

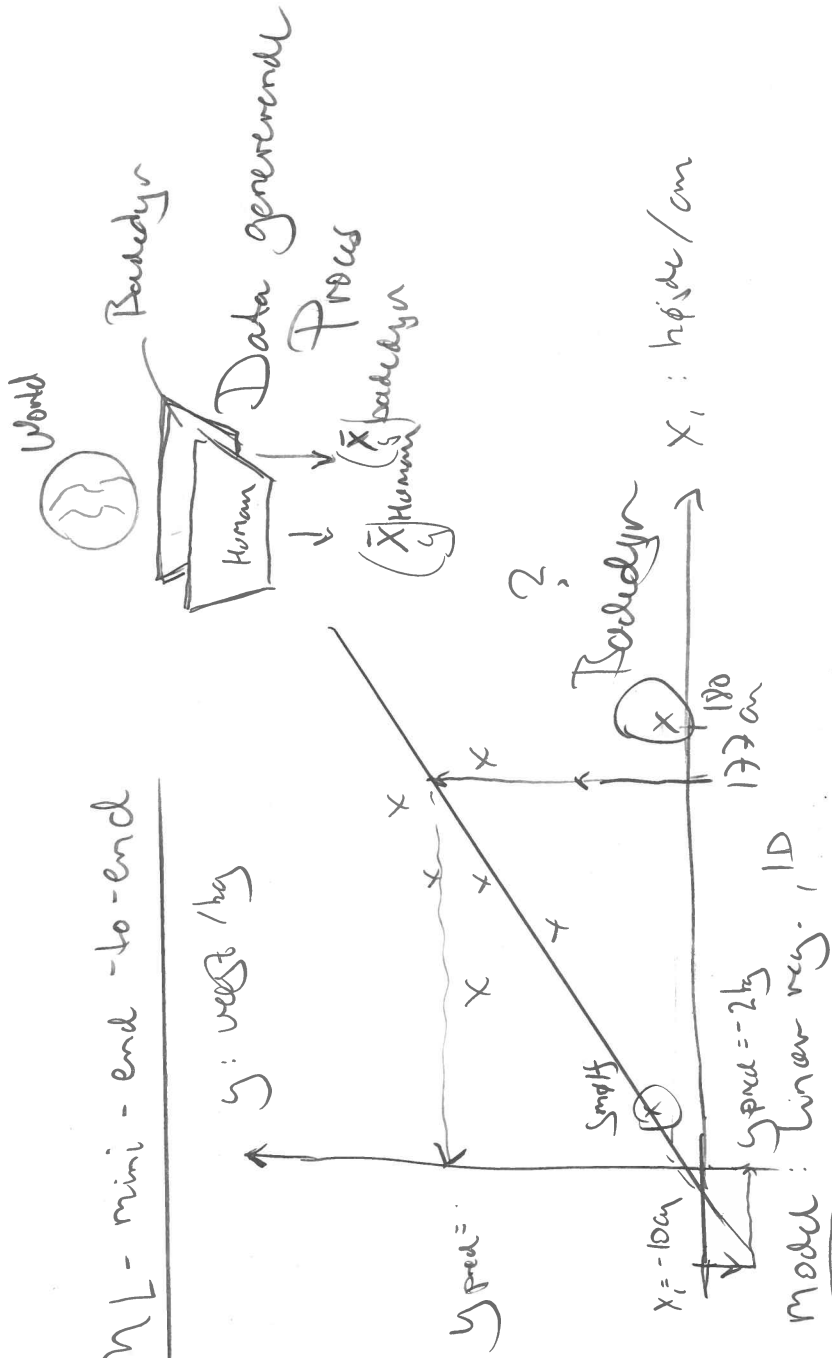
FINAL

Water til LØ1

(3/9-2020)

①

ML - mini - end - to - end



$$\begin{aligned}
 y &= \cancel{dx} + \cancel{f} \\
 &= \Theta_0 x_1 + \Theta_0 \cdot 1 \\
 &= w_1 x_1 + w_0 \cdot 1
 \end{aligned}$$

DATA

2D: $\bar{X} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

3D: $\bar{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$

Model Parameter

Generelt

1D: $\bar{\Theta} = \begin{bmatrix} \Theta_0 \\ \Theta_1 \end{bmatrix}$

2D: $\bar{\Theta} = \begin{bmatrix} \Theta_0 \\ \Theta_1 \\ \Theta_2 \end{bmatrix}$

