Analytics for Business Intelligence

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Home Work 2 Total marks are 15 which provide 7.5% to the total assessment. Students must implement the homework using R language, cut-and-paste of outputs from text book are not permitted (and easily detectable).

The Steps of this homework should be implemented using RStudio and printouts inserted in this document after each step.

Regression with interaction (3 marks)

Step 1 You need create the working directory and connect Boston data file as you did this in Home Work 1.

OUTPUT:

```
setwd("C:/Users/NICSI/Desktop/ABI/HW 2")
library(MASS)
data(Boston)
```

Step 2 include interaction terms in a linear model using the lm() function. The syntax lstat:black tells R to include an interaction term between lstat and black. The syntax lstat*age simultaneously includes lstat, age, and the interaction term lstat×age as predictors; it is a shorthand for lstat+age+lstat:age.

OUTPUT:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
> summary(lm(medv ~ lstat*age, data = Boston))

Call:
lm(formula = medv ~ lstat * age, data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.806  -4.045  -1.333   2.085  27.552 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) 36.0885359  1.4698355  24.553  < 2e-16 ***
lstat       -1.3921168  0.1674555  -8.313 8.78e-16 ***
age         -0.0007209  0.0198792  -0.036   0.9711    
lstat:age    0.0041560  0.0018518   2.244   0.0252 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.149 on 502 degrees of freedom
Multiple R-squared:  0.5557,	Adjusted R-squared:  0.5531 
F-statistic: 209.3 on 3 and 502 DF,  p-value: < 2.2e-16
```

Step 3 (0.5 mark) Use command dim to check how many observations and variables are in the Boston file. Find the names of variables in this file.

RCODE & OUTPUT:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
> dim(Boston)
[1] 506  14
> names(Boston)
 [1] "crim"    "zn"      "indus"   "chas"    "nox"     "rm"      "age"     "dis"     "rad"     "tax"    
[11] "ptratio" "black"   "lstat"   "medv"   
```

Step 4 (0.5 mark) Run the multivariate regression of medv against lstat and age with interaction.

OUTPUT:

```
Console   R Markdown
C:/Users/NICSI/Desktop/ABI/HW 2/
> g1<- lm(medv ~ lstat*age, data = Boston)
>
```

Step 5 (0.5 mark) Is interaction term significant or not. Is the answer difference for confidence probability 5 % and 1%? Formulate the appropriate hypotheses and make a conclusion based on
the relevant p-values.
OUTPUT:

```
Console   R Markdown
C:/Users/NICSI/Desktop/ABI/HW 2/
> summary(g1)

Call:
lm(formula = medv ~ lstat * age, data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.806  -4.045  -1.333   2.085  27.552 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) 36.0885359  1.4698355  24.553  < 2e-16 ***
lstat       -1.3921168  0.1674555  -8.313 8.78e-16 ***
age         -0.0007209  0.0198792  -0.036   0.9711    
lstat:age    0.0041560  0.0018518   2.244   0.0252 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.149 on 502 degrees of freedom
Multiple R-squared:  0.5557,	Adjusted R-squared:  0.5531 
F-statistic: 209.3 on 3 and 502 DF,  p-value: < 2.2e-16

>
```

ANSWER:

P-value of Lstat:Age <- .0252

Lstat:Age : H(95% Confidence Interval): if P-value <.05 : Reject Null Hypothesis

Lstat:Age: H(5% Probable Interval): If .05>P-value >.01 : Reject Null Hypothesis

Lstat:Age: H(1% Probable Interval): If P-value < .01 : Reject Null Hypothesis.

Conclusion:
We can see that the last hypothesis is not getting satisfied hence null hypothesis is getting accepted for 1% interval. So the interaction term is significant for 95% and 5% interval but not significant for 1% interval. The interaction term (lstat:age) is highly significant as the p-value of lstat:age is .0252 which is less than 0.05 so we can reject the null hypothesis with 95% confidence.
The answer will be different for confidence probability 5% and 1% because the interaction term has p-value of 0.0252 which is less than 0.05 but higher than 0.01. So for 5% probability confidence the interaction term (lstat:age) will be highly significant as the null hypothesis is rejected while for 1% probability confidence, the interaction term will be insignificant as we cannot reject null hypothesis in this case.

