Give Me Some Credit Data Set from a Kaggle competition

1 Description

This is a kaggle competition data set.

There are 150,000 observations in the kaggle training data.

The Y is: "Person experienced 90 days past due delinquency or worse: Y/N"

Can you predict when an account is going to be delinquent!

Data can be obtained from here: https://www.kaggle.com/c/GiveMeSomeCredit

2 Preprocessing

We download the data and preprocess it first. We split the kaggle training data into a 50% train and 50% test. The kaggle test does not come with y! We made y=1 if delinquent and 0 else.

```
download.file(
    'https://github.com/ChicagoBoothML/MLClassData/raw/master/GiveMeSomeCredit/CreditScoring.csv',
    'CreditScoring.csv')

trainDf = read.csv("CreditScoring.csv")

##remove X (is 1:n)
trainDf = trainDf[,-1]

##add y as factor
trainDf$y = as.factor(trainDf$SeriousDlqin2yrs)
trainDf = trainDf[,-1] # get rid of old y = SeriousDlqin2yrs

##get rid of NumberOfDependents, don't want to deal with NA's
trainDf=trainDf[,-10]
##get rid of MonthlyIncome, don't want to deal with NA's
trainDf=trainDf[,-5]

##split train in train, test
n=nrow(trainDf)
set.seed(99)
ii = sample(1:n,n)
ntest = floor(n/2)
testDf = trainDf[ii[1:ntest],]
trainDf = trainDf[ii[(ntest+1):n],]
```

3 Summary statistics

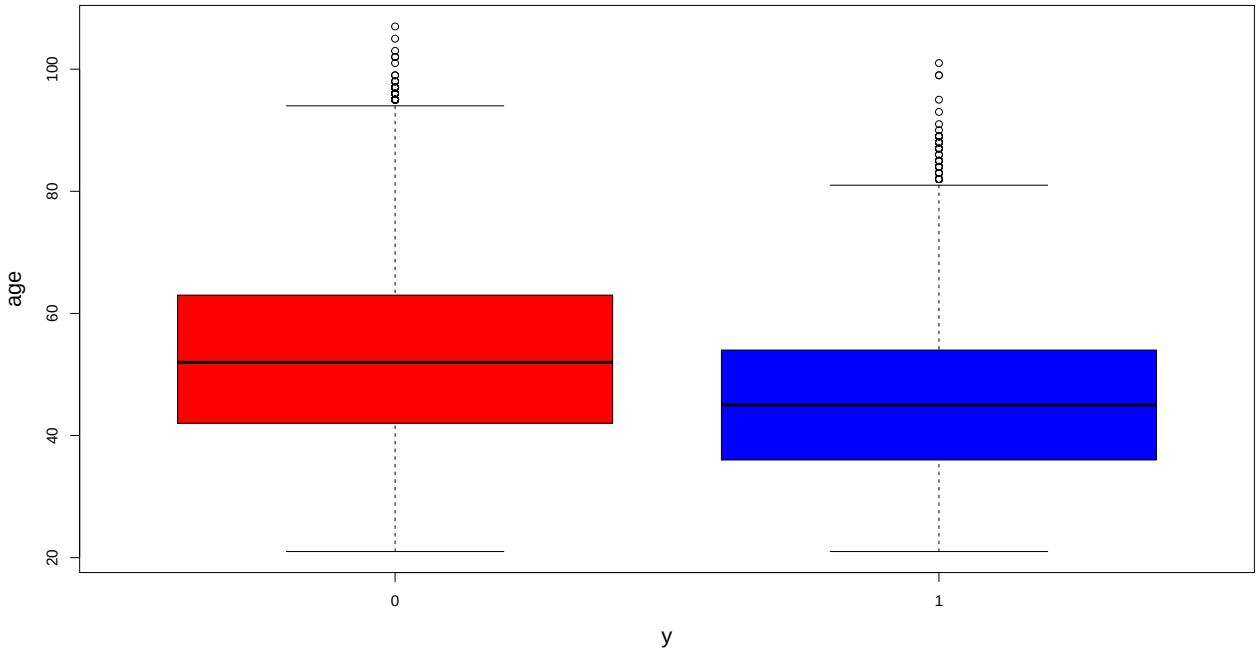
```
table(trainDf$y)
```

```
##
##     0     1
## 70021  4979
```

6 to 7 % of accounts are delinquent.

For example, it looks like older people are less likely to be delinquent.

```
plot(age~y,trainDf,col=c("red","blue"),cex.lab=1.4)
```



4 Fit models

We fit

- logistic regression
- random forest model
- boosting

```
library(ROCR)
```

```
## Loading required package: gplots
```

```
##
## Attaching package: 'gplots'
```

```
## The following object is masked from 'package:stats':
##
##     lowess
```

```
library(tree)
library(randomForest)
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
library(gbm)
```

```
## Loading required package: survival
```

```
## Loading required package: lattice
```

```
## Loading required package: splines
```

```
## Loading required package: parallel
```

```
## Loaded gbm 2.1.1
```

Create some helper function used for evaluation.

