



## PRACTICAL ASSIGNMENT

MSMS – 407 : Practical based on above papers

**Submitted by**

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RAHUL GOSWAMI

M.Sc. Statistics and Computing – 4th Semester

Roll No. 18419STC019

Enrollment No . 404655

DST-CIMS

Institute of Science , BHU

# Practical Assignment

## Problem 1

Generate 100 observations from  $N(0,1)$  using the Box-Muller transformation method and Acceptance Rejection method. You can use double exponential distribution as proposal density. Hence generate from 100 observations from  $N(2, 10)$

### 1.Box-Muller Method

#### Algorithm

1. Generate two random variables  $u_1$  and  $u_2$  from Standard Uniform Distribution
2. Then set

$$Z_1 = \sqrt{-2\log(U_1)}\cos(2\pi U_2)$$

$$Z_2 = \sqrt{-2\log(U_1)}\sin(2\pi U_2)$$

3. Now  $X_1$  and  $X_2$  are independent standard normal variates , now we can transform using following equation

$$Y_1 = X_1\sigma + \mu$$

$$Y_2 = X_2\sigma + \mu$$

Now  $Y_1$  and  $Y_2$  are distributed

$$Y_1, Y_2 \sim N(\mu, \sigma^2)$$

#### Code

```
# To Genereate Random numbers from standard uniform distribution we will us runif() function

U_1 <- runif(50)
U_2 <- runif(50)

# Now Converting Uniform to Standard normal using Box-Muller Method

Z_1 = sqrt(-2*log(U_1))*cos(2*pi*U_2)
Z_2 = sqrt(-2*log(U_2))*sin(2*pi*U_1)

Z <- c(Z_1,Z_2)
print(Z)

## [1] -0.17379567 0.68153044 0.43588063 0.32639272 -1.00962265 -1.06439258
## [7] -0.24345821 -0.62187939 -1.19055170 1.12901894 1.50217148 -0.55009361
## [13] -0.76149107 2.21154299 -0.01079774 1.38087549 1.18475082 0.42274538
## [19] 1.03283520 0.99816181 0.04439397 0.52985986 -0.58530514 -0.06136478
## [25] -1.29188693 -0.63619458 0.21185564 -0.10411944 -0.22787286 0.47086157
## [31] -0.44569445 -0.80387781 1.11368075 -0.48170133 -0.68497063 -1.07467222
```

```

## [37] -2.05132605  0.90546239 -1.00951453  0.71255726  0.29771583  0.05540006
## [43] -1.21881772 -0.64955309 -1.06157260 -0.68202672 -2.00753672 -1.18222646
## [49]  0.70129659 -1.23461662 -1.07649607 -0.22391495 -1.82264651 -0.62638411
## [55] -0.69140744  0.84214576 -0.30567590 -1.02795240  0.07796159  0.46449429
## [61]  2.12044068 -0.89182777 -1.18606230  1.71360022 -0.94930350  0.87375749
## [67]  0.01069264 -1.44211639  1.53383090  1.40233359 -0.59098378  0.46076603
## [73]  1.30138782 -0.33640842  0.47283311 -1.05083749 -0.03589455 -1.60485058
## [79] -0.55953725 -0.10619766 -0.83613957 -1.17602396 -0.19388490  0.77201646
## [85]  1.51358999 -0.36334577  0.36259299  1.39144813 -0.28042191  0.62895265
## [91]  0.70724738 -1.68974485  1.37915362 -1.10187206  1.42027393 -1.13343633
## [97]  0.87251924  0.22864644  1.19651017  0.87932572

```

To transform these to  $N(2, 10)$  we will us

$$X = Z_{0,1}\sigma + \mu$$

So we have  $\mu = 2$  and  $\sigma = \sqrt{10}$  so

```

X = Z*sqrt(10)+2
print(X)

