4 Classification

By: Udit (based on ISLR)

Setup

LDA & QDA is part of **MASS** library.
Naive Bayes is part of **e1071** library.
KNN is part of **class** library.

```
library(ISLR2)
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:ISLR2':
##
##     Boston
```

```
library(class)
library(e1071)

# Stock Market data
attach(Smarket)
dim(Smarket)
```

```
## [1] 1250    9
```

```
names(Smarket)
```

```
## [1] "Year"      "Lag1"      "Lag2"      "Lag3"      "Lag4"      "Lag5"
## [7] "Volume"    "Today"     "Direction"
```

```
summary(Smarket)
```

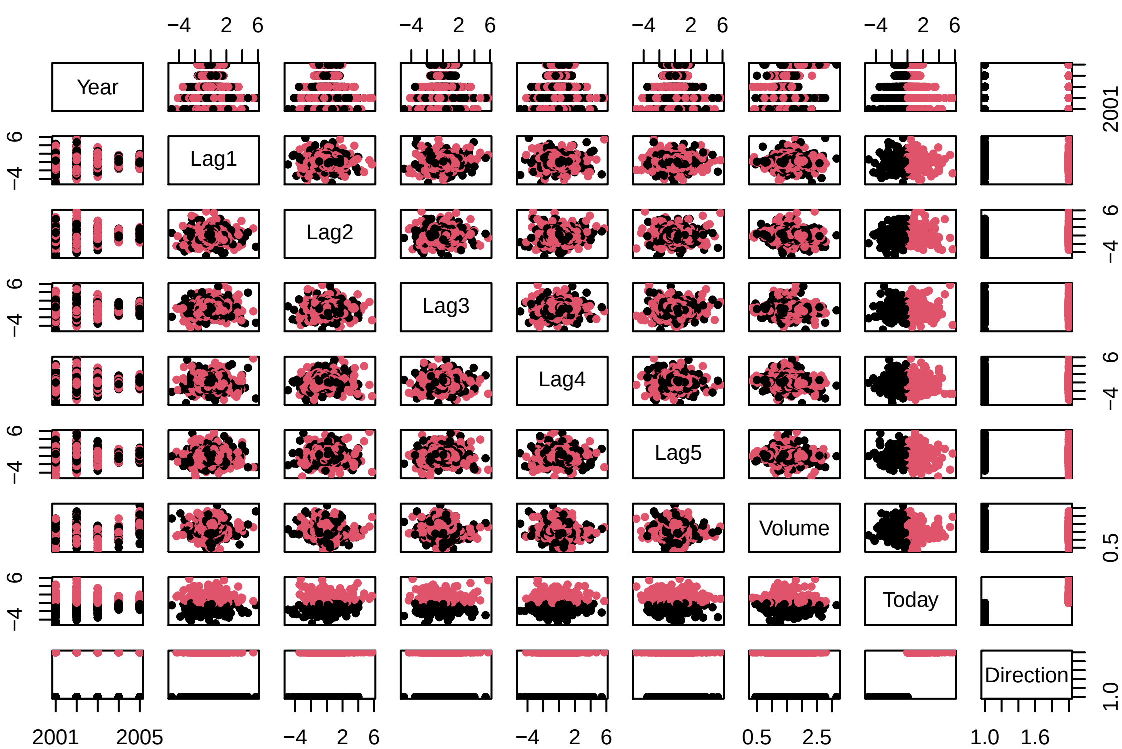
```
##       Year           Lag1                Lag2                Lag3
##  Min.   :2001   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000
##  1st Qu.:2002   1st Qu.:-0.639500   1st Qu.:-0.639500   1st Qu.:-0.640000
##  Median :2003   Median : 0.039000   Median : 0.039000   Median : 0.038500
##  Mean   :2003   Mean   : 0.003834   Mean   : 0.003919   Mean   : 0.001716
##  3rd Qu.:2004   3rd Qu.: 0.596750   3rd Qu.: 0.596750   3rd Qu.: 0.596750
##  Max.   :2005   Max.   : 5.733000   Max.   : 5.733000   Max.   : 5.733000
##       Lag4                Lag5              Volume           Today
##  Min.   :-4.922000   Min.   :-4.92200   Min.   :0.3561   Min.   :-4.922000
```

```
##  1st Qu.:-0.640000   1st Qu.:-0.64000   1st Qu.:1.2574   1st Qu.:-0.639500
##  Median : 0.038500   Median : 0.03850   Median :1.4229   Median : 0.038500
##  Mean   : 0.001636   Mean   : 0.00561   Mean   :1.4783   Mean   : 0.003138
##  3rd Qu.: 0.596750   3rd Qu.: 0.59700   3rd Qu.:1.6417   3rd Qu.: 0.596750
##  Max.   : 5.733000   Max.   : 5.73300   Max.   :3.1525   Max.   : 5.733000
##  Direction
##  Down:602
##  Up  :648
##
##
##
##
```

```r
round(cor(Smarket[,-9]),2)
```

```
##         Year  Lag1  Lag2  Lag3  Lag4  Lag5 Volume Today
## Year    1.00  0.03  0.03  0.03  0.04  0.03   0.54  0.03
## Lag1    0.03  1.00 -0.03 -0.01  0.00 -0.01   0.04 -0.03
## Lag2    0.03 -0.03  1.00 -0.03 -0.01  0.00  -0.04 -0.01
## Lag3    0.03 -0.01 -0.03  1.00 -0.02 -0.02  -0.04  0.00
## Lag4    0.04  0.00 -0.01 -0.02  1.00 -0.03  -0.05 -0.01
## Lag5    0.03 -0.01  0.00 -0.02 -0.03  1.00  -0.02 -0.03
## Volume 0.54  0.04 -0.04 -0.04 -0.05 -0.02   1.00  0.01
## Today   0.03 -0.03 -0.01  0.00 -0.01 -0.03   0.01  1.00
```

```r
pairs(Smarket, col=Smarket$Direction, pch=20)
```



