

Lecture 4:

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

Bayes rule for 2 r.v's x, y

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

Assume θ was fixed i.e. $\theta \sim \text{Deg}(\theta_0)$

$\rightarrow P(X=x | \theta = \theta_0)$ Jmf, JDF. equal to likelihood

$$P(\theta) = \begin{cases} 1 & \text{if } \theta = \theta_0 \\ 0 & \text{otherwise (0!t)} \end{cases}$$

$$\Rightarrow P(\theta | x) = \begin{cases} \frac{P(x | \theta = \theta_0)}{P(x)} & \text{if } \theta = \theta_0 \\ 0 & \text{if } \theta \neq \theta_0 \end{cases}$$

$$P(x) = \sum_{\theta \in \Theta} P(x | \theta) P(\theta) = P(x | \theta = \theta_0)$$

$$= \int_{\Theta} P(x | \theta) P(\theta) d\theta$$

no information about θ .

Whole thing.
USEless

Assume θ is a non degenerate r.v.

$P(\theta|x)$.

$$P(\theta|x) = \frac{\overbrace{P(x|\theta)}^{\text{Likelihood}} \overbrace{P(\theta)}^{\text{Prior}}}{\underbrace{P(x)}}.$$

Prior predictive distribution.

$$= \frac{P(x, \theta)}{\sum_{\theta \in \Theta} P(x, \theta)}$$

Prior:- Your thoughts about θ before you see any data.

Posterior:- Your thought about θ after you see the data, x .

For example: $F = \text{iid Bernoulli}$, But

~~$\theta \sim \text{Bernoulli}$~~ $\theta \sim \text{Beta}$

* Fore example

$T = \text{iid Bernoulli}$, But

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

$$\theta = \{0.5, 0.75\}$$

$$X = \{0, 1, 1\}$$

$$P(\theta = 0.75 | X) > P(\theta = 0.5 | X)$$

$$= \frac{0.25 \times 0.75^3 \times 0.5}{P(X|\theta=0.75)P(\theta=0.75) + P(X|\theta=0.5)P(\theta=0.5)}$$

$$P(X|\theta=0.75)P(\theta=0.75) + P(X|\theta=0.5)P(\theta=0.5)$$

$$\hookrightarrow P(X) = \sum_{\theta \in H} P(X|\theta)P(\theta)$$

$$= \frac{0.5^3 \times 0.5}{P(X|\theta=0.75)P(\theta=0.75) + P(X|\theta=0.5)P(\theta=0.5)}$$

$$P(X|\theta=0.75)P(\theta=0.75) + P(X|\theta=0.5)P(\theta=0.5)$$

$P(X)$ is the same.

$$\Rightarrow P(\theta = 0.75 | X) = 0.53$$

$$\Rightarrow P(\theta = 0.5 | X) = 0.47$$

We need $P(\theta = 0.75)$ and $P(\theta = 0.5)$

Assume Principle of indifference:-

all $\theta \in \Theta$ are equally likely i.e

$$P(\theta) = \frac{1}{|\Theta|}$$

$$P(\theta) = \begin{cases} \frac{1}{2} & \text{if } \theta = 0.5 \\ \frac{1}{2} & \text{if } \theta = 0.75 \\ 0 & \text{otherwise} \end{cases}$$

$$P(\theta) \xrightarrow{X} P(\theta | X)$$

Bayesian
Conditionalism

$$x \in \mathcal{X} = \{0,1\} \times \{0,1\} \times \{0,1\}$$

$$= \{ \langle 1,1,1 \rangle, \langle 1,1,0 \rangle, \langle 1,0,1 \rangle, \langle 0,1,1 \rangle, \langle 0,0,1 \rangle, \\ \langle 0,1,0 \rangle, \langle 1,0,0 \rangle, \langle 0,0,0 \rangle \}$$

$P(x = \langle 1,1,1 \rangle | \theta = 0.75)$

	$\langle 1,1,1 \rangle$	$\langle 1,1,0 \rangle$	$\langle 1,0,1 \rangle$	$\langle 0,1,1 \rangle$	$\langle 0,0,1 \rangle$	$\langle 0,1,0 \rangle$	$\langle 1,0,0 \rangle$	$\langle 0,0,0 \rangle$	
0.75	0.422	0.191	0.047	0.016	0.5				$P(\theta)$
0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	
									2

$$P(\theta = 0.75 | x = \langle 1,1,0 \rangle) = \frac{\boxed{}}{\boxed{} + \boxed{}}$$

$$P(\theta | x) = \frac{P(x | \theta) P(\theta)}{P(x)} = \frac{P(x, \theta)}{\sum_{\theta \in \Theta} P(x, \theta)} = \frac{P(x, \theta)}{P(x)}$$

Another example:-

$T = \text{iid Bernoulli}$, But

$$C \oplus = (0, 1)$$

$$\mathcal{H}_0 = \{ \underset{1}{0.1}, \underset{2}{0.25}, \underset{3}{0.5}, \underset{4}{0.75}, \underset{5}{0.9} \}$$

↓ subset

$$X: \langle 0, 1, 1 \rangle$$

$$\text{Prior? } P(\theta) = \begin{cases} \frac{1}{5} \cdot P(\theta) = \frac{1}{5} & \text{if } \theta \in \mathcal{H}_0 \\ 0 & \text{o/t} \end{cases}$$

Principle of indifference.

