Course Project Writeup

Richard Creamer

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Summary

Data Preparation

- I chose to use a Random Forest
- Since the implementation of Random Forest handles cross-validation, I only created Train and Test sets (80:20)

Model Selection

- I followed the lecture's advice and used rfcv() to evaluate cross-validation OOB error estimates
- I subsetted data down to 53 columns including 'classe' y column (discard column if NA/blank count > nrows/2)
- I used ranked Linear Model coefficients to extract 20 features which should perform well
- I also used the Random Forest importance() output's feature error estimates for possible feature reduction, but rejected this because the plots (below) do not clearly delineate less-important features
- I then fit Random Forests over a grid/range of 'mtry' and 'ntree' parameters to find the best-performing values for these parameters for the full 52-feature training set (rf52)
- I did the same thing (grid/range of 'mtry' and 'ntree') for a 20-features derived data frame using the Linear Model coefficients for subsetting

Model Evaluation and OOB Error Estimates

- I then evaluated the performance of rf52 and rf20 on the TEST set
- I then compared the TEST set performance for the rf52 and rf20 Random Forests to the rfcv() and the Random Forests' built-in OOB estimates:

Random Forest rf52 (trained using 52 features, mtry=2, ntree=20)

- Train accuracy: 1.00000
- TEST set prediction accuracy: 99.1847%
- Random Forest rf52 built-in OOB error estimate: 2.3445%

Random Forest rf20 (trained using 20 features, mtry=2, ntree=50)

- Train accuracy: 1.00000
- TEST set prediction accuracy: 99.4395%
- Random Forest rf20 built-in OOB error estimate: 0.91%

rfcv() OOB Error Estimates by Variable Count

- 52 variables: 0.005542460
- 26 variables: 0.007581066
- 13 variables: 0.009683379
- 6 variables: 0.045104160

- 3 variables: 0.109320252
- 1 variable: 0.596929350

Prediction on Project 20-row Prediction Set (pml-testing.csv)

- rf52: B A B A A E D B A A B C B A E E A B B B
- rf20: B A B A A E D B A A B C B A E E A B B B

Discussion

The rf20 Random Forest had slightly better performance than the rf52 RF even though the rf20 RF was trained using only 20 features. I think the reason for this is that my grid search parameter optimization function assigned 50 trees to the rf20 RF whereas it only assigned 20 trees to the rf52 RF.

Notes

- I added a separate PDF file containing this R Markdown Course Project write-up
- I added a separate PDF file to my repo containing the test script's output (plots manually inserted)
- I added a separate CpScript.R file to my repo containing the test script 'driver' and various other 'helper' functions
- The R code is rather messy do to the sequence of steps taken and the print statements (sorry)
- The CpScript.R has a 'driver' test function named cpTest(), but only the steps inside this function are listed in this Rmd write-up, not the outer function itself
- Many of my helper functions return tuples containing multiple named return values

IMPORTANT: I could not get knitr to work with code chunks which call functions in another chunk. Therefore, I am having to submit the code in chunks but NOT labeled as {r} code, and instead, am including a code chunk at the bottom with my entire (large) .R file. As a result, the chunks in the write-up do not have syntax highlighting/coloring. This also forced me to manually insert both the code's output as well as HTML tags to intersperse my plots' PNG files instead of being generated by R/knitr. SORRY! Full code at bottom WITH syntax highlighting.

Begin 'Test Driver' Code Chunks, Output, and Plots

Loading and Processing the Data

Note: return value 'd' is a tuple

```
Code:
# load data, create and split data frames, shuffle rows, results stored in d tuple
d <- loadData( subDir, doPrint = TRUE )

Output:
[1] ---> loading data...
[1] ...done reading data and creating data frames
```

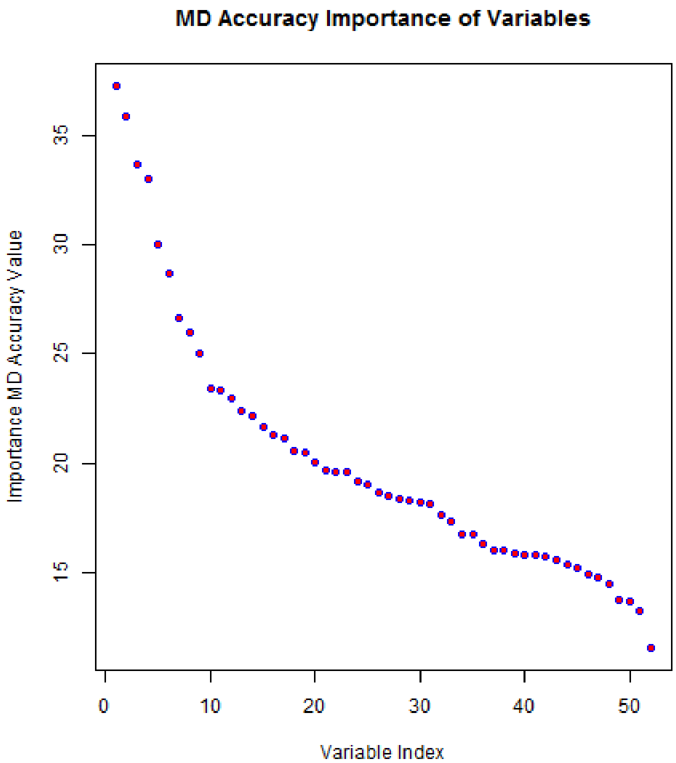
Assessing rfcv() Error Data for Feature Selection

