Lab: Logistic Regression, LDA, QDA, and KNN

Code

Stock Market Data

Hide

```
#importing the library
library(ISLR)
names(Smarket)
```

```
[1] "Year"      "Lag1"      "Lag2"      "Lag3"      "Lag4"      "Lag5"      "Volume"    "Today"     "Di
rection"
```

Hide

```
#Stock Market Dataset shape
dim(Smarket)
```

```
[1] 1250    9
```

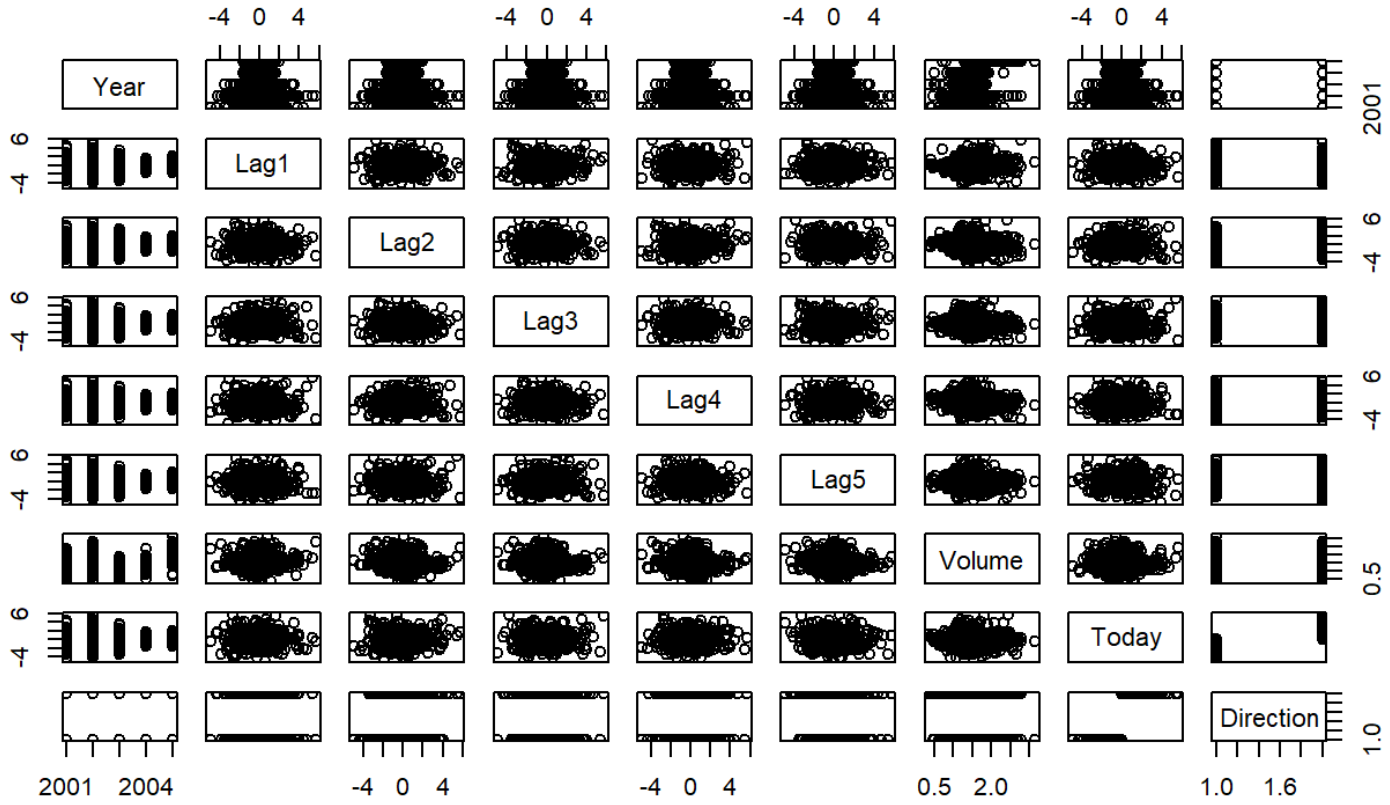
Hide

```
summary(Smarket)
```

```
      Year           Lag1                Lag2                Lag3                Lag4                La
g5              Volume
 Min.   :2001   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000   Min.
:-4.92200   Min.   :0.3561
 1st Qu.:2002   1st Qu.:-0.639500   1st Qu.:-0.639500   1st Qu.:-0.640000   1st Qu.:-0.640000   1st Q
u.:-0.64000   1st Qu.:1.2574
 Median :2003   Median : 0.039000   Median : 0.039000   Median : 0.038500   Median : 0.038500   Median
: 0.03850   Median :1.4229
 Mean   :2003   Mean   : 0.003834   Mean   : 0.003919   Mean   : 0.001716   Mean   : 0.001636   Mean
: 0.00561   Mean   :1.4783
 3rd Qu.:2004   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Q
u.: 0.59700   3rd Qu.:1.6417
 Max.   :2005   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000   Max.
: 5.73300   Max.   :3.1525
     Today           Direction
 Min.   :-4.922000   Down:602
 1st Qu.:-0.639500   Up  :648
 Median : 0.038500
 Mean   : 0.003138
 3rd Qu.: 0.596750
 Max.   : 5.733000
```