3D: $\bar{\Theta} = \begin{bmatrix} \Theta_0 \\ \Theta_1 \\ \Theta_2 \\ \Theta_3 \end{bmatrix}$

ML - mini c-to-e

Hypothesis Function:

$$\boxed{h(\bar{x}; \bar{\theta}) = \bar{y}_{\text{pred}}} \quad \text{bias} \quad \text{led} \quad (\hat{y})$$

input DATA model params. = $\theta_1 X_1 + \theta_0 \cdot 1$

for $h = \text{linear reg.}$

~~(0) Find DATA~~ ~~Final~~

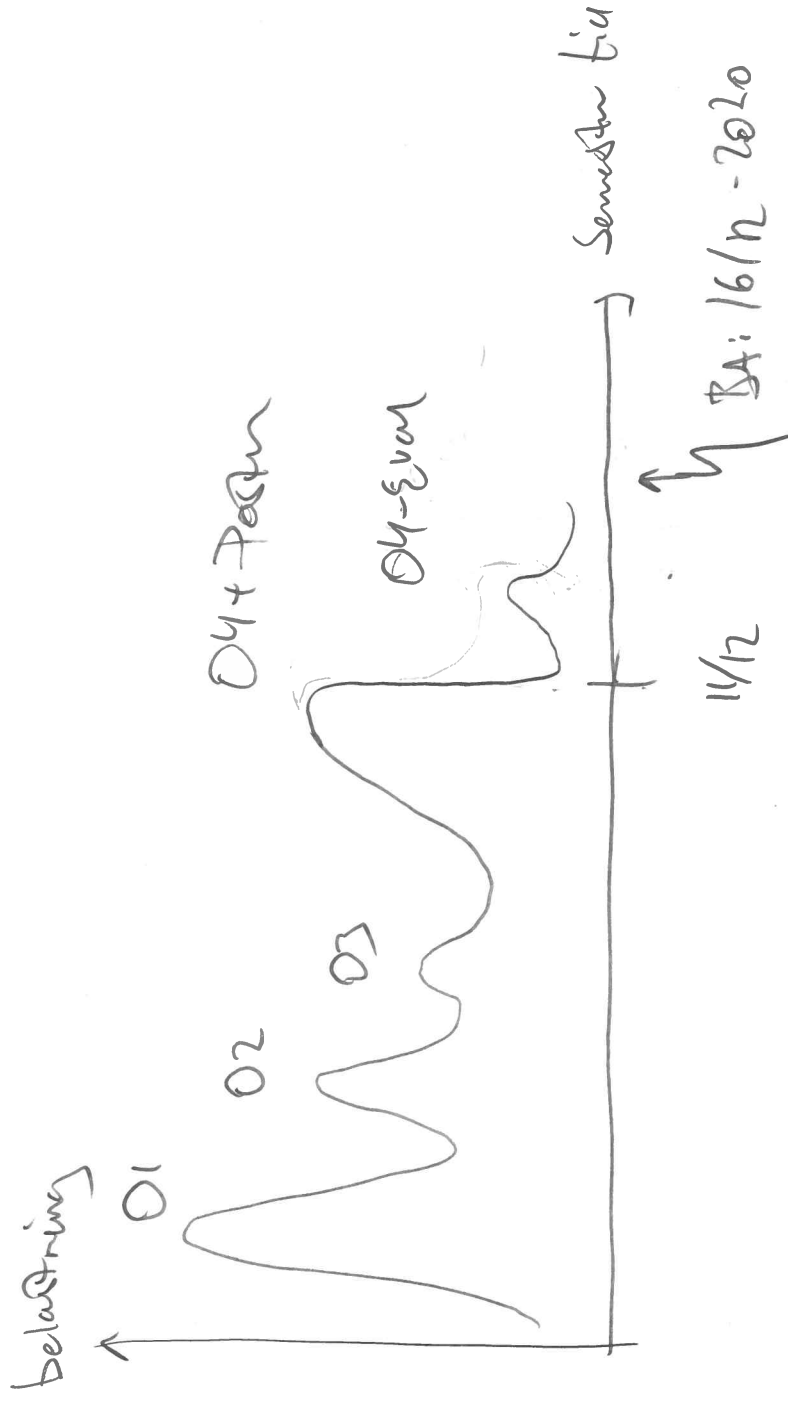
ML: i) using $h(\cdot)$

2) train / fit ; $\bar{\theta} \Rightarrow \text{optimize}$, best $\bar{\theta}^* \Rightarrow \text{minimize fcl} (L(\cdot))$

3) predict på nye Data \Rightarrow generalisering

X) Problemer i) data outliers ; ii) dimensionalitet ; iii) ...

