

Subject: Statistical Inference Topic: Bays estimation

Definition:

Let be a $f\left(\frac{x}{\theta}\right) = f(x; \theta)$ given density of a given sample X_1, X_2, \dots, X_n .

Then the posterior density is given by $f\left(\frac{\theta}{\underline{X}}\right) = \frac{f\left(\frac{\underline{X}}{\theta}\right)g(\theta)}{\int f\left(\frac{\underline{X}}{\theta}\right)g(\theta)d(\theta)}$

$f\left(\frac{\underline{X}}{\theta}\right) = \prod_{i=1}^n f\left(\frac{x_i}{\theta}\right)$ is the likelihood function and $g(\theta)$ is prior density . Then the bays

$E\left(\frac{T(\theta)}{\underline{X}}\right) = \int T(\theta)f\left(\frac{\theta}{\underline{X}}\right)d\theta$ estimatoris given by

Where $T(\theta)$ is the function of parameter whose

$E\left(\frac{\theta}{\underline{X}}\right) = \int \theta f\left(\frac{\theta}{\underline{X}}\right)d\theta$ baysestimator is to be found. If θ is the parameter then $T(\theta) = \theta$

whose estimator is to be

computed then (i.e.) $E\left(\frac{\theta}{\underline{X}}\right) = \theta^*$ are required bays

estimators.

Procedure:

If we have probability density functions $f\left(\frac{x}{\theta}\right)$ with parameter ' θ '. Then obtain

the likelihood function as $f\left(\frac{\underline{X}}{\theta}\right)$ and multiply it with given prior density. (i.e.) $f\left(\frac{\underline{X}}{\theta}\right)g(\theta)$

where $g(\theta)$ is the prior density then we find $\int f\left(\frac{\underline{X}}{\theta}\right)g(\theta)d\theta$

then obtain the posterior density which is given by $f\left(\frac{\theta}{\underline{X}}\right) = \frac{f\left(\frac{\underline{X}}{\theta}\right)g(\theta)}{\int f\left(\frac{\underline{X}}{\theta}\right)g(\theta)d(\theta)}$

Then lastly the bayes estimator of ' θ ' is given by $\theta^* = E\left(\frac{\theta}{\underline{X}}\right) = \int \theta f\left(\frac{\theta}{\underline{X}}\right) d\theta$

Properties of Bayes Estimation

Following are the properties of bayes estimation

- 1- Bayes estimator is always a function of minimal sufficient statistic.
- 2- Bayes estimator is a constant estimator.
- 3- It is a "BAN" (Best Asymptotic Normal Property) estimator.
- 4- Bayes estimator is corresponding to the known prior distribution which is optimum.

Loss Function

Let ' T ' denote on estimator of " $T(\theta)$ " then loss function $\&(t, \theta)$ is defined as real valued function satisfying

- (i) $\&(t, \theta) \geq 0$ For all t and θ
- (ii) $\&(t, \theta) = 0$ For $t = T(\theta)$ i.e. it is a measure of error .

Squared Error Loss function

$\&(t, \theta) = [t - T(\theta)]^2$ is called Squared Error Loss function. It increase as the error $t - T(\theta)$ increase in magnitude.

Absolute Error Loss function

$\&(t, \theta) = |t - T(\theta)|$ Is called the absolute error loss function . it is increase as the $[t - T(\theta)]$ increse.

Risk function

For a given loss function $\&(t, \theta)$ the risk function $R_t(\theta)$ of an estimator $t = \&(X_1, X_2, \dots, X_n)$ is defined to be $R_t(\theta) = E[\&(t, \theta)]$. i.e. the risk function is the average loss.

Question 1 :

Suppose that the time to failure ' T ' of an electric tube is an exponential random variable with parameter ' θ '. We also assume the prior density for ' θ ' as $g(\theta) = 160e^{-160\theta}$. Then obtain the Bayes estimator.

