HW2_6337_2023

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Loading required libraries and cleaning environment

```
rm(list = ls())
demo = T
require(psych)
```

```
## Loading required package: psych
```

```
require(data.table)
```

```
## Loading required package: data.table
```

```
require(dplyr)
```

```
## Loading required package: dplyr
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:data.table':
##
##     between, first, last
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
require(ggplot2)
```

```
## Loading required package: ggplot2
```

```
##
## Attaching package: 'ggplot2'
```

```
## The following objects are masked from 'package:psych':
##
##     %+%, alpha
```

```
require(rlist)
```

```
## Loading required package: rlist
```

```
if(demo) {setwd("~/Library/Mobile Documents/com~apple~CloudDocs/School Work/Sem 2/BUAN 6
337/BUAN_6337_Predictive_Analysis/HW/HW-3")}
```

1 (R) (Weak) Law of Large Numbers • (a) Consider a continuous random variable Xi ~ Uni f orm [0, 2]. What is E [Xi] and Var(Xi)?

Ans: The mean (expected value) of a continuous uniform distribution [a, b] is given by:

$$E[X] = \frac{(a+b)}{2}$$

In this case, a = 0 and b = 2, so we have:

$$E[Xi] = \frac{(0+2)}{2} = 1$$

Therefore, the expected value of Xi is 1.

The variance of a continuous uniform distribution [a, b] is given by:

$$Var[X] = \frac{(b-a)^2}{12}$$

In this case, a = 0 and b = 2, so we have:

$$Var[Xi] = \frac{(2-0)^2}{12} = \frac{1}{3}$$

Therefore, the variance of Xi is $\frac{1}{3}$.

• (b) Consider the Xi defined above in (a) for i = 1, 2, …, n, where each Xi ⊥ Xj whenever i/= j. Consider the sample mean

What is E [X̄ n] and Var (X̄ n)? (The answer might be a function of n).

Ans: The sample mean of n independent and identically distributed (i.i.d.) random variables Xi has the following properties:

$$E[X\bar{n}] = E[\frac{1}{n}\sum X_i] = \frac{1}{n}\sum E[X_i] = \frac{1}{n} \times n \times E[X_i] = E[X_i]$$

$$\mathrm{Var}[X\bar{n}] = \mathrm{Var}[\frac{1}{n}\sum X_i] = \frac{1}{n^2}\sum \mathrm{Var}[X_i]$$

Since each Xi is uniformly distributed on [0, 2], we know from part (a) that $\mathrm{E}[Xi] = 1$ and $\mathrm{Var}[Xi] = \frac{1}{3}$. Therefore:

$$\mathrm{E}[X\bar{n}] = \mathrm{E}[Xi] = 1$$

$$\mathrm{Var}[X\bar{n}] = \mathrm{Var}[\frac{1}{n}\sum X_i] = \frac{1}{n^2}\sum \mathrm{Var}[X_i] = \frac{1}{n^2}\times n \times \frac{1}{3} = \frac{1}{3n}$$

Therefore, the expected value of the sample mean X̄n is 1, and the variance of the sample mean X̄n is $\frac{1}{3n}$.

Now repeat the following (c)-(e) for $n = 1, 2, 3, 5, 10, 50, 100, 1000, 3000$. Use the for loops to execute (c)-(e). • (c) (R) Generate a size n vector of independent Uni f orm [0, 2] random variables and cal- culate its sample mean X- n. • (d)(R)Take $|X\bar{n} - \mathrm{E}[Xi]|$ and report the value. • (e) (R) Now consider a continuous transformation $ f(x) = 2x^2 – 5x + 1 + 1 $. Take $|f(X\bar{n}) - f(\mathrm{E}[Xi])|$

```
n = c(1, 2, 3, 5, 10, 50, 100, 1000, 3000)

Q1 = function(n){

  # c
  x = runif(n,0,2)
  x_bar = mean(x)

  #d
  e_x = 1
  diff = abs(x_bar - e_x)

  #e
  quad = function(x)
  {
    return (2*x^2 - 5*x + 1 + (1/(3*x)))
  }

  diff_function = abs(quad(x_bar)-quad(e_x))
  return(list(n=n,mean=x_bar,diff=diff,diff_func=diff_function))
}

for(i in n){
  assign(paste0("v",i),Q1(i))
  if(demo){print(get(paste0("v",i)))}

}
```

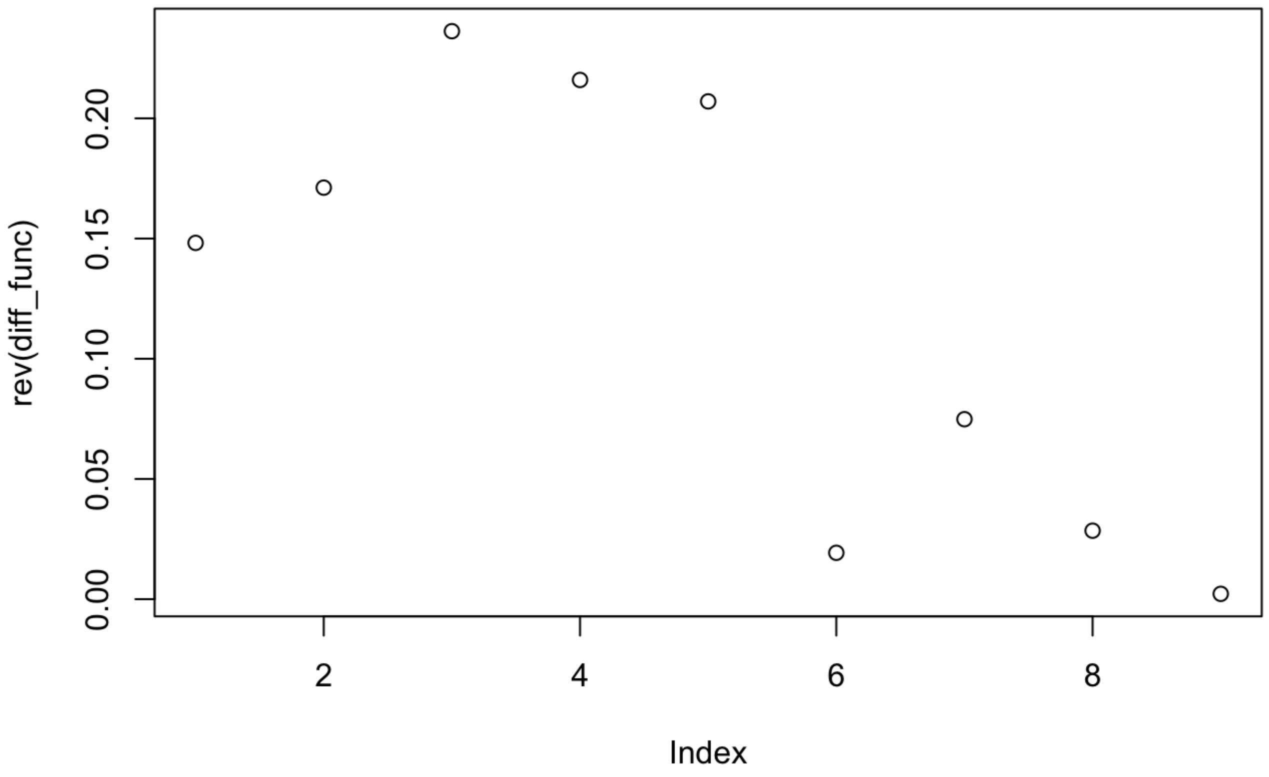
```
## $n
## [1] 1
##
## $mean
## [1] 1.735443
##
## $diff
## [1] 0.7354432
##
## $diff_func
## [1] 0.2050508
##
## $n
## [1] 2
##
## $mean
## [1] 0.5152572
##
## $diff
## [1] 0.4847428
##
## $diff_func
## [1] 1.268287
##
## $n
## [1] 3
##
## $mean
## [1] 1.185106
##
## $diff
## [1] 0.1851063
##
## $diff_func
## [1] 0.1686422
##
## $n
## [1] 5
##
## $mean
## [1] 0.5854188
##
## $diff
## [1] 0.4145812
##
## $diff_func
## [1] 0.9943958
##
## $n
## [1] 10
##
## $mean
## [1] 0.8363083
##
## $diff
## [1] 0.1636917
##
## $diff_func
## [1] 0.2825254
##
## $n
## [1] 50
##
## $mean
## [1] 0.9681545
##
## $diff
## [1] 0.03184545
##
## $diff_func
## [1] 0.04483804
##
## $n
## [1] 100
##
## $mean
## [1] 1.085284
##
## $diff
## [1] 0.08528407
##
## $diff_func
## [1] 0.09693141
##
## $n
## [1] 1000
##
## $mean
## [1] 0.9596919
##
## $diff
## [1] 0.04030811
##
## $diff_func
## [1] 0.05755796
##
## $n
## [1] 3000
##
## $mean
## [1] 0.9981179
##
## $diff
## [1] 0.001882081
```

```
##
## $diff_func
## [1] 0.002517709
```

• (f) What happens to the reported value in (d) and (e) as n increases? Discuss.

Ans: As n increases, the difference between the theoretical value and practical value tends towards 0. This implies larger the sample, the results are better statistically.

```
diff_func = c()
for(i in n){
  diff_func = append((Q1(i)$diff_func),diff_func)
}
plot(rev(diff_func))
```



2 (R) The Central Limit Theorem • (a) Consider a continuous random variable $Xi \sim \text{Uniform}[0, 2]$. What is $E[X_i]$ and $Var(X_i)$?

$$\text{Mean} = \frac{a+b}{2} = 1$$

$$\text{Var} = \frac{1}{3}$$

• (b) Consider the Xi defined above in (a) for i = 1, 2, …, n, where each $Xi \perp Xj$ whenever $i \neq j$. Consider the sample mean⁻1n Xn := n ∑Xi. i=1 What is $E[X\bar{n}]$ and $Var(X\bar{n})$? (The answer would be a function of n).

Ans:

$$E[X_n] = \frac{1}{n} \times n \times 1 = 1$$

$$E[X_{n=6}] = 1$$

$$Var[X_n] = \frac{1}{\sqrt{n}} \times n \times 0.3333 = 0.041667$$

• (c) Consider the transformation

$$Y_n := \sqrt{n} \times (X_n - E[X_i])$$

What is E [Yn] and Var (Yn)?

Ans:

$$E[Y_n] = \sqrt{n} \times 0 = 0$$

$$var = \frac{1}{3}$$

• (d) Consider the transformation √ (X- n – E [X i]) Zn:= npVar(Xi). What is E [Zn] and Var (Zn)?

$$E[Z_n] = 0$$

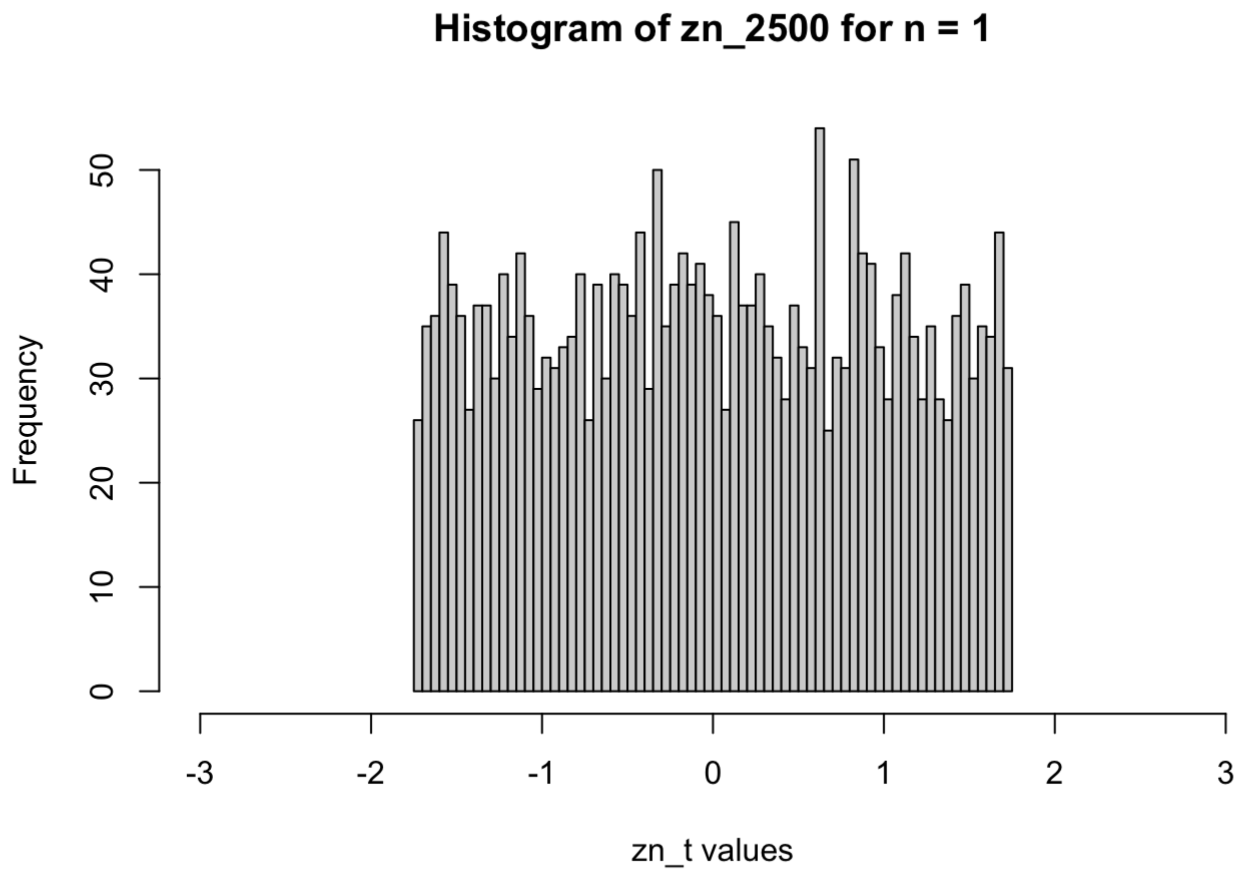
$$Var[Z_n] = 1$$

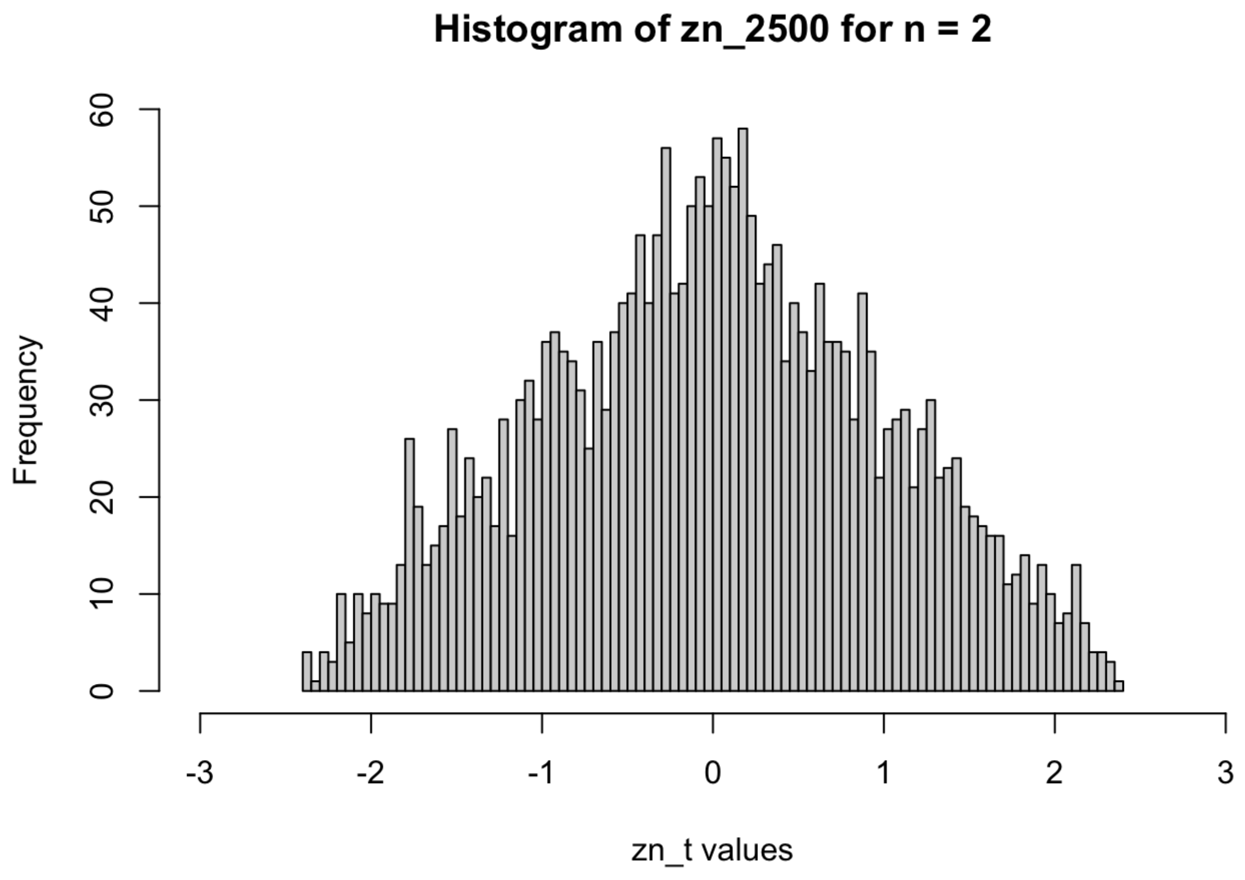
Now repeat the following for n = 1, 2, 3, 5, 10, 50, 100, 1000, 3000. Use the for loops to execute (e)-(m). • (e) (R)Generate t = 1,2,3,4,5,6,7,8,9,10,11,…,2500 n×1 vectors of independent $Uniform[0, 2]$ random variables and calculate its sample mean $X\bar{n}t$ respectively for each t. Denote this size 2500 vector as

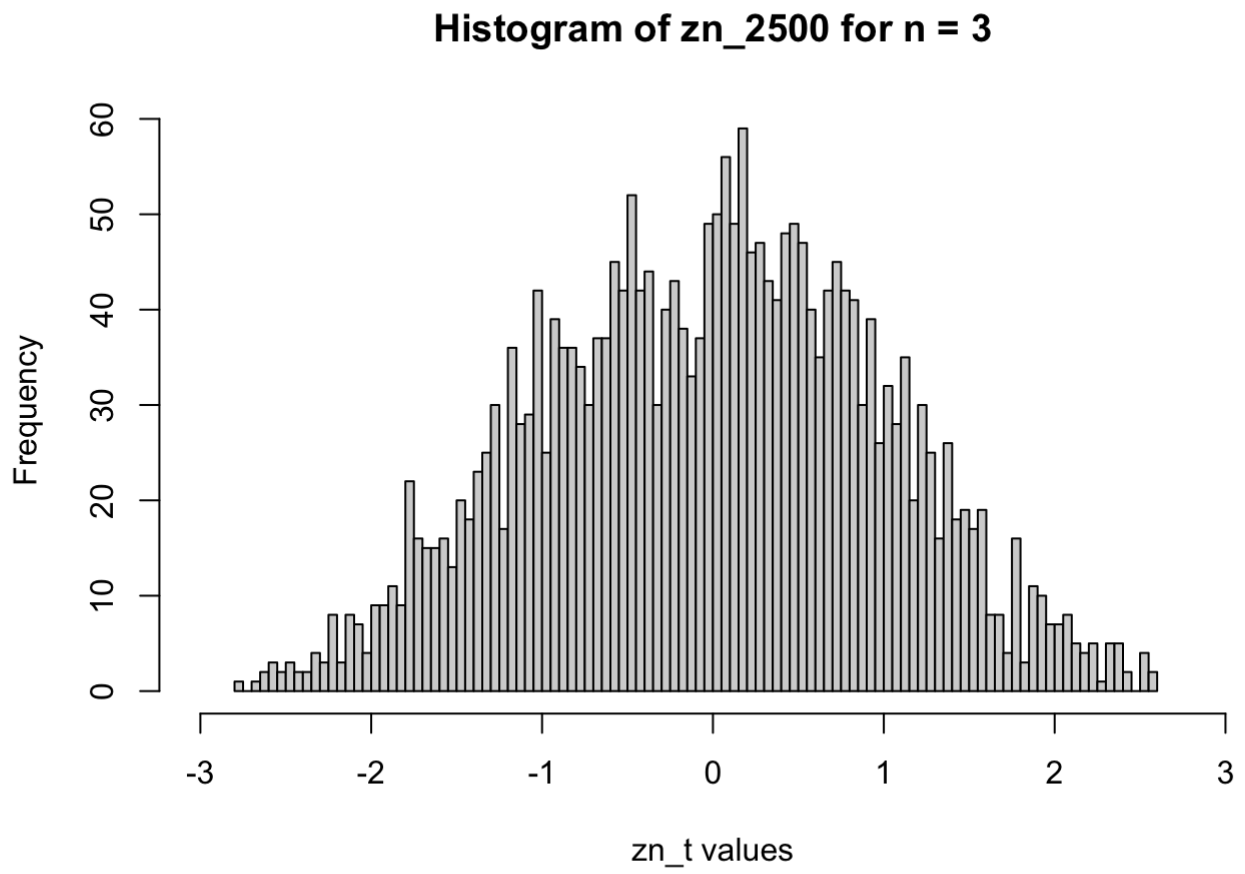
$$v_2 500 \equiv \bar{X_1}, \bar{X_2}, \ldots, \bar{X_2}500$$

