STAT 388 Final

STAT 351/488

Predictive Analytics - Exam 2

Due December 10, 2019

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Problems 1-4

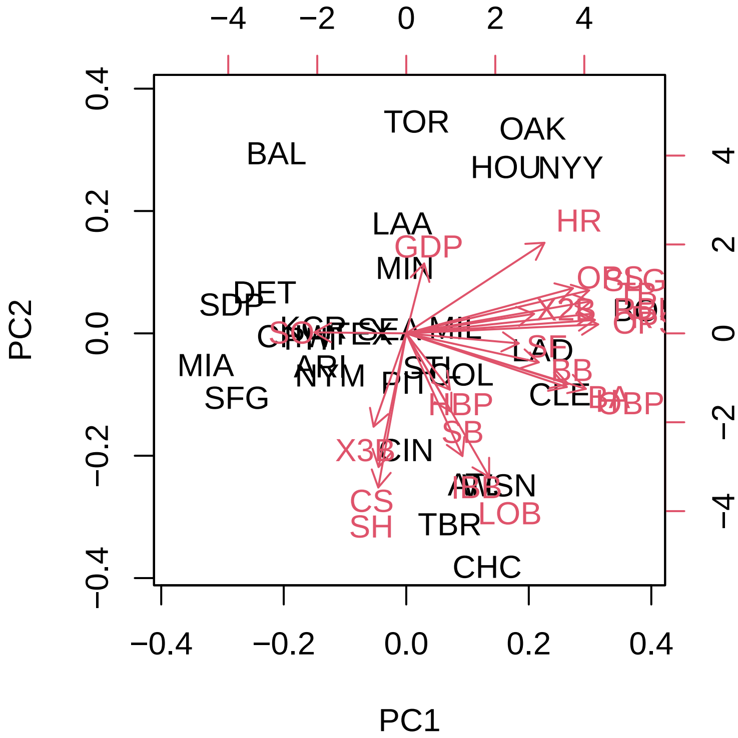
```
rm(list=ls())
"Problem 1:" # The main ideas of STAT 388: Predictive Analytics use sampling theory, non-parametric met
"Problem 2:" # We may choose to use a more restrictive method like a linear model if we are afraid of o
"Problem 3:" # In supervised learning, we have a set of "n" observations with "p" predictors and a resp
"Problem 4a:" # Generalized additive models (GAMs), logistic regression, principal component analysis (
"Problem 4b:" # Generalized additive models (GAMs), LASSO, ridge regression, random forests, and CART c
"Problem 4c:" # Principal component analysis (PCA) and hierarchical clustering are considered unsupervi
```

