

R Assignment 3

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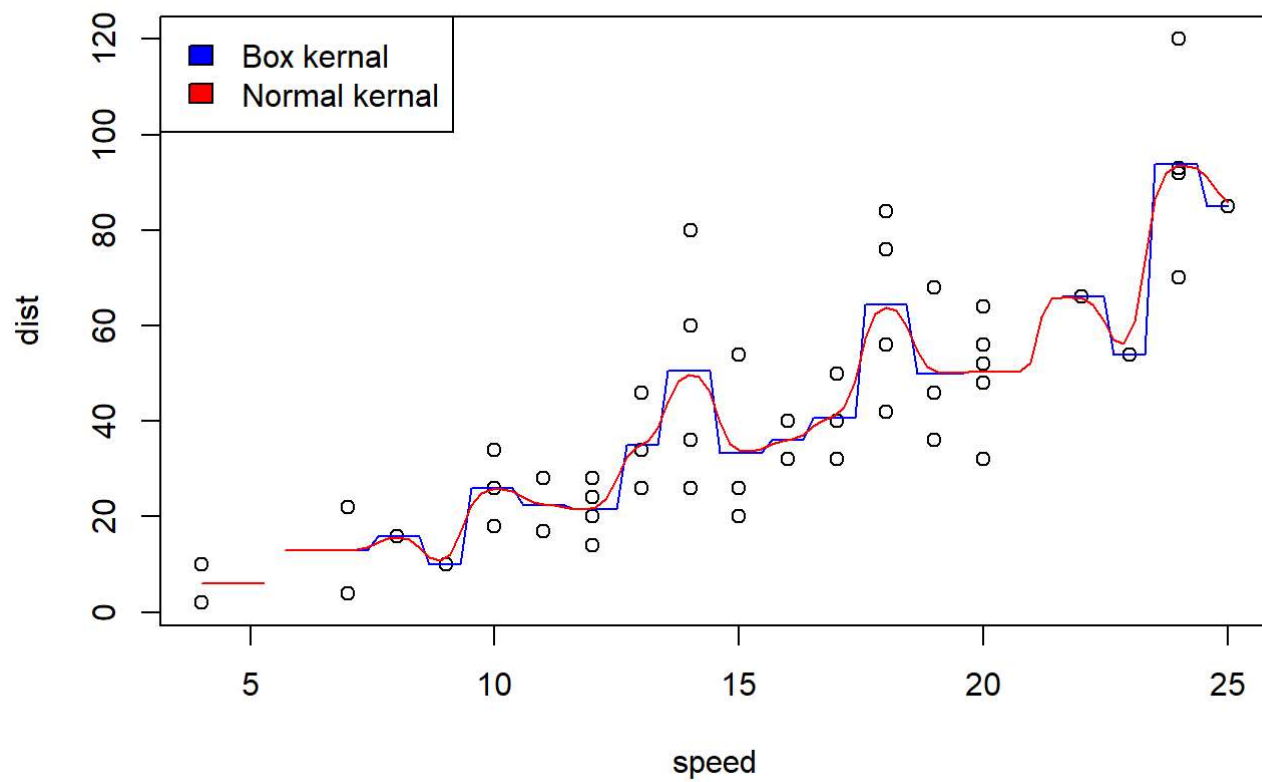
- Question 1
 - (a)
 - (b)
 - (c)
 - (d)
- Question 2
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 - (a)
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 - (a)
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Question 1

(a)

```
data("cars")
data <- na.omit(cars)
attach(data)
plot(speed, dist)
fit1 <- ksmooth(speed, dist, kernel="box",
                 bandwidth=1)
fit2 <- ksmooth(speed, dist, kernel="normal",
                 bandwidth=1)

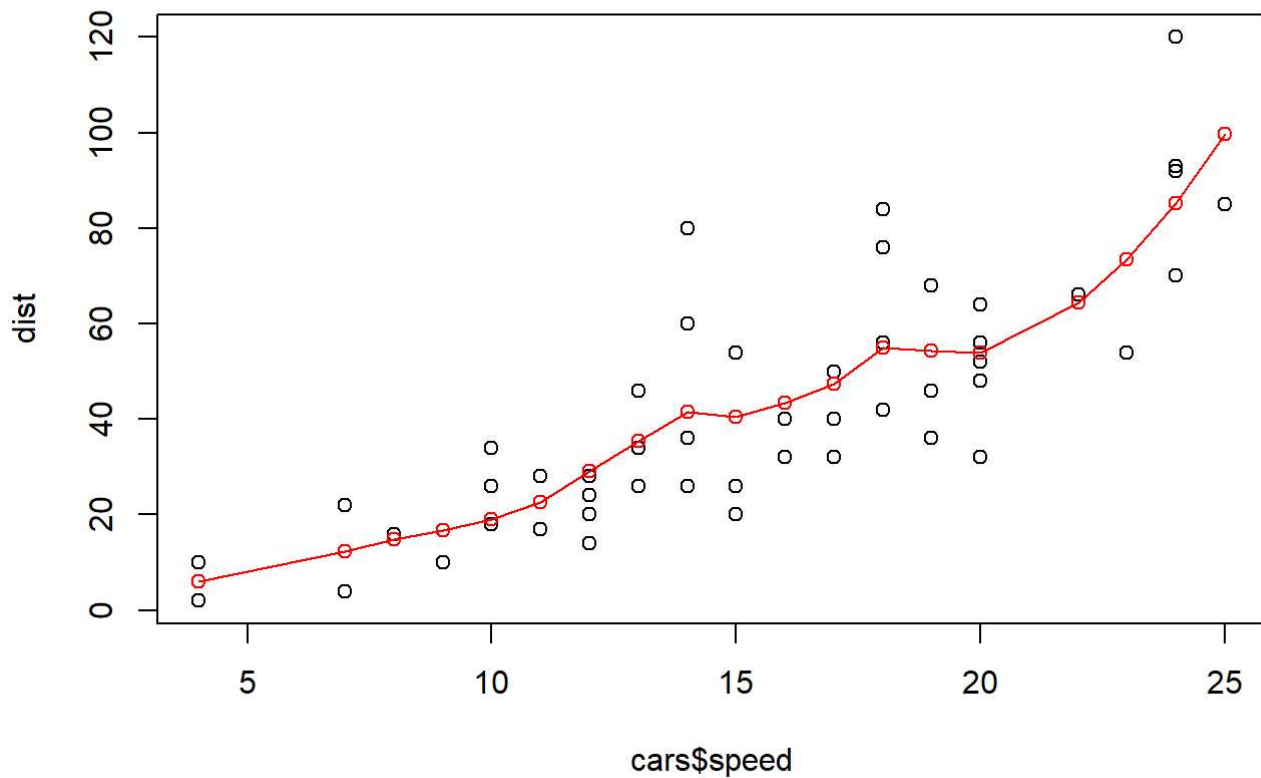
lines(fit1, col="blue", lwd=1)
lines(fit2, col="red", lwd=1)
legend("topleft", legend = c("Box kernal", "Normal kernal"),
      fill = c("blue", "red"))
```



```
detach(data)
```

