

# SC-HW1

ID : 111024517

Name : 鄭家豪

due on 02/27

## (1) Weibull distribution:

- Sampling by inverse CDF method:

$F(x) = 1 - \exp(-(x/\theta)^\beta) \sim U(0, 1)$ , by Probability integral transformation.

Do some calculation, we have

$$F^{-1}(y) = \theta \times (\ln \frac{1}{1-y})^{1/\beta}, \text{ where } Y \sim U(0, 1).$$

- Algorithm:

step 1: fixed  $(\theta, \beta)$ , generate  $U \sim U(0, 1)$

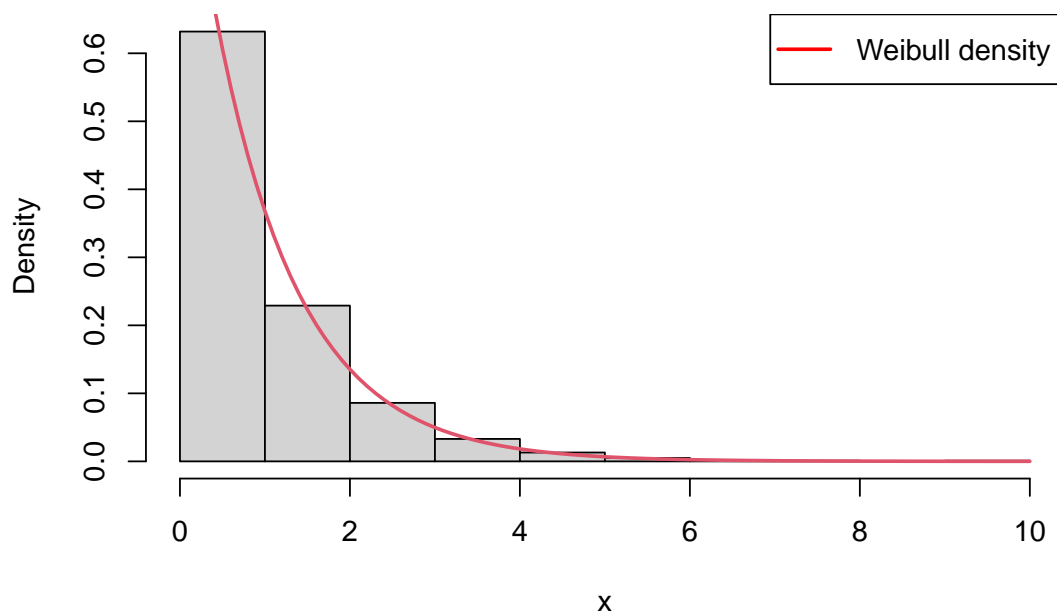
step 2:  $X = F^{-1}(U) \sim \text{Weibull}(\theta, \beta)$

```
Weibull <- function(n,scale,shape){  
  x <- c()  
  set.seed(1)  
  for(i in 1:n){  
    x[i] <- scale*(log(1/(1-runif(1))))^(1/shape)  
  }  
  hist(x,freq = F,  
        main="Histogram of Weibull by inverse CDF")  
  curve(dweibull(x,shape,scale),col=2, lwd=2, add=T)  
  legend("topright",legend = c("Weibull density"),  
        col=c("red"), lty=c(1), pch=c(-1), lwd=2)  
  table <- data.frame("efficiency(empirical)" = length(x)/n,  
                      "efficiency(theoretical)" = 1)  
  return(kable(table,row.names = F))  
}
```

- $n=1000; (\theta, \beta) = (1, 1)$  (i.e. Exp(1)):

```
Weibull(1000,1,1)
```

## Histogram of Weibull by inverse CDF



efficiency.empirical.	efficiency.theoretical.
1	1

由於這裡採用，Weibull random variable 由 Uniform random variable 藉由 inverse CDF method 轉換得來的，所以 empirical and theoretical efficiency 皆等於 1，都不受 parameters  $(\theta, \beta)$  所影響。由以上的例子驗證此結論。

## (2) Pareto distribution:

- Sampling by inverse CDF method:

$F(x) = \int_0^x \frac{\beta}{\theta} (1 + t/\theta)^{-(\beta+1)} dt = 1 - (1 + x/\theta)^{-\beta} \sim U(0, 1)$ , by Probability integral transformation.