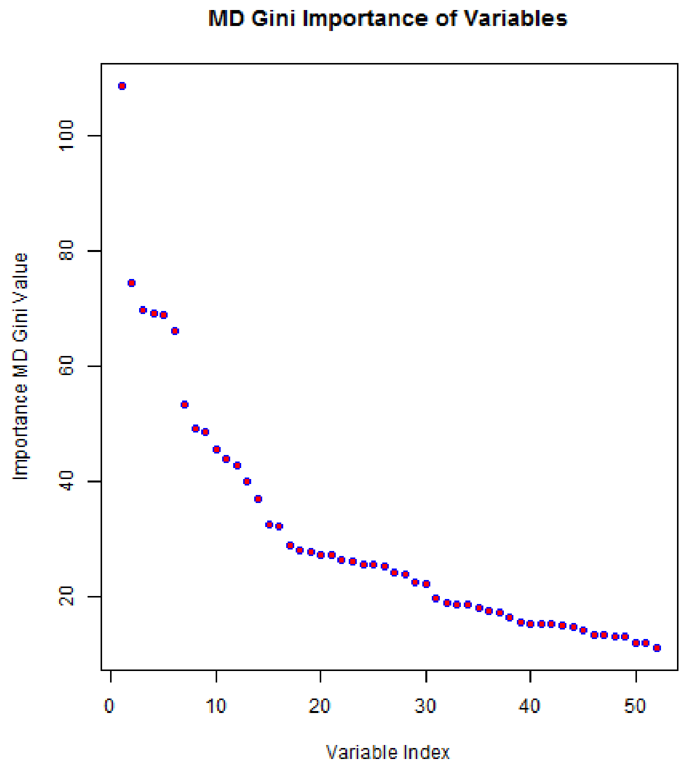
Note: the plot resulting from the code, below, did not contain any obvious pattern to use for separating important from less-important features.

```
Code:
# see if rfcv() variable importance useful for features selection
evalRfcvVarImport( d$trainDf, nrows=2000, doPrint=TRUE )

Output:
```

```
[1] plotting Random Forest variable importance() metrics
[1] no clear dividing line differentiating important vs. unimportant variables
```



