

# Lesson 12

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

## Chapter 6 Orthogonality and least squares

► 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

## The Gram-Schmidt Process

Given a basis  $\{\mathbf{x}_1, \dots, \mathbf{x}_p\}$  for a subspace  $W$  of  $\mathbb{R}^n$ . Define:

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

$$\mathbf{v}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1$$

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\mathbf{x}_3 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 - \frac{\mathbf{x}_3 \cdot \mathbf{v}_2}{\mathbf{v}_2 \cdot \mathbf{v}_2} \mathbf{v}_2$$

$$\vdots$$

$$\mathbf{v}_p = \mathbf{x}_p - \frac{\mathbf{x}_p \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 - \frac{\mathbf{x}_p \cdot \mathbf{v}_2}{\mathbf{v}_2 \cdot \mathbf{v}_2} \mathbf{v}_2 - \dots - \frac{\mathbf{x}_p \cdot \mathbf{v}_{p-1}}{\mathbf{v}_{p-1} \cdot \mathbf{v}_{p-1}} \mathbf{v}_{p-1}$$

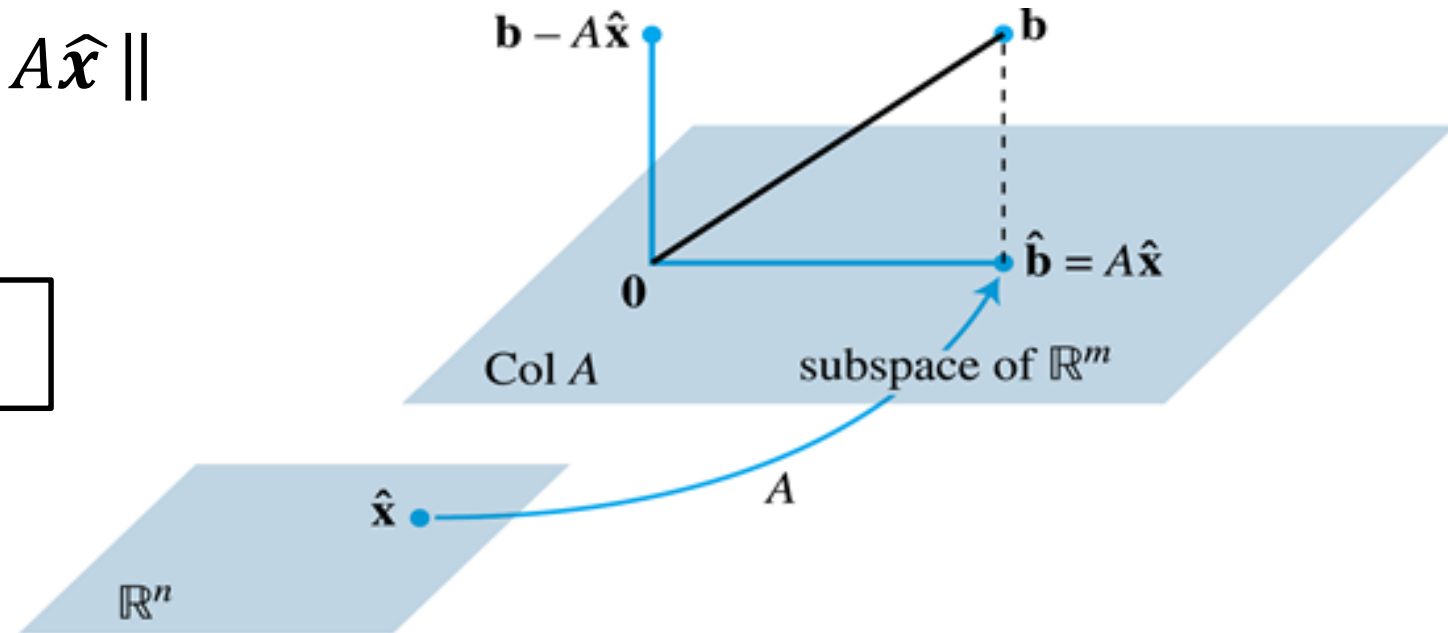
Then  $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$  is an orthogonal basis for  $W$ ,

and  $\text{Span}\{\mathbf{x}_1, \dots, \mathbf{x}_k\} = \text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$  for  $k = 1, \dots, p$

