

Lee 3 2/2/17 Mark 341

Law of total prob. $P(A) = \sum_{i=1}^K P(A|B_i) P(B_i)$ by msa. cond. coll. evts.

$$\Rightarrow P(A) = \sum_{i=1}^K P(A|B_i) P(B_i) = \sum_{i=1}^K P(A|B_i) P(B_i)$$

likelihood/prob of data

$$P(B|A) = \frac{P(A|B) P(B)}{P(A)} \leftarrow \text{prior on param of interest}$$

$$= \frac{P(A|B) P(B)}{\sum_{i=1}^K P(A|B_i) P(B_i)} \quad \text{Bayes Thm}$$

$$P(B) \xrightarrow[\text{data/evidence}]{A} P(B|A)$$

Posterior on param of interest

Your answer gets better with data.

Another way to think about prob:

$$\text{Odds}(A) := \frac{P(A)}{P(A^c)} = \frac{P(A)}{1-P(A)}$$

assume $P(A) \in (0, 1)$ i.e. $\neq 0, \neq 1$

Odds = 4 "4:1" i.e. 4 times out of 5 it will occur on avg.

Range? $(0, \infty)$

$$\text{Odds}_A(A) := \frac{1}{\text{Odds}_A(A^c)} = \frac{P(A^c)}{P(A)} = \frac{1-P(A)}{P(A)}$$

"odds against"

4:1 odds against \Rightarrow 4 times out of 5 it will not occur.

$$P(A) = 0.2, P(B) = 0.06, P(A|B) = 0.036$$

$$P(A|B) = \frac{0.036}{0.06} = 0.6, P(A|B^c) = \frac{P(A, B^c)}{P(B^c)} = \frac{0.164}{0.94} = 0.174$$

$$P(A) = P(A|B) + P(A|B^c)$$

$$0.2 = 0.06 + P(A|B^c) \Rightarrow P(A|B^c) = 0.14$$

$$P(B|A) = P(A|B) P(B)$$

$$P(B^c|A) = P(A|B^c) P(B^c)$$

$$\Rightarrow \frac{P(B|A)}{P(B^c|A)} = \frac{P(A|B)}{P(A|B^c)} \frac{P(B)}{P(B^c)}$$

posterior odds

11
0.22

likelihood ratio

11
3.44

prior odds

11
0.064

16:1 odds against

$$P(A|B) = \frac{0.036}{0.06} = 0.6$$

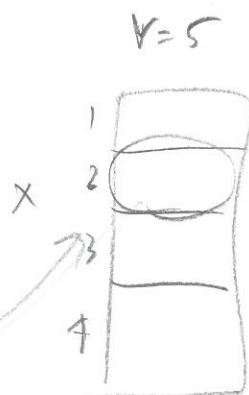
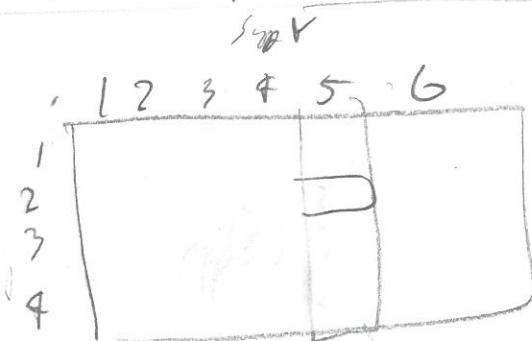
$$P(A|B^c) = \frac{0.164}{0.94} = 0.174$$

$$P(B, B^c) = P(A) - P(A|B) = 0.2 - 0.036 = 0.164$$

5:1 odds against

data

What is Bayes' theorem?



$$P(X=2|Y=5) = \frac{P(X=2, Y=5)}{P(Y=5)}$$

Bayes rule for r.v. usually denoted

$$P(X|Y) = \frac{P(X, Y)}{P(Y)}$$

or in long hand...

$$P(X=x|Y=y) = \frac{P(X=x, Y=y)}{P(Y=y)}$$

$$P(X=1, Y=5) + P(X=2, Y=5) + P(X=3, Y=5) + P(X=4, Y=5)$$

Normalization Law of Total Prob

$$\Rightarrow P(Y) = \sum_{x \in \mathcal{X}(X)} P(X, Y)$$

for PMFs

$$\text{or } P(Y) = \sum_{x \in \mathcal{X}(X)} P(X|Y) P(X)$$

$$\Rightarrow f_Y(y) = \int_{x \in \mathcal{X}(X)} f_{X,Y}(x, y) dx$$

for PDFs

$$\text{or } f_Y(y) = \int_{x \in \mathcal{X}(X)} f_{X|Y}(x|y) f_X(x) dx$$

Back to the story...

