Profile

Title: "Practical Machine Learning: Course Project"

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introduction

This report reviews and predicts the patterns of physical exercises by individuals using data from devices such as Jawbone Up, Nike FuelBand, and Fitbit. Machine learning algorithm is applied to the 20 test cases available in the test data. ML Algortihms for Predictions are produced as well as Decision Tree.

Datasets

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

R Code for peer reviews

The R code for this project can be reviewed on my GitHub repo with the link:

https://github.com/remydozie/Cousera_Mechine_Learning.git

Processing

```
library(caret)
```

Load Required Packages & Set Seeds

```
## Warning: package 'caret' was built under R version 3.2.4
```

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

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

```
## Warning: package 'ggplot2' was built under R version 3.2.4
```

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

```
## Warning: package 'rpart.plot' was built under R version 3.2.4
```

```
library(RColorBrewer)
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 3.2.4

## Rattle: A free graphical interface for data mining with R.
## Version 4.1.0 Copyright (c) 2006-2015 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.2.4

## 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(knitr)
set.seed(12345)
```

```
trainUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
testUrl <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
training <- read.csv(url(trainUrl), na.strings=c("NA","#DIV/0!",""))
testing <- read.csv(url(testUrl), na.strings=c("NA","#DIV/0!",""))
```

Load & Process Data

```
#60% Training data & 40% Test data rule is applied.
inTrain <- createDataPartition(y=training$classe, p=0.6, list=FALSE)
myTraining <- training[inTrain, ]; myTesting <- training[-inTrain, ]
dim(myTraining)
```

Prepare Test & Training Data

```
## [1] 11776   160
```

```
dim(myTesting)
```

```
## [1] 7846  160
```

```
myDataNZV <- nearZeroVar(myTraining, saveMetrics=TRUE)
myNZVvars <- names(myTraining) %in% c("new_window", "kurtosis_roll_belt", "kurtosis_picth_belt",
"kurtosis_yaw_belt", "skewness_roll_belt", "skewness_roll_belt.1", "skewness_yaw_belt",
"max_yaw_belt", "min_yaw_belt", "amplitude_yaw_belt", "avg_roll_arm", "stddev_roll_arm",
"var_roll_arm", "avg_pitch_arm", "stddev_pitch_arm", "var_pitch_arm", "avg_yaw_arm",
"stddev_yaw_arm", "var_yaw_arm", "kurtosis_roll_arm", "kurtosis_picth_arm",
"kurtosis_yaw_arm", "skewness_roll_arm", "skewness_pitch_arm", "skewness_yaw_arm",
"max_roll_arm", "min_roll_arm", "min_pitch_arm", "amplitude_roll_arm", "amplitude_pitch_arm",
"kurtosis_roll_dumbbell", "kurtosis_picth_dumbbell", "kurtosis_yaw_dumbbell", "skewness_roll_dumbbell",
"skewness_pitch_dumbbell", "skewness_yaw_dumbbell", "max_yaw_dumbbell", "min_yaw_dumbbell",
"amplitude_yaw_dumbbell", "kurtosis_roll_forearm", "kurtosis_picth_forearm", "kurtosis_yaw_forearm",
"skewness_roll_forearm", "skewness_pitch_forearm", "skewness_yaw_forearm", "max_roll_forearm",
"max_yaw_forearm", "min_roll_forearm", "min_yaw_forearm", "amplitude_roll_forearm",
"amplitude_yaw_forearm", "avg_roll_forearm", "stddev_roll_forearm", "var_roll_forearm",
"avg_pitch_forearm", "stddev_pitch_forearm", "var_pitch_forearm", "avg_yaw_forearm",
"stddev_yaw_forearm", "var_yaw_forearm")
myTraining <- myTraining[!myNZVvars]
# Review the revised value of observations
dim(myTraining)
```

