

$$A_1 = \begin{bmatrix} 2 & 3 \\ 3 & 9 \end{bmatrix} \quad x^T A x > 0 \quad \forall x \neq 0, \quad x \in \mathbb{R}^2$$

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 2 & 3 \\ 3 & 9 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 2x_1 + 3x_2 \\ 3x_1 + 9x_2 \end{bmatrix}$$

$$= 2x_1^2 + \underbrace{3x_1x_2 + 3x_1x_2}_{6x_1x_2} + 9x_2^2$$

$$= \underbrace{(x_1 + 3x_2)^2}_{x_1^2 + 9x_2^2 + 6x_1x_2} + x_1^2 > 0 \Rightarrow A_1 \text{ indef } (+)$$

$$A_2 = \begin{bmatrix} 2 & 3 \\ 3 & 6 \end{bmatrix} = 2x_1^2 + 6x_1x_2 + 6x_2^2$$

$$= (x_1 + 3x_2)^2 + x_1^2 - 3x_2^2 \stackrel{\text{no es}}{\Rightarrow} \text{def } (+)$$

$\mathcal{P}_2(\mathbb{R}) = \text{polynomials of degree } \leq 2 \text{ (self. prod.)}$

$$B = \{1, 1+x, x^2+x\}$$

$$B_1 = \{1, x, x^2\}$$

$$\langle p, q \rangle = p(0)q(0) + p(1)q(1) + p(-1)q(-1)$$

$$a_0 + a_1 x + a_2 x^2 = p$$

$$\vec{p} = \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix}$$

$$p = \sum_{i=1}^n \langle p, g_i \rangle g_i$$

elemente
des Bases

von \mathcal{P}_2

\mathcal{K}^n

$$(\vec{p}, 0, \dots), (0, \vec{p}, 0, \dots)$$

$$\hat{x} = x/2$$

• $P_1(\mathbb{R})$ is span of the following de
~~degree~~ 1

$$B = \{1, x\}$$

$$p = a_0 + a_1 x$$

$$q = b_0 + b_1 x$$

$$\langle p, q \rangle = p(0)q(0) + p(3)q(3)$$

$$= a_0 b_0 + (a_0 + a_1 \cdot 3)(b_0 + b_1 \cdot 3)$$

$$= 2a_0 b_0 + a_0 b_1 \cdot 3 + 3b_0 a_1$$

$$+ a_1 b_1 \cdot 3^2$$

$$\begin{bmatrix} 2 & 3 \\ 3 & 9 \end{bmatrix}$$

$$\langle p, q \rangle = \underbrace{\begin{bmatrix} a_0 & a_1 \end{bmatrix}}_{\hat{p}^T} \underbrace{\begin{bmatrix} 2 & 3 \\ 3 & 9 \end{bmatrix}}_{A_1} \underbrace{\begin{bmatrix} b_0 \\ b_1 \end{bmatrix}}_{\hat{q}} = \hat{p}^T A_1 \hat{q}$$

Se define distancia de Mahalanobis.

x, y r.v. con = distrib.
 $d(x, y) = \sqrt{(x - y)^T \Sigma^{-1} (x - y)}$

$$\Sigma > 0 \Rightarrow \Sigma^{-1} > 0$$

$$\Sigma \text{ cov}(x, y)$$

\downarrow
 $\langle x, y \rangle = x^T \Sigma^{-1} y$

$\text{Def } \oplus$
 $\mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$
 $\langle x, y \rangle = x^T \Sigma^{-1} y$

• $\phi: \mathbb{R} \rightarrow \mathbb{R}$

$$\phi(x) = x^2$$

$\phi: \mathbb{R} \rightarrow \mathbb{R}$
 $\phi(x) = x^2$
 surjective

is surjective (not onto)
 $\phi(0) = 0$

• $\phi: \mathbb{R} \rightarrow \mathbb{R}$ $\phi(x) = x$
 is injective

is surjective (onto)

• $\phi: \mathbb{R} \rightarrow \mathbb{R}$, $\phi(x) = x^3 - 3x = x(x^2 - 3)$
 is injective
 is surjective

• $\phi: \mathbb{R} \rightarrow \mathbb{R}$, $\phi(x) = x^3 \Rightarrow$ is injective
 is surjective \Rightarrow bijective

$$\Phi: \mathbb{R}^3 \rightarrow \mathbb{R}^3 \quad \Phi(x) = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} x$$

is ~~isomorphism~~

$$R = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \end{bmatrix} \begin{bmatrix} 3k \\ 0 \\ -k \end{bmatrix} = \begin{bmatrix} 3k - 3k \\ 3k - 3k \end{bmatrix}$$

$$\Phi_2: \mathbb{R} \rightarrow \mathbb{R}^3 \quad \Phi(x) = \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix}$$

($x = a_0 + a_1 x + a_2 x^2$) \rightarrow isomorphism

$$\Phi\left(\frac{1}{x} + x\right) = \frac{1}{x} \Phi(1) + \Phi(x)$$

$$\Phi: \mathbb{R}^3 \rightarrow \mathbb{R}^3 \quad \Phi(x) = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} x$$

$$\Phi: \mathbb{R}^3 \rightarrow \mathbb{R}^3 \quad \Phi(x) = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} x \rightarrow \text{automorphism}$$

is invertible

En de van. selecties $\| \cdot \|_{x^2} < \infty$

\hookrightarrow En van $\in V$ $\forall \vec{v} \in V$ (over \mathbb{R})