# Least-squares problems

- Find an  $\hat{\mathbf{x}}$  that makes  $\|\mathbf{b} - A\hat{\mathbf{x}}\|$  as small as possible

$$A\hat{\mathbf{x}} = \text{proj}_{\text{Col } A} \mathbf{b} = \hat{\mathbf{b}}$$



## Theorem 6.13: The normal equations

The set of least-squares solutions of  $A\mathbf{x} = \mathbf{b}$  coincides with the nonempty set of solutions of the normal equations  $A^T A\mathbf{x} = A^T \mathbf{b}$

# Least-Squares fitting of curves

Fitting data to known functions:  $y = \beta_0 f_0(x) + \beta_1 f_1(x) + \cdots + \beta_k f_k(x)$

*Known (fitting) functions* (pointing to  $f_0(x), f_1(x), \dots, f_k(x)$ )

*Linear model = Linear in the unknown parameters  $\beta_i$*  (pointing to  $\beta_0, \beta_1, \dots, \beta_k$ )

Data points:  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$

Determine the unknown parameters  $\beta_0, \dots, \beta_k$  that minimize the sum of square residuals:

$$\sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \|\mathbf{y} - \hat{\mathbf{y}}\|^2, \quad \hat{\mathbf{y}} = X\boldsymbol{\beta}$$

That is, find a least-squares solution of:  $X\boldsymbol{\beta} = \mathbf{y}$

*Observation vector*      *Design matrix*      *Parameter vector*      *Residual vector*

where:  $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$        $X = \begin{bmatrix} f_0(x_1) & f_1(x_1) & \cdots & f_k(x_1) \\ f_0(x_2) & f_1(x_2) & \cdots & f_k(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ f_0(x_n) & f_1(x_n) & \cdots & f_k(x_n) \end{bmatrix}$        $\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}$        $\boldsymbol{\varepsilon} = \mathbf{y} - \hat{\mathbf{y}} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$

## 6.7 Inner Product Spaces

$$\langle u, v \rangle$$

**Inner product (dot product):**  $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$

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

- $\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u}$
- $(\mathbf{u} + \mathbf{v}) \cdot \mathbf{w} = \mathbf{u} \cdot \mathbf{w} + \mathbf{v} \cdot \mathbf{w}$
- $(c\mathbf{u}) \cdot \mathbf{v} = \mathbf{u} \cdot (c\mathbf{v})$
- $\mathbf{u} \cdot \mathbf{u} \geq 0$  and  $\mathbf{u} \cdot \mathbf{u} = 0 \iff \mathbf{u} = \mathbf{0}$
- The **norm** (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 **normalized** (unit vector) if:  $\|\mathbf{v}\| = 1$
- The **distance** 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 **angle**  $\theta$  between two vectors is given by:  $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| \|\mathbf{v}\| \cos(\theta)$

Definition:

The **inner product** defined on a vector space  $V$  is a function that to any pair of vectors,  $\mathbf{u}$  and  $\mathbf{v}$  assigns a real number and fulfill the following axioms for all  $\mathbf{u}$ ,  $\mathbf{v}$  and  $\mathbf{w}$  in  $V$  and all scalars  $c$ :

1.  $\langle \mathbf{u}, \mathbf{v} \rangle = \langle \mathbf{v}, \mathbf{u} \rangle$

2.  $\langle \mathbf{u} + \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{v}, \mathbf{w} \rangle + \langle \mathbf{u}, \mathbf{w} \rangle$

3.  $\langle c\mathbf{u}, \mathbf{v} \rangle = c \langle \mathbf{u}, \mathbf{v} \rangle$