MLE's have issues... all frequentist stats has issues...

Why don't we consider θ our area of interest? X ok for data.

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)}$$

What's wrong?

(1) $P(\theta)??$ θ is one immutable value!! $P(\theta)$ is degenerate! $\sim \text{deg}(\theta)$
and you don't know it!!

(2) $P(x)$ makes no sense... you can't calc. prob of data without knowing θ , so using $P(x) = \sum_{\theta_0 \in \Theta} P(x|\theta_0)P(\theta_0)$ has $P(\theta_0)$ which will be 0 except for when $\theta_0 = \theta \Rightarrow P(\theta_0) = 1$
 $\Rightarrow P(x) = P(x|\theta)$

\Rightarrow (3) $P(\theta|x) = P(\theta) = 1$ if θ is its true value. Clearly not useful!

Frequentism: θ is a value

Bayesian: data... but we can use $P(\theta)$ to represent uncertainty in this value a priori. $\Rightarrow \theta$ is a r.v.

$$\Rightarrow P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)}$$

Now is coherent

" \leftarrow How is this calc?

and by Bayes Thm $P(\theta|x) = \frac{P(x|\theta)P(\theta)}{\sum_{\theta_0 \in \Theta} P(x|\theta_0)P(\theta_0)}$ or $\frac{P(x|\theta)P(\theta)}{\int P(x|\theta_0)P(\theta_0)d\theta_0}$

X: Data (the effect)

θ : Model (the cause)

$P(X|\theta)$ effect | cause

$P(\theta|X)$ cause | effect \Rightarrow the "inverse problem"

What does this mean. Let X be Bernoulli, $X = (0, 1, 1)$
and these two models $\theta = 0.75$ $\theta = 0.25$... absurd ... but let's go with it...

$$P(X|\theta = 0.75) = .25 \cdot .75 \cdot .75 = .141$$

$$P(X|\theta = 0.25) = .75 \cdot .25 \cdot .25 = .047$$

Model #2 is more likely but what is explicitly $P(\theta = 0.75 | X)$?

$$= \frac{P(X|\theta=0.75) P(\theta=0.75)}{P(X)} = \frac{P(X|\theta=0.75) P(\theta=0.75)}{P(X|\theta=0.75) P(\theta=0.75) + P(X|\theta=0.25) P(\theta=0.25)}$$

Result of Bayes theorem

Need $P(\theta=0.75)$, $P(\theta=0.25)$. Reminder... we are allowed to consider our prior uncertainty in the model param what should we choose?

$$P(\theta) = \begin{cases} 0.75 & \text{up } \frac{1}{2} \\ 0.25 & \text{up } \frac{1}{2} \end{cases}$$

"Principle of indifference": All models equally likely a priori

X and θ are both r.v.'s. let's visualize them

$$\theta \in \Theta = \{0.75, 0.25\}$$

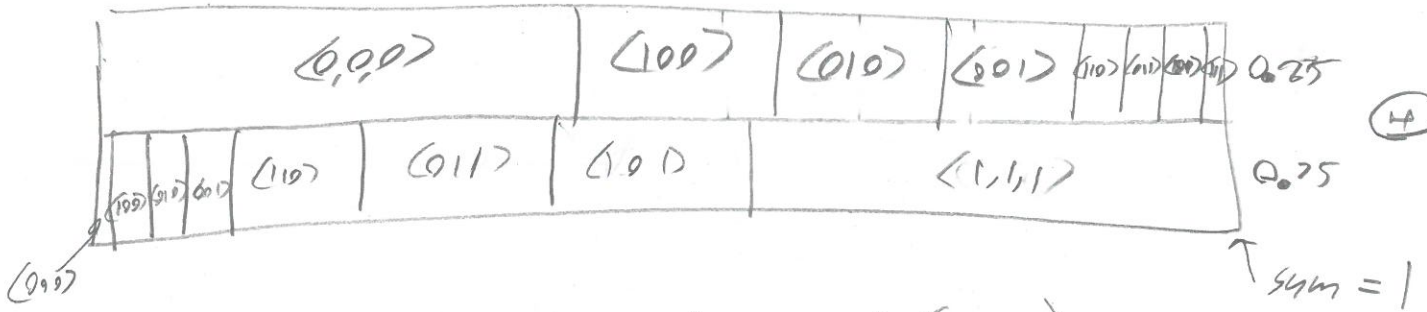
$$X \in \mathcal{X} = \text{supp}[X]^3 = \{0,1\} \times \{0,1\} \times \{0,1\}$$