The following function is used to compute the deviance of a model

```
# deviance loss function
# y should be 0/1
# phat are probabilities obtain by our algorithm
# wht shrinks probs in phat towards .5 --- this helps avoid numerical problems don't use log(0)!
lossf = function(y,phat,wht=0.0000001) {
   if(is.factor(y)) y = as.numeric(y)-1
   phat = (1-wht)*phat + wht*.5
   py = ifelse(y==1, phat, 1-phat)
   return(-2*sum(log(py)))
}
```

The following will get confucion matrix:

```
# deviance loss function
# y should be 0/1
# phat are probabilities obtain by our algorithm
# thr is the cut off value - everything above thr is classified as 1
getConfusionMatrix = function(y,phat,thr=0.5) {
   if(is.factor(y)) y = as.numeric(y)-1
   yhat = ifelse(phat > thr, 1, 0)
```

```
   tb = table(predictions = yhat,
                    actual = y)
   rownames(tb) = c("predict_0", "predict_1")
   return(tb)
}
```

And finally, this function gives miss-classification rate:

```
# deviance loss function
# y should be 0/1
# phat are probabilities obtain by our algorithm
# thr is the cut off value - everything above thr is classified as 1
lossMR = function(y,phat,thr=0.5) {
   if(is.factor(y)) y = as.numeric(y)-1
   yhat = ifelse(phat > thr, 1, 0)
   return(1 - mean(yhat == y))
}
```

We need a place to store results

```
phatL = list() #store the test phat for the different methods here
```

4.1 Logistic regression

We fit a logistic regression model using all variables

```
lgfit = glm(y~., trainDf, family=binomial)
print(summary(lgfit))
```

```
##
## Call:
## glm(formula = y ~ ., family = binomial, data = trainDf)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -3.120  -0.389  -0.317  -0.258   4.178
##
## Coefficients:
##                                        Estimate
## (Intercept)                           -1.28e+00
## RevolvingUtilizationOfUnsecuredLines -4.05e-05
## age                                   -3.18e-02
## NumberOfTime30.59DaysPastDueNotWorse  5.00e-01
## DebtRatio                             -2.65e-06
## NumberOfOpenCreditLinesAndLoans       -6.69e-03
## NumberOfTimes90DaysLate               4.49e-01
## NumberRealEstateLoansOrLines          3.65e-02
## NumberOfTime60.89DaysPastDueNotWorse -9.15e-01
##                                       Std. Error
## (Intercept)                             5.63e-02
## RevolvingUtilizationOfUnsecuredLines   7.76e-05
## age                                     1.16e-03
## NumberOfTime30.59DaysPastDueNotWorse   1.56e-02
## DebtRatio                               9.61e-06
## NumberOfOpenCreditLinesAndLoans         3.51e-03
```

```
## NumberOfTimes90DaysLate                2.13e-02
## NumberRealEstateLoansOrLines           1.46e-02
## NumberOfTime60.89DaysPastDueNotWorse   2.49e-02
##                                      z value
## (Intercept)                          -22.68
## RevolvingUtilizationOfUnsecuredLines   -0.52
## age                                  -27.35
## NumberOfTime30.59DaysPastDueNotWorse   32.07
## DebtRatio                             -0.28
## NumberOfOpenCreditLinesAndLoans        -1.91
## NumberOfTimes90DaysLate                21.02
## NumberRealEstateLoansOrLines            2.49
## NumberOfTime60.89DaysPastDueNotWorse  -36.78
##                                     Pr(>|z|)
## (Intercept)                           <2e-16
## RevolvingUtilizationOfUnsecuredLines    0.602
## age                                   <2e-16
## NumberOfTime30.59DaysPastDueNotWorse   <2e-16
## DebtRatio                              0.783
## NumberOfOpenCreditLinesAndLoans         0.057
## NumberOfTimes90DaysLate                <2e-16
## NumberRealEstateLoansOrLines            0.013
## NumberOfTime60.89DaysPastDueNotWorse   <2e-16
##
## (Intercept)                          ***
## RevolvingUtilizationOfUnsecuredLines
## age                                  ***
## NumberOfTime30.59DaysPastDueNotWorse ***
## DebtRatio
## NumberOfOpenCreditLinesAndLoans      .
## NumberOfTimes90DaysLate              ***
## NumberRealEstateLoansOrLines         *
## NumberOfTime60.89DaysPastDueNotWorse ***
## ---
## Signif. codes:
## 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36629  on 74999  degrees of freedom
## Residual deviance: 33728  on 74991  degrees of freedom
## AIC: 33746
##
## Number of Fisher Scoring iterations: 6
```

