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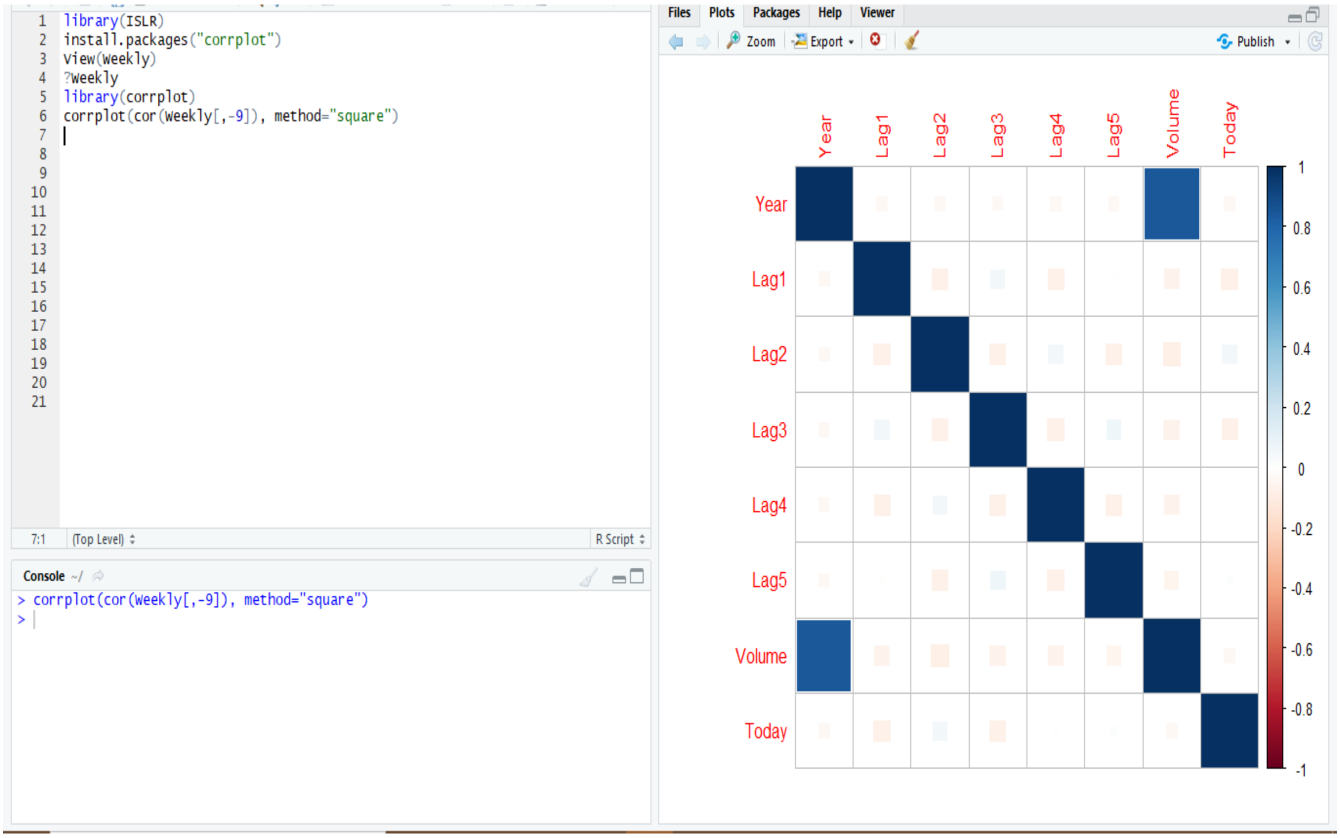
CS 5565 Dr. Song

10.

(a)

The plot does not show any linear relationship between predictors



(b)

The only variable which has low p value(<0.05) is lag2. Hence, it is the only predictor to be considered as statistically significant

```
attach(Weekly)
a<-glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,data = Weekly,family = binomial)
summary(a)

10:1    (Top Level) ÷
```