Do some calculation, we have

$$F^{-1}(y) = \theta \times \left[ \left( \frac{1}{1-y} \right)^{1/\beta} - 1 \right], \text{ where } Y \sim U(0, 1).$$

- Algorithm:

step 1: fixed  $(\theta, \beta)$ , generate  $U \sim U(0, 1)$

step 2:  $X = F^{-1}(U) \sim \text{Pareto}(\theta, \beta)$

```
pareto <- function(n,scale,shape){
  x <- c()
  set.seed(2)
```

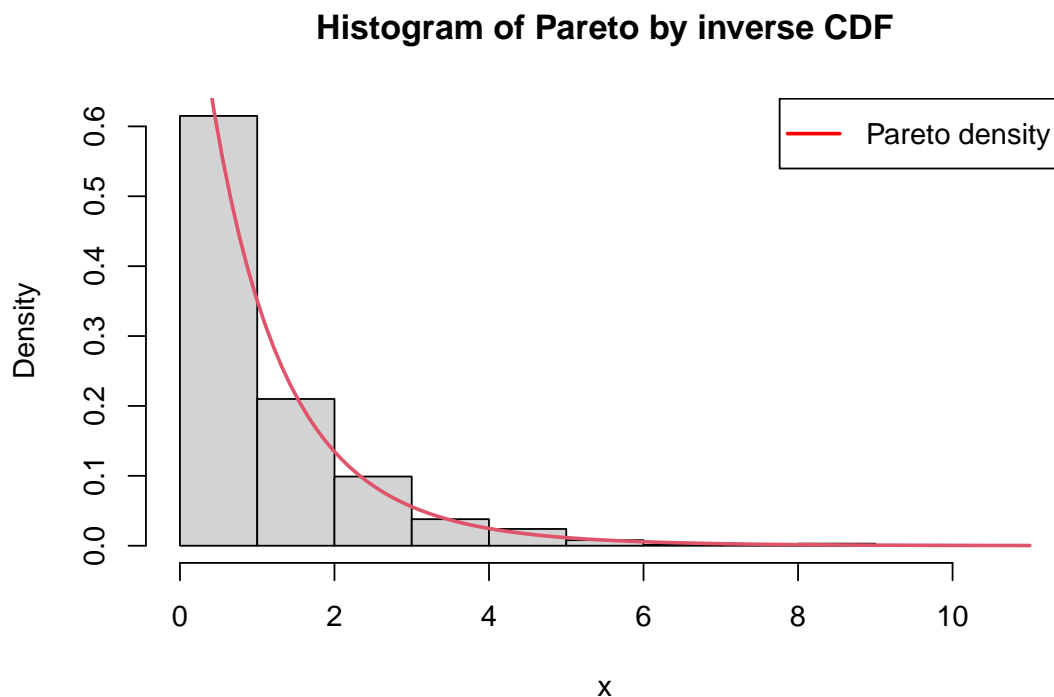
```

for(i in 1:n){
  x[i] <- scale*(1/(1-runif(1))^(1/shape)-1)
}
f = function(x,scale,shape){
  y <- c()
  for(i in 1:length(x)){
    y[i] <- shape/(scale*(1+x[i]/scale)^(shape+1))
  }
  return(y)
}
hist(x,freq = F,
      main="Histogram of Pareto by inverse CDF")
curve(f(x,scale,shape), col=2, lwd=2, add=T)
legend("topright",legend = c("Pareto density"),
       col=c("red"), lty=c(1), pch=c(-1), lwd=2)
table <- data.frame("efficiency(empirical)" = length(x)/n,
                    "efficiency(theoretical)" = 1)
return(kable(table,row.names = F))
}

```

- $n=1000; (\theta, \beta) = (10, 10)$  :

```
pareto(1000,10,10)
```



efficiency.empirical.	efficiency.theoretical.
1	1

由於這裡採用，Pareto random variable 由 Uniform random variable 藉由 inverse CDF method 轉換得來的，所以 empirical and theoretical efficiency 皆等於 1，都不受 parameters  $(\theta, \beta)$  所影響。由以上的例子，驗證此結論。

### (3) skewed distribution I:

- Rejection sampling:

Do some simplification to  $f(x)$ :

$$f(x) = \begin{cases} \frac{2r^2}{1+r^2}\phi_1(x) = f_1(x) & \text{if } x \geq 0 \\ \frac{2}{1+r^2}\phi_2(x) = f_2(x) & \text{if } x < 0 \end{cases}, \text{ where } \begin{cases} \phi_1 : \text{pdf of } N(0, r^2) \\ \phi_2 : \text{pdf of } N(0, 1/r^2) \end{cases}$$

For any  $x$ :

$$\frac{f_1(x)}{f_2(x)} = r^2 \times \frac{1/r}{r} \times \exp\left(-\frac{x^2}{2}\left(\frac{1}{r^2} - r^2\right)\right) = \begin{cases} \geq 1 & \text{if } r \geq 1 \\ \in (0, 1) & \text{if } r \in (0, 1) \end{cases}$$

Set:

$$\text{proposal } g(x) = \begin{cases} \phi_1(x), & \text{if } r \geq 1 \\ \phi_2(x), & \text{if } r \in (0, 1) \end{cases}, x \in \mathbb{R}$$

$$M = M(r) = \begin{cases} \frac{2r^2}{1+r^2}, & \text{if } r \geq 1 \\ \frac{2}{1+r^2}, & \text{if } r \in (0, 1) \end{cases}$$