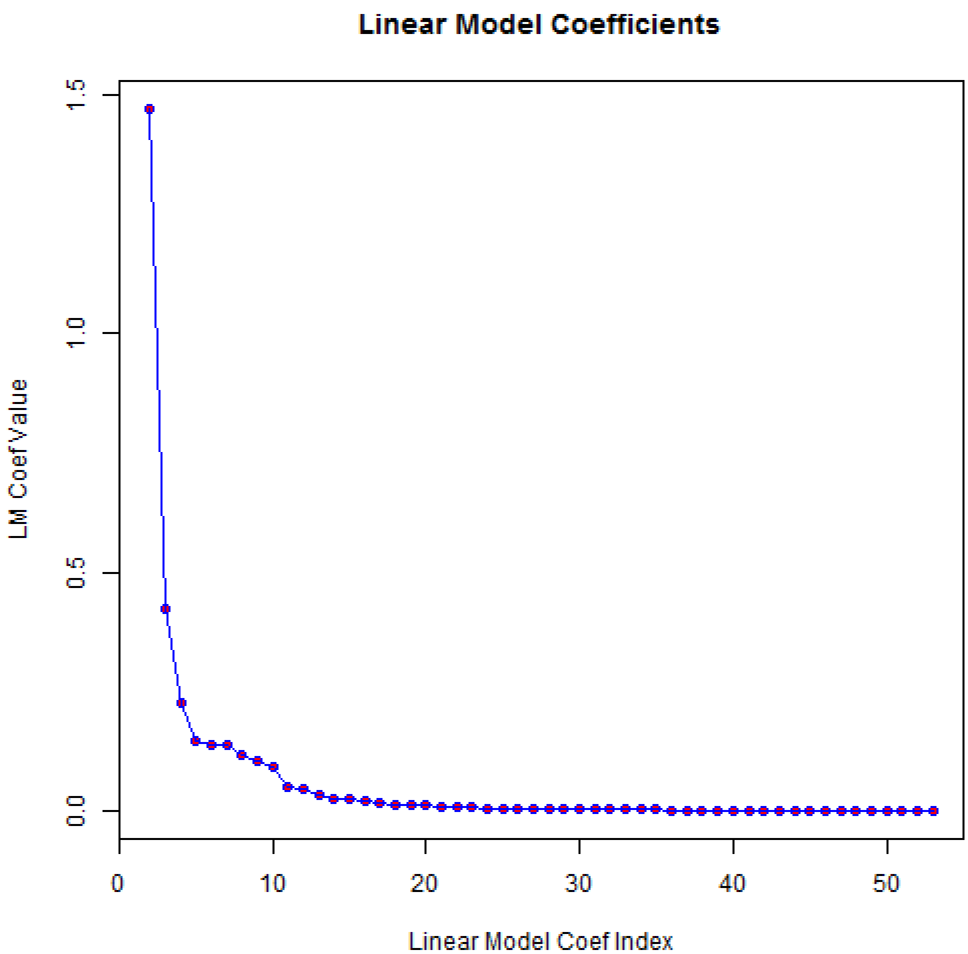


Fitting a Linear Model and Extracting 20 Largest Coefficients

Note: the plot resulting from the code below DID show that the error flattened out after using approximately 20 features.

```
Code:
# get sorted coefficients from Linear Model fit to see if useful
# for feature selection
lmBest20Coeffs <- getMostImportantLmCoeffs( d$trainDf, nrows=1000, doPrint=TRUE )

Output:
[1] ---> assessing whether Linear Model coefficients offer useful variable importance
rankings...
[1] plotting Linear Model coefficients sorted in decreasing order
```



Finding Best 'ntree' and 'mtry' Random Forests for 52-feature TRAIN Set

Note: below, the code calls a function which chooses the best Random Forest and its 'mtry' and 'ntree' parameters over a range of values for these two variables.

```
Code:
# fit Random Forests over a grid of ranges for params 'mtry' and 'ntree'
# use full 52 features in training set
pr( "---> examining Random Forest performance for a range of 'mtry' and 'ntree'
parameters..." )
mtryVals <- c( 2, 5, 10 )
ntreeVals <- c( 1, 2, 3, 5, 10, 20 )
rf52 <- findBestRfParams( d$trainDf, mtryVals, ntreeVals, doPrint = TRUE ) # rf52 is a
tuple
pr( "--> Random Forest accuracy values for evaluated (mtry, ntree) grid pairs:" )
pr( "--> NOTE: row names are mtry values; column names are ntree values" )
pr( "--> NOTE: matrix entries are classification accuracy on train set" )
cat( "\n" )
pr( rf52$accMatrix )
cat( "\n" )
pr( "--->parameters from best 52-feature Random Forest:" )
pr( sprintf( "resultant rf52: train accuracy=%f mtry=%d ntree=%d OOB error=%f",
    rf52$bestAcc, rf52$bestMtry, rf52$bestNtree, getOob( rf52$bestRf ) ) )
cat( "\n" )
```

```
# now just print out the Random Forest to get confusion matrix and OOB error est.
pr( "---> printing best (rf52) Random Forest for above parameters: " )
pr( rf52$bestRf )
cat( "\n" )

Output:
[1] ---> examining Random Forest performance for a range of 'mtry' and 'ntree'
parameters...
[1] evaluating Random Forest w/ mtry=2 ntree=1
[1] evaluating Random Forest w/ mtry=2 ntree=2
[1] evaluating Random Forest w/ mtry=2 ntree=3
[1] evaluating Random Forest w/ mtry=2 ntree=5
[1] evaluating Random Forest w/ mtry=2 ntree=10
[1] evaluating Random Forest w/ mtry=2 ntree=20
[1] evaluating Random Forest w/ mtry=5 ntree=1
[1] evaluating Random Forest w/ mtry=5 ntree=2
[1] evaluating Random Forest w/ mtry=5 ntree=3
[1] evaluating Random Forest w/ mtry=5 ntree=5
[1] evaluating Random Forest w/ mtry=5 ntree=10
[1] evaluating Random Forest w/ mtry=5 ntree=20
[1] evaluating Random Forest w/ mtry=10 ntree=1
[1] evaluating Random Forest w/ mtry=10 ntree=2
[1] evaluating Random Forest w/ mtry=10 ntree=3
[1] evaluating Random Forest w/ mtry=10 ntree=5
[1] evaluating Random Forest w/ mtry=10 ntree=10
[1] evaluating Random Forest w/ mtry=10 ntree=20

[1] --> Random Forest accuracy values for evaluated (mtry, ntree) grid pairs:
[1] --> NOTE: row names are mtry values; column names are ntree values
[1] --> NOTE: matrix entries are classification accuracy on train set

           1         2         3         5        10        20
2  0.9548321 0.9512009 0.9906989 0.9978977 0.9997452 1.0000000
5  0.9720966 0.9693572 0.9950946 0.9984710 0.9998726 1.0000000
10 0.9684016 0.9678282 0.9948398 0.9984073 0.9998726 0.9999363

[1] --->parameters from best 52-feature Random Forest:
[1] resultant rf52: train accuracy=1.000000 mtry=2 ntree=20 OOB error=0.023445

[1] ---> printing best (rf52) Random Forest for above parameters:

Call:
 randomForest(formula = classe ~ ., data = df, mtry = mt, ntree = nt)
               Type of random forest: classification
                     Number of trees: 20
No. of variables tried at each split: 2

        OOB estimate of  error rate: 2.34%
Confusion matrix:
     A    B    C    D    E class.error
A 4394   22    9   14    2  0.01058320
B   45 2951   32   14   10  0.03309305
C    7   45 2610   30    7  0.03297518
D   12    3   63 2480   10  0.03426791
E    2   15    4   22 2893  0.01464578
```