Console ~/

```
    Direction, Lag1, Lag2, Lag3, Lag4, Lag5, Today, Volume, Year

> a<-glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,data = Weekly,family = binomial)
> summary(a)

Call:
glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 +
    Volume, family = binomial, data = Weekly)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6949  -1.2565   0.9913   1.0849   1.4579

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.26686    0.08593   3.106   0.0019 **
Lag1        -0.04127    0.02641  -1.563   0.1181
Lag2         0.05844    0.02686   2.175   0.0296 *
Lag3        -0.01606    0.02666  -0.602   0.5469
Lag4        -0.02779    0.02646  -1.050   0.2937
Lag5        -0.01447    0.02638  -0.549   0.5833
Volume      -0.02274    0.03690  -0.616   0.5377
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1496.2  on 1088  degrees of freedom
Residual deviance: 1486.4  on 1082  degrees of freedom
AIC: 1500.4

Number of Fisher Scoring iterations: 4

> 
```

(c)

Total weekly trend:

(54+557)/(54+48+430+557)=0.5611

Up weekly trends:

557/(430+557)=0.9207

Down weekly trends:

54/(430+54)=0.1115

From the above information, we can conclude that the model predicted the up weekly trend 92.07% correctly.

```r
attach(Weekly)
fit<-glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume, data=Weekly,family=binomial)
summary(fit)
prob= predict(Weekly.fit, type='response')
pred =rep("Down", length(prob))
pred[prob > 0.5] = "Up"
table(pred, Direction)
```

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Console ~/

```
Lag4         -0.02779    0.02646  -1.050    0.2937
Lag5         -0.01447    0.02638  -0.549    0.5833
Volume       -0.02274    0.03690  -0.616    0.5377
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1496.2  on 1088  degrees of freedom
Residual deviance: 1486.4  on 1082  degrees of freedom
AIC: 1500.4

Number of Fisher Scoring iterations: 4

> prob= predict(Weekly.fit, type='response')
> pred =rep("Down", length(prob))
> pred[prob > 0.5] = "Up"
> table(pred, Direction)
      Direction
pred   Down  Up
  Down   54  48
  Up    430 557
>
```

(d)

From below, we can say that the model gave 62.5% accuracy rate. While the downward and upward trends gives 91.80% and 20.83% accuracy.

This means that the model is predicting downward trends way more correct than the upward trends

```
train = (Year<2009)
rows <-Weekly[!train,]
model<-glm(Direction~Lag2, data=Weekly,family=binomial, subset=train)
prob= predict(model, rows, type = "response")
pred = rep("Down", length(prob))
pred[prob > 0.5] = "Up"
Direct = Direction[!train]
table(pred, Direct)
mean(pred == Direct)
```

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Console ~/

```
> train = (Year<2009)
> rows <-Weekly[!train,]
> model<-glm(Direction~Lag2, data=Weekly,family=binomial, subset=train)
> prob= predict(model, rows, type = "response")
> pred = rep("Down", length(prob))
> pred[prob > 0.5] = "Up"
> Direct = Direction[!train]
> table(pred, Direct)
      Direct
pred   Down Up
  Down    9  5
  Up     34 56
> mean(pred == Direct)
[1] 0.625
>
```

(e)

The logistic and lda are giving the same accuracy rates.

```
library(MASS)
fit<-lda(Direction~Lag2, data=Weekly,family=binomial, subset=train)
pred<-predict(fit, rows)
table(pred$class, Direct)
mean(pred$class==Direct)
```

```
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```

```
Console ~/
> model<-glm(Direction~Lag2, data=Weekly,family=binomial, subset=train)
> prob= predict(model, rows, type = "response")
> pred = rep("Down", length(prob))
> pred[prob > 0.5] = "Up"
> Direct = Direction[!train]
> table(pred, Direct)
      Direct
pred   Down Up
  Down    9  5
  Up     34 56
> fit<-lda(Direction~Lag2, data=Weekly,family=binomial, subset=train)
Error in lda(Direction ~ Lag2, data = Weekly, family = binomial, subset = train) :
  could not find function "lda"
> library(MASS)
> fit<-lda(Direction~Lag2, data=Weekly,family=binomial, subset=train)
> pred<-predict(fit, rows)
> table(pred$class, Direct)
      Direct
       Down Up
  Down    9  5
  Up     34 56
> mean(pred$class==Direct)
[1] 0.625
>
```

(f)

The qda is giving the lower accuracy compared to logistic and lda models.

