ISLR 4: Classification

Contents

Logistic Regression: Stock Market

For this example, we use the `Smarket` stock market data from the `ISLR` package. As usual, lets load the library, data, and call a few common commands to get familiar with the data

```r
library(ISLR)
data(Smarket)
```

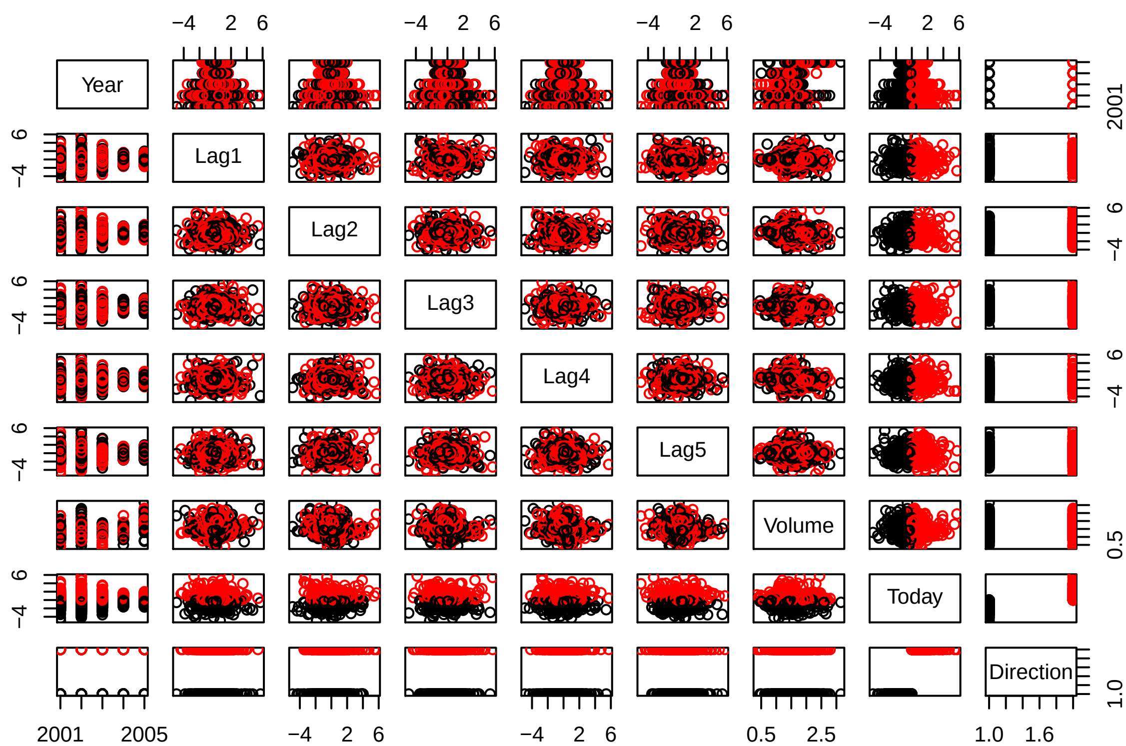
```
?Smarket
```

```r
head(Smarket)
```

```
##   Year   Lag1   Lag2   Lag3   Lag4   Lag5 Volume  Today Direction
## 1 2001  0.381 -0.192 -2.624 -1.055  5.010 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 1.2760  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
```

Lets make a plot with the `pairs` function.

```r
pairs(Smarket, col = Smarket$Direction)
```



Since we are interested in classification, we will use the `glm` function on the specified model in a similar fashion to regression. However, lets set the family argument to "`binomial`" to run the logistic regression.