ITMAL Notes: L01



MMLS-Recap

Matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}$$

(m x n) matrix, 1-indexed

Size-constraints:

$$\begin{aligned} X^+ &= ? \\ X^- &= ? \end{aligned}$$

$$\begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

F. obs

$$\begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

$$\begin{aligned} \vec{v} &= \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_d \end{bmatrix} \\ \vec{w} &= \begin{bmatrix} w_1 & w_2 & \dots & w_d \end{bmatrix} \end{aligned}$$

Python Matrix

$$\begin{matrix} \text{Numpy} \\ \downarrow \\ X_{\text{demo}} = \end{matrix} \begin{bmatrix} 1 & 2 & 3 & 4 \\ 10 & 20 & 30 & 40 \end{bmatrix}$$

$$X.\text{shape} = (2, 4)$$

$$X[\emptyset, 1]^2 = 2.0$$

$$X[\emptyset, -1]^2 = 4.0$$

$$X[:, 1] = [2, 20]$$

row / column

Numpy



row ^ column

Build-in
Python - list-of-list \neq matrix
 $z = [[42]]$

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ML Design Matrix

Sample 1 for $d=4$, $p=4$ [Home]

$$X^{(1)} = \begin{bmatrix} x_1^{(1)} \\ x_2^{(1)} \\ \vdots \\ x_d^{(1)} \end{bmatrix} \rightarrow = \begin{bmatrix} -118 \\ 339 \\ 1416 \\ 38000 \end{bmatrix}$$

x_1 : long / °
 x_2 : lat / °
 x_3 : inhabitants / #
 x_4 : median income / \$

true output: median house value / \$

$$y^{(1)} = 156000$$

Q

Design Matrix

Sample 2

Sample m

$$\bar{X}^{(2)} = \begin{bmatrix} \vdots \\ \vdots \end{bmatrix}$$

$$y^{(2)} =$$

,

Sample m

$$\bar{X}^{(m)} = \begin{bmatrix} \vdots \\ \vdots \end{bmatrix}$$

$$y^{(m)} =$$

$$X = \begin{bmatrix} \bar{X}^{(1)T} \\ \bar{X}^{(2)T} \\ \vdots \\ X^{(m)T} \end{bmatrix}$$

$$y_{true} = \begin{bmatrix} y_{true}^{(1)} \\ y_{true}^{(2)} \\ \vdots \\ y_{true}^{(m)} \end{bmatrix}$$

$$\begin{bmatrix} X_1^{(1)} & X_2^{(1)} & \vdots & X_1^{(m)} & X_2^{(m)} \end{bmatrix} \begin{bmatrix} x_d^{(1)} \\ x_d^{(2)} \\ \vdots \\ x_d^{(m)} \end{bmatrix} \downarrow = \begin{bmatrix} -118 & 33.9 & 1416 & 38000 \end{bmatrix}$$

