Practical Machine Learning

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Data preprocessing

```
library(caret)
```

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

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

```
library(rpart)
library(rpart.plot)
library(randomForest)
```

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

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

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
library(corrplot)
```

Read Data

```
trainRaw <- read.csv("D:/coursera/data/8 Practical Machine Learning/pml-training.csv")
testRaw <- read.csv("D:/coursera/data/8 Practical Machine Learning/pml-testing.csv")

dim(trainRaw)
```

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

```
dim(testRaw)
```

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

Data Cleaning

```
##remove NA values
```

```
trainRaw <- trainRaw[, colSums(is.na(trainRaw)) == 0]
testRaw <- testRaw[, colSums(is.na(testRaw)) == 0]
```

##get rid of some columns that do not contribute much to the accelerometer measurements

```
classe <- trainRaw$classe
trainRemove <- grepl("^X|timestamp|window", names(trainRaw))
trainRaw <- trainRaw[, !trainRemove]
trainCleaned <- trainRaw[, sapply(trainRaw, is.numeric)]
trainCleaned$classe <- classe
testRemove <- grepl("^X|timestamp|window", names(testRaw))
testRaw <- testRaw[, !testRemove]
testCleaned <- testRaw[, sapply(testRaw, is.numeric)]
```

##split the cleaned training set into a pure training data set (70%) and a validation data set (30%)
##use the validation data set to conduct cross validation in future steps

```
set.seed(22519) # For reproducibile purpose
inTrain <- createDataPartition(trainCleaned$classe, p=0.70, list=F)
trainData <- trainCleaned[inTrain, ]
testData <- trainCleaned[-inTrain, ]
```

Data Modelling

##Fit a predictive model for activity recognition using Random Forest algorithm
##because it automatically selects important variables and is robust to correlated covariates & outliers
##We will use 5-fold cross validation when applying the algorithm.

```
controlRf <- trainControl(method="cv", 5)
modelRf <- train(classe ~ ., data=trainData, method="rf", trControl=controlRf, ntree=250)
modelRf
```

```
## Random Forest
##
## 13737 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 10989, 10989, 10991, 10990, 10989
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa      Accuracy SD  Kappa SD
##    2    0.9908278  0.9883961  0.001675093  0.002121380
##   27    0.9911190  0.9887646  0.001755971  0.002222771
##   52    0.9840572  0.9798290  0.003497420  0.004425063
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was mtry = 27.
```

##Then estimate the performance of the model on the validation data set

```
predictRf <- predict(modelRf, testData)
confusionMatrix(testData$classe, predictRf)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1672    1    0    0    1
##          B    5 1129    5    0    0
##          C    0    1 1020    5    0
##          D    0    0   13  949    2
##          E    0    0    1    6 1075
##
## Overall Statistics
##
##                Accuracy : 0.9932
##                  95% CI : (0.9908, 0.9951)
##     No Information Rate : 0.285
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9914
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9970   0.9982   0.9817   0.9885   0.9972
## Specificity            0.9995   0.9979   0.9988   0.9970   0.9985
## Pos Pred Value         0.9988   0.9912   0.9942   0.9844   0.9935
## Neg Pred Value         0.9988   0.9996   0.9961   0.9978   0.9994
## Prevalence             0.2850   0.1922   0.1766   0.1631   0.1832
## Detection Rate         0.2841   0.1918   0.1733   0.1613   0.1827
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9983   0.9981   0.9902   0.9927   0.9979
```

##calculate accuracy

```
accuracy <- postResample(predictRf, testData$classe)
accuracy
```

```
##  Accuracy     Kappa
## 0.9932031 0.9914024
```

##calculate estimated out-of-sample error

```
oose <- 1 - as.numeric(confusionMatrix(testData$classe, predictRf)$overall[1])
oose
```

```
## [1] 0.006796941
```

Predicting for Test Data Set

```
##apply the model to the original testing data set downloaded from the data source
##remove the problem_id column first.
```

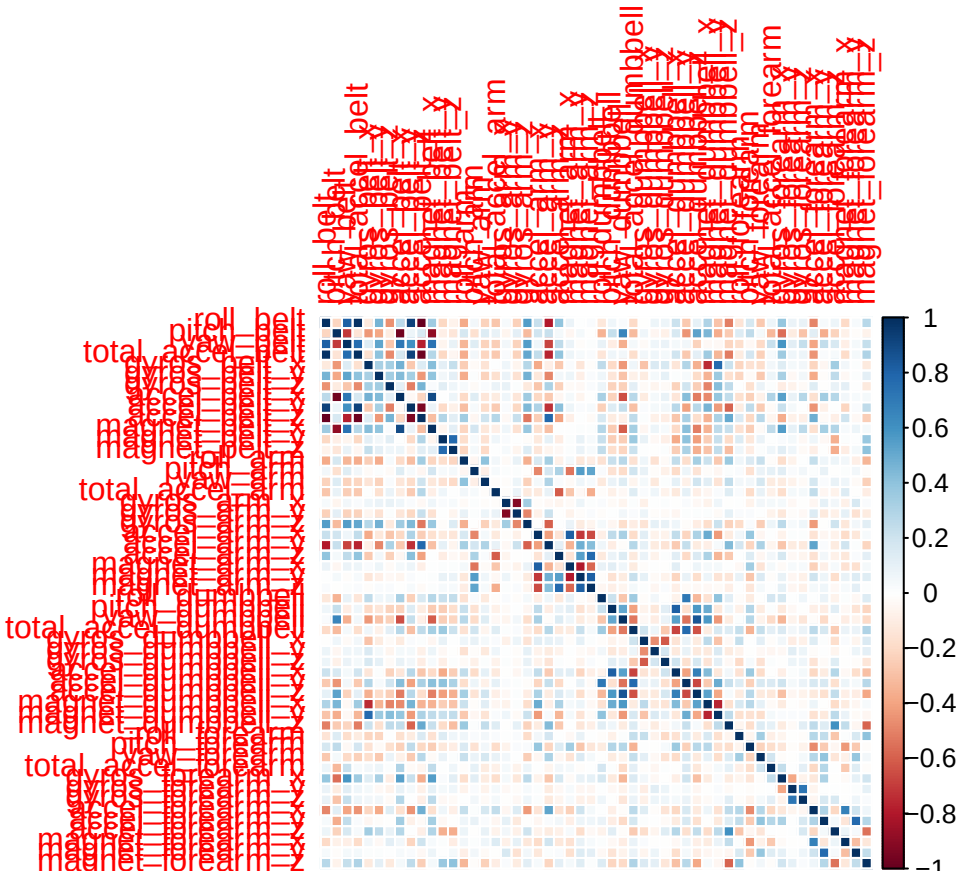
```
result <- predict(modelRf, testCleaned[, -length(names(testCleaned))])
result
```