(b)

```
attach(cars)
plot(cars$speed, dist)
tt1 <- loess(cars$dist ~ speed, data = cars, span=0.5, family="gaussian")
lines(tt1$x, fitted(tt1), col="red", type = "o")
```



(c)

```
speed <- unique(cars$speed)
yhat1 <- na.omit( unique(fit1$y) )
df1 <- as.data.frame(cbind(speed,yhat1))

cars1 <- merge(cars, df1, by=' speed')

sum( (cars1$yhat1-cars1$dist)^2)
```

```
## [1] 6764.783
```

```
sum( (fitted(tt1)-cars$dist)^2 )
```

```
## [1] 9299.113
```

From the MSE, we can see that the Nadaraya-Watson Kernel Regression model fits better.

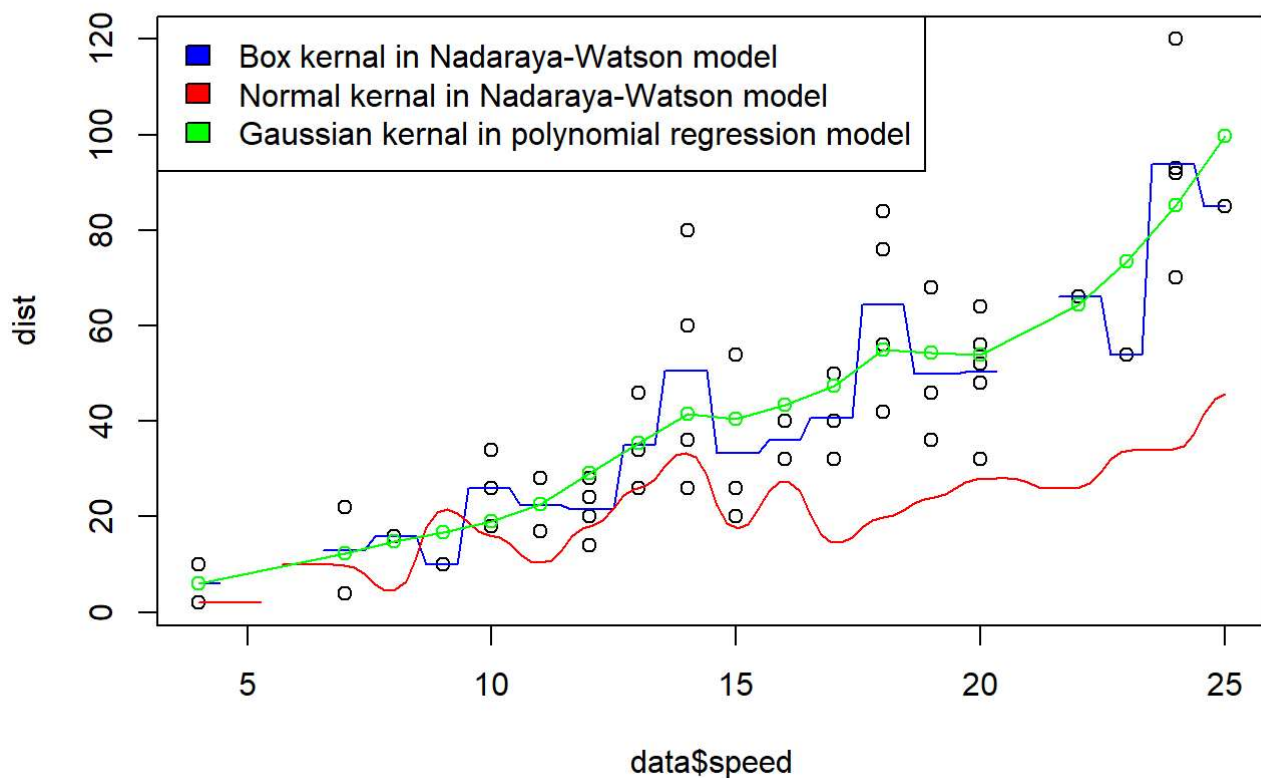
(d)

```
data("cars")
data <- na.omit(cars)
attach(data)
```

```
## The following object is masked _by_ .GlobalEnv:  
##  
## speed
```

```
## The following objects are masked from cars:  
##  
## dist, speed
```

```
plot(data$speed, dist)  
  
lines(ksmooth(data$speed, dist, kernel="box",  
             bandwidth=1), col="blue", lwd=1)  
lines(ksmooth(speed, dist, kernel="normal",  
             bandwidth=1), col="red", lwd=1)  
legend("topleft", legend = c("Box kernel in Nadaraya-Watson model",  
                             "Normal kernel in Nadaraya-Watson model",  
                             "Gaussian kernel in polynomial regression model"),  
      fill = c("blue", "red", "green"))  
  
lines(ttl$x, fitted(ttl), col="green", type = "o", lwd = 1)
```



```
detach(data)
```

