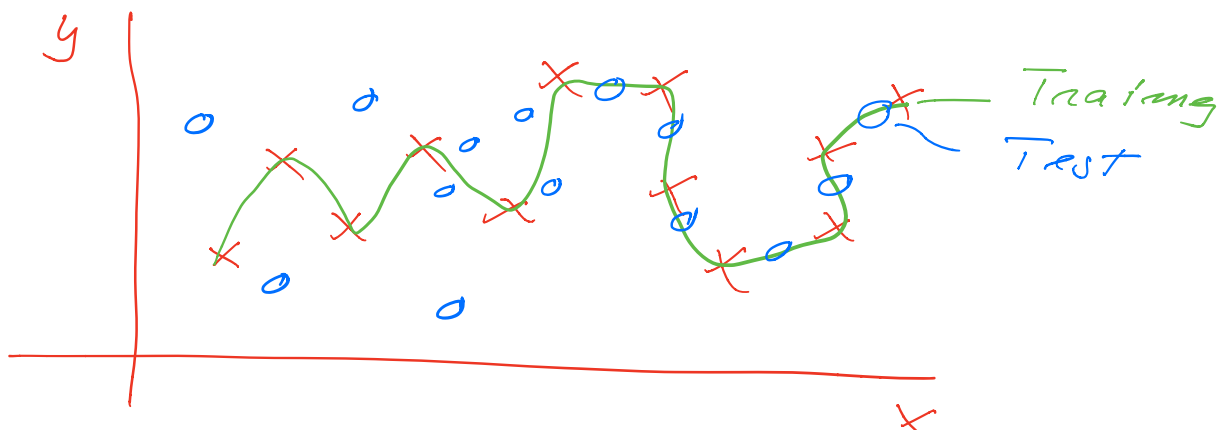
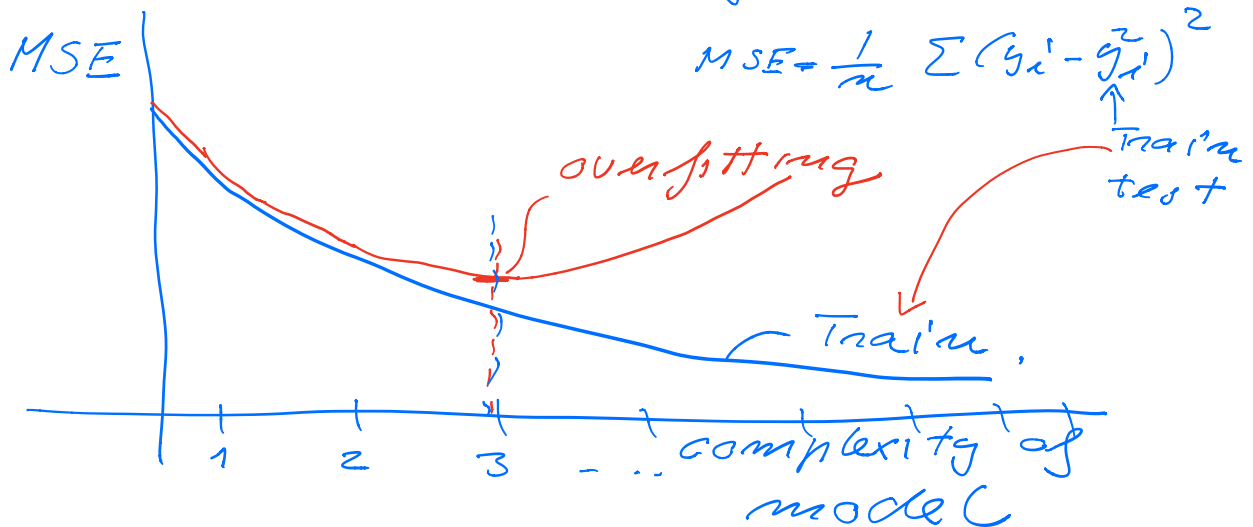


Some Elements from statistics

- split in training and test
- have a polynomial approx

$$\tilde{y}_i = \tilde{y}(x_i) = \sum_{j=0}^{p-1} \beta_j x_i^j$$

$$MSE = \frac{1}{n} \sum (y_i - \tilde{y}_i)^2$$



Moments

$$PDF = p(x)$$

continuous case

$$E[x^n] = \int x^n p(x) dx$$

mean value $\mu = E[x]$
Discrete pdf.

$$\mu = E[x] = \sum_{i=1}^n p(x_i) x_i$$

$$E[x^n] = \sum_{i=1}^n p(x_i) x_i^n$$

variance

$$\begin{aligned} \sigma^2 &= \text{var}[x] = \int (x-\mu)^2 p(x) dx \\ &= E[x^2] - \mu^2 \\ \text{var}[x] &= \sum_{i=1}^n (x_i - \mu)^2 p(x_i) \end{aligned}$$

often $p(x)$ is unknown,

\Rightarrow sample mean

$$\mu \neq \bar{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$$

sample variance

$$\sigma^2 \neq \bar{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{\mu})^2$$

covariance (sample)

$$\sigma(x, y) = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{\mu}_x)(y_i - \bar{\mu}_y)$$

$\sigma(x, y)$ (exact $p(x, y)$)

$$= \iint dx dy p(x,y) (x - \mu_x)(y - \mu_y)$$

$$= E[xy] - E[x]E[y]$$

$$= \iint dx dy p(x,y) x \cdot y - \mu_x \cdot \mu_y$$

if x and y are i.i.d

$$p(x,y) = p(x)p(y)$$

$$\iint dx dy p(x)p(y) x \cdot y =$$

$$\int dx p(x) x \int dy p(y) dy$$

$$= \mu_x \cdot \mu_y \Rightarrow$$

$$\text{covariance} = \sigma(x,y) = 0$$

$$x = y \Rightarrow \sigma(x,y) = \sigma(x,x) = \sigma^2(x)$$

Three variables x, y, z

$$x = [x_0, x_1, \dots, x_{n-1}]$$

$$y = [y_0, y_1, \dots, y_{n-1}]$$

$$z = [z_0, z_1, \dots, z_{n-1}]$$

covariance matrix

$$\begin{bmatrix} \boxed{\sigma(x,x)} & \sigma(x,y) & \sigma(x,z) \\ \sigma(x,y) & \sigma(y,y) & \sigma(y,z) \\ \sigma(x,z) & \sigma(y,z) & \sigma(z,z) \end{bmatrix}$$

variance

correlation matrix =

covariance divided by
the variance!

$$\begin{bmatrix} 1 & x & y \\ x & 1 & x \\ x & x & 1 \end{bmatrix}$$