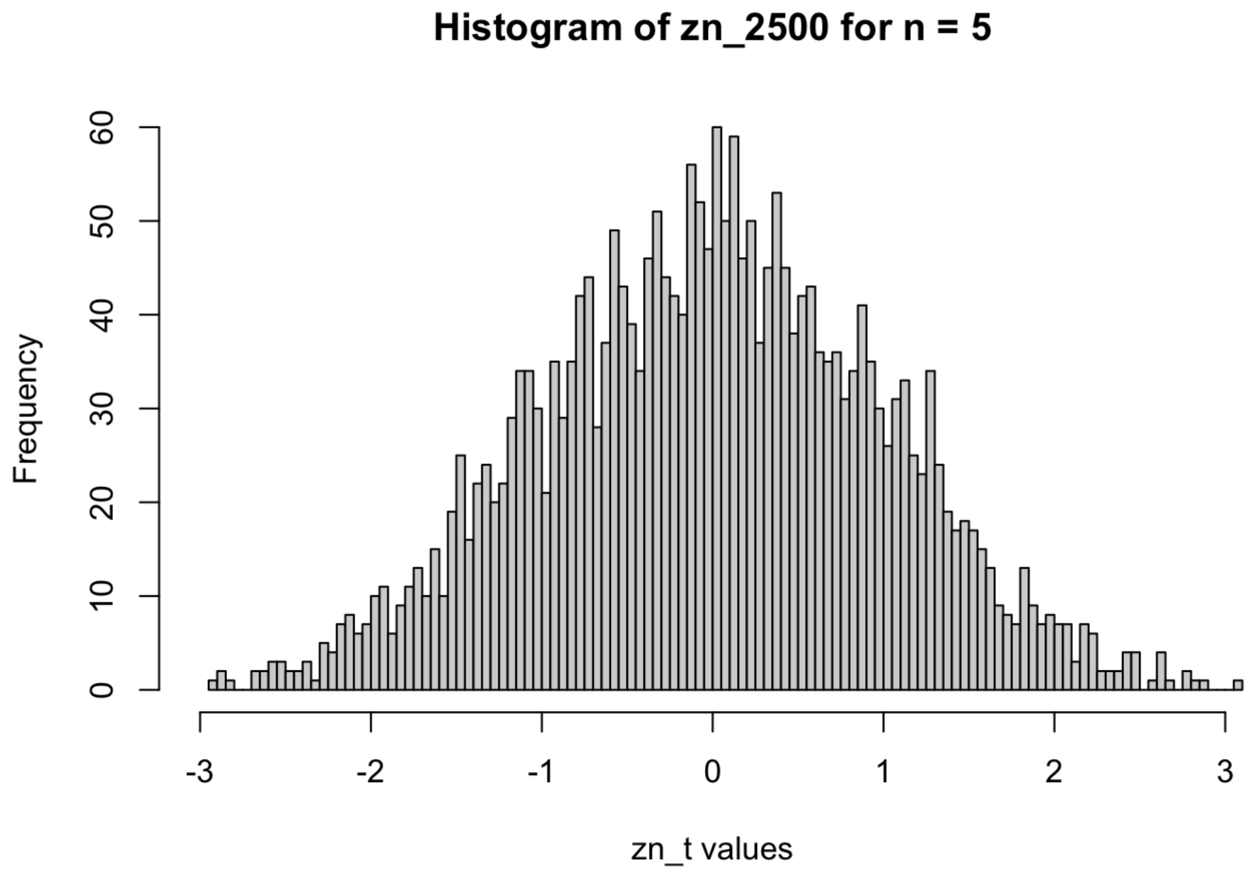
for now.

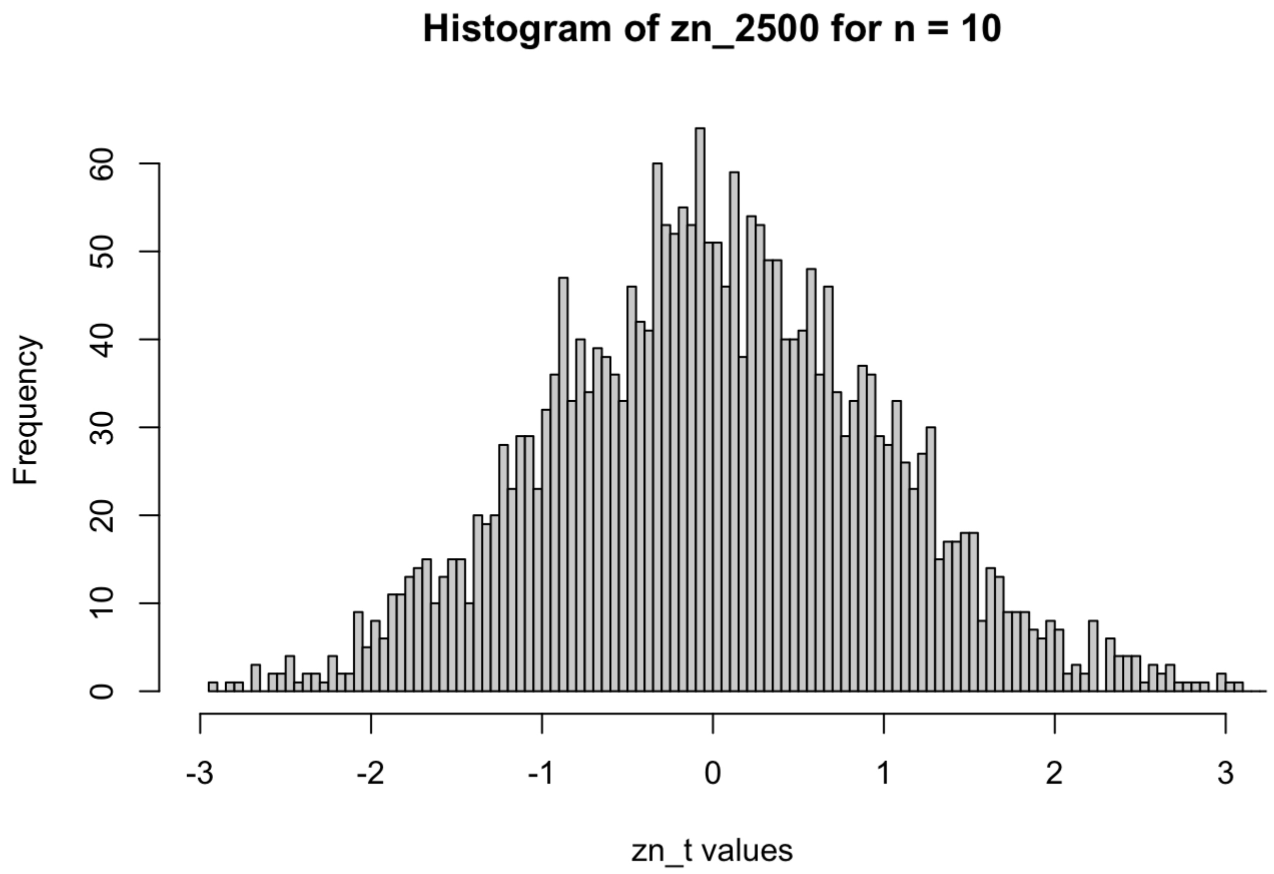
```
n = c(1, 2, 3, 5, 10, 50, 100, 1000, 3000)

Q2 = function(n){

  t = c(1:2500)
  v = replicate(length(t), runif(i, 0, 2))
  if (n == 1) {
    vn_2500 = v
  } else {
    vn_2500 = apply(v, 2, mean)
  }



  vn_2500_bar = mean(vn_2500)
  vn_2500_var = var(vn_2500)

  e_xi = 1
  yn_2500 = sqrt(n)*(vn_2500 - e_xi)

  mean_yn_2500 = mean(yn_2500)
  var_yn_2500 = var(yn_2500)

  var_xi = 1/3
  zn_2500 = sqrt(n)*(vn_2500 - e_xi)/sqrt(var_xi)

  mean_zn_2500 = mean(zn_2500)
  var_zn_2500 = var(zn_2500)

  return(list(n=n, vn = vn_2500, mean_vn = vn_2500_bar, var_vn = vn_2500_var, zn = zn_25
00, mean_zn = mean_zn_2500,yn = yn_2500, var_zn = var_zn_2500))
}
for(i in n){
  assign(paste0("f",i),Q2(i))
}
for(i in n){
  hist(Q2(i)$zn, breaks = 100,
       main = paste("Histogram of zn_2500 for n = ", i, sep = ""),
       xlab = "zn_t values",
       xlim = c(-3,3))
}
```

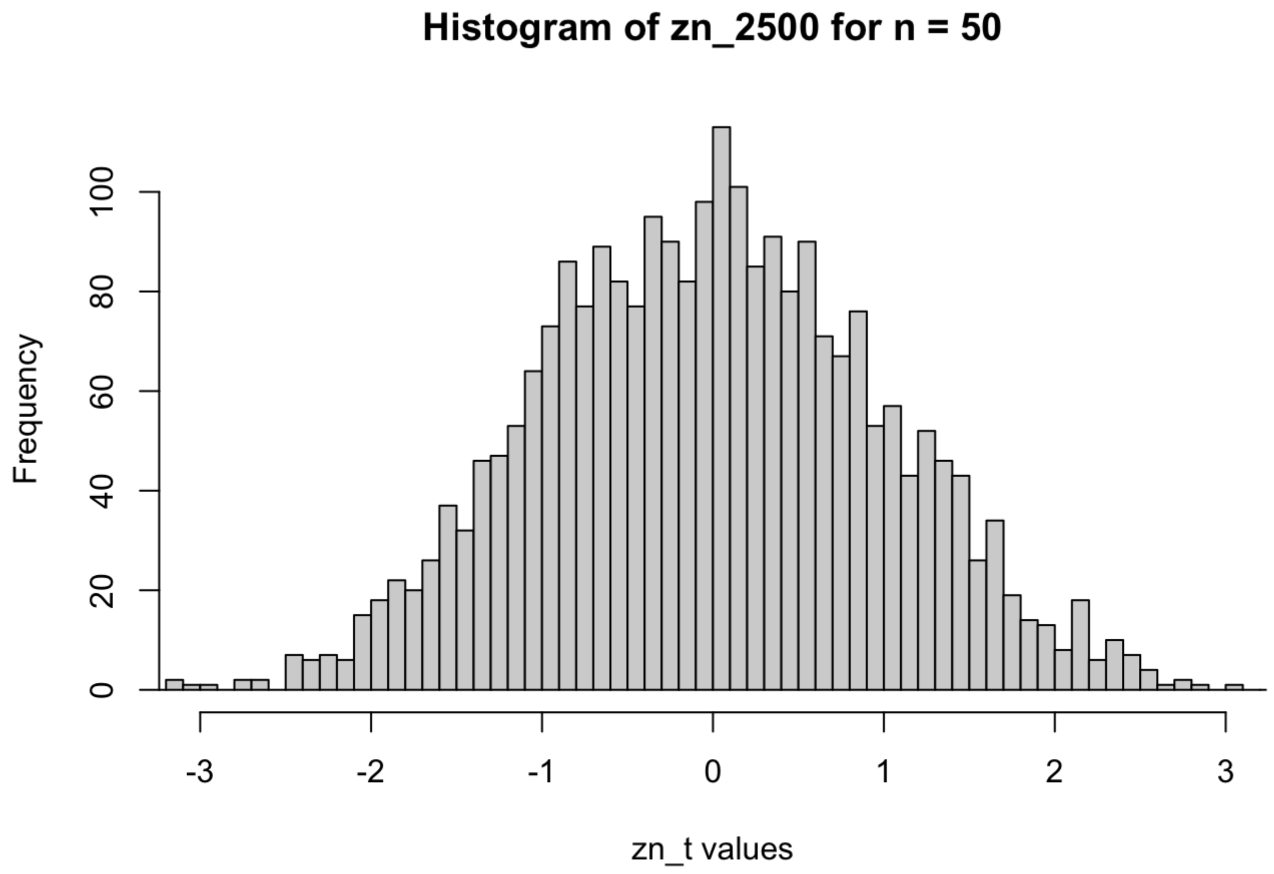

Histogram of zn_2500 for n = 1
Frequency
0
10
20
30
40
50
-3
-2
-1
0
1
2
3
zn_t values

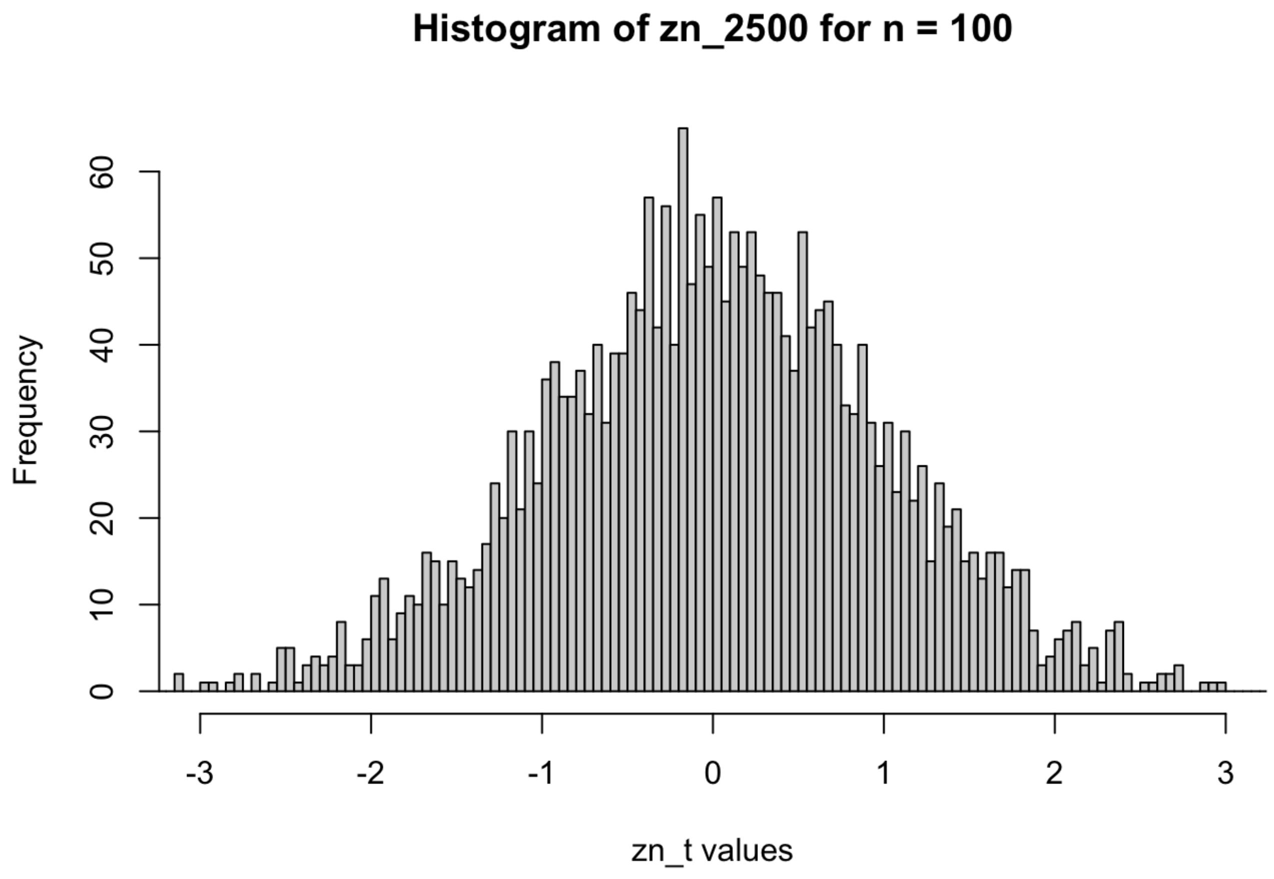

Histogram of zn_2500 for n = 2
Frequency
0
10
20
30
40
50
60
-3
-2
-1
0
1
2
3
zn_t values

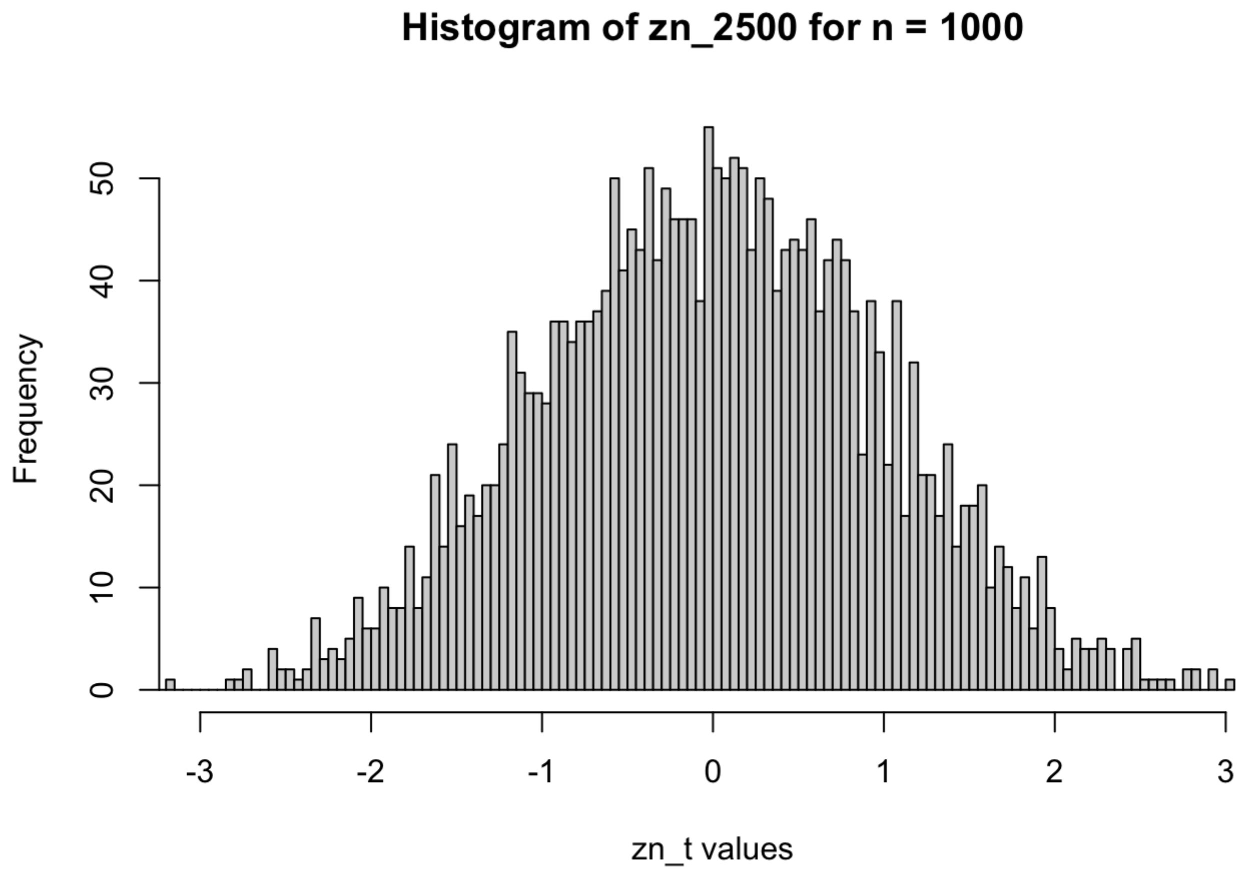

Histogram of zn_2500 for n = 3
Frequency
0
10
20
30
40
50
60
-3
-2
-1
0
1
2
3
zn_t values