Logistic Regression

```r
glm.fit = glm(Direction~.-Year-Today, data=Smarket, family=binomial)
summary(glm.fit)
```

```
##
## Call:
## glm(formula = Direction ~ . - Year - Today, 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
```

```r
# Predicted probabilities are close to 50% as expected
predict(glm.fit, type="response")[1:5]
```

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

```r
# Probability to Classification
glm.probs = predict(glm.fit, type="response")
glm.pred  = ifelse(glm.probs>0.5, "Up", "Down")

# Confusion Matrix
attach(Smarket)
```

```
## The following objects are masked from Smarket (pos = 3):
##
##     Direction, Lag1, Lag2, Lag3, Lag4, Lag5, Today, Volume, Year
```

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

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

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

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

```r
# Make Training & Test data
train = Year<2005
glm.fit = glm(Direction~. - Today -Year, data=Smarket, family=binomial,
                 subset=train)
glm.probs = predict(glm.fit, newdata=Smarket[!train,],type="response")
glm.preds = ifelse(glm.probs>0.5, "Up", "Down")

# Check performance - possible overfitting
Direction.test = Smarket$Direction[!train]
table(glm.preds, Direction.test)
```

```
##          Direction.test
## glm.preds Down Up
##      Down   77 97
##      Up     34 44
```

```r
mean(glm.preds==Direction.test)
```

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

```r
# 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")
contrasts(Direction)
```

```
##      Up
## Down  0
## Up    1
```

```r
glm.preds = ifelse(glm.probs>0.5, "Up", "Down")
table(glm.preds, Direction.test)
```

```
##          Direction.test
## glm.preds Down  Up
##      Down   35  35
##      Up     76 106
```

```r
mean(glm.preds==Direction.test)
```

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

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

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

```r
summary(glm.fit)
```

```
##
## Call:
## glm(formula = Direction ~ Lag1 + Lag2, family = binomial, data = Smarket,
##     subset = train)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.345  -1.188   1.074   1.164   1.326
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.03222    0.06338   0.508    0.611
## Lag1        -0.05562    0.05171  -1.076    0.282
## Lag2        -0.04449    0.05166  -0.861    0.389
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1383.3  on 997  degrees of freedom
## Residual deviance: 1381.4  on 995  degrees of freedom
## AIC: 1387.4
##
## Number of Fisher Scoring iterations: 3
```

Linear Discriminant Analysis

```r
lda.fit = lda(Direction~Lag1+Lag2, subset=Year<2005)
lda.fit
```

```
## Call:
## lda(Direction ~ Lag1 + Lag2, subset = Year < 2005)
##
## 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
```

```
Smarket.test = subset(Smarket, Year>=2005)
lda.pred = predict(lda.fit, Smarket.test)
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
```

```
table(lda.pred$class, Smarket.test$Direction)
```

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

```
mean(lda.pred$class == Smarket.test$Direction)
```

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

Quadratic Discriminant Analysis

```
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
```

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

```
##
##         Down  Up
##   Down    30  20
##   Up      81 121
```

```r
mean(qda.pred$class == Smarket.test$Direction)
```

