

Punto 4

De esta manera se simula la serie y se obtiene:

```
library(knitr)
library(astsa)
library(forecast)

xt <- rbinom(11,size = 1,p=0.5)
xt_1 <- xt[-1]
xt <- xt[-11]
y=5+xt-0.65*xt_1
y
```

```
## [1] 5.35 6.00 4.35 6.00 4.35 5.35 5.35 5.35 6.00 5.00
```

Luego, usando $\hat{\gamma}(h) = n^{-1} \sum_{t=1}^{n-h} (y_{t+h} - \bar{y})(y_t - \bar{y})$, dividiendo este por la varianza, y haciendolo para $n = 10, 100, 200, 500$ y 1000 se obtiene:

$n=10$:

```
xt <- rbinom(11,size = 1,p=0.5)
xt_1 <- xt[-1]
xt <- xt[-11]
y=5+xt-0.65*xt_1

s2 <- c()
var_1 <- var(y)
for (h in 1:6){
  s <- 0
  for (i in 1:(length(y)-h)){
    s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
    s <- s+s1
  }
  s <- s*(1/length(y))/var_1
  s2 <- c(s2,s)
}
s2
```

```
## [1] -0.19278065 -0.27342550 0.14416222 -0.01389098 -0.01736372 -0.22557879
```

$n=100$:

```
xt <- rbinom(101,size = 1,p=0.5)
xt_1 <- xt[-1]
xt <- xt[-101]
y=5+xt-0.65*xt_1

s2 <- c()
var_1 <- var(y)
for (h in 1:6){
  s <- 0
  for (i in 1:(length(y)-h)){
```

```

    s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
    s <- s+s1
  }
  s <- s*(1/length(y))/var_1
  s2 <- c(s2,s)
}
s2

```

```
## [1] -0.48087600  0.10842344 -0.07562534  0.02226791 -0.12739693  0.03522338
```

n=200:

```

xt <- rbinom(201,size = 1,p=0.5)
xt_1 <- xt[-1]
xt <- xt[-201]
y=5+xt-0.65*xt_1

s2 <- c()
var_1 <- var(y)
for (h in 1:6){
  s <- 0
  for (i in 1:(length(y)-h)){
    s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
    s <- s+s1
  }
  s <- s*(1/length(y))/var_1
  s2 <- c(s2,s)
}
s2

```

```
## [1] -0.423983388 -0.068123734  0.005044254  0.045404805 -0.046867154
## [6]  0.025482457
```

n=500:

```

xt <- rbinom(501,size = 1,p=0.5)
xt_1 <- xt[-1]
xt <- xt[-501]
y=5+xt-0.65*xt_1

s2 <- c()
var_1 <- var(y)
for (h in 1:6){
  s <- 0
  for (i in 1:(length(y)-h)){
    s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
    s <- s+s1
  }
  s <- s*(1/length(y))/var_1
  s2 <- c(s2,s)
}
s2

```

```
## [1] -0.438388365  0.007187857 -0.092431222  0.094333367 -0.019742824
## [6] -0.008599897
```

n=1000:

```
xt <- rbinom(1001,size = 1,p=0.5)
xt_1 <- xt[-1]
xt <- xt[-1001]
y=5+xt-0.65*xt_1

s2 <- c()
var_1 <- var(y)
for (h in 1:6){
  s <- 0
  for (i in 1:(length(y)-h)){
    s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
    s <- s+s1
  }
  s <- s*(1/length(y))/var_1
  s2 <- c(s2,s)
}
s2
```

```
## [1] -0.410746349 -0.076491628  0.012053527  0.011051280  0.008794145
## [6]  0.021403615
```

- b) Para cada $n = 10, 100, 200, 500$ y 1000 , simule 1000 repeticiones, y calcule el ACF muestral para el rezago 10 , verifique la distribución de muestras grandes del ACF.

Para esto, se hacen 1000 repeticiones de la simulación y para cada repetición se guardan los 10 rezagos calculados (para $n=10$ se hace con el rezago 9) y del vector con todos los rezagos de todas las repeticiones se hace el gráfico de densidad. De esta manera se obtiene:

