

Ex

P(HC)? yes.

P(HC | MIT)?

$$P(C | P(C|MIT) < P(C|MIT) \\ \downarrow \swarrow \\ MIT. < P(C|C \cdot MIT)$$

P(HC | MIT)

<f>. Explain toward prob high.
 $P(HC) < P(H|BC)$.

Model selection.

have data (evidence & multiple models)

Mis

pick most model ($\max P(M|data)$).

Ex] 2 coins: fair ($P(H) = 0.5$) C_1 ^{assumptions} $\propto P(X_1 = x_1, \dots, X_n = x_n | Y=y) \cdot P(Y=y) \text{ const}$
 unfair ($P(H) = 1$) C_2 $\propto P(X_1 = x_1 | Y=y) \cdot P(\dots) \cdot P(X_n = x_n | Y=y)$
 2 models ① Draw coin randomly & flip $\times 3$
 ② draw coin "flip" $\times 3$.

data = HHT.

- assume. prior $\ominus P(M_1) = P(M_2) = \frac{1}{2}$

$$\text{MAX } P(M=M_i | data) = \frac{P(data | M=M_i) P(M_i)}{P(data)} \leftarrow \text{const.}$$

$$M_1 = P(HHT | M_1) = \frac{3}{4} \cdot \frac{3}{4} \cdot \frac{1}{4} = \frac{9}{64}$$

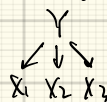
$$P(H) = P(H | C_1) \cdot P(C_1) + P(H | C_2) \cdot P(C_2) = \frac{1}{2} \cdot \frac{1}{2} + 1 \cdot \frac{1}{2} = \frac{3}{4}$$

$$M_2 = \frac{P(HHT | M_2)}{P(HHT | C_1) \cdot P(C_1) + P(HHT | C_2) \cdot P(C_2)} = \frac{(\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2}) \cdot \frac{1}{2} + (1 \cdot 1 \cdot 0) \cdot \frac{1}{2}}{\frac{1}{16} + 0} = \frac{1}{16}$$

Applications

Naive Bayes Classification

- assumption "features are cond indep. of each other given classification" "given parents"



Ex] "likes toy" (inverse "likes veggies")
 (for entire pop.)

"given child" "toy" \perp "veggies".

training pts (data) \rightarrow calculate prob.

$$\text{Classification} = \max_{\text{posterior prob.}} \left(\underbrace{P(Y=y | data)}_{\text{joint prob.}} \right) = \underbrace{P(data | Y=y)}_{P(data)} \cdot \underbrace{P(Y=y)}_{\text{prior}}$$