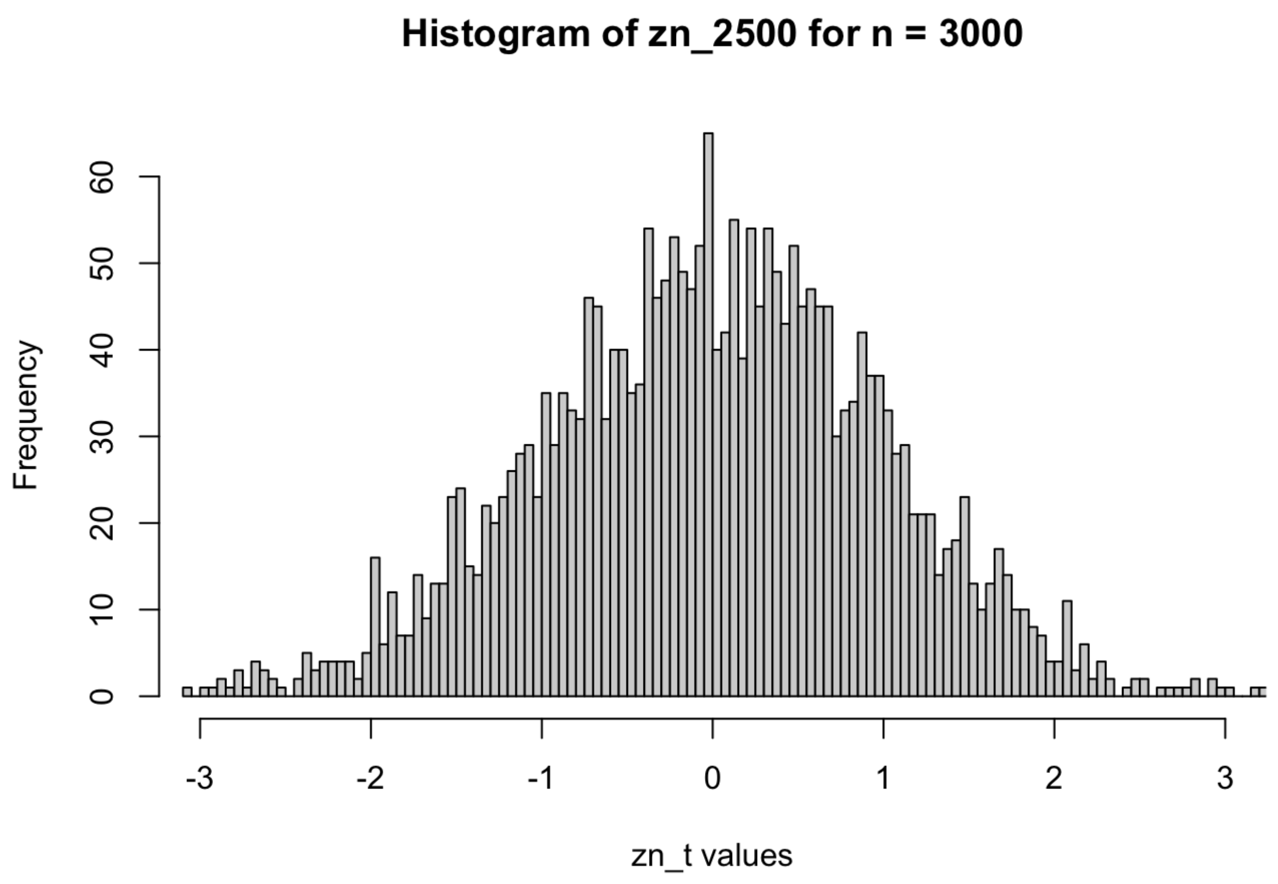

Histogram of zn_2500 for n = 5
Frequency
0
10
20
30
40
50
60
-3
-2
-1
0
1
2
3
zn_t values


Histogram of zn_2500 for n = 10
Frequency
0
10
20
30
40
50
60
-3
-2
-1
0
1
2
3
zn_t values

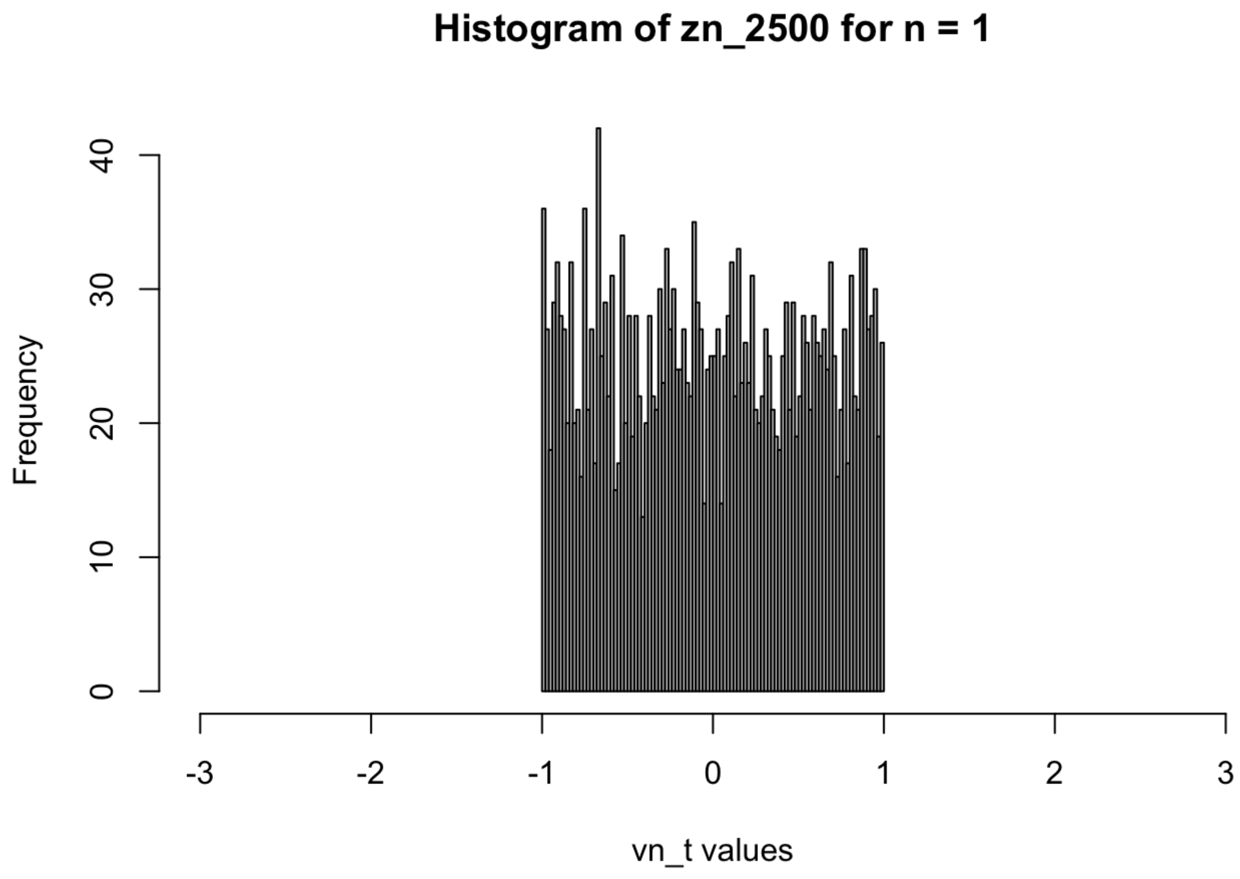

Histogram of zn_2500 for n = 50
Frequency
0
20
40
60
80
100
-3
-2
-1
0
1
2
3
zn_t values

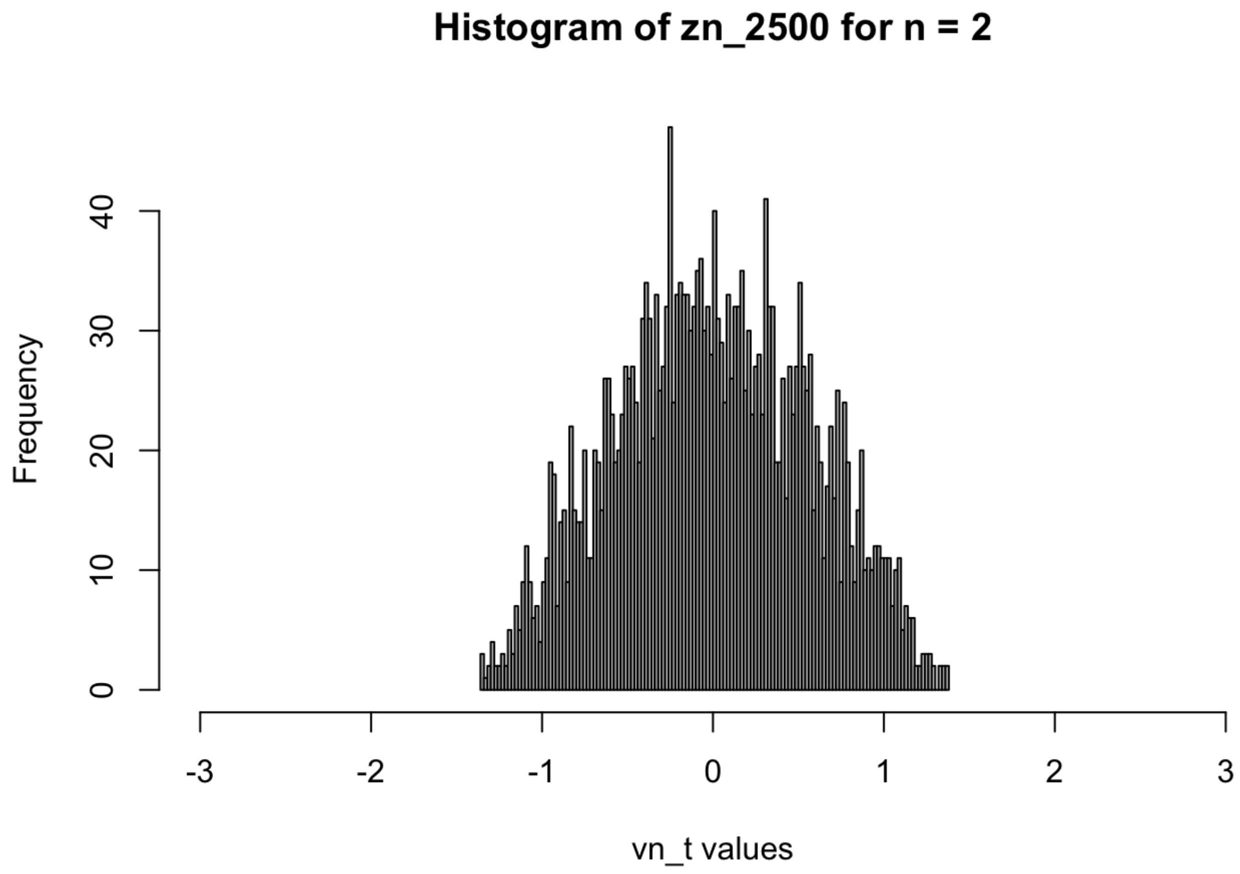

Histogram of zn_2500 for n = 100
Frequency
0
10
20
30
40
50
60
-3
-2
-1
0
1
2
3
zn_t values

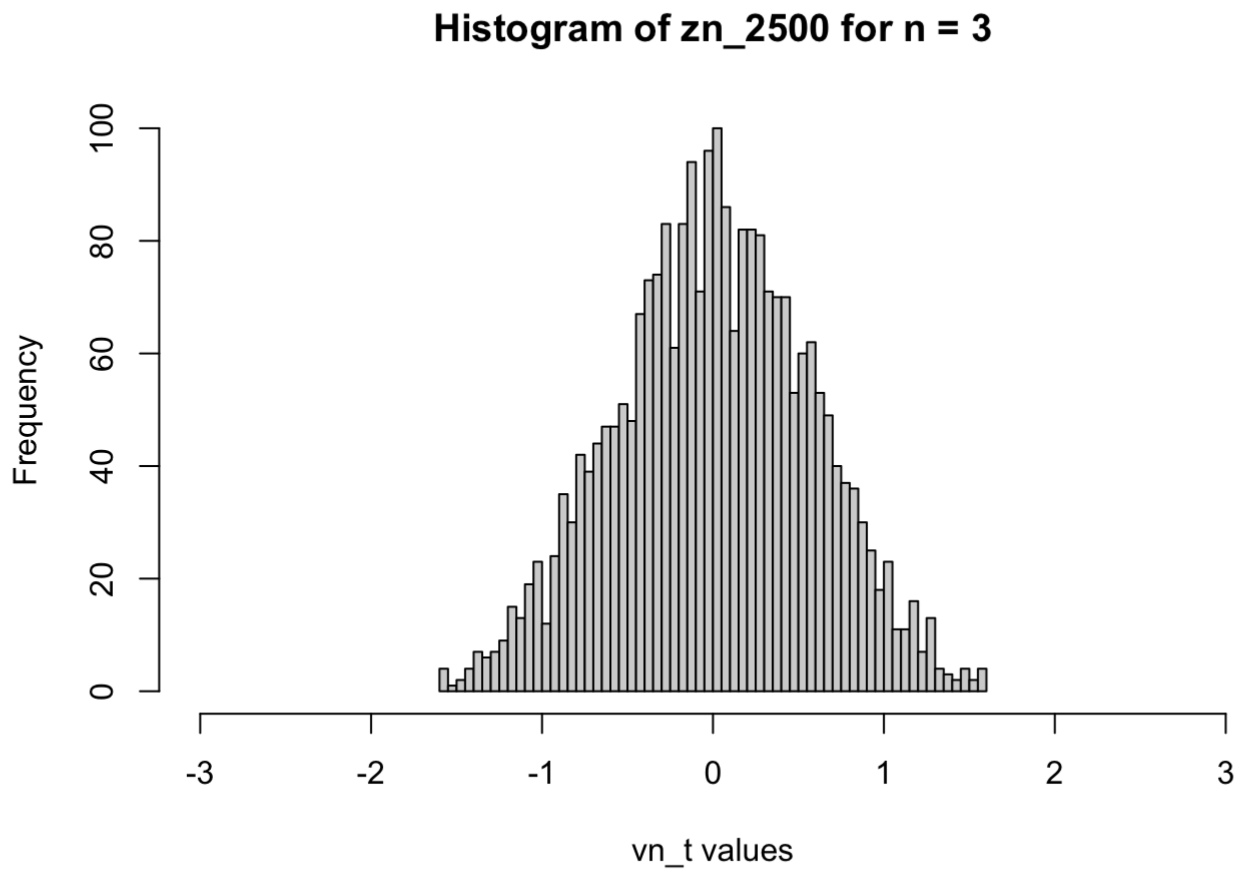

Histogram of zn_2500 for n = 1000
Frequency
0
10
20
30
40
50
-3
-2
-1
0
1
2
3
zn_t values

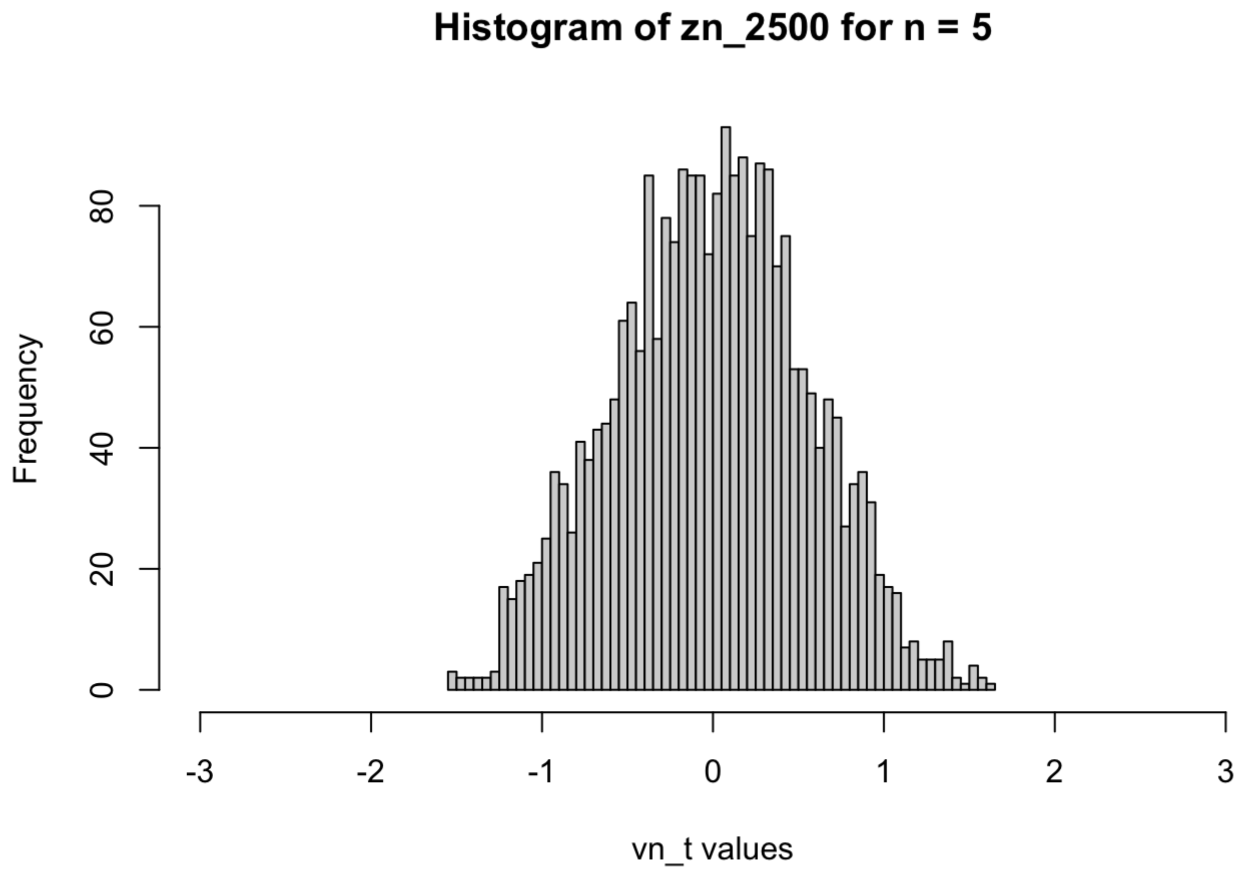


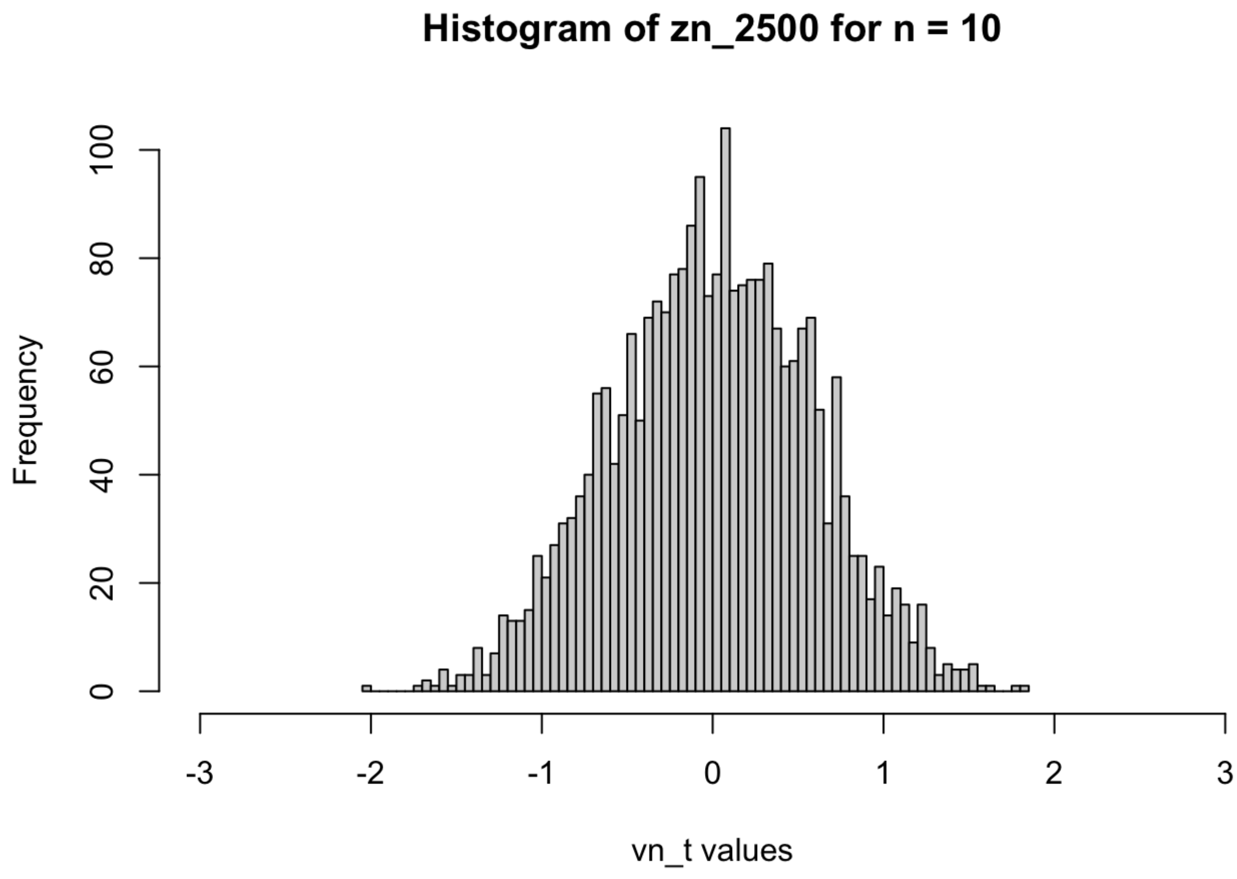
```
for(i in n){
  hist(Q2(i)$yn, breaks = 100,
       main = paste("Histogram of zn_2500 for n = ", i, sep = ""),
       xlab = "vn_t values",
       xlim = c(-3,3))
}
```

