



Indian Institute of Management  
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Bayesian Analysis  
Assignment

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# Bayesian Analysis Assignment

## Question 1:

Q1)

$x$	0.415	0.409
$P(x)$	0.5	0.5

$$\begin{aligned} E(x) &= \sum x \cdot P(x) \\ &= 0.415 \times 0.5 + 0.409 \times 0.5 \\ &= 0.412 \end{aligned}$$

$$\text{Var}(x) = E(x^2) - [E(x)]^2$$

$$\begin{aligned} E(x^2) &= \sum x^2 \cdot P(x) \\ &= (0.415)^2 (0.5) + (0.409)^2 (0.5) \\ &= 0.1697 \end{aligned}$$

$$\begin{aligned} \text{Var}(x) &= 0.1697 - (0.412)^2 \\ &= 0.000009 \end{aligned}$$

Now, matching moments

$$E(x) = 0.412 = \frac{a}{a+b}$$

$$\text{Var}(x) = 0.000009 = \frac{ab}{(a+b)^2(a+b+1)}$$

$$\frac{a}{a+b} = 0.412$$

$$a = 0.412a + 0.412b$$

$$0.588a = 0.412b$$

$$\boxed{a = 0.7b} \rightarrow \textcircled{1}$$

$$\frac{\cancel{0.7b}}{\cancel{0.7b} + b} = \cancel{0.412} \quad -$$

$$\frac{0.7b}{0.7b + b}$$

$$\frac{ab}{(a+b)^2(a+b+1)} = 0.000009$$

$$\frac{0.7b \cdot b}{(0.7b + b)^2(0.7b + b + 1)}$$

$$\frac{0.7b^2}{(1.7b)^2(1.7b + 1)} = \frac{\cancel{0.7b}^2}{2.89\cancel{b}^2(1.7b + 1)}$$

$$= \frac{0.2424}{(1.7b + 1)} = 0.000009$$



$$(1.7b + 1) = 26938.8$$

$$1.7b = 26937.8$$

$$b = 15845.8$$

$$a = 11102.8$$

Part (ii)

$$a_1 = a + n$$

$$b_1 = b + n - s$$

$$s = \frac{61}{150} = 0.4$$

$$a_1 = 11102.8 + 2$$

$$a_1 = 11102.8 + 61$$

$$b_1 = 15845.8 + 150 - 61$$

$$a_1 = 11163.8$$

$$b_1 = 15934.8$$

Posterior:  $B(a_1, b_1)$

$$20^{\text{th}} \text{ percentile} = \text{qbeta}(0.2, a_1, b_1)$$

$$= 0.409$$

$$= 40.9\%$$



Question 2:

Q2]  $x \rightarrow$  random variable

$$f(x) = \mu e^{-\mu x} \quad x \in (0, \infty)$$
$$\mu > 0$$

$\mu$  = rate parameter

(avg rate of arrivals per unit time)

→ This follows exponential distribution with known rate.

Prior for  $\mu$ :

$\mu \sim$  Gamma distribution  $G(\gamma_0, \lambda_0)$

$$\mu \sim G(1, 0.2)$$

Data:  $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$   
7      5      8      4      6

$$L(\mathbf{x}|\mu) = \mu^n e^{-\sum_{i=1}^n \mu x_i} \quad x_i \in (0, \infty)$$

$$= \mu^n e^{-\sum_{i=1}^n (\mu x_i)}$$

$$L(\mathbf{x}|\mu) = \mu^n e^{-\mu \sum_{i=1}^n x_i}$$

Part (i)

Posterior for  $\mu$

$$\pi(\mu/x) \propto L(x/\mu) \pi(\mu) \quad \mu > 0$$

$$\pi(\mu/x) \propto \mu^5 e^{-\sum_{i=1}^5 (\mu \gamma_i)} \quad x$$

$$\propto \underbrace{\lambda_0}_{\text{constant}} x^{\gamma_0} \mu^{\gamma_0 - 1} e^{-\lambda_0 \mu}$$

$$\propto \mu^{\gamma_0 - 1} e^{-\left[\lambda_0 + \sum_{i=1}^5 \mu \gamma_i\right]} \quad \mu > 0$$

