

FoDA

L5

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Bayesian

Inference

Bayes' Rule

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

$\propto$   
proportional  
to

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

possibly unknown  
but fixed constant  $c$ .

posterior

$$P(M|D)$$

arg max  
M  $\rightarrow$  MAP estimate

$L(M)$  likelihood

$$\propto f(D|M) \cdot \pi(M)$$

prior  $\pi$

arg max  
M  $\rightarrow$  MLE

# Average Height

Given  $D = \{x_1, x_2, \dots, x_n\} = \{1, 3, 5, 9, 12\}$   
estimate height  $M$  of typical student  
at U. of U.

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prior  $r(M) = \mathcal{N}_{66, 6}(M) = \frac{1}{\sqrt{\pi \cdot 72}} \exp\left(-\frac{(M-66)^2}{2 \cdot 6^2}\right)$

mean  $\mu=66$       std-dev  $\sigma=6$   
inches

MLE (from like-likelihood of data  $D$ )  
= 5.5 feet

likelihood  $f(D|M) = \prod_{x \in D} g(x) = \prod_{x \in D} N_{\mu, \sigma^2}(x)$

assume  $\sigma = 2$



independence

$$= \prod_{x \in D} \left( \frac{1}{\sqrt{8\pi}} \cdot \exp\left(-\frac{1}{8}(M-x)^2\right) \right)$$

$$r(M) = \frac{1}{\sqrt{72\pi}} \exp\left(-\frac{(M-66)^2}{72}\right)$$

0.02      0.02

$\sigma = 6$   
 $\rho = 0.1$

posterior

$$P(M|D) \propto f(D|M) \cdot r(M)$$

$$\ln(P(M|D)) \propto \ln(f(D|M)) + \ln(r(M)) + C$$

$$\propto \left( \sum_{x \in D} \left(-\frac{1}{8}(M-x)^2\right) \right) - \frac{1}{72} (M-66)^2 + C'$$

50

$$\propto - \left( \sum_{x \in D} (M-x)^2 \right) - (M-66)^2 + C''$$

450

# Weighted Average

$(x_i, w_i)$

n values  $x_1, x_2, \dots, x_n$

weight

n weights  $w_1, w_2, \dots, w_n$

$w_i \geq 0$

$$\bar{x} = \frac{\sum_{i=1}^n w_i \cdot x_i}{\sum_{i=1}^n w_i}$$

$$W = \sum_{i=1}^n w_i$$

$$p_i = \frac{w_i}{W} \in [0, 1]$$

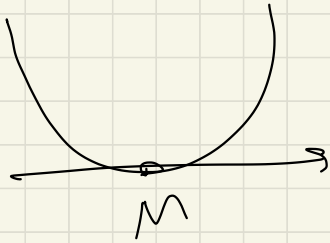
$$E[x_i] = \sum_{i=1}^n p_i \cdot x_i$$

$$\sum_{i=1}^n p_i = 1$$

$n$  values  $X = \{x_1, x_2, \dots, x_n\}$

$$S(M) = \sum_{i=1}^n (x_i - M)^2 = \sum_{i=1}^n (M^2 - 2x_i M + x_i^2)$$

$$= nM^2 - \left(2 \sum_{i=1}^n x_i\right)M + \sum_{i=1}^n x_i^2$$



$$\frac{\partial S(M)}{\partial M} = 2nM - 2 \sum_{i=1}^n x_i = 0$$

$$M = \frac{1}{n} \sum_{i=1}^n x_i$$

$$P(M|D) \propto \exp(\ln(P(M|D) \pm c))$$

- compare models

$$M_1, M_2 \quad P(M_1|D) > P(M_2|D)$$

$$\frac{P(M_1|D)}{P(M_2|D)} = z$$

- Marginalize over models

$$\sum_{M \in \mathcal{M}} P(M|D) \cdot h(M) \delta_M$$


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$$\sum_{M \in \mathcal{M}} P(M|D)$$