Clean & Verify Data

```
## [1] 11776   100
```

```
myTraining <- myTraining[c(-1)]
trainingV3 <- myTraining
for(i in 1:length(myTraining)) {
if( sum( is.na( myTraining[, i] ) ) /nrow(myTraining) >= .6 ) {
for(j in 1:length(trainingV3)) {
if( length( grep(names(myTraining[i]), names(trainingV3)[j]) ) ==1)  {
trainingV3 <- trainingV3[ , -j] #Remove that column
}
}
}
}
dim(trainingV3)
```

```
## [1] 11776    58
```

```
myTraining <- trainingV3
rm(trainingV3)
clean1 <- colnames(myTraining)
clean2 <- colnames(myTraining[, -58])
myTesting <- myTesting[clean1]
testing <- testing[clean2]
dim(myTesting)
```

```
## [1] 7846   58
```

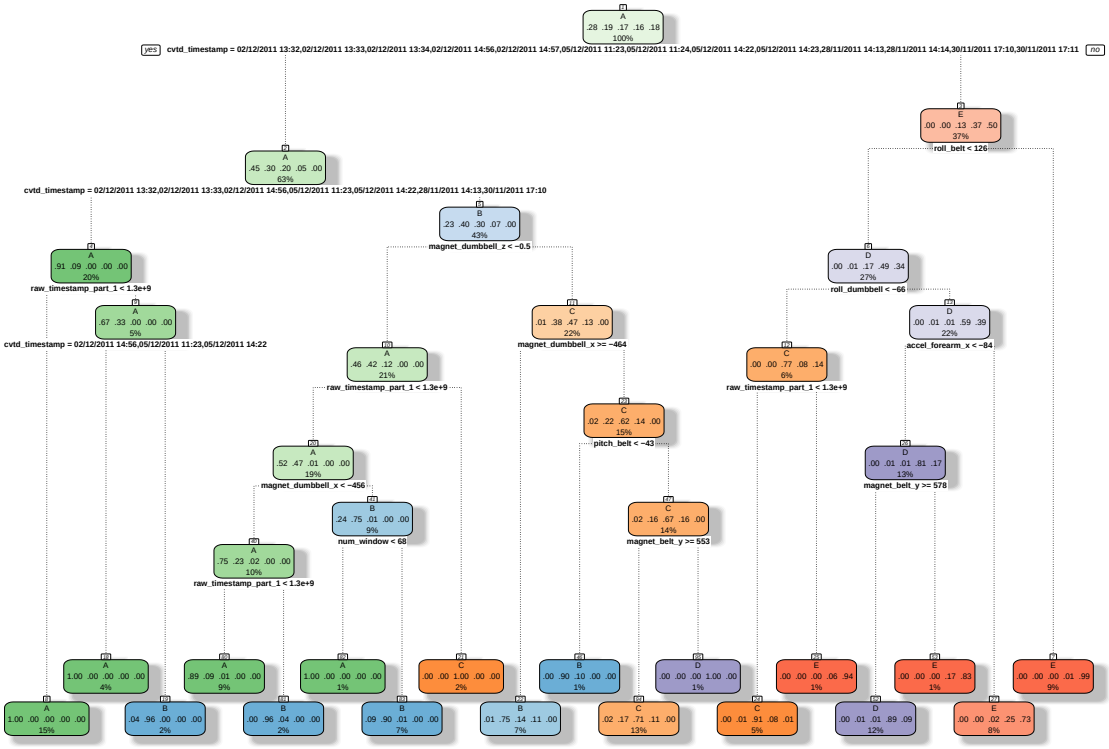
```
dim(testing)
```

```
## [1] 20 57
```

```
for (i in 1:length(testing) ) {
for(j in 1:length(myTraining)) {
if( length( grep(names(myTraining[i]), names(testing)[j]) ) ==1)  {
class(testing[j]) <- class(myTraining[i])
}
}
}
testing <- rbind(myTraining[2, -58] , testing)
testing <- testing[-1,]
```

```
modFitA1 <- rpart(classe ~ ., data=myTraining, method="class")
fancyRpartPlot(modFitA1)
```