\* Algorithm:

step 1: fixed  $r$ , generate  $Y \sim g$  and  $U \sim U(0, 1)$ ,  $Y$  and  $U$  are indep;

step 2: let  $X=Y$  if  $U \leq \frac{f(y)}{M(r) \times g(y)}$ , and reject the draw otherwise.

```
rej_3 <- function(n,r){
  M = function(r){
    z = 0
    if (r >=1){ z = 2*r^2/(1+r^2)}
    else { z = 2/(1+r^2)}
    return(z)
  }
  f = function(x,r){
```

```

y = c()
for (i in 1:length(x)){
  if (x[i] < 0) {y[i] <- 2/(1+r^2)*dnorm(x[i],mean = 0,sd = 1/r)}
  else{y[i] <- 2*r^2/(1+r^2)*dnorm(x[i],mean = 0,sd = r)}
}
return(y)
}

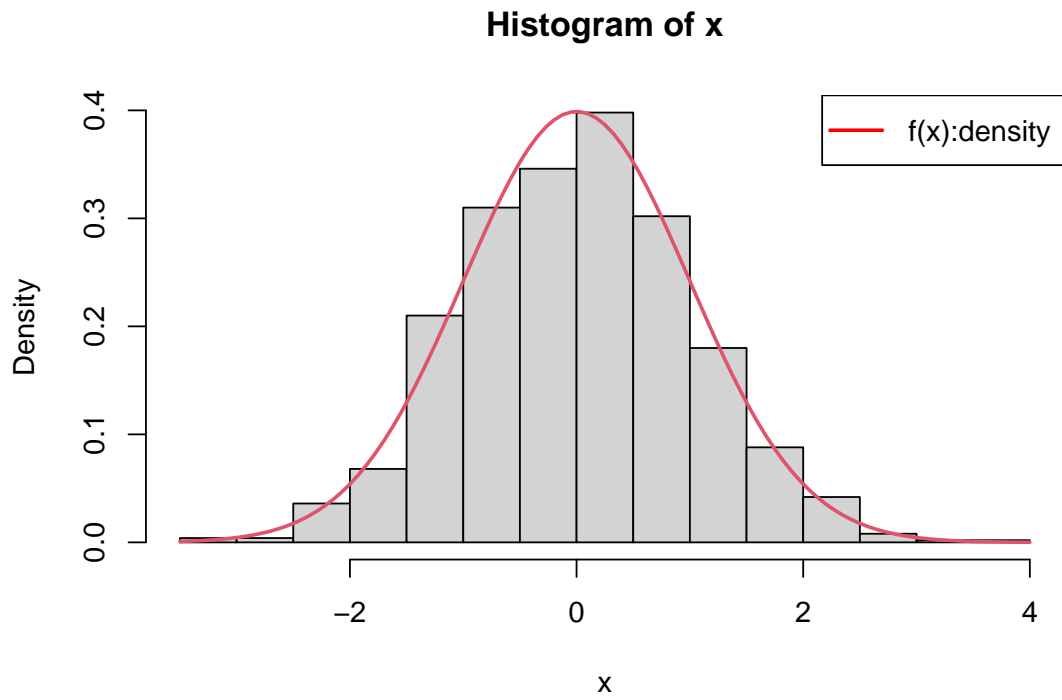
g = function(x,r){
  y <- c()
  if (r >= 1){y <- dnorm(x,mean = 0,sd = r)}
  else{y <- dnorm(x,mean = 0,sd = 1/r)}
  return(y)
}

set.seed(3)
y <-c()
if (r >= 1){y <- rnorm(n,mean = 0,sd = r)}
else{y <- rnorm(n,mean = 0,sd = 1/r)}
u <- runif(n,0,1)
x = y[u <= f(y,r)/(M(r)*g(y,r))]
hist(x, 20, probability=T)
curve(f(x,r), col=2, lwd=2, add=T)
legend("topright",legend = c("f(x):density"),
      col=c("red"), lty=c(1), pch=c(-1), lwd=2)
table <- data.frame("efficiency(empirical)" = length(x)/n,
                    "efficiency(theoretical)" = 1/M(r))
return(kable(table,row.names = F))
}

```

- $n=1000$  ;  $r = 1$ :