Hide

```
#pairplot
pairs(Smarket)
```



Hide

```
# The command below gives an error message because the Direction variable is qualitative.

cor(Smarket)
```

```
Error in cor(Smarket) : 'x' must be numeric
```

Hide

```
cor(Smarket[,-9])
```

```
             Year         Lag1         Lag2         Lag3         Lag4         Lag5
Year   1.00000000  0.029699649  0.030596422  0.033194581  0.035688718  0.029787995
Lag1   0.02969965  1.000000000 -0.026294328 -0.010803402 -0.002985911 -0.005674606
Lag2   0.03059642 -0.026294328  1.000000000 -0.025896670 -0.010853533 -0.003557949
Lag3   0.03319458 -0.010803402 -0.025896670  1.000000000 -0.024051036 -0.018808338
Lag4   0.03568872 -0.002985911 -0.010853533 -0.024051036  1.000000000 -0.027083641
Lag5   0.02978799 -0.005674606 -0.003557949 -0.018808338 -0.027083641  1.000000000
Volume 0.53900647  0.040909908 -0.043383215 -0.041823686 -0.048414246 -0.022002315
Today  0.03009523 -0.026155045 -0.010250033 -0.002447647 -0.006899527 -0.034860083
              Volume        Today
Year    0.53900647  0.030095229
Lag1    0.04090991 -0.026155045
Lag2   -0.04338321 -0.010250033
Lag3   -0.04182369 -0.002447647
Lag4   -0.04841425 -0.006899527
Lag5   -0.02200231 -0.034860083
Volume  1.00000000  0.014591823
Today   0.01459182  1.000000000
```

