

# Computational Statistics (732A90) Lab5

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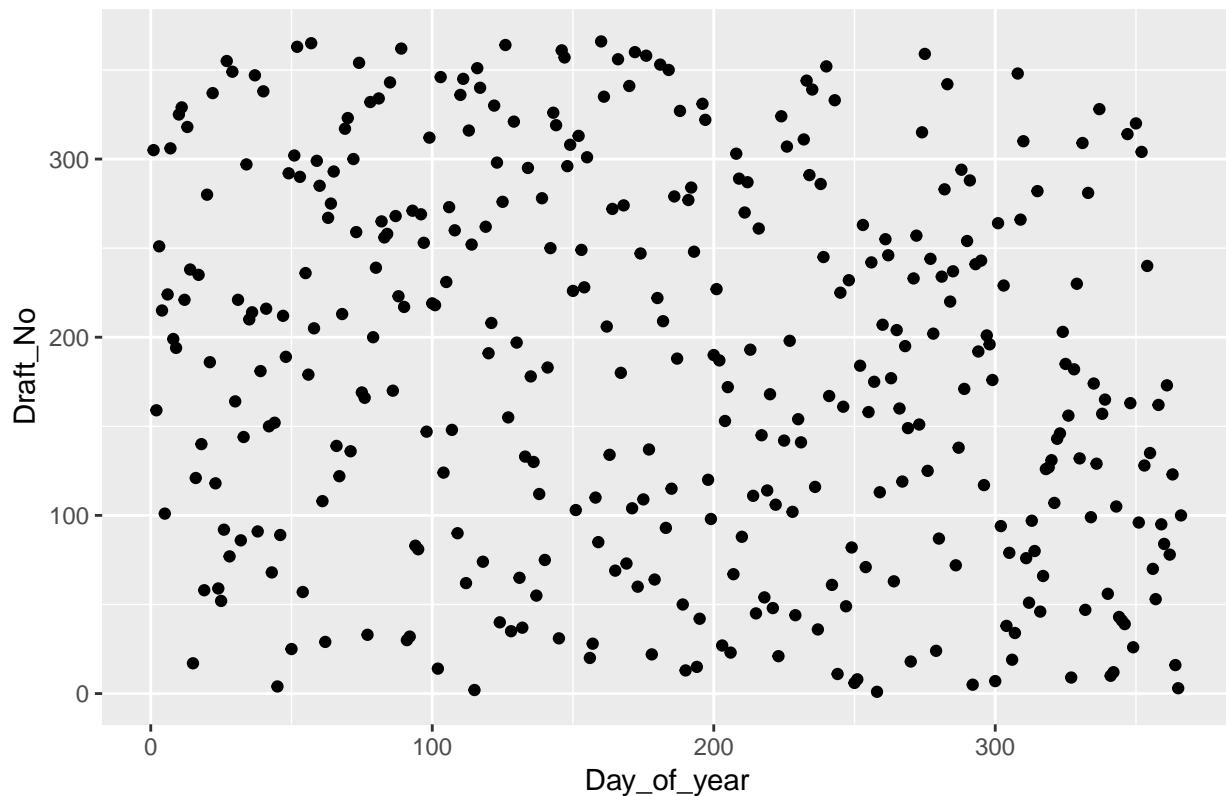
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## Question 1: Hypothesis testing

1. Make a scatterplot of  $Y(\text{draft\_no})$  versus  $X(\text{day\_of\_year})$  and conclude whether the lottery looks random.

```
lottery <- read.csv("lottery.csv", sep=";")  
  
ggplot(lottery, aes(x=Day_of_year, y = Draft_No)) + geom_point() +  
  ggtitle("Plot of Draft Number vs. day of birth")
```