Using rfcv() to Evaluate CV OOB Error

```
Code:
# now use rfcv() to evaluate cross-validation error
pr( "---> computing rfcv() cross-validation error - this may take several minutes..." )
set.seed( 1 )
rfcvOutput <- rfcv( d$trainDf[, -53], d$trainDf[, 53] )
pr( "...done computing rfcv() output" )
pr( "rfcv() cross-validation estimates for training set vs. number variables used:")
pr( rfcvOutput$error.cv )
cat( "\n" )

Output:
[1] ---> computing rfcv() cross-validation error - this may take several minutes...
[1] ...done computing rfcv() output
[1] rfcv() cross-validation estimates for training set vs. number variables used:
         52          26          13           6           3           1
0.005542460 0.007581066 0.009683379 0.045104160 0.109320252 0.596929350
```

Evaluating TEST set accuracy of Random Forest (rf52) Trained on 52 Features

```
Code:
# compute performance of rf52 best 52-feature random forest on T-E-S-T set
acc <- evalRf( rf52$bestRf, d$testDf )
pr( sprintf( "accuracy of best (rf52) Random Forest on 20%% TEST set: %f", acc ) )
cat( "\n" )

Output:
[1] accuracy of best (rf52) Random Forest on 20% TEST set: 0.991847
```

Finding Best 'ntree' and 'mtry' Random Forests for 20-feature TRAIN Set

Note: because I was using fewer features, the 'mtry' and 'ntree' ranges I used for evaluation ranged to higher values than for the rf52 Random Forest grid search.

```
Code:
# additional exercise: find best 20-feature Random Forest using Linear Model top-20
coeffs
pr( "---> As additional exercise fit Random Forest to top-20 features from Linear Model"
)
lmBest20Coeffs[ 21 ] = "classe" # Need to append the 'classe' to feature list
best20TrainDf <- d$trainDf[, lmBest20Coeffs ] # subset training set, only the 20 'top'
features
mtryVals <- c( 2, 5, 10 ) # use different parameter ranges as expect lower accuracy using
fewer features
ntreeVals <- c( 10, 50, 100, 200 ) # ditto
rf20 <- findBestRfParams( d$trainDf, mtryVals, ntreeVals, doPrint = TRUE )
pr( "--> Random Forest accuracy values for evaluated (mtry, ntree) grid pairs:" )
pr( "--> NOTE: row names are mtry values; column names are ntree values" )
pr( "--> NOTE: matrix entries are classification accuracy on train set" )
cat( "\n" )

pr( rf20$accMatrix )
cat( "\n" )
pr( "--->parameters from best 20-feature Random Forest:" )
pr( sprintf( "resultant rf20: train accuracy=%f mtry=%d ntree=%d OOB error=%f",
```

```
              rf20$bestAcc, rf20$bestMtry, rf20$bestNtree, getOob( rf20$bestRf ) ) )
cat( "\n" )

# PRINT BEST RANDOM FOREST (to get OOB and confusion matrix)
pr( "---> printing best Random Forest for above parameters: " )
pr( rf20$bestRf )
cat( "\n" )

Output:
[1] ---> As additional exercise fit Random Forest to top-20 features from Linear Model
[1] evaluating Random Forest w/ mtry=2 ntree=10
[1] evaluating Random Forest w/ mtry=2 ntree=50
[1] evaluating Random Forest w/ mtry=2 ntree=100
[1] evaluating Random Forest w/ mtry=2 ntree=200
[1] evaluating Random Forest w/ mtry=5 ntree=10
[1] evaluating Random Forest w/ mtry=5 ntree=50
[1] evaluating Random Forest w/ mtry=5 ntree=100
[1] evaluating Random Forest w/ mtry=5 ntree=200
[1] evaluating Random Forest w/ mtry=10 ntree=10
[1] evaluating Random Forest w/ mtry=10 ntree=50
[1] evaluating Random Forest w/ mtry=10 ntree=100
[1] evaluating Random Forest w/ mtry=10 ntree=200

[1] --> Random Forest accuracy values for evaluated (mtry, ntree) grid pairs:
[1] --> NOTE: row names are mtry values; column names are ntree values
[1] --> NOTE: matrix entries are classification accuracy on train set

          10 50 100 200
2  0.9997452  1   1   1
5  0.9998726  1   1   1
10 0.9998726  1   1   1

[1] --->parameters from best 20-feature Random Forest:
[1] resultant rf20: train accuracy=1.000000 mtry=2 ntree=50 OOB error=0.009110

[1] ---> printing best Random Forest for above parameters:

Call:
 randomForest(formula = classe ~ ., data = df, mtry = mt, ntree = nt)
               Type of random forest: classification
                     Number of trees: 50
No. of variables tried at each split: 2

        OOB estimate of  error rate: 0.91%
Confusion matrix:
     A    B    C    D    E class.error
A 4430    7    0    3    1 0.002476920
B   21 3020    8    1    2 0.010484928
C    3   28 2663    5    1 0.013703704
D    3    0   42 2519    4 0.019080997
E    0    3    1   10 2922 0.004768392
```