Step 6 (1 Mark) Implement the multiple linear regression of medv against lstat and age without interaction (or just see the results in HW1). Compare these two models with and without interact-ion.

OUTPUT:

Console R Markdown

C:/Users/NICSI/Desktop/ABI/HW 2/

```
> multmode <- lm(medv~lstat+age,data=Boston)
> summary(multmode)

Call:
lm(formula = medv ~ lstat + age, data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.981  -3.978  -1.283   1.968  23.158 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 33.22276    0.73085  45.458  < 2e-16 ***
lstat       -1.03207    0.04819 -21.416  < 2e-16 ***
age          0.03454    0.01223   2.826  0.00491 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.173 on 503 degrees of freedom
Multiple R-squared:  0.5513,	Adjusted R-squared:  0.5495 
F-statistic:   309 on 2 and 503 DF,  p-value: < 2.2e-16
```

Step 7 (0.5 mark) Compare the residual standard errors for these two models.

ANSWER:
From the above calculated summary of the two models, Residual standard error for g1 model (with interaction) = 6.149 on 502 degrees of freedom.
The residual Standard error of both the models are almost the same so it won't make any significance impact on the model.

Nonlinear transform of predictors (3 marks)

Step 1 (1 mark) The lm() function can also accommodate non-linear transformations of the predictors. For instance, given a predictor *X*, we can create a predictor X^2 using I(X^2). The function I() is needed since the ^ has a special meaning I() in a formula; wrapping as we do allows the standard usage in R, which is to raise X to the power 2. We now perform a regression of medv onto lstat and $lstat^2$.

OUTPUT:

```
Console    R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
> int1<- (Boston$lstat)^2
> g2<- lm(medv~lstat+int1,data=Boston)
> summary(g2)

Call:
lm(formula = medv ~ lstat + int1, data = Boston)

Residuals:
     Min       1Q   Median       3Q      Max 
-15.2834  -3.8313  -0.5295   2.3095  25.4148 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 42.862007   0.872084   49.15   <2e-16 ***
lstat       -2.332821   0.123803  -18.84   <2e-16 ***
int1         0.043547   0.003745   11.63   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.524 on 503 degrees of freedom
Multiple R-squared:  0.6407,	Adjusted R-squared:  0.6393 
F-statistic: 448.5 on 2 and 503 DF,  p-value: < 2.2e-16
```

Step 2 (1 mark) Build the single regression of medv (results can be taken from HW1) against lstat. Compare linear and quadratic model using the adjuster R-squared.

OUTPUT:

```
Console    R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
> g3<- lm(medv~lstat,data= Boston)
> summary(g3)

Call:
lm(formula = medv ~ lstat, data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.168  -3.990  -1.318   2.034  24.500 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 34.55384    0.56263   61.41   <2e-16 ***
lstat       -0.95005    0.03873  -24.53   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.216 on 504 degrees of freedom
Multiple R-squared:  0.5441,	Adjusted R-squared:  0.5432 
F-statistic: 601.6 on 1 and 504 DF,  p-value: < 2.2e-16

> 
```

INFERENCE:

The adjusted R-squared value increases only if the new term improves the model more than would be expected by chance. It decreases when a predictor improves the model by less than expected by chance.

In the Quadratic model we see the adjusted R-squared value of **0.6393(g2)** is higher than the adjusted R-squared value of **0.5432(g3)** in Linear model. Since the value 0.6393 in quadratic model is closer to 1 and, 0.5432 in linear model is closer to 0, this indicates that the Quadratic model has a better fit hence making it a better model.

Step 3 (1 mark) Use the anova() function to further quantify the extent to which the quadratic fit is superior to the linear fit. The anova() function performs a hypothesis test comparing the two models. The null hypothesis is that the two models fit the data equally well, and the alternative hypothesis is that the full model is superior.

