

Lecture 5.

\mathcal{X} : iid Bernoulli

$$\Theta = \{0.5, 0.75\} \subset (0,1)$$

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

$$P(\theta | X_1 = 0) = \begin{cases} \frac{1}{3} & \text{if } \theta = 0.75 \\ \frac{2}{3} & \text{if } \theta = 0.5 \end{cases}$$

Picture

$$P(\theta = 0.75 | X_2 = 1) = \frac{\overbrace{P(X_2 = 1 | \theta = 0.75)}^{0.75} \overbrace{P(\theta = 0.75)}^{1/3}}{\underbrace{P(X_2 = 1 | \theta = 0.75)}_{0.75} \underbrace{P(\theta = 0.75)}_{1/3} + \underbrace{P(X_2 = 1 | \theta = 0.5)}_{0.5} \underbrace{P(\theta = 0.5)}_{2/3}}$$
$$= 0.429$$

$$P(\theta | X_2 = 1) = \begin{cases} 0.429 & \text{if } \theta = 0.75 \\ 0.571 & \text{if } \theta = 0.5 \end{cases}$$

$$\begin{aligned}
 P(\theta = .75 | X_3 = 1) &= \frac{P(X_3 = 1 | \theta = .75) P(\theta = .75)}{P(X_3 = 1 | \theta = .75) P(\theta = .75) + P(X_3 = 1 | \theta = .5) P(\theta = .5)} \\
 &= \frac{.75 \cdot .421}{.75 \cdot .421 + .5 \cdot .571}
 \end{aligned}$$

$$P(\theta | X_3 = 1) = \begin{cases} .53 & \text{if } \theta = .75 \\ .47 & \text{if } \theta = .5 \end{cases}$$

$$\begin{aligned}
 \hat{P}(\theta | x) &= \frac{P(x | \theta) P(\theta)}{P(x)} \\
 &= \frac{P(x | \theta) P(\theta)}{\sum_{\theta \in \Theta} P(x | \theta) P(\theta)}
 \end{aligned}$$

Generally, We want to show,

$$P(\theta | x_1, \dots, x_n) = \frac{P(x_n | \theta) P(\theta | x_1, \dots, x_{n-1})}{\sum_{\theta \in \Theta} P(x_n | \theta) P(\theta | x_1, \dots, x_{n-1})}$$

Start with the full formula,

$$P(\theta | x_1, \dots, x_n) = \frac{P(x_1, \dots, x_n | \theta) P(\theta)}{P(x_1, \dots, x_{n-1}, x_n)} = \frac{P(x_1, \dots, x_n | \theta) P(\theta)}{P(x)}$$

$$= \frac{P(x_1 | \theta) \dots P(x_{n-1} | \theta) P(x_n | \theta) P(\theta)}{P(x_n | x_1, \dots, x_{n-1}) P(x_1, \dots, x_{n-1})}$$

$P(A|B)$

$= P(A|B)$

$P(B)$

$$= \frac{P(x_n | \theta) P(x_1, \dots, x_{n-1} | \theta) P(\theta)}{P(x_n | x_1, \dots, x_{n-1}) P(x_1, \dots, x_{n-1})}$$

$P(\theta | x_1, \dots, x_{n-1})$

posterior where

Sees the data x_1, \dots, x_{n-1}

$$\rightarrow P(X) = \sum_Y P(X, Y)$$

$$P(X_n | X_1, \dots, X_{n-1})$$

$$= \sum_{\theta \in \Theta} P(X_n, \theta | X_1, \dots, X_{n-1})$$

$$= \sum_{\theta \in \Theta} P(X_n | \theta, X_1, \dots, X_{n-1}) P(\theta | X_1, \dots, X_{n-1})$$

$$P(X_n | \theta, X_1, \dots, X_{n-1}) = \frac{P(X_1, \dots, X_{n-1}, X_n, \theta)}{P(X_1, \dots, X_{n-1}, \theta)}$$

$$P(X_n | \theta)$$

$$= \frac{P(X_1 | \theta) \cdots P(X_{n-1} | \theta) P(X_n | \theta)}{P(X_1 | \theta) \cdots P(X_{n-1} | \theta)}$$

once you know θ nothing we need

map \rightarrow Maximum a posterior estimate

$$\hat{\theta}_{\text{map}} = \underset{\theta \in \Theta_0}{\operatorname{argmax}} \{ P(\theta | x) \}$$

$$= \underset{\theta \in \Theta_0}{\operatorname{argmax}} \{ P(x | \theta) P(\theta) \}$$

$$= \underset{\theta \in \Theta_0}{\operatorname{argmax}} P(x | \theta) = \hat{\theta}_{\text{MLE}}$$