Fit Model & Plot Decision Tree



Rattle 2016−Apr−03 21:50:06 Nnadozie

```
predictionsA1 <- predict(modFitA1, myTesting, type = "class")
confusionMatrix(predictionsA1, myTesting$classe)
```

Developing Confusion Matrix

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2150   60    7    1    0
##          B   61 1260   69   64    0
##          C   21  188 1269  143    4
##          D    0   10   14  857   78
##          E    0    0    9  221 1360
##
## Overall Statistics
##
##                Accuracy : 0.8789
##                  95% CI : (0.8715, 0.8861)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8468
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9633   0.8300   0.9276   0.6664   0.9431
## Specificity            0.9879   0.9693   0.9450   0.9845   0.9641
## Pos Pred Value         0.9693   0.8666   0.7809   0.8936   0.8553
## Neg Pred Value         0.9854   0.9596   0.9841   0.9377   0.9869
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2740   0.1606   0.1617   0.1092   0.1733
## Detection Prevalence   0.2827   0.1853   0.2071   0.1222   0.2027
## Balanced Accuracy      0.9756   0.8997   0.9363   0.8254   0.9536
```

```
modFitB1 <- randomForest(classe ~. , data=myTraining)
predictionsB1 <- predict(modFitB1, myTesting, type = "class")
confusionMatrix(predictionsB1, myTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2231    2    0    0    0
##          B    1 1516    2    0    0
##          C    0    0 1366    3    0
##          D    0    0    0 1282    2
##          E    0    0    0    1 1440
##
```

```
## Overall Statistics
##
##                Accuracy : 0.9986
##                  95% CI : (0.9975, 0.9993)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9982
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9996   0.9987   0.9985   0.9969   0.9986
## Specificity            0.9996   0.9995   0.9995   0.9997   0.9998
## Pos Pred Value         0.9991   0.9980   0.9978   0.9984   0.9993
## Neg Pred Value         0.9998   0.9997   0.9997   0.9994   0.9997
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2843   0.1932   0.1741   0.1634   0.1835
## Detection Prevalence   0.2846   0.1936   0.1745   0.1637   0.1837
## Balanced Accuracy      0.9996   0.9991   0.9990   0.9983   0.9992
```

```
modFitB1 <- randomForest(classe ~. , data=myTraining)
predictionsB1 <- predict(modFitB1, myTesting, type = "class")
confusionMatrix(predictionsB1, myTesting$classe)
```

Developing ML Algortihms for Predictions (Random Forest)

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2231    2    0    0    0
##          B    1 1516    2    0    0
##          C    0    0 1366    3    0
##          D    0    0    0 1282    2
##          E    0    0    0    1 1440
##
## Overall Statistics
##
##                Accuracy : 0.9986
##                  95% CI : (0.9975, 0.9993)
##     No Information Rate : 0.2845
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9982
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
```

```
## Sensitivity            0.9996   0.9987   0.9985   0.9969   0.9986
## Specificity            0.9996   0.9995   0.9995   0.9997   0.9998
## Pos Pred Value         0.9991   0.9980   0.9978   0.9984   0.9993
## Neg Pred Value         0.9998   0.9997   0.9997   0.9994   0.9997
## Prevalence             0.2845   0.1935   0.1744   0.1639   0.1838
## Detection Rate         0.2843   0.1932   0.1741   0.1634   0.1835
## Detection Prevalence   0.2846   0.1936   0.1745   0.1637   0.1837
## Balanced Accuracy      0.9996   0.9991   0.9990   0.9983   0.9992
```

```
predictionsB2 <- predict(modFitB1, testing, type = "class")
pml_write_files = function(x){
n = length(x)
for(i in 1:n){
filename = paste0("problem_id_",i,".txt")
write.table(x[i],file=filename,quote=FALSE,row.names=FALSE,col.names=FALSE)
}
}
pml_write_files(predictionsB2)
```