$$\pi(\mu/x) \equiv \text{Gamma}(\gamma_1, \lambda_1) \quad n=5$$

$$\downarrow$$

$$\gamma_1 = \gamma_0 + n$$

$$-\mu \left( \sum_{i=1}^n x_i - \lambda_0 \right)$$

$$\lambda_1 = \lambda_0 + \sum_{i=1}^n \mu x_i$$

*valid parameter*

$$\gamma_1 = \gamma_0 + n$$

$$\lambda_1 = \lambda_0 + \sum_{i=1}^n x_i$$

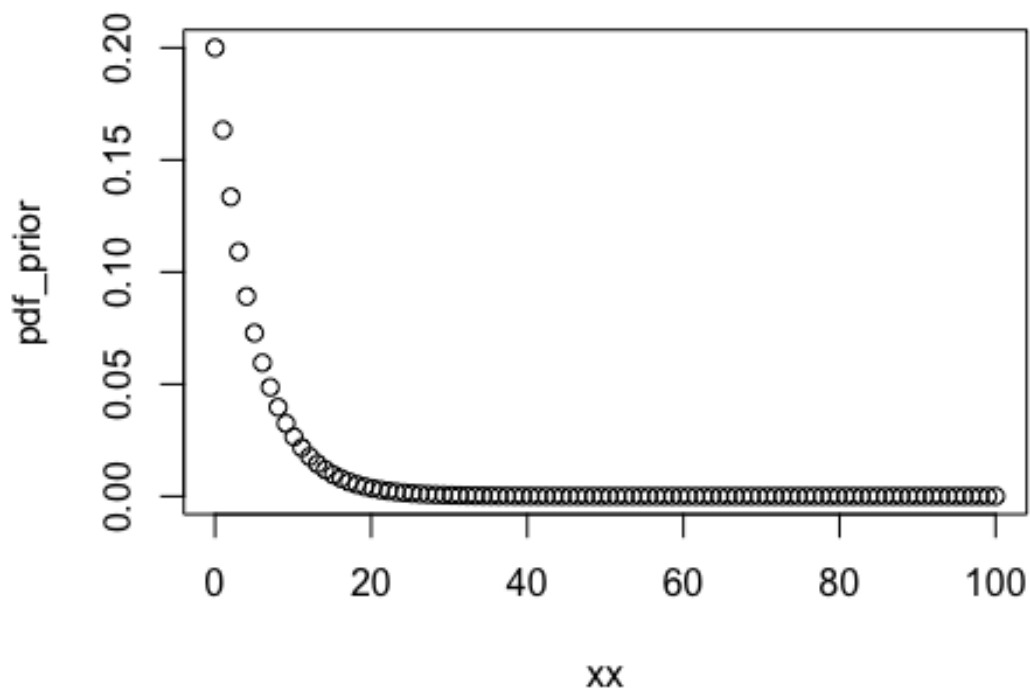


## R Code:

```
#Data
x <- c(7,5,8,4,6)
n<- length(x)

#Prior
nu0<- 1
lambda0<- 0.2

#Prior Distribution
xx<- seq(0,100,length=100)
pdf_prior<- dgamma(xx,shape=nu0,rate=lambda0)
plot(xx,pdf_prior)
```



```
#Posterior for mu
nu1<- nu0+n
nu1

## [1] 6

lambda1<- lambda0 + sum(x)
lambda1

## [1] 30.2

post_mean<- nu1/lambda1
post_mean

## [1] 0.1986755
```

## Part (ii)

# 95% CL

```
high<-qgamma(.975, shape=nu1, rate=lambda1)
low<-qgamma((1-.975), shape=nu1, rate=lambda1)
c(low,high)
```

```
## [1] 0.07291041 0.38636861
```

## Part (iii)

#Predictive distribution

N<-1000

```
rtheta<- rgamma(N, shape=nu1, rate=lambda1)
prob<- 1- pexp(q = 7, rate = rtheta)
mean(prob)
```

```
## [1] 0.2868927
```

## Question 3:

③ Sampling distribution of Poissons with sample size  $n$ ,  
Prior distribution  $\rightarrow$  constant / uniform

Likelihood:

$$L(\lambda | x) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!}$$
$$= \frac{e^{-n\lambda} \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!}$$

Prior  $P(\lambda) = \frac{1}{a}$   $a = \text{constant}$ .