Question 2

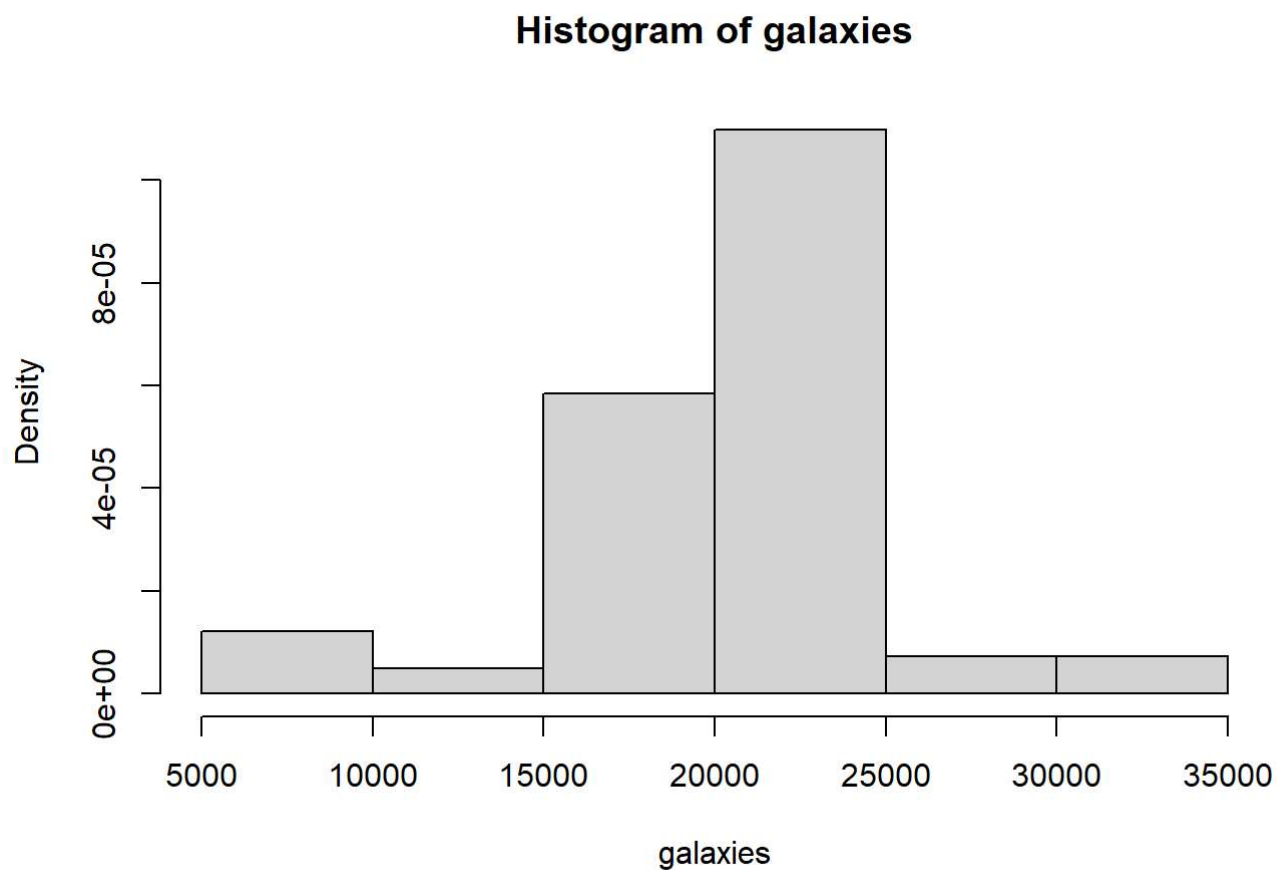
```
library(MASS)
summary(galaxies)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	9172	19532	20834	20828	23133	34279

