STATS hw4

August 12, 2018

1 Chapter 8: Exercise 10

1.1 a

```
In [1]: library(ISLR)
        data(Hitters)
        # summary(Hitters)
        sum(is.na(Hitters$Salary))
```

```
Warning message:
package ISLR was built under R version 3.4.2
```

59

```
In [2]: Hitters = na.omit(Hitters)
        sum(is.na(Hitters$Salary))
```

0

```
In [3]: Hitters$Salary = log(Hitters$Salary)
```

1.2 b

```
In [4]: Hitters.train = head(Hitters,200)
        Hitters.test = tail(Hitters,-200)
```

1.3 c

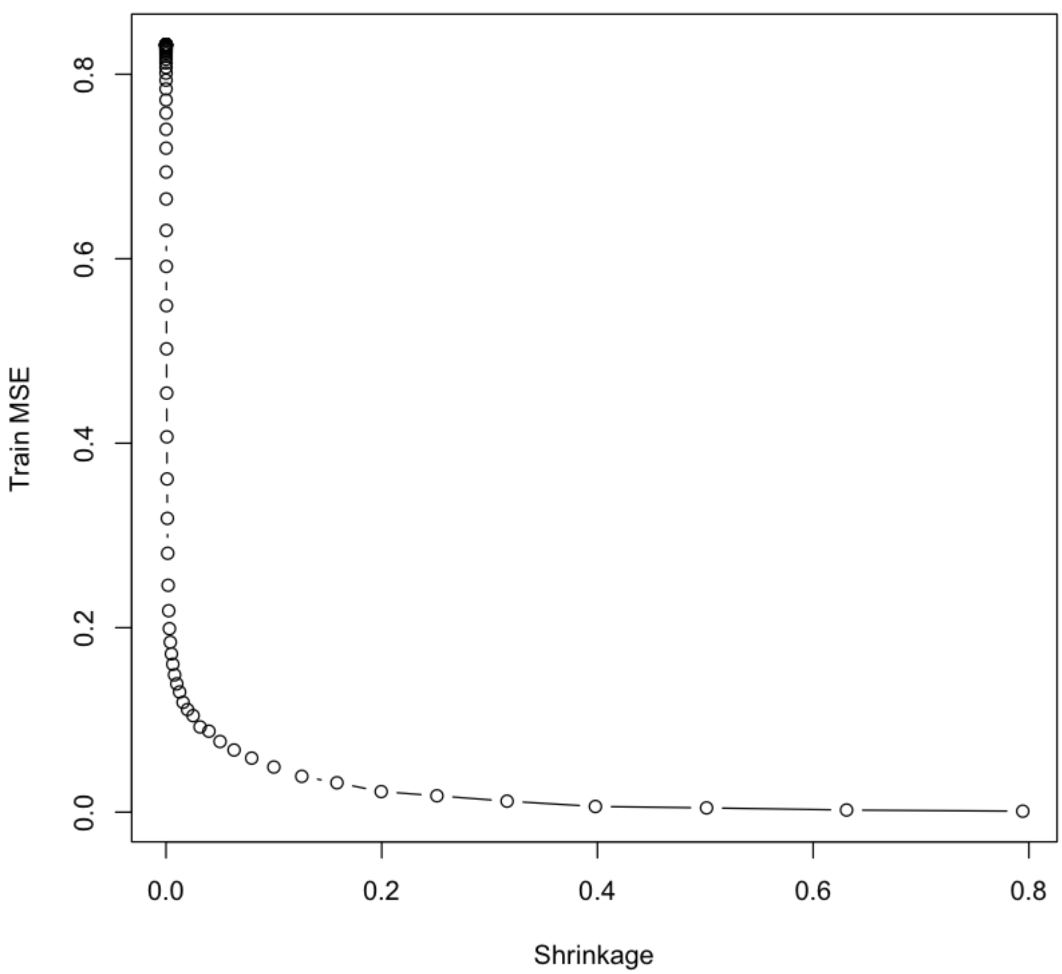
```
In [5]: library(gbm)
        set.seed(1)
        p = seq(-10, -0.1, by = 0.1)
        n = length(p)
        lambda = 10^p
        boost.train_errors = rep(1, n)
        boost.test_errors = rep(1, n)
```

```
Loading required package: survival
Loading required package: lattice
Loading required package: splines
```

```
Loading required package: parallel
Loaded gbm 2.1.3
```