```

```

## [1]  1.45040982  4.15518847  3.37837556  3.03214441 -1.19270716 -1.36590487
## [7]  1.23011755  0.03344469 -1.76485504  5.57027138  6.75028332  0.26045128
## [13] -0.40804621  8.99351301  1.96585454  6.36671170  5.74651105  3.33683827
## [19]  5.26611169  5.15646478  2.14038607  3.67556400  0.14910262  1.80594754
## [25] -2.08530518 -0.01182392  2.66994637  1.67074541  1.27940276  3.48899503
## [31]  0.59059041 -0.54208483  5.52176775  0.47672665 -0.16606732 -1.39841195
## [37] -4.48686254  4.86332348 -1.19236525  4.25330391  2.94146011  2.17519038
## [43] -1.85424005 -0.05406722 -1.35698732 -0.15675788 -4.34838853 -1.73852831
## [49]  4.21769455 -1.90420054 -1.40417947  1.29191875 -3.76371435  0.01919952
## [55] -0.18642230  4.66309872  1.03336794 -1.25067092  2.24653619  3.46885990
## [61]  8.70542219 -0.82020703 -1.75065831  7.41887969 -1.00196126  4.76306378
## [67]  2.03381309 -2.56037245  6.85039919  6.43456818  0.13114520  3.45707013
## [73]  6.11534961  0.93618318  3.49522957 -1.32303993  1.88649145 -3.07498314
## [79]  0.23058787  1.66417351 -0.64410549 -1.71891431  1.38688212  4.44133042
## [85]  6.78639181  0.85099979  3.14661970  6.40014535  1.11322805  3.98892292
## [91]  4.23651259 -3.34344239  6.36126669 -1.48442539  6.49130054 -1.58424038
## [97]  4.75914809  2.72304354  5.78369739  4.78067209

```

## 2. Acceptance Rejection Method

### Algorithm

1. Choose a density that is easy to sample from.
2. Find a constant  $c$  such that Equation 4.6 is satisfied.
3. Generate a random number  $Y$  from the density .
4. Generate a uniform random number  $U$ .
5. If

$$U \leq \frac{f(Y)}{cg(Y)}$$

, then accept  $X=Y$  , else go to step 3

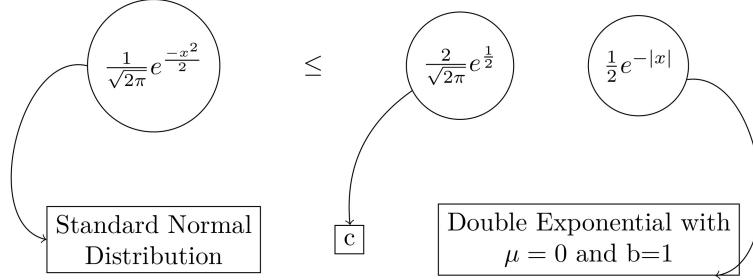
First of all we will solve following inequality

$$\begin{aligned}
 \frac{1}{2}(|x| - 1)^2 &\geq 0 \\
 \Rightarrow \frac{1}{2}(x^2 + 1 - 2|x|) &\geq 0
 \end{aligned}$$

$$\Rightarrow \frac{1}{2}x^2 + \frac{1}{2} - |x| \geq 0$$

$$\frac{-x^2}{2} \leq \frac{1}{2} - |x|$$

$$\frac{1}{\sqrt{2\pi}}e^{\frac{-x^2}{2}} \leq \frac{1}{\sqrt{2\pi}}e^{\frac{1}{2}-|x|}$$



Now we have  $c = 1.3154892$  so now

### Code

```
c = (2*exp(0.5))/sqrt(2*pi)
Z = c()
while(length(Z) < 100){
  a = rlaplace(1)
  u = runif(1)
  if( u <= dnorm(a)/(c*dlaplace(a))){
    Z = c(Z,a)}
}
print(Z)

## [1] 0.50379376 0.84718517 -0.31652393 -0.99849262 1.15232095 0.78807060
## [7] 0.14717076 -0.85559646 1.43827133 -0.92068039 1.22377419 -1.00383856
## [13] 0.33665475 -0.51385016 -0.95029580 1.21475944 1.11830397 0.41569651
## [19] 0.32193055 -0.49757534 0.84900648 -0.10950972 0.44713618 0.57728493
## [25] 0.18828238 -0.04683103 0.25098764 0.12338719 -0.61898634 0.99606023
## [31] -1.29365759 -0.94807143 0.32394370 0.91542255 1.27587766 -2.04767306
## [37] 0.36399468 0.36345637 0.77940609 0.61272328 0.08049606 0.45775524
## [43] 0.69243113 -0.64834320 0.49843780 0.39880048 -1.31355335 1.53824654
## [49] 0.80495250 0.64106658 0.27927370 -0.73764418 0.99808747 0.65853811
## [55] -0.03859097 -1.60994265 0.41889010 -1.14248590 -0.26977847 -0.16885982
## [61] -0.83385940 0.50997719 -0.07478001 -0.07273755 -2.04370635 1.14305461
## [67] -2.13284945 -0.46071695 -0.41564908 1.25023490 -0.10597037 0.43862393
## [73] -0.61868603 -0.04173852 -0.35211231 -0.89058099 -0.77220789 -0.54206509
## [79] 0.71056921 0.33023729 -0.60321162 0.75821441 -0.80445072 0.96333834
## [85] -1.27913131 -0.28171597 -1.29368102 -2.06433598 -0.28105272 -0.69700992
## [91] 2.19454066 1.76133052 0.30665610 0.09626922 -0.32757525 -0.32352353
## [97] -0.34589649 -1.77448604 -0.08132519 0.31856421
```

