

Bayesisk sannsynlighetsteori i maskinl ring

Klassifiserer : Gitt data (for trening, og for inferens),
designer et sample til en viss klasse

Decision rule : Bin rt tilfelle :

$X \rightarrow C_1 \text{ ders m } \mu(C_1 | X=x) > \mu(C_2 | X=x)$

ellers $x \rightarrow C_2$

↑
Klasse

Gitt at Data
↓ ↙

Posterior = Likelihood x Prior → Hvor stor andel
i data av de
forskj. klassene.

↓ ↓

$\mu(C_i | x)$ = $\mu(x | C_i) \cdot P(C_i)$

↙ ↘

F.eks. norm. f rdeling ↑ Tre varianter

Uni $\rightarrow \sigma_u, \mu_u$
Vgs $\rightarrow \sigma_v, \mu_v$
Grunnskole $\rightarrow \sigma_g, \mu_g$

Normalfordelinge

$$N(\mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

μ : Middelverdien ESTIMERT

σ : St. avvik ESTIMERT

$$\hat{\mu} = \frac{x_1 + x_2 + \dots + x_N}{N}$$

$$\hat{\sigma} = \frac{\sqrt{(x_1 - \hat{\mu})^2 + (x_2 - \hat{\mu})^2 + \dots + (x_N - \hat{\mu})^2}}{N}$$

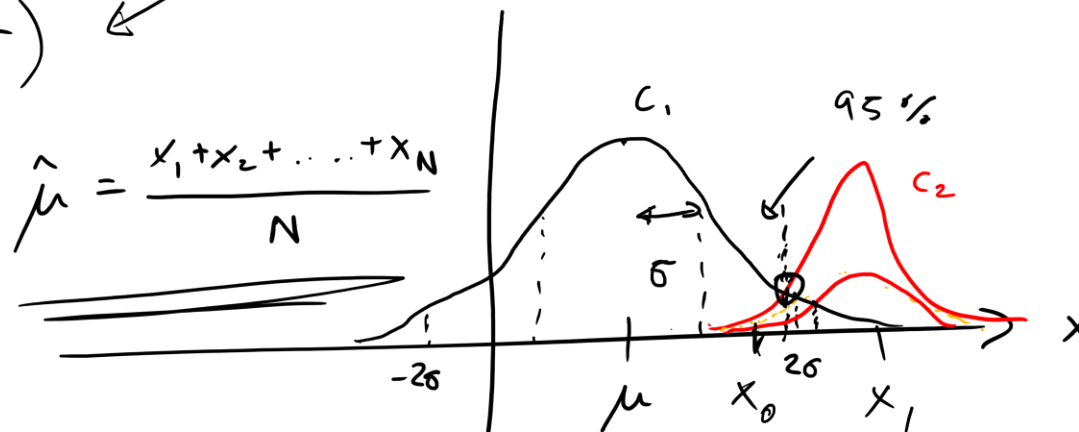
Kalles også MLE : "Maximum likelihood Estimation"

likelihood : $\mathcal{X} = \{x_1, x_2, x_3, \dots, x_N\} \begin{matrix} \nearrow \mu \\ \searrow \sigma \end{matrix}$

$$L(x) = p(x_1) \cdot p(x_2) \cdot p(x_3) \cdot \dots \cdot p(x_N)$$

$$= \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x_1-\mu}{\sigma}\right)^2} \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x_2-\mu}{\sigma}\right)^2} \cdot \dots \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x_N-\mu}{\sigma}\right)^2}$$

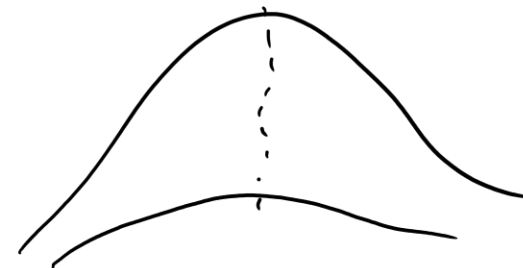
(se s. 70 i Alpaydin)



$$P(C_2) = \frac{N_2}{N_{tot}}$$

$$N_2 = \frac{1}{4} N_1$$

$$N_{tot} = N_2 + N_1$$



4 a) Spam-filter baseres på Bow-modell

Ser på d ord som kan opptrer. Opptrer ord $\#m$ i e-post,
 så settes feature $\#m$ til 1 ($x_m = 1$), $m = 1, \dots, d$

En e-post $\rightarrow \vec{X} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix} \sim \text{Bernoulli}(\vec{\pi})$

$$p_{\vec{\pi}}^+(\vec{x}) = \begin{cases} \pi_m & \text{om } x_m = 1 \\ (1 - \pi_m) & \text{om } x_m = 0 \end{cases}$$

$\uparrow \uparrow$
 SSH for at ord nr. m opptrer

$$= \frac{\pi_m^x (1 - \pi_m)^{1-x}}{\text{for } x \in \{0, 1\}}$$

Så for d ord i en e-post vil vi ha følgende ssh-fordeling (likelihood)

$$\begin{aligned} p^+(\vec{x} | \vec{\pi}) &= p_1(x) \cdot p_2(x) \cdot \dots \cdot p_d(x) \\ &= \pi_1^{x_1} (1 - \pi_1)^{1-x_1} \cdot \pi_2^{x_2} (1 - \pi_2)^{1-x_2} \cdot \dots \cdot \pi_d^{x_d} (1 - \pi_d)^{1-x_d} \\ &= \prod_{m=1}^d \pi_m^{x_m} (1 - \pi_m)^{1-x_m} \end{aligned}$$

$\{\pi_m\}^{+/-}$ må estimeres (for + og - kategori)

Hvordan: Gitt N spam og M ikke-spam, altså tot. $N+M$ samples

$$\hat{\pi}_m^+ = \frac{1}{N} \sum_{j=1}^N x_m^{+j} = \frac{1}{N} (1 + 1 + 1 + 0 + 0 + 1 + 1 + 1 \dots +)$$

$$\hat{\pi}_m^- = \frac{1}{M} \sum_{j=1}^M x_m^{-j}$$

Discriminant - funksjoner :

$$g_+(x^{\text{test}}) = \prod_{m=1}^d (\hat{\pi}_m^+)^{x_m^{\text{test}}} (1 - \hat{\pi}_m^+)^{(1-x_m^{\text{test}})} \frac{N}{N+M}$$

Prior
↓

$$g_-(x^{\text{test}}) = \prod_{m=1}^d (\hat{\pi}_m^-)^{x_m^{\text{test}}} (1 - \hat{\pi}_m^-)^{(1-x_m^{\text{test}})} \frac{M}{N+M}$$