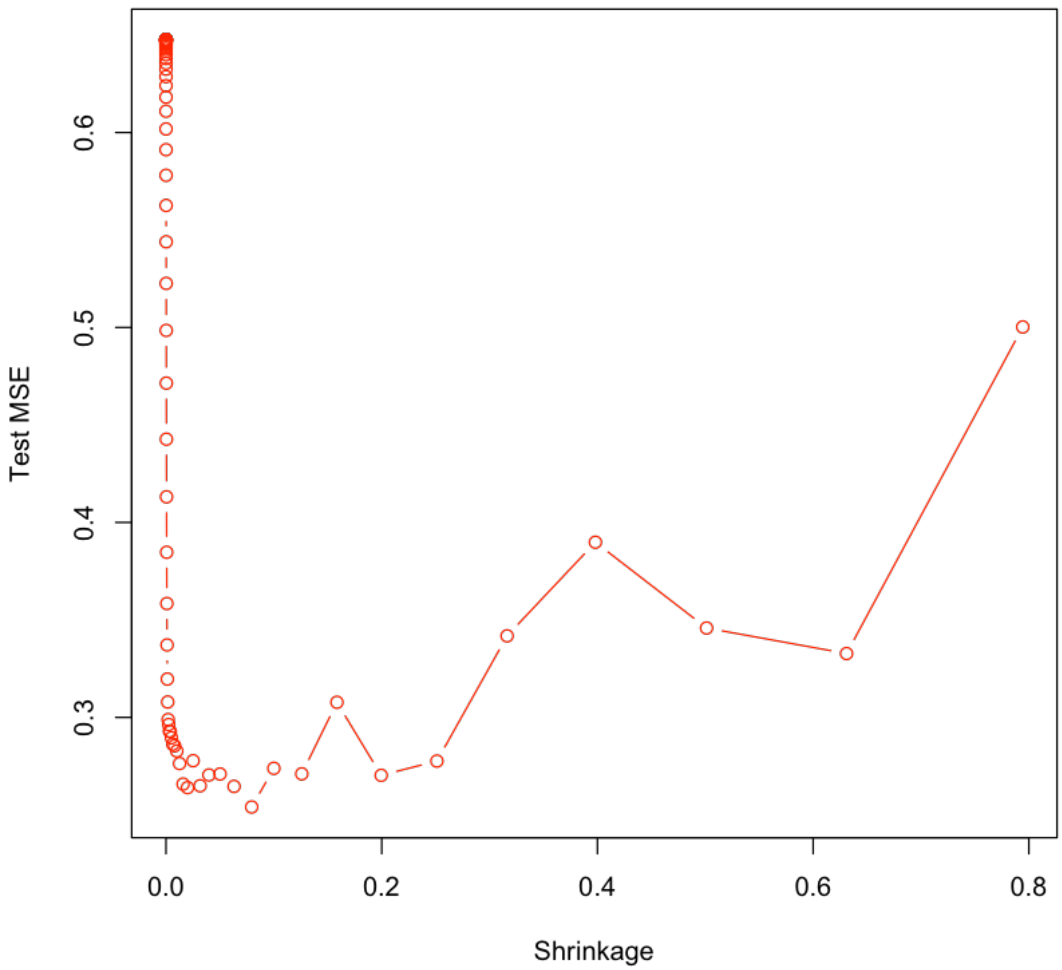
```
In [6]: for (i in 1:n)
        {
            boost.fit = gbm(Salary ~ ., data = Hitters.train, distribution = "gaussian",
                n.trees = 1000, shrinkage = lambda[i])
            boost.train_pred = predict(boost.fit, Hitters.train, n.trees = 1000)
            boost.test_pred = predict(boost.fit, Hitters.test, n.trees = 1000)
            boost.train_errors[i] = mean((Hitters.train$Salary - boost.train_pred)^2)
            boost.test_errors[i] = mean((Hitters.test$Salary - boost.test_pred)^2)
        }
```

```
In [7]: plot(lambda, boost.train_errors, type = "b", xlab = "Shrinkage", ylab = "Train MSE")
```



1.4 d

```
In [8]: plot(lambda, boost.test_errors, type = "b", xlab = "Shrinkage", ylab = "Test MSE", col =
```