```
data(galaxies)
n <- length(galaxies)
s <- sd(galaxies)
hstars <- 3.491*s*n^{-1/3} # the best bandwidth
iqr <- IQR(galaxies)
```

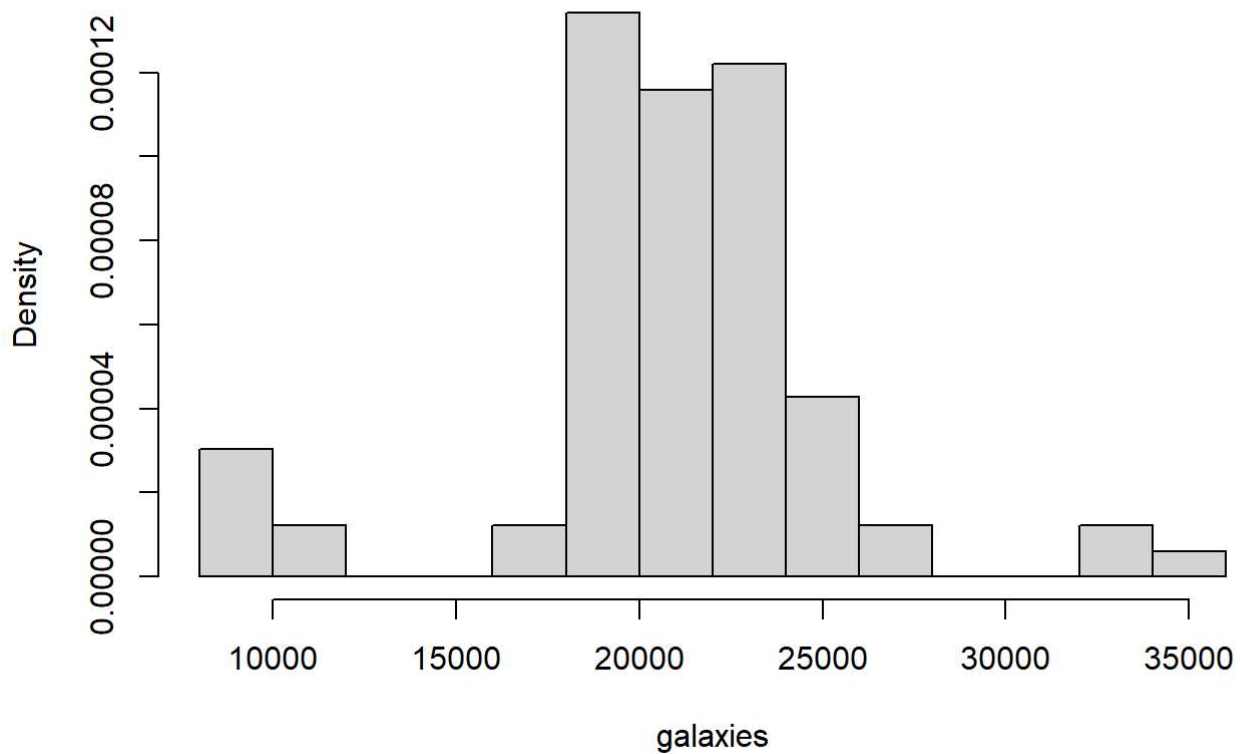
The best bandwidth is 3667.1992299, then we perform histogram smoothing.

```
nobreaks <- (max(galaxies)-min(galaxies))/hstars
hist(galaxies,breaks=round(nobreaks),probability=TRUE)
```