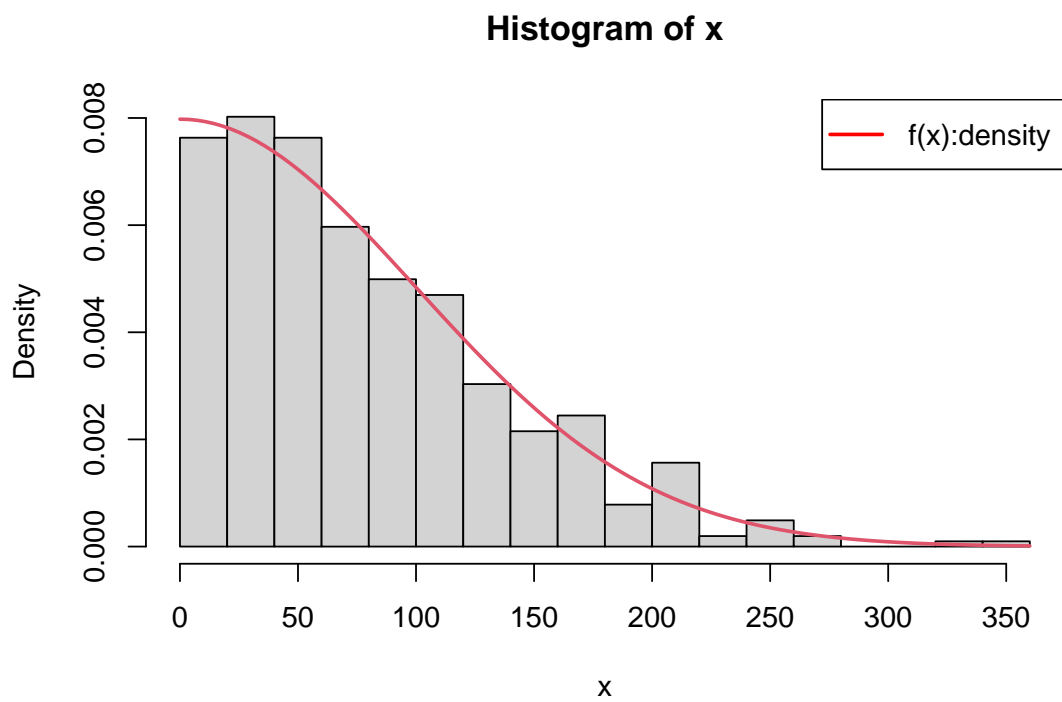
```
rej_3(1000,1)
```



efficiency.empirical.	efficiency.theoretical.
1	1

- $n=1000$  ;  $r = 100$ :

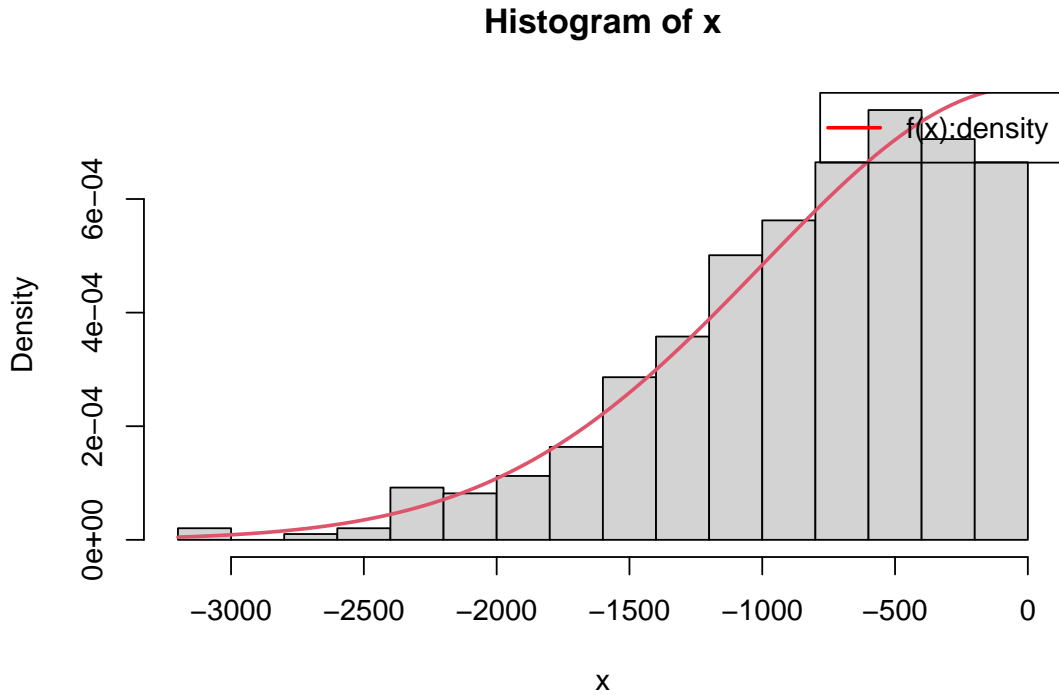
```
rej_3(1000,100)
```



efficiency.empirical.	efficiency.theoretical.
0.511	0.50005

- $n=1000$  ;  $r = 0.001$ :

```
rej_3(1000,0.001)
```



efficiency.empirical.	efficiency.theoretical.
0.489	0.5000005

由於  $M = M(r)$ ，為一個  $v$  的函數，故  $\text{theoretical efficiency} = 1/M = 1/M(r)$ ，其  $\text{efficiency}$  會受  $\text{parameter } r$  影響。另外，以上任取三個不同的  $r$ ，從所得到的模擬結果，可以觀察出其  $\text{empirical efficiency}$  一致於  $\text{theoretical efficiency}$ 。由以上的例子，驗證此結論。

#### (4) skewed distribution II:

- Rejection sampling:

$$\begin{aligned}
 f(x) &= 2h(x)G(\alpha x) \\
 &\leq 2h(x) \times 1 \quad (\because G(\alpha x) \leq 1, \forall x)
 \end{aligned}$$

Set:

$$M = 2$$

proposal  $g(x) = h(x)$  : pdf of the  $t_v$  distribution

- Algorithm:

step 1: generate  $Y \sim t_v$  and  $U \sim U(0, 1)$ ,  $Y$  and  $U$  are indep;