Predictions are stored for later analysis

```
phat = predict(lgfit, testDf, type="response")
phatL$logit = matrix(phat,ncol=1)
```

4.2 Random Forest

We fit random forest models for a few different settings.

```
set.seed(99)

##settings for randomForest
p=ncol(trainDf)-1
mtryv = c(p, sqrt(p))
ntreev = c(500,1000)
(setrf = expand.grid(mtryv,ntreev))  # this contains all settings to try
```

```
##   Var1 Var2
## 1 8.00  500
## 2 2.83  500
## 3 8.00 1000
## 4 2.83 1000
```

```
colnames(setrf)=c("mtry","ntree")
phatL$rf = matrix(0.0,nrow(testDf),nrow(setrf))  # we will store results here

###fit rf
for(i in 1:nrow(setrf)) {
   #fit and predict
   frf = randomForest(y~., data=trainDf,
                      mtry=setrf[i,1],
                      ntree=setrf[i,2],
                      nodesize=10)
   phat = predict(frf, newdata=testDf, type="prob")[,2]
   phatL$rf[,i]=phat
}
```

4.3 Boosting

We fit boosting models for a few different settings.

```
##settings for boosting
idv = c(2,4)
ntv = c(1000,5000)
shv = c(.1,.01)
(setboost = expand.grid(idv,ntv,shv))
```

```
##   Var1 Var2 Var3
## 1    2 1000 0.10
## 2    4 1000 0.10
## 3    2 5000 0.10
## 4    4 5000 0.10
## 5    2 1000 0.01
## 6    4 1000 0.01
## 7    2 5000 0.01
## 8    4 5000 0.01
```

```
colnames(setboost) = c("tdepth","ntree","shrink")
phatL$boost = matrix(0.0,nrow(testDf),nrow(setboost))
```

Remember to convert to numeric 0,1 values for boosting.

```
trainDfB = trainDf; trainDfB$y = as.numeric(trainDfB$y)-1
testDfB = testDf; testDfB$y = as.numeric(testDfB$y)-1
```

Fitting

```
for(i in 1:nrow(setboost)) {
   ##fit and predict
   fboost = gbm(y~., data=trainDfB, distribution="bernoulli",
               n.trees=setboost[i,2],
               interaction.depth=setboost[i,1],
               shrinkage=setboost[i,3])

   phat = predict(fboost,
                  newdata=testDfB,
                  n.trees=setboost[i,2],
                  type="response")

   phatL$boost[,i] = phat
}
```

5 Analysis of results

5.1 Miss-classification rate

Let us first look at miss-classification rate.

For **logistic regression** we have:

```
getConfusionMatrix(testDf$y, phatL[[1]][,1], 0.5)
```

```
##            actual
```

```
## predictions     0     1
##   predict_0 69812  4849
##   predict_1   141   198
```

```
cat('Missclassification rate = ', lossMR(testDf$y, phatL[[1]][,1], 0.5), '\n')
```

```
## Missclassification rate =  0.0665
```

For **random forest** we have:

```
nrun = nrow(setrf)
for(j in 1:nrun) {
  print(setrf[j,])
  print("Confusion Matrix:")
  print(getConfusionMatrix(testDf$y, phatL[[2]][,j], 0.5))
  cat('Missclassification rate = ', lossMR(testDf$y, phatL[[2]][,j], 0.5), '\n')
}
```

```
##   mtry ntree
## 1    8   500
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 68986  3963
##   predict_1   967  1084
## Missclassification rate =  0.0657
##   mtry ntree
## 2 2.83   500
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69190  4047
##   predict_1   763  1000
## Missclassification rate =  0.0641
##   mtry ntree
## 3    8  1000
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 68992  3982
##   predict_1   961  1065
## Missclassification rate =  0.0659
##   mtry ntree
## 4 2.83  1000
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69189  4039
##   predict_1   764  1008
## Missclassification rate =  0.064
```

For **boosting** we have:

```
nrun = nrow(setboost)
for(j in 1:nrun) {
  print(setboost[j,])
  print("Confusion Matrix:")
  print(getConfusionMatrix(testDf$y, phatL[[3]][,j], 0.5))
  cat('Missclassification rate = ', lossMR(testDf$y, phatL[[3]][,j], 0.5), '\n')
}
```