```
##  [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
```

Appendix

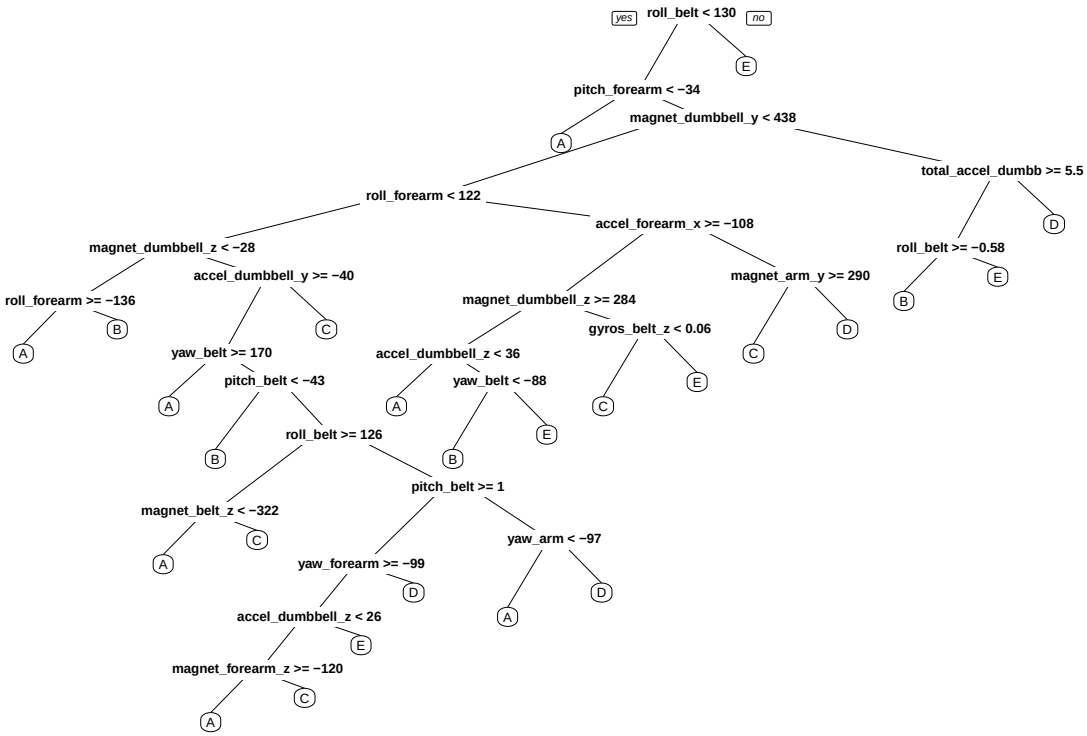
```
##Correlation Matrix Visualization
```

```
corrPlot <- cor(trainData[, -length(names(trainData))])
corrplot(corrPlot, method="color")
```




```
##Tree Visualization
```

```
treeModel <- rpart(classe ~ ., data=trainData, method="class")
prp(treeModel) # fast plot
```


yes
roll_belt < 130
no
E
pitch_forearm < −34
magnet_dumbbell_y < 438
A
total_accel_dumbb >= 5.5
roll_forearm < 122
accel_forearm_x >= −108
D
magnet_dumbbell_z < −28
roll_belt >= −0.58
accel_dumbbell_y >= −40
magnet_arm_y >= 290
E
roll_forearm >= −136
magnet_dumbbell_z >= 284
B
gyros_belt_z < 0.06
A
B
C
yaw_belt >= 170
accel_dumbbell_z < 36
C
D
pitch_belt < −43
yaw_belt < −88
A
A
E
C
E
roll_belt >= 126
B
B
pitch_belt >= 1
magnet_belt_z < −322
yaw_arm < −97
A
C
yaw_forearm >= −99
A
D
D
accel_dumbbell_z < 26
E
magnet_forearm_z >= −120
C
A