EPPS6323
Knowledge Mining

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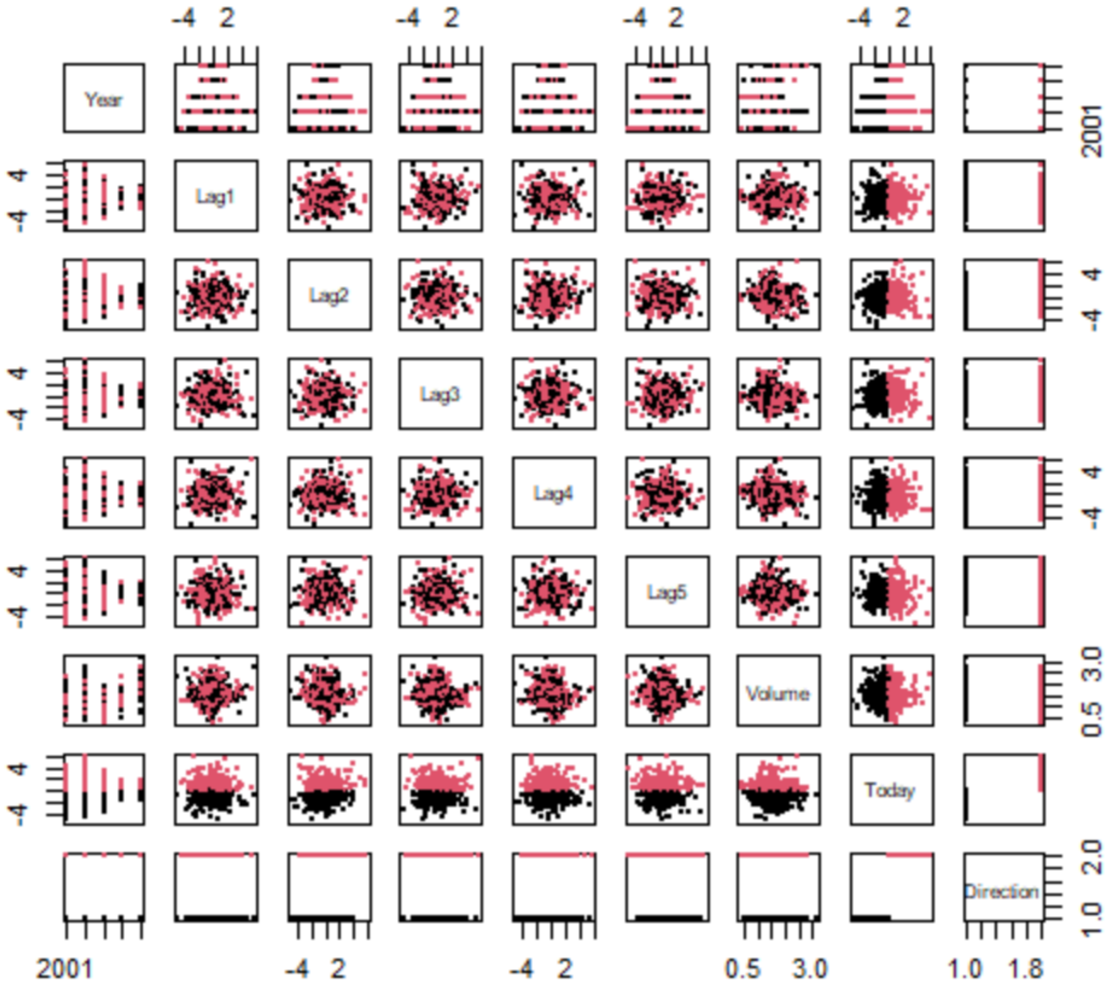
Assignment 7

```
> require(ISLR)
Loading required package: ISLR
Warning message:
package ‘ISLR’ was built under R version 4.2.3
> # Check dataset Smarket
> ?Smarket
> names(Smarket)
[1] "Year"      "Lag1"      "Lag2"      "Lag3"      "Lag4"      "Lag5"      "Volume"    "Today"     "Direction"
> summary(Smarket)
      Year           Lag1                Lag2                Lag3                Lag4                Lag5         
 Min.   :2001   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.92200  
 1st Qu.:2002   1st Qu.:-0.639500   1st Qu.:-0.639500   1st Qu.:-0.640000   1st Qu.:-0.640000   1st Qu.:-0.64000  
 Median :2003   Median : 0.039000   Median : 0.039000   Median : 0.038500   Median : 0.038500   Median : 0.03850  
 Mean   :2003   Mean   : 0.003834   Mean   : 0.003919   Mean   : 0.001716   Mean   : 0.001636   Mean   : 0.00561  
 3rd Qu.:2004   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.59700  
 Max.   :2005   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.73300  
     Volume           Today              Direction 
 Min.   :0.3561   Min.   :-4.922000   Down:602  
 1st Qu.:1.2574   1st Qu.:-0.639500   Up  :648  
 Median :1.4229   Median : 0.038500             
 Mean   :1.4783   Mean   : 0.003138             
 3rd Qu.:1.6417   3rd Qu.: 0.596750             
 Max.   :3.1525   Max.   : 5.733000             
> # Create a dataframe for data browsing
> sm=Smarket
> # Bivariate Plot of inter-lag correlations
> pairs(Smarket,col=Smarket$Direction,cex=.5, pch=20)
```




```
> # Logistic regression
> glm.fit=glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,
+             data=Smarket,family=binomial)
> summary(glm.fit)
```