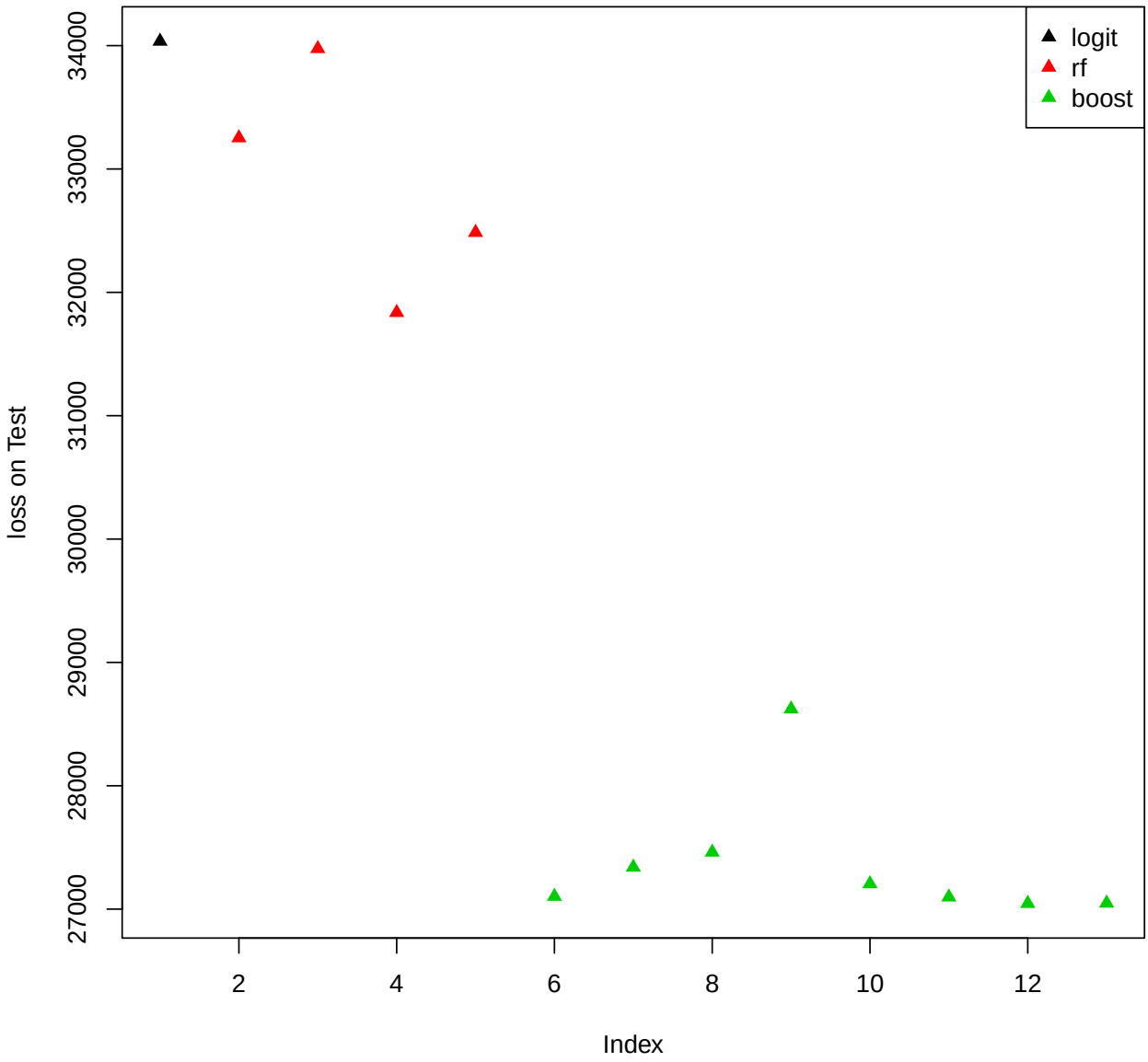
```
##   tdepth ntree shrink
## 1      2  1000    0.1
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69257  4045
##   predict_1   696  1002
## Missclassification rate =  0.0632
##   tdepth ntree shrink
## 2      4  1000    0.1
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69184  4077
##   predict_1   769   970
## Missclassification rate =  0.0646
##   tdepth ntree shrink
## 3      2  5000    0.1
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69176  4115
##   predict_1   777   932
## Missclassification rate =  0.0652
##   tdepth ntree shrink
## 4      4  5000    0.1
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 68992  4048
##   predict_1   961   999
## Missclassification rate =  0.0668
##   tdepth ntree shrink
## 5      2  1000   0.01
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69310  4077
##   predict_1   643   970
## Missclassification rate =  0.0629
##   tdepth ntree shrink
## 6      4  1000   0.01
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
```

```
##   predict_0 69292  4038
##   predict_1   661  1009
## Missclassification rate =  0.0627
##   tdepth ntree shrink
## 7      2  5000   0.01
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69281  4046
##   predict_1   672  1001
## Missclassification rate =  0.0629
##   tdepth ntree shrink
## 8      4  5000   0.01
## [1] "Confusion Matrix:"
##            actual
## predictions     0     1
##   predict_0 69261  4071
##   predict_1   692   976
## Missclassification rate =  0.0635
```