Posterior:

$$P(\lambda | x) = \frac{e^{-n\lambda} \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!} \cdot \frac{1}{a}$$
$$\Rightarrow P(\lambda | x) \propto e^{-n\lambda} \lambda^{\sum_{i=1}^n x_i}$$



$$\lambda \sim \text{Gamma}(\gamma_1, \lambda_1)$$

$$\Rightarrow \sum_{i=1}^n x_i \leftarrow \gamma_1$$

$$n \leftarrow \lambda_1$$

$$\text{posterior mean } \lambda = \frac{\gamma_1}{n} = \frac{\sum x_i}{n}$$

$$\lambda | x = \text{Gamma}(\sum x_i, n)$$

(iii)

Posterior predictive distribution:-

$$P(x_{\text{new}} | x) = \int_0^{\infty} P(x_{\text{new}} | \lambda) \cdot P(\lambda | x) \cdot d\lambda$$

$$= \int_0^{\infty} \left[ \frac{\lambda^{x_{\text{new}}} e^{-\lambda}}{(x_{\text{new}})!} \right] \cdot \left[ \frac{(n)^{\sum x_i} e^{-\sum x_i}}{\Gamma(\sum x_i)} \lambda^{\sum x_i - 1} \right] d\lambda$$



$$= \frac{(\eta) \epsilon x_i}{\Gamma(\epsilon x_i) \Gamma(\lambda_{new} + 1)} \int_0^{\infty} \lambda^{\lambda_{new} + \epsilon x_i - \eta} e^{-\lambda} d\lambda$$

$$= \frac{\eta^{\epsilon x_i}}{\Gamma(\epsilon x_i) \Gamma(\lambda_{new} + 1)} \frac{\Gamma(\lambda_{new} + \epsilon x_i)}{\eta^{\lambda_{new} + \epsilon x_i}}$$

$$= \frac{\Gamma(\lambda_{new} + \epsilon x_i)}{\Gamma(\epsilon x_i) \Gamma(\lambda_{new} + 1)} \left( \frac{\eta}{\eta + 1} \right)^{\epsilon x_i} \left( \frac{1}{\eta + 1} \right)^{\lambda_{new}}$$

⇒ Negative binomial with mean  
 $\frac{\epsilon x_i}{\eta}$  and variance

$$\frac{\epsilon x_i}{\eta^2} (\eta + 1)$$



(ii) average = 200      10 weeks.

$$\Rightarrow \text{average} \times 10 = \sum x_i$$

$$\Rightarrow \sum x_i = 200 \times 10 = 2000$$

$$\sum x_i = 2000$$

$$n = 10$$

Gamma prior  $\Rightarrow \text{Gamma}(2000, 10)$

Predictive:-

$$N = 1000$$

$$y_{\text{heta}} \sim \text{gamma}(N, 2000, 10)$$

### Problem-3.R

#Data

```
x <- c(28, 15, 11, 21, 11, 17, 21, 15, 14, 18)
```

```

n<- length(x)

#Prior is flat uniform distribution

#Posterior for mu

nu1<- sum(x)
nu1

## [1] 171

lambda1<- n
lambda1

## [1] 10

# 95% CL
high<-qgamma(.975, shape=nu1, rate=lambda1)
low<-qgamma((1-.975),shape=nu1, rate=lambda1)
c(low,high)

## [1] 14.63300 19.75635

```

## Question 4:

### Problem-4.R

```

#prior
values<- seq(991,1010)
probability<- rep(.05,20)

#Data
x<-c(1003,995,999,1001,994,998,996,1002,1004,998,994,994,995,995,1001,997,1006,997,998,994)
n<-length(x)
sigma<-sqrt(32)
sigma

## [1] 5.656854

```

#### Part(i)

```

#Posterior distribution for mu
posterior<-c()
for(i in 1:20){
  mu<-values[i]
  likelihood<- prod(dnorm(x,mu,sigma))
  posterior<-c(posterior,likelihood*0.05)
}

posterior_prob<-posterior/sum(posterior)
result <- data.frame(Value=values, Proba=round(posterior_prob,3))
result

##      Value Proba
## 1      991 0.000
## 2      992 0.000
## 3      993 0.000
## 4      994 0.002