Evaluating TEST set accuracy of Random Forest (rf20) Trained on 20 Features

```
Code:
# compute performance of rf20 Random Forest on T-E-S-T set (20% of train set rows)
pr( "---> evalute top-20 feature Random Forest: " )
acc <- evalRf( rf20$bestRf, d$testDf )
pr( sprintf( "accuracy of best (rf20) Random Forest on 20%% TEST set: %f", acc ) )
cat( "\n" )

Output:
[1] ---> evalute top-20 feature Random Forest:
[1] accuracy of best (rf20) Random Forest on 20% TEST set: 0.994395
```

Using rf52 and rf20 Models to Predict Labels for 20-Row Project Data (pml-testing.csv)

```
Code:
# use rf52 to predict labels for course project 20-row data set (pml-testing.csv)
pr( "---> use rf52 to predict labels for course project 20-row data set (pml-testing.csv"
)
predsRf52 <- predict( rf52$bestRf, d$predDf )
pr( predsRf52 )
cat( "\n")

# use rf20 to predict labels for course project 20-row data set (pml-testing.csv)
pr( "---> use rf20 to predict labels for course project 20-row data set (pml-testing.csv"
)
predsRf20 <- predict( rf20$bestRf, d$predDf )
pr( predsRf20 )
cat( "\n")

Output:
[1] ---> use rf52 to predict labels for course project 20-row data set (pml-testing.csv
 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
 B  A  B  A  A  E  D  B  A  A  B  C  B  A  E  E  A  B  B  B
Levels: A B C D E

[1] ---> use rf20 to predict labels for course project 20-row data set (pml-testing.csv
 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
 B  A  B  A  A  E  D  B  A  A  B  C  B  A  E  E  A  B  B  B
Levels: A B C D E
```