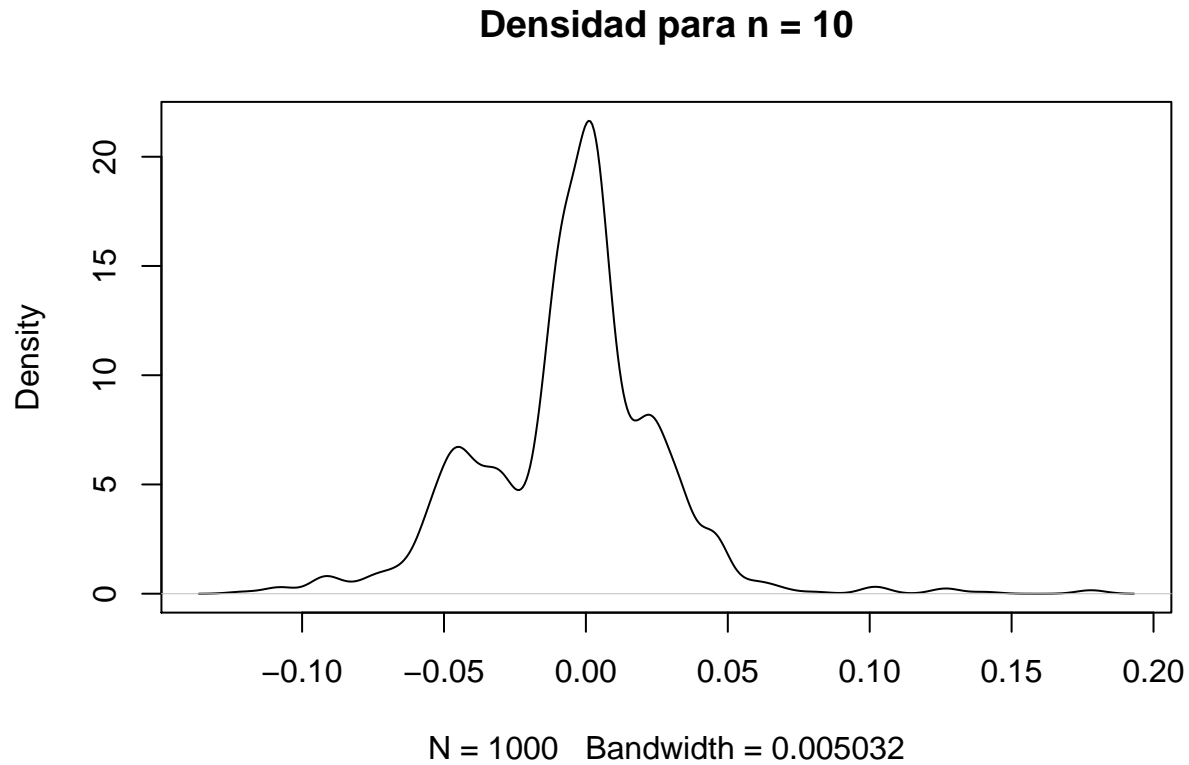
```
s3 <- c()
for (ii in 1:1000){
  n=10
  xt <- rbinom(n+1,size = 1,p=0.5)
  xt_1 <- xt[-1]
  xt <- xt[-n+1]
  y=5+xt-0.65*xt_1

  s2 <- c()
  var_1 <- var(y)
  for (h in 1:9){
    s <- 0
    for (i in 1:(length(y)-h)){
      s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
      s <- s+s1
    }
    s <- s*(1/length(y))/var_1
    s2 <- c(s2,s)
  }
  s3 <- c(s3,s2[9])
}
```

```

}
dens_1 <- density(na.omit(s3))
plot(dens_1,main = 'Densidad para n = 10')

