ML project

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R Markdown

This is code and documentation for the Coursera Data Science machine learning project. The goal of the project is to use sensor data to train a classifier to distinguish between different exercises that were performed. To accomplish this, the data sets were downloaded and input into data frames.

```
trainingURL <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testingURL  <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
training <- read.csv(trainingURL)
testing  <- read.csv(testingURL)
```

Data Assessment

The data sets start with 160 columns or variables, in which many are either unrelated to solving the classification problem or are uninformative. Let's start by looking at part of the data summary:

```
summary(training[,1:16])
```

```
##        X            user_name    raw_timestamp_part_1 raw_timestamp_part_2
##  Min.   :    1   adelmo  :3892   Min.   :1.322e+09    Min.   :   294
##  1st Qu.: 4906   carlitos:3112   1st Qu.:1.323e+09    1st Qu.:252912
##  Median : 9812   charles :3536   Median :1.323e+09    Median :496380
##  Mean   : 9812   eurico  :3070   Mean   :1.323e+09    Mean   :500656
##  3rd Qu.:14717   jeremy  :3402   3rd Qu.:1.323e+09    3rd Qu.:751891
##  Max.   :19622   pedro   :2610   Max.   :1.323e+09    Max.   :998801
##
##          cvtd_timestamp  new_window    num_window      roll_belt
##  28/11/2011 14:14: 1498   no :19216   Min.   :  1.0   Min.   :-28.90
##  05/12/2011 11:24: 1497   yes:  406   1st Qu.:222.0   1st Qu.:  1.10
##  30/11/2011 17:11: 1440               Median :424.0   Median :113.00
##  05/12/2011 11:25: 1425               Mean   :430.6   Mean   : 64.41
##  02/12/2011 14:57: 1380               3rd Qu.:644.0   3rd Qu.:123.00
##  02/12/2011 13:34: 1375               Max.   :864.0   Max.   :162.00
##  (Other)         :11007
##    pitch_belt          yaw_belt       total_accel_belt kurtosis_roll_belt
##  Min.   :-55.8000   Min.   :-180.00   Min.   : 0.00             :19216
##  1st Qu.:  1.7600   1st Qu.: -88.30   1st Qu.: 3.00    #DIV/0!  :   10
##  Median :  5.2800   Median : -13.00   Median :17.00    -1.908453:    2
##  Mean   :  0.3053   Mean   : -11.21   Mean   :11.31    -0.016850:    1
##  3rd Qu.: 14.9000   3rd Qu.:  12.90   3rd Qu.:18.00    -0.021024:    1
##  Max.   : 60.3000   Max.   : 179.00   Max.   :29.00    -0.025513:    1
##                                                        (Other)  :  391
##  kurtosis_picth_belt kurtosis_yaw_belt skewness_roll_belt skewness_roll_belt.1
##           :19216            :19216            :19216             :19216
```

```
##  #DIV/0!  :   32     #DIV/0!:  406     #DIV/0!  :    9    #DIV/0!  :   32
##  47.000000:    4                       0.000000 :    4    0.000000 :    4
##  -0.150950:    3                       0.422463 :    2    -2.156553:    3
##  -0.684748:    3                       -0.003095:    1    -3.072669:    3
##  -1.750749:    3                       -0.010002:    1    -6.324555:    3
##  (Other)  :  361                       (Other)  :  389    (Other)  :  361
```

If we look at the first eight columns, we can see values that should be irrelevant to identifying the activity such as user_name, timestamps, and information on the data window. We can also see that some of variables contain mostly #DIV/0! or NA values, which we must remove from consideration.

Data Cleaning

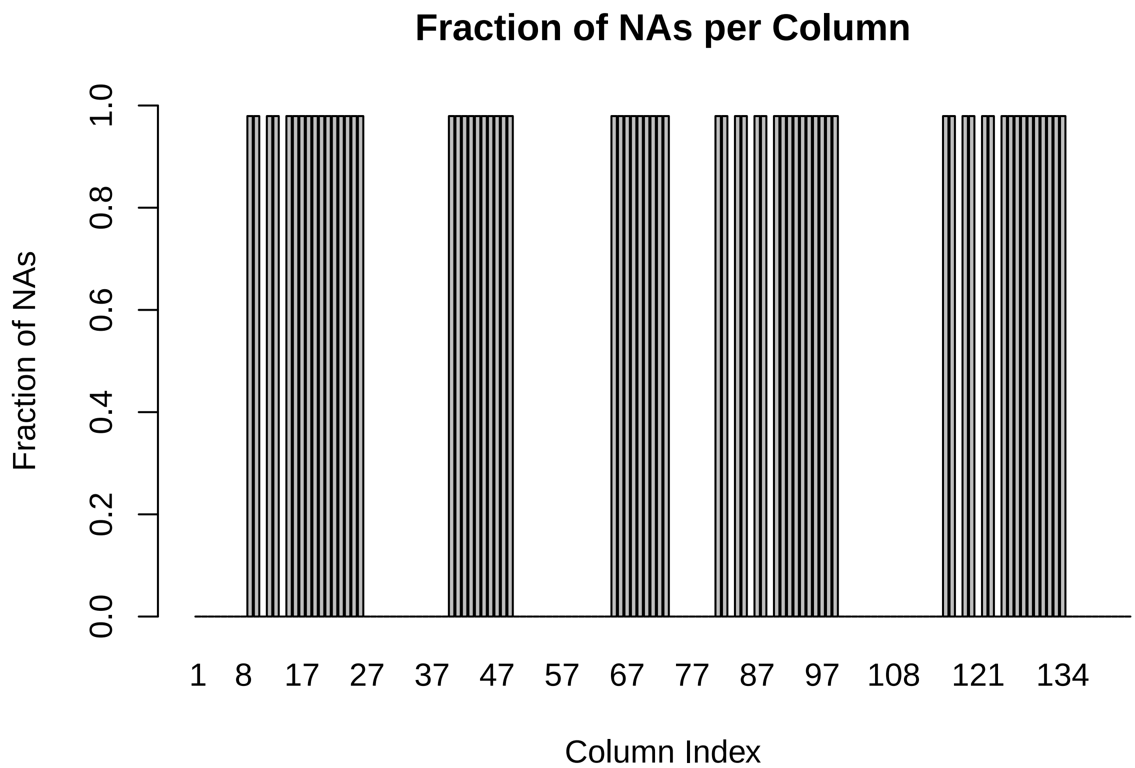
To deal with these irrelevant variables, we remove them from the training and testing data sets. Some columns removed were identified as useless for classification based on the summary (mostly #DIV/0! values) and some by their lack of relevancy to the classification problem.

```
# ID no information columns
useless_cols <- c("X", "user_name", "raw_timestamp_part_1",
    "raw_timestamp_part_2","cvtd_timestamp","new_window", "num_window",
    "kurtosis_yaw_belt", "skewness_yaw_belt", "amplitude_yaw_belt",
    "kurtosis_yaw_dumbbell", "skewness_yaw_dumbbell", "amplitude_yaw_dumbbell",
    "kurtosis_yaw_forearm", "skewness_yaw_forearm", "amplitude_yaw_forearm")
training <- select(training, -useless_cols)         # remove those columns
testing  <- select(testing, -useless_cols)
```