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

Naive Bayes

```r
nb.fit = naiveBayes(Direction~Lag1+Lag2, data=Smarket, subset=train)
nb.fit
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##     Down       Up
## 0.491984 0.508016
##
## Conditional probabilities:
##       Lag1
## Y             [,1]     [,2]
##   Down  0.04279022 1.227446
##   Up   -0.03954635 1.231668
##
##       Lag2
## Y             [,1]     [,2]
##   Down  0.03389409 1.239191
##   Up   -0.03132544 1.220765
```

```r
mean(Lag1[train][Direction[train]=="Down"])
```

```
## [1] 0.04279022
```

```r
sd(Lag1[train][Direction[train]=="Down"])
```

```
## [1] 1.227446
```

```r
nb.pred = predict(nb.fit, Smarket.test)
table(nb.pred, Smarket.test$Direction)
```

```
##
## nb.pred Down  Up
##    Down   28  20
##    Up     83 121
```

```r
mean(nb.pred == Smarket.test$Direction)
```

```
## [1] 0.5912698
```

```r
predict(nb.fit, Smarket.test, type="raw")[1:5,]
```

```
##           Down        Up
## [1,] 0.4873164 0.5126836
## [2,] 0.4762492 0.5237508
## [3,] 0.4653377 0.5346623
## [4,] 0.4748652 0.5251348
## [5,] 0.4901890 0.5098110
```

KNN

```r
attach(Smarket)
```

```
## The following objects are masked from Smarket (pos = 3):
##
##     Direction, Lag1, Lag2, Lag3, Lag4, Lag5, Today, Volume, Year

## The following objects are masked from Smarket (pos = 4):
##
##     Direction, Lag1, Lag2, Lag3, Lag4, Lag5, Today, Volume, Year
```

```r
ls()
```

```
##  [1] "Direction.test" "glm.fit"        "glm.pred"       "glm.preds"
##  [5] "glm.probs"      "lda.fit"        "lda.pred"       "nb.fit"
##  [9] "nb.pred"        "qda.fit"        "qda.pred"       "Smarket.test"
## [13] "train"
```

```r
xlag = cbind(Lag1, Lag2)
xlag[1:5,]
```

```
##        Lag1   Lag2
## [1,]  0.381 -0.192
## [2,]  0.959  0.381
## [3,]  1.032  0.959
## [4,] -0.623  1.032
## [5,]  0.614 -0.623
```

```r
knn.pred = knn(xlag[train,], xlag[!train,], Direction[train], k=1)
table(knn.pred,Direction[!train])
```

```
##
## knn.pred Down Up
##     Down   43 58
##     Up     68 83
```

```
mean(knn.pred == Direction[!train])
```

```
## [1] 0.5
```

```
for(i in 1:10){
knn.pred = knn(xlag[train,], xlag[!train,], Direction[train], k=i)
table(knn.pred,Direction[!train])
print(c(i,mean(knn.pred == Direction[!train])))
}
```

```
## [1] 1.0 0.5
## [1] 2.000000 0.515873
## [1] 3.0000000 0.5277778
## [1] 4.000000 0.531746
## [1] 5.000000 0.484127
## [1] 6.0 0.5
## [1] 7.0000000 0.4642857
## [1] 8.0000000 0.4801587
## [1] 9.0000000 0.4960317
## [1] 10.0000000  0.5119048
```

KNN - Example 2

```
attach(Caravan)
dim(Caravan)
```

```
## [1] 5822   86
```

```
names(Caravan)  #85 demographic indicators
```

```
##  [1] "MOSTYPE"  "MAANTHUI" "MGEMOMV"  "MGEMLEEF" "MOSHOOFD" "MGODRK"
##  [7] "MGODPR"   "MGODOV"   "MGODGE"   "MRELGE"   "MRELSA"   "MRELOV"
## [13] "MFALLEEN" "MFGEKIND" "MFWEKIND" "MOPLHOOG" "MOPLMIDD" "MOPLLAAG"
## [19] "MBERHOOG" "MBERZELF" "MBERBOER" "MBERMIDD" "MBERARBG" "MBERARBO"
## [25] "MSKA"     "MSKB1"    "MSKB2"    "MSKC"     "MSKD"     "MHHUUR"
## [31] "MHKOOP"   "MAUT1"    "MAUT2"    "MAUT0"    "MZFONDS"  "MZPART"
## [37] "MINKM30"  "MINK3045" "MINK4575" "MINK7512" "MINK123M" "MINKGEM"
## [43] "MKOOPKLA" "PWAPART"  "PWABEDR"  "PWALAND"  "PPERSAUT" "PBESAUT"
## [49] "PMOTSCO"  "PVRAAUT"  "PAANHANG" "PTRACTOR" "PWERKT"   "PBROM"
## [55] "PLEVEN"   "PPERSONG" "PGEZONG"  "PWAOREG"  "PBRAND"   "PZEILPL"
## [61] "PPLEZIER" "PFIETS"   "PINBOED"  "PBYSTAND" "AWAPART"  "AWABEDR"
## [67] "AWALAND"  "APERSAUT" "ABESAUT"  "AMOTSCO"  "AVRAAUT"  "AAANHANG"
## [73] "ATRACTOR" "AWERKT"   "ABROM"    "ALEVEN"   "APERSONG" "AGEZONG"
## [79] "AWAOREG"  "ABRAND"   "AZEILPL"  "APLEZIER" "AFIETS"   "AINBOED"
## [85] "ABYSTAND" "Purchase"
```

```
summary(Purchase)
```

```
##   No  Yes
## 5474  348
```

```r
round(348/5822,4)*100
```

```
## [1] 5.98
```

```r
standard.X = scale(Caravan[,-86])
var(Caravan[,1:2]); var(standard.X[,1:2])
```

```
##              MOSTYPE   MAANTHUI
## MOSTYPE  165.0378474 -0.2018823
## MAANTHUI  -0.2018823  0.1647078

##              MOSTYPE    MAANTHUI
## MOSTYPE   1.00000000 -0.03872126
## MAANTHUI -0.03872126  1.00000000
```

```r
test <- 1:1000
test.X = standard.X[test,]
test.Y = Purchase[test]

train.X = standard.X[-test,]
train.Y = Purchase[-test]

set.seed(1)
knn.pred <- knn(train.X, test.X, train.Y, k=1)
mean(test.Y == knn.pred)
```

```
## [1] 0.882
```

```r
# Error rate
mean(test.Y != knn.pred)
```

```
## [1] 0.118
```

```r
mean(test.Y != "No")  # no skill, always predicting "no"
```

```
## [1] 0.059
```

```r
# How about only positive cases
table(knn.pred, test.Y)
```