5.2 Deviance

Plot test set loss — deviance:

```
lossL = list()
nmethod = length(phatL)
for(i in 1:nmethod) {
   nrun = ncol(phatL[[i]])
   lvec = rep(0,nrun)
   for(j in 1:nrun) lvec[j] = lossf(testDf$y, phatL[[i]][,j])
   lossL[[i]]=lvec; names(lossL)[i] = names(phatL)[i]
}
lossv = unlist(lossL)
plot(lossv, ylab="loss on Test", type="n")
nloss=0
for(i in 1:nmethod) {
   ii = nloss + 1:ncol(phatL[[i]])
   points(ii,lossv[ii],col=i,pch=17)
   nloss = nloss + ncol(phatL[[i]])
}
legend("topright",legend=names(phatL),col=1:nmethod,pch=rep(17,nmethod))
```

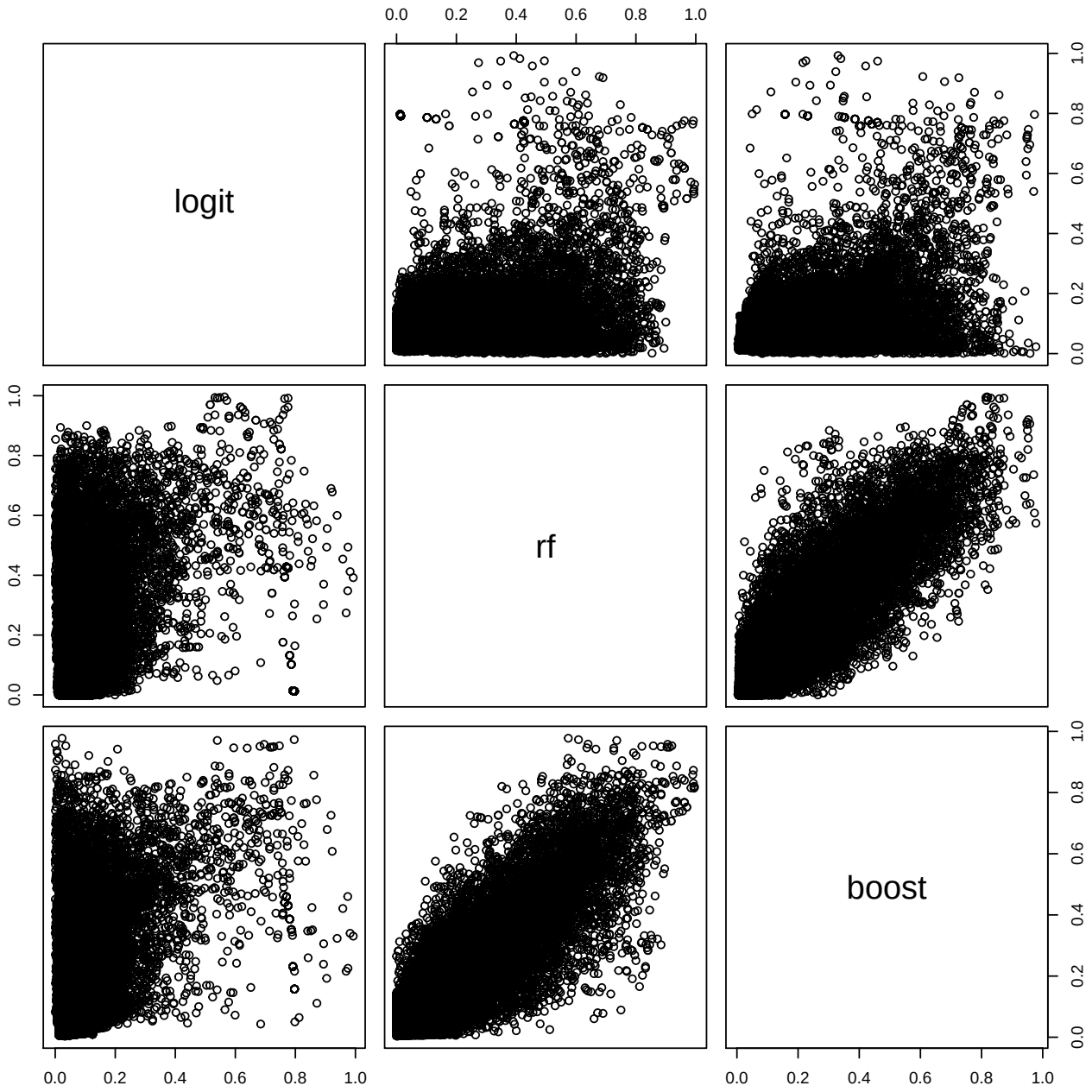


From each method class, we choose the one that has the lowest error on the validation set.

```
nmethod = length(phatL)
phatBest = matrix(0.0,nrow(testDf),nmethod) #pick off best from each method
colnames(phatBest) = names(phatL)
for(i in 1:nmethod) {
   nrun = ncol(phatL[[i]])
   lvec = rep(0,nrun)
   for(j in 1:nrun) lvec[j] = lossf(testDf$y,phatL[[i]][,j])
   imin = which.min(lvec)
   phatBest[,i] = phatL[[i]][,imin]
   phatBest[,i] = phatL[[i]][,1]
}
```