1.5 e

```
In [9]: lm.fit = lm(Salary ~ ., data = Hitters.train)
        lm.pred = predict(lm.fit, Hitters.test)
        mean((Hitters.test$Salary - lm.pred)^2)
```

0.491795937545494

```
In [10]: library(glmnet)
         set.seed(1)
         xtrain = model.matrix(Salary ~ ., data = Hitters.train)
         ytrain = Hitters.train$Salary
         xtest = model.matrix(Salary ~ ., data = Hitters.test)
         lasso.fit = glmnet(xtrain, ytrain, alpha = 1)
         lasso.pred = predict(lasso.fit, s = 0.01, newx = xtest)
         mean((Hitters.test$Salary - lasso.pred)^2)
```

```
Warning message:
package glmnet was built under R version 3.4.4Loading required package: Matrix
Loading required package: foreach
Warning message:
package foreach was built under R version 3.4.3Loaded glmnet 2.0-16
```

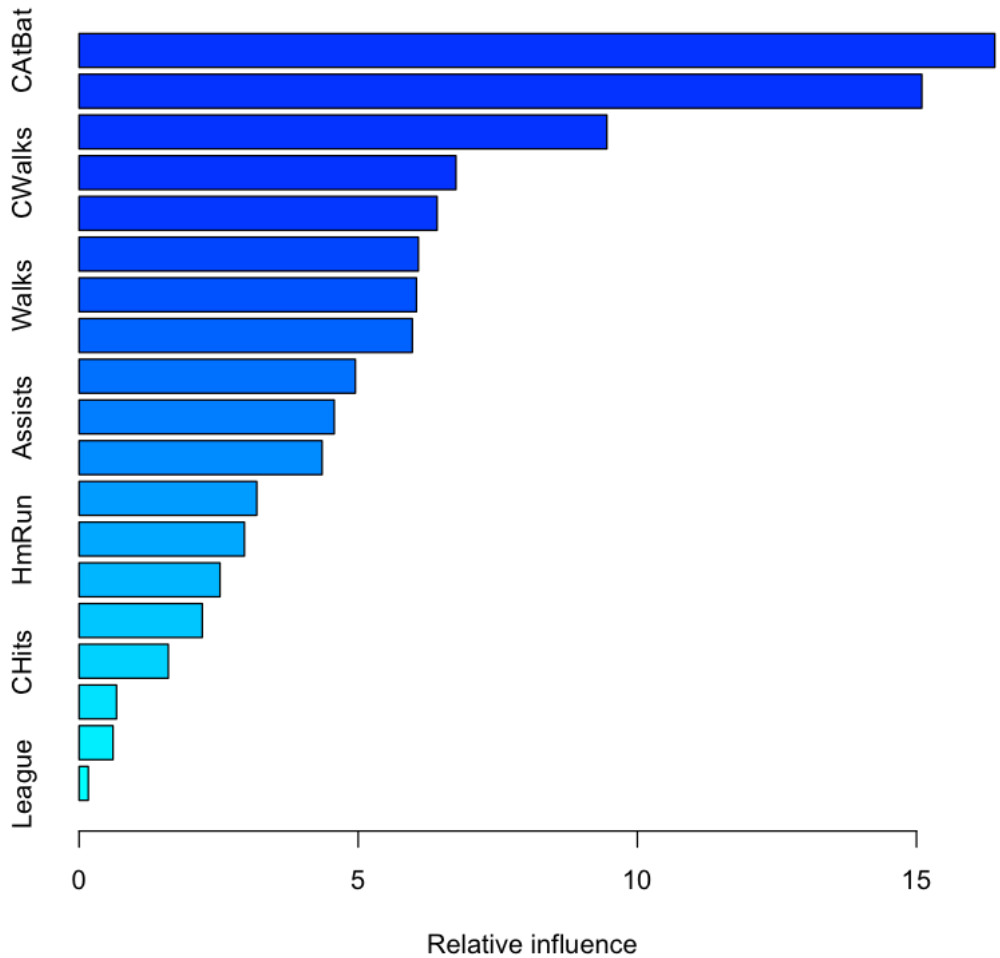
0.470053732710274

The test MSE of boosting is lower than both of the regression methods.