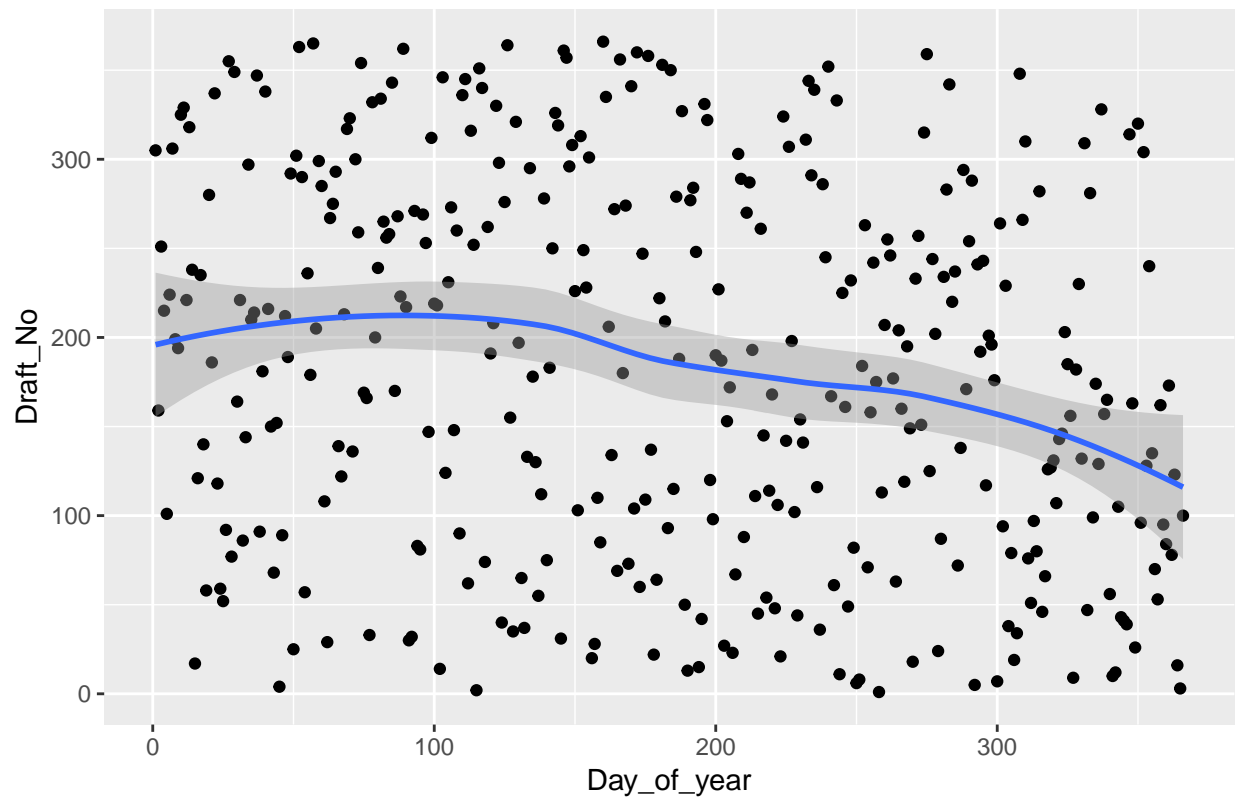
Plot of Draft Number vs. day of birth



2. Compute an estimate  $\hat{Y}$  of the expected response as a function of  $X$  by using a loess smoother (use `loess()`), put the curve  $\hat{Y}$  versus  $X$  in the previous graph and state again whether the lottery looks random.

```
ggplot(lottery, aes(x=Day_of_year, y = Draft_No)) +  
  geom_point() +  
  geom_smooth(method = loess) +  
  ggtitle("Plot of Draft Number vs. Day of birth")
```