Solution :- As given the electric tube is an exponential random variable with parameter ' θ '

$$X \sim \exp(\theta)$$

$$f(x; \theta) = f\left(\frac{X}{\theta}\right) = \theta e^{-\theta x} \quad 0 \leq X < \infty$$

The likelihood function is

$$f(\underline{X}; \theta) = \theta^n e^{-\theta \sum X}$$

And prior density is

$$g(\theta) = 160e^{-160\theta}$$

$$\text{Now } f(\underline{X}; \theta) \cdot g(\theta) = 160\theta^n e^{-\theta(160 + \sum X)}$$

We know that the posterior density function is

$$\begin{aligned} f\left(\frac{\theta}{\underline{X}}\right) &= \frac{f\left(\frac{\underline{X}}{\theta}\right)g(\theta)}{\int_{-\infty}^{\infty} f\left(\frac{\underline{X}}{\theta}\right)g(\theta)d\theta} \rightarrow (A) \\ \int_0^{\infty} f(\underline{X}; \theta) \cdot g(\theta) d\theta &= \int_0^{\infty} 160\theta^n e^{-\theta \sum X} e^{-160\theta} d\theta \\ &= 160 \int_0^{\infty} \theta^n e^{-\theta(160 + \sum X)} d\theta \\ &= 160 \int_0^{\infty} \theta^{n+1-1} e^{\frac{-\theta}{(160 + \sum X)^{-1}}} d\theta \end{aligned}$$

Comparing with gamma function

$$\begin{aligned} &= 160 \sqrt{n+1} [(160 + \sum X)^{-1}]^{n+1} \\ &= 160 \sqrt{n+1} \frac{1}{(160 + \sum X)^{n+1}} \end{aligned}$$

Now put in eq (A)

$$f\left(\frac{\theta}{\underline{X}}\right) = \frac{160\theta^n e^{-\theta(160 + \sum X)}}{160 \sqrt{n+1} \left(\frac{1}{160 + \sum X} \right)^{n+1}}$$

$$= \frac{\theta^n e^{-\theta(160 + \sum X)}}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1}$$

Now the bayes estimator is

$$E\left(\frac{T(\theta)}{\underline{X}}\right) = \theta^* = \int \theta f\left(\frac{\theta}{\underline{X}}\right) d\theta$$

$$= \int_0^\infty \frac{\theta \cdot \theta^n e^{-\theta(160 + \sum X)}}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1} d\theta$$

$$= \frac{1}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1} \int_0^\infty \theta^{n+2-1} e^{-\theta(\sum X + 160)} d\theta$$

Comparing with gamma function

$$\begin{aligned} &= \frac{\int_0^\infty \theta^{n+2-1} e^{-\theta(\sum X + 160)} d\theta}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1} \\ &= \frac{\int_0^\infty \theta^{n+2-1} e^{-\theta(\sum X + 160)} d\theta}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1} \\ &= \frac{\int_0^\infty \theta^{n+2-1} e^{-\theta(\sum X + 160)} d\theta}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1} \\ &= \frac{(n+1) \int_0^\infty \theta^{n+1} e^{-\theta(\sum X + 160)} d\theta}{\int_0^\infty \frac{1}{160 + \sum X} d\theta}^{n+1} \\ E\left(\frac{T(\theta)}{\underline{X}}\right) &= \frac{n+1}{160 + \sum X} \quad \therefore n+2 - n - 1 \\ &= \frac{n+1}{160 + n\bar{X}} \quad \therefore 1 \end{aligned}$$

So $\theta^* = \frac{n+1}{160 + n\bar{X}}$ is the bayes estimator of the given parameter ' θ ' .

Question 2 :

Assume that the number of time 'X' that the weight switch can be turned on population until fails in geometric random variable with parameter 'P'. The prior density of unknown parameter

'P' is $g(p) = \frac{\overline{a+b}}{\overline{a} \overline{b}} P^{a-1} (1-P)^{b-1}; 0 \leq P \leq 1.$

Here $a = 3.995, b = 3991, \sum X_i = 1000$

For a random sample of size "25" . Find P^* for P?

