Practical Machine Learning - Course Project

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Background

Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement - a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it. In this project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available from the website here: http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

Data

The training data for this project are available here:

https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv

The test data are available here:

https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv

The data for this project come from this source: http://groupware.les.inf.puc-rio.br/har. If you use the document you create for this class for any purpose please cite them as they have been very generous in allowing their data to be used for this kind of assignment.

Loading Data

Loading the required machine learning library:

```
library(caret)
```

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

```
## Loading required package: ggplot2
```

```
library(randomForest)
```

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

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

```
library(e1071)
```

The training and testing data are loaded from given link as:

```
if (!file.exists("./data/pml-training.csv")) {
  download.file("https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv", destfile = "./data/pml-training.csv")
}
if (!file.exists("./data/pml-testing.csv")) {
  download.file("https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv", destfile = "./data/pml-testing.csv")
}
testing <- read.csv("./data/pml-testing.csv", sep = ",", na.strings = c("", "NA"))
training <- read.csv("./data/pml-training.csv", sep = ",", na.strings = c("", "NA"))

dim(testing)
```

```
## [1]  20 160
```

```
dim(training)
```

```
## [1] 19622   160
```

Cleaning Data

Keeping just column of interest only from column 8 to 59 as :

```
# Remove columns full of NAs and first 7 features (column) as they are time-series from testing
features <- names(testing[,colSums(is.na(testing)) == 0])[8:59]
# Only use features used in test cases.
training <- training[,c(features,"classe")]
testing <- testing[,c(features,"problem_id")]

dim(testing)
```

```
## [1] 20 53
```

```
dim(training)
```

```
## [1] 19622    53
```

Partitioning Training Data

Partitioning Training data into 75% training data and 25% testing data for testing after model is constructed.

```
#### seed for reproducibility
set.seed(1024)
into_Train = createDataPartition(training$classe, p = 0.75, list = F)
sub_training = training[into_Train,]
sub_testing = training[-into_Train,]

dim(sub_training)
```

```
## [1] 14718    53
```

```
dim(sub_testing)
```

```
## [1] 4904   53
```

Feature Selection

Feature that are highly correlated about (>90%) are dropped.

```
outcome = which(names(sub_training) == "classe")
highCorrCols = findCorrelation(abs(cor(sub_training[,-outcome])),0.90)
sub_training = sub_training[,-highCorrCols]
outcome = which(names(sub_training) == "classe")
```

The highly correlated features are :

```
highly_Correlated_Features = names(sub_training)[highCorrCols]
highly_Correlated_Features
```

```
## [1] "roll_arm"          "pitch_belt"        "magnet_belt_z"
## [4] "magnet_belt_y"     "magnet_dumbbell_y" "roll_forearm"
## [7] "accel_arm_z"
```

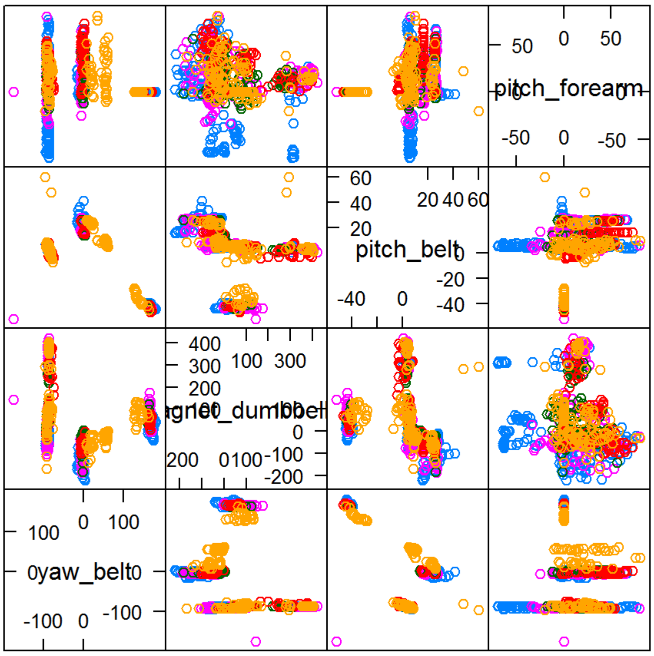
```
#### the dimension of sub_training after dropping these features
dim(sub_training)
```

```
## [1] 14718    46
```

Feature Importance using Random Forest

Discovering important features using Random Forest as random forest method reduces overfitting and is good for nonlinear features. The important 4 features are plotted

```r
fsRF = randomForest(sub_training[,-outcome], sub_training[,outcome], importance = T)
rfImp = data.frame(fsRF$importance)
impFeatures = order(-rfImp$MeanDecreaseGini)
inImp = createDataPartition(sub_training$classe, p = 0.05, list = F)
featurePlot(sub_training[inImp,impFeatures[1:4]],sub_training$classe[inImp], plot = "pairs")
```



Scatter Plot Matrix

The most important features are :

```r
names(sub_training[inImp,impFeatures[1:4]])
```

```
## [1] "yaw_belt"          "magnet_dumbbell_z" "pitch_belt"
## [4] "pitch_forearm"
```