4.  $\langle \mathbf{u}, \mathbf{u} \rangle \geq 0$  and  $\langle \mathbf{u}, \mathbf{u} \rangle = 0 \iff \mathbf{u} = \mathbf{0}$

Ex 1      $\mathbf{u}, \mathbf{v} \in \mathbb{R}^2$ :      $\langle \mathbf{u}, \mathbf{v} \rangle = 4u_1v_1 + 5u_2v_2$      (Weighted dot-product)

Consider  $\mathbb{R}^2$  and let an inner product be defined as

$$\langle \mathbf{u}, \mathbf{v} \rangle = 2u_1v_1 + 3u_2v_2$$

Let two vectors be given as

$$\mathbf{u} = \begin{bmatrix} -1 \\ 2 \end{bmatrix} \text{ and } \mathbf{v} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

What is  $\langle \mathbf{u}, \mathbf{v} \rangle$ ?



Ex 2     $\mathbf{p}, \mathbf{q} \in \mathbb{P}_n$ :  $\langle \mathbf{p}, \mathbf{q} \rangle = p(t_0)q(t_0) + p(t_1)q(t_1) + \cdots + p(t_n)q(t_n)$ ;  $t_0, t_1, \dots, t_n \in \mathbb{R}$

Ex 3     $\mathbf{p}, \mathbf{q} \in \mathbb{P}_2$ :  $\langle \mathbf{p}, \mathbf{q} \rangle = p(t_0)q(t_0) + p(t_1)q(t_1) + p(t_2)q(t_2)$ ;  $t_0 = 0, t_1 = 1/2, t_2 = 1$

$$\mathbf{p}(t) = 12t^2; \quad \mathbf{q}(t) = 2t - 1$$

$$\mathbf{p}(t_0) = 0; \quad \mathbf{q}(t_0) = -1 \qquad \mathbf{p}(t_0)\mathbf{q}(t_0) = 0$$

$$\mathbf{p}(t_1) = 3; \quad \mathbf{q}(t_1) = 0 \qquad \mathbf{p}(t_1)\mathbf{q}(t_1) = 0 \qquad \langle \mathbf{p}, \mathbf{q} \rangle = 12$$

$$\mathbf{p}(t_2) = 12; \quad \mathbf{q}(t_2) = 1 \qquad \mathbf{p}(t_2)\mathbf{q}(t_2) = 12$$

### *Diskussion:*

Hvis  $t_2$  i eksemplet på foregående slide, i stedet for at antage værdien 1, var  $\frac{1}{2}$ , ville der gælde følgende:

- $p$  og  $q$  er ortogonale for  $\mathbf{p}, \mathbf{q} \in \mathbb{P}_2$ , da  $\langle \mathbf{p}, \mathbf{q} \rangle = 0$

Vil ortogonaliteten også gælde for  $\mathbf{p}, \mathbf{q} \in \mathbb{P}_n$ ? Begrund svaret ...

In a vector space where an inner product has been defined

The length / norm of a vector  $\mathbf{v}$

$$\|\mathbf{v}\| = \sqrt{\langle \mathbf{v}, \mathbf{v} \rangle}$$

The distance between two vectors  $\mathbf{u}$  and  $\mathbf{v}$  is

$$\|\mathbf{u} - \mathbf{v}\|$$

Two vectors are orthogonal if

$$\langle \mathbf{u}, \mathbf{v} \rangle = 0$$

# Orthogonal Projection and Best Approximation

Let  $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$  be an orthogonal basis for a subspace  $W$  of vector space  $V$ ,  $\mathbf{y}$  any vector in  $V$ . Then:

