mathbf{v}$  orthogonal  $\Leftrightarrow \|\mathbf{u} + \mathbf{v}\|^2 = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2$

## Definition

Let  $W$  be a subspace of  $\mathbb{R}^n$ . The set of all vectors in  $\mathbb{R}^n$  which are orthogonal to all vectors in  $W$  is called the *orthogonal complement to  $W$*  and is denoted  $W^\perp$ .

*W vinkelret*

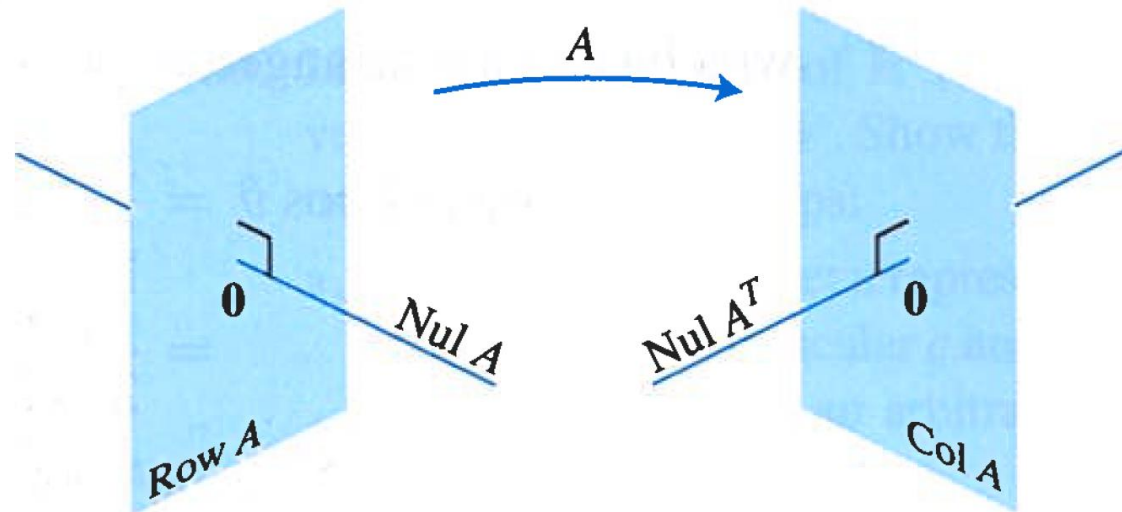
*Ortogonal/vinkelrette  
komplement*



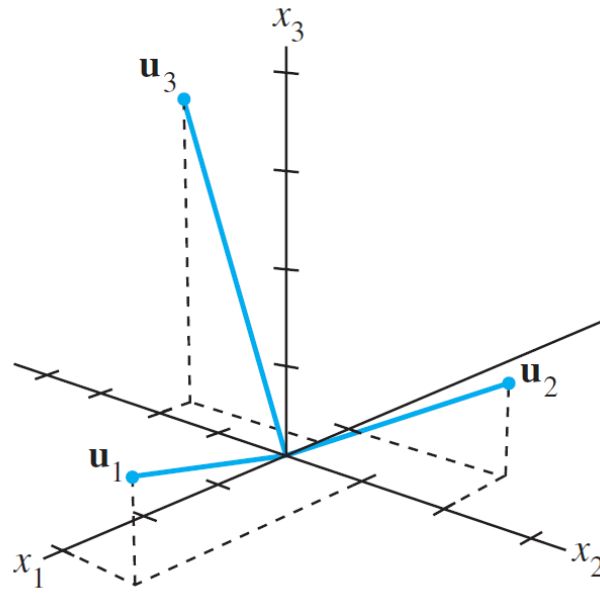
1. A vector  $\mathbf{v}$  is in  $W^\perp$  if and only if  $\mathbf{v}$  is orthogonal to every vector in a set that spans  $W$ .
2.  $W^\perp$  is a subspace of  $\mathbb{R}^n$

Let  $A$  be an  $m \times n$  matrix. The orthogonal complement of the row space of  $A$  is the null space of  $A$ , and the orthogonal complement of the column space of  $A$  is the null space of  $A^T$ :

$$(\text{Row } A)^\perp = \text{Nul } A \quad \text{and} \quad (\text{Col } A)^\perp = \text{Nul } A^T$$