1.6 f

```
In [11]: best_lambda = lambda[which.min(boost.test_errors)]
         boost.best = gbm(Salary ~ ., data = Hitters.train, distribution = "gaussian",
             n.trees = 1000, shrinkage = best_lambda)
         summary(boost.best)
```

	var	rel.inf
CAtBat	CAtBat	16.4028631
CRuns	CRuns	15.0957847
PutOuts	PutOuts	9.4543457
CWalks	CWalks	6.7508573
CRBI	CRBI	6.4133341
CHmRun	CHmRun	6.0778920
Walks	Walks	6.0434466
Years	Years	5.9694890
Hits	Hits	4.9492273
Assists	Assists	4.5706789
RBI	RBI	4.3533790
AtBat	AtBat	3.1830285
HmRun	HmRun	2.9616488
Runs	Runs	2.5244563
Errors	Errors	2.2067482
CHits	CHits	1.5986893
Division	Division	0.6707407
NewLeague	NewLeague	0.6083337
League	League	0.1650564



`CAtBat`,`CRuns`,`PutOuts` are most important predictors in the boosted model.

1.7 g

```
In [12]: library(rpart)
         library(ipred)
         bagging.fit = bagging(Salary ~ ., data = Hitters.train, coob=TRUE)
         bagging.pred = predict(bagging.fit, Hitters.test)
         mean((Hitters.test$Salary - bagging.pred)^2)
```

0.278460475018155

2 Chapter 8, Exercise 11 (p. 335)

2.1 a

```
In [38]: library(ISLR)
         data(Caravan)
         train = 1:1000
         Caravan$Purchase = ifelse(Caravan$Purchase == "Yes", 1, 0)
         Caravan.train = Caravan[train, ]
         Caravan.test = Caravan[-train, ]
```

2.2 b

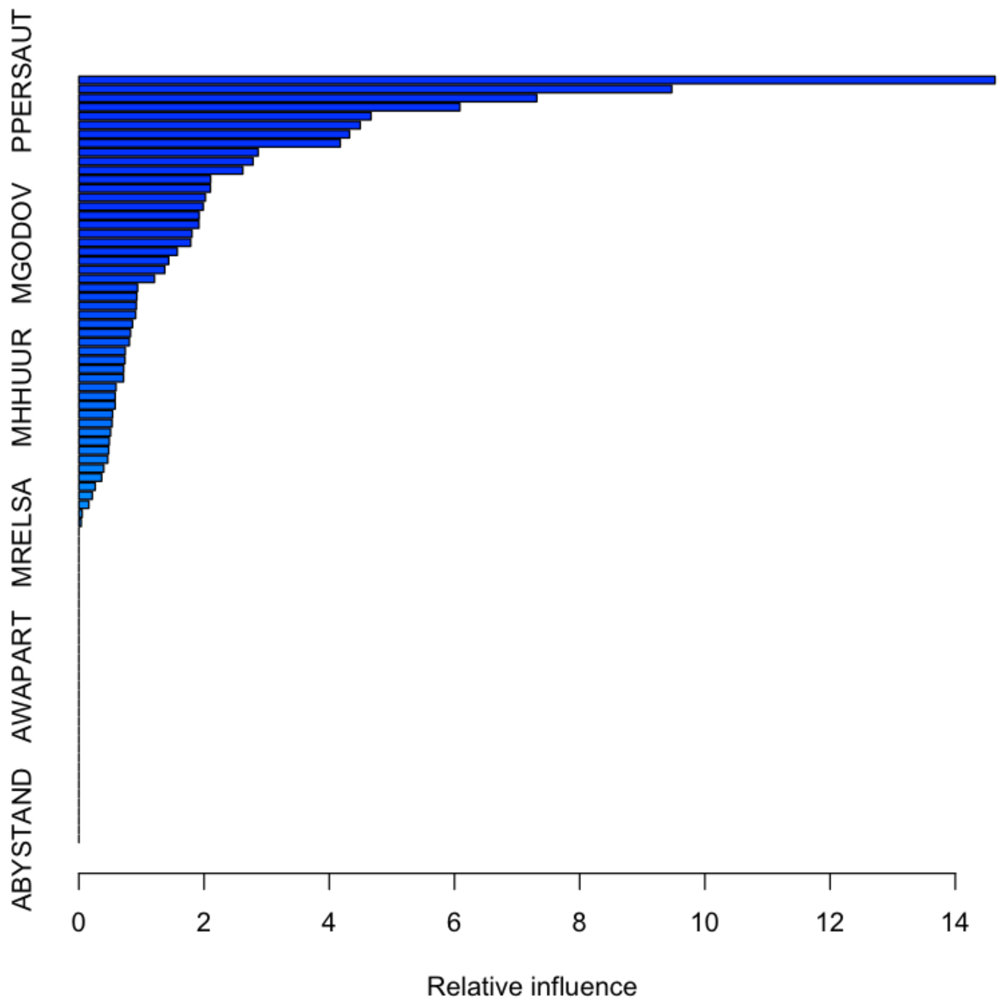
```
In [39]: library(gbm)
         set.seed(1)
         boost.fit = gbm(Purchase ~ ., data = Caravan.train, n.trees = 1000, shrinkage = 0.01)
```

```
Distribution not specified, assuming bernoulli ...


Warning message in gbm.fit(x, y, offset = offset, distribution = distribution, w = w, :
variable 50: PVRAAUT has no variation.Warning message in gbm.fit(x, y, offset = offset, distribu
variable 71: AVRAAUT has no variation.
```

```
In [42]: summary(boost.fit)
```