We can plot $\hat{p}$ for best models on the test set

```
pairs(phatBest)
```

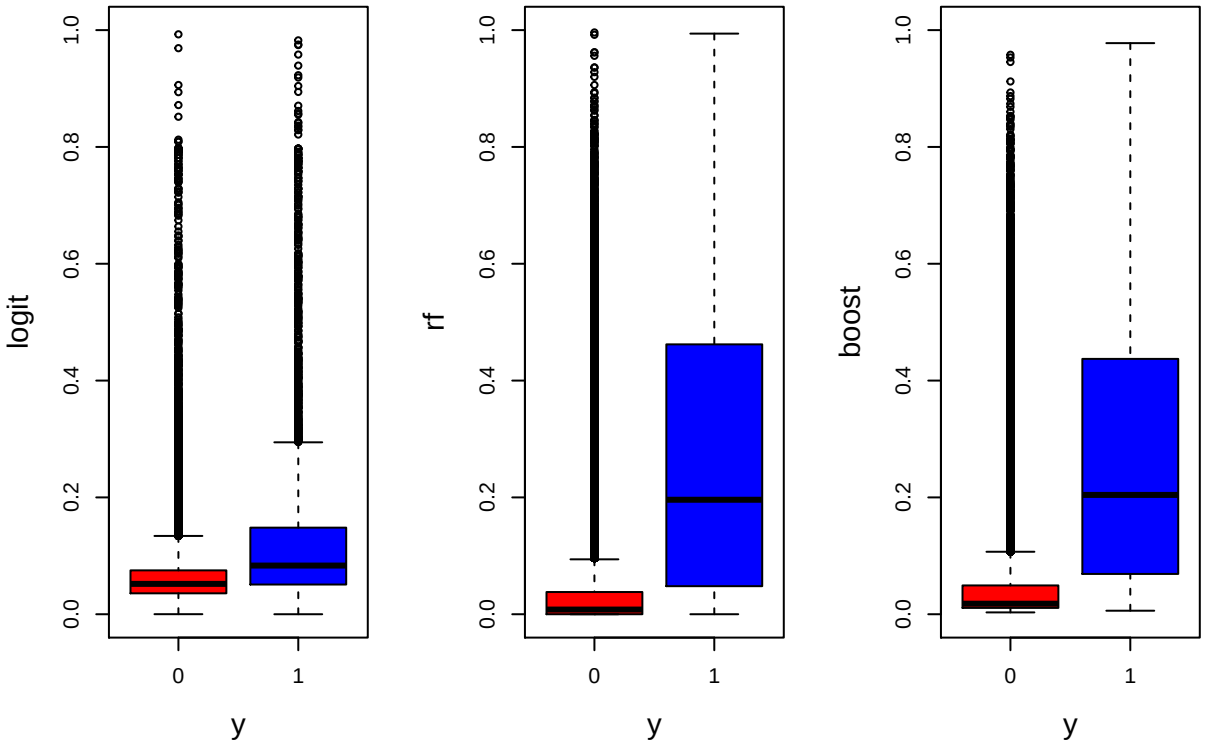


Each plot relates $\hat{p}$ to y.

Going from left to right, $\hat{p}$ is from logit, random forests, and boosting.

```
colnames(phatBest) = c("logit", "rf", "boost")
tempdf = data.frame(phatBest,y = testDf$y)

par(mfrow=c(1,3))
plot(logit~y,tempdf,ylim=c(0,1),cex.lab=1.4,col=c("red","blue"))
plot(rf~y,tempdf,ylim=c(0,1),cex.lab=1.4,col=c("red","blue"))
plot(boost~y,tempdf,ylim=c(0,1),cex.lab=1.4,col=c("red","blue"))
```



Boosting and random forests both look **pretty good**!
Both are **dramatically better than logit**!

5.3 Expected value of a classifier

Our **cost/benefit matrix** looks like this

```
cost_benefit = matrix(c(0,-0.25,0,1), nrow=2)
print(cost_benefit)
```

```
##       [,1] [,2]
## [1,]  0.00    0
## [2,] -0.25    1
```

Let us target everyone with $\hat{p} > 0.2$.

