

14] The mean and median of the posterior distribution are Bayesian analogs of point estimators. M404 53

15] It is possible to use an improper prior ($\pi(\theta) \geq 0$ is not a pdf or pmf because it does not integrate or sum to 1), but the posterior must be a pdf (or a pmf).

ex) $\pi(\theta) = \frac{1}{\theta}, \theta > 0$
 $\pi(\theta) = 1, \theta \in \mathbb{R}$ } improper pdfs

16] The predictive density (pdf or pmf)

$$f(\underbrace{x_{n+1}}_{\text{often omit subscript}} | x_1, \dots, x_n) = f(x_{n+1} | \underline{x})$$

$$= \int f(x_{n+1} | \underline{\theta}) \pi(\underline{\theta} | \underline{x}) d\underline{\theta}$$

is the updated unconditional (marginal)

pdf (or pmf) for x_{n+1} given the data \underline{x} .

17) Although you can find $E(X_{n+1}) =$ 53.5
bad notation

$E(X_{n+1}|X)$ using the predictive density $(E(X_{n+1}) = \int x f(x|x) dx)$,

it is often easier to use $E(X_{n+1}) = E[E(X_{n+1}|X)]$

$= E[E(X_{n+1}|\Theta)|X] =$ Bayesian Premium.

ex) claim sizes follow a single parameter Pareto dist with $\alpha = 3$ and Θ where $\Theta \sim U[1,4]$. An insured selected at random submits 4 claims of sizes 2, 3, 5, and 7.

- Find i) the posterior mean of Θ
- ii) the expected size of the next claim,
- iii) the posterior prob that the next claim will be greater than 3,
- iv) the posterior prob that the next claim will be less than 1.5.

Soln). $\pi(\theta) = \frac{1}{3}, 1 \leq \theta \leq 4$ $= \frac{1}{3} I(1 \leq \theta \leq 4)$

$f(x|\theta) = \frac{3\theta^3}{x^4}, x \geq \theta$ $= \frac{3\theta^3}{x^4} I(x \geq \theta)$

$$f(x|\theta) = \prod_{i=1}^4 e(x_i|\theta) \propto \theta^{12} I[\bar{x}_4 \geq \theta] \quad M404 \ 54$$

$$= \theta^{12}, \theta \leq 2 \quad = \theta^{12} I(\theta \leq 2)$$

$$\pi(\theta|x) \propto \pi(\theta) f(x|\theta) \propto \theta^{12} I(\theta \leq 2) I(1 \leq \theta \leq 4)$$

$$= \theta^{12} I(1 \leq \theta \leq 2)$$

$$\int_1^2 c \theta^{12} d\theta = c \frac{\theta^{13}}{13} \Big|_1^2 = c \left(\frac{2^{13} - 1}{13} \right) \stackrel{\text{set}}{=} 1, \quad c = \frac{13}{2^{13} - 1}$$

$$\text{So } \pi(\theta|x) = \frac{13}{2^{13} - 1} \theta^{12}, \quad 1 \leq \theta \leq 2.$$

$$i) E(\Theta|x) = \int_1^2 \theta \pi(\theta|x) d\theta = \int_1^2 \frac{13}{2^{13} - 1} \theta^{13} d\theta$$

$$= \frac{13}{2^{13} - 1} \frac{\theta^{14}}{14} \Big|_1^2 = \frac{13}{2^{13} - 1} \frac{2^{14} - 1}{14} = \boxed{1.8573}$$

$$ii) E[X_{n+1}|x] = E[E[X_{n+1}|\Theta]|x] = E\left[\frac{\alpha \Theta}{\alpha - 1} \Big| x\right] = E[1.5 \Theta | x]$$

single parameter Pareto(α, Θ)
 $\alpha = 3$

$$= 1.5 E(\Theta|x) = 1.5 (1.8573) = \boxed{2.78595}$$

\uparrow
by (i)

iii), iv) "next claim" means X_{n+1}

Let $f(x_{n+1} | x) = f(x | x) = \int \underbrace{f(x|\theta)}_{x>0} \underbrace{\pi(\theta|x)}_{\theta \in [1,2]}$ $d\theta$
 single parameter pareto