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

```r
10/(69+10)
```

```
## [1] 0.1265823
```

```r
# Changing K (can be tested through CV)
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
```

```r
5/(19+5)
```

```
## [1] 0.2083333
```

```r
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
```

```r
4/15
```

```
## [1] 0.2666667
```

```r
# Compare with Logistic Regression
glm.fits = glm(Purchase ~., data=Caravan, subset=-test, family=binomial)
```

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

```r
glm.probs = predict(glm.fits, Caravan[test,], type="response")

pred.Y = ifelse(glm.probs>0.5, "Yes", "No")
table(pred.Y, test.Y)  # Recall = 0
```

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

```r
# Changing threshold
pred.Y = ifelse(glm.probs>0.25, "Yes", "No")
table(pred.Y, test.Y)  # Recall = 0
```

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

Poisson Regression

```r
attach(Bikeshare)
dim(Bikeshare)
```

```
## [1] 8645   15
```

```r
names(Bikeshare)
```

```
##  [1] "season"     "mnth"       "day"        "hr"         "holiday"
##  [6] "weekday"    "workingday" "weathersit" "temp"       "atemp"
## [11] "hum"        "windspeed"  "casual"     "registered" "bikers"
```

```r
# Linear Regression ######
mod.lm <- lm(bikers~mnth+hr+workingday+temp+weathersit, data=Bikeshare)
summary(mod.lm)
```

```
##
## Call:
## lm(formula = bikers ~ mnth + hr + workingday + temp + weathersit,
##     data = Bikeshare)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -299.00  -45.70   -6.23   41.08  425.29
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 -68.632      5.307 -12.932  < 2e-16 ***
## mnthFeb                       6.845      4.287   1.597 0.110398
## mnthMarch                    16.551      4.301   3.848 0.000120 ***
## mnthApril                    41.425      4.972   8.331  < 2e-16 ***
## mnthMay                      72.557      5.641  12.862  < 2e-16 ***
## mnthJune                     67.819      6.544  10.364  < 2e-16 ***
## mnthJuly                     45.324      7.081   6.401 1.63e-10 ***
## mnthAug                      53.243      6.640   8.019 1.21e-15 ***
## mnthSept                     66.678      5.925  11.254  < 2e-16 ***
## mnthOct                      75.834      4.950  15.319  < 2e-16 ***
## mnthNov                      60.310      4.610  13.083  < 2e-16 ***
## mnthDec                      46.458      4.271  10.878  < 2e-16 ***
## hr1                         -14.579      5.699  -2.558 0.010536 *
## hr2                         -21.579      5.733  -3.764 0.000168 ***
## hr3                         -31.141      5.778  -5.389 7.26e-08 ***
## hr4                         -36.908      5.802  -6.361 2.11e-10 ***
## hr5                         -24.135      5.737  -4.207 2.61e-05 ***
## hr6                          20.600      5.704   3.612 0.000306 ***
## hr7                         120.093      5.693  21.095  < 2e-16 ***
## hr8                         223.662      5.690  39.310  < 2e-16 ***
## hr9                         120.582      5.693  21.182  < 2e-16 ***
## hr10                         83.801      5.705  14.689  < 2e-16 ***
## hr11                        105.423      5.722  18.424  < 2e-16 ***
```

```
## hr12                        137.284      5.740  23.916  < 2e-16 ***
## hr13                        136.036      5.760  23.617  < 2e-16 ***
## hr14                        126.636      5.776  21.923  < 2e-16 ***
## hr15                        132.087      5.780  22.852  < 2e-16 ***
## hr16                        178.521      5.772  30.927  < 2e-16 ***
## hr17                        296.267      5.749  51.537  < 2e-16 ***
## hr18                        269.441      5.736  46.976  < 2e-16 ***
## hr19                        186.256      5.714  32.596  < 2e-16 ***
## hr20                        125.549      5.704  22.012  < 2e-16 ***
## hr21                         87.554      5.693  15.378  < 2e-16 ***
## hr22                         59.123      5.689  10.392  < 2e-16 ***
## hr23                         26.838      5.688   4.719 2.41e-06 ***
## workingday                    1.270      1.784   0.711 0.476810
## temp                        157.209     10.261  15.321  < 2e-16 ***
## weathersitcloudy/misty      -12.890      1.964  -6.562 5.60e-11 ***
## weathersitlight rain/snow   -66.494      2.965 -22.425  < 2e-16 ***
## weathersitheavy rain/snow -109.745     76.667  -1.431 0.152341
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 76.5 on 8605 degrees of freedom