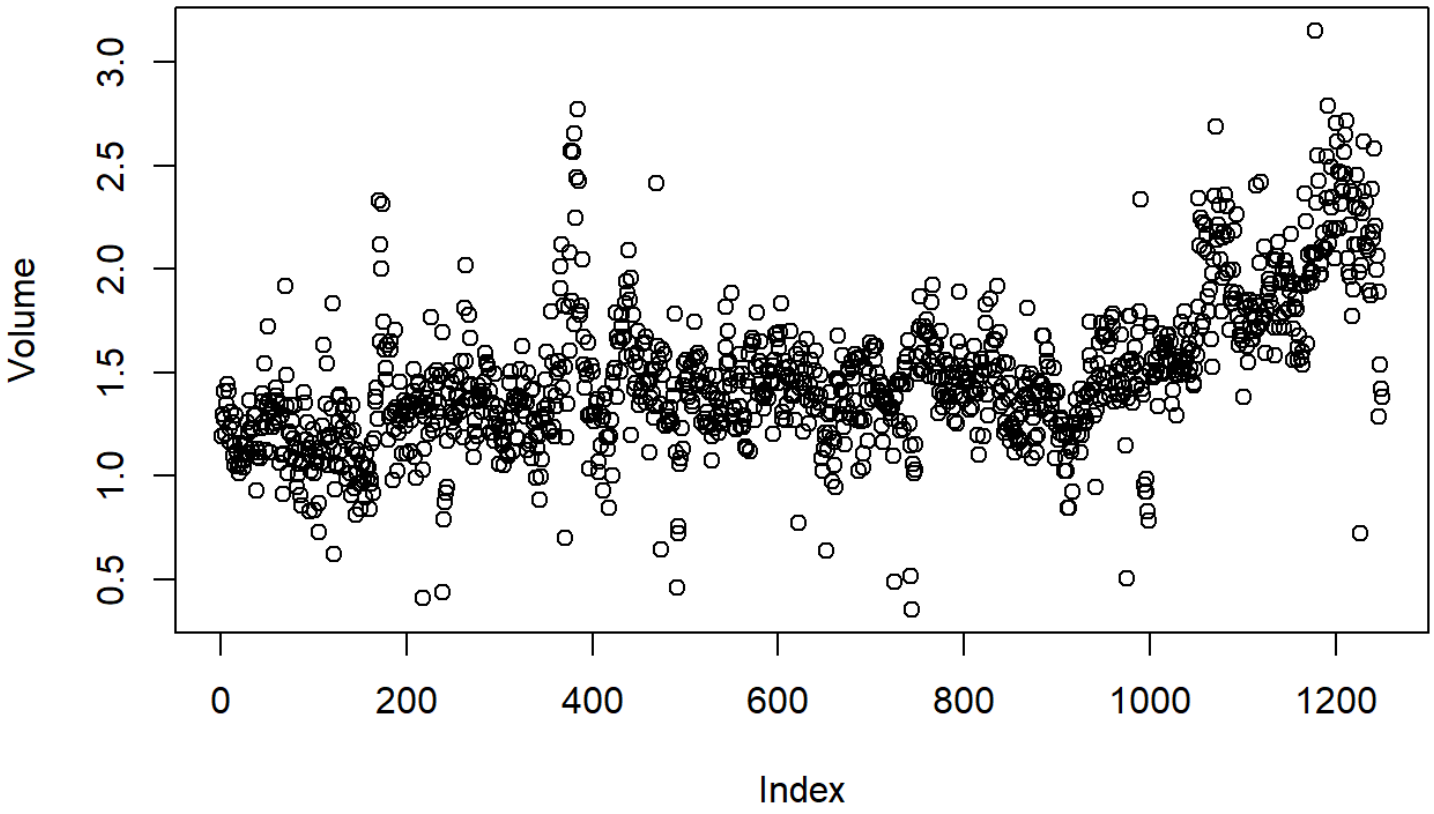
Hide

```
attach(Smarket)
```

```
The following objects are masked from Smarket (pos = 3):

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

Hide

```
plot(Volume)
```



Logistics Regression

Hide

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

```
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
```

Hide

```
coef(glm.fits)
```

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

Hide

```
summary(glm.fits)$coef
```

```
               Estimate Std. Error    z value  Pr(>|z|)
(Intercept) -0.126000257 0.24073574 -0.5233966 0.6006983
Lag1        -0.073073746 0.05016739 -1.4565986 0.1452272
Lag2        -0.042301344 0.05008605 -0.8445733 0.3983491
Lag3         0.011085108 0.04993854  0.2219750 0.8243333
Lag4         0.009358938 0.04997413  0.1872757 0.8514445
Lag5         0.010313068 0.04951146  0.2082966 0.8349974
Volume       0.135440659 0.15835970  0.8552723 0.3924004
```

Hide

```
summary(glm.fits)$coef[,4]
```

```
(Intercept)        Lag1        Lag2        Lag3        Lag4        Lag5
  0.6006983   0.1452272   0.3983491   0.8243333   0.8514445   0.8349974
     Volume
  0.3924004
```

Hide

```
glm.probs=predict(glm.fits,type="response")
glm.probs[1:10]
```

```
        1         2         3         4         5         6         7         8
0.5070841 0.4814679 0.4811388 0.5152224 0.5107812 0.5069565 0.4926509 0.5092292
        9        10
0.5176135 0.4888378
```

Hide

```
contrasts(Direction)
```

```
     Up
Down  0
Up    1
```

Hide

```
glm.pred=rep("Down",1250)
```

Hide

```
glm.pred[glm.probs>.5]="Up"
table(glm.pred,Direction)
```

```
        Direction
glm.pred Down  Up
    Down  145 141
    Up    457 507
```

Hide