```
hstariqr <- 2.6*iqr*n^{-1/3}
nobreaks2 <- (max(galaxies)-min(galaxies))/hstariqr
hist(galaxies,breaks=round(nobreaks2),probability=TRUE)
```

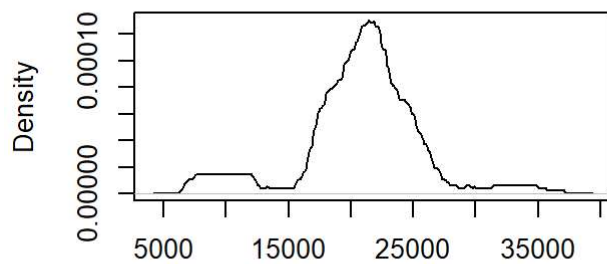
Histogram of galaxies



Next, we perform density function estimation with uniform, triangular, epanechnikov and gaussian kernel.

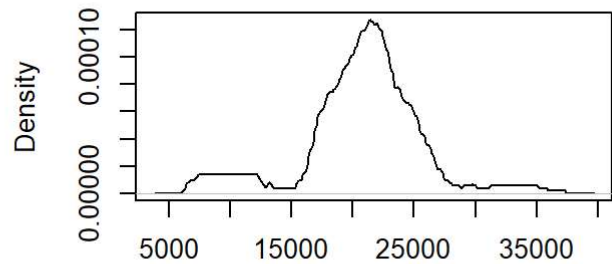
```
par(mfrow = c(2, 2))
plot(density(galaxies, kernel="rectangular", bw=1700),
     main="rectangular kernal with bw = 1700")
plot(density(galaxies, kernel="rectangular", bw=1800),
     main="rectangular kernal with bw = 1800")
plot(density(galaxies, kernel="rectangular", bw=1900),
     main="rectangular kernal with bw = 1900")
plot(density(galaxies, kernel="rectangular", bw=2000),
     main="rectangular kernal with bw = 2000")
```

rectangular kernal with bw = 1700



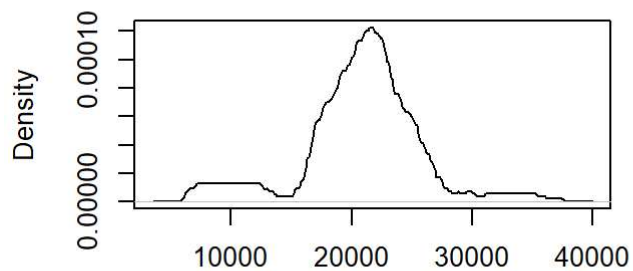
N = 82 Bandwidth = 1700

rectangular kernal with bw = 1800



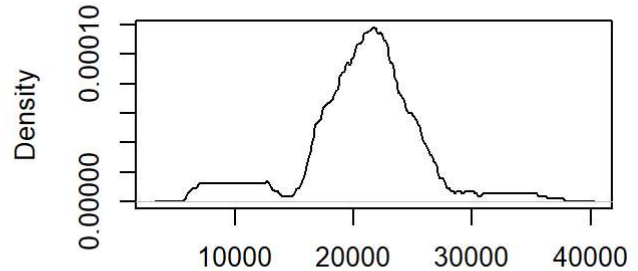
N = 82 Bandwidth = 1800

rectangular kernal with bw = 1900



N = 82 Bandwidth = 1900

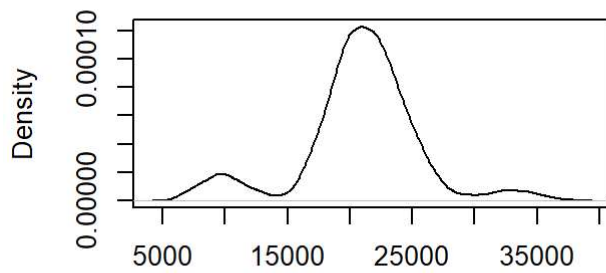
rectangular kernal with bw = 2000



N = 82 Bandwidth = 2000

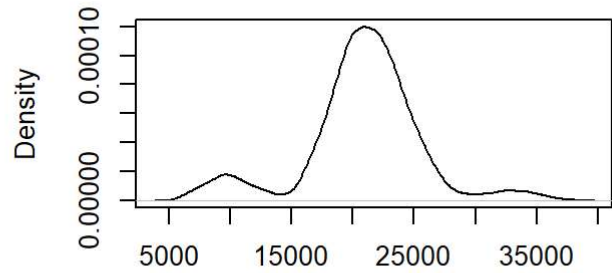
```
par(mfrow = c(2, 2))
plot(density(galaxies, kernel="triangular", bw=1700),
     main="triangular kernal with bw = 1700")
plot(density(galaxies, kernel="triangular", bw=1800),
     main="triangular kernal with bw = 1800")
plot(density(galaxies, kernel="triangular", bw=1900),