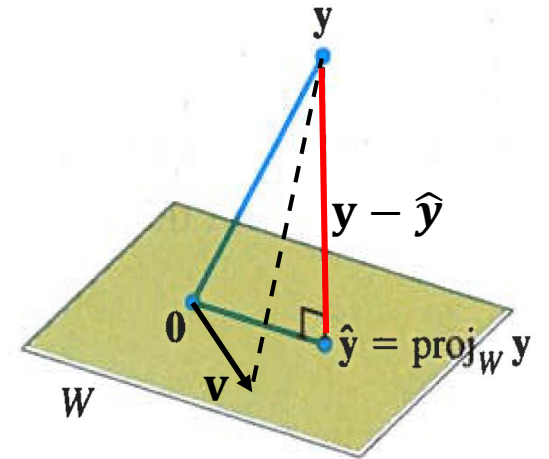
$$\hat{\mathbf{y}} = \frac{\langle \mathbf{y}, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 + \dots + \frac{\langle \mathbf{y}, \mathbf{v}_p \rangle}{\langle \mathbf{v}_p, \mathbf{v}_p \rangle} \mathbf{v}_p = \text{proj}_W \mathbf{y}$$

is the orthogonal projection of  $\mathbf{y}$  on  $W$ .

$\hat{\mathbf{y}}$  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  $\hat{\mathbf{y}}$ .



## The Gram-Schmidt Process

Given a basis  $\{\mathbf{x}_1, \dots, \mathbf{x}_p\}$  for a subspace  $W$  of vectorspace  $V$ . Define:

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

$$\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$$

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\langle \mathbf{x}_3, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_3, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2$$

$$\vdots$$

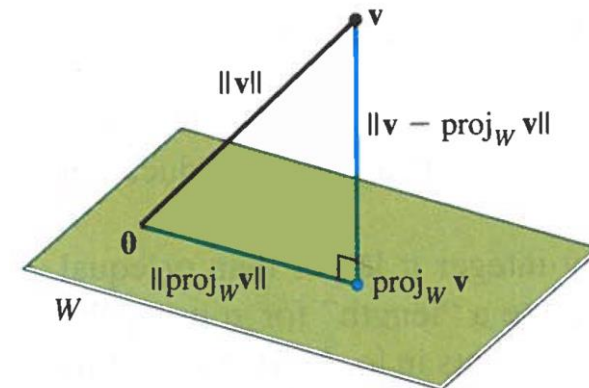
$$\mathbf{v}_p = \mathbf{x}_p - \frac{\langle \mathbf{x}_p, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_p, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2 - \dots - \frac{\langle \mathbf{x}_p, \mathbf{v}_{p-1} \rangle}{\langle \mathbf{v}_{p-1}, \mathbf{v}_{p-1} \rangle} \mathbf{v}_{p-1}$$

Then  $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$  is an orthogonal basis for  $W$  and

$\text{Span}\{\mathbf{x}_1, \dots, \mathbf{x}_k\} = \text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$  for  $k = 1, \dots, p$

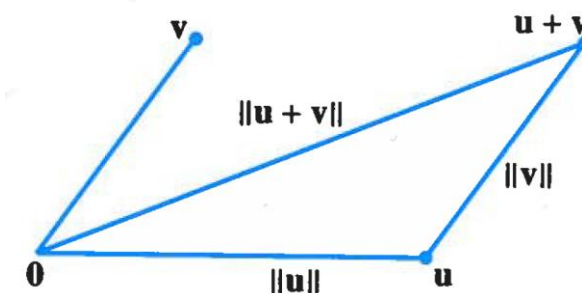
## Theorem 6.16: The Cauchy-Schwartz Inequality

For all vectors  $\mathbf{u}, \mathbf{v}$  in  $V$ :  $|\langle \mathbf{u}, \mathbf{v} \rangle| \leq \|\mathbf{u}\| \|\mathbf{v}\|$



## Theorem 6.17: The Triangle Inequality

For all vectors  $\mathbf{u}, \mathbf{v}$  in  $V$ :  $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$