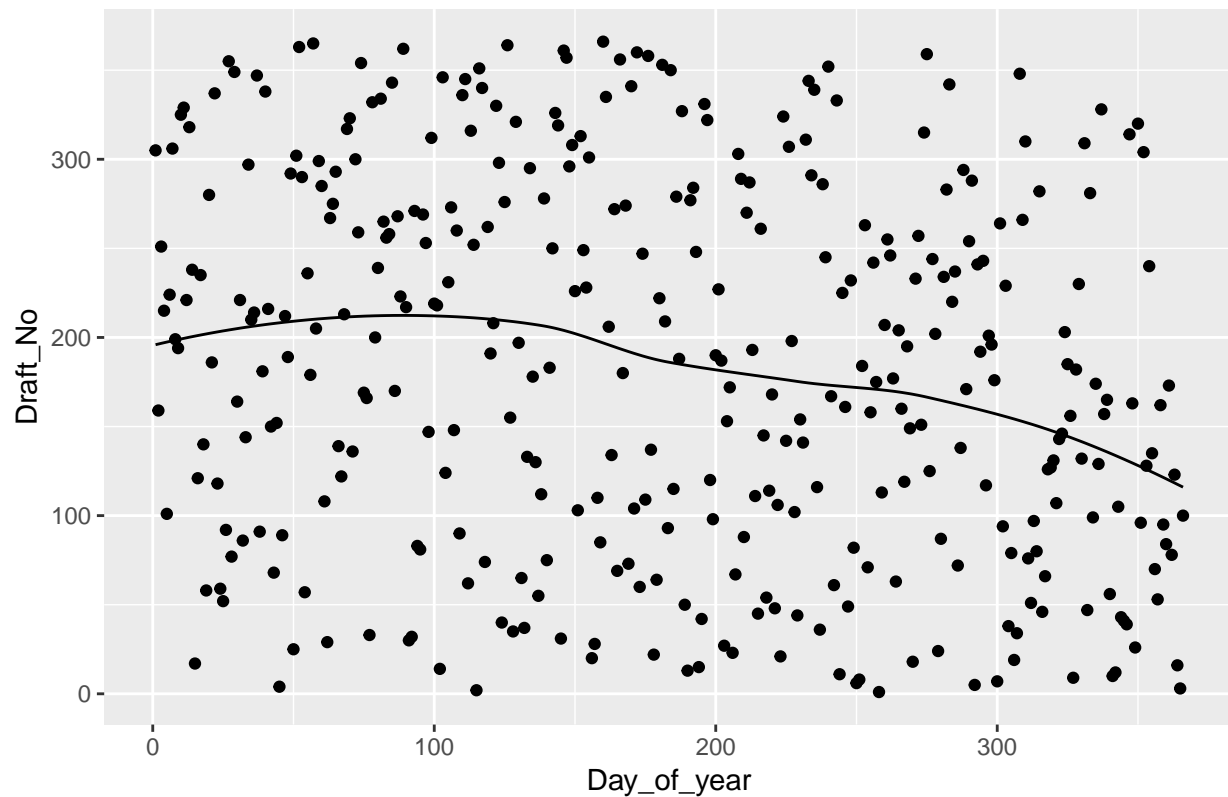
Plot of Draft Number vs. Day of birth



```
model <- loess(Draft_No ~ Day_of_year, lottery)
lottery$Y_hat <- predict(model, lottery)

ggplot(lottery, aes(x=Day_of_year, y = Draft_No)) +
  geom_point() +
  geom_line(aes(y = Y_hat)) +
  ggtitle("Plot of Draft Number vs. Day of birth without using ggplot loess")
```

Plot of Draft Number vs. Day of birth without using ggplot loess



3. To check whether the lottery is random, it is reasonable to use test statistics

$$T = \frac{\hat{Y}(X_b) - \hat{Y}(X_a)}{X_b - X_a}$$

Where  $X_b = \operatorname{argmax}_x Y(X)$  and  $X_a = \operatorname{argmin}_x Y(X)$ .

If this value is significantly greater than zero, then there should be a trend in the data and the lottery is not random. Estimate the distribution of T by using a non-parametric bootstrap with  $B = 2000$  and comment whether the lottery is random or not. What is the p-value of the test?

```
library("boot")

stat1 <- function(data, index){
  data <- data[index,]
  model <- loess(Draft_No ~ Day_of_year, data)
  res <- predict(model, data)
  X_a <- data$Day_of_year[which.max(data$Draft_No)]
  X_b <- data$Day_of_year[which.min(data$Draft_No)]
  Y_a <- res[X_a]
  Y_b <- res[X_b]
  answer <- ((Y_b - Y_a) / (X_b - X_a))
  return(answer)
}
```

```
res <- boot(data=lottery, statistic = stat1, R=2000)
print(boot.ci(res))
```