Full R Code with Syntax Highlighting and Coloring

```
#######
# Usage:
# source( "CpScript.R" )
# set 'subDir' variable if != local sub-directory 'data'
# cpTest()
#######

library( randomForest )

## Warning: package 'randomForest' was built under R version 3.1.1

## randomForest 4.6-10
## Type rfNews() to see new features/changes/bug fixes.
```

```
cpScript <- function( subDir = "data" ) {

    repoDir <-
"D:/OldLaptop/D_Drive/JohnsHopkinsCoursera/8_PracticalMLCoursera/hw/CourseProjRepo"

    # load data, create and split data frames, shuffle rows, results stored in d tuple
    d <- loadData( subDir, doPrint = TRUE )

    # see if rfcv() variable importance useful for features selection
    evalRfcvVarImport( d$trainDf, nrows=2000, doPrint=TRUE )

    # get sorted coefficients from Linear Model fit to see if useful
    # for feature selection
    lmBest20Coeffs <- getMostImportantLmCoeffs( d$trainDf, nrows=1000, doPrint=TRUE )

    # fit Random Forests over a grid of ranges for params 'mtry' and 'ntree'
    # use full 52 features in training set
    pr( "---> examining Random Forest performance for a range of 'mtry' and 'ntree'
parameters..." )
    mtryVals <- c( 2, 5, 10 )
    ntreeVals <- c( 1, 2, 3, 5, 10, 20 )
    rf52 <- findBestRfParams( d$trainDf, mtryVals, ntreeVals, doPrint = TRUE ) # rf52 is
a tuple
    pr( "--> Random Forest accuracy values for evaluated (mtry, ntree) grid pairs:" )
    pr( "--> NOTE: row names are mtry values; column names are ntree values" )
    pr( "--> NOTE: matrix entries are classification accuracy on train set" )
    cat( "\n" )
    pr( rf52$accMatrix )
    cat( "\n" )
    pr( "--->parameters from best 52-feature Random Forest:" )
    pr( sprintf( "resultant rf52: train accuracy=%f mtry=%d ntree=%d OOB error=%f",
        rf52$bestAcc, rf52$bestMtry, rf52$bestNtree, getOob( rf52$bestRf ) ) )
    cat( "\n" )

    # now just print out the Random Forest to get confusion matrix and OOB error est.
    pr( "---> printing best (rf52) Random Forest for above parameters: " )
    pr( rf52$bestRf )
    cat( "\n" )

    # now use rfcv() to evaluate cross-validation error
    pr( "---> computing rfcv() cross-validation error - this may take several minutes..."
)
    set.seed( 1 )
    rfcvOutput <- rfcv( d$trainDf[, -53], d$trainDf[, 53] )
    pr( "...done computing rfcv() output" )
    pr( "rfcv() cross-validation estimates for training set vs. number variables used:")
    pr( rfcvOutput$error.cv )
    cat( "\n" )

    # compute performance of rf52 best 52-feature random forest on T-E-S-T set
    acc <- evalRf( rf52$bestRf, d$testDf )
    pr( sprintf( "accuracy of best (rf52) Random Forest on 20%% TEST set: %f", acc ) )
    cat( "\n" )

    # additional exercise: find best 20-feature Random Forest using Linear Model top-20
```

```
coeffs
    pr( "---> As additional exercise fit Random Forest to top-20 features from Linear 
Model" )
    lmBest20Coeffs[ 21 ] = "classe" # Need to append the 'classe' to feature list
    best20TrainDf <- d$trainDf[, lmBest20Coeffs ] # subset training set, only the 20 
'top' features
    mtryVals <- c( 2, 5, 10 ) # use different parameter ranges as expect lower accuracy 
using fewer features
    ntreeVals <- c( 10, 50, 100, 200 ) # ditto
    rf20 <- findBestRfParams( d$trainDf, mtryVals, ntreeVals, doPrint = TRUE )
    pr( "--> Random Forest accuracy values for evaluated (mtry, ntree) grid pairs:" )
    pr( "--> NOTE: row names are mtry values; column names are ntree values" )
    pr( "--> NOTE: matrix entries are classification accuracy on train set" )
    cat( "\n" )

    pr( rf20$accMatrix )
    cat( "\n" )
    pr( "--->parameters from best 20-feature Random Forest:" )
    pr( sprintf( "resultant rf20: train accuracy=%f mtry=%d ntree=%d OOB error=%f",
                 rf20$bestAcc, rf20$bestMtry, rf20$bestNtree, getOob( rf20$bestRf ) ) )
    cat( "\n" )

    # PRINT BEST RANDOM FOREST (to get OOB and confusion matrix)
    pr( "---> printing best Random Forest for above parameters: " )
    pr( rf20$bestRf )
    cat( "\n" )

    # compute performance of rf20 Random Forest on T-E-S-T set (20% of train set rows)
    pr( "---> evalute top-20 feature Random Forest: " )
    acc <- evalRf( rf20$bestRf, d$testDf )
    pr( sprintf( "accuracy of best (rf20) Random Forest on 20%% TEST set: %f", acc ) )
    cat( "\n" )

    # use rf52 to predict labels for course project 20-row data set (pml-testing.csv)