In geometric distribution

$$f\left(\frac{X}{P}\right) = pq^{x-1}$$

Taking likelihood function

$$f\left(\frac{X}{P}\right) = p^n q^{\sum (X-1)}$$

$$f\left(\frac{X}{P}\right) = p^n q^{\sum X - n}$$

The prior density is

$$g(p) = \frac{\overline{a+b}}{\overline{a} \overline{b}} P^{a-1} (1-P)^{b-1}$$

Now $f\left(\frac{X}{P}\right)g(p) = \frac{\overline{a+b}}{\overline{a} \overline{b}} P^{n+a-1} (1-P)^{\sum X - n + b - 1}$

As we that the posterior density

$$f\left(\frac{P}{X}\right) = \frac{f\left(\frac{X}{P}\right)g(P)}{\int_{-\infty}^{\infty} f\left(\frac{X}{P}\right)g(p)dP}$$

$$\int_{-\infty}^{\infty} f\left(\frac{X}{P}\right)g(p)dp = \frac{\overline{a+b}}{\overline{a} \overline{b}} P^{a+n-1} (1-P)^{b+\sum X - n - 1} dP$$

Comparing with beta of type 1st

$$= \frac{\overline{a+b}}{\overline{a} \overline{b}} \beta(a+n, b+\sum X-n)$$

$$= \frac{\overline{a+b}}{\overline{a} \overline{b}} \frac{\overline{a+n} \overline{b+\sum X-n}}{\overline{a+n+b+\sum X-n}}$$

$$= \frac{\overline{a+b}}{\overline{a} \overline{b}} \frac{\overline{a+n} \overline{b+\sum X-n}}{\overline{a+b+\sum X}}$$

Put in Esq. (A)

$$\begin{aligned} f\left(\frac{\theta}{X}\right) &= \frac{\frac{\overline{a+b}}{\overline{a} \overline{b}} P^{n+a-1} (1-p)^{\sum X-n+b-1}}{\frac{\overline{a+b}}{\overline{a} \overline{b}} \frac{\overline{a+n} \overline{b+\sum X-n}}{\overline{a+b+\sum X}}} \\ &= \frac{\overline{a+b+\sum X} P^{n+a-1} (1-p)^{\sum X-n+b-1}}{\overline{n+a} \overline{b+\sum X-n}} \end{aligned}$$

Now the bayes estimator is

$$\begin{aligned} P^* &= E\left(\frac{T(P)}{X}\right) = \int f\left(\frac{P}{X}\right) dP \\ &= \frac{\overline{a+b+\sum X}}{\overline{n+a} \overline{b+\sum X-n}} \int_0^1 P^{a+n-1-1} (1-p)^{\sum X-n+b-1} dP \end{aligned}$$

Comparing with beta type 1st

$$\begin{aligned} P^* &= \frac{\overline{a+b+\sum X}}{\overline{n+a} \overline{b+\sum X-n}} \frac{\overline{a+n+1} \overline{\sum X-n+b}}{\overline{a+n+1+\sum X-n+b}} \\ &= \frac{\overline{a+b+\sum X}}{\overline{n+a} \overline{\sum X+b-n}} \frac{(a+n) \overline{a+n} \overline{\sum X+b-n}}{(\sum X+a+b) \overline{\sum X+a+b}} \end{aligned}$$

$$P^* = \frac{(a+n)}{(\sum X+a+b)}$$

Which is required bayes estimator of P

Now substitute the given values for P^*

$$n = 25, a = 3.995, b = 3991, \sum X_i = 1000$$

$$\begin{aligned} P^* &= \frac{3.995 + 25}{1000 + 3.991 + 3.995} \\ &= \frac{28.995}{4994.995} \\ &= 0.005805 \end{aligned}$$

Which is the required result .

Question 3 :

Let X_1, X_2, \dots, X_n be a random sample from a bernulli distribution with p.d.f $f\left(\frac{X}{\theta}\right) = \theta^x (1 - \theta)^{1-x}$. Assume that the prior density of θ is given by $g(\theta) = I_{(0,1)}(\theta)$ (i.e) θ

is uniformly distributed over the interval (0,1). Obtain the posterior bayes estimator of θ and

$T(\theta) = \theta(1 - \theta)$ and also that the estimators are not unbiased?