## 6.2 Orthogonal Sets



## Definitions

A set of vectors  $S = \{\mathbf{u}_1 \cdots \mathbf{u}_n\}$  in  $\mathbb{R}^n$  with  $\mathbf{u}_i \perp \mathbf{u}_j$  for all  $i \neq j$

That is:  $\mathbf{u}_i \cdot \mathbf{u}_j = 0$  for all  $i \neq j$

An orthogonal set of vectors  $S = \{\mathbf{u}_1 \cdots \mathbf{u}_n\}$  in  $\mathbb{R}^n$  with  $\|\mathbf{u}_i\| = 1$  for all  $i = 1, \dots, n$ .

That is:  $\mathbf{u}_i \cdot \mathbf{u}_j = \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$

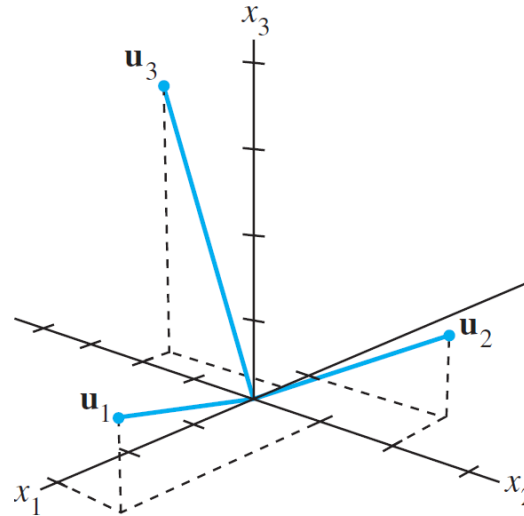


## Ex 2

$$\mathbf{u}_1 = \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix} \quad \mathbf{u}_2 = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix} \quad \mathbf{u}_3 = \begin{bmatrix} -1/2 \\ -2 \\ 7/2 \end{bmatrix}$$

*Diskussion:*

Udgør vektorerne  $\mathbf{u}_1$ ,  $\mathbf{u}_2$  og  $\mathbf{u}_3$  et ortogonalt set?  
- Og hvis ja, er det da også orto-*normalt*?



Theorem 6.4:

$S = \{\mathbf{u}_1 \cdots \mathbf{u}_p\}$  is an orthogonal set of nonzero vectors in  $\mathbb{R}^n$   
 $\Rightarrow S$  is a linearly independent basis for  $\text{span}\{S\}$

Theorem 6.5: *Basis that is also an orthogonal set*



Let  $\{\mathbf{u}_1 \cdots \mathbf{u}_p\}$  be an orthogonal basis for a subspace  $W$  of  $\mathbb{R}^n$ .

For each  $\mathbf{y}$  in  $W$ , the weights in the linear combination

$$\mathbf{y} = c_1 \mathbf{u}_1 + \cdots + c_p \mathbf{u}_p$$

are given by

$$c_j = \frac{\mathbf{y} \cdot \mathbf{u}_j}{\mathbf{u}_j \cdot \mathbf{u}_j}; \quad (j = 1, \dots, p)$$

Ex 3

$$\mathbf{u}_1 = \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix}$$

$$\mathbf{u}_2 = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$$

$$\mathbf{u}_3 = \begin{bmatrix} -1/2 \\ -2 \\ 7/2 \end{bmatrix}$$

$$\mathbf{y} = \begin{bmatrix} 6 \\ 1 \\ -8 \end{bmatrix}$$

$$\|\mathbf{u}_1\| = \sqrt{11}$$

$$\|\mathbf{u}_2\| = \sqrt{6}$$

$$\|\mathbf{u}_3\| = \sqrt{33/2}$$

$\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3\} \rightarrow$  Orthogonal set