if $\Theta_0 = \Theta = \{0, 1\}$
 \uparrow
 base
 id
 null

true of (preferability of theta) $P(\theta)$

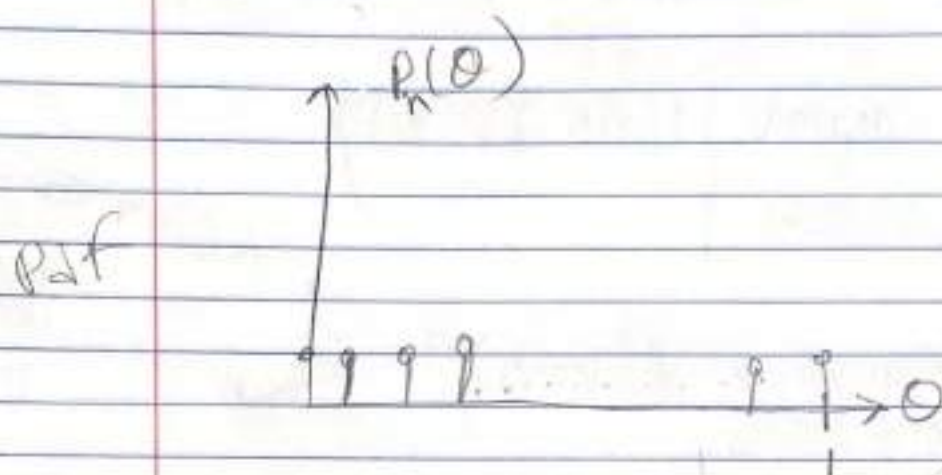
is determined by the principle of indifference

Why is $\Theta_0 = \{ \theta_1, \theta_2, \dots \}$ ~~$\neq \{0, 1\}$~~ a bad idea?

$$\Theta_0 = \left\{ 0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1 \right\} \quad P(\theta) = \left\{ \frac{1}{5} \forall \theta \right\}$$

$$\Theta_0 = \left\{ 0, \frac{1}{10}, \dots, \frac{9}{10}, 1 \right\} \quad P(\theta) = \left\{ \frac{1}{11} \forall \theta \right\}$$

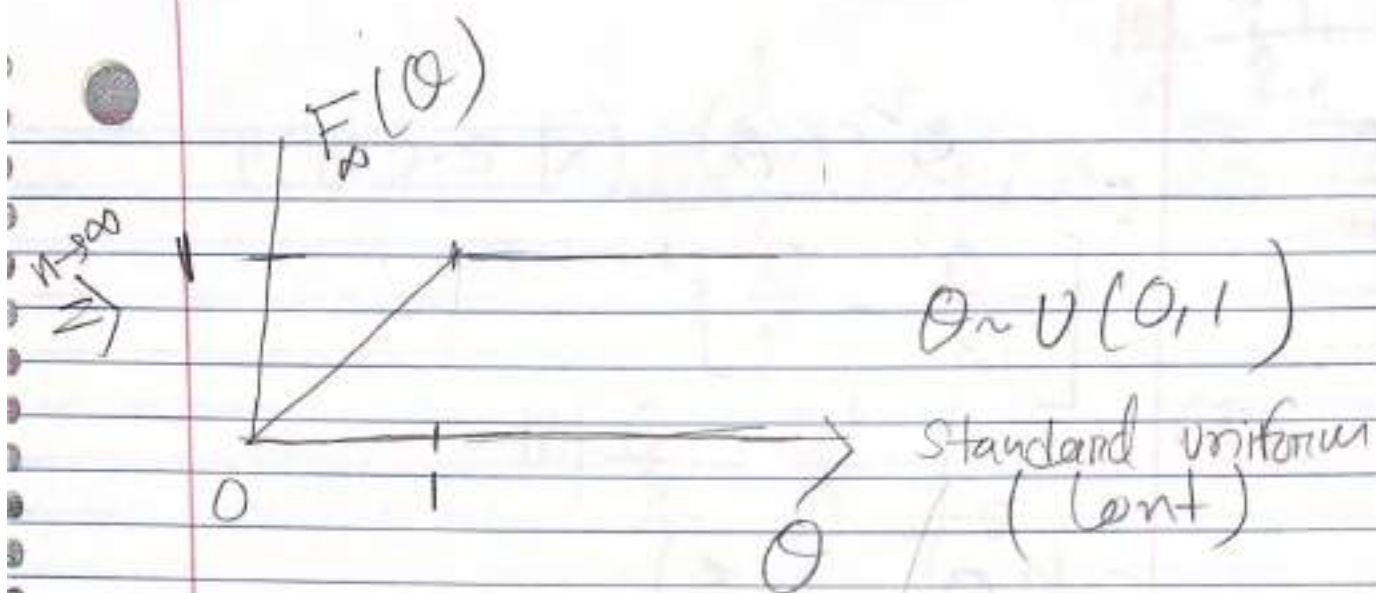
$$\textcircled{H} \theta(n) = \left\{ 0, n, \dots, \frac{n-1}{n}, 1 \right\} \quad p(\theta) = \frac{1}{n+1} \quad \forall \theta$$