The p.d.f of bernulli distribution is

$$f\left(\frac{X}{\theta}\right) = \theta^x (1 - \theta)^{1-x}$$

Then L.H.F is

$$f\left(\frac{X}{\theta}\right) = \theta^{\sum x} (1 - \theta)^{n - \sum x}$$

And prior density function

$$g(\theta) = 1$$

$$f\left(\frac{X}{\theta}\right)g(\theta) = \theta^{\sum x} (1 - \theta)^{n - \sum x}$$

As the posterior density function is

$$f\left(\frac{\theta}{X}\right) = \frac{f\left(\frac{X}{\theta}\right)g(\theta)}{\int f\left(\frac{X}{\theta}\right)g(\theta)d(\theta)} \longrightarrow (A)$$

$$\begin{aligned}
\text{Now } \int_{-\infty}^{\infty} f\left(\frac{\underline{X}}{\underline{P}}\right)g(\theta)d\theta &= \int_0^1 \theta^{\sum X} (1-\theta)^{n-\sum X} d\theta \\
&= \int_0^1 \theta^{\sum X+1-1} (1-\theta)^{n-\sum X+1-1} d\theta
\end{aligned}$$

Comparing with Beta type first

$$\begin{aligned}
&= \beta(\sum X + 1, n - \sum X + 1) \\
&= \frac{\overline{\sum X + 1} \overline{n - \sum X + 1}}{\overline{\sum X + 1 + n - \sum X + 1}} \\
&= \frac{\overline{\sum X + 1} \overline{n - \sum X + 1}}{\overline{n + 2}}
\end{aligned}$$

Put in eq (A)

$$\begin{aligned}
f\left(\frac{\theta}{\underline{X}}\right) &= \frac{\theta^{\sum X} (1-\theta)^{n-\sum X}}{\overline{\sum X + 1} \overline{n - \sum X + 1}} \\
&= \overline{n + 2} \frac{\theta^{\sum X} (1-\theta)^{n-\sum X}}{\overline{\sum X + 1} \overline{n - \sum X + 1}}
\end{aligned}$$

Now the Bayes Estimator for θ is

$$\begin{aligned}
\theta^* &= E\left(\frac{T(\theta)}{\underline{X}}\right) = \int_0^1 \theta f\left(\frac{\theta}{\underline{X}}\right) d\theta \\
&= \frac{\overline{n + 2}}{\overline{\sum X + 1} \overline{n - \sum X + 1}} \int_0^1 \theta^{\sum X+2-1} (1-\theta)^{n-\sum X+1-1} d\theta
\end{aligned}$$

Comparing with Beta type 1st

$$\begin{aligned}
&= \frac{\overline{n+1+1}}{\overline{\sum X+1} \overline{n-\sum X+1}} \frac{\overline{\sum X+2} \overline{n-\sum X+1}}{\overline{\sum X+2+n-\sum X+1}} \\
&= \frac{\overline{n+2}}{\overline{\sum X+1}} \frac{\overline{\sum X+1}}{\overline{n+3}} \\
&= \frac{\overline{n+2}(\sum X+1)}{(n+2)\overline{n+2}}
\end{aligned}$$

$$\theta^* = \frac{\sum X+1}{n+2} \text{ Which is the required bayes estimator for "}\theta\text{"}$$

Now Bayes estimator for $\theta^* (1-\theta)^*$ is

$$\begin{aligned}
\theta^* (1-\theta)^* &= E\left(\frac{T(\theta)}{\underline{X}}\right) = \int_0^1 \theta(1-\theta) f\left(\frac{\theta}{\underline{X}}\right) d\theta \\
&= \frac{\overline{n+2}}{\overline{\sum X+1} \overline{n-\sum X+1}} \int_0^1 \theta^{\sum X+2-1} (1-\theta)^{n-\sum X+2-1} d\theta
\end{aligned}$$

Comparing with Beta type 1st

$$\begin{aligned}
&= \frac{\overline{n+2}}{\overline{\sum X+1} \overline{n-\sum X+1}} \beta(\sum X+2, n-\sum X+2) \\
&= \frac{\overline{n+2}}{\overline{\sum X+1} \overline{n-\sum X+1}} \frac{\overline{\sum X+2} \overline{n-\sum X+2}}{\overline{\sum X+2+n-\sum X+2}} \\
&= \frac{\overline{n+2}(\sum X+1) \overline{\sum X+1} (n-\sum X+1) \overline{n-\sum X+1}}{\overline{\sum X+1} \overline{n-\sum X+1} \overline{n+4}} \\
&= \frac{\overline{n+2}(\sum X+1)(n-\sum X+1)}{(n+3)(n+2) \overline{n+2}}
\end{aligned}$$

$$\theta^* (1 - \theta)^* = \frac{(\sum X + 1)(n - \sum X + 1)}{(n + 2)(n + 3)} \text{ Which is the required Bayes estimator}$$