```
(507+145)/1250
```

```
[1] 0.5216
```

Hide

```
mean(glm.pred==Direction)
```

```
[1] 0.5216
```

Hide

```
train=(Year<2005)
Smarket.2005=Smarket[!train,]
dim(Smarket.2005)
```

```
[1] 252   9
```

Hide

```
Direction.2005=Direction[!train]
glm.fits=glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume,data=Smarket,family=binomial,subset=train)
```

Hide

```
glm.probs=predict(glm.fits,Smarket.2005,type="response")
glm.pred=rep("Down",252)
glm.pred[glm.probs>.5]="Up"
```

Hide

```
table(glm.pred,Direction.2005)
```

```
        Direction.2005
glm.pred Down Up
    Down   77 97
    Up     34 44
```

Hide

```
mean(glm.pred==Direction.2005)
```

```
[1] 0.4801587
```

Hide

```
mean(glm.pred!=Direction.2005)
```

```
[1] 0.5198413
```

Hide

```
glm.fits=glm(Direction~Lag1+Lag2,data=Smarket,family=binomial,subset=train)
glm.probs=predict(glm.fits,Smarket.2005,type="response")
glm.pred=rep("Down",252)
glm.pred[glm.probs>.5]="Up"
```

Hide

```
table(glm.pred,Direction.2005)
```

```
        Direction.2005
glm.pred Down  Up
    Down   35  35
    Up     76 106
```

Hide