What if I want the most likely value of θ given X ?

$$P(\theta|x) := \operatorname{argmax}_{\theta \in \mathcal{H}_0} \{ P(\theta|x) \}$$

$$\theta \in \mathcal{H}_0$$

$$= \operatorname{argmax} \left\{ \frac{P(x|\theta) P(\theta)}{P(x)} \right\}$$

MAP = Maximum of Posterior.

$$\hat{\theta}_{\text{MAP}} = \underset{\theta \in \Theta}{\text{argmax}} \{ p(x|\theta) p(\theta) \}$$

under the principle of indifference.

$$\uparrow \text{argmax} \{ p(x|\theta) \}$$

$$\theta \in \Theta$$

\downarrow

$$\therefore \mathcal{L}(\theta, x) = \hat{\theta}_{\text{MLE}}$$

Pmf of
Bernoulli

$$= p^x (1-p)^{1-x}$$

p if $x=1$
$1-p$ if $x=0$

$$p(x=0|\theta=0.1) p(x=1|\theta=0.1) p(x=1|\theta=0.1)$$

Standard Pmf
of Bernoulli

$$P(x|\theta=0.1) = 0.1^x \times 0.9^{1-x} = 0.009$$

$$P(x|\theta=0.25) = 0.25^x \times 0.75^{1-x} = 0.047$$

$$P(x|\theta=0.5) = 0.5^x \times 0.5^{1-x} = 0.125$$

$$P(x|\theta=0.75) = 0.75^x \times 0.25^{1-x} = 0.141$$

$$P(x|\theta=0.9) = 0.9^x \times 0.01^{1-x} = 0.081$$

$$\hat{\theta}_{\text{MAP}} = 0.75$$

→ pmf

$$\sum_{x \in X} P(X) = 1, \quad \text{likelihood } \sum_{\theta \in \Theta} P(X|\theta) = 1$$

pmf

$$\sum_{\theta \in \Theta} P(\theta) = 1, \quad \sum_{\theta \in \Theta} P(\theta|x) = 1$$

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

under
principle

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

of indifference

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

$$P(\theta = .75|x) = \frac{.141}{.009 + .047 + .125 + .141 + .081}$$

$$= \frac{.141}{.403} = 0.35$$

$$P(\theta = .75) \longrightarrow P(\theta = .75|x)$$

↓
0.35

$$0.2 \xrightarrow{X} 0.35$$

\Downarrow

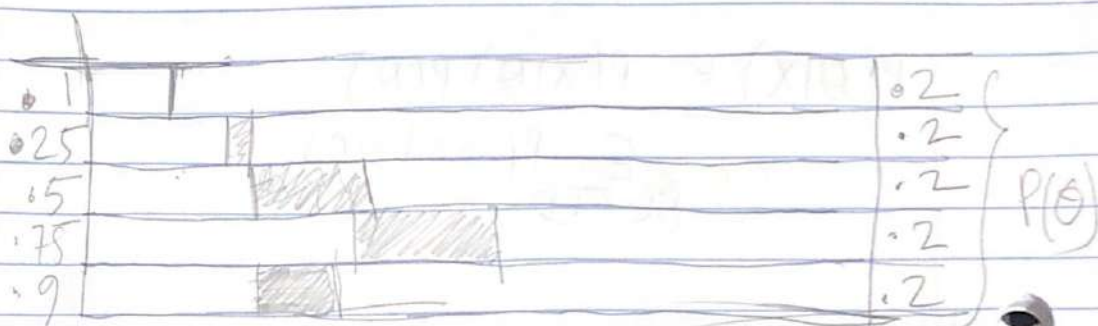
\Downarrow

$$P(\theta = 0.75)$$

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

without
data

given data



For example,

$\mathcal{T} = \text{iid Bernoulli}$ But

$$\mathcal{C}(\Theta) = (0, 1)$$

$$\Theta = \{0.5, 0.75\}$$

$$X = \langle 0, 1, 1 \rangle$$

Principle of indifference

$$P(\theta) = 0.5$$

$$P(\theta = 0.75 | x_1, x_2, x_3)$$

After seeing x_1 ,

$$P(\theta = 0.75 | x_1 = 0)$$

$$= \frac{\cancel{P(\theta=0.75)} P(x_1=0 | \theta=0.75) P(\theta=0.75)}{P(x_1=0 | \theta=0.75) P(\theta=0.75) + P(x_1=0 | \theta=0.5) P(\theta=0.5)}$$

$$+ P(x_1=0 | \theta=0.5) P(\theta=0.5)$$

$$= \frac{0.25}{0.25 + 0.5} = \frac{1}{3}$$

$$\Rightarrow \cancel{P(0.5 | \theta)}$$

$$P(\theta=0.5 | x_1=0) = 2/3$$

Now my prior changes;

$$P(\theta) = \begin{cases} 1/3 & \text{if } \theta = 0.75 \\ 2/3 & \text{if } \theta = 0.5 \end{cases}$$

$$p(\theta | x_2) = \frac{p(x_2 | \theta) P(\theta)}{P(x_2)}$$