OUTCOME:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/

> anova(g2,g3)
Analysis of Variance Table

Model 1: medv ~ lstat + int1
Model 2: medv ~ lstat
  Res.Df   RSS Df Sum of Sq     F    Pr(>F)
1    503 15347
2    504 19472 -1   -4125.1 135.2 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
```

INFERENCE:
The F-statistic is 135.2 and the associated p-value is almost zero. This shows clear evidence that the model containing the predictors lstat and lstat2(Quadratic model) is far superior to the model that only contains the predictor lstat(Linear Model).
Hence , it can be inferred that quadratic model is a better model then linear model.

Classification: Logistic regression (9 marks)

We will begin by examining some numerical and graphical summaries of the Smarket data, which is part of the ISLR library. This data set consists of percentage returns for the S&P 500 stock index over 1, 250 days, from the beginning of 2001 until the end of 2005. For each date, we have recorded the percentage returns for each of the five previous trading days, Lag1 through Lag5. We have also recorded Volume (the number of shares traded on the previous day, in billions), Today (the percentage return on the date in question) and Direction (whether the market was Up or Down on this date).

Step 1 (0.5 mark) Open library (ISLR) and check the name of variables in Smarket file and provide the summary statistics for all variables.

Output:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
> library(ISLR)
> data(Smarket)
> str(Smarket)
'data.frame':   1250 obs. of  9 variables:
 $ Year     : num  2001 2001 2001 2001 2001 ...
 $ Lag1     : num  0.381 0.959 1.032 -0.623 0.614 ...
 $ Lag2     : num  -0.192 0.381 0.959 1.032 -0.623 ...
 $ Lag3     : num  -2.624 -0.192 0.381 0.959 1.032 ...
 $ Lag4     : num  -1.055 -2.624 -0.192 0.381 0.959 ...
 $ Lag5     : num  5.01 -1.055 -2.624 -0.192 0.381 ...
 $ Volume   : num  1.19 1.3 1.41 1.28 1.21 ...
 $ Today    : num  0.959 1.032 -0.623 0.614 0.213 ...
 $ Direction: Factor w/ 2 levels "Down","Up": 2 2 1 2 2 2 1 2 2 2 ...
> summary(Smarket)
      Year           Lag1                Lag2                Lag3                Lag4          
 Min.   :2001   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000  
 1st Qu.:2002   1st Qu.:-0.639500   1st Qu.:-0.639500   1st Qu.:-0.640000   1st Qu.:-0.640000  
 Median :2003   Median : 0.039000   Median : 0.039000   Median : 0.038500   Median : 0.038500  
 Mean   :2003   Mean   : 0.003834   Mean   : 0.003919   Mean   : 0.001716   Mean   : 0.001636  
 3rd Qu.:2004   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750  
 Max.   :2005   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000  
      Lag5              Volume           Today              Direction 
 Min.   :-4.92200   Min.   :0.3561   Min.   :-4.922000   Down:602  
 1st Qu.:-0.64000   1st Qu.:1.2574   1st Qu.:-0.639500   Up  :648  
 Median : 0.03850   Median :1.4229   Median : 0.038500             
 Mean   : 0.00561   Mean   :1.4783   Mean   : 0.003138             
 3rd Qu.: 0.59700   3rd Qu.:1.6417   3rd Qu.: 0.596750             
 Max.   : 5.73300   Max.   :3.1525   Max.   : 5.733000             
> 
```

Step 2 (0.5 mark) Use the cor() function produces a matrix that contains all of the pairwise correlations among the predictors in a data set. Use the parameter [,9] because the Direction (#9) variable is qualitative.