## Multiple R-squared:  0.6745, Adjusted R-squared:  0.6731
## F-statistic: 457.3 on 39 and 8605 DF,  p-value: < 2.2e-16
```

```
# Alternate Coding for qualitative variables - no base; Coeff(last level) = Sum of other Coeffs.
contrasts(Bikeshare$hr) = contr.sum(24)
contrasts(Bikeshare$mnth) = contr.sum(12)

mod.lm2 <- lm(bikers~mnth+hr+workingday+temp+weathersit, data=Bikeshare)
summary(mod.lm2)
```

```
##
## Call:
## lm(formula = bikers ~ mnth + hr + workingday + temp + weathersit,
##     data = Bikeshare)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -299.00  -45.70   -6.23   41.08  425.29
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 73.5974     5.1322  14.340  < 2e-16 ***
## mnth1                      -46.0871     4.0855 -11.281  < 2e-16 ***
## mnth2                      -39.2419     3.5391 -11.088  < 2e-16 ***
## mnth3                      -29.5357     3.1552  -9.361  < 2e-16 ***
## mnth4                       -4.6622     2.7406  -1.701  0.08895 .
## mnth5                       26.4700     2.8508   9.285  < 2e-16 ***
## mnth6                       21.7317     3.4651   6.272 3.75e-10 ***
## mnth7                       -0.7626     3.9084  -0.195  0.84530
## mnth8                        7.1560     3.5347   2.024  0.04295 *
## mnth9                       20.5912     3.0456   6.761 1.46e-11 ***
## mnth10                      29.7472     2.6995  11.019  < 2e-16 ***
## mnth11                      14.2229     2.8604   4.972 6.74e-07 ***
```

```
## hr1                        -96.1420     3.9554 -24.307  < 2e-16 ***
## hr2                       -110.7213     3.9662 -27.916  < 2e-16 ***
## hr3                       -117.7212     4.0165 -29.310  < 2e-16 ***
## hr4                       -127.2828     4.0808 -31.191  < 2e-16 ***
## hr5                       -133.0495     4.1168 -32.319  < 2e-16 ***
## hr6                       -120.2775     4.0370 -29.794  < 2e-16 ***
## hr7                        -75.5424     3.9916 -18.925  < 2e-16 ***
## hr8                         23.9511     3.9686   6.035 1.65e-09 ***
## hr9                        127.5199     3.9500  32.284  < 2e-16 ***
## hr10                        24.4399     3.9360   6.209 5.57e-10 ***
## hr11                       -12.3407     3.9361  -3.135  0.00172 **
## hr12                         9.2814     3.9447   2.353  0.01865 *
## hr13                        41.1417     3.9571  10.397  < 2e-16 ***
## hr14                        39.8939     3.9750  10.036  < 2e-16 ***
## hr15                        30.4940     3.9910   7.641 2.39e-14 ***
## hr16                        35.9445     3.9949   8.998  < 2e-16 ***
## hr17                        82.3786     3.9883  20.655  < 2e-16 ***
## hr18                       200.1249     3.9638  50.488  < 2e-16 ***
## hr19                       173.2989     3.9561  43.806  < 2e-16 ***
## hr20                        90.1138     3.9400  22.872  < 2e-16 ***
## hr21                        29.4071     3.9362   7.471 8.74e-14 ***
## hr22                        -8.5883     3.9332  -2.184  0.02902 *
## hr23                       -37.0194     3.9344  -9.409  < 2e-16 ***
## workingday                   1.2696     1.7845   0.711  0.47681
## temp                       157.2094    10.2612  15.321  < 2e-16 ***
## weathersitcloudy/misty     -12.8903     1.9643  -6.562 5.60e-11 ***
## weathersitlight rain/snow  -66.4944     2.9652 -22.425  < 2e-16 ***
## weathersitheavy rain/snow -109.7446    76.6674  -1.431  0.15234
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 76.5 on 8605 degrees of freedom
## Multiple R-squared:  0.6745, Adjusted R-squared:  0.6731
## F-statistic: 457.3 on 39 and 8605 DF,  p-value: < 2.2e-16
```

```r
# No impact to predictions
sum((predict(mod.lm)-predict(mod.lm2))^2)
```

```
## [1] 1.426274e-18
```

```r
all.equal(predict(mod.lm), predict(mod.lm2))
```

```
## [1] TRUE
```