    pr( "---> use rf52 to predict labels for course project 20-row data set (pml-
testing.csv" )
    predsRf52 <- predict( rf52$bestRf, d$predDf )
    pr( predsRf52 )
    cat( "\n")

    # use rf20 to predict labels for course project 20-row data set (pml-testing.csv)
    pr( "---> use rf20 to predict labels for course project 20-row data set (pml-
testing.csv" )
    predsRf20 <- predict( rf20$bestRf, d$predDf )
    pr( predsRf20 )
    cat( "\n")

    # RETURN LIST OF SELECTED VARIABLES FOR CALLER
    list( data=d, lmBest20Coeffs=lmBest20Coeffs, rf52=rf52, rf20=rf20,
          rfcvOutput=rfcvOutput, predsrf52=predsrf52, predsRf20=predsRf20 )
}

###########
# helper function which fits a Linear Model and returns
# return value = 20 largest sorted coefficients of Linear Model
```

```
getMostImportantLmCoeffs <- function( df, nrows=0, doPrint=FALSE ) {
    if ( nrows == 0 )
        nrows = nrow( df )
    # EVAL LINEAR MODEL COEFFICIENT RANKING FOR *FEATURE SELECTION* (result: useful)
    # now try ranking variables by Linear Model coefficient values
    if ( doPrint )
        pr( "---> assessing whether Linear Model coefficients offer useful variable
importance rankings..." )
    classeIdx <- getColIdx( df, "classe" )
    y <- as.numeric( df[ 1:nrows, classeIdx ] ) # use only 1,000 rows for LM fit
    lmDf <- cbind( df[ 1:nrows , 1:classeIdx - 1 ], y  )
    set.seed( 1 ) # set RNG seed for reproducibility
    lmFit <- lm( y ~ . , data = lmDf )
    sortedCoeffs <- sort( abs( lmFit$coefficients ), decreasing = TRUE )
    nCoeffs <- length( sortedCoeffs )
    sortedCoeffNames <- names( sortedCoeffs[2:nCoeffs ] )
    lm20MostImpFeatures <- names(sortedCoeffs)[2:21]  # skip intercept = coef[1]
    # plot linear model coefficients largest-to-smallest; skipping intercept coefficient
    plotLmCoeffVals( 2:nCoeffs, sortedCoeffs[2:nCoeffs], doPrint=doPrint )
    if ( doPrint )
        cat( "\n" )
    lmBest20Coeffs <- sortedCoeffNames[2:21]
}

###########
# helper function to use rfcv() output ranking of variables to see
# if the rankings are useful for feature selection/reduction
evalRfcvVarImport <- function( df, nrows=0, doPrint = FALSE ) {
    # evaluate rfcv() output to see if useful for feature selection
    if ( nrows == 0 )
        nrows = nrow( df )
    set.seed( 1 )
    rf <- randomForest( classe ~ ., data = df[1:nrows, ], importance = TRUE )
    impVal <- as.data.frame( importance( rf ) )
    impValMda <- impVal[ rev( order( impVal$MeanDecreaseAccuracy ) ), ]
    impValGini <- impVal[ rev( order( impVal$MeanDecreaseGini ) ), ]
    mdaDf <- data.frame( rownames( impValMda ), impValMda$MeanDecreaseAccuracy )
    giniDf <- data.frame( rownames( impValGini ), impValGini$MeanDecreaseGini )
    nVars <- nrow( mdaDf )
    # plot the results
    par( mfrow = c( 1, 2 ) )
    plotImportanceData( 1:nVars, mdaDf[,2], giniDf[,2], doPrint=doPrint )
    # plot conclusion - no clear dividing line between important vs. unimportant
variables
    # results not actionable
    if ( doPrint ) {
        pr( "no clear dividing line differentiating important vs. unimportant variables"
)
        cat( "\n" )
    }
}

###########
# helper function to load, subset, and shuffle data
# output: various data frames
```

```
# read and subset/process 2 CSV files, create data frames
loadData <- function( subDir = "data", doPrint = FALSE ) {
    if ( doPrint )
        pr( "---> loading data..." )
    trainFile <- file.path( subDir, "pml-training.csv" )
    testFile <- file.path( subDir, "pml-testing.csv" )
    trainFileDf <- prepDf( read.csv( trainFile ) )
    predDf <- prepDf( read.csv( testFile ) ) # 20-row prediction file
    set.seed( 1 ) # set seed for shuffle operation
    nrows <- nrow( trainFileDf )
    trainFileDf <- trainFileDf[ sample( nrows ), ] # randomly shuffle rows
    # Partition: 80% train, 20% test
    trainDf <- trainFileDf[ 1 : as.integer( 0.8 * nrows ), ]
    testDf <- trainFileDf[ as.integer( nrow( trainDf ) + 1 ) : nrows, ]
    if ( doPrint ) {
        pr( "...done reading data and creating data frames")
        cat( "\n" )
    }
    list( trainDf=trainDf, testDf=testDf, predDf=predDf )
}

###########
# helper function to evaluate Random Foresets over range of mtry and ntree parameter
findBestRfParams <- function( df, mtryVals, ntreeVals, doPrint = FALSE ) {
    bestAcc <- 0
    bestMtry <- 0
    bestNtree <- 0
    bestRf <- NULL