$\lim_{n \rightarrow \infty} p_n(\theta) = 0 = \textcircled{H} \theta(\omega)$ is not a discrete rv anymore.



$$\lim_{n \rightarrow \infty} F_n(\theta) = \begin{cases} 0 & \text{if } \theta < 0 \\ 1 & \text{if } \theta > 1 \\ 0 & \text{if } \theta \in (0, 1) \end{cases}$$



$P(\theta) \approx U(0,1)$ Principle of
 default prior Indifference

iid bernoulli
 $X = \langle 0, 1, 1 \rangle$ $P(X|\theta) = (1-\theta)\theta^2$
 for any X

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

$\theta \sim U(0,1)$

$f_{\theta}(\theta) = \begin{cases} 1 & 0 \leq \theta \leq 1 \\ 0 & \text{otherwise} \end{cases}$

$$f_{\theta}(\theta) = \frac{P(X|\theta) P(\theta)}{\int_0^1 P(X|\theta) P(\theta) d\theta} = \frac{P(X|\theta)}{\int_0^1 P(X|\theta) d\theta}$$

$$\frac{\theta^2(1-\theta)}{\left[\frac{\theta^3}{3} - \frac{\theta^4}{4}\right]'$$

$$= 12\theta^2(1-\theta)$$

density function

$$\hat{\theta}_{\text{map}} = \underset{\theta \in (0,1)}{\text{argmax}} \{ 12\theta^2(1-\theta) \}$$

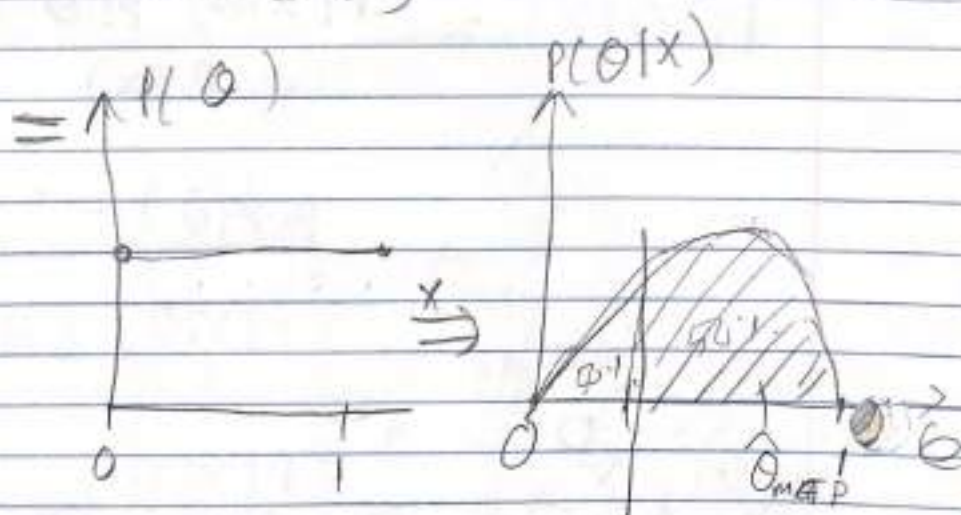
$$\theta \in (0,1)$$

$$f'(\theta) = 2\theta - 3\theta^2 = 0$$

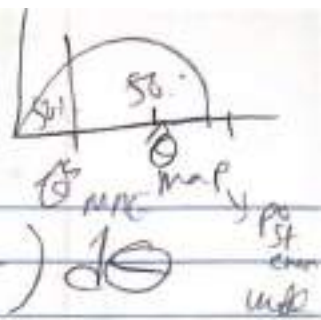
$$f(\theta) = \theta^2 - \theta^3 \quad 2 - 3\theta = 0$$

$$\hat{\theta}_{\text{map}} = \frac{2}{3}$$

$$= \underset{\theta \in (0,1)}{\text{argmax}} \{ \theta^2(1-\theta) \} = \bar{x} = \hat{\theta}_{\text{MLE}}$$



$$P(\theta > 0.5 | X) = \int_{0.5}^1 12\theta^2(1-\theta) d\theta$$



$$= 12 \left[\frac{\theta^3}{3} - \frac{\theta^4}{4} \right]_{0.5}^1 = 0.688$$

Posterior median

$$\hat{\theta}_{MAE} := \text{Med}[\theta | X] = a \text{ s.t.}$$

Mean

absolute
error.