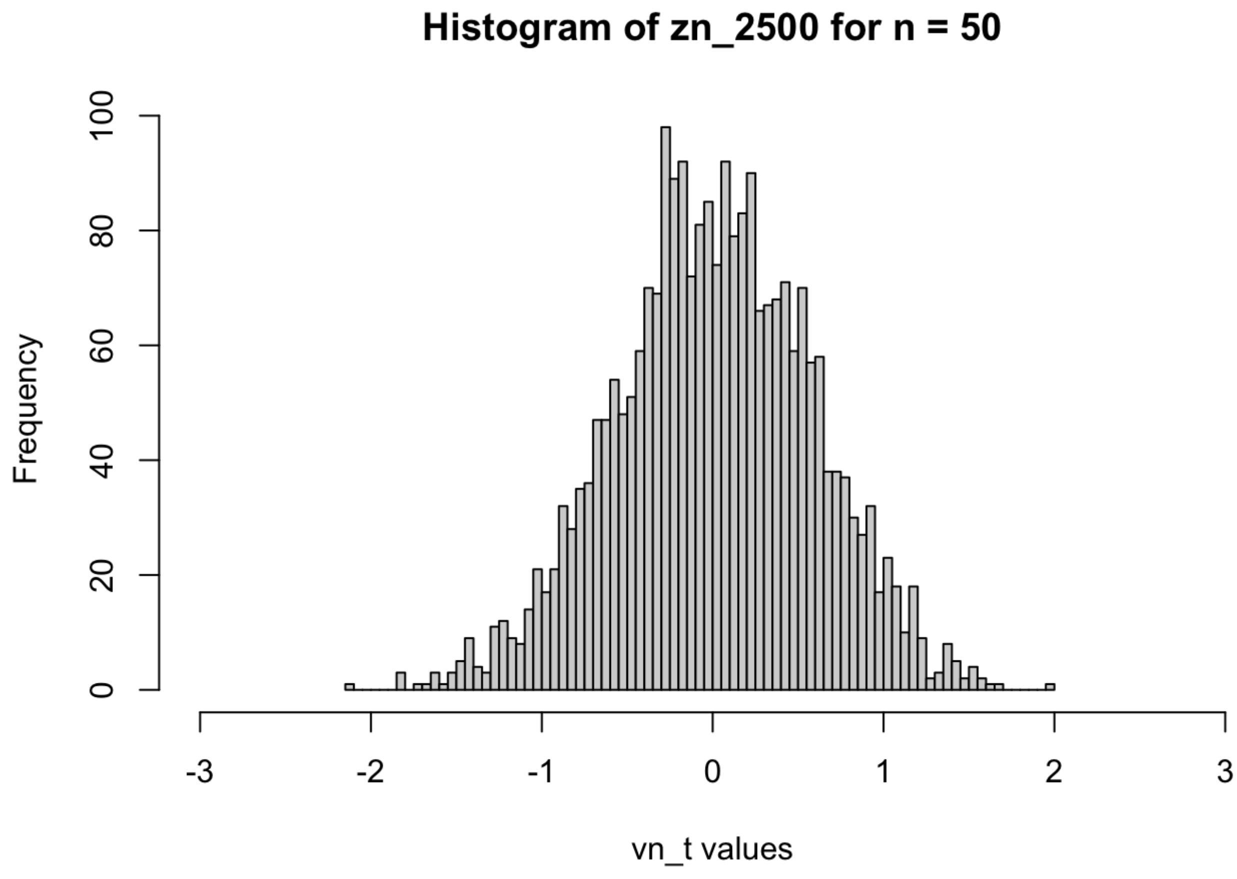

Histogram of zn_2500 for n = 1
Frequency
0
10
20
30
40
-3
-2
-1
0
1
2
3
vn_t values

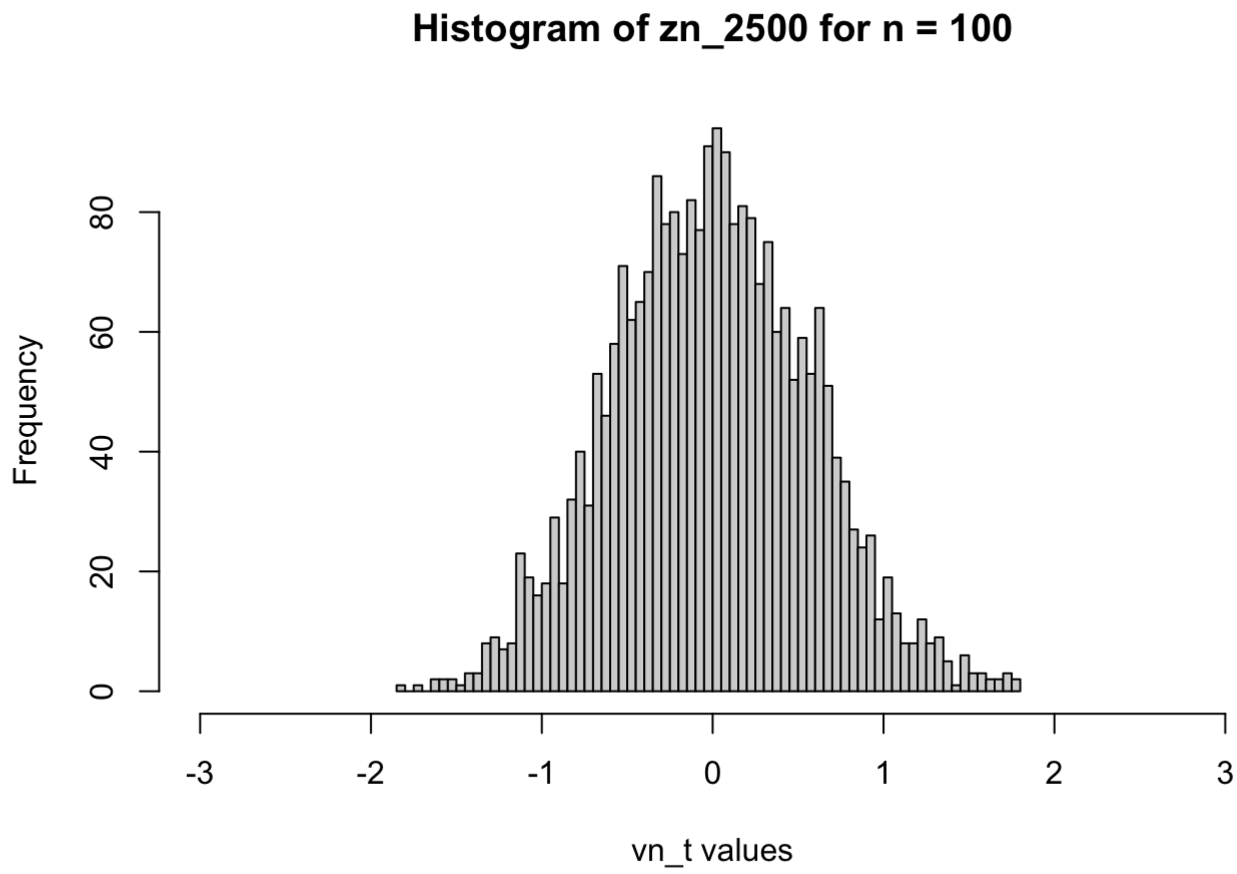

Histogram of zn_2500 for n = 2
Frequency
0
10
20
30
40
-3
-2
-1
0
1
2
3
vn_t values

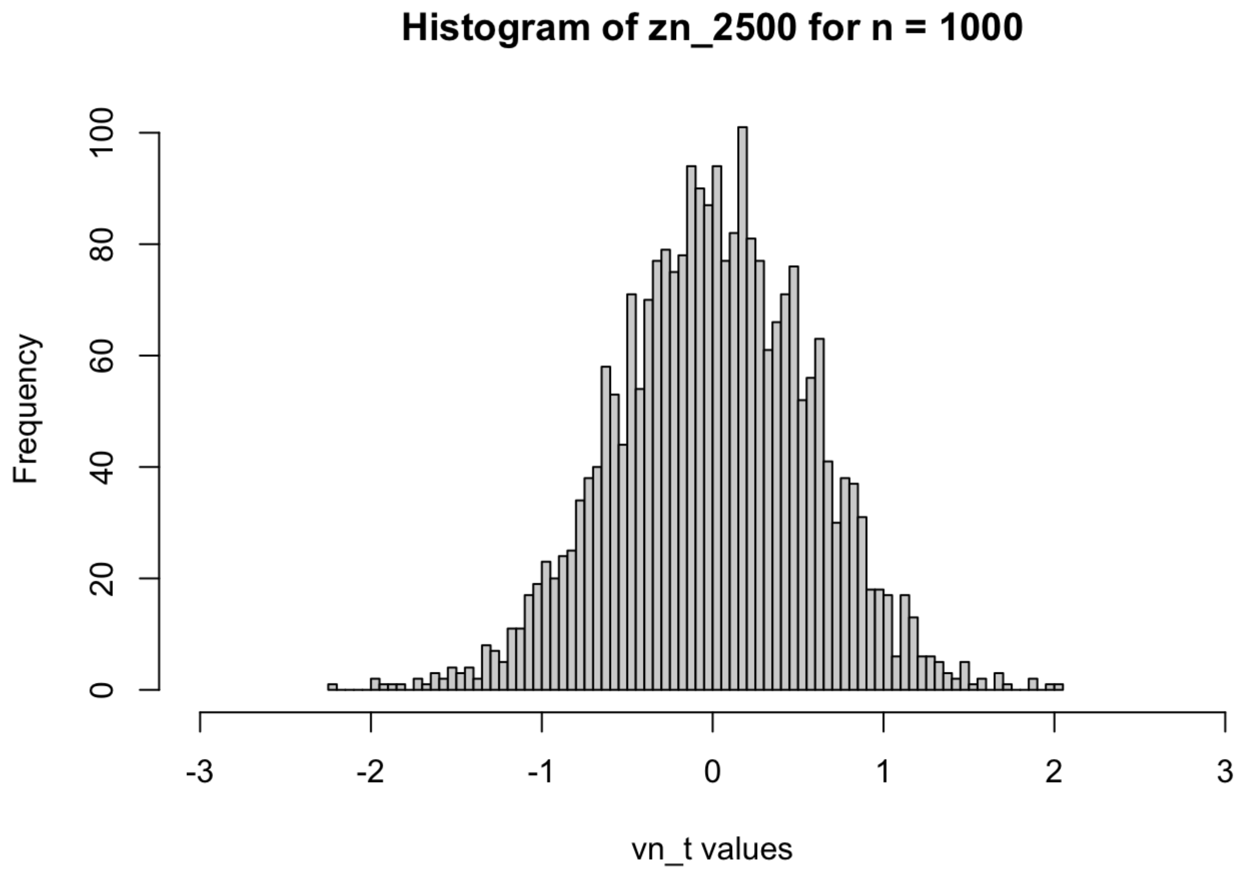

Histogram of zn_2500 for n = 3
Frequency
0
20
40
60
80
100
-3
-2
-1
0
1
2
3
vn_t values

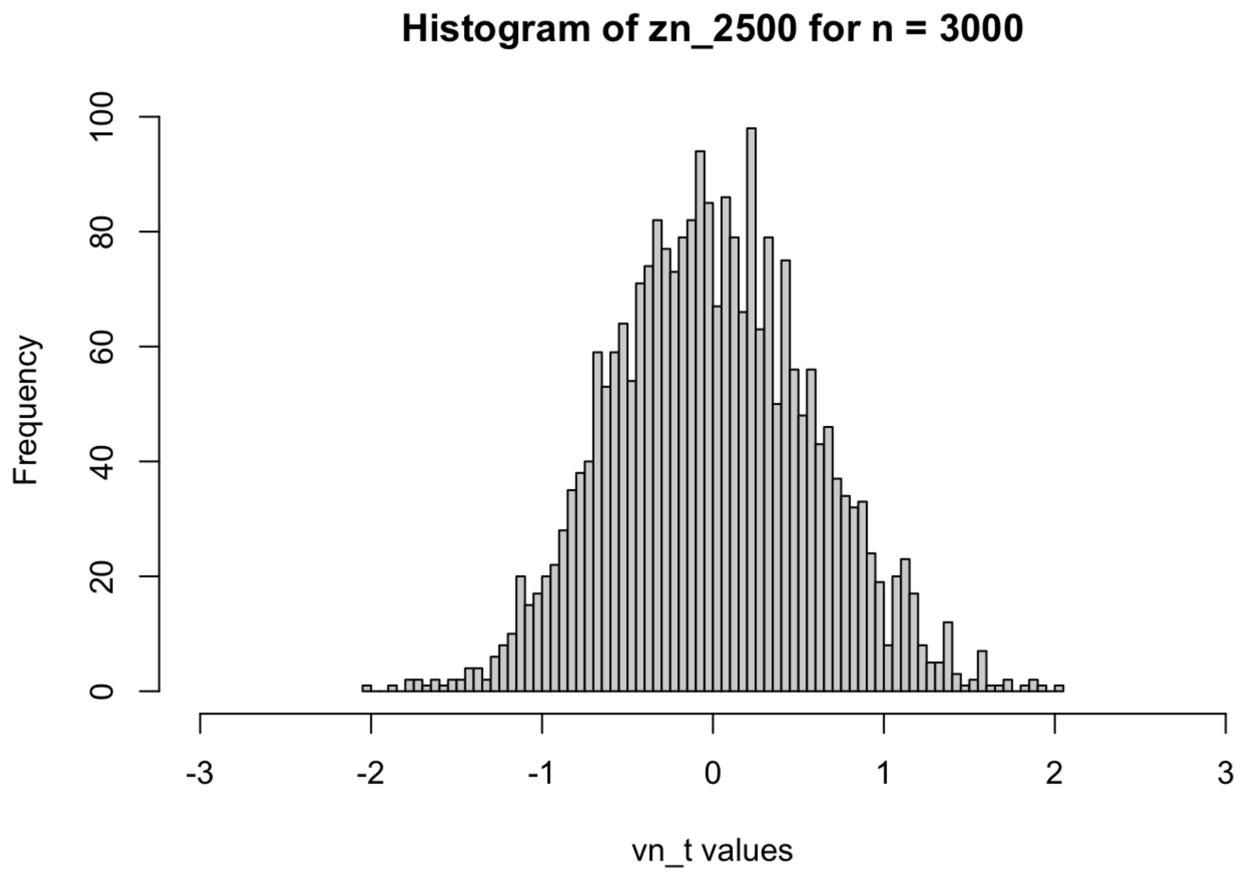

Histogram of zn_2500 for n = 5
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
vn_t values


Histogram of zn_2500 for n = 10
Frequency
0
20
40
60
80
100
-3
-2
-1
0
1
2
3
vn_t values


Histogram of zn_2500 for n = 50
Frequency
0
20
40
60
80
100
-3
-2
-1
0
1
2
3
vn_t values


Histogram of zn_2500 for n = 100
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
vn_t values


Histogram of zn_2500 for n = 1000
Frequency
0
20
40
60
80
100
-3
-2
-1
0
1
2
3
vn_t values



• (m) What happens to the reported values in (f), (h), (k) and histograms in (i) and (l) as n increases? Discuss.

3 (R) WLLN with Simple Regression

In this exercise, you will generate datasets for simple regression yourself, and then try to esti- mate the model parmaters to examine the properties of simple regression OLS estimators as the sample size n grows. Repeat the following for n = 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30, 50, 75, 100, 250, 500, 1000, 2000, 3000. Use the for loops as necessary.

• (a) (R) Generate a n × 1 column vector of Uniform[0, 12] random variable and denote it as x.

• (b) (R) Generate a n × 1 column vector of Uni f orm [−4, 4] random variable and denote it as u. • (c) (R) Generate the y vector using the following formula: yi = 3 + 2xi + ui for each i = 1, 2, 3, …, n. That is, i’th row of x and u corresponds to i’th observation. • (d) (R) Now you have a Monte-Carlo dataset of size n. Estimate the β in the following model using OLS. (Recall the formula d .) What is the calculated value of βOLS,n? Report.

```
n = c(2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30, 50, 75, 100, 250, 500, 1000, 2000, 3000)

Q3 <- function(n) {

  x = matrix(runif(n, 0, 12), nrow = i, ncol = 1)

  u = matrix(runif(n, -4, 4), nrow = i, ncol = 1)

  y = 3 + (2 * x) + u

  cov_xy = cov(x, y)
  var_x = var(x)
  hat_beta = cov_xy/var_x

  abs_beta = abs(hat_beta - 2)

  return(list(n=n,x=x,u=u,y=y,cov_xy=cov_xy,var_x=var_x,hat_beta=hat_beta,abs_beta=abs_b
eta))
}

for(i in n){
  assign(paste0("x",i),Q3(i))
}
```

4 In this exercise, you will generate datasets for simple regression yourself, and then try to esti- mate the model parmaters to examine the properties of simple regression OLS estimators as the sample size n grows. Repeat the following for n = 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30, 50, 75, 100, 250, 500, 1000, 2000, 3000. Use the for loops as necessary.

• (a) (R) Generate a n × 1 column vector of Uni f orm [0, 12] random variable and denote it as x. • (b) (R) Generate a n × 1 column vector of Uni f orm [−4, 4] random variable and denote it as u. • (c) (R) Generate the y vector using the following formula: yi = 3 + 2xi + ui for each i = 1, 2, 3, …, n. That is, i'th row of x and u corresponds to i'th observation. • (d) (R) Now you have a Monte-Carlo dataset of size n. Estimate the β in the following model