# Inner product for continuous functions

$$\langle \mathbf{p}, \mathbf{q} \rangle = \int_a^b p(t)q(t)dt$$

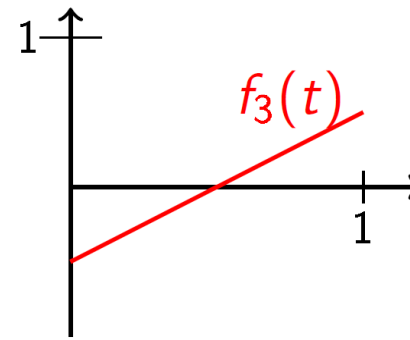
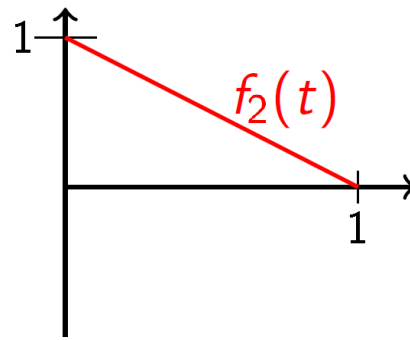
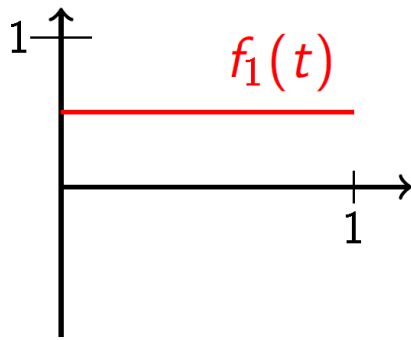
is an inner product of  
continuous functions on  $[a, b]$

Funktionerne  $p$  og  $q$  er *ortogonale*, hvis integralet – evalueret mellem  $a$  og  $b$  – giver 0.

Let the inner product for continuous function defined on the interval  $[0, 1]$  be given by

$$\langle f, g \rangle = \int_0^1 f(t)g(t)dt$$

Three functions,  $f_1(t)$ ,  $f_2(t)$  and  $f_3(t)$  are given as



Which pair(s) of functions is orthogonal?

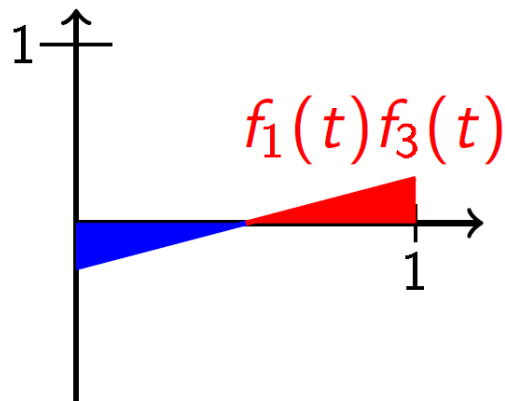
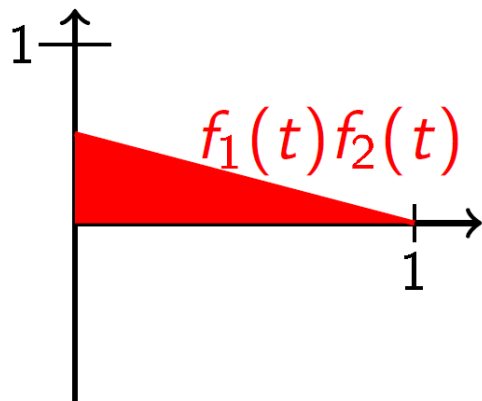


The functions are given by

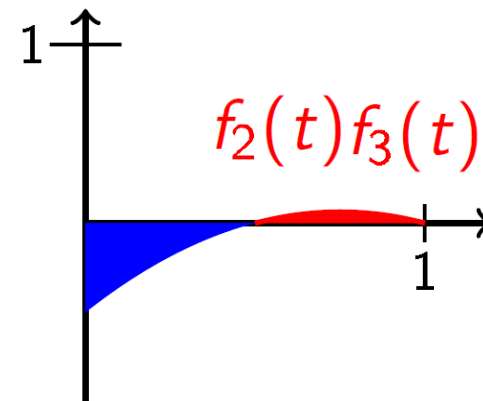
$$f_1(t) = \frac{1}{2}, \quad f_2(t) = 1 - t, \quad f_3(t) = -\frac{1}{2} + t$$

and hence

$$f_1(t)f_2(t) = \frac{1}{2}(1-t), \quad f_1(t)f_3(t) = -\frac{1}{4} + \frac{1}{2}t, \quad f_2(t)f_3(t) = (1-t)\left(-\frac{1}{2} + t\right)$$



OK!