Problem 5

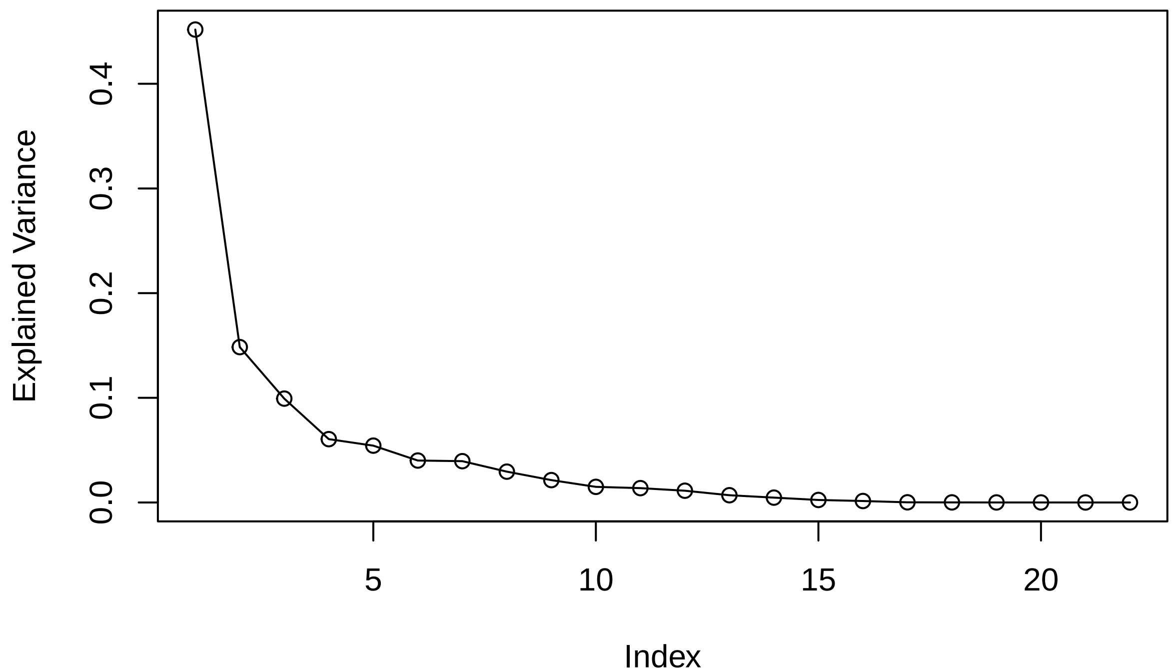
```
data <- read.csv(file="/Users/newuser/Desktop/Notes/Undergraduate/STAT 338 - Predictive Analytics/MLB20
data <- data[-(31:32),]
row.names(data) <- data$Tm
data <- data[,-(1:7)]
summary(prcomp(data,scale.=TRUE))
```

```
## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     3.1527 1.8069 1.47755 1.15377 1.09271 0.93897 0.93166
## Proportion of Variance 0.4518 0.1484 0.09923 0.06051 0.05427 0.04008 0.03945
## Cumulative Proportion  0.4518 0.6002 0.69944 0.75995 0.81422 0.85430 0.89375
##                            PC8     PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation     0.80496 0.68555 0.57310 0.54911 0.49714 0.39002 0.31890
## Proportion of Variance 0.02945 0.02136 0.01493 0.01371 0.01123 0.00691 0.00462
## Cumulative Proportion  0.92321 0.94457 0.95950 0.97321 0.98444 0.99135 0.99598
##                          PC15    PC16    PC17    PC18    PC19    PC20    PC21
## Standard deviation     0.2297 0.17469 0.05617 0.04042 0.01472 0.01291 0.00788
## Proportion of Variance 0.0024 0.00139 0.00014 0.00007 0.00001 0.00001 0.00000
## Cumulative Proportion  0.9984 0.99976 0.99991 0.99998 0.99999 1.00000 1.00000
##                             PC22
## Standard deviation     6.743e-16
## Proportion of Variance 0.000e+00
## Cumulative Proportion  1.000e+00
```

