

lec 5 2/4/18 Prob 341

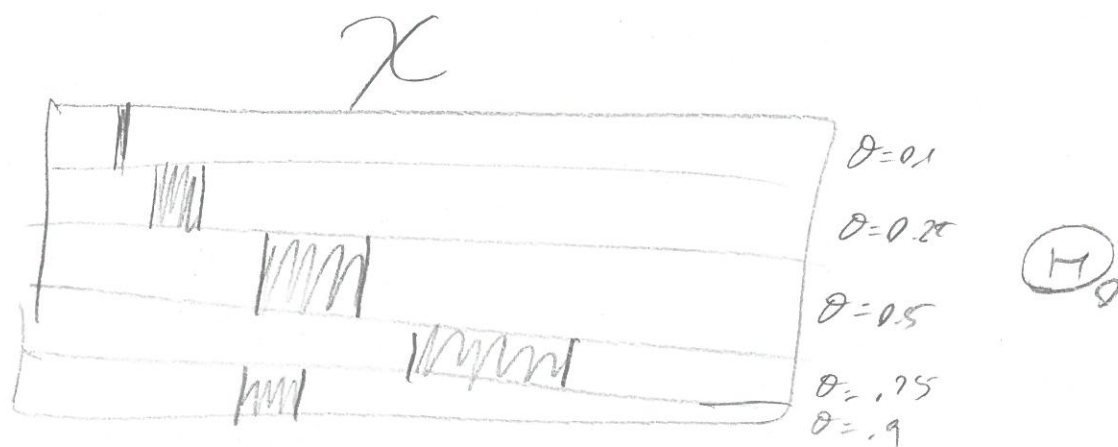
$F = \text{Bernoulli}$

$X = (0, 1, 1)$

$$\Theta_0 = \{0.1, 0.25, 0.5, 0.75, 0.9\}$$

$\theta \sim U(\Theta_0)$ i.e. discrete uniform on the elements of Θ_0 i.e. $P(\theta) = 0.2$

We want to find $P(\theta|x)$. Before we do that... draw picture.



$P(X|\theta)$ represents the prop. of area in any slice.

$$P(X|\theta=0.1) = 0.009$$

$$P(X|\theta=0.25) = 0.047$$

$$P(X|\theta=0.5) = 0.125$$

$$P(X|\theta=0.75) = 0.141$$

$$P(X|\theta=0.9) = 0.061$$

$P(\theta|x)$ is the slices div by the total area of all slices

What is best model already? Biggest slice of the slices $\theta = 0.75$

Already you see its $P(\theta|x)$ is going to be the largest

Bigger slice of the slices is a form of pt. estimation (over guess of θ)!

$$\hat{\theta}_{\text{MAP}} = \underset{\theta \in \mathcal{H}_0}{\text{argmax}} \{ P(\theta|x) \} = \underset{\theta \in \mathcal{H}_0}{\text{argmax}} \left\{ \frac{P(x|\theta) P(\theta)}{P(x)} \right\}$$

↑
Max. a posteriori
Bayesian estimate
(AKA "posterior mode")

$$= \underset{\theta \in \mathcal{H}_0}{\text{argmax}} \{ P(x|\theta) P(\theta) \}$$

since $P(x)$ is a normalizing constant $\neq f(\theta)$

$$= \underset{\theta \in \mathcal{H}_0}{\text{argmax}} \{ P(x|\theta) \}$$

since $P(\theta)$ is the same for all $\theta \in \mathcal{H}_0$ $\neq f(\theta)$

$$= \hat{\theta}_{\text{MLE}}$$

$$P(\theta|x) = \underbrace{P(x|\theta)}_{\text{scale based on prior belief (height)}} \cdot \underbrace{P(\theta)}_{\text{normalise so all } P(\theta|x) \text{'s add up to 1 (relative to other slices)}}$$

Under principle of difference...

$$P(\theta|x) = \frac{P(x|\theta) P(\theta)}{\sum_{\theta \in \mathcal{H}_0} P(x|\theta) P(\theta)} = \frac{P(x|\theta)}{P(x|\theta_1) + \dots + P(x|\theta_K)}$$

use this for... $P(\theta = .75 | x = (0,1))$

$$= \frac{0.191}{0.007 + .047 + .125 + .141 + .061} = \frac{.191}{.383} \approx 37\%$$

$\hat{\theta}_{\text{MAP}} = \hat{\theta}_{\text{MLE}}$ but $0.75 \neq 0.66$ why? Our choice of prior did not cover all of the parameter space! $\mathcal{H}_0 \neq \mathcal{H} = (0,1)$ (for $Z = \text{Bernoulli}$)

Main skeptic of Bayesian stats: Prior could be wrong!

Let's look at data one at a time $\Theta = \{0.25, 0.75\}$ (independent) $X_1 = 0$ (3)

What we know from ... prior and X_1

let $P(\Theta | X_1)$ be our new prior.

\Rightarrow No longer indifferent!