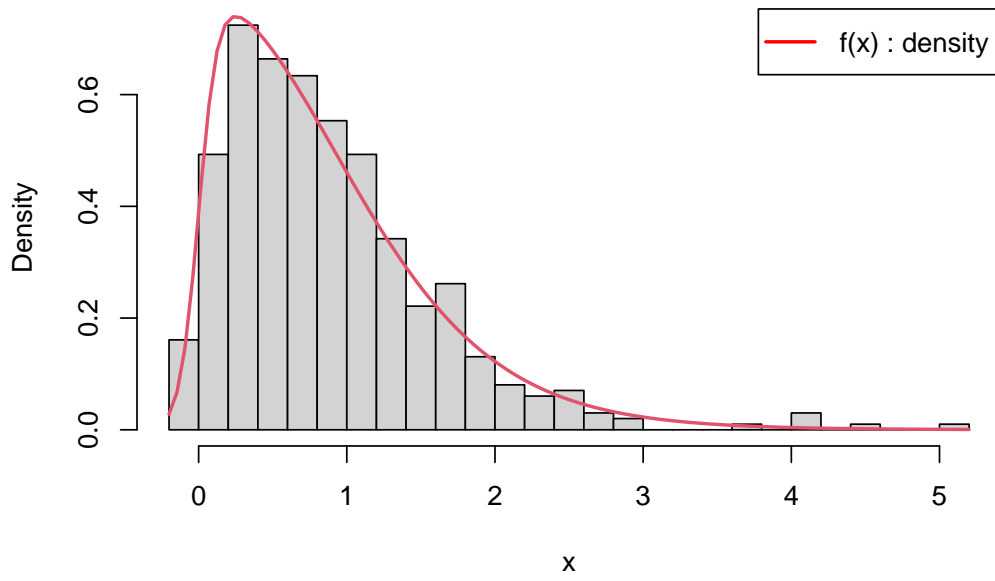
step 2: let  $X=Y$  if  $U \leq \frac{f(y)}{2 \times g(y)}$ , and reject the draw otherwise.

```
rej_4 <- function(n,alpha,v){  
  M=2  
  f = function(x,alpha,v){  
    y = c()  
    for(i in 1:length(x)){  
      y[i] <- 2*dt(x[i],df = v)*pt(alpha*x[i],df = v)  
    }  
    return(y)  
  }  
  #g = dt(x,v)  
  set.seed(4)  
  u = runif(n,0,1)  
  y <- rt(n,df = v)  
  x = y[u <= f(y,alpha,v)/(M*dt(x = y,df = v))]  
  hist(x, 20, probability=T)  
  curve(f(x,alpha,v), col=2, lwd=2, add=T)  
  legend("topright",legend = c("f(x) : density"),  
        col=c("red"), lty=c(1), pch=c(-1), lwd=2)  
  table <- data.frame("efficiency(empirical)" = length(x)/n,  
                     "efficiency(theoretical)" = 1/M)  
  return(kable(table,row.names = F))  
}
```

- $n=1000$  ;  $(\alpha, v) = (10, 10)$  :



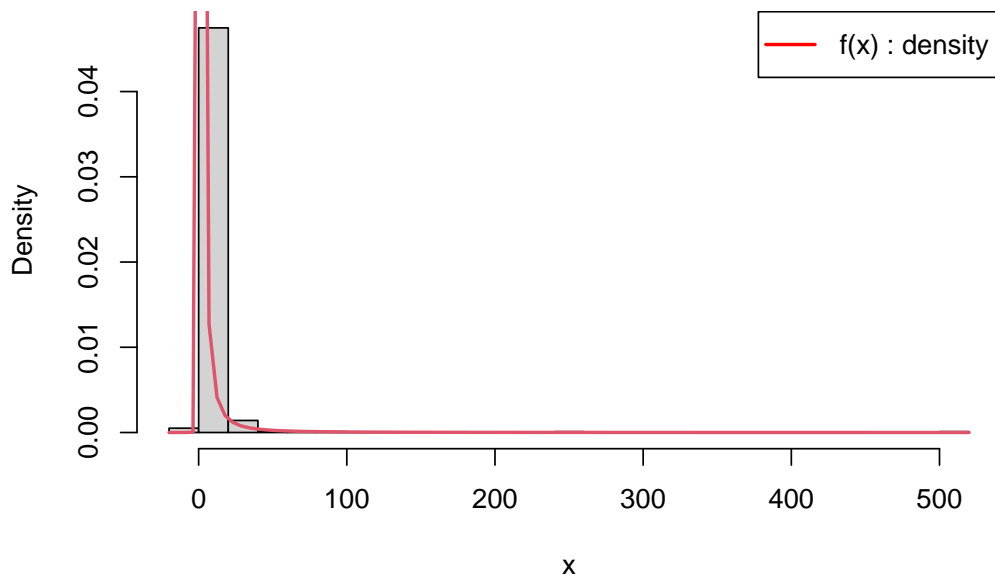
### Histogram of x



efficiency.empirical.	efficiency.theoretical.
0.497	0.5

- $n=1000$  ;  $(\alpha, v) = (99, 1)$  :