*Beregning:*

Bestem koefficienterne i linearkombinationen

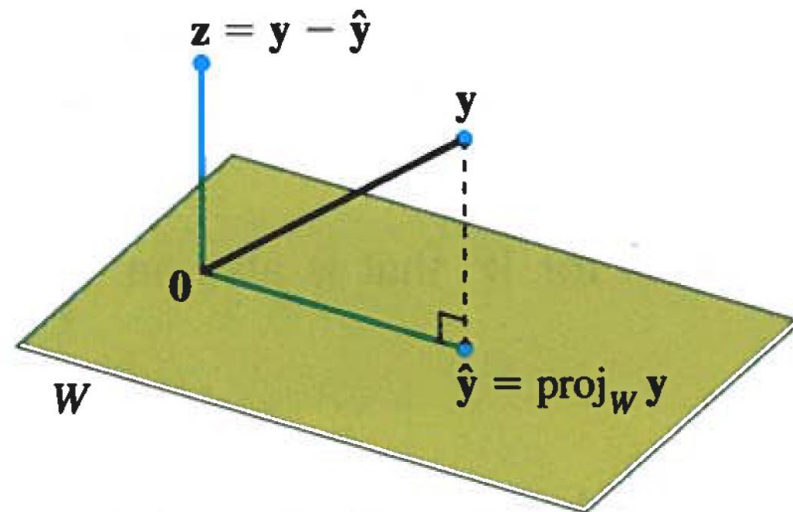
$$= c_1 \mathbf{u}_1 + c_2 \mathbf{u}_2 + c_3 \mathbf{u}_3$$

$$c_1 = 1$$

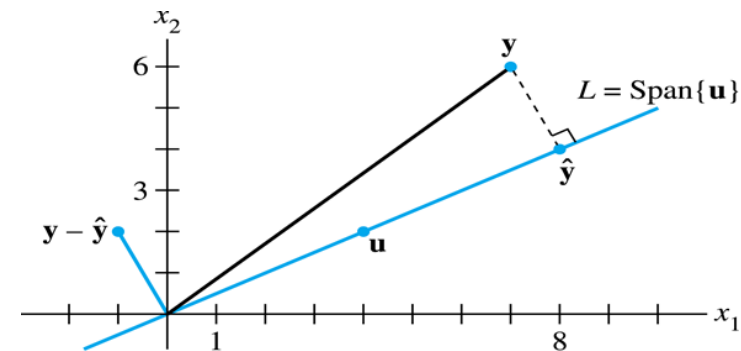
$$c_2 = -2$$

$$c_3 = -2$$

## 6.3 Orthogonal Projections



# Orthogonal projection

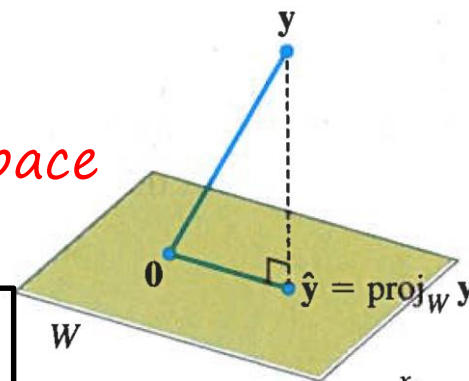


$$\hat{\mathbf{y}} = \frac{\mathbf{y} \cdot \mathbf{u}}{\mathbf{u} \cdot \mathbf{u}} \mathbf{u} = \frac{\|\mathbf{y}\| \|\mathbf{u}\| \cos(\theta)}{\|\mathbf{u}\|^2} \mathbf{u} = \|\mathbf{y}\| \cos(\theta) \mathbf{e}_u = \text{proj}_L \mathbf{y}$$

Projection of  $\mathbf{y}$  on line  $L$  spanned by  $\mathbf{u}$

$$\hat{\mathbf{y}} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \cdots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p = \text{proj}_W \mathbf{y}$$