	var	rel.inf
PPERSAUT	PPERSAUT	14.6350478
MKOOPKLA	MKOOPKLA	9.4709165
MOPLHOOG	MOPLHOOG	7.3145742
MBERMIDD	MBERMIDD	6.0865197
PBRAND	PBRAND	4.6676612
MGODGE	MGODGE	4.4946326
ABRAND	ABRAND	4.3242776
MINK3045	MINK3045	4.1759062
MOSTYPE	MOSTYPE	2.8640258
PWAPART	PWAPART	2.7819107
MAUT1	MAUT1	2.6192915
MBERARBG	MBERARBG	2.1048051
MSKA	MSKA	2.1018515
MAUT2	MAUT2	2.0217251
MSKC	MSKC	1.9868434
MINKGEM	MINKGEM	1.9212271
MGODPR	MGODPR	1.9177754
MBERHOOG	MBERHOOG	1.8071062
MGODOV	MGODOV	1.7869391
PBYSTAND	PBYSTAND	1.5727959
MSKB1	MSKB1	1.4355140
MFWEKIND	MFWEKIND	1.3726426
MRELGE	MRELGE	1.2080518
MOPLMIDD	MOPLMIDD	0.9379197
MINK7512	MINK7512	0.9259072
MINK4575	MINK4575	0.9174599
MGODRK	MGODRK	0.9076554
MFGEKIND	MFGEKIND	0.8574537
MZPART	MZPART	0.8253107
MRELOV	MRELOV	0.8073125
PAANHANG	PAANHANG	0
PTRACTOR	PTRACTOR	0
PWERKT	PWERKT	0
PBROM	PBROM	0
PPERSONG	PPERSONG	0
PGEZONG	PGEZONG	0
PWAOREG	PWAOREG	0
PZEILPL	PZEILPL	0
PPLEZIER	PPLEZIER	0
PFIETS	PFIETS	0
PINBOED	PINBOED	0
AWAPART	AWAPART	0
AWABEDR	AWABEDR	0
AWALAND	AWALAND	0
ABESAUT	ABESAUT	0
AMOTSCO	AMOTSCO	0
AVRAAUT	AVRAAUT	0
AAANHANG	AAANHANG	0
ATRACTOR	ATRACTOR	0
AWERKT	AWERKT	0
ABROM	ABROM	0



PPERSAUT, MKOOPKLA and MOPLHOOG are the most important predictors

2.3 c

```
In [47]: boost.prob = predict(boost.fit, Caravan.test, n.trees = 1000, type = "response")
         boost.pred = ifelse(boost.prob > 0.2, 1, 0)
         table(Caravan.test$Purchase, boost.pred)
```

```
   boost.pred
       0    1
  0 4410  123
  1  256   33
```

```
In [48]: 33/(33+123)
```

0.211538461538462
21.1% of the people predicted to make a purchase by boosting model do make one.
KNN:

```
In [52]: library(class)
         knn.pred = knn(Caravan.train, Caravan.test, Caravan.train$Purchase, k = 3, l = 0, prob
         table(Caravan.test$Purchase, knn.pred)
```

```
   knn.pred
       0    1
  0 4474   59
  1  279   10
```

```
In [53]: 10/(59+10)
```