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

```r
summary(smarket_logistic)
```

```
##
## 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
```

Next, lets pass the `smarket_logistic` model to the `predict` function, and define the argument type as `response`. This will turn give us a vector of probabilities. We can view the first 5 and we see that basically, its about a 50/50 chance of

```r
logistic_probs <- predict(smarket_logistic, type = "response")

logistic_probs[1:5]
```

```
##         1         2         3         4         5
## 0.5070841 0.4814679 0.4811388 0.5152224 0.5107812
```

We can turn these probabilities into classification by setting a threshold at 0.50 or 50%. the `ifelse` function is helpful for performing the classification and the `table` function for displaying the results.

```r
logistic_pred <- ifelse(logistic_probs > 0.5, "Up", "Down")

table(logistic_pred, Smarket$Direction)
```

```
##
## logistic_pred Down  Up
##          Down  145 141
##          Up    457 507
```

```r
mean(logistic_pred==Smarket$Direction)
```

```
## [1] 0.5216
```

Make training and test set

While that was interesting, we used all the data available so we've probably over-fit the model. Lets subset the data to `train` the `logistic_probs` model on the data prior to 2005, and then run then test it on the data after 2005. We can do this be creating a logical index to identify values prior to 2005, and then use that index to subset the `Smarket` data.frame. Note, the `glm` function has a `subset` argument which you can use to directly pass the index to.

```
train <- Smarket$Year < 2005

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

The `predict` function does not have the subset argument, so one must the `!` logical negation operator within the `Smarket` data.frame extraction brackets to indicate an interest in returning values which are the opposite of the index provided. In other words, use the `logistic_probs` model to make predictions on data after 2005.

```
     logistic_probs <- predict(smarket_logistic, newdata = Smarket[!train,], type="response")
```

Finally, classify probabilities as either "Up" and "Down" and call the `table` function to create a confusion matrix as well as the `mean` function.

```
     logistic_pred  <- ifelse(logistic_probs > 0.5, "Up", "Down")

     Direction_2005 <- Smarket$Direction[!train]

     table(logistic_pred, Direction_2005)
```

```
##              Direction_2005
## logistic_pred Down Up
##          Down   77 97
##          Up     34 44
```

```
     mean(logistic_pred == Direction_2005)
```

```
## [1] 0.4801587
```

Fit smaller model

Repeat the process with just `Lag1` and `Lag2` variables.

```
smarket_logistic <- glm(Direction~Lag1+Lag2, data=Smarket, family=binomial, subset=train)

  logistic_probs <- predict(smarket_logistic, newdata=Smarket[!train, ], type = "response")

   logistic_pred <- ifelse(logistic_probs > 0.5, "Up", "Down")
```

```
mean(logistic_pred == Direction_2005)
```

```
## [1] 0.5595238
```

```
class_table <- table(logistic_pred, Direction_2005)

class_table
```

```
##              Direction_2005
## logistic_pred Down  Up
```

```
##          Down   35  35
##          Up     76 106
```

```r
class_table[4]/sum(class_table[2,])
```

```
## [1] 0.5824176
```

```r
predict(smarket_logistic, newdata=data.frame(Lag1=c(1.2,1.5), Lag2=c(1.1,-0.8)), type="response")
```

```
##         1         2
## 0.4791462 0.4960939
```

Linear Discriminant Analysis

Lets load Ripley's `MASS` package

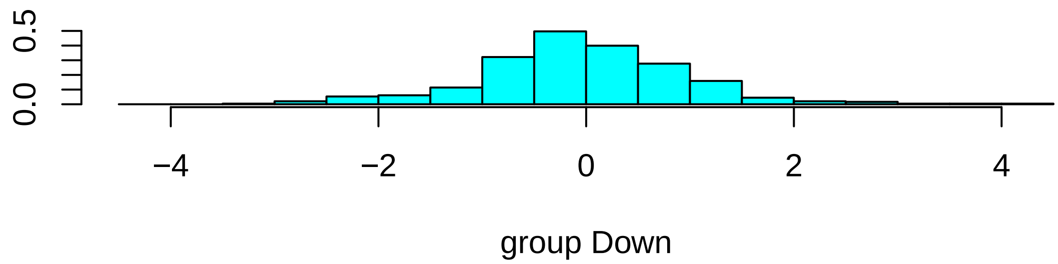
```r
library(MASS)
data(Smarket)
```

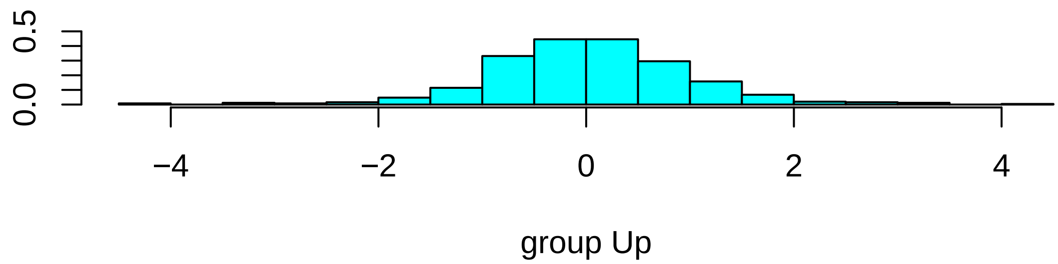
Again, we are going to try and predict the `Smarket` data by using the returns of the last two days on all data prior to 2005.