# OPGAVE 1

Løs opgaverne:

**4 og 6**

i eksamensopgavesættet fra 2012.

Eksamenssættet ligger tilgængeligt på Blackboard under lektion 12.

## 6.8 Applications of Inner Product Spaces

$$\langle f, g \rangle = \int_0^{2\pi} f(t)g(t)dt$$

# Weighted Least-Squares

$n$  observations/measurements:  $\mathbf{y} = (y_1, y_2, \dots, y_n) \in \mathbb{R}^n$

↳ some more accurate/reliable than others

The best approximation  $\hat{\mathbf{y}}$  in a subspace  $V$  of  $\mathbb{R}^n$  (fx a curve) that minimize the sum of weighted squares of errors:

$$\text{Weighted } SS(E) = w_1^2(y_1 - \hat{y}_1)^2 + \dots + w_n^2(y_n - \hat{y}_n)^2 = \|W\mathbf{y} - W\hat{\mathbf{y}}\|^2$$

with the inner product:

$$\langle \mathbf{x}, \mathbf{y} \rangle = w_1^2 x_1 y_1 + \dots + w_n^2 x_n y_n = (w_1 x_1)(w_1 y_1) + \dots + (w_n x_n)(w_n y_n) = W\mathbf{x} \cdot W\mathbf{y}$$

and the weight diagonal matrix:

$$W = \begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & w_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_n \end{bmatrix}$$

## Weighted Least-Squares

Let  $\text{Col } A = V$  then  $\hat{\mathbf{y}} = A\hat{\mathbf{x}}$  and we seek a solution  $\hat{\mathbf{x}}$  that minimize:

$$\text{Weighted } SS(E) = \|W\mathbf{y} - W\hat{\mathbf{y}}\|^2 = \|W\mathbf{y} - WA\hat{\mathbf{x}}\|^2$$

That is the ordinary least-squares solution to:

$$WA\mathbf{x} = W\mathbf{y}$$

With the normal equation:

$$(WA)^T WA\mathbf{x} = (WA)^T W\mathbf{y} \quad \text{See Theorem 6.13}$$

# Weighted Least-Squares

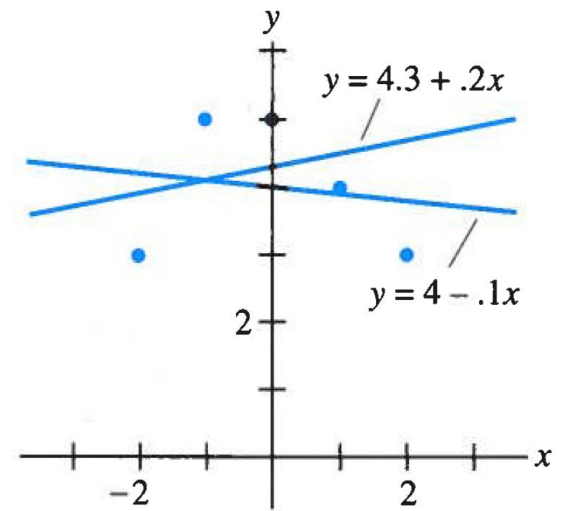
5 measurements/data points:  $(x, y) = (-2, 3), (-1, 5), (0, 5), (1, 4), (2, 3)$

Error: Small

Large

Weight: 2

1



Best line:  $y = \beta_0 + \beta_1 x$  ?