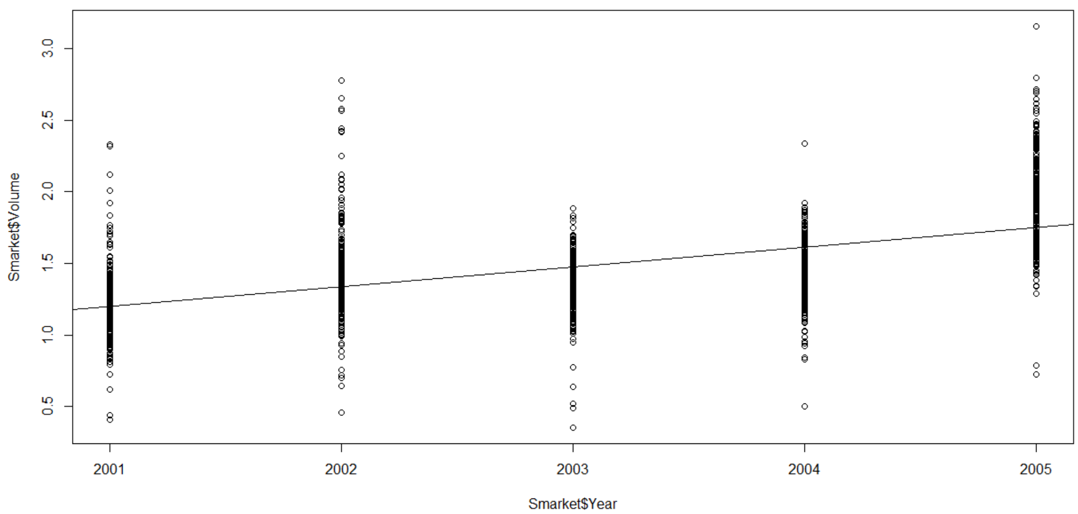
OUTPUT:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
> cor(Smarket[, -9])
             Year         Lag1         Lag2         Lag3         Lag4         Lag5      Volume        Today
Year   1.00000000  0.029699649  0.030596422  0.033194581  0.035688718  0.029787995  0.53900647  0.030095229
Lag1   0.02969965  1.000000000 -0.026294328 -0.010803402 -0.002985911 -0.005674606  0.04090991 -0.026155045
Lag2   0.03059642 -0.026294328  1.000000000 -0.025896670 -0.010853533 -0.003557949 -0.04338321 -0.010250033
Lag3   0.03319458 -0.010803402 -0.025896670  1.000000000 -0.024051036 -0.018808338 -0.04182369 -0.002447647
Lag4   0.03568872 -0.002985911 -0.010853533 -0.024051036  1.000000000 -0.027083641 -0.04841425 -0.006899527
Lag5   0.02978799 -0.005674606 -0.003557949 -0.018808338 -0.027083641  1.000000000 -0.02200231 -0.034860083
Volume 0.53900647  0.040909908 -0.043383215 -0.041823686 -0.048414246 -0.022002315  1.00000000  0.014591823
Today  0.03009523 -0.026155045 -0.010250033 -0.002447647 -0.006899527 -0.034860083  0.01459182  1.000000000
> 
```

Step 3 (1 mark) Explain why volume is correlated with year. Illustrate this graphically.

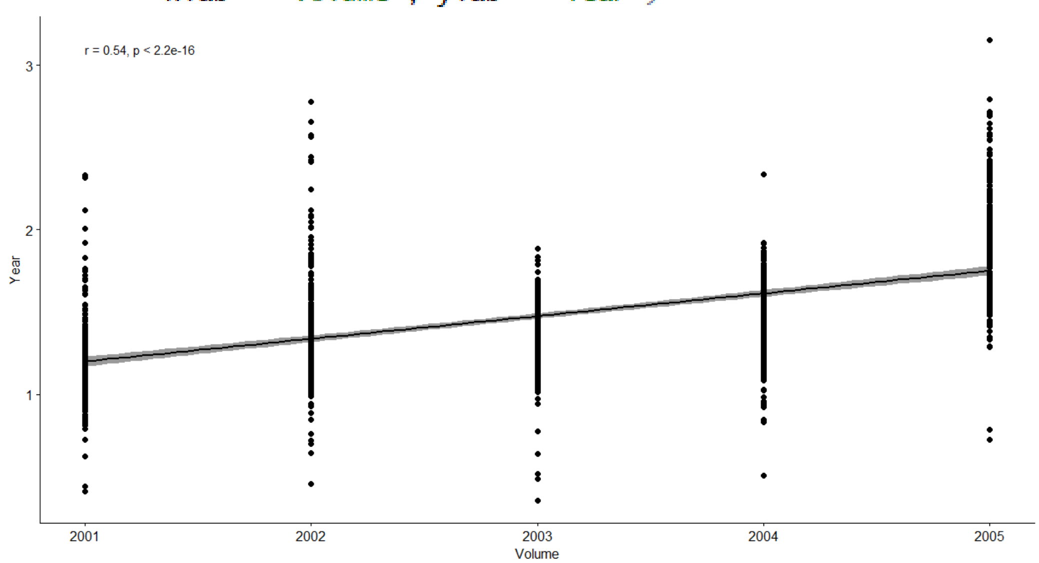
OUTPUT:
Volume has maximum collinearity with year and the values .539.