    accMatrix <- matrix( nrow=length( mtryVals ), ncol=length( ntreeVals ) )
    rownames( accMatrix ) <- as.character( mtryVals )
    colnames( accMatrix ) <- as.character( ntreeVals )
    for ( i in 1:length( mtryVals ) ) {                     # mtry
        mt <- mtryVals[ i ]
        for ( j in 1:length( ntreeVals ) ) {                # ntree
            nt <- ntreeVals[ j ]
            if ( doPrint )
                pr( sprintf( "evaluating Random Forest w/ mtry=%d ntree=%d", mt, nt ) )
            set.seed( 1 )
            rf <- randomForest( classe ~ ., data=df, mtry=mt, ntree=nt )
            acc <- evalRf( rf, df )
            accMatrix[i, j] = acc
            if ( acc > bestAcc ) {
                bestMtry <- mt
                bestNtree <- nt
                bestRf <- rf
                bestAcc <- acc
            }
        }
    }
    if ( doPrint )
        cat( "\n" )
    list( bestAcc=bestAcc, bestMtry=bestMtry, bestNtree=bestNtree,
          bestRf=bestRf, accMatrix=accMatrix )
}
```

```r
###########
# helper method to get OOB error estimate from Random Forest
getOob <- function( rf ) {
    rf$err.rate[rf$ntree, 1 ]
}



###########
# helper method to evaluate classification accuracy of Random Forest wrt a data frame
evalRf <- function( rf, df )  {
    predTestSet <- predict( rf, df ) # use Test set, NOT Cross-Validation set
    numAgree <- sum( predTestSet == df$classe )
    modelTestAccur <- numAgree/length( predTestSet )
}

###########
# helper method to reduce line lengths
pr <- function( msg ) {
    print( msg, quote = FALSE )
}

###########
# helper to de-clutter script code
plotLmCoeffVals <- function( coefIdxs, coefVals, doPrint=FALSE ) {

    if ( doPrint )
        pr( "plotting Linear Model coefficients sorted in decreasing order" )

    # plot to screen and knitr
    plot( coefIdxs, coefVals, pch=21, col="blue", bg="red",
          xlab="Linear Model Coef Index",
          ylab="LM Coef Value",
          main="Linear Model Coefficients" )
    lines(coefIdxs, coefVals, col="blue" )

    # also plot to PNG file
    png( "LmCoeff.png", height = 512, width = 512 )
    par( family = "sans" )
    plot( coefIdxs, coefVals, pch=21, col="blue", bg="red",
          xlab="Linear Model Coef Index",
          ylab="LM Coef Value",
          main="Linear Model Coefficients" )
    lines(coefIdxs, coefVals, col="blue" )
    dev.off()

    if ( doPrint )
        cat( "\n" )
}

###########
# helper to de-clutter script code
plotImportanceData <- function( varIndices, mdaVals, mdGiniVals, doPrint=FALSE ) {

    if ( doPrint )
```

```r
        pr( "plotting Random Forest variable importance() metrics" )

    # plot to screen and knitr
    plot( varIndices, mdaVals,
          xlab="Variable Index",
          ylab="Importance MD Accuracy Value",
          main="MD Accuracy Importance of Variables",
          pch=21, col="blue", bg="red" )
    plot( varIndices, mdGiniVals,
          xlab="Variable Index",
          ylab="Importance MD Gini Value",
          main="MD Gini Importance of Variables",
          pch=21, col="blue", bg="red" )

    # plot to file as well
    png( "RfImpVarMetrics.png", height = 512, width = 900 )
    par( family = "sans" )
    par( mfrow = c( 1, 2 ) )
    plot( varIndices, mdaVals,
        xlab="Variable Index",
        ylab="Importance MD Accuracy Value",
        main="MD Accuracy Importance of Variables",
        pch=21, col="blue", bg="red" )
    plot( varIndices, mdGiniVals,
        xlab="Variable Index",
        ylab="Importance MD Gini Value",
        main="MD Gini Importance of Variables",
        pch=21, col="blue", bg="red" )
    dev.off()
    if ( doPrint )
        cat( "\n" )
}

###########
# helper function to subset, coerce data
prepDf <- function( df ) {
    ## discard first 7 columns - may not be good for general data sets
    df <- df[ , 8:ncol( df ) ]
    ## discard columns with number na/blanks > num rows in data frame
    colNaSums <- apply( df, 2, function(x) { length( which ( is.na(x) | x == "" ) ) } )
    df <- df[ ,colNaSums < nrow(df)/2 ]
    ## coerce integers to numeric
    for ( i in 1:ncol( df ) ) {
        if ( class( df[ 1, i ] ) == "integer" )
            df[ , i ] <- as.numeric( df[ , i ] )
    }
    df # Caller must do the shuffling
}

###########
# a function which returns the numeric index of column in a data frame given the column
name
getColIdx <- function( df, colName ) {
    grep( colName, colnames( df ) )
}
```