0.144927536231884
Logistic:

```
In [59]: lm.fit = glm(as.factor(Purchase) ~ .-Purchase, data = Caravan.train, family = binomial)
         lm.prob = predict(lm.fit, Caravan.test, type = "response")
         lm.pred = ifelse(lm.prob > 0.2, 1, 0)
         table(Caravan.test$Purchase, lm.pred)
```

```
Warning message:
glm.fit: fitted probabilities numerically 0 or 1 occurredWarning message in predict.lm(object, n
prediction from a rank-deficient fit may be misleading
```

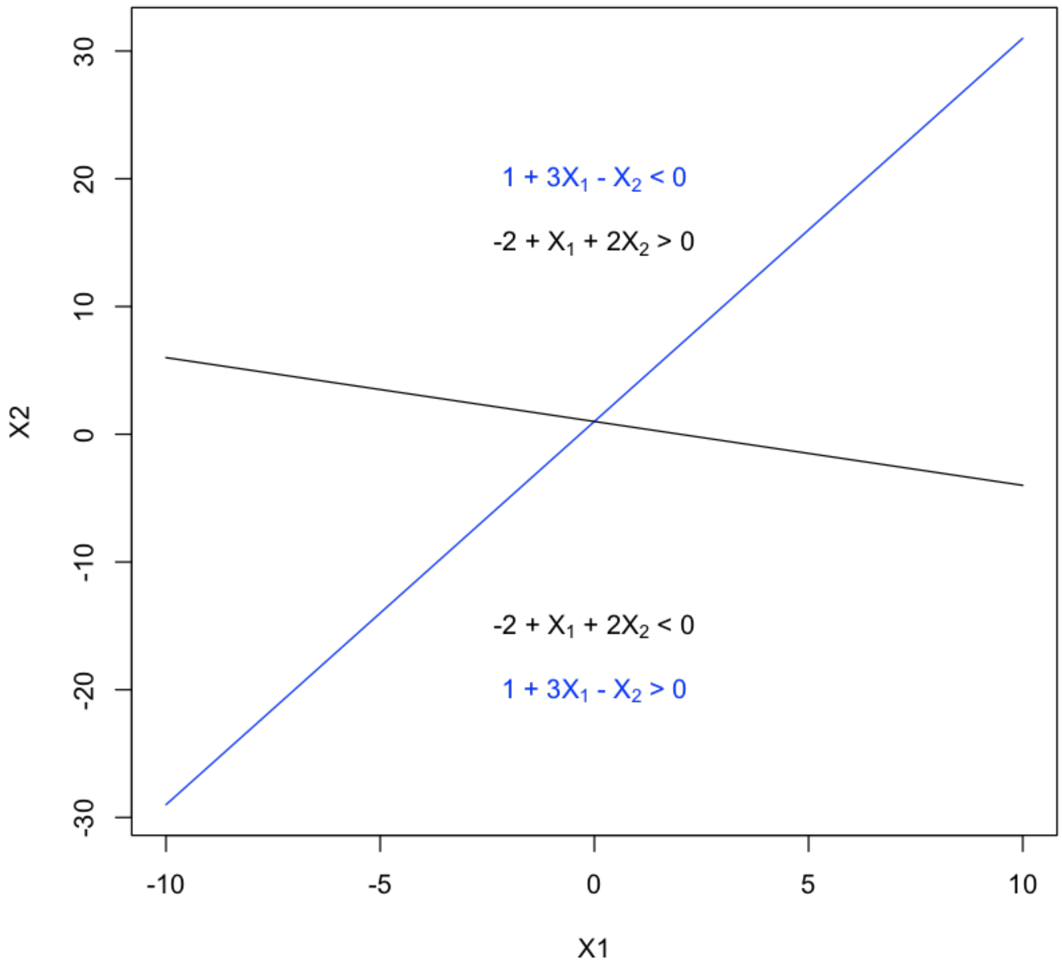
```
   lm.pred
       0    1
  0 4183  350
  1  231   58
```

```
In [60]: 58/(350 + 58)
```