```
> library(ggplot2)
> plot(Smarket$Year,Smarket$Volume)
> #Reflect a positive relationship between the two variables.
>
> #The trend line of the same:
> abline(lm(Volume~Year,data=Smarket))
```



INFERENCE:

```
library("ggpubr")
ggscatter(Smarket, x = "Year", y = "Volume",
          add = "reg.line", conf.int = TRUE,
          cor.coef = TRUE, cor.method = "pearson",
          xlab = "Volume", ylab = "Year")
```



By both the plots, we can see a gradual rise in the Volume from Year 2001 to 2005. So, we can say that the Volume is increasing over the Years in a linear model.

Step 4 (1 mark) Fit a logistic regression model in order to predict Direction using Lag1 through Lag5 and Vol ume. The glm() function fits *generalized linear models*, a class of models that includes logistic regression. The syntax of the glm() function is similar to that of lm(), except that we mu st pass in the argument family=binomial in order to tell R to run a logistic regression rather than some other type of generalized linear model.

RCODE & OUTPUT:

```
> g4<-glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,family=binomial,data=Smarket)
>
```

Step 5 (1 mark) Analyze the logistic Table in order our ability to predict trading Volume using the informatio n about lags.

Output:

Console R Markdown

C:/Users/NICSI/Desktop/ABI/HW 2/

```
Residual Deviance: 1728        AIC: 1742
> summary(g4)

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

>
```

INFERENCE:

Lag1 has the smallest p-value of 0.145 out of all the predictors but it is still large enough. Therefore, the lag variables are not associated with the response Direction.

Also, a negative coefficient indicates a reverse association. So, if the market had a positive return yesterday, then it will mostly have a less positive or negative return today.

Step 6 (0.5 mark) Use the coef() function in order to access just the coefficients for this fitted model. Check the consistency with the previous step.

Console R Markdown

C:/Users/NICSI/Desktop/ABI/HW 2/

```
> coef(g4)
 (Intercept)         Lag1         Lag2         Lag3         Lag4         Lag5       Volume
-0.126000257 -0.073073746 -0.042301344  0.011085108  0.009358938  0.010313068  0.135440659
>
```

INFERENCE:
The results for the coefficients for g4 model are consistent with the previous step since, the values of the coefficients are same.

Step 7 (0.5 mark) Use the summary() function to access particular aspects of the fitted model, such as the p-values for the coefficients.

OUTPUT:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/
Residual Deviance: 1728        AIC: 1742
> summary(g4)

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

> 
```

Since the p-value for all the lag variables is greater than .05 hence we can say it is safe to remove the lag variable for classification .

Step 8 (0.5 mark) Use the predict() function, which can be used to predict the probability that the market will go up, given values of the predictors. The type="response" option tells R to output probabilities of the form $P(Y = 1|X)$, as opposed to other information such as the logit. If no data set is supplied to the predict() function, then the probabilities are computed for the training data that was used to fit the logistic regression model. Print the first ten probabilities.