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

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.446  -1.203   1.065   1.145   1.326

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.126000   0.240736  -0.523    0.601
Lag1        -0.073074   0.050167  -1.457    0.145
Lag2        -0.042301   0.050086  -0.845    0.398
Lag3         0.011085   0.049939   0.222    0.824
Lag4         0.009359   0.049974   0.187    0.851
Lag5         0.010313   0.049511   0.208    0.835
Volume       0.135441   0.158360   0.855    0.392

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1731.2  on 1249  degrees of freedom
Residual deviance: 1727.6  on 1243  degrees of freedom
AIC: 1741.6

Number of Fisher Scoring iterations: 3

> glm.probs=predict(glm.fit,type="response")
> glm.probs[1:5]
        1         2         3         4         5
0.5070841 0.4814679 0.4811388 0.5152224 0.5107812
> glm.pred=ifelse(glm.probs>0.5,"Up","Down")
> attach(Smarket)
> table(glm.pred,Direction)
        Direction
glm.pred Down  Up
    Down  145 141
    Up    457 507
> mean(glm.pred==Direction)
[1] 0.5216
> # Make training and test set for prediction
> train = Year<2005
> glm.fit=glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,
+              data=Smarket,family=binomial, subset=train)
> glm.probs=predict(glm.fit,newdata=Smarket[!train,],type="response")
> glm.pred=ifelse(glm.probs >0.5,"Up","Down")
> Direction.2005=Smarket$Direction[!train]
> table(glm.pred,Direction.2005)
        Direction.2005
glm.pred Down Up
    Down   77 97
```

```
    Up     34 44
> mean(glm.pred==Direction.2005)
[1] 0.4801587
> #Fit smaller model
> glm.fit=glm(Direction~Lag1+Lag2,
+              data=Smarket,family=binomial, subset=train)
> glm.probs=predict(glm.fit,newdata=Smarket[!train,],type="response")
> glm.pred=ifelse(glm.probs >0.5,"Up","Down")
> table(glm.pred,Direction.2005)
        Direction.2005
glm.pred Down  Up
    Down   35  35
    Up     76 106
> mean(glm.pred==Direction.2005)
[1] 0.5595238
> # Check accuracy rate
> 106/(76+106)
[1] 0.5824176
>
> # Can you interpret the results?
```

The model first listed only has an approximate 48% accuracy rate in predicting the market fluctuation at the time; this is not much better than just taking a blind guess. According to our readings of ISLR Chapter 4 by Daniela Witten, by making adjustments to the model, and re-examining using logistical regression. All lag values were removed except for Lag 1 and Lag 2 which displayed the highest levels of predictability value in this model. In so doing, we are able to increase the model predictability to 58%, a significant improvement when compared to the previous results.