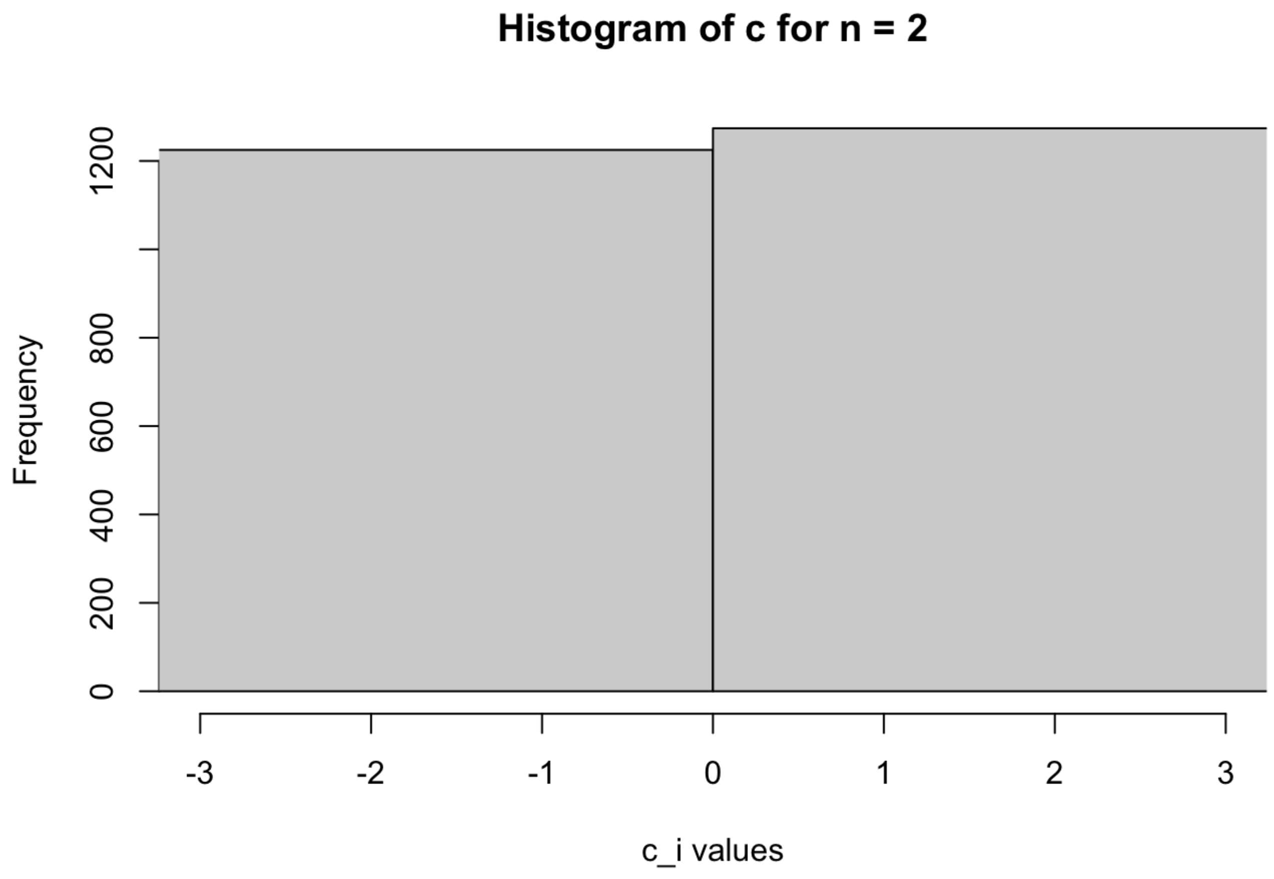
$$yi = \alpha + \beta xi + ui$$

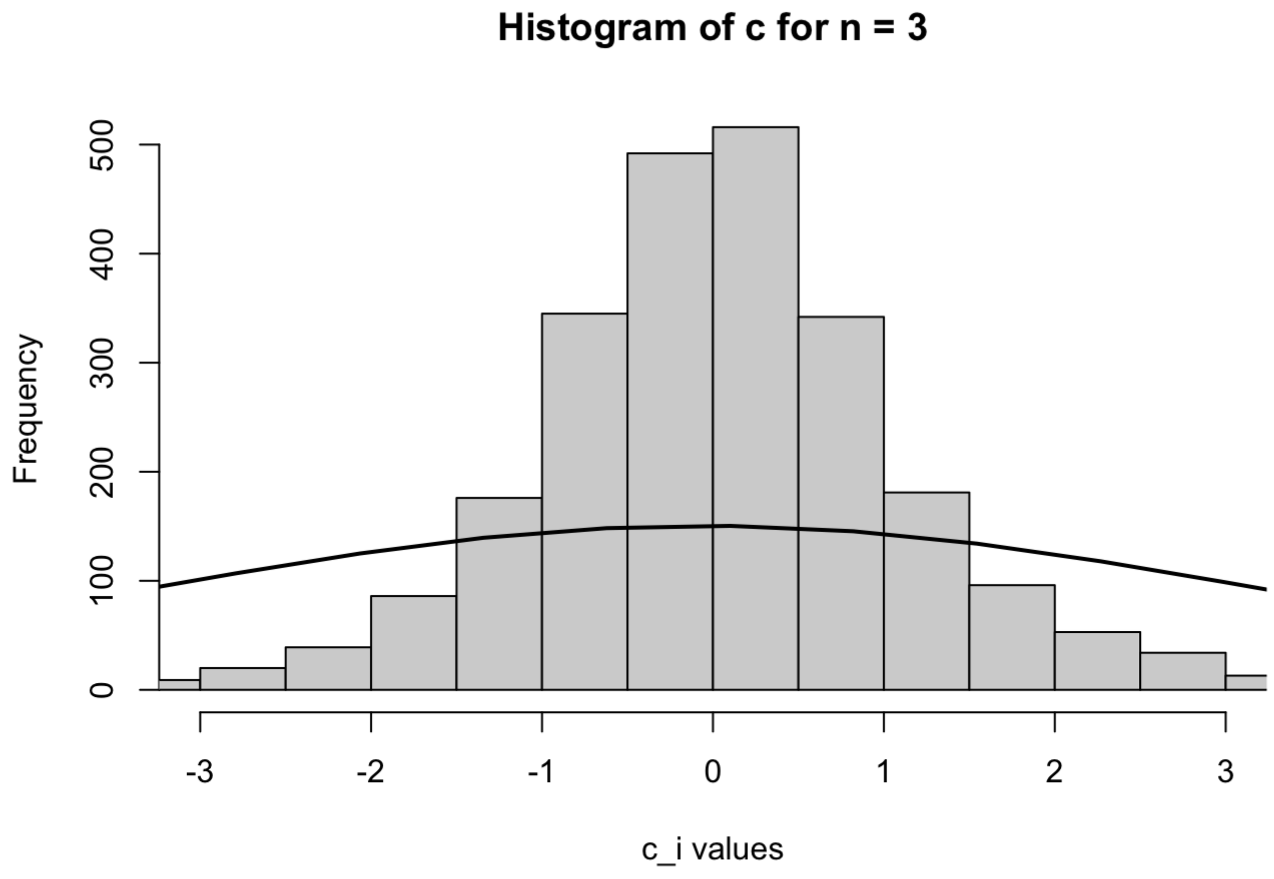
• (e) (R) Repeat (a)-(d) for 2,500 times. You must have 2,500 β̂OLS,n estimates in the memory ˆ1 ˆ2 ˆ2500 ′ at the end of this sub-question. Denote this size 2,500 vector by b = βOLS,n, βOLS,n, …, βOLS,n . • (f) (R) Calculate the variance of b and report. • (g) (R) Subtract 2 from b and multiply (c1, c2, …., c2500), i.e., n on each element of b and denote this as

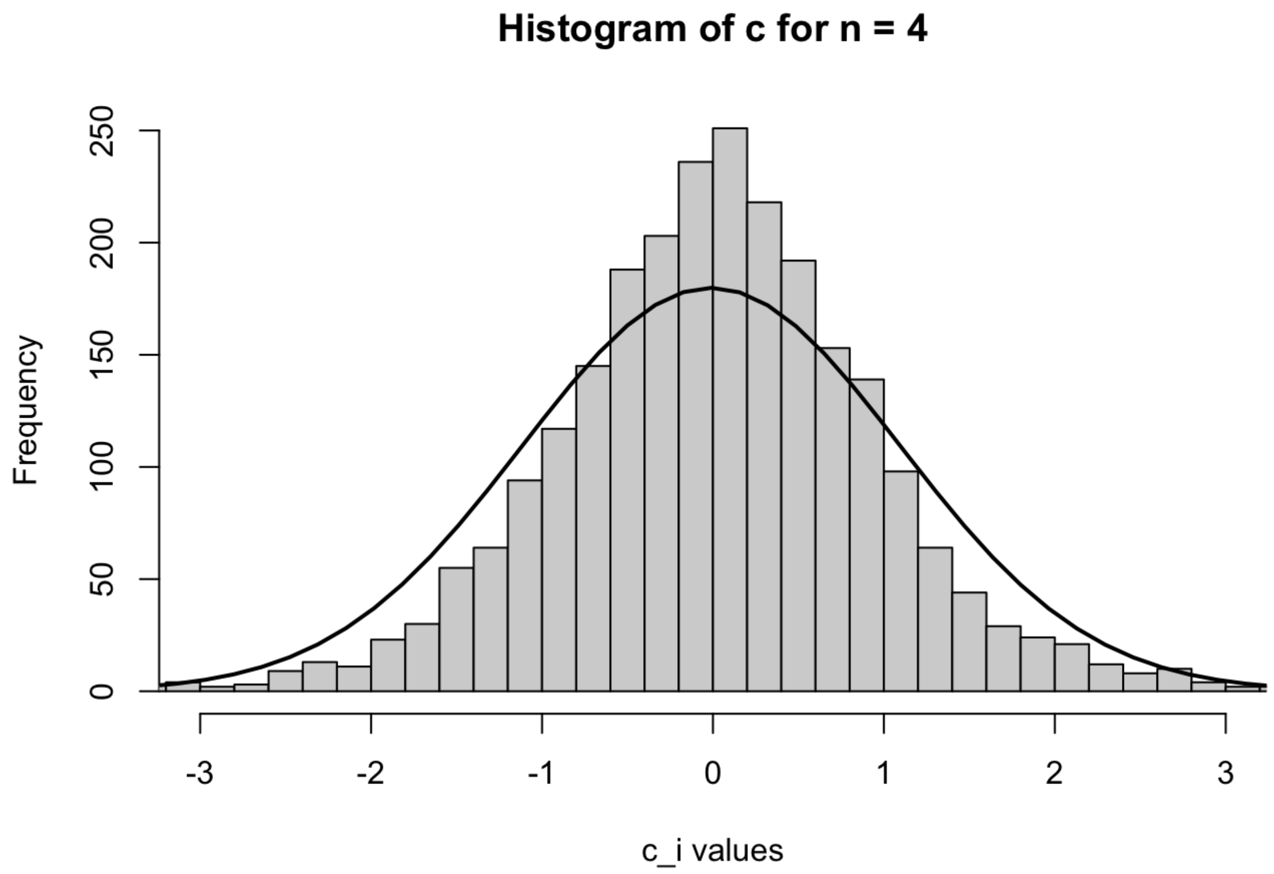
$$c_i = \sqrt{n} \times (\hat{\beta}^{i}_{OLS,n} - 2)$$

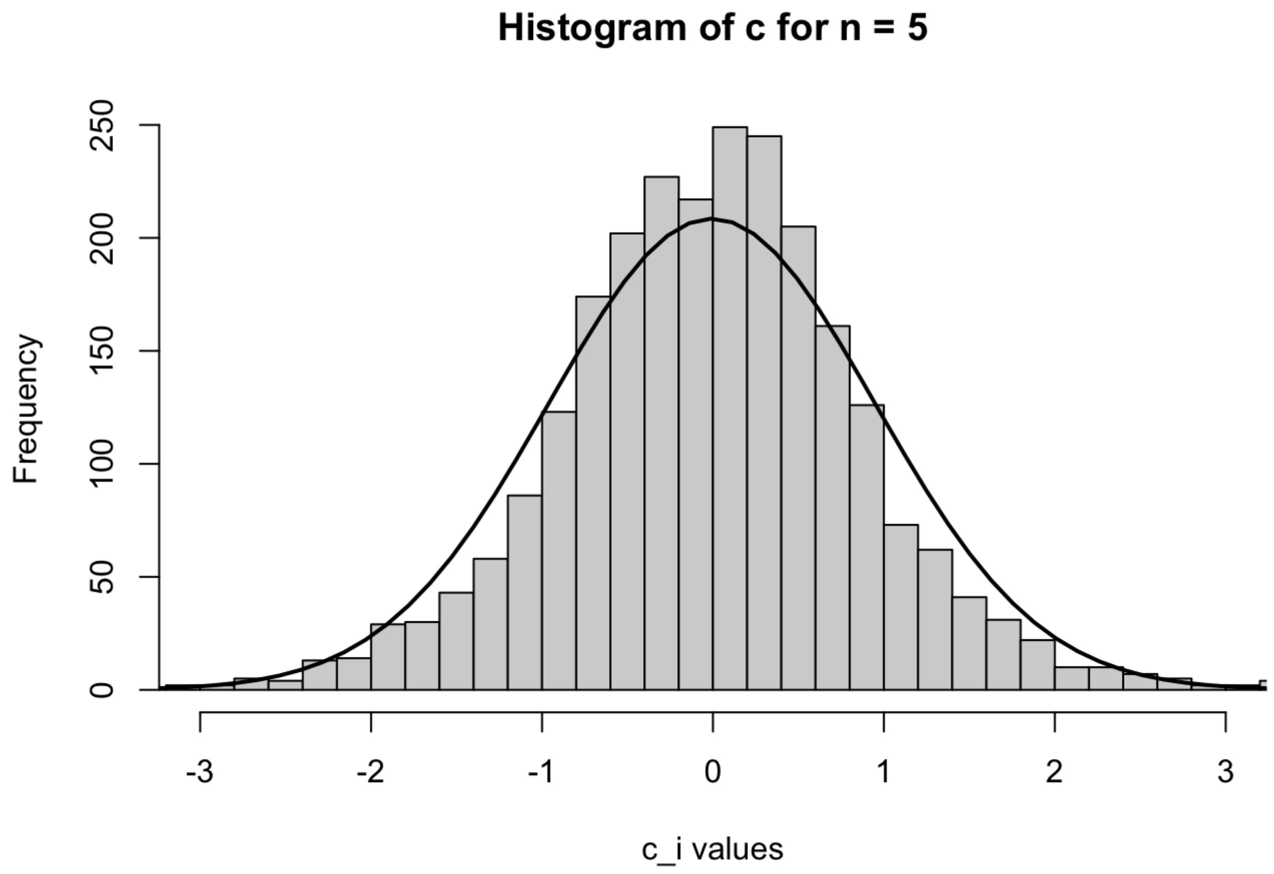
using OLS. Save it in the memory.

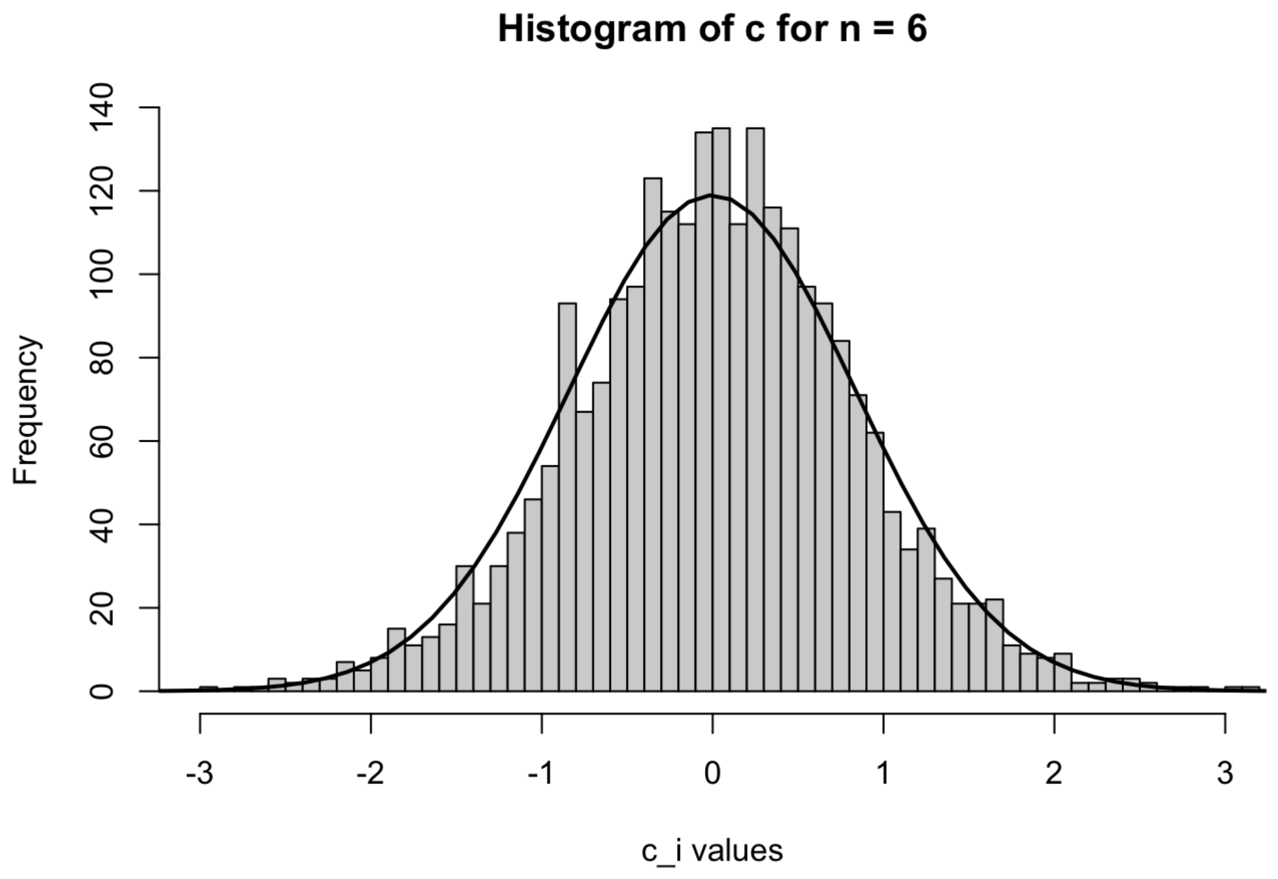
```
n = c(2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30, 50, 75, 100, 250, 500, 1000, 2000, 3000)

Q4 <- function(n){
  b <- c()
  for (j in c(1:2500)) {

    # a
    x = matrix(runif(n, 0, 12), nrow = n, ncol = 1)

    # b
    u = matrix(runif(n, -4, 4), nrow = n, ncol = 1)

    # c
    y = 3 + (2 * x) + u

    # d
    cov_xy = cov(x, y)
    var_x = var(x)
    beta_hat = cov_xy/var_x
    b = append(b, beta_hat)
  }
  #  f
  var_b = var(b)

  c = sqrt(n)*(b - 2)
  return(list(n=n,b=b,var_b=var_b,c=c))
}

for(i in n){
  assign(paste0("q",i),Q4(i))
  hist_data <- hist(Q4(i)$c, breaks = 100,
       main = paste("Histogram of c for n = ", i, sep = ""),
       xlab = "c_i values",
       xlim = c(-3,3))
    x_values <- seq(min(Q4(i)$c), max(Q4(i)$c), length = 100)
    y_values <- dnorm(x_values, mean = mean(Q4(i)$c), sd = sd(Q4(i)$c))
    y_values <- y_values * diff(hist_data$mids[1:2]) * length(Q4(i)$c)
    lines(x_values, y_values, lwd = 2)
}
```

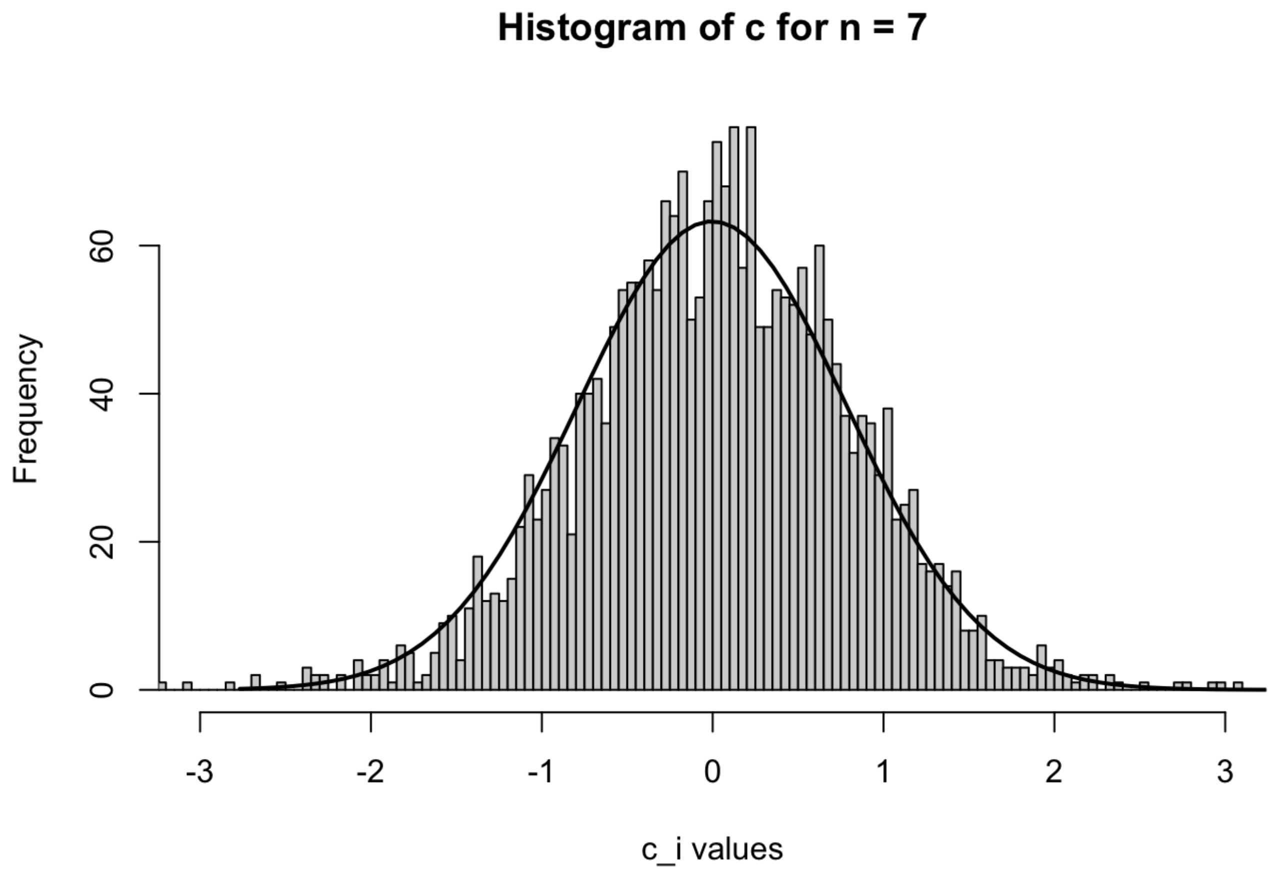

Histogram of c for n = 2
Frequency
0
200
400
600
800
1200
-3
-2
-1
0
1
2
3
c_i values