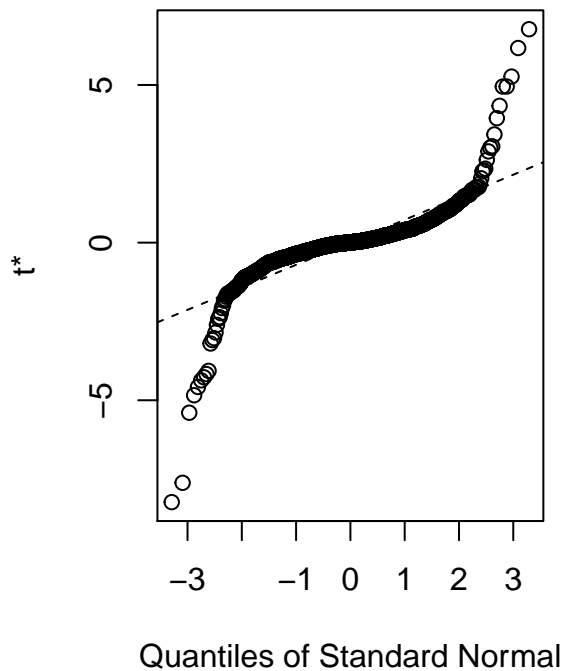
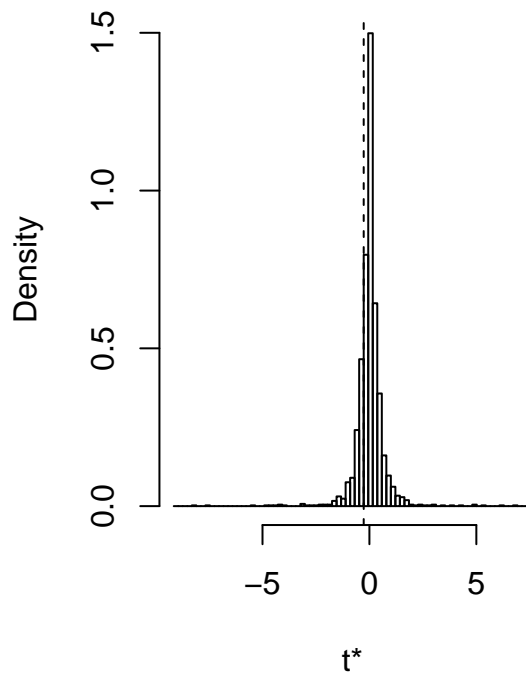
```
## Warning in boot.ci(res): bootstrap variances needed for studentized
## intervals

## Warning in norm.inter(t, adj.alpha): extreme order statistics used as
## endpoints

## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 2000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = res)
##
## Intervals :
## Level      Normal          Basic
## 95%  (-1.9456,  0.8549 )  (-1.7641,  0.5903 )
##
## Level      Percentile      BCa
## 95%  (-1.1247,  1.2298 )  (-8.2307,  0.0948 )
## Calculations and Intervals on Original Scale
## Warning : BCa Intervals used Extreme Quantiles
## Some BCa intervals may be unstable
```

```
plot(res)
```