```



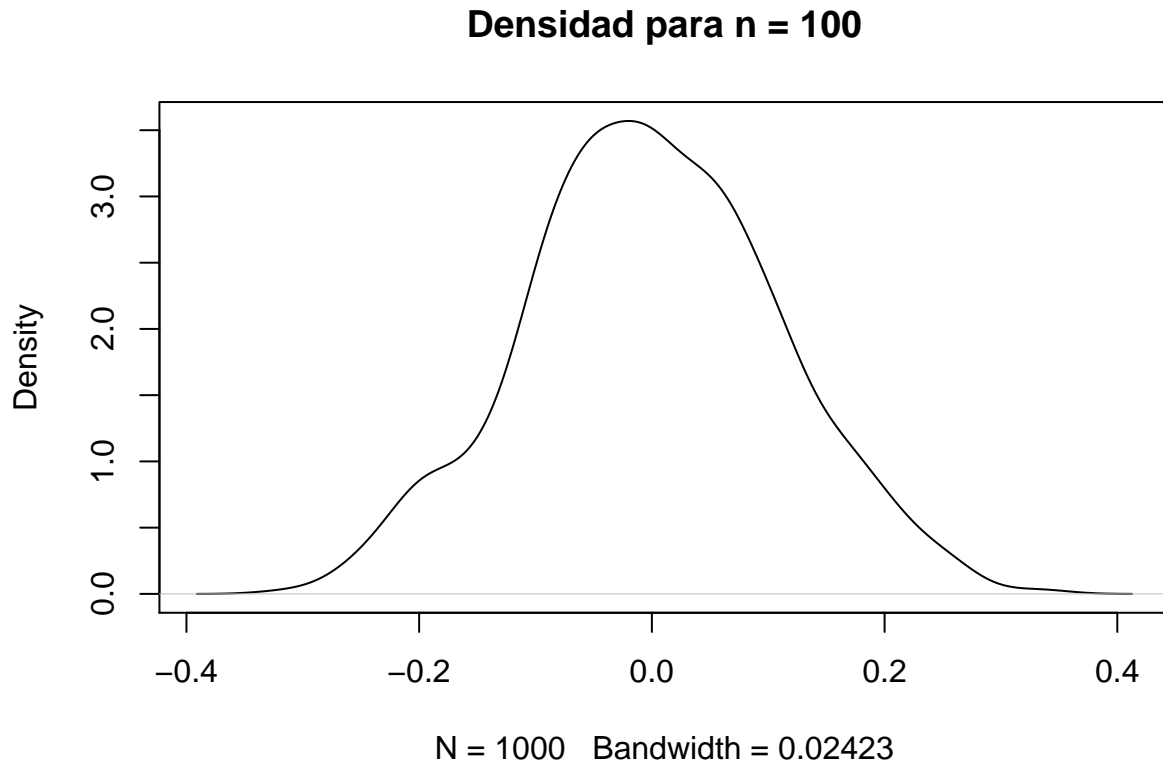
```

s3 <- c()
for (ii in 1:1000){
  n=100
  xt <- rbinom(n+1,size = 1,p=0.5)
  xt_1 <- xt[-1]
  xt <- xt[-n+1]
  y=5+xt-0.65*xt_1

  s2 <- c()
  var_1 <- var(y)
  for (h in 1:10){
    s <- 0
    for (i in 1:(length(y)-h)){
      s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
      s <- s+s1
    }
    s <- s*(1/length(y))/var_1
    s2 <- c(s2,s)
  }
  s3 <- c(s3,s2[10])
}

```

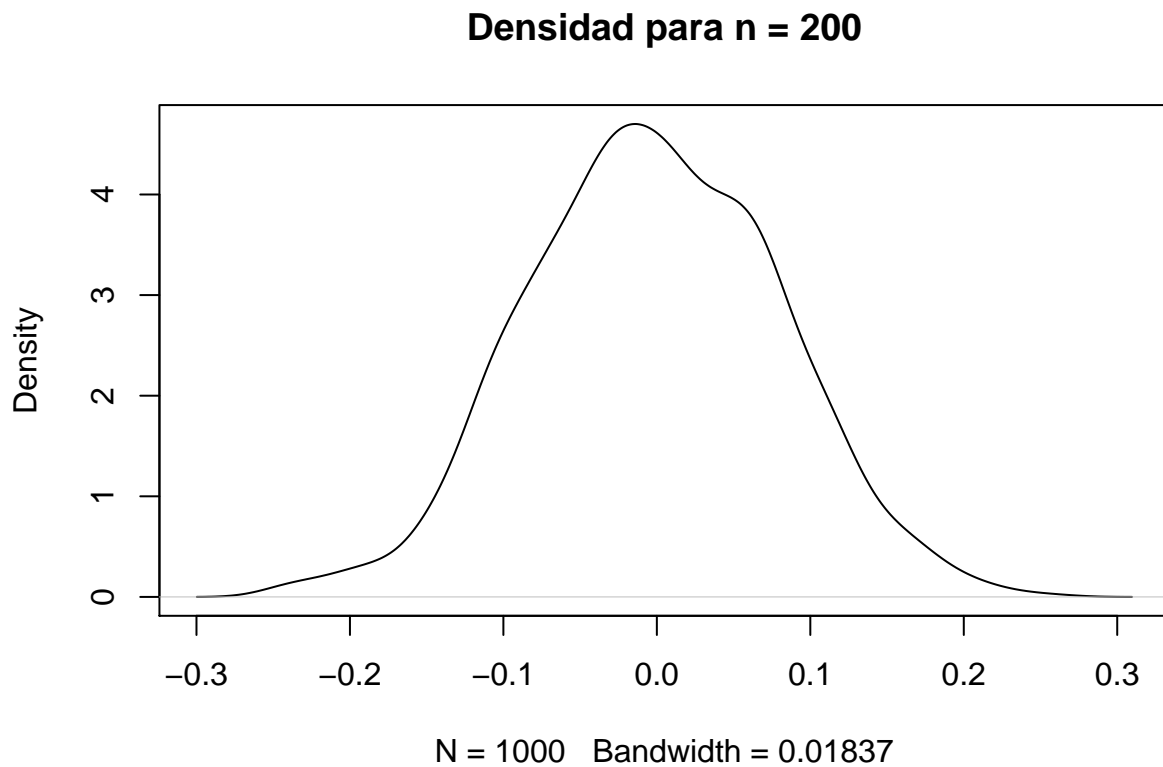
```
dens_1 <- density(na.omit(s3))
plot(dens_1,main = 'Densidad para n = 100')
```



```
s3 <- c()
for (ii in 1:1000){
  n=200
  xt <- rbinom(n+1,size = 1,p=0.5)
  xt_1 <- xt[-1]
  xt <- xt[-n+1]
  y=5+xt-0.65*xt_1

  s2 <- c()
  var_1 <- var(y)
  for (h in 1:10){
    s <- 0
    for (i in 1:(length(y)-h)){
      s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
      s <- s+s1
    }
    s <- s*(1/length(y))/var_1
    s2 <- c(s2,s)
  }
  s3 <- c(s3,s2[10])
}
dens_1 <- density(na.omit(s3))
```