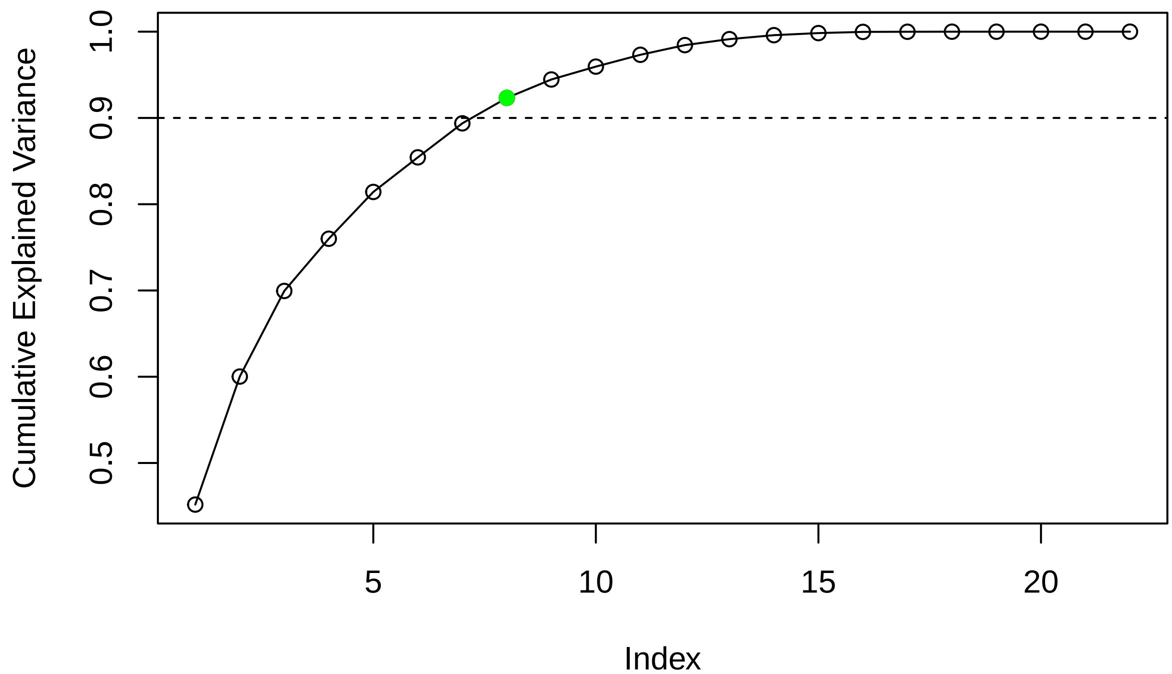
```
biplot(prcomp(data,scale.=TRUE))
```



```
plot(prcomp(data,scale.=TRUE)$sdev^2/sum(prcomp(data,scale.=TRUE)$sdev^2),ylab="Explained Variance",typ
```



```
# I would choose to keep 10 principal components. Ten principal components would explain over 95 percen
plot(cumsum(prcomp(data,scale.=TRUE)$sdev^2/sum(prcomp(data,scale.=TRUE)$sdev^2)),ylab="Cumulative Expla
abline(.9,0,lty=2)
points(8,cumsum(prcomp(data,scale.=TRUE)$sdev^2/sum(prcomp(data,scale.=TRUE)$sdev^2))[8],col="green",pch
```




```
cumsum(prcomp(data,scale.=TRUE)$sdev^2/sum(prcomp(data,scale.=TRUE)$sdev^2))[5:9] # Checking variance v
```

```
## [1] 0.8142246 0.8543007 0.8937546 0.9232072 0.9445701
```

```
# Eight principal components are needed to explain at least 90 percent of the variance.
```

Problem 6

```
library(glmnet)
set.seed(1012)
datam <- model.matrix(SB~.,data=data)
ridge <- glmnet(datam,data$SB,alpha=0,lambda=10^seq(10,-2,length=100))
best <- min(ridge$lambda)
error <- mean((predict(ridge,s=best,newx=datam)-data$SB)^2)
c(best,error)
```

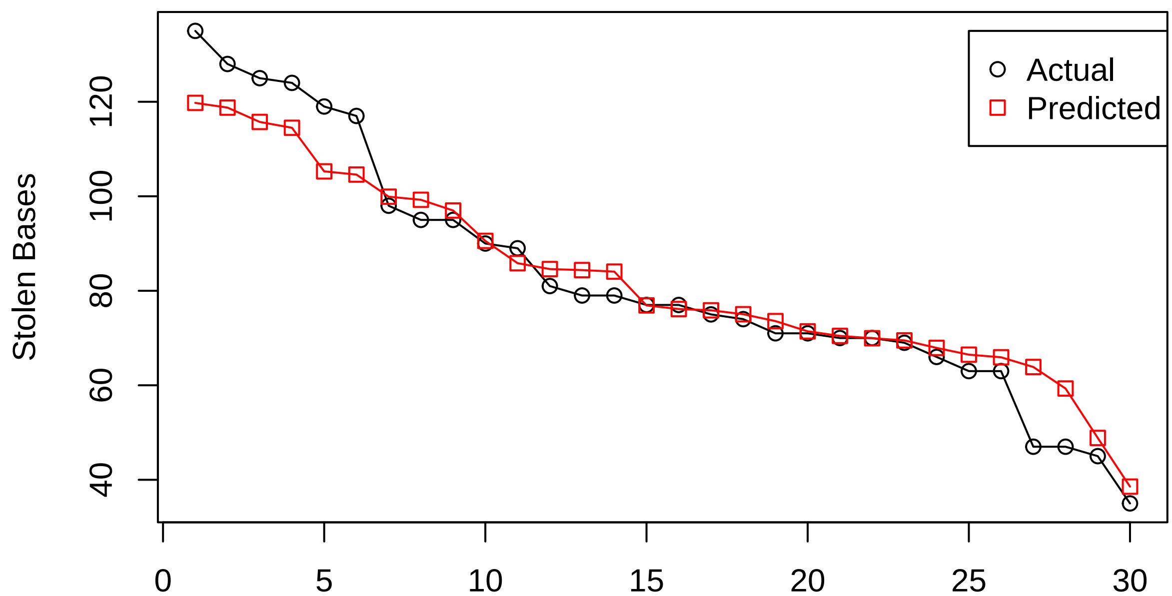
```
## [1]   0.0100 232.1994
```

```
predict(ridge,s=best,newx=datam)
```

```
##            s1
## ARI  69.50173
## ATL  75.04257
## BAL  66.48307
## BOS 105.26975
## CHC  99.25818
## CHW  85.83858
## CIN  76.90235
## CLE 119.76569
## COL 115.73317
## DET  67.91607
## HOU  69.96026
## KCR  90.56135
## LAA  84.59150
```