**Histogram of  $t^*$**



4. Implement a function depending on data and B that tests the hypothesis H0: Lottery is random versus H1: Lottery is non-random by using a permutation test with statistics T. The function is to return the p-value of this test. Test this function on our data with  $B = 2000$ .

```
my_permu <- function(data, index){
  data <- data[index,]
  model <- loess(Draft_No ~., data)
  res <- predict(model, data)
  X_a <- data$Day_of_year[which.max(data$Draft_No)]
  X_b <- data$Day_of_year[which.min(data$Draft_No)]
  Y_a <- res[X_a]
  Y_b <- res[X_b]
  answer <- ((Y_b - Y_a) / (X_b - X_a))
  return(answer)
}

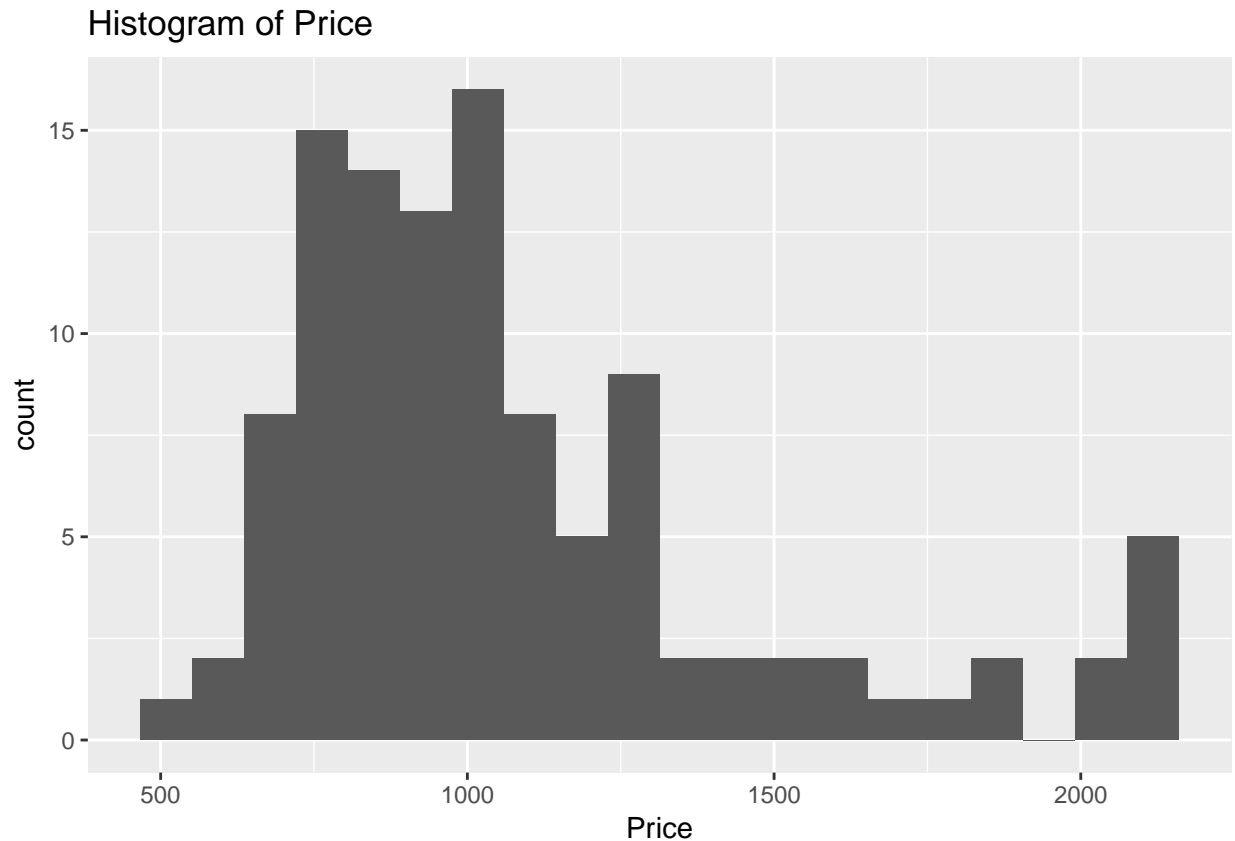
data <- lottery
data$Month <- NULL
res <- boot(data=lottery, statistic = stat1, R=2000)
```

## Question 2: Bootstrap, jackknife and confidence intervals

1. Plot the histogram of Price. Does it remind any conventional distribution? Compute the mean price.

```
price_data <- read.csv("prices1.csv", sep=";")

ggplot(data=price_data, aes(Price)) +
  geom_histogram(bins=20) +
  ggtitle("Histogram of Price")
```



2. Estimate the distribution of the mean price of the house using bootstrap. Determine the bootstrap bias-correction and the variance of the mean price. Compute a 95% confidence interval for the mean price using bootstrap percentile, bootstrap BCa, and first-order normal approximation