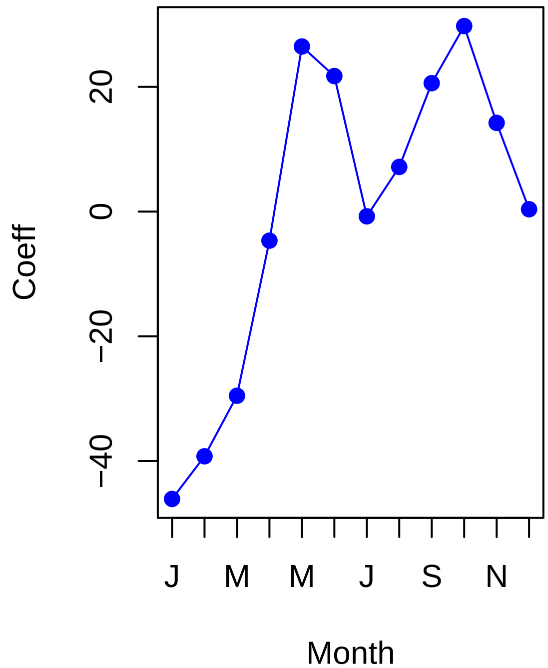
```r
# Coeff for December
-sum(coef(mod.lm2)[2:12])
```

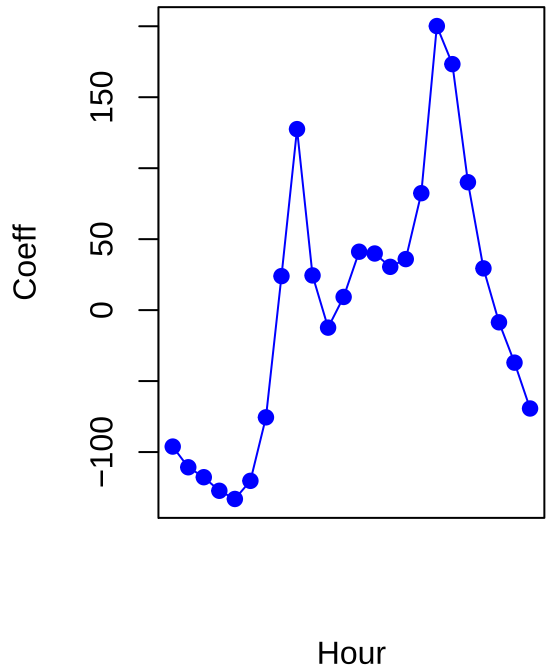
```
## [1] 0.3705817
```

```r
# Plotting Coeff
par(mfrow=c(1,2))
coef.months = c(coef(mod.lm2)[2:12], -sum(coef(mod.lm2)[2:12]))
```

```r
plot(coef.months, xlab="Month", ylab="Coeff", xaxt="n", col="blue", pch=19, type="o")
axis(side=1, at=1:12, labels=c("J","F","M","A","M","J","J","A","S","O","N","D"))

coef.hrs = c(coef(mod.lm2)[13:35], -sum(coef(mod.lm2)[13:35]))
plot(coef.hrs, xlab="Hour", ylab="Coeff", xaxt="n", col="blue", pch=19, type="o")
```





