

Wp3 - Bayesian hypothesis comparison

Vaccine vs Control treatment

f_v = prob of disease in V group

f_c = " " in C group

H_1 : V is better than control : $f_v < f_c$

H_0 : $V = C$: $f_v = f_c$

$$P(H_1|D) = \frac{P(D|H_1) \cdot P(H_1)}{P(D)}$$

$$P(H_2|D) = \frac{P(D|H_2) \cdot P(H_2)}{P(D)}$$

$$P(D) = \sum_{\text{all hypotheses}} P(D|H_i) \cdot P(H_i)$$

b.t

$$\frac{P(H_1|D)}{P(H_2|D)} = \frac{P(D|H_1) \cdot P(H_1)}{P(D|H_2) \cdot P(H_2)}$$

i f $P(H_1) = P(H_2)$ prior

$$\left\{ \frac{P(H_1|D)}{P(H_2|D)} = \frac{P(D|H_1)}{P(D|H_2)} \right\}$$

$H_1 \leftrightarrow H_0 \rightarrow$ compare the evidences of D
under the two hypotheses

$P(D|H) \rightarrow$ integrate to all values of the parameters
that define H .

$$P(D|H_1) = \int_{f_c} \int_{\substack{f_v \\ f_v < f_c}} P(D|f_v, f_c) \cdot P(f_c, f_v) df_c df_v$$

$$P(D|H_0) = \int_f P(D|f_v, f_c) P(f, f) df$$

$$\int_0^1 df_c \int_0^{f_c} df_v \frac{n_v}{f_v (1-f_v)} \frac{N_v - n_v}{f_c} \frac{n_c}{f_c (1-f_c)} \frac{N_c - n_c}{f_c (1-f_c)}$$

$$\frac{P(D|H_1)}{P(D|H_0)} = \frac{\int_0^1 df_c \int_0^{f_c} df_v \frac{n_v}{f_v (1-f_v)} \frac{N_v - n_v}{f_c} \frac{n_c}{f_c (1-f_c)} \frac{N_c - n_c}{f_c (1-f_c)}}{\int_0^1 df f^{n_v} (1-f)^{N_v - n_v} f^{n_c} (1-f)^{N_c - n_c}}$$

$$\left. \begin{array}{l} N_c = 10 \\ n_c = 3 \end{array} \right\}$$

$$\left. \begin{array}{l} N_v = 30 \\ n_v = 3 \end{array} \right\}$$

$$\approx \frac{0.003}{0.001} \approx 3$$

$H_1 : H_0$

1 : 1

↓

3 : 1

← data

→ go to code

Occam's razor

If several models can explain the observations,
always go with the simpler model.

why?
simplicity
restlehrs
avoid overfitting
bayes tells us so

Consider two nested hypotheses

H_1

$\# \text{param } H_1 > \# \text{param } H_2.$

H_2

$H_2 \subset H_1$

(y_i, x_i)

$H_1 : y_i = w_0 + w_1 x_i$

$H_2 : y_i = w_0$

* If ML fit of parameters to data.

H_1 will always be more favorable

* If bayesian comparison of H_1, H_2 ?

$$\frac{P(H_1|D)}{P(H_2|D)} = \frac{P(D|H_1)}{P(D|H_2)}$$

$$P(D|H_1) = \int_{P_1} P(D|P_1) P(P_1) dP_1$$

$$P(D|H_2) = \int_{P_2} P(D|P_2) \cdot P(P_2) dP_2$$

$$\begin{aligned} \log P(D|P_1) &\approx \log P(D|P_1^*) + \frac{1}{2} \frac{\delta^2 \log P(D|P_1)}{\delta P_1^2} \bigg|_{P_1=P_1^*} (P_1 - P_1^*)^2 \\ &= \log P(D|P_1^*) - \frac{(P_1 - P_1^*)^2}{2\sigma_1^2} \end{aligned}$$

$$\sigma_1^2 = - \frac{1}{\frac{\delta^2 \log P(D|P_1)}{\delta P_1^2} \bigg|_{P_1=P_1^*}}$$

Then

$$P(D|P_1) \approx P(D|P_1^*) e^{-\frac{(P_1 - P_1^*)^2}{2\sigma_1^2}}$$

$$P(P_1) = \begin{cases} \frac{1}{P^+ - P^-} \equiv \frac{1}{\sigma_1} & P^- \leq P_1 \leq P^+ \\ 0 & \text{otherwise} \end{cases}$$

$$P(D|H_1) = P(D|P_1^*) \int_{P^-}^{P^+} e^{-\frac{(P_1 - P_1^*)^2}{2\sigma_1^2}} \frac{1}{\sigma_1} dP_1$$

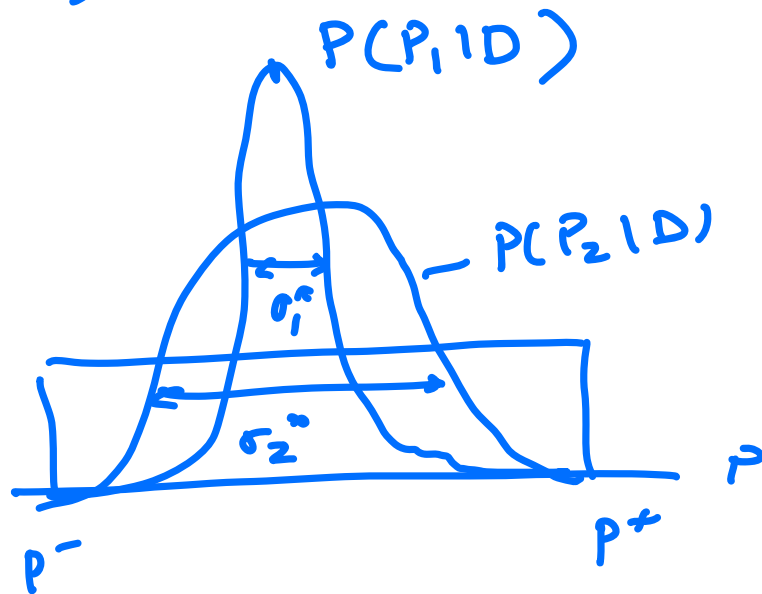
$$\approx P(D|P_1^*) \sqrt{2\pi} \sigma_1^* / \sigma_1$$

$$\frac{P(H_1|D)}{P(H_2|D)} = \underbrace{\frac{P(D|P_1^*)}{P(D|P_2^*)}}_{\text{Maximum Likelihood term}} \underbrace{\frac{\sigma_1^*/\sigma_1}{\sigma_2^*/\sigma_2}}_{\text{Bayesian Occam's razor}}$$

$$H_1 \supset H_2 \quad P(D|P_1^*) > P(D|P_2^*)$$

depends on σ_1^*/σ_2

if $\sigma_1^* < \sigma_2^*$ H_2 has chance to win



Example

One or two different bacterial colonies?