$= \int_1^{\min(2,x)=m} \frac{3\theta^3}{x^4} \frac{13}{2^{13}-1} \theta^{12} d\theta$ } bound for integral
 20: has $x > 0$ and $\theta \in [1,2]$ so $1 \leq \theta \leq m$

$= \frac{39}{2^{13}-1} \frac{1}{x^4} \int_1^m \theta^{15} d\theta = \frac{39}{2^{13}-1} \frac{1}{x^4} \frac{\theta^{16}}{16} \Big|_1^m$

$= \frac{39}{2^{13}-1} \frac{1}{x^4} \frac{m^{16}-1}{16}$

$= \left[\frac{39}{(2^{13}-1)16} \frac{x^{16}-1}{x^4}, \quad 1 \leq x < 2 \right.$

$\left. \frac{39}{(2^{13}-1)16} \frac{2^{16}-1}{x^4}, \quad x \geq 2 \right]$

iii) $P(x_{n+1} > 3 | x) = \frac{39(2^{16}-1)}{(2^{13}-1)16} \int_3^{\infty} x^{-4} dx$

$= \frac{39(2^{16}-1)}{(2^{13}-1)16} \frac{x^{-3}}{-3} \Big|_3^{\infty} = \frac{39(2^{16}-1)}{(2^{13}-1)16} \frac{1}{3(3^3)}$

$= \frac{19.5021}{3(3^3)} = \boxed{0.2408}$

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$$iv) P(X_{n+1} \leq 1.5 | X) = \frac{39}{(2^{13}-1)16} \int_1^{1.5} x^{12} - x^{-4} dx$$

do on HW 8

18] ^{p407} The Bayesian estimator or Bayes estimator $\hat{\theta}$ minimizes the expected posterior loss function.

A) For the (mean) square error loss function, the Bayesian point estimator is the mean of the posterior distribution:
 $\hat{\theta} = E(\theta | X)$. $l(\hat{\theta}, \theta) = (\hat{\theta} - \theta)^2$

A) is always used for credibility.

B) For the absolute value of the error loss function, the Bayesian point estimator is the median $\hat{\theta} = \pi_{0.5}$ of the posterior distribution. $l(\hat{\theta}, \theta) = |\hat{\theta} - \theta|$

C) For the zero one loss $l(\hat{\theta}, \theta) = \begin{cases} 0, & \theta = \hat{\theta} \\ 1, & \theta \neq \hat{\theta} \end{cases}$ or $k \rightarrow \begin{cases} 1, & \theta \neq \hat{\theta} \\ 0, & \theta = \hat{\theta} \end{cases}$

the Bayesian point estimator $\hat{\theta}$ = the mode of the posterior distribution.

19] ^{P410} Bayesian credibility intervals (a,b) (555)

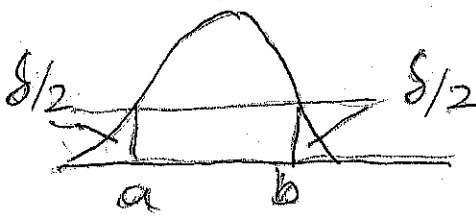
are the analogs of the CI where "credibility" has nothing to do with "actuarial credibility." want $\int_a^b \pi(\theta|x) d\theta \geq 1-\delta$.

The highest posterior density credibility set is the smallest set $(a_1, b_1) \cup \dots \cup (a_k, b_k)$

where $\sum_{i=1}^k \int_{a_i}^{b_i} \pi(\theta|x) d\theta \geq 1-\delta$.