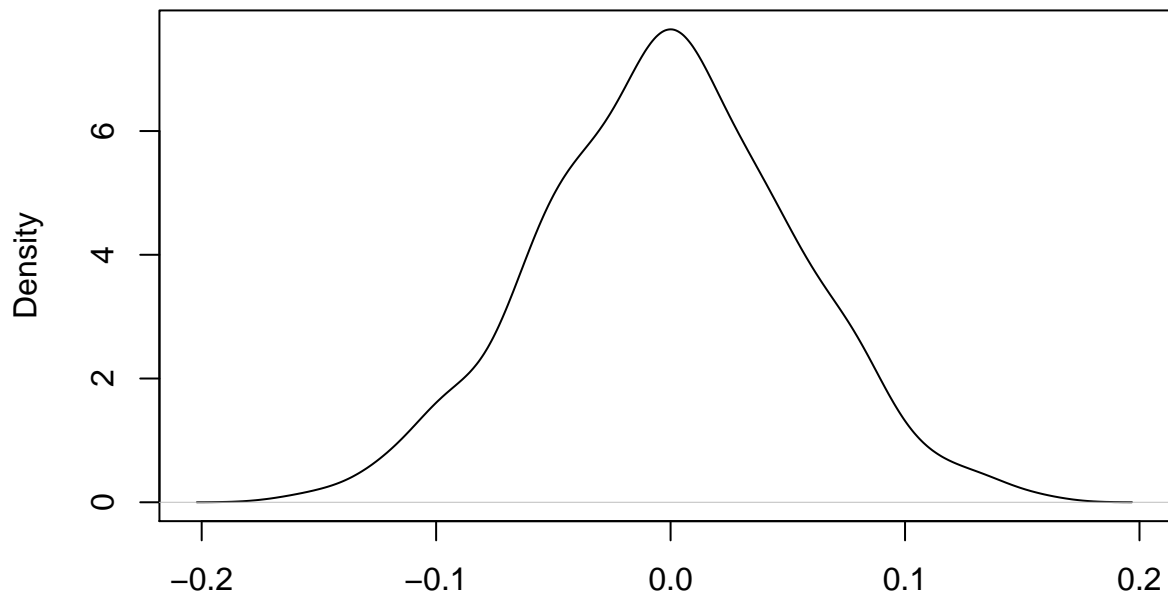
```
plot(dens_1,main = 'Densidad para n = 200')
```



```
s3 <- c()
for (ii in 1:1000){
  n=500
  xt <- rbinom(n+1,size = 1,p=0.5)
  xt_1 <- xt[-1]
  xt <- xt[-n+1]
  y=5+xt-0.65*xt_1

  s2 <- c()
  var_1 <- var(y)
  for (h in 1:10){
    s <- 0
    for (i in 1:(length(y)-h)){
      s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
      s <- s+s1
    }
    s <- s*(1/length(y))/var_1
    s2 <- c(s2,s)
  }
  s3 <- c(s3,s2[10])
}
dens_1 <- density(na.omit(s3))
plot(dens_1,main = 'Densidad para n = 500')
```