Expected values of targeting is below:

```
confMat = getConfusionMatrix(testDf$y, phatBest[,1], 0.2)
print(confMat)
```

```
##            actual
## predictions     0     1
##   predict_0 68897  4224
##   predict_1  1056   823
```

```
cat("Expected value of targeting using logistic regression = ",
    sum(sum(confMat * cost_benefit)), "\n")
```

```
## Expected value of targeting using logistic regression =  559
```

```
confMat = getConfusionMatrix(testDf$y, phatBest[,2], 0.2)
print(confMat)
```

```
##            actual
## predictions     0     1
##   predict_0 65486  2552
##   predict_1  4467  2495
```

```
cat("Expected value of targeting using random forests = ",
    sum(sum(confMat * cost_benefit)), "\n")
```

```
## Expected value of targeting using random forests =  1378
```

```
confMat = getConfusionMatrix(testDf$y, phatBest[,3], 0.2)
print(confMat)
```

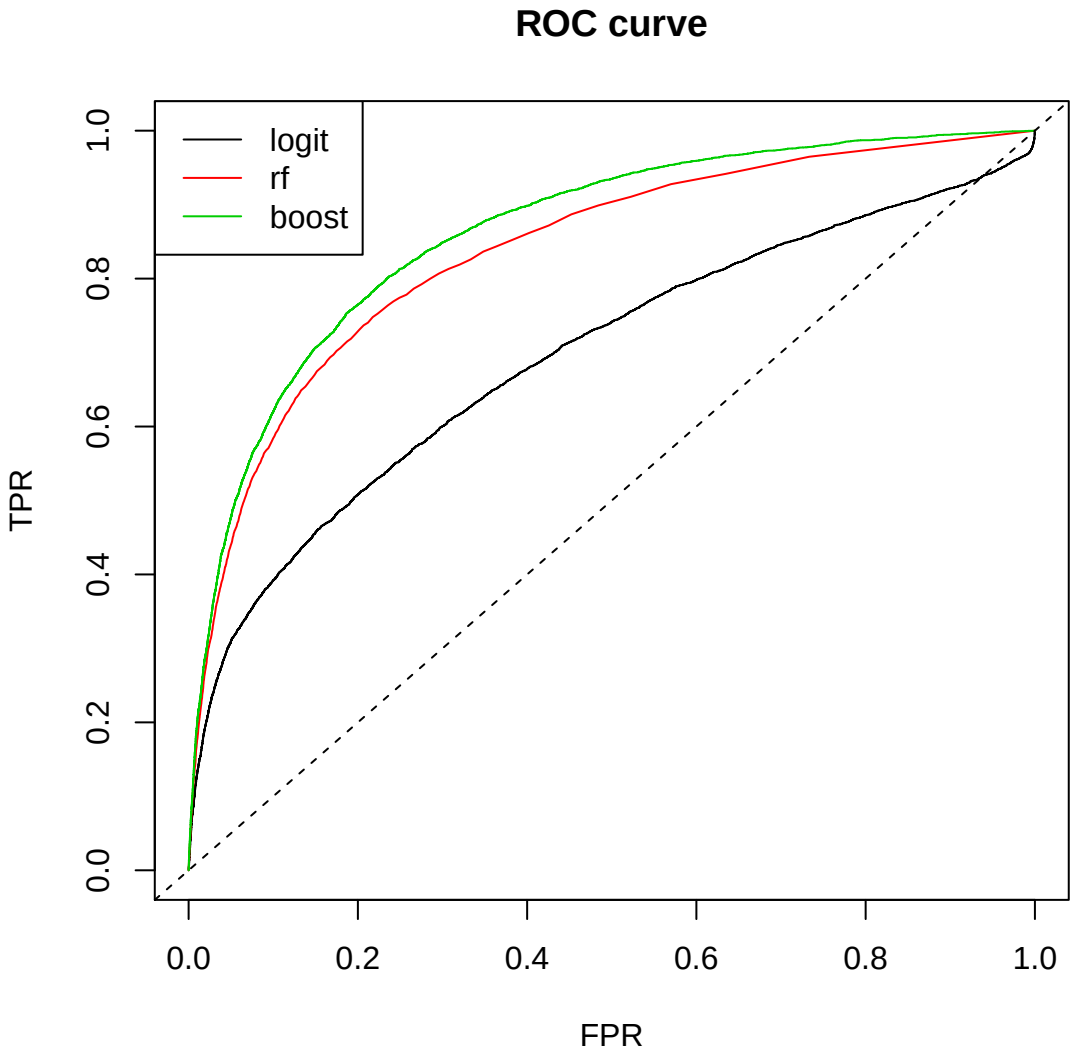
```
##            actual
## predictions     0     1
##   predict_0 65997  2507
##   predict_1  3956  2540
```

```
cat("Expected value of targeting using boosting = ",
    sum(sum(confMat * cost_benefit)), "\n")
```

```
## Expected value of targeting using boosting =  1551
```