```
fit = qda(Direction ~ Lag2, data = Weekly, subset = train)
rows <-Weekly[!train,]
pred = predict(fit, rows)$class
Direct = Direction[!train]
table(pred, Direct)
mean(pred == Direct)
```

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Console ~/

```
> fit = qda(Direction ~ Lag2, data = Weekly, subset = train)
> rows <-Weekly[!train,]
> pred = predict(fit, rows)$class
> Direct = Direction[!train]
> table(pred, Direct)
      Direct
pred   Down Up
  Down    0  0
  Up     43 61
> mean(pred == Direct)
[1] 0.5865385
> 
```

(g)

The knn model is giving a 50% accuracy.

```
library(class)
train = (Year<2009)
train1=as.matrix(Lag2[train])
Direct = Direction[!train]
test=as.matrix(Lag2[!train])
Direct1 =Direction[train]
set.seed(1)
pred=knn(train1,test,Direct1,k=1)
table(pred,Direct)
mean(pred == Direct)
```

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Console ~/

```
> library(class)
> train = (Year<2009)
> train1=as.matrix(Lag2[train])
> Direct = Direction[!train]
> test=as.matrix(Lag2[!train])
> Direct1 =Direction[train]
> set.seed(1)
> pred=knn(train1,test,Direct1,k=1)
> table(pred,Direct)
      Direct
pred   Down Up
  Down   21 30
  Up     22 31
> mean(pred == Direct)
[1] 0.5
>
```

(h)

From this we say that the logistic and lda models are giving the better accuracy rates(62.5%)

(i)

The below shows the logistic model, which is giving a 54.06% accuracy

```
fit<-glm(Direction~Lag2:Lag4+Lag2, data=Weekly,family=binomial, subset=train)
rows <-Weekly[!train,]
prob= predict(fit, rows, type = "response")
pred = rep("Down", length(logWeekly.prob))
pred[prob > 0.5] = "Up"
Direct = Direction[!train]
table(pred, Direct)
mean(pred == Direct)

```

```
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```

```
Console ~/
> fit<-glm(Direction~Lag2:Lag4+Lag2, data=Weekly,family=binomial, subset=train)
> rows <-Weekly[!train,]
> prob= predict(fit, rows, type = "response")
> pred = rep("Down", length(logWeekly.prob))
> pred[prob > 0.5] = "Up"
> Direct = Direction[!train]
> table(pred, Direct)
      Direct
pred   Down  Up
  Down    5  18
  Up    219 274
> mean(pred == Direct)
[1] 0.5406977
>
```

The lda model is giving 55.2% accuracy

```
fit<-lda(Direction~Lag2:Lag4+Lag2, data=Weekly,family=binomial, subset=train)
pred<-predict(fit, rows)
table(pred$class, Direct)
mean(pred$class==Direct)

```

```
122:1    (Top Level) ÷
```

```
Console ~/
> fit<-lda(Direction~Lag2:Lag4+Lag2, data=Weekly,family=binomial, subset=train)
> pred<-predict(fit, rows)
> table(pred$class, Direct)
      Direct
       Down  Up
  Down    5  12
  Up    219 280
> mean(pred$class==Direct)
[1] 0.5523256
>
```

When k=1 and k=2, the knn model is giving accuracy rates 49.4% and 52.1%

```
Week.train=as.matrix(Lag2[train])
Week.test=as.matrix(Lag2[!train])
train.Direction =Direction[train]
set.seed(1)
Direct = Direction[!train]
Weekknn.pred=knn(Week.train,Week.test,train.Direction,k=1)
table(Weekknn.pred,Direct)
mean(Weekknn.pred == Direct)
Weekknn.pred1=knn(Week.train,Week.test,train.Direction,k=2)
mean(Weekknn.pred1 == Direct)
```

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Console ~/

```
> Week.train=as.matrix(Lag2[train])
> Week.test=as.matrix(Lag2[!train])
> train.Direction =Direction[train]
> set.seed(1)
> Direct = Direction[!train]
> Weekknn.pred=knn(Week.train,Week.test,train.Direction,k=1)
> table(Weekknn.pred,Direct)
            Direct
Weekknn.pred Down  Up
        Down   90 127
        Up    134 165
> mean(Weekknn.pred == Direct)
[1] 0.494186
> Weekknn.pred1=knn(Week.train,Week.test,train.Direction,k=2)
> mean(Weekknn.pred1 == Direct)
[1] 0.5213178
>
```

From this we can conclude that the lda and logistic models are giving a better accuracy rates for this data.

11.