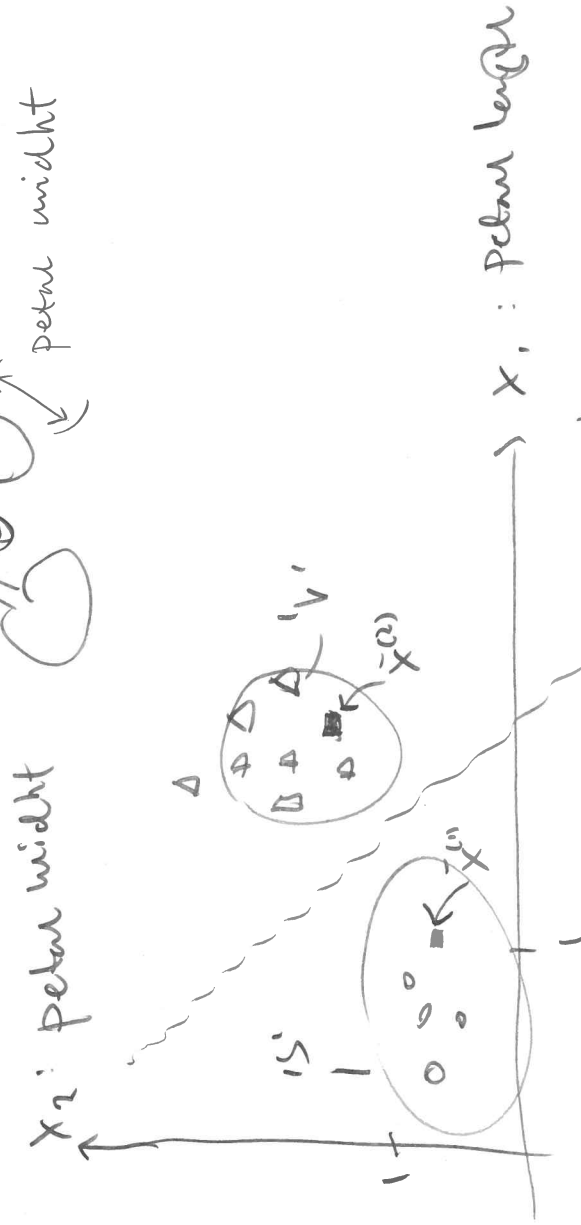
$d=4$ (Housing Data)

$$d=4 \downarrow = \begin{bmatrix} 156000 \\ \vdots \end{bmatrix}$$

Wage range augmented sum: $(\bar{X} \mid \bar{y})$

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Iris Data



Classes:

I: Setosa 'S' ○

II: Versicolour 'V' ▽

III: Virginica 'x' Δ

↳ 3 classes only for this demo

Design Matrix

$$\bar{x}^{(1)} = \begin{bmatrix} x_{1(1)} \\ x_{2(1)} \end{bmatrix} = \begin{bmatrix} 1.2 \\ 0.5 \end{bmatrix}$$

$$\bar{x}^{(2)} = \begin{bmatrix} x_{1(2)} \\ x_{2(2)} \end{bmatrix} = \begin{bmatrix} 4.5 \\ 1.2 \end{bmatrix}$$

$$y_{true}^{(1)} = 'S'$$

$$y_{true}^{(2)} = 'V'$$

decision boundary

$$\bar{X} = \begin{bmatrix} \bar{x}^{(1)T} \\ \bar{x}^{(2)T} \end{bmatrix} = \begin{bmatrix} 1.2 & 0.5 \\ 4.5 & 1.2 \end{bmatrix}$$

$$\bar{y}_{true} = \begin{bmatrix} y_{true}^{(1)} \\ y_{true}^{(2)} \end{bmatrix} = \begin{bmatrix} 'S' \\ 'V' \end{bmatrix}$$

Cost Fun

lin. reg model

$$h(\bar{x}; \bar{\theta}) = y_{pred}$$

$$= \theta_0 + \theta_1 x + \theta_0 \cdot 1$$

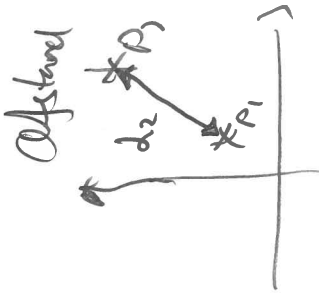
Fit: best $\bar{\theta}$? \Rightarrow Optimize

$$h^{(i)}(\bar{x}^{(i)}; \bar{\theta}) = y_{pred}^{(i)} \quad \text{vs} \quad y_{true}^{(i)}$$

DIFF \Rightarrow Cost/error

$$L^{(i)}(y_{true}^{(i)}, y_{pred}^{(i)}) = ?$$

$$\mathcal{L}_2: \sqrt{(\bar{p}_1 - \bar{p}_2)^2}$$



$$J = \sum_i L^{(i)} = \sum_{i=1}^m L^{(i)} + L^{(2)}$$

$$= L(y_{pred}^{(1)}, y_{true}^{(1)}) + L(y_{pred}^{(2)}, y_{true}^{(2)})$$

$$= L(h(\bar{x}^{(1)}; \bar{\theta}), y_{true}^{(1)}) + L(h(\bar{x}^{(2)}; \bar{\theta}), y_{true}^{(2)})$$

numerical/symbolic

Solve for $\bar{\theta}^*$

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$i=42$; Data Sample #42

