# Stock Market Prediction

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#### Overview

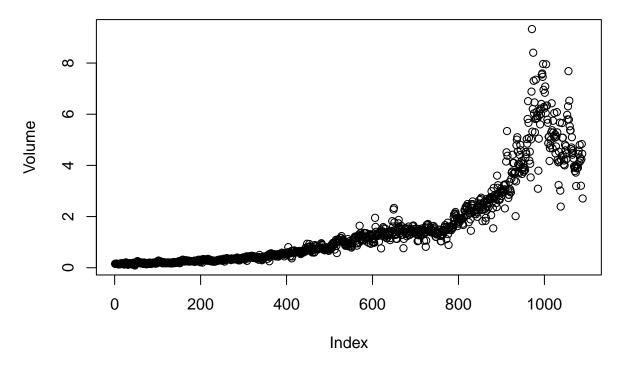
We will try to build a classification model for Stock Maret data for 1089 weekly returns for 21 years, from the beginning of 1990 to the end of 2010. Our goal is to predict the trend of the market as "Up" or "Down" given some predictors; returns for Lag 1 to Lag5 & Volume

#### Dataset

```
names(Weekly)
[1] "Year"
              "Lag1"
                         "Lag2"
                                                          "Lag5"
                                    "Lag3"
                                               "Lag4"
[7] "Volume"
              "Today"
                         "Direction"
head(Weekly)
              Lag2
                    Lag3
                           Lag4
                                 Lag5
                                         Volume Today Direction
 Year
        Lag1
             1.572 -3.936 -0.229 -3.484 0.1549760 -0.270
      0.816
                                                          Down
Down
3 1990 -2.576 -0.270 0.816 1.572 -3.936 0.1598375
                                               3.514
                                                            Uр
4 1990
       3.514 -2.576 -0.270  0.816  1.572  0.1616300  0.712
                                                            Uр
       0.712 3.514 -2.576 -0.270 0.816 0.1537280 1.178
5 1990
                                                            Uр
6 1990
      1.178 0.712 3.514 -2.576 -0.270 0.1544440 -1.372
                                                          Down
attach(Weekly)
cor(Weekly[1:8])
```

```
Year
                        Lag1
                                  Lag2
                                             Lag3
                                                         Lag4
      1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923
Year
Lag1
      -0.03228927 1.000000000 -0.07485305 0.05863568 -0.071273876
      -0.03339001 -0.074853051 1.00000000 -0.07572091 0.058381535
Lag2
Lag3
      Lag4
      -0.03112792 -0.071273876 0.05838153 -0.07539587 1.000000000
Lag5
      -0.03051910 -0.008183096 -0.07249948 0.06065717 -0.075675027
Volume 0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617
Today
     -0.03245989 -0.075031842 0.05916672 -0.07124364 -0.007825873
                      Volume
             Lag5
                                  Today
Year
      -0.008183096 -0.06495131 -0.075031842
Lag1
Lag2
      -0.072499482 -0.08551314 0.059166717
      0.060657175 -0.06928771 -0.071243639
Lag3
Lag4
      -0.075675027 -0.06107462 -0.007825873
Lag5
       1.000000000 -0.05851741 0.011012698
Volume -0.058517414 1.00000000 -0.033077783
       0.011012698 -0.03307778 1.000000000
Today
```

### plot(Volume)



### Logistic Regression

```
glm.fit=glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,family = binomial,data=Weekly)
summary(glm.fit)
```

```
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 **
                        0.02641 -1.563
                                         0.1181
Lag1
            -0.04127
Lag2
            0.05844
                        0.02686
                                 2.175
                                         0.0296 *
            -0.01606
                        0.02666 -0.602
                                         0.5469
Lag3
                                -1.050
                                         0.2937
Lag4
            -0.02779
                        0.02646
Lag5
            -0.01447
                        0.02638
                                -0.549
                                         0.5833
Volume
            -0.02274
                        0.03690 -0.616
                                         0.5377
```

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 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
contrasts(Direction)
     Uр
Down 0
Uр
glm.probabilities=predict(glm.fit,type="response")
glm.prediction=rep("Down",dim(Weekly)[1])
glm.prediction[glm.probabilities>0.5]="Up"
table(glm.prediction,Direction)
              Direction
glm.prediction Down Up
          Down 54 48
          ďΩ
               430 557
mean(glm.prediction==Direction)
[1] 0.5610652
mean(glm.prediction!=Direction)
```

### Training & Testing Model

[1] 0.4389348