```
mean(glm.pred==Direction.2005)
```

```
[1] 0.5595238
```

Hide

```
106/(106+76)
```

```
[1] 0.5824176
```

Hide

```
predict(glm.fits,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

Now we will perform LDA on the Stock market data

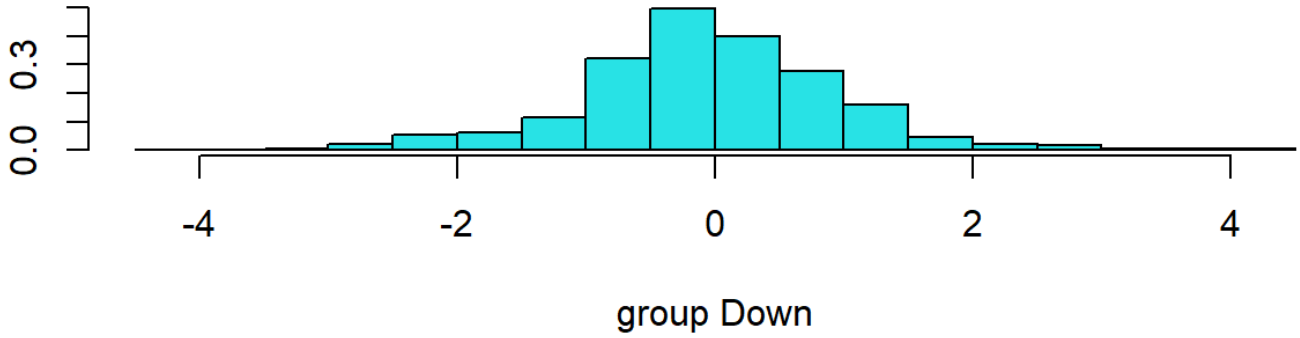
Hide

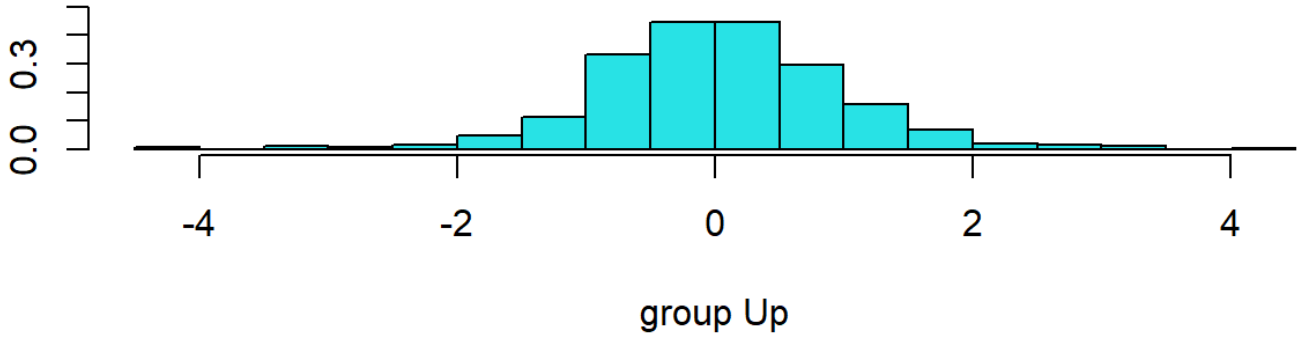
```
library(MASS)
#fitting the model
lda.fit=lda(Direction~Lag1+Lag2,data=Smarket,subset=train)
lda.fit
```

```
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
```

Hide

```
plot(lda.fit)
```





Hide

```
lda.pred=predict(lda.fit, Smarket.2005)
names(lda.pred)
```

```
[1] "class"     "posterior" "x"
```

Hide

```
lda.class=lda.pred$class
table(lda.class,Direction.2005)
```

```
         Direction.2005
lda.class Down  Up
     Down   35  35
     Up     76 106
```

Hide

```
mean(lda.class==Direction.2005)
```

```
[1] 0.5595238
```

Hide

```
sum(lda.pred$posterior[,1]>=.5)
```

```
[1] 70
```

Hide

```
#Notice that the posterior probability output by the model corresponds to the probability that the mark
et will decrease:

sum(lda.pred$posterior[,1]<.5)
```

```
[1] 182
```

Hide

```
lda.pred$posterior[1:20,1]
```

```
      999      1000      1001      1002      1003      1004      1005      1006      1007      1008
1009      1010      1011      1012
0.4901792 0.4792185 0.4668185 0.4740011 0.4927877 0.4938562 0.4951016 0.4872861 0.4907013 0.4844026 0.4
906963 0.5119988 0.4895152 0.4706761
     1013      1014      1015      1016      1017      1018
0.4744593 0.4799583 0.4935775 0.5030894 0.4978806 0.4886331
```

Hide

```
lda.class[1:20]
```

```
 [1] Up   Up   Up   Up   Up   Up   Up   Up   Up   Up   Up   Down Up   Up   Up   Up   Up   Down Up   Up
Levels: Down Up
```

Hide

```
sum(lda.pred$posterior[,1]>.9)
```

```
[1] 0
```

Quadratic Discriminant Analysis

Hide

```
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
```

Hide

```
qda.class=predict(qda.fit,Smarket.2005)$class
table(qda.class,Direction.2005)
```

```
         Direction.2005
qda.class Down  Up
     Down   30  20
     Up     81 121
```

Hide

```
mean(qda.class==Direction.2005)
```

```
[1] 0.5992063
```

K-Nearest Neighbors

Here we have gone through the procedure of creating KNN classifier and seeing the outputs from it.

Hide

```
library(class)
```

Hide

```
train.X=cbind(Lag1,Lag2)[train,]
test.X=cbind(Lag1,Lag2)[!train,]
train.Direction=Direction[train]
set.seed(1)
```

Hide

```
knn.pred=knn(train.X,test.X,train.Direction,k=1)
table(knn.pred,Direction.2005)
```

```
        Direction.2005
knn.pred Down Up
    Down   43 58
    Up     68 83
```

Hide

```
(83+43)/252
```

```
[1] 0.5
```

Hide

```
knn.pred=knn(train.X,test.X,train.Direction,k=3)
table(knn.pred,Direction.2005)
```

```
        Direction.2005
knn.pred Down Up
    Down   48 54
    Up     63 87
```

Hide

```
mean(knn.pred==Direction.2005)
```

```
[1] 0.5357143
```

An Application to Caravan Insurance Data

Here we have gone through the process of seeing an application to Caravan Insurance Data from what we learnt.