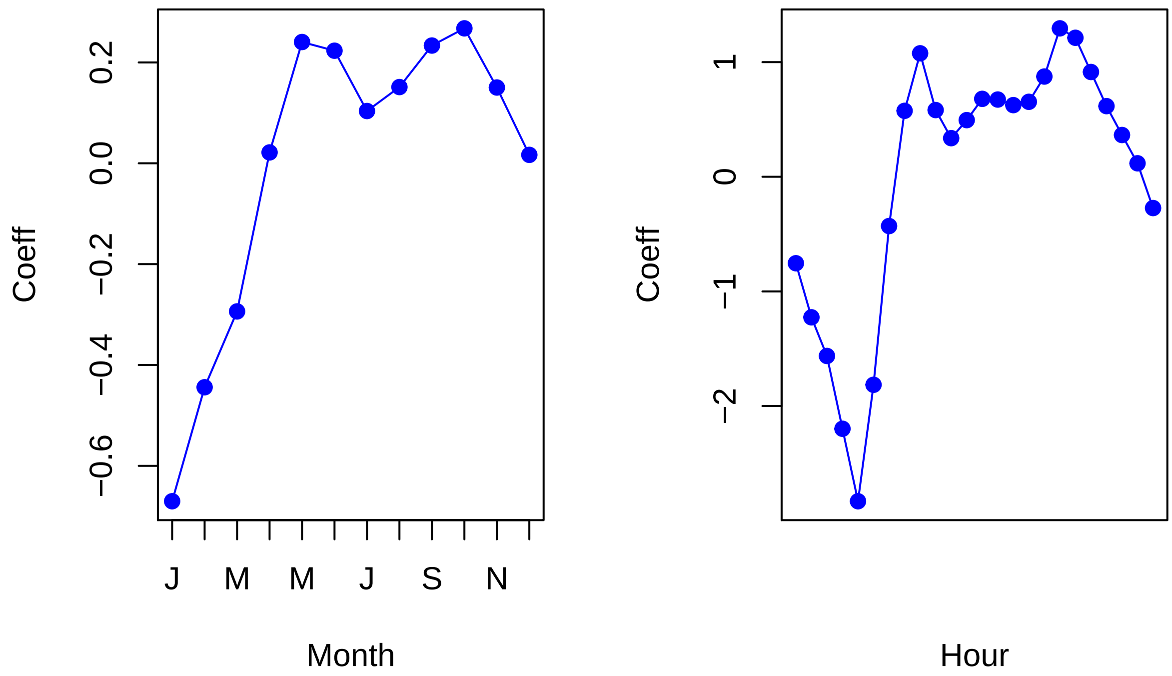

```r
# Poisson Regression ######
mod.pois <- glm(bikers~mnth+hr+workingday+temp+weathersit, data=Bikeshare,
                family=poisson)
summary(mod.pois)
```

```
##
## Call:
## glm(formula = bikers ~ mnth + hr + workingday + temp + weathersit,
##     family = poisson, data = Bikeshare)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -20.7574   -3.3441   -0.6549    2.6999   21.9628
##
## Coefficients:
##                            Estimate Std. Error  z value Pr(>|z|)
## (Intercept)                4.118245   0.006021  683.964  < 2e-16 ***
## mnth1                     -0.670170   0.005907 -113.445  < 2e-16 ***
## mnth2                     -0.444124   0.004860  -91.379  < 2e-16 ***
```