```
train=Year<2007

Data.predictors=Weekly[!train,]
Data.response=Direction[!train]

glm.fit=glm(Direction~Lag2,data=Weekly,family=binomial,subset=train)
summary(glm.fit)</pre>
```

```
Call:
glm(formula = Direction ~ Lag2, family = binomial, data = Weekly,
   subset = train)
Deviance Residuals:
  Min 1Q Median
                           30
-1.374 -1.277 1.036 1.081
                                1.261
Coefficients:
           Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.23057
                       0.06818 3.382 0.000721 ***
            0.03837
                       0.03304 1.162 0.245435
Lag2
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 1207.6 on 879 degrees of freedom
Residual deviance: 1206.3 on 878 degrees of freedom
AIC: 1210.3
Number of Fisher Scoring iterations: 4
glm.probabilities=predict(glm.fit,Data.predictors,type="response")
glm.prediction=rep("Down",length(Data.response))
glm.prediction[glm.probabilities>0.5]="Up"
table(glm.prediction,Data.response)
             Data.response
glm.prediction Down Up
                5
         Down
                91 110
         Uр
mean(glm.prediction==Data.response)
[1] 0.5502392
mean(glm.prediction!=Data.response)
[1] 0.4497608
Linear Discriminant Analysis
lda.fit=lda(Direction~Lag2,data=Weekly,subset=train)
lda.fit
```

#### Call:

lda(Direction ~ Lag2, data = Weekly, subset = train)

Prior probabilities of groups:

Down U

0.4409091 0.5590909

### Group means:

Lag2

Down 0.0982732

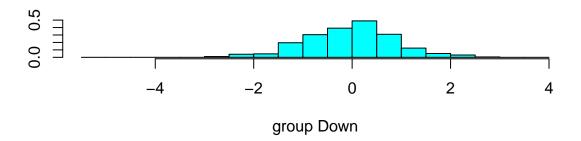
Up 0.2610650

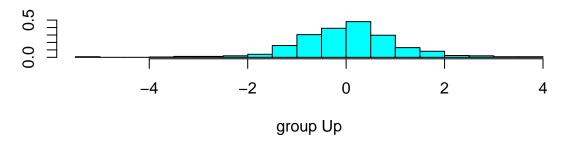
### Coefficients of linear discriminants:

LD1

Lag2 0.4849425

### plot(lda.fit)





lda.prediction=predict(lda.fit, Data.predictors)
lda.class=lda.prediction\$class
table(lda.class,Data.response)

Data.response

lda.class Down Up

Down 5 3

Up 91 110

```
mean(lda.class==Data.response)
[1] 0.5502392
mean(lda.class!=Data.response)
[1] 0.4497608
Quadratic Discriminant Analysis
qda.fit=qda(Direction~Lag2,data=Weekly,subset=train)
qda.fit
Call:
qda(Direction ~ Lag2, data = Weekly, subset = train)
Prior probabilities of groups:
     Down
0.4409091 0.5590909
Group means:
         Lag2
Down 0.0982732
Up 0.2610650
qda.prediction=predict(qda.fit, Data.predictors)
qda.class=lda.prediction$class
table(qda.class,Data.response)
         Data.response
qda.class Down Up
     Down
     Uр
           91 110
mean(qda.class==Data.response)
[1] 0.5502392
mean(qda.class!=Data.response)
[1] 0.4497608
```

## K-Nearest Neighbors

```
train.X=cbind(Lag1,Lag2)[train,]
test.X=cbind(Lag1,Lag2)[!train,]
train.Direction=Direction[train]
set.seed(1)
knn.pred=knn(train.X,test.X,train.Direction,k=1)
table(knn.pred,Data.response)
        Data.response
knn.pred Down Up
    Down
           52 50
           44 63
    Uр
mean(knn.pred==Data.response)
[1] 0.5502392
knn.pred=knn(train.X,test.X,train.Direction,k=3)
table(knn.pred,Data.response)
        Data.response
knn.pred Down Up
           53 50
    Down
           43 63
    Uр
mean(knn.pred==Data.response)
```

[1] 0.5550239

### Conclusions

We have compared the performance on test data for 2008 to 2010 on different classifiers trained from 1990 to 2007. The classification alrotighms used were Logistic Regression, Linear Discriminant Analysis, Quadratic Distriminant Analysis & K-Nearest Neighbors and they all perform the same, having a correct classification score of 55% which is only slightly better than random guessing thus we can conclude that this dataset is not a great predictor to beat the market