Bias correction

$$T1 = 2.T(D) - \frac{1}{D} \sum_{i=1}^B T_i^*$$

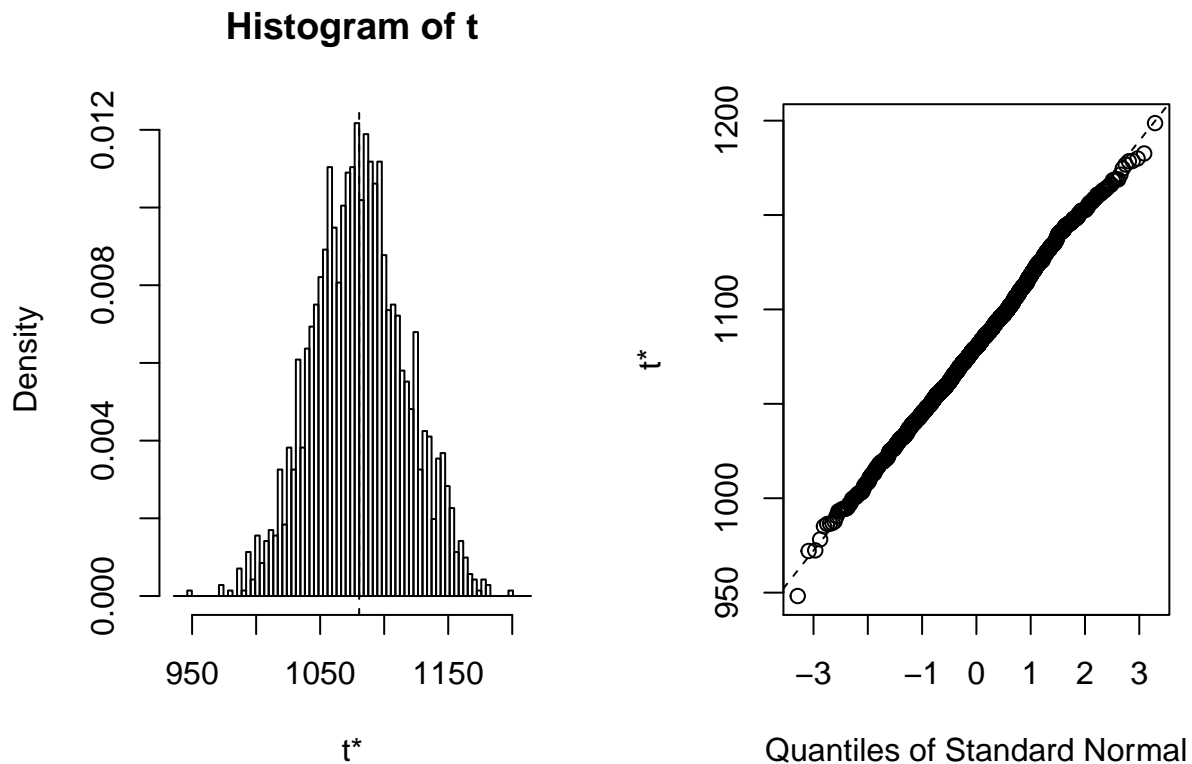
```
# Estimation of mean of Price
stat_mean <- function(data, index){
  data <- data[index,]
  answer <- mean(data$Price)
  return(answer)
}

res <- boot::boot(data=price_data, statistic = stat_mean, R=2000)
res

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot::boot(data = price_data, statistic = stat_mean, R = 2000)
```

```
##
##
## Bootstrap Statistics :
##      original      bias      std. error
## t1* 1080.473 0.3080682    36.16977
```

```
plot(res,index = 1)
```



```
#95% CI for mean using percentile
boot.ci(res, index=1, type=c('perc'))
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 2000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = res, type = c("perc"), index = 1)
##
## Intervals :
## Level      Percentile
## 95%      (1011, 1152 )
## Calculations and Intervals on Original Scale
```

```
#95% CI for mean using bca
boot.ci(res, index=1, type=c('bca'))
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 2000 bootstrap replicates
##
```



```

## CALL :
## boot.ci(boot.out = res, type = c("bca"), index = 1)
##
## Intervals :
## Level      BCa
## 95%      (1015, 1156 )
## Calculations and Intervals on Original Scale
#95% CI for mean using first order normal
boot.ci(res, index=1, type=c('norm'))

## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 2000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = res, type = c("norm"), index = 1)
##
## Intervals :
## Level      Normal
## 95%      (1009, 1151 )
## Calculations and Intervals on Original Scale
# Bias-correction and Variance of Price

stat_bias_correction <- function(data, index){
  t_d <- 2*mean(data$Price)
  data2 <- data[index,]
  answer <- t_d - mean(data2$Price)
  return(answer)
}

res <- boot(data=price_data, statistic = stat_bias_correction, R=2000)
res

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = price_data, statistic = stat_bias_correction, R = 2000)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1* 1080.473  0.7735909    35.29654

print(boot.ci(res))

## Warning in boot.ci(res): bootstrap variances needed for studentized
## intervals

## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 2000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = res)
##

```

```
## Intervals :
## Level      Normal      Basic
## 95%   (1011, 1149 )   (1009, 1150 )
##
## Level      Percentile      BCa
## 95%   (1011, 1152 )   (1007, 1148 )
## Calculations and Intervals on Original Scale

# Variance using bootstrap
stat_varience <- function(data, index){
  data2 <- data[index,]
  n <- length(data2)
  answer <- (1/(n-1)) * sum(data2$Price - mean(data2$Price))^2
  return(answer)
}

res <- boot(data=price_data, statistic = stat_varience, R=2000)
res

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = price_data, statistic = stat_varience, R = 2000)
##
##
## Bootstrap Statistics :
##              original              bias
## t1* 0.00000000000000000000000002481542 0.0000000000000000000000000141906
##              std. error
## t1* 0.00000000000000000000000001538808
```