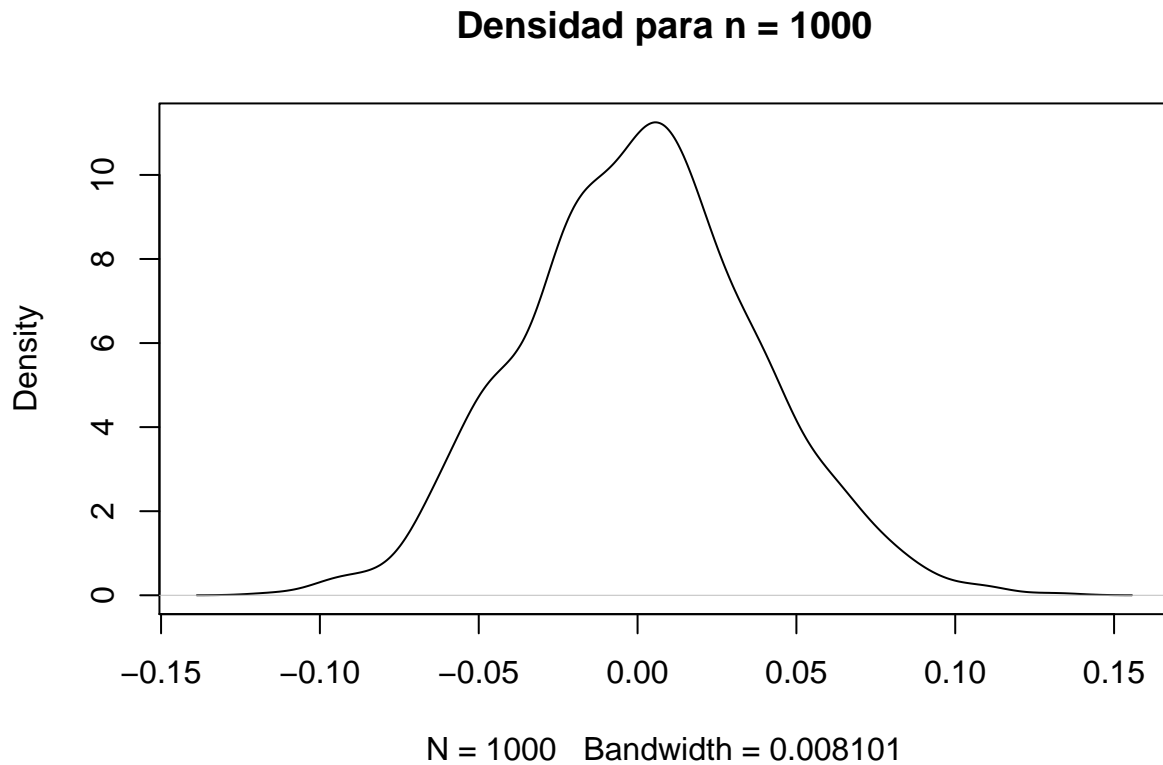
Densidad para n = 500



N = 1000 Bandwidth = 0.01228

```
s3 <- c()
for (ii in 1:1000){
  n=1000
  xt <- rbinom(n+1,size = 1,p=0.5)
  xt_1 <- xt[-1]
  xt <- xt[-n+1]
  y=5+xt-0.65*xt_1

  s2 <- c()
  var_1 <- var(y)
  for (h in 1:10){
    s <- 0
    for (i in 1:(length(y)-h)){
      s1 <- (y[i+h]-mean(y))*(y[i]-mean(y))
      s <- s+s1
    }
    s <- s*(1/length(y))/var_1
    s2 <- c(s2,s)
  }
  s3 <- c(s3,s2[10])
}
dens_1 <- density(na.omit(s3))
plot(dens_1,main = 'Densidad para n = 1000')
```



Según la distribución de muestras grandes para el ACF, dice en (Shumway, 2011) que “bajo condiciones generales, si x_t es ruido blanco, entonces para n grande, el ACF muestral está distribuido aproximadamente normal con media cero y varianza específica (fórmula)...”. Dice en la nota que “The general conditions are that x_t is iid with finite fourth moment. A sufficient condition for this to hold is that x_t is white Gaussian noise. Precise details are given in Theorem A.7 in Appendix A.”

En este caso x_t no es ruido blanco, pero su comportamiento es muy similar, por lo que se espera que la distribución para muestras grandes del ACF sea también aproximadamente normal y esto se observó en los gráficos realizados.