Hide

```
dim(Caravan)
```

```
[1] 5822   86
```

Hide

```
attach(Caravan)
```

```
The following objects are masked from Caravan (pos = 3):

    AAANHANG, ABESAUT, ABRAND, ABROM, ABYSTAND, AFIETS, AGEZONG, AINBOED, ALEVEN, AMOTSCO, APERSAUT, AP
ERSONG, APLEZIER,
    ATRACTOR, AVRAAUT, AWABEDR, AWALAND, AWAOREG, AWAPART, AWERKT, AZEILPL, MAANTHUI, MAUT0, MAUT1, MAU
T2, MBERARBG, MBERARBO,
    MBERBOER, MBERHOOG, MBERMIDD, MBERZELF, MFALLEEN, MFGEKIND, MFWEKIND, MGEMLEEF, MGEMOMV, MGODGE, MG
ODOV, MGODPR, MGODRK,
    MHHUUR, MHKOOP, MINK123M, MINK3045, MINK4575, MINK7512, MINKGEM, MINKM30, MKOOPKLA, MOPLHOOG, MOPLL
AAG, MOPLMIDD, MOSHOOFD,
    MOSTYPE, MRELGE, MRELOV, MRELSA, MSKA, MSKB1, MSKB2, MSKC, MSKD, MZFONDS, MZPART, PAANHANG, PBESAU
T, PBRAND, PBROM,
    PBYSTAND, PFIETS, PGEZONG, PINBOED, PLEVEN, PMOTSCO, PPERSAUT, PPERSONG, PPLEZIER, PTRACTOR, Purcha
se, PVRAAUT, PWABEDR,
    PWALAND, PWAOREG, PWAPART, PWERKT, PZEILPL
```

Hide

```
summary(Purchase)
```

```
  No  Yes
5474  348
```

Hide

```
348/5822
```

```
[1] 0.05977327
```

Hide

```
standardized.X=scale(Caravan[,-86])
var(Caravan[,1])
```

```
[1] 165.0378
```

Hide

```
var(Caravan[,2])
```

```
[1] 0.1647078
```

Hide

```
var(standardized.X[,1])
```

```
[1] 1
```

Hide

```
var(standardized.X[,2])
```

```
[1] 1
```

Hide

```
test=1:1000
train.X=standardized.X[-test,]
test.X=standardized.X[test,]
train.Y=Purchase[-test]
test.Y=Purchase[test]
set.seed(1)
knn.pred=knn(train.X,test.X,train.Y,k=1)
```

Hide

```
mean(test.Y!=knn.pred)
```

```
[1] 0.118
```

Hide

```
mean(test.Y!="No")
```

```
[1] 0.059
```

Hide

```
table(knn.pred,test.Y)
```

```
        test.Y
knn.pred  No Yes
     No  873  50
     Yes  68   9
```

Hide

```
9/(68+9)
```

```
[1] 0.1168831
```

Hide

```
knn.pred=knn(train.X,test.X,train.Y,k=3)
table(knn.pred,test.Y)
```

```
        test.Y
knn.pred  No Yes
     No  920  54
     Yes  21   5
```

Hide

```
5/26
```

```
[1] 0.1923077
```

Hide

```
knn.pred=knn(train.X,test.X,train.Y,k=5)
table(knn.pred,test.Y)
```

```
        test.Y
knn.pred  No Yes
     No  930  55
     Yes  11   4
```

Hide

```
4/15
```

```
[1] 0.2666667
```

Hide

```
glm.fits=glm(Purchase~.,data=Caravan,family=binomial,subset=-test)
```

```
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

Hide

```
glm.probs=predict(glm.fits,Caravan[test,],type="response")
glm.pred=rep("No",1000)
glm.pred[glm.probs>.5]="Yes"
```

Hide

```
table(glm.pred,test.Y)
```

```
        test.Y
glm.pred  No Yes
     No  934  59
     Yes   7   0
```

Hide

```
glm.pred=rep("No",1000)
glm.pred[glm.probs>.25]="Yes"
table(glm.pred,test.Y)
```

```
        test.Y
glm.pred  No Yes
     No  919  48
     Yes  22  11
```

Hide

```
11/(22+11)
```

```
[1] 0.3333333
```

So from both KNN and Logistic Regression we can see the Logistic Regression gives better output.

End of Classification Lab