Now we check that whether estimator is biased or unbiased.

$$\theta^* = \frac{\sum X + 1}{n + 2} \therefore E(X) = \theta$$

$$E(\theta^*) = \frac{E(\sum X + 1)}{n + 2}$$

$$= \frac{\sum E(X) + 1}{n + 2} = \frac{n\theta + 1}{2} \neq \theta$$

$$\text{And } \theta^* (1 - \theta)^* = \frac{(\sum X + 1)(\sum X - n + 1)}{(n + 3)(n + 2)}$$

$$E(\theta^* (1 - \theta)^*) = \frac{(n\theta + 1)(n\theta - n + 1)}{(n + 3)(n + 2)} \neq \theta(1 - \theta)$$

So these Bayes estimator are not the unbiased i.e biased estimator

Question: 4

Statement:

If $X_i \sim$ poisson distribution with parameter ' θ ' with assume that a prior density

$g(\theta) = \frac{1}{m!} \left(\frac{m+1}{\theta_o} \right)^{m+1} \theta^m e^{-(m+1)\theta/\theta_o}$ for a random sample of size 'n'. Find the bay's estimator for parameter ' θ ' .

Solution:- As $X \rightarrow$ Pioson distribution with p.d.f

$$f\left(\frac{m}{\theta}\right) = \frac{e^{-\theta} \theta^m}{m!} \quad m : 1, 2, 3, \dots, \infty$$

As we know that the posterior density is

$$f\left(\frac{\theta}{m}\right) = \frac{f\left(\frac{m}{\theta}\right)g(\theta)}{\int f\left(\frac{m}{\theta}\right)g(\theta)d(\theta)} \longrightarrow (A)$$

Taking likelihood function of p.d.f

$$\text{Now } f\left(\frac{m}{\theta}\right) = \frac{e^{-m\theta} \theta^{\Sigma m}}{\prod_{i=1}^m m!}$$

The prior density is

$$g(\theta) = \frac{1}{m!} \left(\frac{m+1}{\theta_o}\right)^{m+1} \theta^m e^{-(m+1)\theta/\theta_o}$$

$$f\left(\frac{m}{\theta}\right)g(\theta) = \frac{e^{-m\theta} \theta^{\Sigma m}}{\prod_{i=1}^m m!} \frac{1}{m!} \left(\frac{m+1}{\theta_o}\right)^{m+1} \theta^m e^{-(m+1)\theta/\theta_o}$$

$$f\left(\frac{m}{\theta}\right)g(\theta) = \frac{\left(\frac{m+1}{\theta_o}\right)^{m+1}}{m! \prod_{i=1}^m m!} \theta^{\Sigma m+m} e^{-\theta(m+\frac{m+1}{\theta_o})}$$

$$\int f\left(\frac{m}{\theta}\right)g(\theta) = \frac{\left(\frac{m+1}{\theta_o}\right)^{m+1}}{m! \prod_{i=1}^m m!} \int_0^{\infty} \theta^{\Sigma m+m+1-1} e^{-\theta/(m+\frac{m+1}{\theta_o})^{-1}} d\theta$$

Comparing with gamma function

$$\int f\left(\frac{m}{\theta}\right)g(\theta) = \frac{\left(\frac{m+1}{\theta_o}\right)^{m+1}}{m! \prod_{i=1}^m m!} \frac{1}{\Sigma m + m + 1} \left[\left(m + \frac{m+1}{\theta_o} \right)^{-1} \right]^{\Sigma m + m + 1}$$

$$\int f\left(\frac{m}{\theta}\right) g(\theta) = \frac{\left(\frac{m+1}{\theta_o}\right)^{m+1}}{m! \prod_{i=1}^m m!} \left[\frac{1}{\left(m + \frac{m+1}{\theta_o}\right)} \right]^{\Sigma m + m + 1}$$