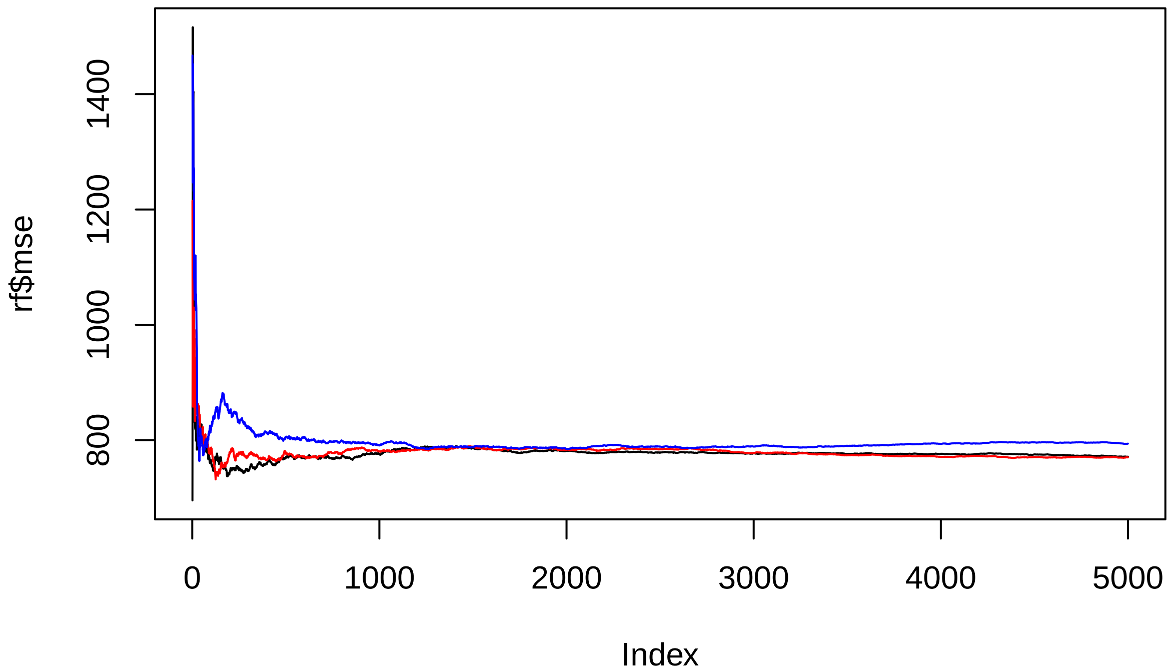
```
## LAD  76.13351
## MIA  63.86756
## MIL 114.49542
## MIN  65.93084
## NYM  84.37697
## NYY  73.58157
## OAK  38.55491
## PHI  48.85468
## PIT  75.86908
## SDP  96.98848
## SEA 104.59534
## SFG  70.45173
## STL  59.31710
## TBR 118.76694
## TEX  84.05801
## TOR  71.41790
## WSN  99.91569
```

```r
plot(sort(data$SB,decreasing=TRUE),xlab="",ylab="Stolen Bases",type="o")
points(sort(predict(ridge,s=best,newx=datam),decreasing=TRUE),pch=0,col="red",type="o")
legend(25,135,c("Actual","Predicted"),col=c("black","red"),pch=c(1,0))
```