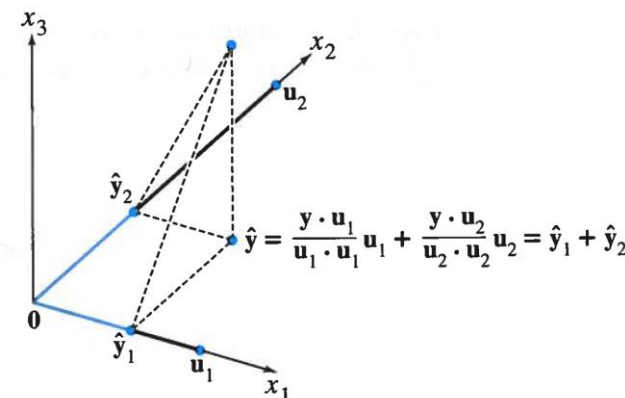
Projection of  $\mathbf{y}$  on subspace  $W$  spanned by  $\mathbf{u}_1, \dots, \mathbf{u}_p$



where  $W = \text{Span}\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$

Orthogonal set

The projection of  $\mathbf{y}$  in the direction defined by  $\mathbf{u}_p$



## Theorem 6.8 - The Orthogonal Decomposition Theorem

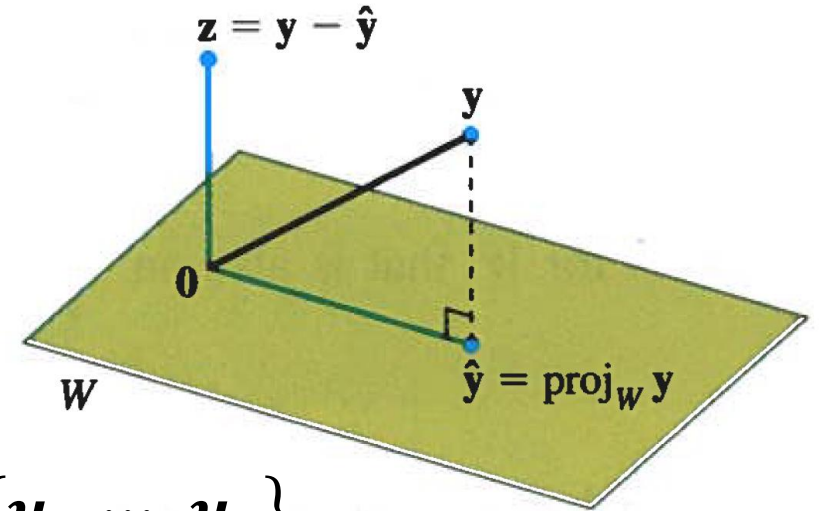
$$\mathbf{y} = c_1 \mathbf{u}_1 + \cdots + c_n \mathbf{u}_n = \hat{\mathbf{y}} + \mathbf{z} \in \mathbb{R}^n$$

where

$$\hat{\mathbf{y}} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \cdots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p = \text{proj}_W \mathbf{y} \in W = \text{Span}\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$$

$$\mathbf{z} = \mathbf{y} - \hat{\mathbf{y}} = \frac{\mathbf{y} \cdot \mathbf{u}_{p+1}}{\mathbf{u}_{p+1} \cdot \mathbf{u}_{p+1}} \mathbf{u}_{p+1} + \cdots + \frac{\mathbf{y} \cdot \mathbf{u}_n}{\mathbf{u}_n \cdot \mathbf{u}_n} \mathbf{u}_n = \text{proj}_{W^\perp} \mathbf{y} \in W^\perp = \text{Span}\{\mathbf{u}_{p+1}, \dots, \mathbf{u}_n\}$$

$$\mathbf{z} = \mathbf{y} - \hat{\mathbf{y}} \perp \hat{\mathbf{y}}$$



# Basis representation

Let  $\{\mathbf{b}_1 \cdots \mathbf{b}_p\}$  be an non-orthogonal basis for a subspace  $W$  of  $\mathbb{R}^n$ :

$$\mathbf{y} = c_1 \mathbf{b}_1 + \cdots + c_p \mathbf{b}_p; \quad c_j: \begin{bmatrix} b_{11} & \cdots & b_{1p} \\ \vdots & \vdots & \vdots \\ b_{n1} & \cdots & b_{np} \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_p \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_p \end{bmatrix}$$