Put in (A)

$$f\left(\frac{\theta}{m}\right) = \frac{\frac{\left(\frac{m+1}{\theta_o}\right)^{m+1}}{m! \prod_{i=1}^m m!} \theta^{\Sigma m + m} e^{-\theta(m + \frac{m+1}{\theta_o})}}{\frac{\left(\frac{m+1}{\theta_o}\right)^{m+1}}{m! \prod_{i=1}^m m!} \left[\frac{1}{\left(m + \frac{m+1}{\theta_o}\right)} \right]^{\Sigma m + m + 1}}$$

$$f\left(\frac{\theta}{m}\right) = \frac{\theta^{\Sigma m + m} e^{-\theta(m + \frac{m+1}{\theta_o})}}{\left[\frac{1}{\left(m + \frac{m+1}{\theta_o}\right)} \right]^{\Sigma m + m + 1}}$$

Now the bayes estimator is

$$\begin{aligned} \theta^* &= E\left(\frac{\tau(\theta)}{m}\right) = \int \theta f\left(\frac{\theta}{m}\right) d\theta \\ &= \frac{1}{\left[\frac{1}{\left(m + \frac{m+1}{\theta_o}\right)} \right]^{\Sigma m + m + 1}} \int_0^{\infty} \theta^{\Sigma m + m + 2 - 1} e^{-\theta(m + \frac{m+1}{\theta_o})} d\theta \end{aligned}$$

Comparing with gamma function

$$\begin{aligned}
&= \frac{1}{\left[\frac{1}{\left(m + \frac{m+1}{\theta_o} \right)} \right]^{\Sigma m + m + 1}} \left[\frac{1}{\left(m + \frac{m+1}{\theta_o} \right)} \right]^{\Sigma m + m + 2} \\
&= \frac{(\Sigma m + m + 1) \left[\frac{1}{\left(m + \frac{m+1}{\theta_o} \right)} \right]^{\Sigma m + m + 1}}{\left[\frac{1}{\left(m + \frac{m+1}{\theta_o} \right)} \right]^{\Sigma m + m + 1}} \\
&\theta^* = \frac{(\Sigma m + m + 1)}{\left(m + \frac{m+1}{\theta_o} \right)}
\end{aligned}$$

Which is the required bayes estimator for ' θ '

Question: 5

Statement:

Let $X_1, X_2, X_3, \dots, X_n$ be a random sample from a normal density with mean ' θ ' and variance ' 1 '. Consider estimation ' θ ' with a square error loss function. Assume that ' θ ' has a normal distribution with mean μ_o and variance 1. Obtain Bayes estimator for ' θ '.

As we know that the posterior density is

$$f\left(\frac{\theta}{X}\right) = \frac{f\left(\frac{X}{\theta}\right)g(\theta)}{\int f\left(\frac{X}{\theta}\right)g(\theta)d(\theta)} \longrightarrow (A)$$

As $X \rightarrow N(\theta, 1)$

$$f\left(\frac{X}{\theta}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-\theta)^2}$$

Taking likelihood function

$$f\left(\frac{X}{\theta}\right) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2}\sum(x-\theta)^2}$$

$$f\left(\frac{X}{\theta}\right) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2}[\sum x^2 + n\theta^2 - 2\theta\sum x]}$$

$$f\left(\frac{X}{\theta}\right) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2}[\sum x^2 + n\theta^2 - 2\theta n\bar{x}]}$$

The prior density is $\theta \rightarrow N(\mu_o, 1)$

$$g(\theta) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\theta - \mu_o)^2}$$

$$f\left(\frac{X}{\theta}\right)g(\theta) = \left(\frac{1}{\sqrt{2\pi}}\right)^{n+1} e^{-\frac{1}{2}[\sum x^2 + n\theta^2 + \theta^2 + \mu_o^2 - 2\theta\mu_o - 2\theta n\bar{x}]}$$

$$f\left(\frac{X}{\theta}\right)g(\theta) = \left(\frac{1}{\sqrt{2\pi}}\right)^{n+1} e^{-\frac{1}{2}[\sum x^2 + (n+1)\theta^2 + \mu_o^2 - 2\theta(\mu_o + n\bar{x})]}$$

$$f\left(\frac{X}{\theta}\right)g(\theta) = \left(\frac{1}{\sqrt{2\pi}}\right)^{n+1} e^{-\frac{1}{2}[\sum x^2 + \mu_o^2]} e^{-\frac{1}{2}[(n+1)\theta^2 - 2\theta(\mu_o + n\bar{x})]}$$