5.4 ROC curves

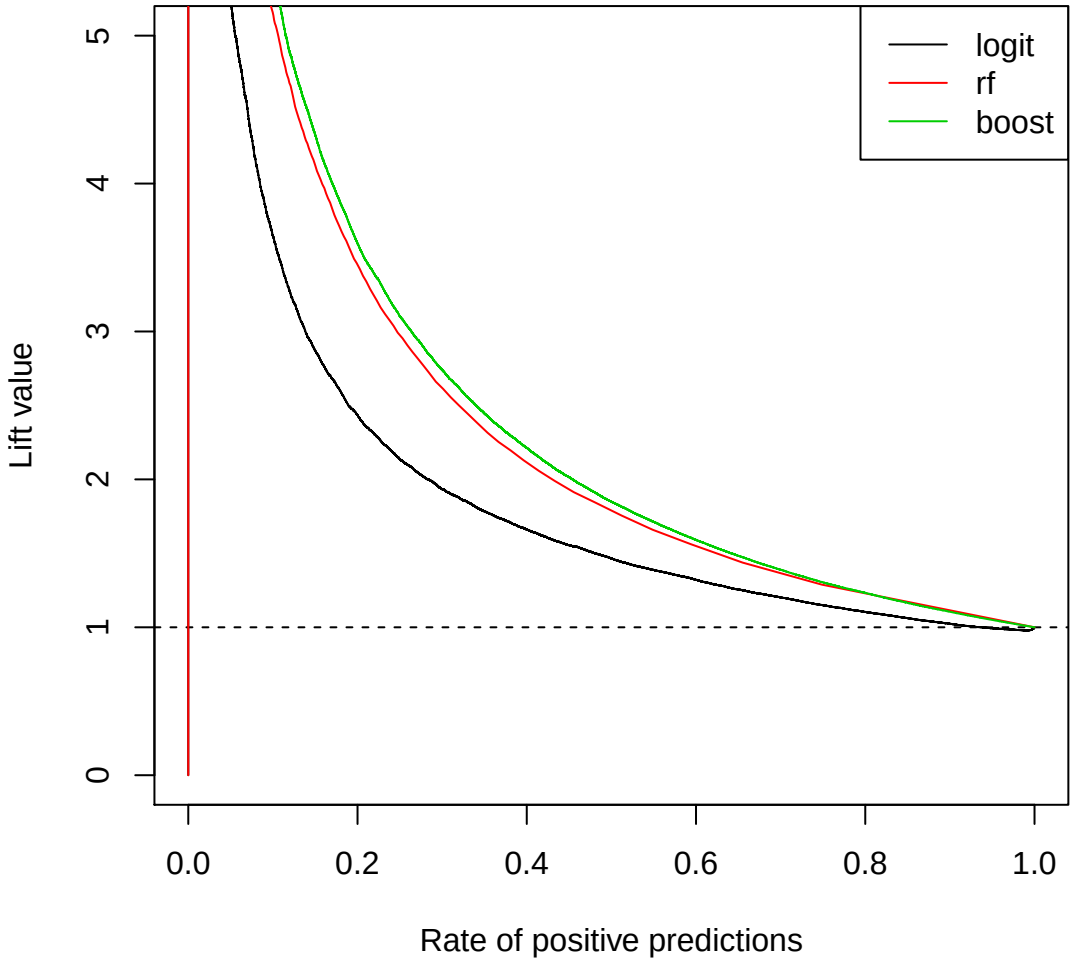
```
plot(c(0,1),c(0,1),xlab='FPR',ylab='TPR',main="ROC curve",cex.lab=1,type="n")
for(i in 1:ncol(phatBest)) {
   pred = prediction(phatBest[,i], testDf$y)
   perf = performance(pred, measure = "tpr", x.measure = "fpr")
   lines(perf@x.values[[1]], perf@y.values[[1]],col=i)
}
abline(0,1,lty=2)
legend("topleft",legend=names(phatL),col=1:nmethod,lty=rep(1,nmethod))
```



5.5 Lift curves

```
pred = prediction(phatBest[,1], testDf$y)
perf = performance(pred, measure = "lift", x.measure = "rpp")
plot(perf, col=1, ylim=c(0,5))
abline(h=1, lty=2)

for(i in 2:ncol(phatBest)) {
   pred = prediction(phatBest[,i], testDf$y)
   perf = performance(pred, measure = "lift", x.measure = "rpp")
   lines(perf@x.values[[1]], perf@y.values[[1]],col=i)
}
legend("topright",legend=names(phatL),col=1:nmethod,lty=rep(1,nmethod))
```



5.6 Cummulative response

```
pred = prediction(phatBest[,1], testDf$y)
perf = performance(pred, measure = "tpr", x.measure = "rpp")
plot(perf, col=1, ylim=c(0,1))
abline(h=1, lty=2)
abline(0,1,lty=2)
for(i in 2:ncol(phatBest)) {
   pred = prediction(phatBest[,i], testDf$y)
   perf = performance(pred, measure = "tpr", x.measure = "rpp")
   lines(perf@x.values[[1]], perf@y.values[[1]],col=i)
}
legend("bottomright",legend=names(phatL),col=1:nmethod,lty=rep(1,nmethod))
```