0.142156862745098
The fraction by boosting is higher.

3 Chapter 9, Exercise 1 (p. 368)

```
In [76]: X1 = -10:10
         X2 = 1 + 3 * X1
         plot(X1, X2, type = "l", col = "blue")
         text(c(0), c(-20), TeX("1 + 3X_1 - X_2 > 0"), col = "blue")
         text(c(0), c(20), TeX("1 + 3X_1 - X_2 < 0"), col = "blue")
         lines(X1, 1 - X1/2)
         text(c(0), c(-15), TeX("-2 + X_1 + 2X_2 < 0"))
         text(c(0), c(15), TeX("-2 + X_1 + 2X_2 > 0"))
```



4 Chapter 9, Exercise 8 (p. 371)

```
In [77]: library(ISLR)
         data(OJ)
```

4.1 a

```
In [80]: istrain = sample(nrow(OJ), 800)
         OJ.train = OJ[istrain, ]
         OJ.test = OJ[-istrain, ]
```

4.2 b

```
In [89]: library(e1071)
         svm.fit = svm(Purchase ~ ., kernel = "linear", data = OJ.train, cost = 0.01)
         summary(svm.fit)
```

```
Call:
svm(formula = Purchase ~ ., data = OJ.train, kernel = "linear", cost = 0.01)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  0.01
      gamma:  0.05555556

Number of Support Vectors:  419

 ( 209 210 )


Number of Classes:  2

Levels:
 CH MM
```

Support vector classifier has 419 support vectors (209 CH, 210 MM) out of 800 training points.

4.3 c

Training Error Rate:

```
In [91]: train.pred = predict(svm.fit, OJ.train)
         table(OJ.train$Purchase, train.pred)
         mean(OJ.train$Purchase != train.pred)
```

```
    train.pred
      CH  MM
  CH 443  56
  MM  71 230
```

0.15875
Test Error Rate:

In [92]:
```
test.pred = predict(svm.fit, OJ.test)
table(OJ.test$Purchase, test.pred)
mean(OJ.test$Purchase != test.pred)
```

```
    test.pred
      CH  MM
  CH 133  21
  MM  34  82
```

0.203703703703704

4.4 d

In [95]:
```
set.seed(1)
svm.tune = tune(svm, Purchase ~ ., data = OJ.train, kernel = "linear", ranges = list(co
    1, by = 0.25)))
summary(svm.tune)
```

```
Parameter tuning of svm:

- sampling method: 10-fold cross validation

- best parameters:
 cost
  0.1

- best performance: 0.15625

- Detailed performance results:
          cost   error dispersion
1   0.01000000 0.16750 0.02838231
2   0.01778279 0.17125 0.02208726
3   0.03162278 0.17000 0.02776389
4   0.05623413 0.16375 0.02729087
5   0.10000000 0.15625 0.03076005
6   0.17782794 0.15750 0.03446012
7   0.31622777 0.16250 0.03173239
8   0.56234133 0.15875 0.03283481
9   1.00000000 0.15875 0.03120831
10  1.77827941 0.16000 0.02622022
11  3.16227766 0.16000 0.03106892
12  5.62341325 0.16250 0.03061862
13 10.00000000 0.15625 0.02585349
```

4.5 e

In [108]:
```
svm.fit_best = svm(Purchase ~ ., kernel = "linear", data = OJ.train, cost = 0.1)
train.pred = predict(svm.fit_best, OJ.train)
table(OJ.train$Purchase, train.pred)
train_error = mean(OJ.train$Purchase != train.pred)
train_error
test.pred = predict(svm.fit_best, OJ.test)
table(OJ.test$Purchase, test.pred)
test_error = mean(OJ.test$Purchase != test.pred)
test_error
```

```
    train.pred
      CH  MM
  CH 444  55
  MM  66 235
```