So we have  $\mu = 2$  and  $\sigma = \sqrt{10}$  so

```
X = Z*sqrt(10)+2
print(X)

## [1] 3.59313574 4.67903472 0.99906344 -1.15751089 5.64395880 4.49209805
## [7] 2.46539480 -0.70563356 6.54821330 -0.91144703 5.86991379 -1.17441627
## [13] 3.06459580 0.37506312 -1.00509917 5.84140663 5.53638768 3.31454778
```

```

## [19] 3.01803379 0.42652861 4.68479422 1.65369984 3.41396874 3.82553524
## [25] 2.59540117 1.85190728 2.79369261 2.39018455 0.04259334 5.14981901
## [31] -2.09090451 -0.99806509 3.02439992 4.89482027 6.03467944 -4.47531079
## [37] 3.15105225 3.14934997 4.46469848 3.93760115 2.25455090 3.44754918
## [43] 4.18965948 -0.05024121 3.57619872 3.26111786 -2.15382041 6.86436268
## [49] 4.54548331 4.02723053 2.88314100 -0.33263573 5.15622971 4.08248036
## [55] 1.87796463 -3.09108567 3.32464680 -1.61285762 1.14688559 1.46601837
## [61] -0.63689496 3.61268947 1.76352485 1.76998366 -4.46276692 5.61465606
## [67] -4.74466217 0.54308510 0.68560220 5.95358990 1.66489227 3.38705064
## [73] 0.04354299 1.86801122 0.88652312 -0.81626437 -0.44193577 0.28583969
## [79] 4.24701713 3.04430199 0.09247738 4.39768448 -0.54389655 5.04634332
## [85] -2.04496836 1.10913589 -2.09097858 -4.52800354 1.11123326 -0.20413891
## [91] 8.93974690 7.56981615 2.96973173 2.30442999 0.96411612 0.97692876
## [97] 0.90617924 -3.61141757 1.74282716 3.00738850

```

## Problem 2

Let us consider the following dataset follows an exponential distribution with scale parameter  $\theta$ . Let us consider the prior for  $\theta$ . Obtain posterior distribution, Bayes estimator, and 0.95 HPD interval for the parameter.

3.29, 7.53, 0.48, 2.03, 0.36, 0.07, 4.49, 1.05, 9.15, 3.67, 2.22, 2.16, 4.06, 11.62, 8.26, 1.96, 9.13, 1.78, 3.81, 17.02

The density of the data model will be given by

$$f(x|\theta) = \frac{1}{\theta} e^{-\frac{x}{\theta}}$$

Let us notify  $\sum_{i=1}^n x_i = S_n$  now the likelihood will be given by

$$L(x|\theta) = \left(\frac{1}{\theta}\right)^n e^{-\frac{S_n}{\theta}}$$

Now Since we do not have any info about  $\theta$  let us assume non-informative prior

$$\pi(\theta) = \frac{1}{\theta}$$

Then the posterior will be given by

$$\begin{aligned} \pi(\theta|x) &= \frac{\frac{1}{\theta} \cdot \left(\frac{1}{\theta}\right)^n e^{-\frac{S_n}{\theta}}}{\int_0^\infty \frac{1}{\theta} \cdot \left(\frac{1}{\theta}\right)^n e^{-\frac{S_n}{\theta}}} \\ \pi(\theta|x) &= \frac{S_n^n}{\Gamma(n)} \cdot \left(\frac{1}{\theta}\right)^{n+1} e^{-\frac{S_n}{\theta}} \end{aligned}$$