Problem 7

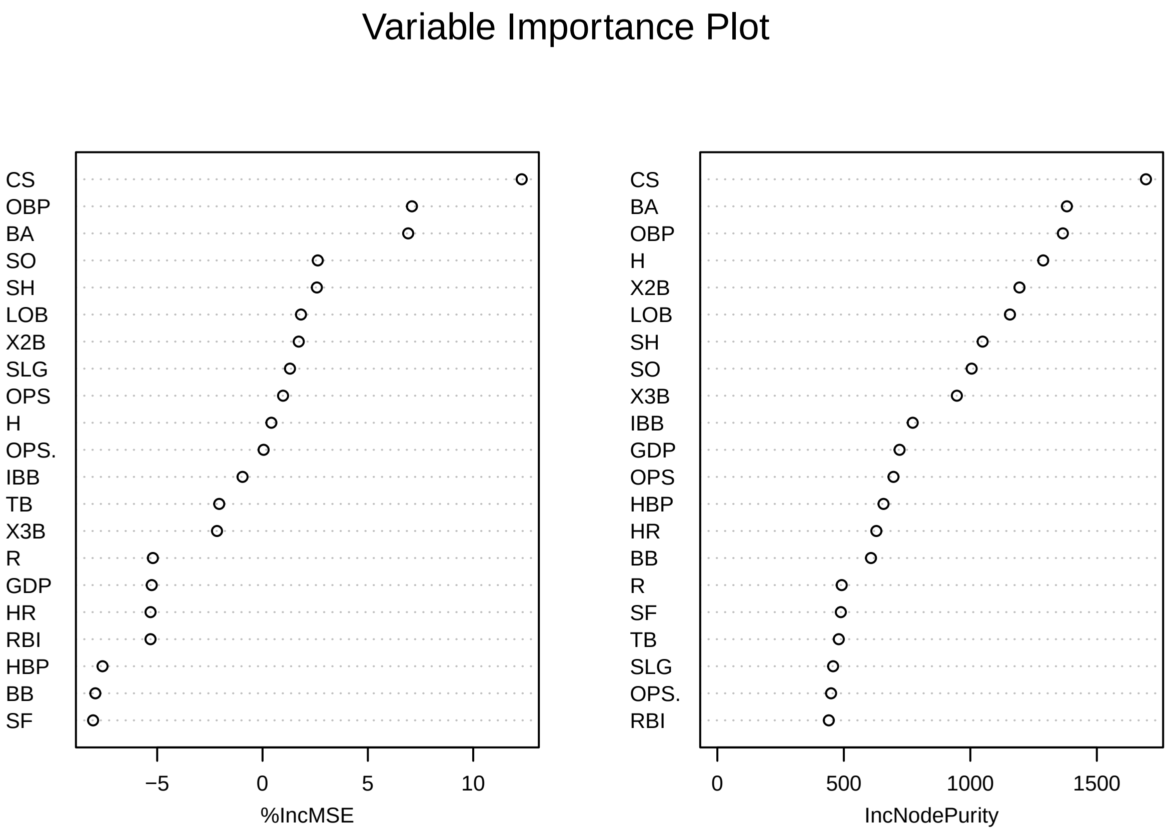
```r
library(randomForest)
set.seed(1012)
rf <- randomForest(SB~.,data=data,ntree=5000,importance=TRUE) # Choosing arbitrary number of trees
rf4 <- randomForest(SB~.,data=data,ntree=5000,importance=TRUE,mtry=4) # Choosing different numbers of v
rf11 <- randomForest(SB~.,data=data,ntree=5000,importance=TRUE,mtry=11)
plot(rf$mse,type="l")
points(1:5000,rf4$mse,type="l",col="red")
points(1:5000,rf11$mse,type="l",col="blue")
```




```r
summary(rf$mse)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   695.4   774.6   776.7   777.1   779.1  1516.1
```