$$X = \begin{bmatrix} 1 & -2 \\ 1 & -1 \\ 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix}; \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}; \quad \mathbf{y} = \begin{bmatrix} 3 \\ 5 \\ 5 \\ 4 \\ 3 \end{bmatrix}; \quad W = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \Rightarrow WX = \begin{bmatrix} 2 & -4 \\ 2 & -2 \\ 2 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix}; \quad W\mathbf{y} = \begin{bmatrix} 6 \\ 10 \\ 10 \\ 4 \\ 3 \end{bmatrix}$$

$$\text{The normal equation: } (WX)^T WX \boldsymbol{\beta} = (WX)^T W\mathbf{y} \Rightarrow \begin{bmatrix} 14 & -9 \\ -9 & 25 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 59 \\ -34 \end{bmatrix} \Rightarrow \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 4.3 \\ 0.20 \end{bmatrix}$$

$\Rightarrow$  **Weighted least-squares line:  $y = 4.3 + 0.20x$**

(Equal weighted least-squares line:  $y = 4.0 - 0.10x$  )

# Fourier Series

Consider the set of trigonometric continuous functions in  $C[0,2\pi]$ :

$$\{1, \cos(t), \cos(2t), \dots, \cos(nt), \sin(t), \sin(2t), \dots, \sin(nt)\}$$

and the inner product:

$$\langle f, g \rangle = \int_0^{2\pi} f(t)g(t)dt$$

For all  $m \neq n$ :

$$\langle \cos(mt), \cos(nt) \rangle = \int_0^{2\pi} \cos(mt)\cos(nt)dt = 0$$

$$\langle \sin(mt), \sin(nt) \rangle = \int_0^{2\pi} \sin(mt)\sin(nt)dt = 0$$

$$\langle \cos(mt), \sin(nt) \rangle = \int_0^{2\pi} \cos(mt)\sin(nt)dt = 0$$

→ Orthogonal set of trigonometric continuous functions in  $C[0,2\pi]$

# Fourier Series

Let  $W = \text{Span}\{1, \cos(t), \cos(2t), \dots, \cos(nt), \sin(t), \sin(2t), \dots, \sin(nt)\}$   
and  $f \in C[0, 2\pi]$ . The projection of  $f$  on  $W$ :

$$\hat{f}(t) = \text{proj}_W f = \frac{a_0}{2} \cdot 1 + a_1 \cos(t) + a_2 \cos(2t) + \dots + a_n \cos(nt) + b_1 \sin(t) + b_2 \sin(2t) + \dots + b_n \sin(nt)$$

where

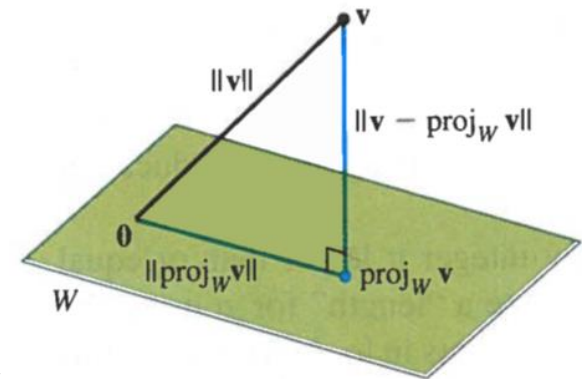
*Fourier series  
of order n*

$$\frac{a_0}{2} = \frac{\langle f, 1 \rangle}{\langle 1, 1 \rangle} = \frac{1}{2\pi} \int_0^{2\pi} f(t) \cdot 1 dt$$

$$a_k = \frac{\langle f, \cos(kt) \rangle}{\langle \cos(kt), \cos(kt) \rangle} = \frac{1}{\pi} \int_0^{2\pi} f(t) \cos(kt) dt$$

$$b_k = \frac{\langle f, \sin(kt) \rangle}{\langle \sin(kt), \sin(kt) \rangle} = \frac{1}{\pi} \int_0^{2\pi} f(t) \sin(kt) dt$$