(a)

```
library(ISLR)
attach(Auto)
summary(Auto)
mpg01 <- rep(0, length(mpg))
View(mpg01)

mpg01 <- rep(0, length(mpg))
mpg01[mpg > median(mpg)] <- 1
Auto <- data.frame(Auto, mpg01)
```

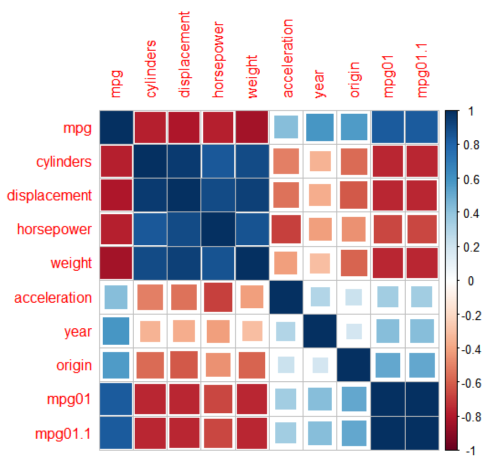
```
64:5   (Top Level)                                                   R Script
Console ~/
 Min.   : 9.00   Min.   :3.000   Min.   : 68.0   Min.   : 46.0   Min.   :1613   Min.   : 8.00   Min.   :70.00   Min.   :1.00
0
 1st Qu.:17.00   1st Qu.:4.000   1st Qu.:105.0   1st Qu.: 75.0   1st Qu.:2225   1st Qu.:13.78   1st Qu.:73.00   1st Qu.:1.00
0
 Median :22.75   Median :4.000   Median :151.0   Median : 93.5   Median :2804   Median :15.50   Median :76.00   Median :1.00
0
 Mean   :23.45   Mean   :5.472   Mean   :194.4   Mean   :104.5   Mean   :2978   Mean   :15.54   Mean   :75.98   Mean   :1.57
7
 3rd Qu.:29.00   3rd Qu.:8.000   3rd Qu.:275.8   3rd Qu.:126.0   3rd Qu.:3615   3rd Qu.:17.02   3rd Qu.:79.00   3rd Qu.:2.00
0
 Max.   :46.60   Max.   :8.000   Max.   :455.0   Max.   :230.0   Max.   :5140   Max.   :24.80   Max.   :82.00   Max.   :3.00
0

                 name         mpg01
 amc matador       :  5   Min.   :0.0
 ford pinto        :  5   1st Qu.:0.0
 toyota corolla    :  5   Median :0.5
 amc gremlin       :  4   Mean   :0.5
 amc hornet        :  4   3rd Qu.:1.0
 chevrolet chevette:  4   Max.   :1.0
 (Other)           :365
> mpg01 <- rep(0, length(mpg))
> mpg01 <- rep(0, length(mpg))
> mpg01[mpg > median(mpg)] <- 1
> Auto <- data.frame(Auto, mpg01)
> Auto
```

(b)

Cylinder, displacement and weight are correlating strongly with mpg01. horsepower and origin also correlate with mpg01.

```
corrplot(cor(Auto[,-9]), method="square")
```

```
67:1   (Top Level)                R Script
Console ~/
80  26          4        96.0         69   2189           18.0
  72       2                  renault 12 (sw)      1       1
81  22          4       122.0         86   2395           16.0
  72       1                  ford pinto (sw)      0       0
82  28          4        97.0         92   2288           17.0
  72       3                  datsun 510 (sw)      1       1
83  23          4       120.0         97   2506           14.5
  72       3      toyouta corona mark ii (sw)      1       1
84  28          4        98.0         80   2164           15.0
  72       1                  dodge colt (sw)      1       1
85  27          4        97.0         88   2100           16.5
  72       3         toyota corolla 1600 (sw)      1       1
86  13          8       350.0        175   4100           13.0
  73       1               buick century 350      0       0
87  14          8       304.0        150   3672           11.5
  73       1                     amc matador      0       0
88  13          8       350.0        145   3988           13.0
  73       1                chevrolet malibu      0       0
89  14          8       302.0        137   4042           14.5
  73       1                ford gran torino      0       0
90  15          8       318.0        150   3777           12.5
  73       1             dodge coronet custom      0       0
91  12          8       429.0        198   4952           11.5
  73       1         mercury marquis brougham      0       0
 [ reached 'max' / getOption("max.print") -- omitted 302 rows
 ]
> corrplot(cor(Auto[,-9]), method="square")
>
```