0.15125

```
    test.pred
      CH  MM
  CH 134  20
  MM  32  84
```

0.192592592592593

4.6 f

In [102]:
```
library(e1071)
svm.fit = svm(Purchase ~ ., kernel = "radial", data = OJ.train, cost = 0.01)
summary(svm.fit)
```

```
Call:
svm(formula = Purchase ~ ., data = OJ.train, kernel = "radial", cost = 0.01)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  0.01
      gamma:  0.05555556

Number of Support Vectors:  604

 ( 301 303 )
```

```
Number of Classes:  2

Levels:
 CH MM
```

```
In [103]: train.pred = predict(svm.fit, OJ.train)
          table(OJ.train$Purchase, train.pred)
          train_error = mean(OJ.train$Purchase != train.pred)
          train_error
          test.pred = predict(svm.fit_best, OJ.test)
          table(OJ.test$Purchase, test.pred)
          test_error = mean(OJ.test$Purchase != test.pred)
          test_error
```

```
    train.pred
      CH  MM
  CH 499   0
  MM 301   0
```

0.37625

```
    test.pred
      CH  MM
  CH 134  20
  MM  32  84
```

0.192592592592593

```
In [104]: set.seed(1)
          svm.tune = tune(svm, Purchase ~ ., data = OJ.train, kernel = "radial", ranges = list(c
              1, by = 0.25)))
          summary(svm.tune)
```

```
Parameter tuning of svm:

- sampling method: 10-fold cross validation

- best parameters:
      cost
 0.5623413
```

```
- best performance: 0.15625

- Detailed performance results:
          cost   error dispersion
1    0.01000000 0.37625 0.05876330
2    0.01778279 0.37625 0.05876330
3    0.03162278 0.36375 0.06599926
4    0.05623413 0.20375 0.03175973
5    0.10000000 0.17625 0.03606033
6    0.17782794 0.17500 0.03061862
7    0.31622777 0.16250 0.03173239
8    0.56234133 0.15625 0.03498512
9    1.00000000 0.15625 0.03644345
10   1.77827941 0.15625 0.02901748
11   3.16227766 0.16500 0.02024160
12   5.62341325 0.16375 0.02972676
13 10.00000000 0.16875 0.03346329
```

In [107]:
```
svm.fit_best = svm(Purchase ~ ., kernel = "radial", data = OJ.train, cost = 0.5623413)
train.pred = predict(svm.fit_best, OJ.train)
table(OJ.train$Purchase, train.pred)
train_error = mean(OJ.train$Purchase != train.pred)
train_error
test.pred = predict(svm.fit_best, OJ.test)
table(OJ.test$Purchase, test.pred)
test_error = mean(OJ.test$Purchase != test.pred)
test_error
```

```
    train.pred
      CH  MM
  CH 460  39
  MM  72 229
```

0.13875

```
    test.pred
      CH  MM
  CH 138  16
  MM  35  81
```

0.188888888888889

4.7 g

In [111]:
```
svm.fit = svm(Purchase ~ ., kernel = "poly", degree = 2, data = OJ.train, cost = 0.01)
summary(svm.fit)
```

```
Call:
svm(formula = Purchase ~ ., data = OJ.train, kernel = "poly", degree = 2,
    cost = 0.01)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  polynomial
       cost:  0.01
     degree:  2
      gamma:  0.05555556
     coef.0:  0

Number of Support Vectors:  606

 ( 301 305 )


Number of Classes:  2

Levels:
 CH MM
```

```
In [112]: train.pred = predict(svm.fit, OJ.train)
          table(OJ.train$Purchase, train.pred)
          train_error = mean(OJ.train$Purchase != train.pred)
          train_error
          test.pred = predict(svm.fit_best, OJ.test)
          table(OJ.test$Purchase, test.pred)
          test_error = mean(OJ.test$Purchase != test.pred)
          test_error
```

```
    train.pred
      CH  MM
  CH 499   0
  MM 301   0
```

0.37625

```
    test.pred
      CH  MM
  CH 134  20
  MM  32  84
```

0.192592592592593

In [113]:
```
svm.fit_best = svm(Purchase ~ ., kernel = "poly", degree = 2, data = OJ.train, cost =
train.pred = predict(svm.fit_best, OJ.train)
table(OJ.train$Purchase, train.pred)
train_error = mean(OJ.train$Purchase != train.pred)
train_error
test.pred = predict(svm.fit_best, OJ.test)
table(OJ.test$Purchase, test.pred)
test_error = mean(OJ.test$Purchase != test.pred)
test_error
```

```
   train.pred
     CH  MM
  CH 470  29
  MM 113 188
```

0.1775

```
   test.pred
     CH  MM
  CH 142  12
  MM  51  65
```

0.233333333333333

Overall, radial basis kernel gives the best result on this data.