Now this is the density of the Inverse Gamma so

$$\pi(\theta|x) \sim \text{Inv-Gamma}(n, S_n)$$

So the bayes estimate will be given by  $\frac{S_n}{n-1}$

## Code

```

xobs <- c(3.29, 7.53, 0.48, 2.03, 0.36, 0.07, 4.49, 1.05, 9.15, 3.67, 2.22, 2.16, 4.06, 11.62, 8.26, 1.96, 9.13, 1.78, 3.81, 17.02)
Bayes_Estimate = sum(xobs)/(length(xobs)-1)
cat("Bayes Estimate of scale parameter is given by ", Bayes_Estimate)

```

```
## Bayes Estimate of scale parameter is given by 4.954737
```

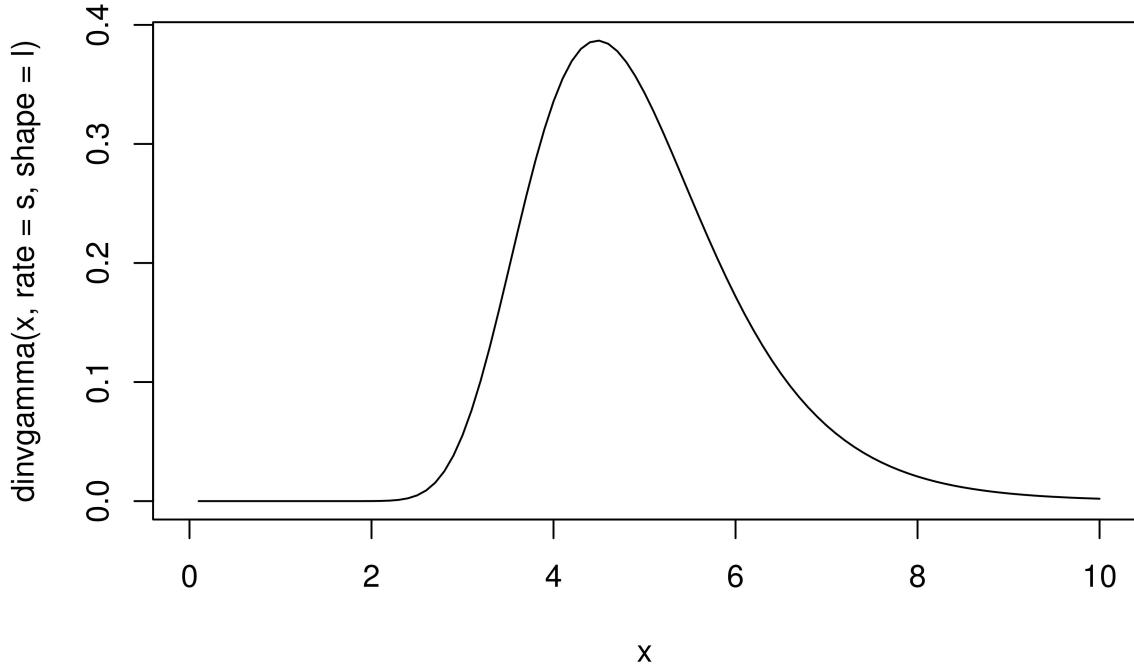
Now **HPDI** will be given by

$$\int_{\theta: \pi(\theta|X) \geq k} \pi(\theta|X) d\theta = 1 - \alpha$$

where  $1 - \alpha = 0.95$ , here it can be thought as a horizontal line is on the posterior density such that the point where the posterior density intersect this line the area between these points will be 0.95

Let us take a look at posterior density function

```
s = sum(xobs)
l = length(xobs)
curve(dinvgamma(x, rate = s, shape = 1), from=0, to=10)
```



Now let us find HPD Code

```
ruler1 <- seq(2, s/(l+1), length=3500) # s/(l+1) is mode of posterior
ruler2 <- seq(s/(l+1), 8, length = 5000)
target = 0.95
tolerance = 0.0005
done<- FALSE
for(i in ruler1)
{
  for(j in ruler2)
  {
    if(round(dinvgamma(i, rate=s, shape = 1), 3) == round(dinvgamma(j, rate=s, shape = 1), 3))
```

```

{
  #print(paste(i, "and", j))
  L <- pinvgamma(i,rate=s,shape=1)
  H <- pinvgamma(j,rate=s,shape=1)
  if (((H-L)<(target+tolerance)) & ((H-L)>(target-tolerance)))
  {
    done <- TRUE
    break
  }
}
if (done){break}
}
HPD.L <- i; HPD.U <- j
print(paste(target*100, "% HPD interval:", HPD.L, "to", HPD.U))
## [1] "95 % HPD interval: 2.94588413015964 to 7.2851736061498"

```