If the posterior is symmetric about the mode

then $(a,b) = \left(\pi_{\frac{\delta}{2}}, \pi_{1-\frac{\delta}{2}} \right) = \text{HPD}$
 $\text{100(1-\delta)\% set}$
 $= \text{equal tail credibility interval.}$



Let $\hat{\theta} = \text{posterior mean}$ and $\hat{\sigma} = \text{posterior SD}$
 $= \sqrt{\text{posterior variance.}}$

An approximate Bayesian $100(1-\delta)\%$ credibility

region is $\hat{\theta} \pm z_{1-\frac{\delta}{2}} \hat{\sigma}$.

$\hat{\theta}$ and $\hat{\sigma}$ depend on n

$\underbrace{\hspace{2cm}}_{1.645, 1.96, \text{ or } 2.576}$

The Bayesian CLT says if $w_n = \theta | x_n$, then $w_n \overset{d}{\rightsquigarrow} N(\hat{\theta}, \hat{\sigma}^2)$ as $n \rightarrow \infty$, i.e. the

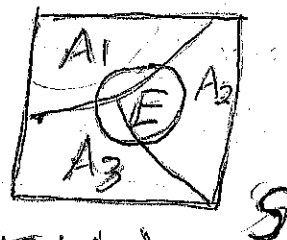
the posterior converges to a normal dist.

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$w_n \rightarrow \lambda_0$
where $\lambda_0 \sim N(\mu, \sigma^2)$

20) The sample space S is partitioned into n subsets A_1, \dots, A_n if $P(A_i) > 0$, $A_i \cap A_j = \emptyset$ for $i \neq j$ and $S = A_1 \cup \dots \cup A_n$.

Then $E = \underbrace{(E \cap A_1) \cup \dots \cup (E \cap A_n)}_{\text{disjoint}}$



and $P(E) = \sum_{i=1}^n P(E \cap A_i) = \sum_{i=1}^n P(A_i) P(E|A_i)$.

21) Let A_1, \dots, A_n partition S .

Bayes rule: $P(A_j | E) = \frac{P(A_j \cap E)}{P(E)} = \frac{\overbrace{P(A_j) P(E|A_j)}^{\text{"Prior" "likelihood"}}}{\underbrace{P(E)}_{\text{"marginal"}}$

$= \frac{P(A_j) P(E|A_j)}{P(A_1) P(E|A_1) + \dots + P(A_n) P(E|A_n)}$

If $n=2$, $A_2 = \bar{A}$. so

$P(A|E) = \frac{P(A) P(E|A)}{P(A) P(E|A) + P(\bar{A}) P(E|\bar{A})}$

ex) C136)

claim amount	prob of claim class 1	amount class 2
250	0.5	0.7
2500	0.3	0.2
60000	0.2	0.1

$P(\text{class 1}) = \frac{2}{3}$

$P(\text{class 2}) = \frac{1}{3}$

class 1 has twice as many claims as class 2. A claim of 250 is observed. Determine the Bayesian estimate of the expected value of the 2nd claim from the same policyholder.

Soln: $P(\text{class 1} | \text{claim} = 250) =$

$$P(\text{claim} = 250 | \text{class 1}) P(\text{class 1})$$

$$P(\text{claim} = 250 | \text{class 1}) P(\text{class 1}) + P(\text{claim} = 250 | \text{class 2}) P(\text{class 2})$$

$$= \frac{0.5 \left(\frac{2}{3}\right)}{0.5 \left(\frac{2}{3}\right) + 0.7 \left(\frac{1}{3}\right)} = \frac{10}{17} \quad \text{so } P(\text{class 2} | \text{claim} = 250) = \frac{7}{17}$$

$$E[\text{claim} | \text{class 1}] = .5(250) + .3(2500) + .2(60000) = 12875$$

$$E[\text{claim} | \text{class 2}] = .7(250) + .2(2500) + .1(60000) = 6675$$

$$E(\text{claim} | 250) = E(\text{claim} | \text{class 1}) P(\text{class 1} | \text{claim} = 250) + E(\text{claim} | \text{class 2}) P(\text{class 2} | \text{claim} = 250)$$

$$= 12875 \frac{10}{17} + 6675 \frac{7}{17} = \boxed{10322}$$

sum to 1