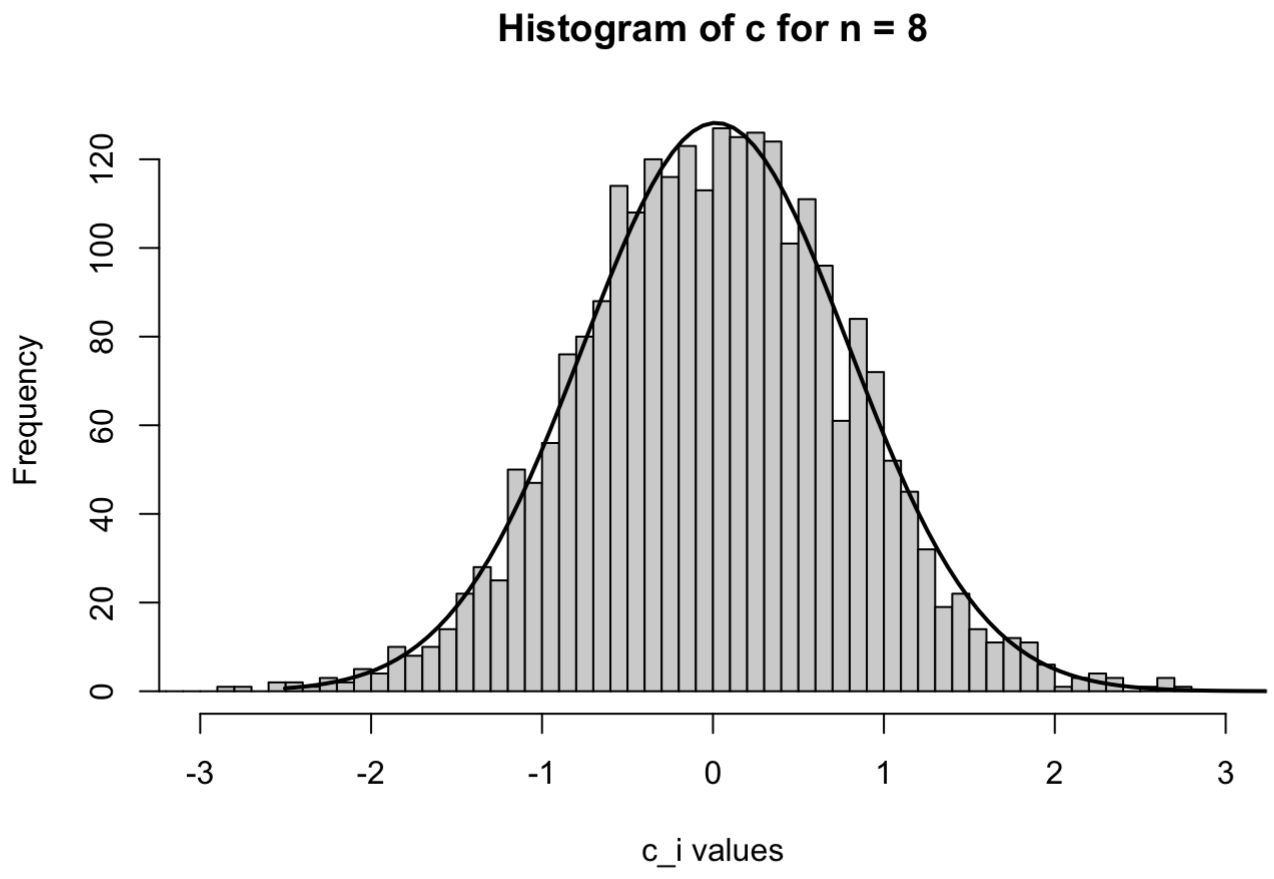

Histogram of c for n = 3
Frequency
0
100
200
300
400
500
-3
-2
-1
0
1
2
3
c_i values

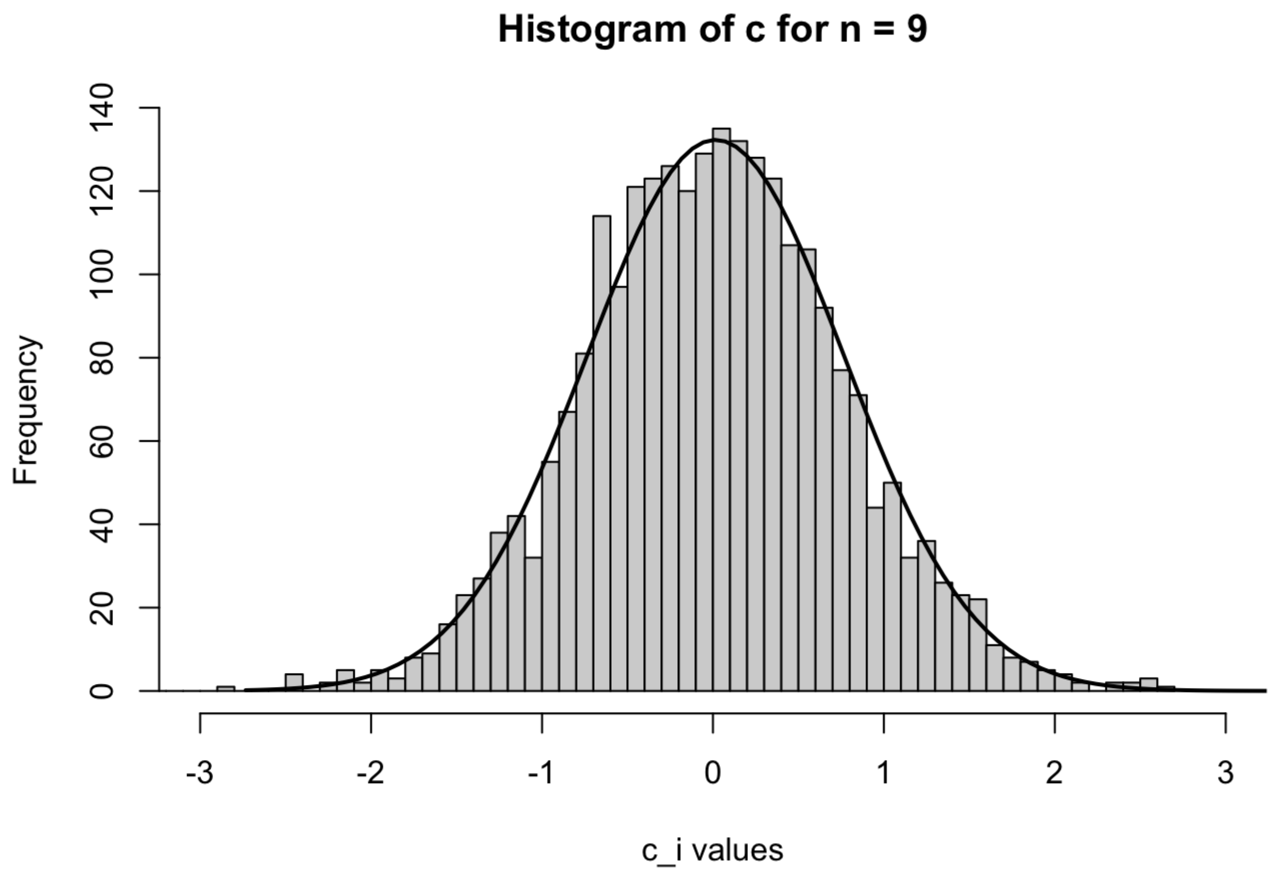

Histogram of c for n = 4
Frequency
0
50
100
150
200
250
-3
-2
-1
0
1
2
3
c_i values

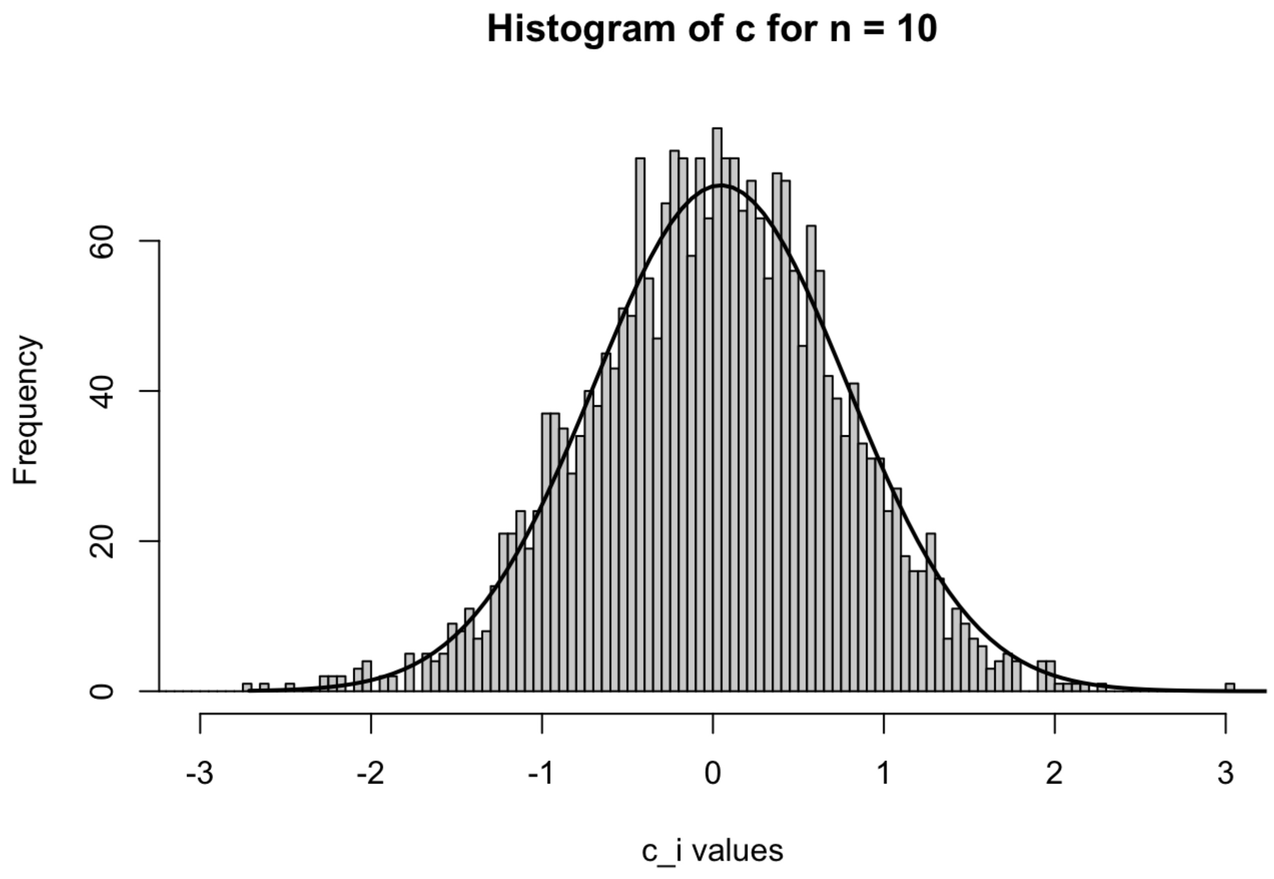

Histogram of c for n = 5
Frequency
0
50
100
150
200
250
-3
-2
-1
0
1
2
3
c_i values

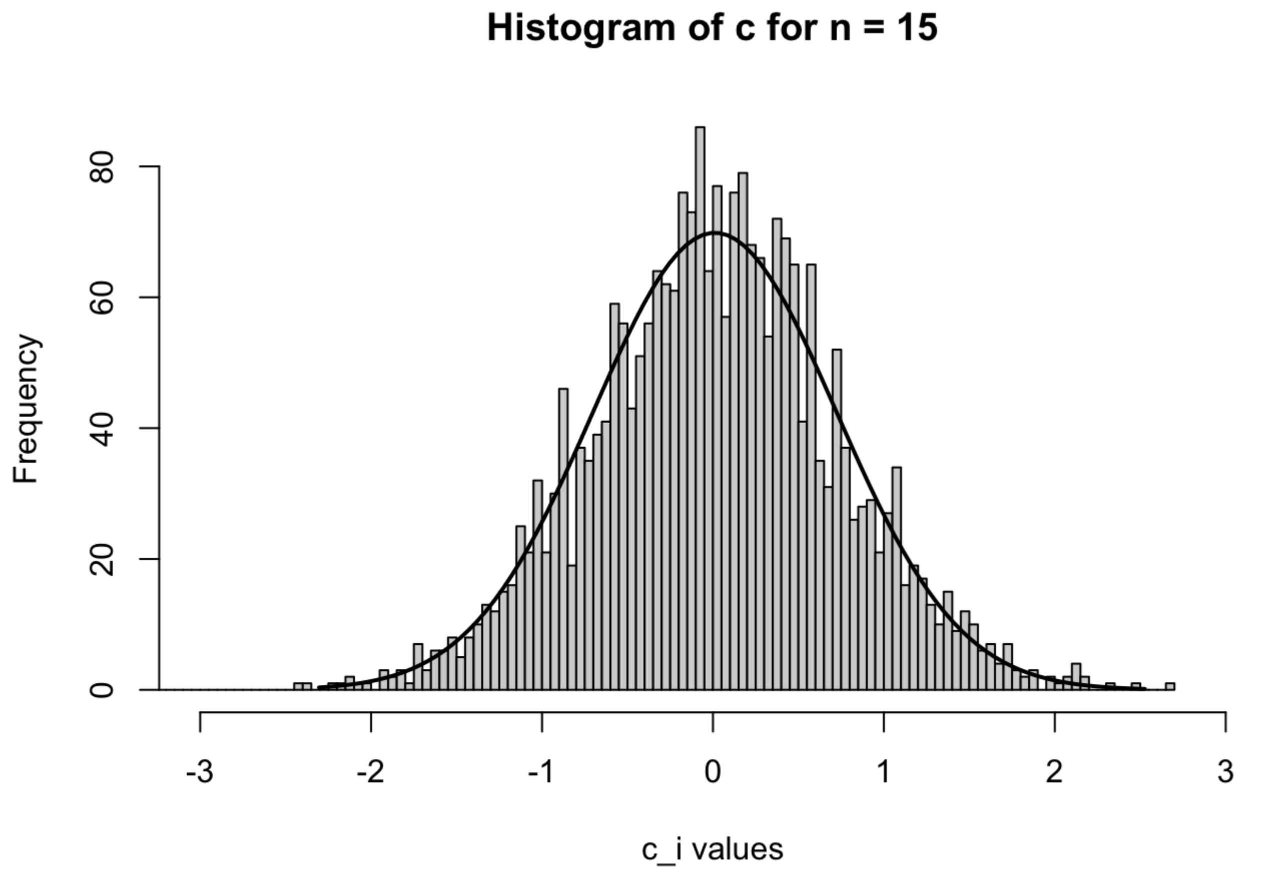

Histogram of c for n = 6
Frequency
0
20
40
60
80
100
120
140
-3
-2
-1
0
1
2
3
c_i values

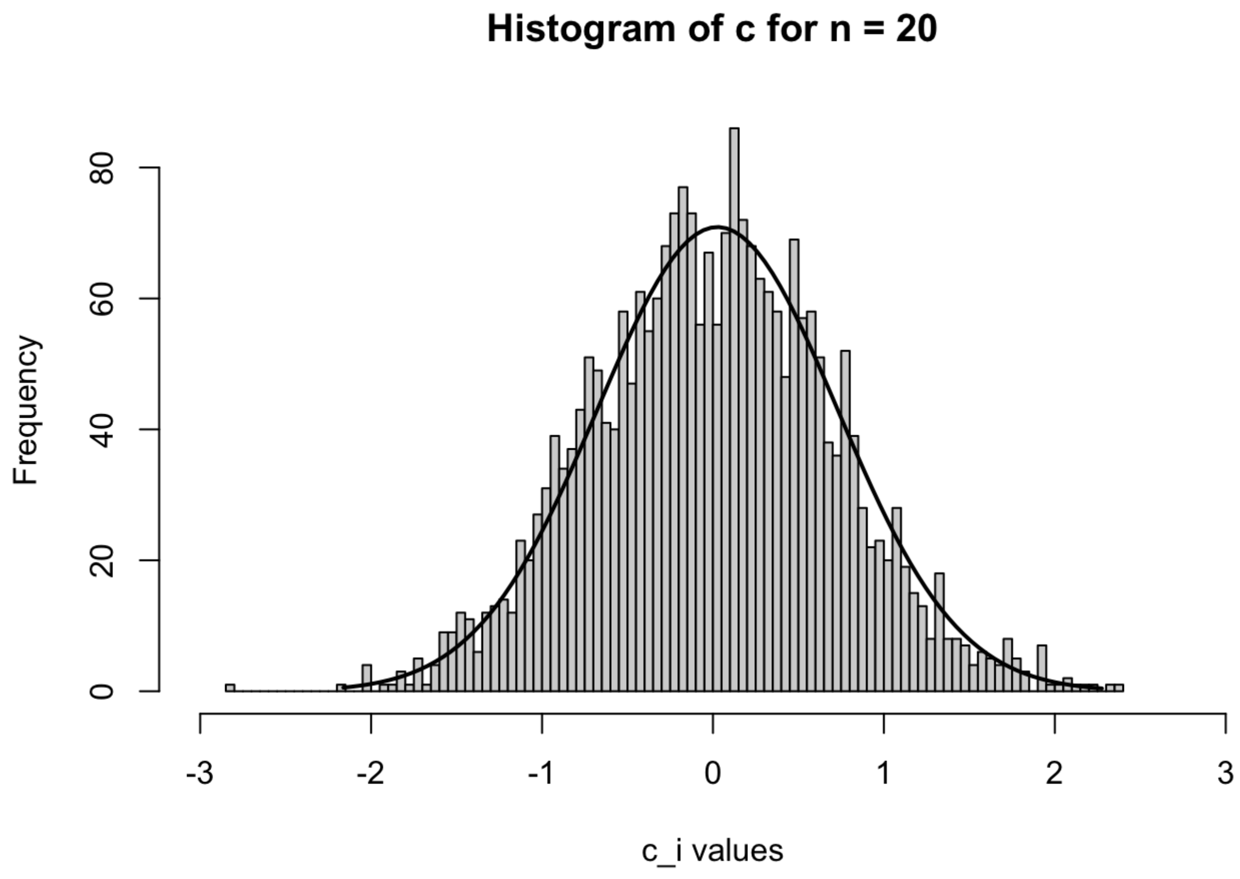

Histogram of c for n = 7
Frequency
0
20
40
60
-3
-2
-1
0
1
2
3
c_i values

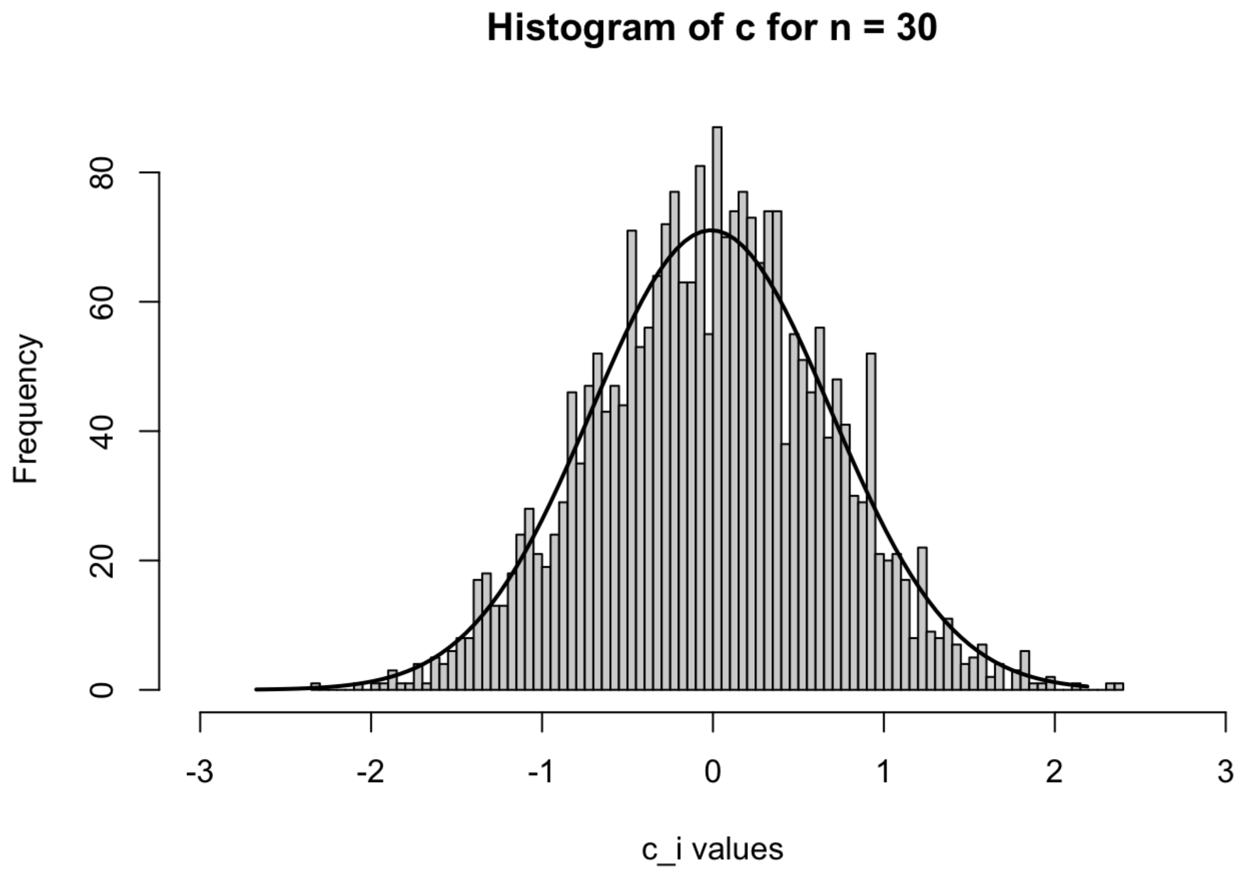

Histogram of c for n = 8
Frequency
0
20
40
60
80
100
120
-3
-2
-1
0
1
2
3
c_i values