$X_2 = 1$

$$P(\Theta = 0.25 | X_1 = 0) = \frac{P(X_1 = 0 | \Theta = 0.25)}{P(X_1 = 0 | \Theta = 0.25) + P(X_1 = 0 | \Theta = 0.75)}$$

$$= \frac{0.25}{0.25 + 0.25} = 0.5$$

$$\Rightarrow P(\Theta = 0.75 | X_1 = 0) = 0.25 = 1 - P(\Theta = 0.25 | X_1 = 0)$$

$$P(\Theta = 0.25 | X_2 = 1) = \frac{P(X_2 = 1 | \Theta = 0.25) P(\Theta = 0.25 | X_1)}{P(X_2 = 1 | \Theta = 0.25) P(\Theta = 0.25 | X_1) + P(X_2 = 1 | \Theta = 0.75) P(\Theta = 0.75 | X_1)}$$

$$= \frac{0.25 \cdot 0.5}{0.25 \cdot 0.5 + 0.75 \cdot 0.25} = 0.5$$

we're back to square 1. For this prior, no information learned. But same?

Now we know prior, X_1, X_2 . Use this as prior

let $P(\Theta | X_2, X_1)$ be new prior when $X_3 = 1$.

$$P(\Theta = 0.25 | X_3 = 1) = \frac{P(X_3 = 1 | \Theta = 0.25) P(\Theta = 0.25 | X_2, X_1)}{P(X_3 = 1 | \Theta = 0.25) P(\Theta = 0.25 | X_2, X_1) + P(X_3 = 1 | \Theta = 0.75) P(\Theta = 0.75 | X_2, X_1)}$$

$$= \frac{0.25 \cdot 0.5}{0.25 \cdot 0.5 + 0.75 \cdot 0.5} = 0.25$$

Same as $P(\Theta = 0.25 | X = (0, 1, 1))$ from previously.

Is this true in general?

$$P(\Theta | X_1, \dots, X_n) = \frac{P(X_1, \dots, X_n | \Theta) P(\Theta)}{P(X_1, \dots, X_n)}$$

$$= \frac{P(X_1 | \Theta) \cdots P(X_n | \Theta) P(\Theta)}{P(X_1, \dots, X_n | X_1) P(X_1)} = P(\Theta | X_1)$$

$$= \frac{P(X_1 | \Theta) \cdots P(X_n | \Theta) P(\Theta)}{P(X_1, \dots, X_n | X_1, X_2) P(X_1, X_2)} = P(\Theta | X_1, X_2)$$

etc...

Why? iid

New question: we have seen X_4 yet. What is it for?

Of course $P(X_4 | \theta) = \theta^{x_4} (1-\theta)^{1-x_4}$ but... you don't know θ .

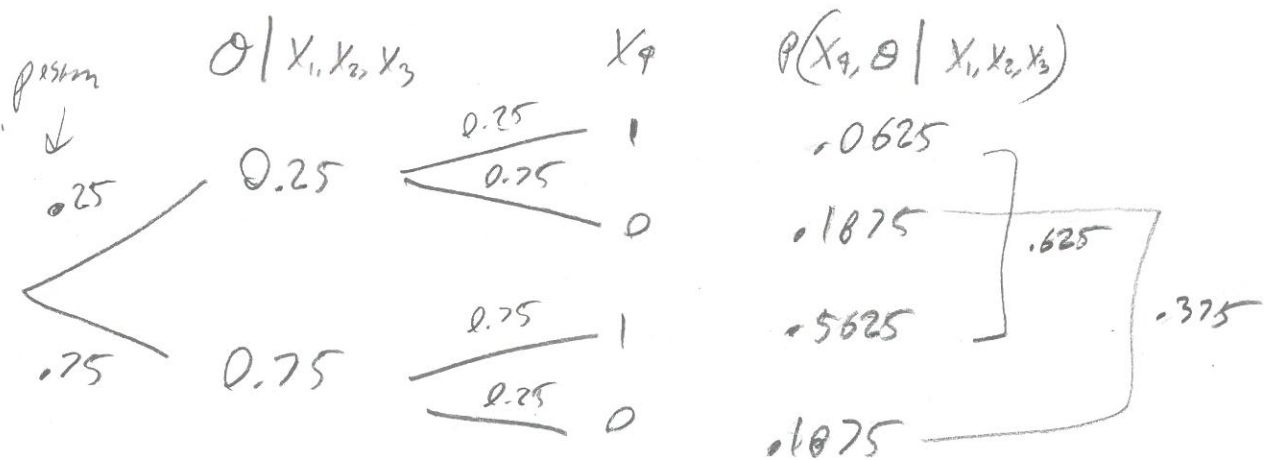
Previously... what did you do?

$$P(X_4 | \theta) \approx P(X_4 | \theta = \hat{\theta}_{MLE} = 0.66) = \text{Bern}(0.66)$$

What's the problem? Uncertainty in $\hat{\theta}_{MLE}$...

Bayesian Solution:

Seek: $P(X_4 | X_1, X_2, X_3)$



$$\Rightarrow P(X_4 | X_1, X_2, X_3) = \text{Bern}(0.625)$$

This incorporates all uncertainty of θ arising de prior & data.