     main="triangular kernal with bw = 1900")
plot(density(galaxies, kernel="triangular", bw=2000),
     main="triangular kernal with bw = 2000")
```

triangular kernal with bw = 1700



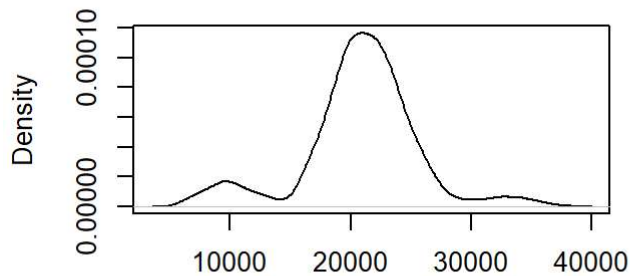
N = 82 Bandwidth = 1700

triangular kernal with bw = 1800



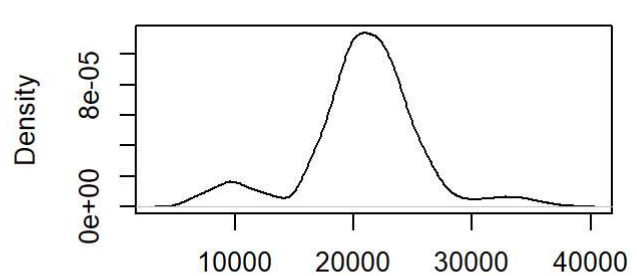
N = 82 Bandwidth = 1800

triangular kernal with bw = 1900



N = 82 Bandwidth = 1900

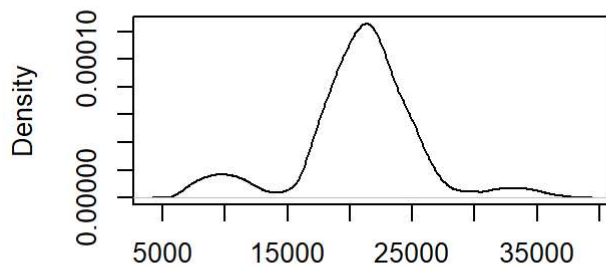
triangular kernal with bw = 2000



N = 82 Bandwidth = 2000

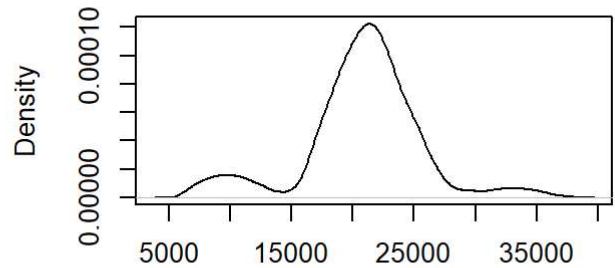
```
par(mfrow = c(2, 2))
plot(density(galaxies, kernel="epanechnikov", bw=1700),
     main="epanechnikov kernal with bw = 1700")
plot(density(galaxies, kernel="epanechnikov", bw=1800),
     main="epanechnikov kernal with bw = 1800")
plot(density(galaxies, kernel="epanechnikov", bw=1900),
     main="epanechnikov kernal with bw = 1900")
plot(density(galaxies, kernel="epanechnikov", bw=2000),
     main="epanechnikov kernal with bw = 2000")
```


epanechnikov kernal with bw = 1700



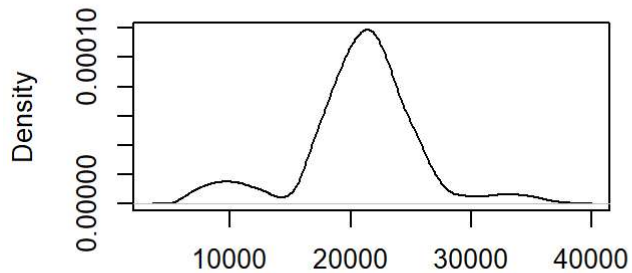
N = 82 Bandwidth = 1700

epanechnikov kernal with bw = 1800



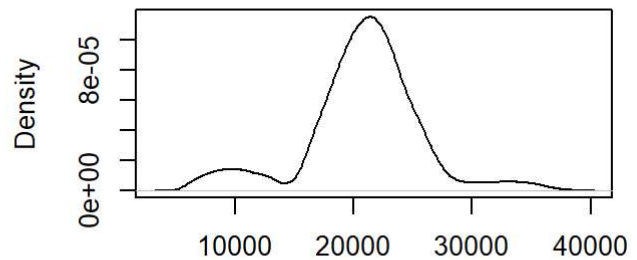
N = 82 Bandwidth = 1800

epanechnikov kernal with bw = 1900



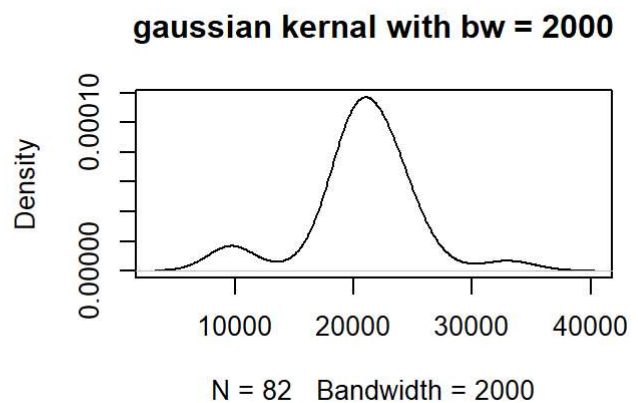
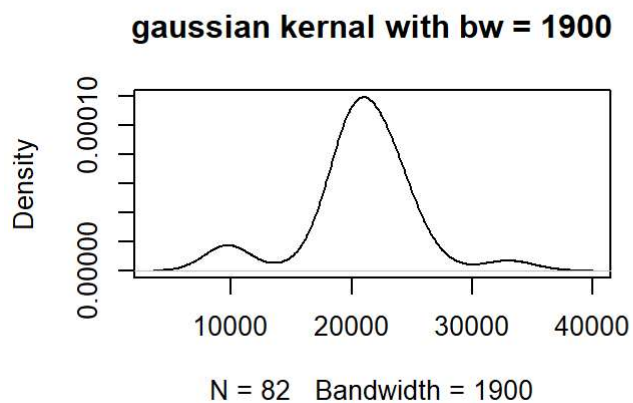
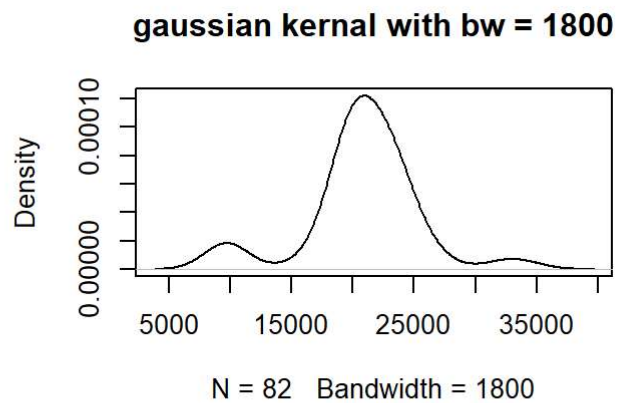
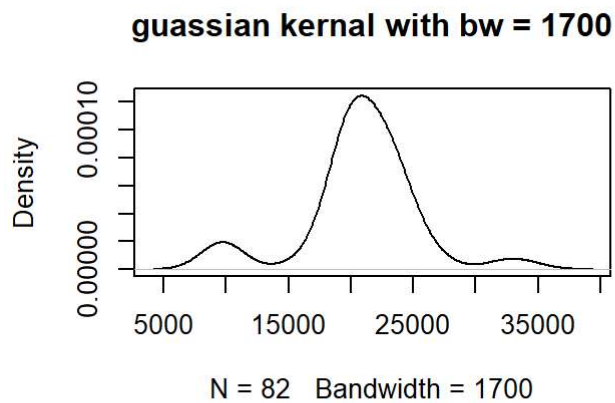
N = 82 Bandwidth = 1900

epanechnikov kernal with bw = 2000



N = 82 Bandwidth = 2000