$$= \arg \min_{\theta \in \Theta} \int_{\Theta} |\hat{\theta} - \theta| P(\theta | X) d\theta = 1/2$$

MAE \rightarrow Minimum
mean absolute error

Posterior expectation/
mean

$$\hat{\theta}_{MMSE} := E[\theta | X]$$

$$= \arg \min_{\theta \in \Theta} \{ (\hat{\theta} - \theta)^2 \}$$

$$\theta \in \Theta$$

x_1, \dots, x_n (general case)

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

$$P(x|\theta) = \theta^{\sum x_i} (1-\theta)^{n-\sum x_i}$$

$$\begin{aligned} P(\theta|x) &= \frac{P(x|\theta) P(\theta)}{P(x)} \\ &= \frac{P(x|\theta) P(\theta)}{\int_{\Theta} P(x|\theta) P(\theta) d\theta} \end{aligned}$$

$$\begin{aligned} \theta &\sim \text{Unif}(0,1) \\ &= \frac{P(x|\theta)}{\int_0^1 P(x|\theta) d\theta} = \frac{\theta^{\sum x_i} (1-\theta)^{n-\sum x_i}}{\int_0^1 \theta^{\sum x_i} (1-\theta)^{n-\sum x_i} d\theta} \end{aligned}$$

famous integral

next page
after this

Beta function

$$B(\alpha, \beta) := \int_0^1 t^{\alpha-1} (1-t)^{\beta-1} dt$$

$$= \frac{0^{\sum x_i} (1-0)^{n-\sum x_i}}{B(\sum x_i + 1, n - \sum x_i + 1)}$$

$$= \text{Beta}(\sum x_i + 1, n - \sum x_i + 1)$$

→ a new r.v.

$$Y \sim \text{Beta}(\alpha, \beta) \Rightarrow \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1}$$

$$\text{Supp}[Y] = (0, 1) = \int_0^1 \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} dy = 1$$

Parameter space: $\alpha, \beta > 0$

$$E[Y] = \int_0^1 y \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} dy$$

$$= \frac{1}{B(\alpha, \beta)} \int_0^1 y^{(\alpha+1)-1} (1-y)^{\beta-1} dy$$

$$= \frac{B(\alpha+1, \beta)}{B(\alpha, \beta)} = \frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta+1)}$$

(multiplication)

$$\frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

Gamma, $\Gamma(\alpha) := \int_0^{\infty} t^{\alpha-1} e^{-t} dt$ for $\alpha > 0$

factorial function for all positive reals
 $(3.7)!$ not defined

Prop

$$(1) \Gamma(\alpha+1) = \alpha \Gamma(\alpha)$$

$$(2) B(\alpha, \beta) = \frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)} \quad \text{proof 368}$$

$$\frac{B(\alpha+1, \beta)}{B(\alpha, \beta)} = \frac{\frac{\Gamma(\alpha+1) \Gamma(\beta)}{\Gamma(\alpha+\beta+1)}}{\frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}}$$

$$= \frac{\frac{\alpha \Gamma(\alpha) \Gamma(\beta)}{(\alpha+\beta) \Gamma(\alpha+\beta)}}{\frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}}$$

$$= \frac{\alpha}{\alpha+\beta}$$

Med = no closed form

$$\mathcal{E}^{\text{beta}}(0.5, \alpha, \beta)$$

$$\text{Mode}(Y) = \arg \max_{y \in (0,1)} \left\{ \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} \right\}$$

$$= \arg \max \left\{ y^{\alpha-1} (1-y)^{\beta-1} \right\}$$

$$= \arg \max \left\{ (\alpha-1) \cdot \ln(y) + (\beta-1) \ln(1-y) \right\}$$

$$r(y) = \frac{\alpha-1}{y} - \frac{\beta-1}{1-y}$$

$$\Rightarrow y_{\text{mode}} = \frac{\alpha-1}{\alpha+\beta-2}$$

if you are careful.

$$f''(y_{\text{mode}}) < 0 \text{ if } \alpha, \beta > 1$$

$$Y \sim \text{Beta}(\overset{\alpha}{1}, \overset{\beta}{1}) = \frac{1}{B(1,1)} y^{(1)-1} (1-y)^{(1)-1}$$

$$= \int_0^1 y^{(1)-1} (1-y)^{(1)-1} dy = \int_0^1 (1)(1) dy$$

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$Y \sim U(0,1) \Rightarrow \text{Beta}(1,1)$

Standard uniform is a

special case of the beta distribution