```r
train <- Smarket$Year < 2005

lda_Smarket <- lda(Direction ~ Lag1 + Lag2, data = Smarket, subset = train)

lda_Smarket
```

```
## Call:
## lda(Direction ~ Lag1 + Lag2, data = Smarket, subset = train)
##
## Prior probabilities of groups:
##     Down       Up
## 0.491984 0.508016
##
## Group means:
##             Lag1        Lag2
## Down  0.04279022  0.03389409
## Up   -0.03954635 -0.03132544
##
## Coefficients of linear discriminants:
##             LD1
## Lag1 -0.6420190
## Lag2 -0.5135293
```

```r
plot(lda_Smarket)
```





So lets see how we predict on year 2005 and the first 5 items of the prediction.

```
Smarket2005 <- subset(Smarket, Year==2005)

lda_pred <- predict(lda_Smarket, Smarket2005)

class(lda_pred)
```

```
## [1] "list"
```

```
data.frame(lda_pred)[1:5,]
```

```
##      class posterior.Down posterior.Up         LD1
## 999     Up      0.4901792    0.5098208  0.08293096
## 1000    Up      0.4792185    0.5207815  0.59114102
## 1001    Up      0.4668185    0.5331815  1.16723063
## 1002    Up      0.4740011    0.5259989  0.83335022
## 1003    Up      0.4927877    0.5072123 -0.03792892
```

We are interested in the `class` column, which is short for classification so lets create a confusion matrix with that. Linear Discriminant Analysis gives us a little bit better results than the logistic regression.

```
table(lda_pred$class, Smarket2005$Direction)
```

```
##
##        Down  Up
##   Down   35  35
##   Up     76 106
```

```r
mean(lda_pred$class==Smarket2005$Direction)
```

```
## [1] 0.5595238
```

Quadratic Discriminant Analysis

And QDA performs both LDA, and logistic regression.

```r
qda.fit <- qda(Direction ~ Lag1 + Lag2, data = Smarket, subset = train)

qda.fit
```

```
## Call:
## qda(Direction ~ Lag1 + Lag2, data = Smarket, subset = train)
##
## Prior probabilities of groups:
##     Down       Up
## 0.491984 0.508016
##
## Group means:
##             Lag1        Lag2
## Down  0.04279022  0.03389409
## Up   -0.03954635 -0.03132544
```

```r
qda.class <- predict(qda.fit, Smarket2005)$class

table(qda.class, Direction_2005)
```

```
##          Direction_2005
## qda.class Down  Up
##      Down   30  20
##      Up     81 121
```

```r
mean(qda.class==Direction_2005)
```

```
## [1] 0.5992063
```

K-Nearest Neighbors

A simple, but very effective classifcation tool, we are going to use the `class` package to run k-nearest neighbors on the `Smarket` data.

```r
library(class)
```

As usual, check out the documentation.

```
?knn
```

First, lets create a matrix, `Xlag` of the first and second lags of the Smarket returns and also define our `train` set. Pass them both to the `knn` function setting the `k` as 3 for the number of neighbors considered.

```r
Xlag <- cbind(Smarket$Lag1, Smarket$Lag2)

train <- Smarket$Year < 2005
```

```r
knn_pred <- knn(train = Xlag[train,], test = Xlag[!train,],
                cl = Smarket$Direction[train], k = 3)
```

Produce the confusion Matrix.

```r
table(knn_pred, Smarket$Direction[!train])
```

```
##
## knn_pred Down Up
##     Down   48 56
##     Up     63 85
```

```r
mean(knn_pred == Smarket$Direction[!train])
```

```
## [1] 0.5277778
```