```
par(mfrow = c(2, 2))
plot(density(galaxies, kernel="gaussian", bw=1700),
     main="gaussian kernal with bw = 1700")
plot(density(galaxies, kernel="gaussian", bw=1800),
     main="gaussian kernal with bw = 1800")
plot(density(galaxies, kernel="gaussian", bw=1900),
     main="gaussian kernal with bw = 1900")
plot(density(galaxies, kernel="gaussian", bw=2000),
     main="gaussian kernal with bw = 2000")
```



Question 3

(a)

```
library(HSAUR3)
```

```
## Warning: 程辑包'HSAUR3'是用R版本4.3.2 来建造的
```

```
## 载入需要的程辑包: tools
```

```
data(foster)

attach(foster)

aggregate(weight, by = list(motgen, litgen), FUN = mean)
```

Group.1 <fct>	Group.2 <fct>	x <dbl>
A	A	63.68000
B	A	52.40000
I	A	54.12500

Group.1 <fct>	Group.2 <fct>	x <dbl>
J	A	48.96000
A	B	52.32500
B	B	60.64000
I	B	53.92500
J	B	45.90000
A	I	47.10000
B	I	64.36667
1-10 of 16 rows	Previous	1 2 Next

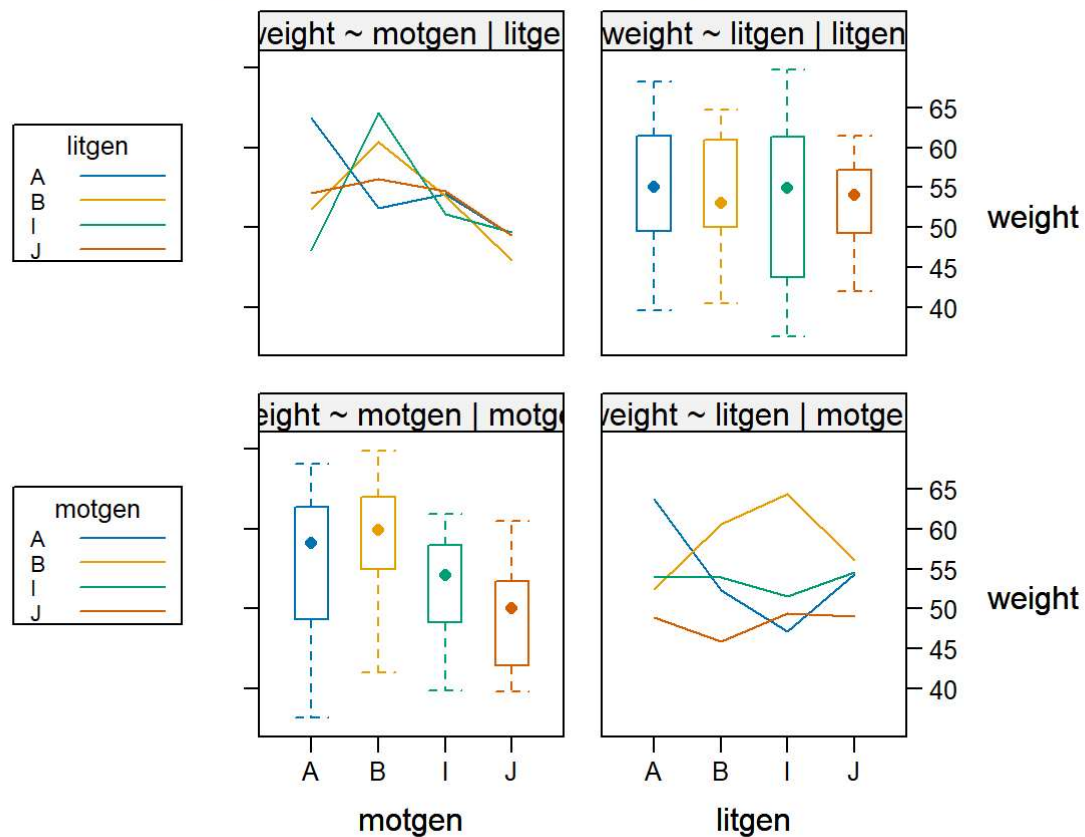
```
aggregate(weight, by = list(motgen, litgen), FUN = sd)
```

Group.1 <fct>	Group.2 <fct>	x <dbl>
A	A	3.273683
B	A	9.374433
I	A	5.321889
J	A	8.760594
A	B	5.533158
B	B	5.647389
I	B	5.114277
J	B	7.636753
A	I	18.103315
B	I	7.124839
1-10 of 16 rows	Previous	1 2 Next

(b)

```
interaction2wt(weight ~ motgen*litgen)
```

weight: main effects and 2-way interactions



See the figures on the diagonal line, lines where have different trends, which means there exists interaction between motgen and litgen.

(c)

```
fit1 <- aov(weight ~ motgen + litgen)
summary(fit1)
```

```
##           Df Sum Sq Mean Sq F value    Pr(>F)
## motgen      3    772   257.20    4.254 0.00905 **
## litgen      3     64    21.21    0.351 0.78870
## Residuals  54   3265    60.46
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Mean weight differs significantly for different motgen categories, but does not differ significantly for different litgen categories.

```
fit2 <- aov(weight ~ motgen * litgen)
summary(fit2)
```

```
##           Df Sum Sq Mean Sq F value Pr(>F)
## motgen      3  771.6   257.20    4.742 0.00587 **
## litgen      3   63.6    21.21    0.391 0.76000
## motgen:litgen 9  824.1    91.56    1.688 0.12005
## Residuals   45 2440.8    54.24
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Mean weight differs significantly for different motgen categories, but does not differ significantly for different litgen categories. Moreover, the interaction is not significant at 0.1 significance level.

(d)

In a one-way ANOVA, the dependent variable is assumed to be normally distributed, and have equal variance in each group.

```
library(car)
```

```
## 载入需要的程辑包: carData
```

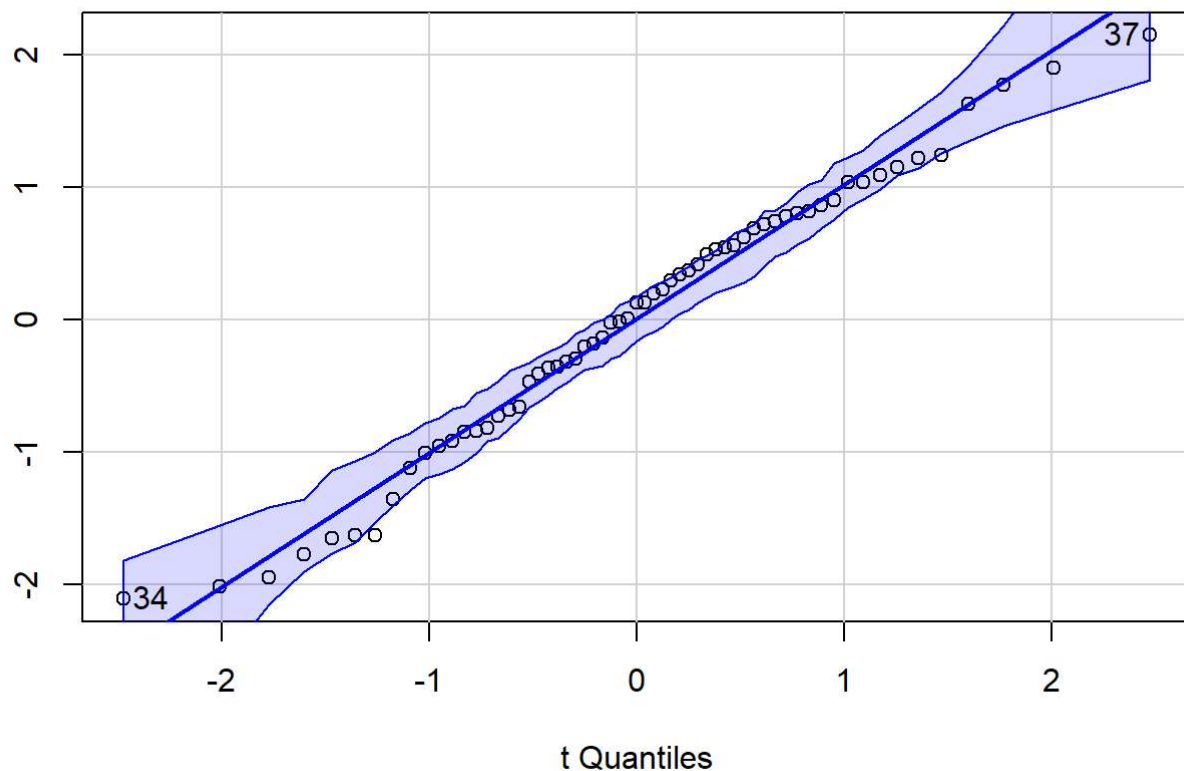
```
##
## 载入程辑包: 'car'
```

