


FoDA L4

Bayes' Rule

MLEs and Log-likelihoods

Sep 1, 2022



Student Names and Personal Pronouns

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my pronouns : he / him / his

Prof Phillips

text \xrightarrow{ML} []
Vector

Review

$$Pr(P=\text{blue} \wedge S=\text{green})$$

points

shirt

	S = green	S = red	S = blue
P = blue	0.3	0.1	0.2
P = white	0.05	0.2	0.15
$P_S(\cdot)$	0.35	0.3	0.35

$P_S(\cdot)$
marginal

$$Pr(P=\text{blue} | S=\text{red})$$

$$= \frac{Pr(P=\text{blue} \wedge S=\text{red})}{Pr(S=\text{red})} = \frac{0.1}{0.3}$$

f_x pdf

$$\int_{\omega \in \Omega} f_x(\omega) d\omega = 1$$

$$f_x(\omega) \in [0, \infty)$$

R.V.s x, y

$$f_{x,y}(x, y) \xrightarrow{\text{marginal}} f_x(x) = \int_{y \in \Omega_y} f(x, y) dy$$

$$f_{x|y}(x, y=g_i) = \frac{f_{x,y}(x, y_i)}{f_y(y_i)}$$

$$f_y(y_i) = \int_{x \in \Omega_x} f(x, y_i) dx$$

Bayes' Rule

Two events M, D

can compute

model

data

$$Pr(M|D) = \frac{Pr(D|M) \cdot Pr(M)}{Pr(D)}$$

$$Pr(M|D) = \frac{Pr(M \cap D)}{Pr(D)}$$

$$Pr(M \cap D) = Pr(M|D) \cdot Pr(D)$$

$$Pr(M \cap D) = Pr(D \cap M) = Pr(D|M) \cdot Pr(M)$$

$$Pr(M|D) \cdot Pr(D) = Pr(D|M) \cdot Pr(M)$$

$$Pr(D) = Pr(D=1)$$

	M=1	M=0
D=1	0.25	0.5
D=0	0.2	0.05

$$Pr(D|M) = \frac{Pr(D \cap M)}{Pr(M)}$$

$$= \frac{0.25}{0.45}$$

$$Pr(M|D) = \frac{Pr(D \cap M)}{Pr(D)} = \frac{0.25}{0.75} = \frac{1}{3}$$

$$Pr(M|D) = \frac{Pr(M \cap D)}{Pr(D)} = \frac{0.25}{0.75} = \frac{1}{3}$$

Cracked Windshield

event: W windshield cracked.

3 factors: A, B, C

$$Pr(A) = 0.5 \quad Pr(B) = 0.3 \quad Pr(C) = 0.2$$

$$Pr(W|A) = 0.01 \quad Pr(W|B) = 0.1 \quad Pr(W|C) = 0.02$$

$$Pr(A|W) = \frac{Pr(W|A) \cdot Pr(A)}{Pr(W)} = \frac{(0.01)(0.5)}{Pr(W)} = \frac{0.005}{Pr(W)}$$

$$Pr(B|W) = \frac{Pr(W|B) \cdot Pr(B)}{Pr(W)} = \frac{(0.1)(0.3)}{Pr(W)} = \frac{0.03}{Pr(W)}$$

$$Pr(C|W) = \frac{Pr(W|C) \cdot Pr(C)}{Pr(W)} = \frac{0.004}{Pr(W)}$$

$M = \text{model}$

$D = \text{data}$

$P_r(M|D)$

$$M \in \mathcal{J}_M$$

↑ spec-
↓ model

maximizes $P(M|D)$

↳ M^*

MAP

maximum
a posteriori

$$M^* = \underset{M \in \mathcal{J}_M}{\text{arg max}} P_r(M|D) = \underset{M \in \mathcal{J}_M}{\text{arg max}} \frac{P_r(D|M) \cdot P_r(M)}{\cancel{P_r(D)}}$$

Maximum
Likelihood
Estimate

↳ MLE assume

$P_r(M)$

constant

posterior
likelihood

$$M^* = \underset{M \in \mathcal{J}_M}{\text{arg max}} P_r(M|D)$$

$$P_r(M|D)$$

$$= \underset{M \in \mathcal{J}_M}{\text{arg max}} P_r(D|M)$$

$$P_r(D|M)$$

$D = \{x_1, x_2, \dots, x_n\}$ independent observations

$M =$ explaining structure in data

1. $D \subset \mathbb{R}^1$ Model: $M =$ value of average height
(Normally distributed)