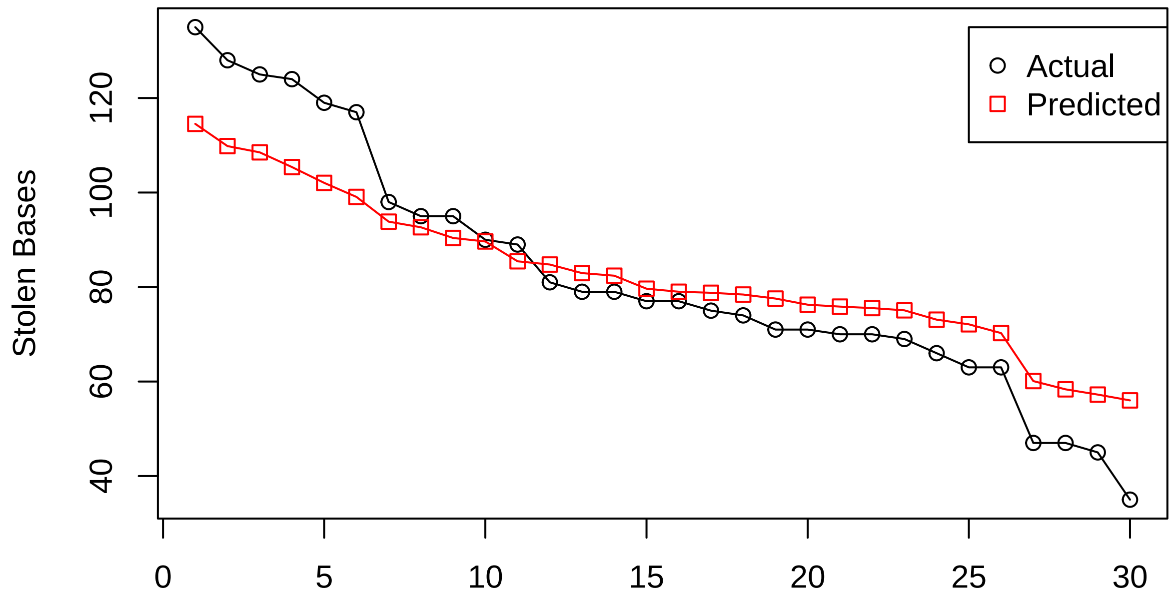
```r
varImpPlot(rf,main="Variable Importance Plot",cex=.7)
```



```r
predict(rf,data)
```