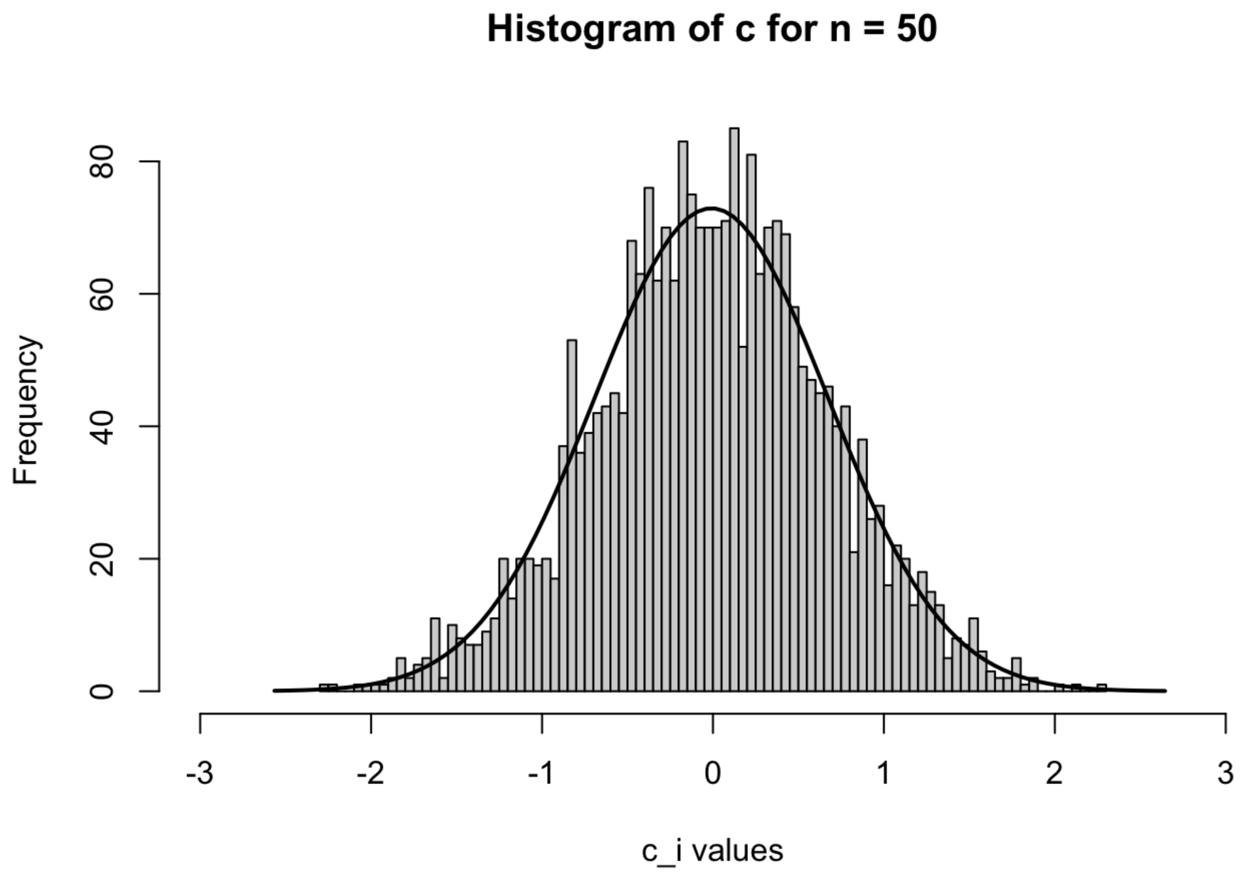

Histogram of c for n = 9
Frequency
0
20
40
60
80
100
120
140
-3
-2
-1
0
1
2
3
c_i values

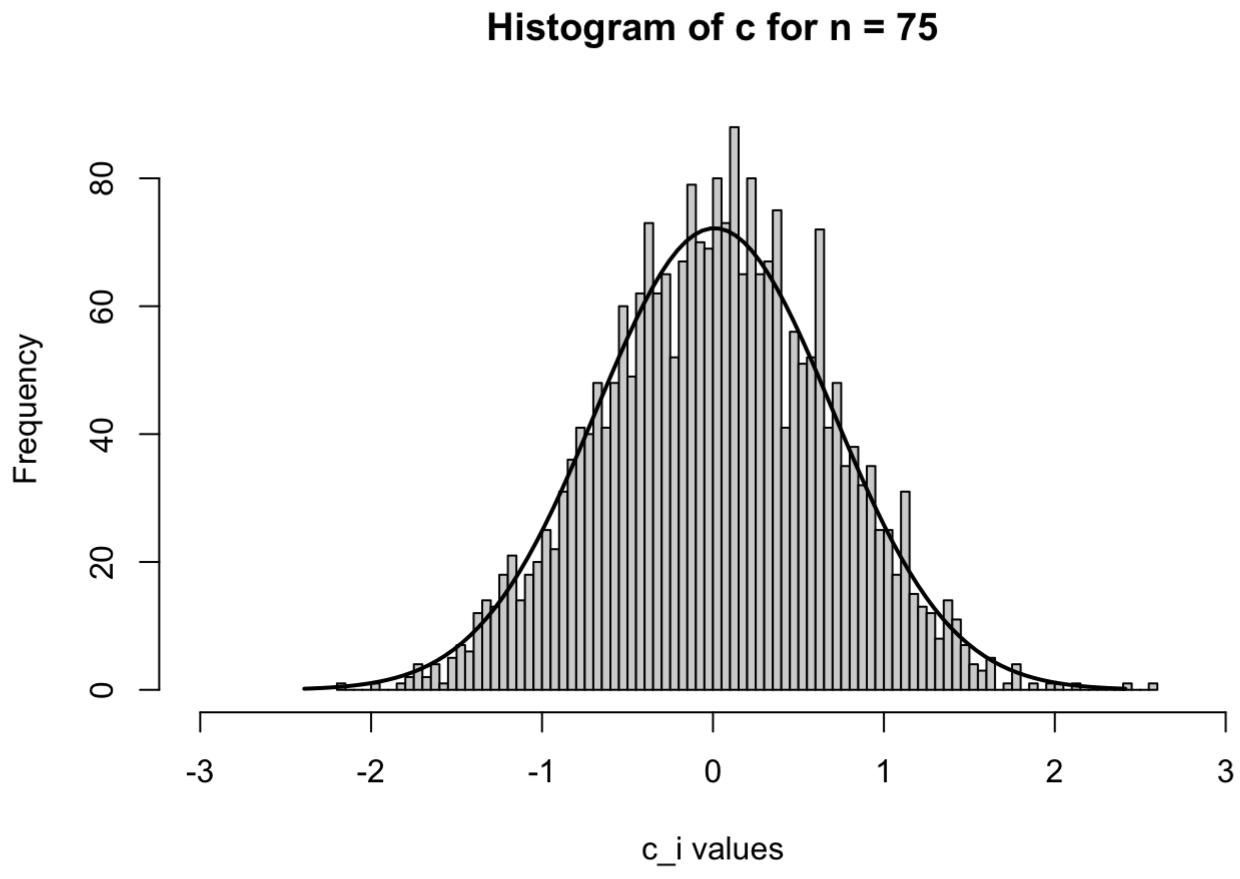

Histogram of c for n = 10
Frequency
0
20
40
60
-3
-2
-1
0
1
2
3
c_i values

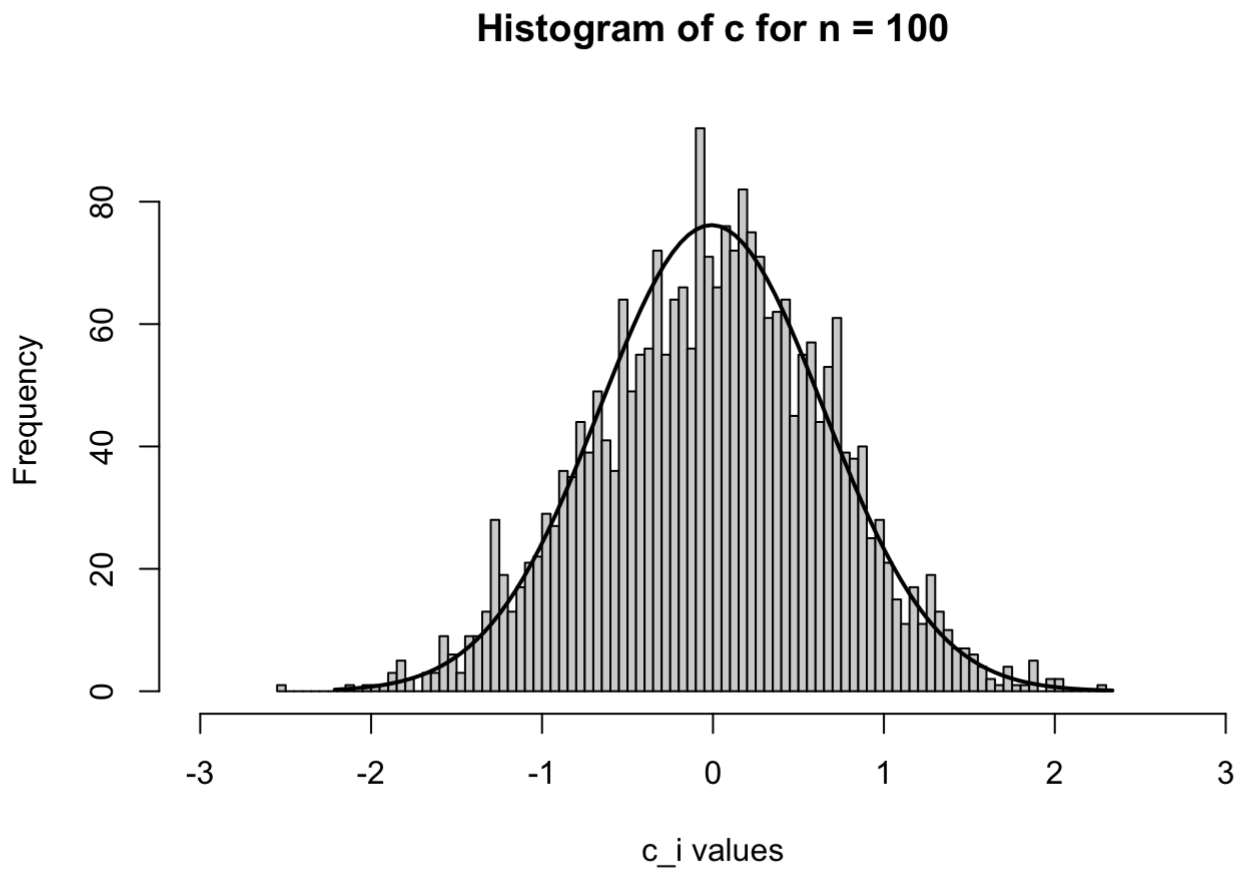

Histogram of c for n = 15
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values

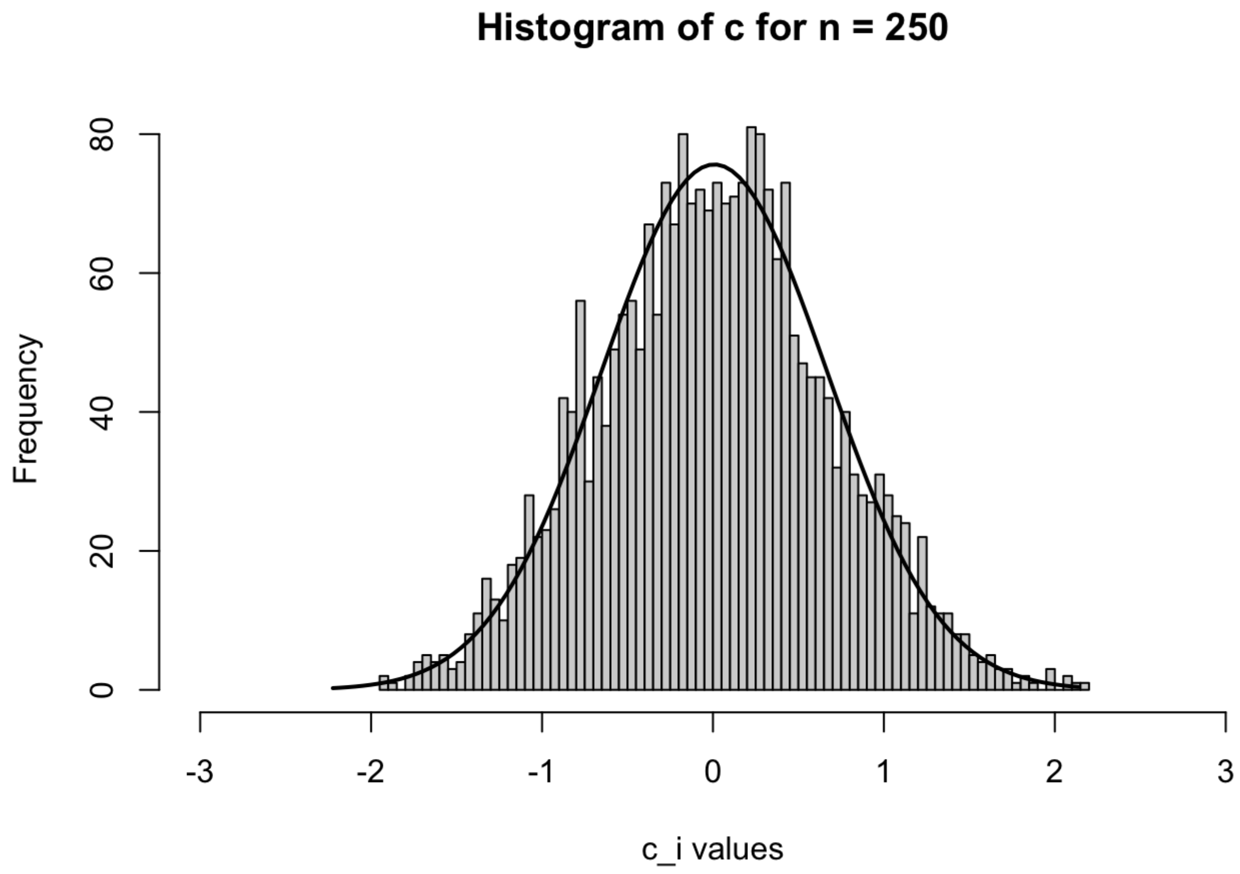

Histogram of c for n = 20
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values

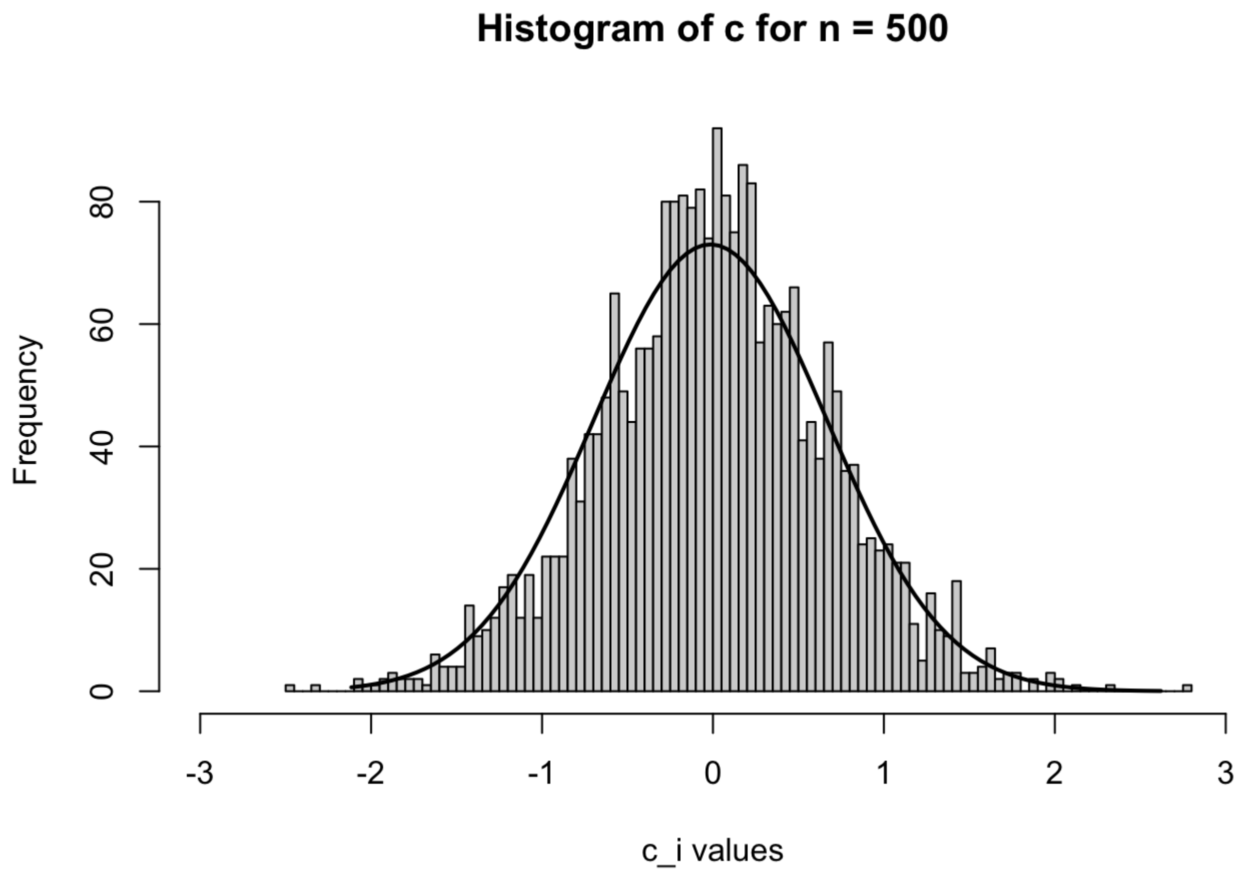

Histogram of c for n = 30
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values

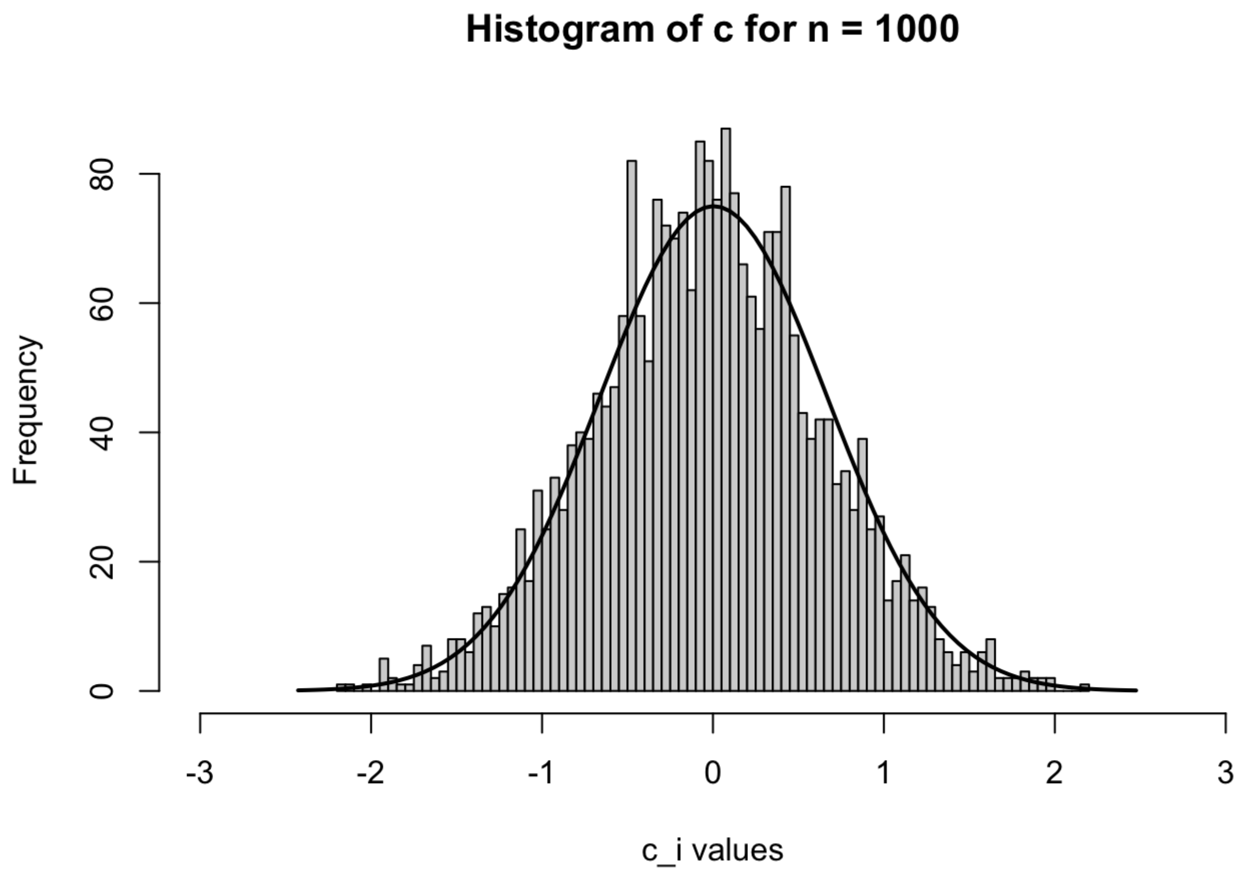

Histogram of c for n = 50
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values