$$\langle x, y \rangle = \| \cdot \|_{x \cdot y}$$

$$\| (y - \hat{y}) \|^2 = \langle (y - \hat{y}), (y - \hat{y}) \rangle$$

$$\text{dist}(y, S) = \| (y - \hat{y}) \|^2$$

\hookrightarrow over \mathbb{R} medium



$$\hookrightarrow ax + b$$

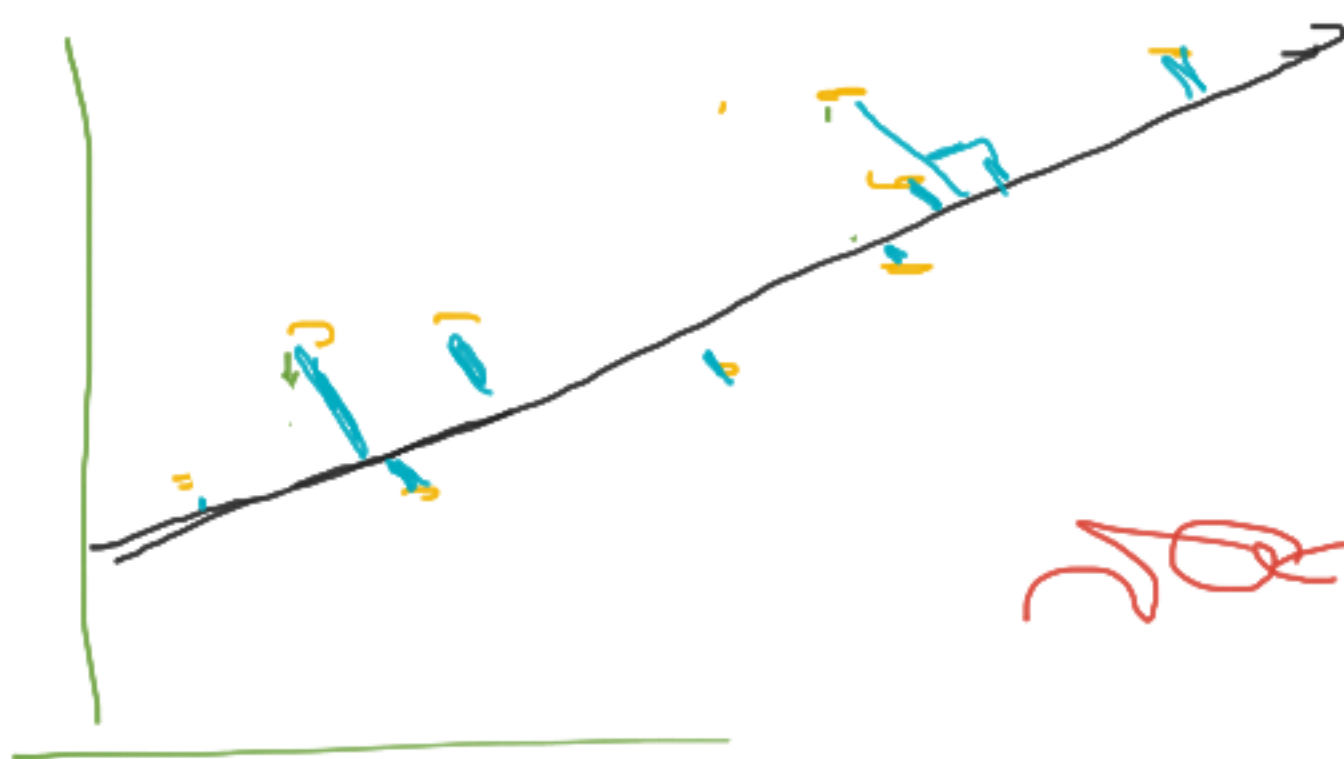
$$\langle y - \hat{y}, 1 \rangle = 0 \quad \forall y \in S$$

$$S = \{ \vec{b}, x \}$$

$$\langle y - \hat{y}, 1 \rangle = 0 = \langle y - (ax + b), 1 \rangle = \| \cdot \|_{y - ax - b}$$

$$\langle y - \hat{y}, x \rangle = 0 = \langle y - (ax + b), x \rangle = \| \cdot \|_{y - ax - b}$$

$$\| \cdot \|_{yx} - a \| \cdot \|_{x^2} - b \| \cdot \|_x$$



$$\text{var}(X) = \{E[X^2] - \{E[X]\}^2\}$$

$$\text{cov}(X, Y) - a \text{var}(X) = 0$$

$$\hookrightarrow a = \frac{\text{cov}(X, Y)}{\text{var}(X)}$$

Least
squares
regression

$$b = E[Y] - \frac{\text{cov}(X, Y)}{\text{var}(X)} E[X]$$

$$\hat{Y} = \frac{\text{cov}(X, Y)}{\text{var}(X)} (X - E[X]) + E[Y]$$

Prozess de Gram-Schmidt

Sei V ein n -f. Vektorraum. $\mathcal{B} = \{v_1, \dots, v_n\}$ eine Basis von V .

$\mathcal{B} = \{v_1, \dots, v_n\} \rightarrow \mathcal{B}' = \{g_1, \dots, g_n\}$
 eine ONB.

$$g_1 = v_1 \rightarrow \|g_1\| = 1$$

$$g_2 = v_2 - \frac{\langle v_2, g_1 \rangle}{\|g_1\|^2} g_1 = v_2 - \langle v_2, g_1 \rangle g_1$$

$$g_3 = v_3 - \frac{\langle v_3, g_1 \rangle}{\|g_1\|^2} g_1 - \frac{\langle v_3, g_2 \rangle}{\|g_2\|^2} g_2$$

$$g_i = v_i - \frac{\langle v_i, g_1 \rangle}{\|g_1\|^2} g_1 - \dots - \frac{\langle v_i, g_{i-1} \rangle}{\|g_{i-1}\|^2} g_{i-1}$$