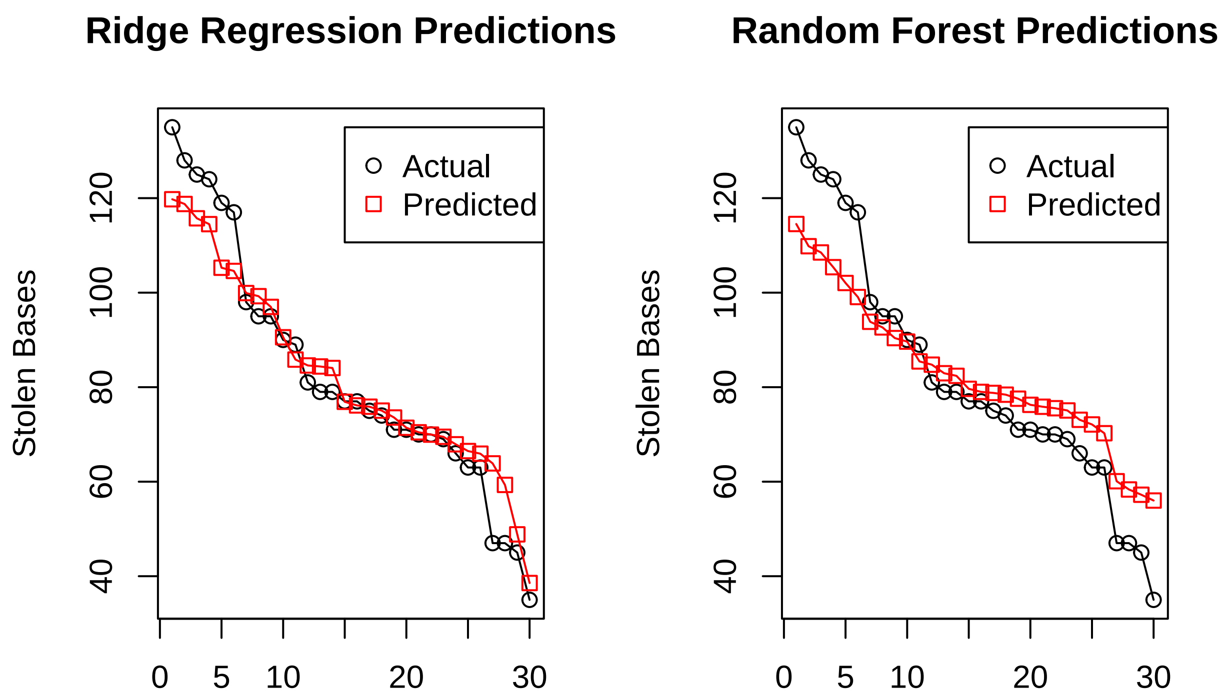
```
##       ARI       ATL       BAL       BOS       CHC       CHW       CIN       CLE
##  77.56218  90.38296  79.64770 109.82626  84.76034  92.64620  82.94535 114.53256
##       COL       DET       HOU       KCR       LAA       LAD       MIA       MIL
##  93.83679  75.07166  75.85750  99.07408  79.00810  82.40049  60.09915 102.04553
##       MIN       NYM       NYY       OAK       PHI       PIT       SDP       SEA
##  57.24135  75.54448  72.10698  58.34966  73.09732  78.78305  89.64224  85.44632
##       SFG       STL       TBR       TEX       TOR       WSN
##  78.41400  70.25515 108.50573  76.26723  56.00902 105.39279
```

```r
plot(sort(data$SB,decreasing=TRUE),xlab="",ylab="Stolen Bases",type="o")
points(sort(predict(rf,data),decreasing=TRUE),pch=0,col="red",type="o")
legend(25,135,c("Actual","Predicted"),col=c("black","red"),pch=c(1,0))
```



Problem 8

```r
par(mfrow=c(1,2))
plot(sort(data$SB,decreasing=TRUE),xlab="",ylab="Stolen Bases",main="Ridge Regression Predictions",type=
points(sort(predict(ridge,s=best,newx=datam),decreasing=TRUE),pch=0,col="red",type="o")
legend(15,135,c("Actual","Predicted"),col=c("black","red"),pch=c(1,0))
plot(sort(data$SB,decreasing=TRUE),xlab="",ylab="Stolen Bases",main="Random Forest Predictions",type="o
points(sort(predict(rf,data),decreasing=TRUE),pch=0,col="red",type="o")
legend(15,135,c("Actual","Predicted"),col=c("black","red"),pch=c(1,0))
```




```
# It looks like the ridge regression model is better in this case.
```

Problem 9

```
rm(list=ls())
n=30                                                                                    # Problem 9a
n
```

```
## [1] 30
```

```
x2=0                                                                                    # Problem 9b
x2 < 0.0396957
```

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

```
x1=1
x1 > 0.0682064
```

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

```
cat("Example point: x1=",x1,", x2=",x2,sep="")
```

```
## Example point: x1=1, x2=0
```

```
# Pruning the tree or choosing a smaller number of trees can help avoid overfitting. # Problem 9c
```

Problems 10-11

```
"Problem 10:" # The number of variables per split "m", usually sqrt(p) for a classification tree and p/
"Problem 11a:" # No, this classifier is not a maximal margin classifier. There is no maximal margin cla
"Problem 11b:" # The boundary could shift slightly to the right or rotate slightly counterclockwise (or
```

Problems 12-13

```
knitr::knit_hooks$set(error = function(x, options) {
  paste0("<pre style=\"color: red;\"><code>", x, "</code></pre>")
  })
Picture_With_Dr._Matthews_And_Dr._Perry_Being_BFFs              # Problem 12
```

```
Three_Reasons_Why_Smash_Mouth_Is_The_Greatest_Band_Of_All_Time # Problem 13
```