(c)

```r
train <- (year %% 2 == 0)
train.auto <- Auto[train,]
test.auto <- Auto[-train,]
```

```
Console ~/
> train <- (year %% 2 == 0)
> train.auto <- Auto[train,]
> test.auto <- Auto[-train,]
>
```

(d)

lda model is giving an error rate of 8.44%

```r
autolda.fit <- lda(mpg01~displacement+horsepower+weight+year+cylinders+origin, data=train.auto)
autolda.pred <- predict(autolda.fit, test.auto)
table(autolda.pred$class, test.auto$mpg01)
mean(autolda.pred$class != test.auto$mpg01)
```

```
Console ~/
> autolda.fit <- lda(mpg01~displacement+horsepower+weight+year+cylinders+origin, data=train.auto)
> autolda.pred <- predict(autolda.fit, test.auto)
> table(autolda.pred$class, test.auto$mpg01)

       0   1
  0 169   7
  1  26 189
> mean(autolda.pred$class != test.auto$mpg01)
[1] 0.08439898
>
```

(e)

Qda is giving an error rate of 9.97%

```r
autoqda.fit <- qda(mpg01~displacement+horsepower+weight+year+cylinders+origin, data=train.auto)
autoqda.pred <- predict(autoqda.fit, test.auto)
table(autoqda.pred$class, test.auto$mpg01)
mean(autoqda.pred$class != test.auto$mpg01)
```

```
Console ~/
> autoqda.fit <- qda(mpg01~displacement+horsepower+weight+year+cylinders+origin, data=train.auto)
> autoqda.pred <- predict(autoqda.fit, test.auto)
> table(autoqda.pred$class, test.auto$mpg01)

       0   1
  0 176  20
  1  19 176
> mean(autoqda.pred$class != test.auto$mpg01)
[1] 0.09974425
>
```

(f)

The logistic regression method is giving an error rate of 8.44%

```
auto.fit<-glm(mpg01~displacement+horsepower+weight+year+cylinders+origin, data=train.auto,family=binomial)
auto.probs = predict(auto.fit, test.auto, type = "response")
auto.pred = rep(0, length(auto.probs))
auto.pred[auto.probs > 0.5] = 1
table(auto.pred, test.auto$mpg01)
mean(auto.pred != test.auto$mpg01)

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```

```
Console ~/
> auto.fit<-glm(mpg01~displacement+horsepower+weight+year+cylinders+origin, data=train.auto,family=binomial)
> auto.probs = predict(auto.fit, test.auto, type = "response")
> auto.pred = rep(0, length(auto.probs))
> auto.pred[auto.probs > 0.5] = 1
> table(auto.pred, test.auto$mpg01)

auto.pred   0   1
        0 174  12
        1  21 184
> mean(auto.pred != test.auto$mpg01)
[1] 0.08439898
>
```

(g)

K=1 is giving a lower error rate compared to k=2 and k=3. This can concluded as the error rate keeps increasing with an increasing value of k.

```
train.K= cbind(displacement,horsepower,weight,cylinders,year, origin)[train,]
test.K=cbind(displacement,horsepower,weight,cylinders, year, origin)[-train,]
set.seed(1)
autok.pred=knn(train.K,test.K,train.auto$mpg01,k=1)
mean(autok.pred != test.auto$mpg01)
autok.pred=knn(train.K,test.K,train.auto$mpg01,k=2)
mean(autok.pred != test.auto$mpg01)
autok.pred=knn(train.K,test.K,train.auto$mpg01,k=3)
mean(autok.pred != test.auto$mpg01)

99:36  (Top Level)
```

```
Console ~/
> train.K= cbind(displacement,horsepower,weight,cylinders,year, origin)[train,]
> test.K=cbind(displacement,horsepower,weight,cylinders, year, origin)[-train,]
> set.seed(1)
> autok.pred=knn(train.K,test.K,train.auto$mpg01,k=1)
> mean(autok.pred != test.auto$mpg01)
[1] 0.07161125
> autok.pred=knn(train.K,test.K,train.auto$mpg01,k=2)
> mean(autok.pred != test.auto$mpg01)
[1] 0.09974425
> autok.pred=knn(train.K,test.K,train.auto$mpg01,k=3)
> mean(autok.pred != test.auto$mpg01)
[1] 0.09462916
>
```