OUTPUT:

```
Console   R Markdown ×
C:/Users/NICSI/Desktop/ABI/HW 2/

> predict<-predict(g4, newdata = NULL,
+          type = c("response"))
> head(predict,n=10)
        1         2         3         4         5         6         7         8         9        10 
0.5070841 0.4814679 0.4811388 0.5152224 0.5107812 0.5069565 0.4926509 0.5092292 0.5176135 0.4888378 
> 
```

Step 9 (0.5 mark) Use contrasts() function, which indicates that R has created a dummy variable with a 1 for Up, to check if these values correspond to the probability of the market going up, rather than down.

```
> contrasts(Direction)
     Up
Down  0
Up    1
```

Step 10 (0.5 mark) Convert these predicted probabilities into class labels, Up or Down, in order to make our prediction more transparent. Check the result with command fix.

OUTPUT:

Console C:/Users/NICSI/Desktop/ABI/HW 2/

```
> glm.pred = rep("Down", 1250)
> glm.pred[predict > 0.5] = "Up"
> fix(Smarket)
>
```

Data Editor

File Edit Help

	Year	Lag1	Lag2	Lag3	Lag4	Lag5	Volume	Today	Direction
1	2001	0.381	-0.192	-2.624	-1.055	5.01	1.1913	0.959	Up
2	2001	0.959	0.381	-0.192	-2.624	-1.055	1.2965	1.032	Up
3	2001	1.032	0.959	0.381	-0.192	-2.624	1.4112	-0.623	Down
4	2001	-0.623	1.032	0.959	0.381	-0.192	1.276	0.614	Up
5	2001	0.614	-0.623	1.032	0.959	0.381	1.2057	0.213	Up
6	2001	0.213	0.614	-0.623	1.032	0.959	1.3491	1.392	Up
7	2001	1.392	0.213	0.614	-0.623	1.032	1.445	-0.403	Down
8	2001	-0.403	1.392	0.213	0.614	-0.623	1.4078	0.027	Up
9	2001	0.027	-0.403	1.392	0.213	0.614	1.164	1.303	Up
10	2001	1.303	0.027	-0.403	1.392	0.213	1.2326	0.287	Up
11	2001	0.287	1.303	0.027	-0.403	1.392	1.309	-0.498	Down
12	2001	-0.498	0.287	1.303	0.027	-0.403	1.258	-0.189	Down
13	2001	-0.189	-0.498	0.287	1.303	0.027	1.098	0.68	Up
14	2001	0.68	-0.189	-0.498	0.287	1.303	1.0531	0.701	Up
15	2001	0.701	0.68	-0.189	-0.498	0.287	1.1498	-0.562	Down
16	2001	-0.562	0.701	0.68	-0.189	-0.498	1.2953	0.546	Up
17	2001	0.546	-0.562	0.701	0.68	-0.189	1.1188	-1.747	Down
18	2001	-1.747	0.546	-0.562	0.701	0.68	1.0484	0.359	Up
19	2001	0.359	-1.747	0.546	-0.562	0.701	1.013	-0.151	Down

Step 11 (0.5 mark) Given these predictions, use the table() function to produce a confusion matrix in order to determine how many observations were correctly classified.

OUTPUT:

```
Console C:/Users/NICSI/Desktop/ABI/HW 2/
> table(glm.pred, Direction)
        Direction
glm.pred Down  Up
    Down  145 141
    Up    457 507
> |
```

Elements on the diagonal of the matrix represent individuals whose default statuses were correctly predicted, while off-diagonal elements represent individuals that were misclassified.