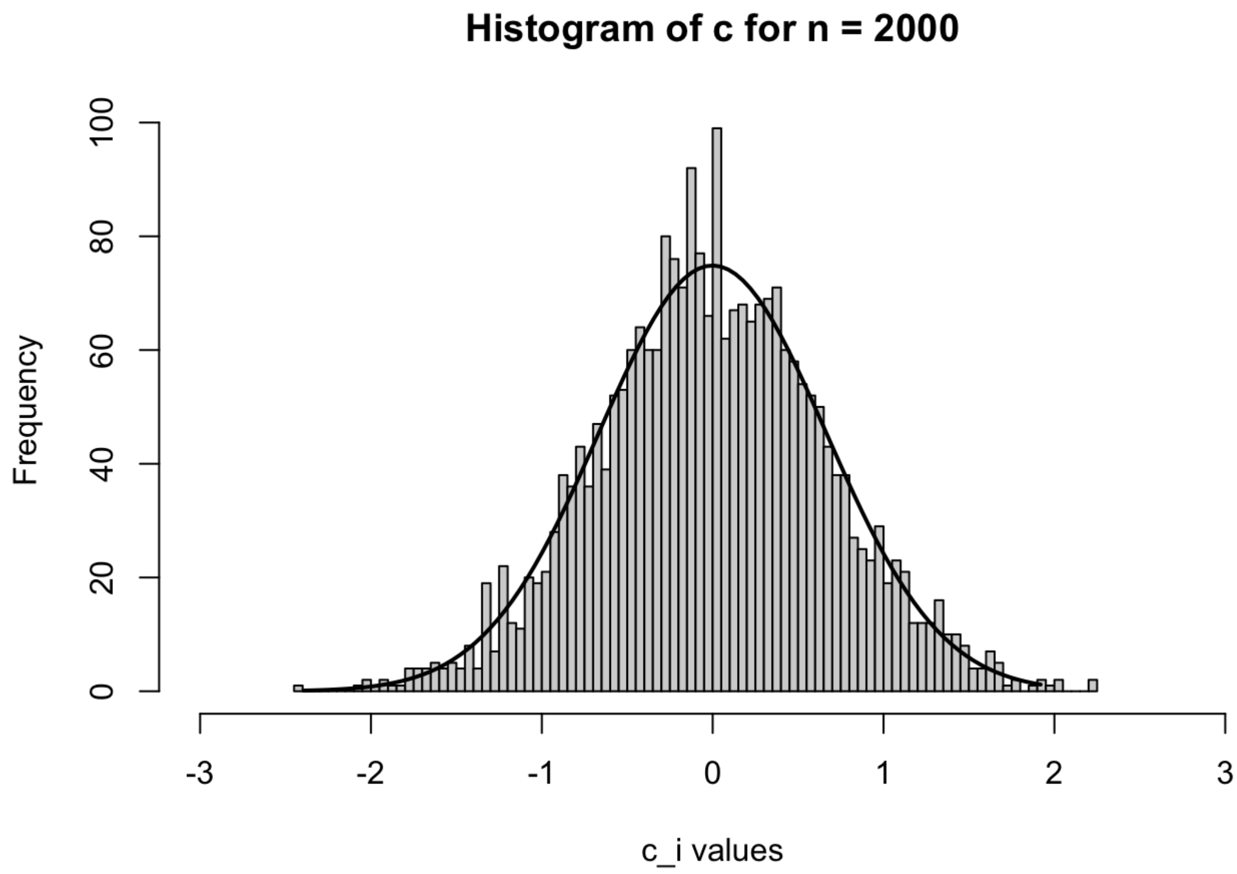

Histogram of c for n = 75
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values

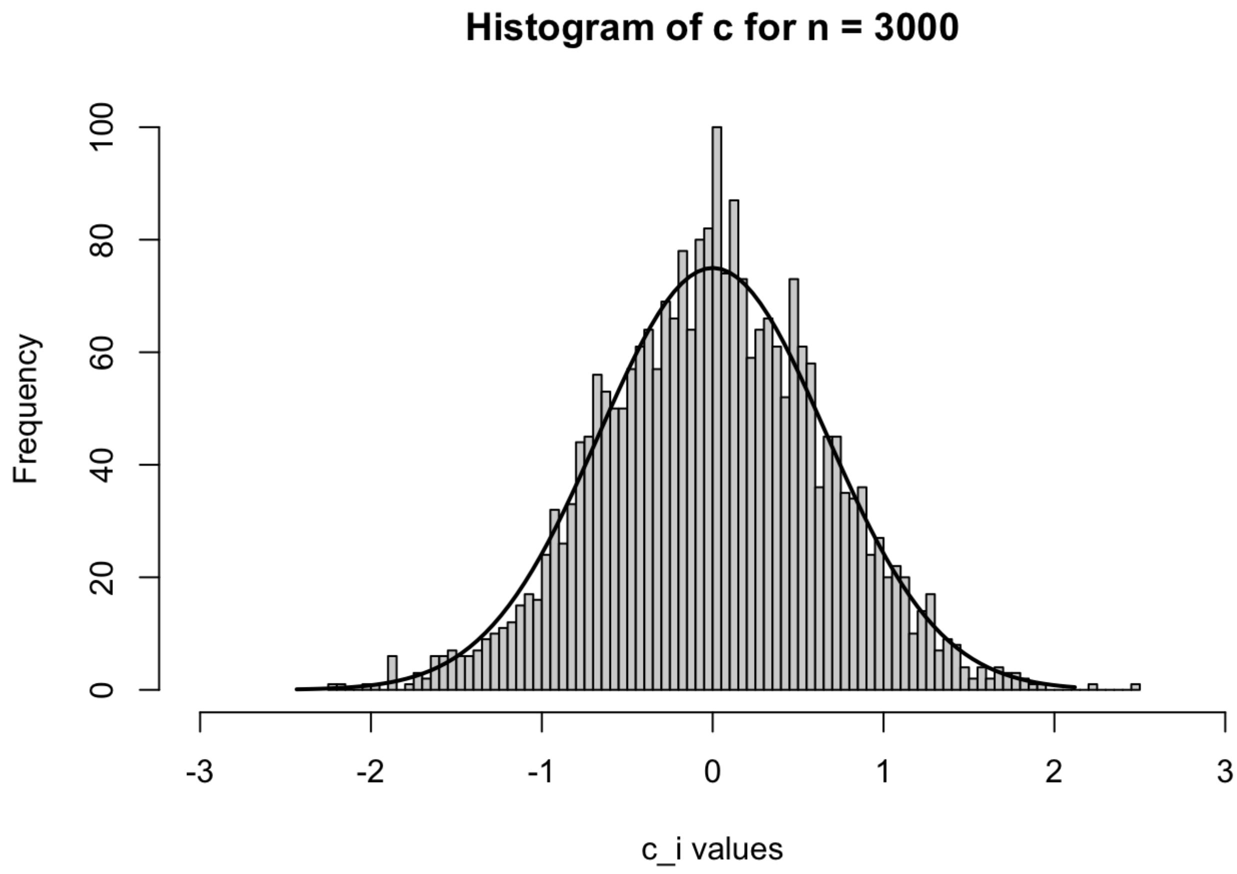

Histogram of c for n = 100
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values


Histogram of c for n = 250
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values


Histogram of c for n = 500
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values


Histogram of c for n = 1000
Frequency
0
20
40
60
80
-3
-2
-1
0
1
2
3
c_i values


Histogram of c for n = 2000
Frequency
c_i values
0
20
40
60
80
100
-3
-2
-1
0
1
2
3


Histogram of c for n = 3000
Frequency
c_i values
0
20
40
60
80
100
-3
-2
-1
0
1
2
3

• (h) What happens to the reported values in (f) and the histogram in (g) as n grows large? Discuss.

5. R. Video Game Sales Regression

The dataset for this exercise is available in VideoGamesSales_Main.csv. This dataset contains information on the global sales and critic and user review ratings for videogames launched between 2001 and 2012 (from www.vgchartz.com).

• Your task is to develop a regression model (using lm()) that links global sales to video game reviews, and explore ways in which the model fit could be improved through suit- able changes to the model specification and vdgmriables. (a) (R) First, create a frequency table of 3 variables: platform, genre, and rating.

```
vdgm <- fread("videogamesales_main.csv",header = T)
if(demo) {str(vdgm)}
```

```
## Classes 'data.table' and 'data.frame':   4413 obs. of  12 variables:
##  $ Name           : chr  "Madden NFL 11" "Sly Cooper and the Thievius Raccoonus" "The
Lord of the Rings: Conquest" "Red Steel 2" ...
##  $ Platform       : chr  "PS3" "PS2" "X360" "Wii" ...
##  $ Genre          : chr  "Sports" "Platform" "Action" "Shooter" ...
##  $ Publisher      : chr  "Electronic Arts" "Sony Computer Entertainment" "Electronic
Arts" "Ubisoft" ...
##  $ Developer      : chr  "EA Tiburon" "Sucker Punch" "Pandemic Studios" "Ubisoft Pari
s" ...
##  $ Rating         : chr  "E" "E" "T" "T" ...
##  $ Global_Sales   : num  2.38 1.21 0.63 0.62 1.43 0.09 0.56 0.33 1.52 0.21 ...
##  $ Year_of_Release: int  2010 2002 2009 2010 2010 2011 2008 2009 2002 2006 ...
##  $ Critic_Score   : int  83 86 55 80 61 70 78 75 38 70 ...
##  $ Critic_Count   : int  36 41 58 73 59 4 47 17 21 9 ...
##  $ User_Score     : num  6.1 8.6 7 8.6 5.7 7 7.6 7.8 5 6.5 ...
##  $ User_Count     : int  68 184 110 178 180 4 36 6 26 10 ...
##  - attr(*, ".internal.selfref")=<externalptr>
```

```
ptl_frq <- table(vdgm$Platform)
gnr_frq <- table(vdgm$Genre)
rating_frq <- table(vdgm$Rating)
```

b. R. Create categorial variables for platform, genre, and rating using data.table. Also create a variable for the age of the game relative to year 2013 (Note that these games were released before 2013).

```
vdgm_2013 <- vdgm[,Platform]
vdgm$Genre<-as.factor(vdgm$Genre)
vdgm$Platform<-as.factor(vdgm$Platform)
vdgm$Rating<-as.factor(vdgm$Rating)
```

c. R. Run a regression with all relevant X variables. Report the adjusted R-squared.

```
lm1 <- lm(Global_Sales ~. - Name - Publisher - Developer,data = vdgm)
summary(lm1)
```

```
##
## Call:
## lm(formula = Global_Sales ~ . - Name - Publisher - Developer,
##     data = vdgm)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -7.931 -0.603 -0.157  0.287 79.609
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        7.487e+01  3.283e+01   2.280 0.022635 *
## PlatformGBA       -3.655e-01  1.932e-01  -1.891 0.058656 .
## PlatformGC        -5.773e-01  1.738e-01  -3.321 0.000905 ***
## PlatformPC        -1.098e+00  1.564e-01  -7.020 2.57e-12 ***
## PlatformPS2       -1.714e-01  1.429e-01  -1.199 0.230416
## PlatformPS3       -2.784e-01  1.474e-01  -1.889 0.058954 .
## PlatformPSP       -3.523e-01  1.574e-01  -2.238 0.025284 *
## PlatformWii        5.711e-01  1.485e-01   3.846 0.000122 ***
## PlatformX360      -5.233e-01  1.472e-01  -3.555 0.000382 ***
## PlatformXB        -7.815e-01  1.597e-01  -4.893 1.03e-06 ***
## GenreAdventure    -2.025e-01  1.695e-01  -1.195 0.232235
## GenreFighting      7.171e-02  1.452e-01   0.494 0.621327
## GenreMisc          3.774e-01  1.375e-01   2.744 0.006099 **
## GenrePlatform      3.196e-02  1.451e-01   0.220 0.825629
## GenrePuzzle       -4.010e-01  2.479e-01  -1.618 0.105776
## GenreRacing        5.483e-02  1.237e-01   0.443 0.657609
## GenreRole-Playing -3.169e-01  1.170e-01  -2.710 0.006762 **
## GenreShooter      -4.054e-02  1.068e-01  -0.380 0.704212
## GenreSimulation    2.353e-01  1.533e-01   1.534 0.125031
## GenreSports       -1.156e-02  1.204e-01  -0.096 0.923500
## GenreStrategy     -2.469e-01  1.635e-01  -1.510 0.131096
## RatingE10+        -3.931e-01  1.069e-01  -3.678 0.000238 ***
## RatingM           -5.186e-01  1.186e-01  -4.374 1.25e-05 ***
## RatingT           -4.798e-01  9.204e-02  -5.213 1.95e-07 ***
## Year_of_Release   -3.745e-02  1.635e-02  -2.291 0.022035 *
## Critic_Score       1.649e-02  3.147e-03   5.241 1.67e-07 ***
## Critic_Count       2.981e-02  2.269e-03  13.139  < 2e-16 ***
## User_Score        -5.491e-02  2.779e-02  -1.976 0.048261 *
## User_Count         8.748e-04  6.559e-05  13.337  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.946 on 4384 degrees of freedom
## Multiple R-squared:  0.1795, Adjusted R-squared:  0.1742
## F-statistic: 34.25 on 28 and 4384 DF,  p-value: < 2.2e-16
```

d. R. Now, generate natural log of the following variables: global sales, critic_score, critic_count, user_socre, user_count as ln_[original_variable_name].

```
vdgm$ln_Global_Sales = log(vdgm$Global_Sales)
vdgm$ln_Critic_Score = log(vdgm$Critic_Score)
vdgm$ln_Critic_Count = log(vdgm$Critic_Count)
vdgm$ln_User_Score = log(vdgm$User_Score)
vdgm$ln_User_Count = log(vdgm$User_Count)
```

e. R. Run a regression with the log of Y variable and report adjusted R-squared.

```
lm2 <- lm(ln_Global_Sales ~. - Name - ln_Critic_Score - ln_Critic_Count - ln_User_Score
- ln_User_Count - Publisher - Developer - Global_Sales,data = vdgm)
summary(lm2)
```

```
##
## Call:
## lm(formula = ln_Global_Sales ~ . - Name - ln_Critic_Score - ln_Critic_Count -
##     ln_User_Score - ln_User_Count - Publisher - Developer - Global_Sales,
##     data = vdgm)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.4449 -0.6634  0.0008  0.6581  4.1020
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)       -4.173e+01  1.731e+01  -2.410 0.015989 *
## PlatformGBA        2.952e-02  1.019e-01   0.290 0.772038
## PlatformGC        -1.457e-01  9.166e-02  -1.589 0.112065
## PlatformPC        -1.713e+00  8.246e-02 -20.775  < 2e-16 ***
## PlatformPS2        4.156e-01  7.533e-02   5.517 3.64e-08 ***
## PlatformPS3        2.372e-01  7.770e-02   3.053 0.002281 **
## PlatformPSP       -7.539e-02  8.301e-02  -0.908 0.363857
## PlatformWii        4.616e-01  7.830e-02   5.895 4.03e-09 ***
## PlatformX360      -1.543e-01  7.762e-02  -1.988 0.046896 *
## PlatformXB        -4.391e-01  8.421e-02  -5.214 1.93e-07 ***
## GenreAdventure    -4.542e-01  8.937e-02  -5.082 3.89e-07 ***
## GenreFighting      1.823e-02  7.654e-02   0.238 0.811773
## GenreMisc          1.828e-01  7.252e-02   2.520 0.011765 *
## GenrePlatform     -3.026e-02  7.650e-02  -0.395 0.692495
## GenrePuzzle       -5.231e-01  1.307e-01  -4.002 6.38e-05 ***
## GenreRacing       -1.086e-01  6.522e-02  -1.665 0.095926 .
## GenreRole-Playing -2.975e-01  6.167e-02  -4.824 1.46e-06 ***
## GenreShooter      -1.345e-01  5.630e-02  -2.389 0.016934 *
## GenreSimulation    2.685e-01  8.085e-02   3.321 0.000905 ***
## GenreSports       -9.037e-02  6.348e-02  -1.423 0.154663
## GenreStrategy     -5.684e-01  8.623e-02  -6.592 4.84e-11 ***
## RatingE10+        -2.287e-01  5.636e-02  -4.057 5.05e-05 ***
## RatingM           -4.326e-01  6.253e-02  -6.919 5.19e-12 ***
## RatingT           -3.404e-01  4.853e-02  -7.014 2.67e-12 ***
## Year_of_Release    1.925e-02  8.622e-03   2.233 0.025624 *
## Critic_Score       2.668e-02  1.659e-03  16.081  < 2e-16 ***
## Critic_Count       2.490e-02  1.196e-03  20.809  < 2e-16 ***
## User_Score        -5.077e-02  1.465e-02  -3.464 0.000537 ***
## User_Count         5.051e-04  3.459e-05  14.605  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.026 on 4384 degrees of freedom
## Multiple R-squared:  0.4555, Adjusted R-squared:  0.452
## F-statistic:   131 on 28 and 4384 DF,  p-value: < 2.2e-16
```

f. R. Run a regression with the log of Y variable as well as log of X variables generated in part d). Report adjusted R-squared.

```
lm3 <- lm(ln_Global_Sales ~. - Global_Sales - Name - Publisher - Developer - Critic_Scor
e - Critic_Count -User_Score - ln_User_Count,data = vdgm)
summary(lm3)
```

```
##
## Call:
## lm(formula = ln_Global_Sales ~ . - Global_Sales - Name - Publisher -
##     Developer - Critic_Score - Critic_Count - User_Score - ln_User_Count,
##     data = vdgm)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.3799 -0.6687  0.0071  0.6726  4.1881
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        -5.970e+01  1.775e+01  -3.363 0.000779 ***
## PlatformGBA         4.049e-02  1.046e-01   0.387 0.698714
## PlatformGC         -1.732e-01  9.380e-02  -1.847 0.064810 .
## PlatformPC         -1.803e+00  8.390e-02 -21.490  < 2e-16 ***
## PlatformPS2         3.656e-01  7.701e-02   4.748 2.12e-06 ***
## PlatformPS3         2.341e-01  7.969e-02   2.937 0.003331 **
## PlatformPSP        -1.171e-01  8.496e-02  -1.378 0.168325
## PlatformWii         4.492e-01  8.011e-02   5.607 2.19e-08 ***
## PlatformX360       -4.764e-02  7.862e-02  -0.606 0.544584
## PlatformXB         -4.573e-01  8.619e-02  -5.305 1.18e-07 ***
## GenreAdventure     -4.630e-01  9.146e-02  -5.062 4.32e-07 ***
## GenreFighting      -6.030e-03  7.824e-02  -0.077 0.938575
## GenreMisc           2.037e-01  7.418e-02   2.746 0.006052 **
## GenrePlatform      -1.965e-02  7.827e-02  -0.251 0.801784
## GenrePuzzle        -4.934e-01  1.338e-01  -3.689 0.000228 ***
## GenreRacing        -7.956e-02  6.672e-02  -1.192 0.233173
## GenreRole-Playing -3.034e-01  6.318e-02  -4.803 1.61e-06 ***
## GenreShooter       -1.192e-01  5.761e-02  -2.069 0.038622 *
## GenreSimulation     2.675e-01  8.279e-02   3.231 0.001244 **
## GenreSports        -9.166e-02  6.449e-02  -1.421 0.155272
## GenreStrategy      -5.638e-01  8.829e-02  -6.386 1.88e-10 ***
## RatingE10+         -2.542e-01  5.765e-02  -4.409 1.06e-05 ***
## RatingM            -4.071e-01  6.403e-02  -6.358 2.25e-10 ***
## RatingT            -3.446e-01  4.975e-02  -6.928 4.89e-12 ***
## Year_of_Release     2.552e-02  8.847e-03   2.885 0.003936 **
## User_Count          6.437e-04  3.454e-05  18.640  < 2e-16 ***
## ln_Critic_Score     1.462e+00  9.917e-02  14.748  < 2e-16 ***
## ln_Critic_Count     5.554e-01  3.008e-02  18.461  < 2e-16 ***
## ln_User_Score      -1.711e-01  8.012e-02  -2.136 0.032741 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.05 on 4384 degrees of freedom
## Multiple R-squared:  0.4299, Adjusted R-squared:  0.4262
## F-statistic: 118.1 on 28 and 4384 DF,  p-value: < 2.2e-16
```

g. Which model (out of part c, e, and f) offers the highest adjusted R-squared? What would be the economic reasoning on why that particular model provides the best fit?

Ans: lm3 has the highest R-squared value. It makes sense that this has the best fit as the sales variable usually been increasing exponentially.

h. Interpret the parameter estimates for each of ‘genre’ in plain English.

Ans: Simulation Games created the highest impact in terms of Global Sales and Sports created the lowest based on the parameter estimates.

i. Interpret the parameter estimate for ‘rating’ in plain English.

Ans: Simulation Games created the highest impact in terms of Global Sales and Sports created the lowest based on the parameter estimates.

i. Interpret the parameter estimate for ‘ln_user_count’ in plain English.

Ans: ln_User_Count has a p_value < 0.05. There we can reject the null hypothesis i.e. the coefficeint of ln_user_count = 0.