2. linear regression

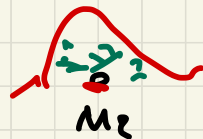
M line in \mathbb{R}^2



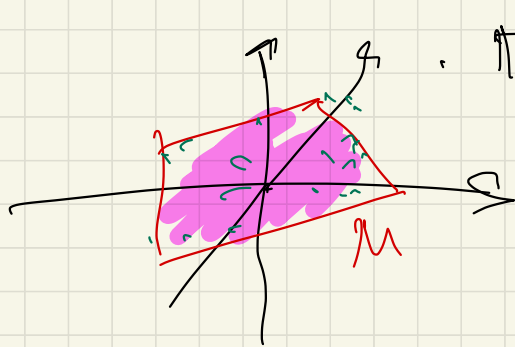
3. clustering

$D \subset \mathbb{R}^d$

M set of points



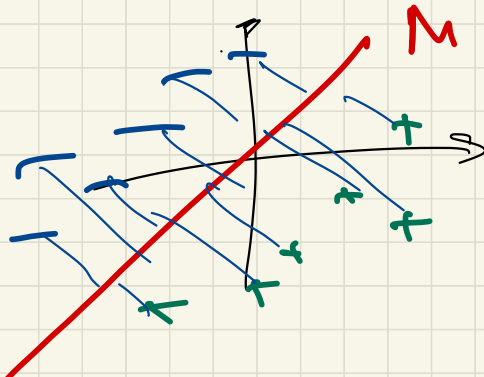
4. PCA $D \in \mathbb{R}^d$ $M \in \mathbb{F}_k$ k -dimensional subspace



dimensionality reduction

5. (linear) classification

$D \in \mathbb{R}^d$ $x_i \in \mathbb{R}^d$ $y_i \in \{-1, +1\}$



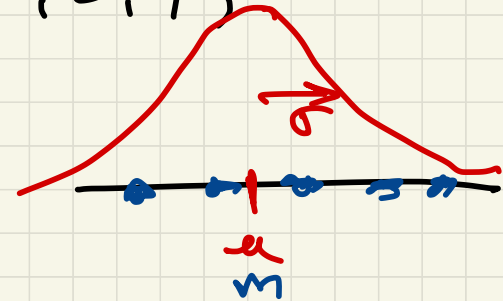
$$D \subset \mathbb{R}^1 = \{x_1, x_2, \dots, x_n\} = \{1, 3, 12, 5, 9\}$$

independent

Modeling

$$x_i \sim \mathcal{N}(\mu, \sigma)$$

model $M = m$



$$m \in \mathbb{R} = \mu_M$$

$$N_{m, \sigma}(x) = g(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(m-x)^2\right)$$

$$P_r(x_i = x \mid M = m)$$

$$P_r(D|M) = \prod_{x_i \in D} g(x_i) = \prod_{x_i \in D} \left(\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(m-x_i)^2\right) \right)$$

$$P_r(D|M) = \prod_{x_i \in D} g(x_i) = \prod_{x_i \in D} \left(\frac{1}{\sqrt{\sigma^2}} \exp\left(-\frac{1}{\sigma^2}(m-x_i)^2\right) \right)$$

$\underset{m \in \mathbb{R}}{\operatorname{arg\,max}}$ $P_r(D|M) = \underset{m \in \mathbb{R}}{\operatorname{arg\,max}} \log(P_r(D|M))$
 log-likelihood $\log(a \cdot b) = \log(a) + \log(b)$

$$= \underset{m}{\operatorname{arg\,max}} \log\left(\prod_{x_i} g(x_i)\right) = \underset{m}{\operatorname{arg\,max}} \sum_{x_i} \log(g(x_i))$$

$$= \underset{m}{\operatorname{arg\,max}} \sum_{x_i} \left(-\frac{1}{\sigma^2}(m-x_i)^2\right) + \cancel{\sum_{x_i} \log\left(\frac{1}{\sqrt{\sigma^2}}\right)}$$

$$= \operatorname{average}(x_1, \dots, x_n)$$