Total correctly classified UP : 507
Total Correctly Classified DOWN: 145

Total Incorrectly Classified UP: 141
Total Incorrectly Classified DOWN: 457

Step 12 (0.5 mark) Calculate the proportion of correct predictions using command mean. Check the results manually using the information from the confusion table.

```
Console C:/Users/NICSI/Desktop/ABI/HW 2/
> (507+145)/(1250)
[1] 0.5216
>
> mean(glm.pred==Smarket$Direction)
[1] 0.5216
> |
```

INFERENCE:
Comparing the mean, manually in the confusion matrix and by computing the mean function, shows us that the diagonal elements of confusion matrix gives correct predictions while the off-diagonal elements show incorrect predictions. Therefore, the model correctly predicted that market will go in Up direction on 507 days and will go in Down direction on 145 days.
The proportion of correct prediction of the movement is 0.5216 or 52.16%.

Step 13 (0.5 mark) The statistics in Step 13 corresponds to the training set equal to the total set of observation. Create the new training set for records from 2001 to 2004. We will then use this vector to create a held out data set of observations from 2005. How many records remains in the test set?

RCODE & OUTPUT:

```
Console C:/Users/NICSI/Desktop/ABI/HW 2/
> train = (Year < 2005)
> # Test data set. 2005
> Smarket.2005 = Smarket[!train, ]
> dim(Smarket.2005)
[1] 252   9
> |
```

INFERENCE:
252 observations from 9 variables remain in the test set.

Step 14 (1 mark) Implement command
`>Direction.2005= Direction [! train]`
The object train is a vector of 1, 250 elements, corresponding to the observations in our data set. The elements of the vector that correspond to observations that occurred before 2005 are set to TRUE, whereas

those that correspond to observations in 2005 are set to FALSE. The object train is a *Boolean* vector, since its elements are TRUE and FALSE.

Fit a logistic regression model using only the subset of the observations that correspond to dates before 2005, using the subset argument. Compute the predictions for 2005 and compare them to the actual movements of the market over that time period. Interpret the results.
OUTPUT:

```
Console C:/Users/NICSI/Desktop/ABI/HW 2/
> Direction.2005 = Direction[!train]
> # Fit the logistic regression using only the train data
> glm.fit<-glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume, data=Smarket, family =binomial, subset= subset)
>
> # Test the model by fitting the test data set into the fitted model
> glm.probs <- predict(glm.fit, Smarket.2005, type = "response")
> # compute the predictions for 2005 and compare them to the actual
> # movements of the market over that time period.
> glm.pred = rep("Down", nrow(Smarket.2005))
> glm.pred[glm.probs > 0.5] = "Up"
> table(glm.pred, Direction.2005)
        Direction.2005
glm.pred Down Up
    Down   77 97
    Up     34 44
>
> # Test error rate
> mean(glm.pred == Direction.2005)
[1] 0.4801587
>
> # Training error rate
> mean(glm.pred != Direction.2005)
[1] 0.5198413
>
```

The training error rate for this model is 52% approximately which is not good for the model. Due to these factors the model would be having significant number of outliers. Hence we refit the model using 2 variables lag1 and lag2..

```
Console C:/Users/NICSI/Desktop/ABI/HW 2/
> # Refit the model using only 2 predictors lag1 and lag2
> glm.fit = glm(Direction ~ Lag1 + Lag2, data = Smarket, family = binomial, subset = train)
> glm.probs = predict(glm.fit, Smarket.2005, type = "response")
> glm.pred = rep("Down", nrow(Smarket.2005))
> glm.pred[glm.probs > 0.5] = "Up"
> 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
>
```

Actual Movement for 2005:
As can be seen the the test error rate: (Predicted correctly/ Total observations of the test data set) has been increased to 56 %(roughly) which is not very good.

To predict Direction for new values of Lag1-Lag2 we simply use the predict() function and feed in a data frame of new values. We want to predict Direction on a day when `Lag1` and `Lag2` equal 1.2 and 1.1, respectively, and on a day when they equal 1.5 and −0.8.

```
> predict(glm.fit, newdata = data.frame(Lag1 = c(1.2, 1.5), Lag2 = c(1.1, -0.8)),
+         type = "response")
        1         2
0.4791462 0.4960939
>
```