### 3. Estimate the variance of the mean price using the jackknife and compare it with the bootstrap estimate

```
stat_jackknife_varience <- function(data, index){
  data2 <- data[-index,]
  n <- length(data2)
  answer <- (1/(n-1)) * sum(data2$Price - mean(data2$Price))^2
  return(answer)
}

res <- boot(data=price_data, statistic = stat_jackknife_varience, R=2000)
res

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = price_data, statistic = stat_jackknife_varience,
##      R = 2000)
##
```

```
##
## Bootstrap Statistics :
##      original                      bias
## t1*      0 0.00000000000000000000002138245
##                      std. error
## t1* 0.000000000000000000000002103544
```

4. Compare the confidence intervals obtained with respect to their length and the location of the estimated mean in these intervals.

## Appendix

```
knitr::opts_chunk$set(echo = TRUE)
options(scipen=999)
library(dplyr)
library(ggplot2)
lottery <- read.csv("lottery.csv", sep=";")

ggplot(lottery, aes(x=Day_of_year, y = Draft_No)) + geom_point() +
  ggtitle("Plot of Draft Number vs. day of birth")
ggplot(lottery, aes(x=Day_of_year, y = Draft_No)) +
  geom_point() +
  geom_smooth(method = loess) +
  ggtitle("Plot of Draft Number vs. Day of birth")

model <- loess(Draft_No ~ Day_of_year, lottery)
lottery$Y_hat <- predict(model, lottery)

ggplot(lottery, aes(x=Day_of_year, y = Draft_No)) +
  geom_point() +
  geom_line(aes(y = Y_hat)) +
  ggtitle("Plot of Draft Number vs. Day of birth without using ggplot loess")

library("boot")

stat1 <- function(data, index){
  data <- data[index,]
  model <- loess(Draft_No ~ Day_of_year, data)
  res <- predict(model, data)
  X_a <- data$Day_of_year[which.max(data$Draft_No)]
  X_b <- data$Day_of_year[which.min(data$Draft_No)]
  Y_a <- res[X_a]
  Y_b <- res[X_b]
  answer <- ((Y_b - Y_a) / (X_b - X_a))
  return(answer)
}

res <- boot(data=lottery, statistic = stat1, R=2000)
print(boot.ci(res))
```

```

plot(res)

my_permu <- function(data, index){
  data <- data[index,]
  model <- loess(Draft_No ~., data)
  res <- predict(model, data)
  X_a <- data$Day_of_year[which.max(data$Draft_No)]
  X_b <- data$Day_of_year[which.min(data$Draft_No)]
  Y_a <- res[X_a]
  Y_b <- res[X_b]
  answer <- ((Y_b - Y_a) / (X_b - X_a))
  return(answer)
}

data <- lottery
data$Month <- NULL
res <- boot(data=lottery, statistic = stat1, R=2000)

price_data <- read.csv("prices1.csv", sep=";")

ggplot(data=price_data,aes(Price)) +
  geom_histogram(bins=20) +
  ggtitle("Histogram of Price")

# Estimation of mean of Price
stat_mean <- function(data, index){
  data <- data[index,]
  answer <- mean(data$Price)
  return(answer)
}

res <- boot::boot(data=price_data, statistic = stat_mean, R=2000)
res
plot(res,index = 1)

#95% CI for mean using percentile
boot.ci(res, index=1, type=c('perc'))

#95% CI for mean using bca
boot.ci(res, index=1, type=c('bca'))

#95% CI for mean using first order normal
boot.ci(res, index=1, type=c('norm'))

# Bias-correction and Variance of Price
stat_bias_correction <- function(data, index){
  t_d <- 2*mean(data$Price)
  data2 <- data[index,]
  answer <- t_d - mean(data2$Price)
  return(answer)
}

```

```

res <- boot(data=price_data, statistic = stat_bias_correction, R=2000)
res
print(boot.ci(res))

# Variance using bootstrap
stat_varience <- function(data, index){
  data2 <- data[index,]
  n <- length(data2)
  answer <- (1/(n-1)) * sum(data2$Price - mean(data2$Price))^2
  return(answer)
}

res <- boot(data=price_data, statistic = stat_varience, R=2000)
res

stat_jackknife_varience <- function(data, index){
  data2 <- data[-index,]
  n <- length(data2)
  answer <- (1/(n-1)) * sum(data2$Price - mean(data2$Price))^2
  return(answer)
}

res <- boot(data=price_data, statistic = stat_jackknife_varience, R=2000)
res

```