### Histogram of x



efficiency.empirical.	efficiency.theoretical.
0.495	0.5

由於  $M = 2$ ，為一個常數，故  $\text{theoretical efficiency} = 1/M = 0.5$ ，其  $\text{efficiency}$  不受  $\text{parameter } (\alpha, v)$  影響。另外，以上是任取  $(\alpha, v)$  所得到的模擬結果，可以觀察出其  $\text{empirical efficiency}$  一致於  $\text{theoretical efficiency}$ 。由以上的例子，驗證此結論。

## (5) 2-dimension:

- Gibbs sampling:

We firstly calculate  $f(x|y)$  and  $f(y|x)$ :

$$f(x) = \int_0^1 f(x, y) dy = 2(1-x) \int_0^1 (1-y)(1-xy)^{-3} dy = 1.$$

$$f(y) = \text{similar to above} = 1.$$

$$f(x|y) = 2(1-x)(1-y)(1-xy)^{-3}, \forall x \in (0, 1) \text{ for fixed } y.$$

$$f(y|x) = 2(1-x)(1-y)(1-xy)^{-3}, \forall y \in (0, 1) \text{ for fixed } x.$$

Consider the rejection sampling:

By probability intergral transformation,

$$\begin{aligned} Z_X &= 1 - F_{X|y}(x) = \int_x^1 f(t|y) dt \\ &= 2(1-y) \left[ \frac{1}{2y} (1-t)(1-ty)^{-2} \Big|_x^1 + \frac{1}{2y} \int_x^1 (1-ty)^{-2} dt \right] \\ &= 2(1-y) \left[ \frac{-(1-x)}{2y(1-xy)^2} + \frac{(1-x)}{2y(1-y)(1-xy)} \right] \\ &= \frac{-(1-x)(1-y)}{y(1-xy)^2} + \frac{1-x}{y(1-xy)} \\ &= \left( \frac{1-x}{1-xy} \right)^2 \sim U(0, 1). \end{aligned}$$

$$\text{Similarly, } Z_Y = 1 - F_{Y|x}(y) = \left( \frac{1-y}{1-xy} \right)^2 \sim U(0, 1).$$

Do some calculation, we have

$$\begin{aligned} X|y &= \frac{\sqrt{Z_X} - 1}{y\sqrt{Z_X} - 1}. \\ Y|x &= \frac{\sqrt{Z_Y} - 1}{x\sqrt{Z_Y} - 1}. \end{aligned}$$

- Algorithm:

step 1: Set  $x^{(0)}, y^{(0)}$  be the initial value, both  $\in (0, 1)$ .

step 2:  $t=t+1$ , by inverse CDF method, draw

$$X \sim f(x|y^{(t-1)}), \text{denoted as } x^{(t)}$$

$$Y \sim f(y|x^{(t-1)}), \text{denoted as } y^{(t)}$$

step 3: repeat step 2 until converge.

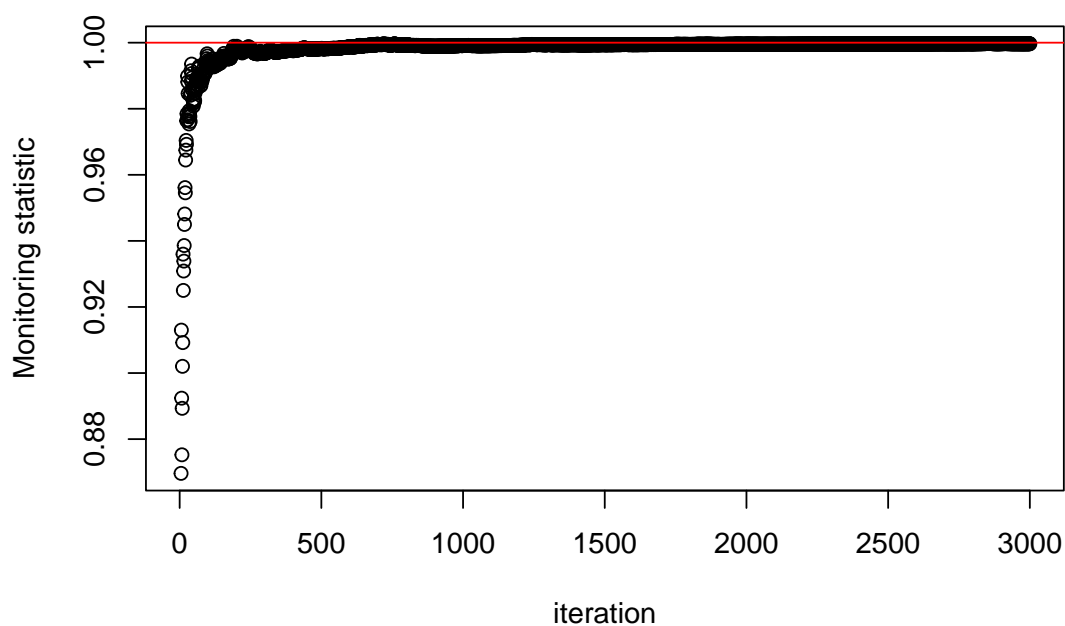
- Check convergence:

1. Set iteration:3000,  $x^{(0)} = 0.5, y^{(0)} = 0.5$ , generating the samples (X,Y)

```
gibb <- function(init, n.iter){
  xx <- matrix(init,1,2)
  x <- xx[1,1]
  for (i in 1:(2*n.iter)){
    zy <- runif(1,0,1)
    zx <- runif(1,0,1)
    y <- (sqrt(zy)-1)/(sqrt(zy)*x-1)
    xx <- rbind(xx,c(x,y))
    x <- (sqrt(zx)-1)/(sqrt(zx)*y-1)
    xx <- rbind(xx,c(x,y))
  }
  return(xx[2*(1:n.iter)-1,])
}
set.seed(231)
n.iter <- 3000
init <- c(0.5,0.5)
test <- gibb(init=init, n.iter=n.iter)
```

2. Check Monitoring statistic  $\sqrt{\hat{R}_n}$  :

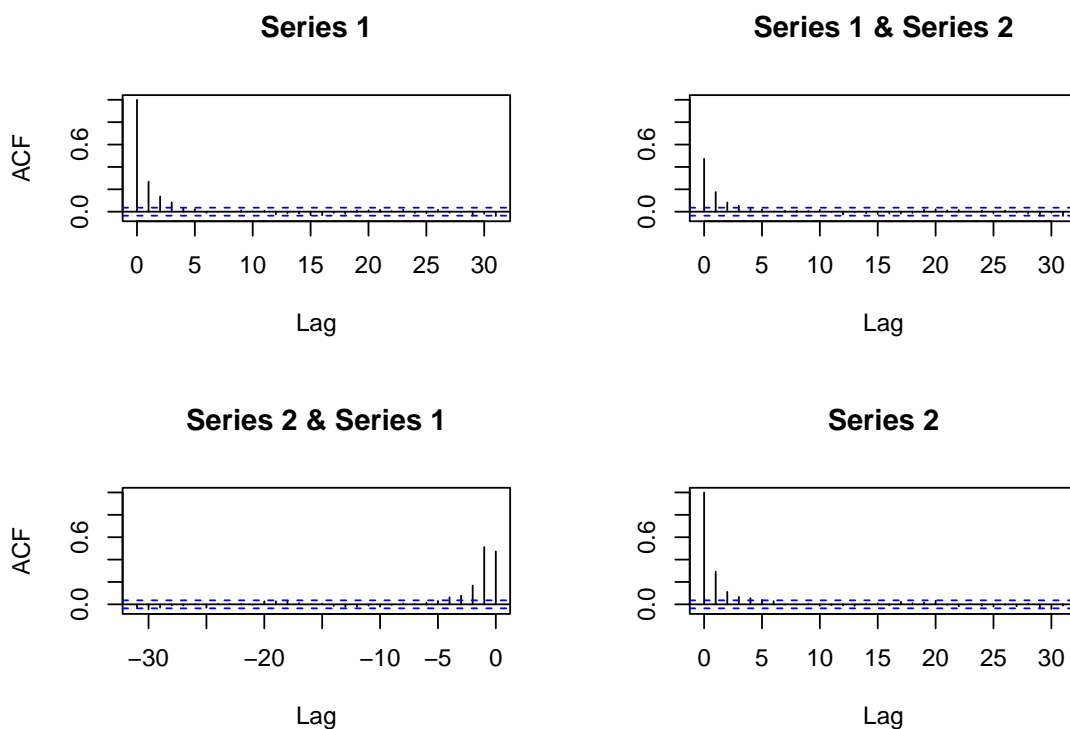
```
gelman.Rhat <- function(mc.draw){
  n.iter <- dim(mc.draw)[1]
  b1 <- w <- rep(0, n.iter)
  for (i in 5:n.iter){
    b1[i] <- var(apply(mc.draw[1:i,],2,mean)) # b1 = b_n/n
    w[i] <- mean(apply(mc.draw[1:i,],2,var)) # within variance: w_n
  }
  Rhat = b1/w+((1:n.iter)-1)/(1:n.iter)
  return(Rhat)
}
plot(gelman.Rhat(test),xlab="iteration",ylab="Monitoring statistic")
abline(h=1,col=c("red"))
```



由上可觀察出， $\sqrt{\hat{R}_n} \xrightarrow{n \text{ is large}} 1$ ，根據理論，所有的抽樣服從一個穩健分布。

- Check serial correlations:

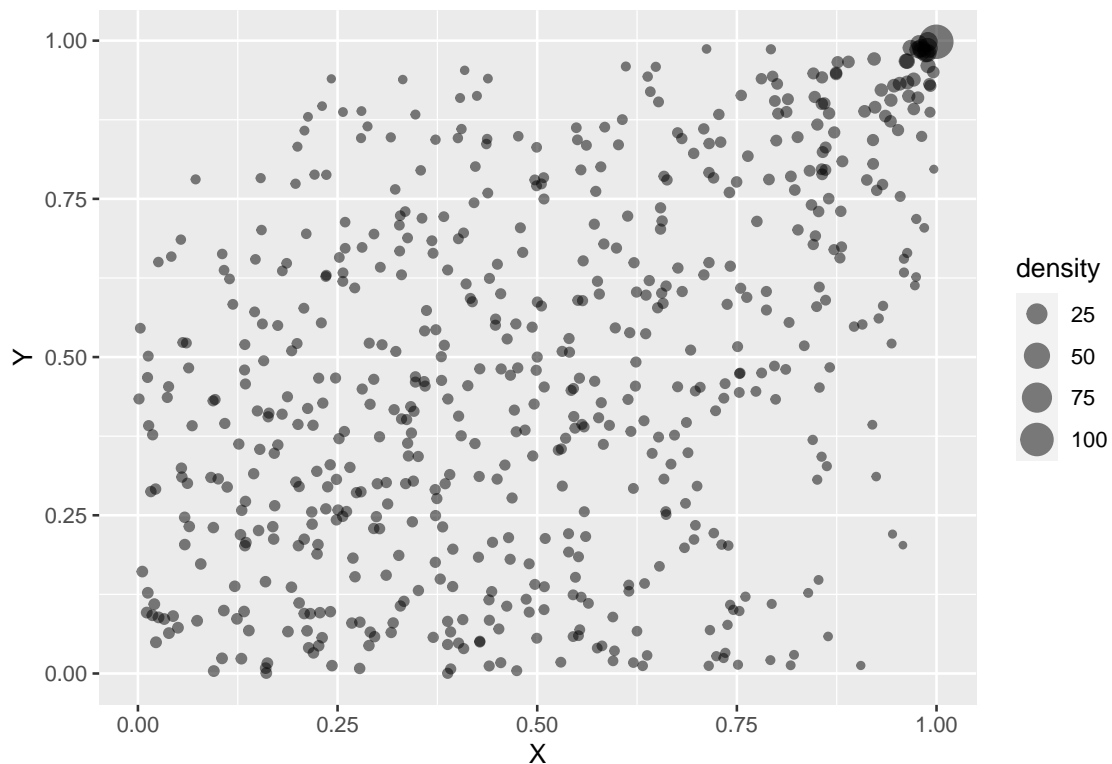
```
acf(test)
```



由上可以看出，大約每 5 個 lag 其 autocorrelation 趨於 0，於是這裡從 3000 個模擬出來的樣本中，抽取  $(X_1, Y_1), (X_6, Y_6), \dots, (X_{2996}, Y_{2996})$  來觀察其 Bubble plot 與原始的  $f(x, y)$  plot 做個對比：

(i) Bubble plot

```
library(ggplot2)
f2 <- function(x,y){
  2*(1-x)*(1-y)*(1-x*y)^(-3)
}
index <- as.integer(seq(1,2996,length=600))
result <- data.frame("X"=test[index,1],
                     "Y"=test[index,2],
                     "density"=f2(test[index,1],
                                   test[index,2]))
ggplot(result, aes(x = X, y =Y, size = density)) +
  geom_point(alpha=0.5) +
  scale_size() +
  scale_alpha()
```



可觀察出，以 $f(x,y)$ “的大小作為點的形狀大小，可以發現點座標越靠近 $X=1$  和  $Y=1$ ”時，其  $f(x,y)$  會非常大。

(ii) density plot

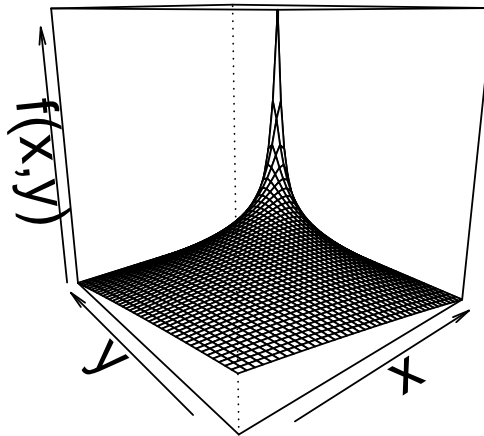
```
f <- function(x){
  2*(1-x[1])*(1-x[2])*(1-x[1]*x[2])^(-3)
}
grid1 <- seq(0.05,1,length=40)
```

```

xy = expand.grid(x=grid1, y=grid1)
z = apply(xy,1,f)

par(mfcol=c(1,1))
persp(grid1, grid1, matrix(z,40,40), theta= -40,
      zlab="f(x,y)", xlab="x", ylab="y", cex.lab=2)

```



可觀察出模擬結果 (Bubble plot) 與原始的  $f(x,y)$  plot 有一定程度上的相似性。

最後，由於這裡採用的抽樣樣本是用 inverse CDF method 轉換得來的，所以 empirical and theoretical efficiency 皆等於 1。