Let $K = \left(\frac{1}{\sqrt{2\pi}}\right)^{n+1} e^{-\frac{1}{2}[\sum x^2 + \mu_o^2]}$

$$f\left(\frac{X}{\theta}\right)g(\theta) = K e^{-\frac{1}{2}[(n+1)\theta^2 - 2\theta(\mu_o + n\bar{x})]}$$

$$f\left(\frac{X}{\theta}\right)g(\theta) = K e^{\frac{n+1}{2}\left[\theta^2 - 2\theta\left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]}$$

Now put in equation (A)

$$f\left(\frac{\theta}{x}\right) = \frac{K e^{\frac{n+1}{2}\left[\theta^2 - 2\theta\left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]}}{K \int_{-\infty}^{\infty} e^{\frac{n+1}{2}\left[\theta^2 - 2\theta\left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]} d\theta}$$

$$\begin{aligned} \int_{-\infty}^{\infty} e^{\frac{n+1}{2}\left[\theta^2 - 2\theta\left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]} d\theta &= \int_{-\infty}^{\infty} e^{\frac{n+1}{2}\left[\theta^2 - 2\theta\left(\frac{\mu_o + n\bar{x}}{n+1}\right) + \left(\frac{\mu_o + n\bar{x}}{n+1}\right)^2 - \left(\frac{\mu_o + n\bar{x}}{n+1}\right)^2\right]} d\theta \\ &= \int_{-\infty}^{\infty} e^{\frac{n+1}{2}\left(\frac{\mu_o + n\bar{x}}{n+1}\right)^2} e^{\frac{n+1}{2}\left[\theta - \left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]^2} d\theta \end{aligned}$$

So,

$$f\left(\frac{\theta}{x}\right) = \frac{e^{\frac{n+1}{2}\left(\frac{\mu_o + n\bar{x}}{n+1}\right)^2} e^{\frac{n+1}{2}\left[\theta - \left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]^2}}{\int_{-\infty}^{\infty} e^{\frac{n+1}{2}\left(\frac{\mu_o + n\bar{x}}{n+1}\right)^2} e^{\frac{n+1}{2}\left[\theta - \left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]^2} d\theta}$$

$$f\left(\frac{\theta}{x}\right) = \frac{e^{\frac{n+1}{2}\left[\theta - \left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]^2}}{\int_{-\infty}^{\infty} e^{\frac{n+1}{2}\left[\theta - \left(\frac{\mu_o + n\bar{x}}{n+1}\right)\right]^2} d\theta} \quad \text{--- (B)}$$

As we know that area under the curve is unity so,

$$\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx = 1$$

$$\int_{-\infty}^{\infty} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx = \sigma\sqrt{2\pi}$$

Now equation (B) become

$$f\left(\frac{\theta}{x}\right) = \frac{e^{\frac{1}{2\sqrt{n+1}}\left[\theta - \left(\frac{\mu_o + nx}{n+1}\right)^2\right]}}{\int_{-\infty}^{\infty} e^{\frac{1}{2\sqrt{n+1}}\left[\theta - \left(\frac{\mu_o + nx}{n+1}\right)^2\right]} d\theta}$$

And

$$\int_{-\infty}^{\infty} e^{\frac{1}{2\sqrt{n+1}}\left[\theta - \left(\frac{\mu_o + nx}{n+1}\right)^2\right]} d\theta = \sqrt{2\pi} \sqrt{\frac{1}{n+1}}$$

It means that

$$\tau(\theta) = \left(\frac{\theta}{x}\right) \rightarrow N\left(\frac{nx + \mu_o}{n+1}, \frac{1}{n+1}\right)$$

Hence $\theta^* = E\left(\frac{\theta}{x}\right) = \frac{nx + \mu_o}{n+1}$ is the required Bayes estimator.