```



```
## 5      995 0.017
## 6      996 0.085
## 7      997 0.223
## 8      998 0.315
## 9      999 0.238
## 10     1000 0.096
## 11     1001 0.021
## 12     1002 0.002
## 13     1003 0.000
## 14     1004 0.000
## 15     1005 0.000
## 16     1006 0.000
## 17     1007 0.000
## 18     1008 0.000
## 19     1009 0.000
## 20     1010 0.000

#Posterior mean
posterior_mean<- sum(values*posterior_prob)
posterior_mean

## [1] 998.05

#Normal Prior for mu ~N(mu0, tau0^2)
mu0<-mean(values)
tau0<-sd(values)
xbar<-mean(x)
mu1<- (xbar * n/sigma^2 + mu0 * 1/tau0^2)/( n/sigma^2+ 1/tau0^2)
mu1

## [1] 998.1571

tau1<- sqrt(1/( n/sigma^2+ 1/tau0^2))
c(mean=mu1, sd=tau1)

##          mean          sd
## 998.157104    1.236954

#Credible Interval
c(low=qnorm(.025,mu1,tau1), high=qnorm((1-.025),mu1,tau1))

##          low          high
## 995.7327 1000.5815
```

### Part (ii):

```
#P(mu<1000 under posterior distribution)
N<-5000
rmu<-rnorm(N, mu1, tau1)
rprob<- pnorm(1000, rmu, sigma)
mean(rprob)

## [1] 0.6249315
```

Part (iii)

$$\mu|\theta \sim N\left(\mu=998, \frac{\sigma^2}{2}\right)$$

$$\sim N\left(\mu=998, \frac{1}{2\theta}\right) \quad \theta = \frac{1}{\sigma^2}$$

$$\theta \sim \text{Gamma}(\gamma_0, \lambda_0)$$

$$\theta \sim \text{Gamma}(40, 10)$$

$$\pi(\theta) \propto \lambda_0^{\gamma_0} \theta^{\gamma_0-1} e^{-\lambda_0 \theta} \quad \theta \in (0, \infty)$$

$\gamma_0 = 40 \quad \lambda_0 = 10$

Posterior for  $\theta$

$$\pi(\theta|x) \propto L(x|\theta) \cdot \pi(\theta) \quad \theta > 0$$

$$\begin{aligned} \pi(\theta|x) &\propto \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^{20} e^{-\sum_{i=1}^{20} \frac{(x_i - \mu)^2}{2\sigma^2}} \cdot \lambda_0^{\gamma_0} \theta^{\gamma_0-1} e^{-\lambda_0 \theta} \quad \theta > 0 \\ &\propto \frac{1}{\sqrt{2\pi}} \theta^{-\frac{20}{2}} e^{-\sum_{i=1}^{20} \frac{(x_i - \mu)^2}{2} \theta} \cdot \lambda_0^{\gamma_0} \theta^{\gamma_0-1} e^{-\lambda_0 \theta} \quad \theta > 0 \end{aligned}$$

$$\propto \frac{\lambda_0^{\gamma_0}}{\theta} e^{-\left(\lambda_0 + \sum_{i=1}^{20} \frac{(x_i - \mu)^2}{2}\right) \theta} \quad \theta > 0$$

$$\pi(\theta|x) \equiv \text{Gamma}(\gamma_1, \lambda_1)$$

$$\equiv \frac{\eta}{2} + \gamma_0, \quad \lambda_0 + \frac{\sum_{i=1}^{\eta} (x_i - \mu)^2}{2} \quad \eta = 20$$



*#Posterior distribution for  $\sigma^2$*

```
nu1<- n/2+40
```

```
nu1
```

```
## [1] 50
```

```
lambda1<-10+sum(((x-998)^2/2))
```

```
lambda1
```

```
## [1] 138.5
```

**$\sigma^2 \sim \text{Gamma}(50, 138.5)$**

```
posterior_sig<-c()
```

```
for(i in 1:20){
```

```
  mu<-values[i]
```

```
  likelihood<- prod(dgamma(x,shape = nu1,rate = lambda1))
```

```
  posterior_sig<-c(posterior_sig,likelihood*0.05)
```

```
}
```

```
posterior_prob1<-posterior_sig/sum(posterior_sig)
```

```
result1 <- data.frame(Value=values, Proba=round(posterior_prob1,3))
```