"data space"

$$= \{(0,0,0), (0,0,1), (0,1,1), (1,1,1), (1,1,0), (1,0,0), (0,1,0), (1,0,1)\}$$

X

5



$$P(X = \langle 000 \rangle \text{ \& } \theta = 0.25) = P(\langle 000 \rangle | \theta = 0.25) P(\theta = 0.25)$$

$$P(X = \langle 100 \rangle \text{ \& } \theta = 0.25) = \frac{0.75^3 \cdot 0.5}{0.412} = .211$$

$$= \frac{.25 \cdot .75^2 \cdot 0.5}{0.141} = .070$$

$$P(X = \langle 110 \rangle \text{ \& } \theta = 0.25) = \frac{.25^2 \cdot 0.75 \cdot 0.5}{.047} = .023$$

$$P(X = \langle 111 \rangle \text{ \& } \theta = 0.25) = \frac{.25^3 \cdot 0.5}{.016} = .008$$

$$P(X = \langle 000 \rangle \text{ \& } \theta = 0.75) = \frac{.25^3 \cdot 0.5}{.016} = .008$$

Opposite!



easily understood the denominator

$$P(X = \langle 011 \rangle) = P(X = \langle 011 \rangle \text{ \& } \theta = 0.25) + P(X = \langle 011 \rangle \text{ \& } \theta = 0.75)$$

$$= .023 + .070 = .094$$

Is this a different piece of evidence? YES



Is θ indep of X?

NO

Knowing θ tells you
something about X,
knowing X tells you
something about θ .

Now what's the prob of $P(\theta = 0.75 | x = (0,1,1))$? $\neq P((0,1,1) | \theta = 0.75)$ 6

$$= \frac{P(x = 0,1,1 \& \theta = 0.75)}{P(x = 0,1,1)}$$

=

$$\frac{\cancel{\text{[scribble]}}}{\cancel{\text{[scribble]}} + \boxed{0.020}} = \frac{.020}{.023 + .020} = 0.75$$

(Coincidence that $\theta = 0.75$)

And of course $P(\theta = 0.25 | x = (0,1,1)) = 1 - P(\theta = 0.75 | x = (0,1,1)) = 0.25$

$$\frac{P(\theta = 0.75)}{0.5} \xrightarrow{\times} \frac{P(\theta = 0.75 | x = (0,1,1))}{0.75}$$

Bayesian Conditional

$$0.75 = \frac{0.141}{0.09 \cdot 0.5}$$

1.504

$$\frac{0.5}{0.5} = 1 \text{ prior odds} = 1$$

$$\frac{P(\theta = 0.75 | x = (0,1,1))}{P(\theta = 0.25 | x = (0,1,1))} = \frac{P(x = (0,1,1) | \theta = 0.75)}{P(x = (0,1,1) | \theta = 0.25)} \frac{P(\theta = 0.75)}{P(\theta = 0.25)}$$

$$\frac{0.75}{0.25} = \frac{.141}{.047} = \frac{.25 \cdot .25 \cdot .75}{.75 \cdot .75 \cdot .25} = 3$$

Note: odds doesn't require computing $P(x)$

posterior odds = 3

$P(x = (0,1,1))$ is the prior on the data... what does the prob of this data look like averaged over prior on θ . "Prior pred. data"

Let $\Theta = \{0.1, 0.25, 0.5, 0.75, 0.9\}$

$$P(\theta) = \begin{cases} 0.25 \\ 0.5 \\ 0.25 \\ 0.1 \end{cases} \text{ up } \frac{1}{5}$$

equally likely

So we have $x = \langle 0, 1, 1 \rangle$

$$P(\theta|x) = \frac{P(x|\theta) P(\theta)}{P(x)} = \left(\frac{1}{P(x)} \right) P(x|\theta) P(\theta) \propto P(x|\theta) P(\theta) \propto P(x|\theta)$$

↑
Same for all values of θ



$$P(\theta=0.75|x) \propto P(x|\theta=0.75) \text{ but how to get constant?}$$

$$\text{multiplied by } \frac{P(\theta)}{P(x)}$$

Σ of all bars

How likely is this data over all possible stories?

Recall $\hat{\theta}_{MLE} = 0.66$ "was best guess" of θ is the "pt. estimate".

What's our best guess of θ now?

$\theta = 0.75$. Why? Most likely given data!

Kind of like MLE!