The columns with high proportions of NA values can be identified by determining what fraction of the values are NA.

```
library(ggplot2)

# compute the fraction of NAs per column
vals <- sapply(names(training), function(Col){mean(sapply(training[,Col], is.na))})
barplot(vals, names.arg=1:length(vals), xlab="Column Index",
        ylab="Fraction of NAs", ylim=c(0,1), main="Fraction of NAs per Column")
```



As can be seen, some of the variables hold values that are almost 98% NAs! We identified and dropped those columns where the fraction of NA values exceeded 90%. The data in the training and test sets were then converted to a data matrix to make all values numeric (ensuring that training and testing columns are the same type), and then converted back to data frames.

```
numericize <- function(df) {  # convert data frame to data matrix and back.
  df <- data.matrix(df)       # forces all values to be numeric type
  data.frame(df)
}

classe <- training$classe           # save the classe values
training <- numericize(training)    # make all training columns numeric values
testing <- numericize(testing)      # make all testing columns numeric values

clean_nas <- function(Data){  # identify all columns that are not all NAs
  nas <- sapply(names(Data), function(Col){mean(sapply(Data[,Col], is.na))})
  names(nas[nas<0.9])         # return the names of the lower NA columns
}

lenNames <- length(names(testing))          # get # of testing columns
keep <- clean_nas(testing[,-lenNames])      # get cols in testing w/ fewer NAs
training <- training[,keep]                 # Drop high NA columns from testing
testing <- testing[,keep]                   # Drop high NA cols in training
```

Data Preprocessing

With the non-useful variables removed, we still have 52 columns in the data sets. To reduce the dimensionality of the data sets further, we apply PCA. By default, the PCA routine in caret only retains enough columns to explain 95% of the observed variance.

```r
library(caret)
preObj <- preProcess(training[,-53], method=c("center","scale"))
scaled_train <- predict(preObj, training[,-53])
scaled_test <- predict(preObj, testing)

preProc <- preProcess(scaled_train, method="pca")
pca_train <- predict(preProc, scaled_train)
pca_test <- predict(preProc, scaled_test)
```

Classification

With the data cleaned and dimensionality reduced to 25, we then moved on to the classification problem. We applied a Random Forest classifier, using 5-fold cross-validation in the training data to reduce bias in the classifier outputs. Training was done in parallel to reduce processing time.

```r
library(parallel)
library(doParallel)

set.seed(314159)
cluster <- makeCluster(5)
registerDoParallel(cluster)

Cols <- names(pca_train)
tControl <- trainControl(method = "cv",
                         number = 5,
                         allowParallel = TRUE)

modfit <- train(pca_train, classe, method='rf', na.action = na.omit,
                       proxy=TRUE, trControl = tControl)

stopCluster(cluster)
registerDoSEQ()
modfit
```

```
## Random Forest
##
## 19622 samples
##    25 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15698, 15697, 15698, 15696, 15699
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9802773  0.9750484
##   13    0.9754867  0.9689883
##   25    0.9668226  0.9580330
```

```
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

Given that the classifier was able to correctly identify 98% of the correct classes in the training data, I expect that the accuracy on the testing data should be above 90%

Results

We can test the accuracy of the classifier on the training data, to see how well it trained:

```
table(classe, predict(modfit, pca_train))
```

```
##
## classe    A    B    C    D    E
##      A 5580    0    0    0    0
##      B    0 3797    0    0    0
##      C    0    0 3422    0    0
##      D    0    0    0 3216    0
##      E    0    0    0    0 3607
```

So far, so good. Let's check the classifier's predictions on the test data:

```
predict(modfit, pca_test)
```

```
##  [1] B A A A A E D B A A B C B A E E A B B B
## Levels: A B C D E
```

These are my predictions for the test data set. We'll see how accurate they were after the project is submitted.