Hard  
work

Let  $\{\mathbf{u}_1 \cdots \mathbf{u}_p\}$  be an orthogonal basis for a subspace  $W$  of  $\mathbb{R}^n$ :

$$\mathbf{y} = c_1 \mathbf{u}_1 + \cdots + c_p \mathbf{u}_p; \quad c_j = \frac{\mathbf{y} \cdot \mathbf{u}_j}{\mathbf{u}_j \cdot \mathbf{u}_j}$$

Fair

Let  $\{\mathbf{e}_{u_1} \cdots \mathbf{e}_{u_p}\}$  be an orthonormal basis for a subspace  $W$  of  $\mathbb{R}^n$ :

$$\mathbf{y} = c_1 \mathbf{e}_{u_1} + \cdots + c_p \mathbf{e}_{u_p}; \quad c_j = \mathbf{y} \cdot \mathbf{e}_{u_j} = \|\mathbf{y}\| \cos(\theta_j)$$

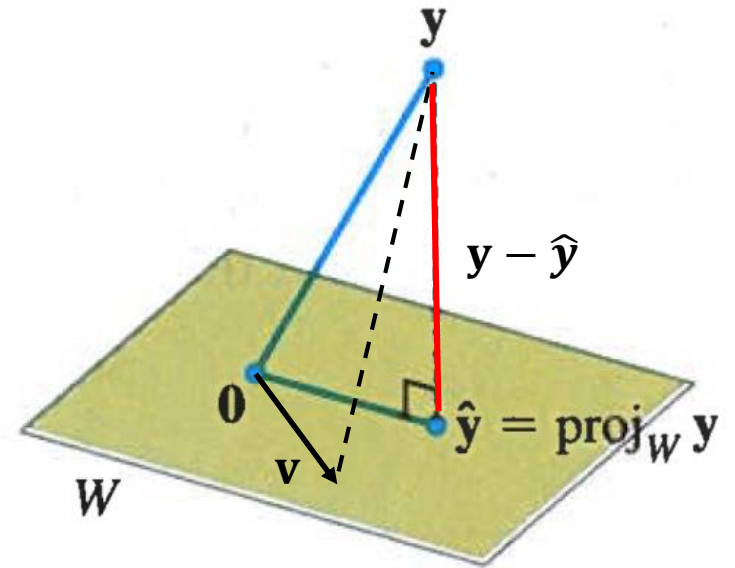
Easy

## Theorem 6.9: The Best Approximation Theorem

Let  $W$  be a subspace of  $\mathbb{R}^n$ , let  $\mathbf{y}$  be any vector in  $\mathbb{R}^n$ , and let  $\hat{\mathbf{y}}$  be the orthogonal projection of  $\mathbf{y}$  onto  $W$ . Then  $\hat{\mathbf{y}}$  is the closest point in  $W$  to  $\mathbf{y}$  in the sense that

$$\|\mathbf{y} - \hat{\mathbf{y}}\| < \|\mathbf{y} - \mathbf{v}\|$$

for all  $\mathbf{v}$  in  $W$  distinct from  $\hat{\mathbf{y}}$ .





### Theorem 6.10

If  $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$  is an orthonormal basis for a subspace  $W$  of  $\mathbb{R}^n$  then

$$\text{proj}_W \mathbf{y} = (\mathbf{y} \cdot \mathbf{u}_1)\mathbf{u}_1 + \dots + (\mathbf{y} \cdot \mathbf{u}_p)\mathbf{u}_p$$

If  $U = [\mathbf{u}_1 \ \dots \ \mathbf{u}_p]$ , then

$$\text{proj}_W \mathbf{y} = UU^T \mathbf{y} \quad \text{for all } \mathbf{y} \text{ in } \mathbb{R}^n$$

## OPGAVE 2

Matricen A her er tæt på at være ortogonal

- Hvad vil det sige, at en matrix er ortogonal?
- "Reparer" på A, således at den bliver ortogonal  
hint: kig på elementet med indeks 3,2

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

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



# Today's words and concepts

Inner product

Orthogonal

Length

Dot product

Orthonormal

Orthonormal basis

Norm

Orthogonal complement

Best approximation

Orthogonal set

Orthogonal matrix

Distance

Orthogonal projection

Orthogonal decomposition