Training

Training by two model i) Random forest ii) k-nearest neighbors

```r
#### Training by KNN
ctrlKNN = trainControl(method = "adaptive_cv")
modelKNN = train(classe ~ ., sub_training, method = "knn", trControl = ctrlKNN)
resultsKNN = data.frame(modelKNN$results)
#### publishing accuracy of KNN
resultsKNN
```

```
##   k  Accuracy     Kappa  AccuracySD     KappaSD .B
## 1 5 0.9062383 0.8813803 0.007638965 0.009645629 10
## 2 7 0.8840727 0.8532752 0.006251121 0.007876520  5
## 3 9 0.8692593 0.8344912 0.004939305 0.006147291  5
```

```r
#### Training By Random Forest
ctrlRF = trainControl(method = "oob")
modelRF = train(classe ~ ., sub_training, method = "rf", ntree = 200, trControl = ctrlRF)
resultsRF = data.frame(modelRF$results)
#### publishing accuracy of Random Forest
resultsRF
```

```
##    Accuracy     Kappa mtry
## 1 0.9925262 0.9905453    2
## 2 0.9933415 0.9915772   23
## 3 0.9908955 0.9884833   45
```

It seems that random forest give a larger accuracy compared to k-nearest neighbors

Testing Out-of-sample error

Looking at confusion matrix between the KNN and RF models to see how much they agree on the test set, and then I compare each model using the test set outcomes.

```
#### fitting KNN models on sub_testing
fitKNN = predict(modelKNN, sub_testing)
#### fitting Random Forest models on sub_testing
fitRF <- predict(modelRF, sub_testing)
```

Comparision of Models using confusionMatrix

RandomForest Versues Test Set

```
confusionMatrix(fitRF,sub_testing$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1392    2    0    0    0
##          B    3  944    5    0    0
##          C    0    3  850   16    0
##          D    0    0    0  787    0
##          E    0    0    0    1  901
##
## Overall Statistics
##
##                Accuracy : 0.9939
##                  95% CI : (0.9913, 0.9959)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9923
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9978   0.9947   0.9942   0.9789   1.0000
## Specificity            0.9994   0.9980   0.9953   1.0000   0.9998
## Pos Pred Value         0.9986   0.9916   0.9781   1.0000   0.9989
## Neg Pred Value         0.9991   0.9987   0.9988   0.9959   1.0000
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2838   0.1925   0.1733   0.1605   0.1837
## Detection Prevalence   0.2843   0.1941   0.1772   0.1605   0.1839
## Balanced Accuracy      0.9986   0.9964   0.9947   0.9894   0.9999
```

KNN Versues Test Set

```
confusionMatrix(fitKNN,sub_testing$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1336   40   16    9    9
##          B   18  847   17    4   38
##          C   16   27  788   51   30
##          D   22   17   19  729   28
##          E    3   18   15   11  796
##
## Overall Statistics
##
##                Accuracy : 0.9168
##                  95% CI : (0.9087, 0.9244)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8948
##  Mcnemar's Test P-Value : 2.057e-09
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
```

```
## Sensitivity            0.9577   0.8925   0.9216   0.9067   0.8835
## Specificity            0.9789   0.9805   0.9694   0.9790   0.9883
## Pos Pred Value         0.9475   0.9167   0.8640   0.8945   0.9442
## Neg Pred Value         0.9831   0.9744   0.9832   0.9817   0.9741
## Prevalence             0.2845   0.1935   0.1743   0.1639   0.1837
## Detection Rate         0.2724   0.1727   0.1607   0.1487   0.1623
## Detection Prevalence   0.2875   0.1884   0.1860   0.1662   0.1719
## Balanced Accuracy      0.9683   0.9365   0.9455   0.9429   0.9359
```

RandomForest Versus KNN

```
confusionMatrix(fitRF,fitKNN)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1338   17   16   20    3
##          B   38  847   29   19   19
##          C   17   20  796   22   14
##          D    8    2   41  726   10
##          E    9   38   30   28  797
##
## Overall Statistics
##
##                Accuracy : 0.9184
##                  95% CI : (0.9104, 0.9259)
##     No Information Rate : 0.2875
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8968
##  Mcnemar's Test P-Value : 8.591e-09
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9489   0.9167   0.8728   0.8908   0.9454
## Specificity            0.9840   0.9736   0.9817   0.9851   0.9741
## Pos Pred Value         0.9598   0.8897   0.9160   0.9225   0.8836
## Neg Pred Value         0.9795   0.9805   0.9713   0.9784   0.9885
## Prevalence             0.2875   0.1884   0.1860   0.1662   0.1719
## Detection Rate         0.2728   0.1727   0.1623   0.1480   0.1625
## Detection Prevalence   0.2843   0.1941   0.1772   0.1605   0.1839
## Balanced Accuracy      0.9665   0.9451   0.9273   0.9379   0.9598
```

The random forest fit is clearly more accurate than the k-nearest neighbors method with 99% accuracy as shown in above.

Submission

Predicting the values for 20 testing data using Random Forest model.

```
predict(modelRF, testing)
```

```
##  [1] 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
```