*Fourier coefficients  
= Coordinates in  
the orthogonal  
trigonometric  
(harmonic/frequency)  
space W*



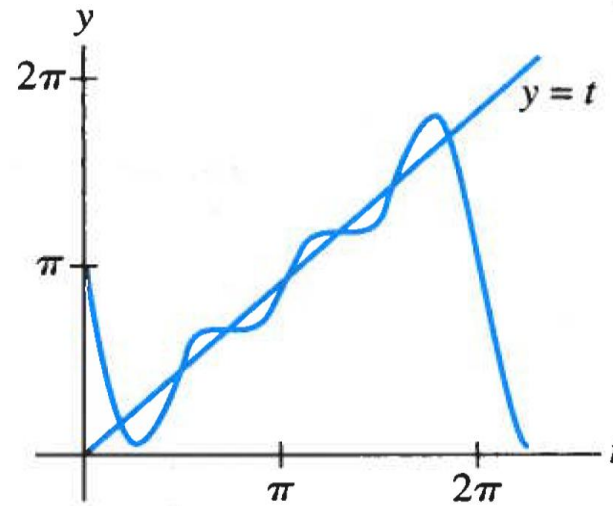


Fourier Series:  $f(t) = t; \quad 0 \leq t \leq 2\pi$

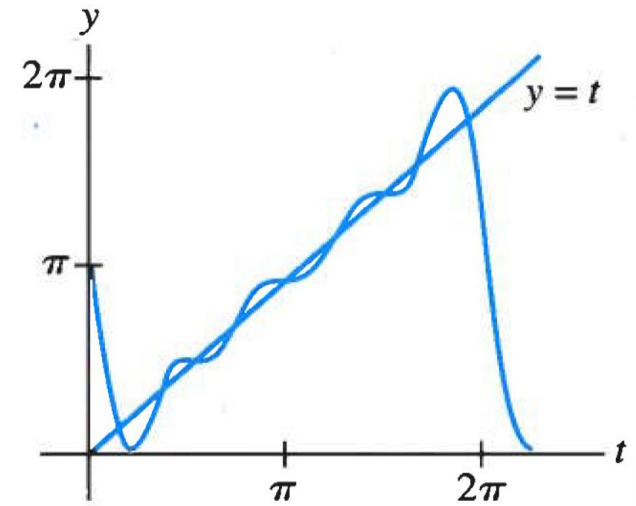
$$\left. \begin{aligned} \frac{a_0}{2} &= \frac{1}{2\pi} \int_0^{2\pi} t dt = \pi \\ a_k &= \frac{1}{\pi} \int_0^{2\pi} t \cdot \cos(kt) dt = 0 \\ b_k &= \frac{1}{\pi} \int_0^{2\pi} t \cdot \sin(kt) dt = -\frac{2}{k} \end{aligned} \right\} \Rightarrow \hat{f}(t) = \pi - 2\sin(t) - \sin(2t) - \frac{2}{3}\sin(3t) - \cdots - \frac{2}{n}\sin(nt)$$

Mean square error:

$$\begin{aligned} &\|f(t) - \hat{f}(t)\|^2 \\ &= \int_0^{2\pi} (f(t) - \hat{f}(t))^2 dt \xrightarrow{n \rightarrow \infty} 0 \end{aligned}$$



(a) Third order



(b) Fourth order

## OPGAVE 2

For Fourier-serien på foregående slide, som approximerer funktionen  $f(t) = t$ :

- Bestem Fourier-koefficienterne for orden 3, 5 og 7
- Plot  $f(t)$  samt de tre Fourier-serier i intervallet  $[0; 2\pi]$
- Beregn kvadratfejlen for hver af de tre serier. Er tallene forventelige sammenlignet med hinanden?

# Today's words and concepts

*Weighted least-squares*

*Inner product*

*The Cauchy-Schwartz Inequality*

*Fourier Series*

*Trigonometric space*

*The Triangle Inequality*

*Inner product spaces*

*Harmonic projections*