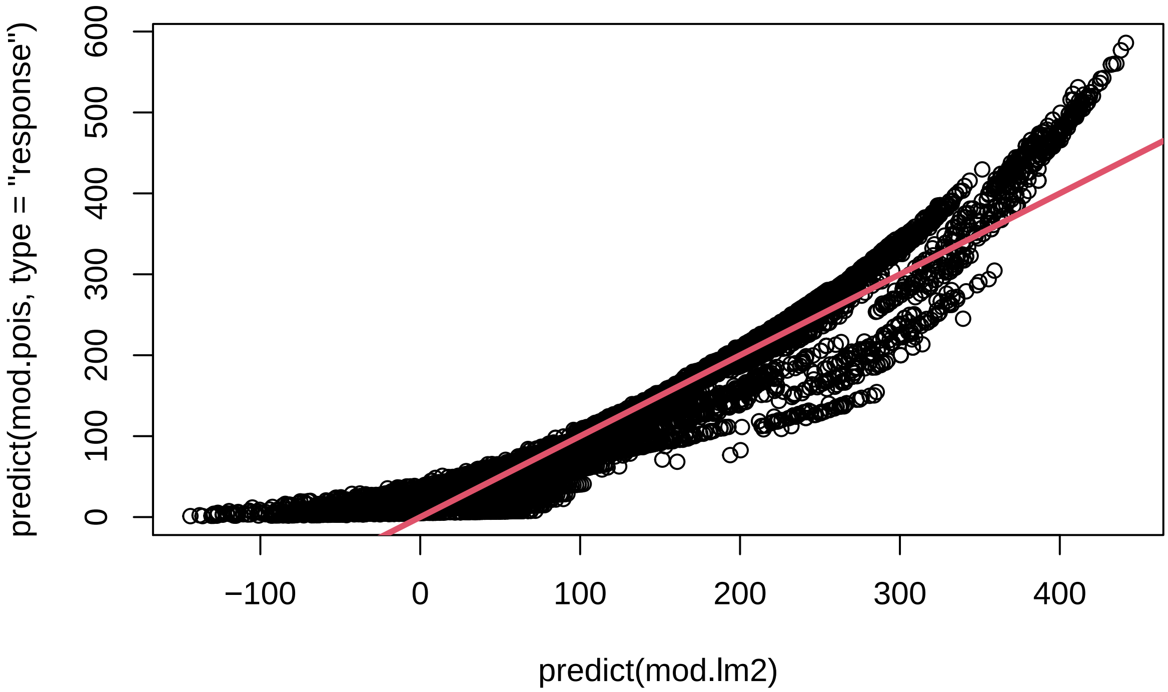
```
## mnth3                      -0.293733   0.004144  -70.886  < 2e-16 ***
## mnth4                       0.021523   0.003125    6.888 5.66e-12 ***
## mnth5                       0.240471   0.002916   82.462  < 2e-16 ***
## mnth6                       0.223235   0.003554   62.818  < 2e-16 ***
## mnth7                       0.103617   0.004125   25.121  < 2e-16 ***
## mnth8                       0.151171   0.003662   41.281  < 2e-16 ***
## mnth9                       0.233493   0.003102   75.281  < 2e-16 ***
## mnth10                      0.267573   0.002785   96.091  < 2e-16 ***
## mnth11                      0.150264   0.003180   47.248  < 2e-16 ***
## hr1                        -0.754386   0.007879  -95.744  < 2e-16 ***
## hr2                        -1.225979   0.009953 -123.173  < 2e-16 ***
## hr3                        -1.563147   0.011869 -131.702  < 2e-16 ***
## hr4                        -2.198304   0.016424 -133.846  < 2e-16 ***
## hr5                        -2.830484   0.022538 -125.586  < 2e-16 ***
## hr6                        -1.814657   0.013464 -134.775  < 2e-16 ***
## hr7                        -0.429888   0.006896  -62.341  < 2e-16 ***
## hr8                         0.575181   0.004406  130.544  < 2e-16 ***
## hr9                         1.076927   0.003563  302.220  < 2e-16 ***
## hr10                        0.581769   0.004286  135.727  < 2e-16 ***
## hr11                        0.336852   0.004720   71.372  < 2e-16 ***
## hr12                        0.494121   0.004392  112.494  < 2e-16 ***
## hr13                        0.679642   0.004069  167.040  < 2e-16 ***
## hr14                        0.673565   0.004089  164.722  < 2e-16 ***
## hr15                        0.624910   0.004178  149.570  < 2e-16 ***
## hr16                        0.653763   0.004132  158.205  < 2e-16 ***
## hr17                        0.874301   0.003784  231.040  < 2e-16 ***
## hr18                        1.294635   0.003254  397.848  < 2e-16 ***
## hr19                        1.212281   0.003321  365.084  < 2e-16 ***
## hr20                        0.914022   0.003700  247.065  < 2e-16 ***
## hr21                        0.616201   0.004191  147.045  < 2e-16 ***
## hr22                        0.364181   0.004659   78.173  < 2e-16 ***
## hr23                        0.117493   0.005225   22.488  < 2e-16 ***
## workingday                  0.014665   0.001955    7.502 6.27e-14 ***
## temp                        0.785292   0.011475   68.434  < 2e-16 ***
## weathersitcloudy/misty     -0.075231   0.002179  -34.528  < 2e-16 ***
## weathersitlight rain/snow -0.575800   0.004058 -141.905  < 2e-16 ***
## weathersitheavy rain/snow -0.926287   0.166782   -5.554 2.79e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 1052921  on 8644  degrees of freedom
## Residual deviance:  228041  on 8605  degrees of freedom
## AIC: 281159
##
## Number of Fisher Scoring iterations: 5
```

```
coef.months = c(coef(mod.pois)[2:12], -sum(coef(mod.pois)[2:12]))
plot(coef.months, xlab="Month", ylab="Coeff", xaxt="n", col="blue", pch=19, type="o")
axis(side=1, at=1:12, labels=c("J","F","M","A","M","J","J","A","S","O","N","D"))

coef.hrs = c(coef(mod.pois)[13:35], -sum(coef(mod.pois)[13:35]))
plot(coef.hrs, xlab="Hour", ylab="Coeff", xaxt="n", col="blue", pch=19, type="o")
```




```r
# Predict
par(mfrow=c(1,1))
plot(predict(mod.lm2), predict(mod.pois, type="response"))
abline(0,1, col=2, lwd=3)
```



Add a new chunk by clicking the *Insert Chunk* button on the toolbar or by pressing *Ctrl+Alt+I*.