```
## The following objects are masked from 'package:HH':
##
##      logit, vif
```

```
fit <- aov(weight ~ litgen)
qqPlot(lm(weight ~ litgen, data=foster)
       ,simulate=TRUE,main="Q-Q PLOT",labels=FALSE)
```

Studentized Residuals(lm(weight ~ litgen, data = foster))

Q-Q PLOT



```
## [1] 34 37
```

```
bartlett.test(weight ~ litgen, data=foster)
```

```
##
## Bartlett test of homogeneity of variances
##
## data: weight by litgen
## Bartlett's K-squared = 6.1503, df = 3, p-value = 0.1045
```

```
outlierTest(fit)
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 37 2.147241      0.036118      NA
```

From qq plot we can discover that dependent variable obeys approximately Gaussian distribution. Then from the bartlett test, $p\text{-value} = 0.1045 > 0.05$, which means variance in each group do not differ significantly. Thus, the assumptions are satisfied.

(e)

```
library(lmPerm)
```

```
## Warning: 程辑包 'lmPerm' 是用 R 版本 4.3.2 来建造的
```

```
set.seed(1234)
model <- aovp(weight ~ motgen * litgen, data = foster, perm = "prob")
```

```
## [1] "Settings:  unique SS "
```

```
summary(model)
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## motgen         3  671.7   223.91    4.128 0.0114 *
## litgen         3   27.7     9.22    0.170 0.9161
## motgen:litgen   9  824.1    91.56    1.688 0.1201
## Residuals     45 2440.8    54.24
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
detach(foster)
```

The results derived by permutation test are almost consistent with those from two-way ANOVA. The permutation test tells us motgen is significant at 0.05 significance level while litgen and interaction does not.

Question 4

(a)

```
library(ISLR)
data(Default)
attach(Default)
summary(Default)
```

```
## default      student      balance      income
## No :9667      No :7056      Min.   :  0.0      Min.   : 772
## Yes: 333      Yes:2944      1st Qu.: 481.7    1st Qu.:21340
##              Median : 823.6    Median :34553
##              Mean   : 835.4    Mean   :33517
##              3rd Qu.:1166.3    3rd Qu.:43808
##              Max.   :2654.3    Max.   :73554
```

```
model <- glm(default ~ student + balance + income, family = binomial())
summary(model)
```

```
##
## Call:
## glm(formula = default ~ student + balance + income, family = binomial())
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.087e+01  4.923e-01 -22.080  < 2e-16 ***
## studentYes  -6.468e-01  2.363e-01  -2.738  0.00619 **
## balance      5.737e-03  2.319e-04  24.738  < 2e-16 ***
## income       3.033e-06  8.203e-06   0.370  0.71152
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 2920.6  on 9999  degrees of freedom
## Residual deviance: 1571.5  on 9996  degrees of freedom
## AIC: 1579.5
##
## Number of Fisher Scoring iterations: 8
```

- The standard error of coefficients associated with student-Yes is 2.363e-01;
- The standard error of coefficients associated with balance is 2.319e-04;
- The standard error of coefficients associated with income is 8.203e-06.

(b)

```
boot.fn=function(formula,data,indices){
  d=data[indices,]
  fit=glm(formula,data=d, family = binomial())
  return(coef(fit))
}
```

(c)

```
library(boot)
```

```
##
## 载入程辑包: 'boot'
```

```
## The following object is masked from 'package:car':
##
##      logit
```

```
## The following object is masked from 'package:HH':
##
##      logit
```



```
## The following object is masked from 'package:survival':  
##  
##      aml
```

```
## The following object is masked from 'package:lattice':  
##  
##      melanoma
```

```
set.seed(1234)  
results=boot(data=Default, statistic=boot.fn, R=500, formula = default ~ student  
             + balance + income )  
print(results)
```

```
##  
## ORDINARY NONPARAMETRIC BOOTSTRAP  
##  
##  
## Call:  
## boot(data = Default, statistic = boot.fn, R = 500, formula = default ~  
##      student + balance + income)  
##  
##  
## Bootstrap Statistics :  
##      original      bias      std. error  
## t1* -1.086905e+01 -1.165716e-02 5.127709e-01  
## t2* -6.467758e-01 -1.240014e-02 2.441341e-01  
## t3*  5.736505e-03  1.221147e-05 2.403813e-04  
## t4*  3.033450e-06 -2.598701e-07 8.640181e-06
```

```
detach(Default)
```

The standard errors derived by `glm()` and our bootstrap function are closed enough to each other. Though our bootstrap function merely replicates 500 times, admittedly it leads to some randomness to some extent, however, its results are numerically consistent with those derived by `glm()`.