Practical Machine Learning Project

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15 августа 2015 г.

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```
#install.packages("caret")
#install.packages("randomForest")
#install.packages("rpart")
#install.packages("rpart.plot")
library("rpart")
library("randomForest")
```

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

```
url="https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
download.file(url, "pml-training.csv",method='curl')

url="https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
download.file(url, "pml-testing.csv",method='curl')
```

Read,view and clean datasets

```
# Class A corresponds to the specified execution of the exercise, while the other
4 classes correspond to common mistakes. Participants were supervised by an experi
enced weight lifter to make sure the execution complied to the manner they were su
pposed to simulate. The exercises were performed by six male participants aged bet
ween 20-28 years, with little weight lifting experience. We made sure that all par
ticipants could easily simulate the mistakes in a safe and controlled manner by us
ing a relatively light dumbbell (1.25kg).
#
# Read more: http://groupware.les.inf.puc-rio.br/har#ixzz3isa6f0Ds

training=read.csv("pml-training.csv",head=T, na.string=c("NA","#DIV/0!", ""))
testing=read.csv("pml-testing.csv",head=T,na.string=c("NA","#DIV/0!", ""))

# Delete columns with more than 20% missing values
training<-training[ , apply(training , 2 ,
                     function (x)  sum(is.na(x)) < 0.2 *nrow(training)) ]
dim(training)
```

```
## [1] 19622    60
```

```
testing<-testing[ , apply(testing , 2 ,
               function (x)  sum(is.na(x)) < 0.2 *nrow(testing)) ]
dim(testing)
```

```
## [1] 20 60
```

```
head(training)[1:10]
```

```
##   X user_name raw_timestamp_part_1 raw_timestamp_part_2   cvtd_timestamp
## 1 1  carlitos           1323084231               788290 05/12/2011 11:23
## 2 2  carlitos           1323084231               808298 05/12/2011 11:23
## 3 3  carlitos           1323084231               820366 05/12/2011 11:23
## 4 4  carlitos           1323084232               120339 05/12/2011 11:23
## 5 5  carlitos           1323084232               196328 05/12/2011 11:23
## 6 6  carlitos           1323084232               304277 05/12/2011 11:23
##   new_window num_window roll_belt pitch_belt yaw_belt
## 1         no         11      1.41       8.07    -94.4
## 2         no         11      1.41       8.07    -94.4
## 3         no         11      1.42       8.07    -94.4
## 4         no         12      1.48       8.05    -94.4
## 5         no         12      1.48       8.07    -94.4
## 6         no         12      1.45       8.06    -94.4
```

```
head(testing)[1:10]
```

```
##   X user_name raw_timestamp_part_1 raw_timestamp_part_2   cvtd_timestamp
## 1 1     pedro           1323095002               868349 05/12/2011 14:23
## 2 2    jeremy           1322673067               778725 30/11/2011 17:11
## 3 3    jeremy           1322673075               342967 30/11/2011 17:11
## 4 4    adelmo           1322832789               560311 02/12/2011 13:33
## 5 5    eurico           1322489635               814776 28/11/2011 14:13
## 6 6    jeremy           1322673149               510661 30/11/2011 17:12
##   new_window num_window roll_belt pitch_belt yaw_belt
## 1         no         74    123.00      27.00    -4.75
## 2         no        431      1.02       4.87   -88.90
## 3         no        439      0.87       1.82   -88.50
## 4         no        194    125.00     -41.60   162.00
## 5         no        235      1.35       3.33   -88.60
## 6         no        504     -5.92       1.59   -87.70
```

```
# Columns 1-7 we can delete too
training <-training[,-c(1:7)]
testing  <-testing[,-c(1:7)]

set.seed(848)
# Random subsampling without replacement (60%)
subsamples= sample(1:nrow(training),size=nrow(training)*0.6,replace=F)
subTraining <- training[subsamples, ]
subTesting <- training[-subsamples, ]
dim(subTraining)
```

```
## [1] 11773    53
```

```
dim(subTesting)
```

```
## [1] 7849   53
```

Frequency of levels (A, B, C, D, E) in the subTraining dataset for variable “classe”

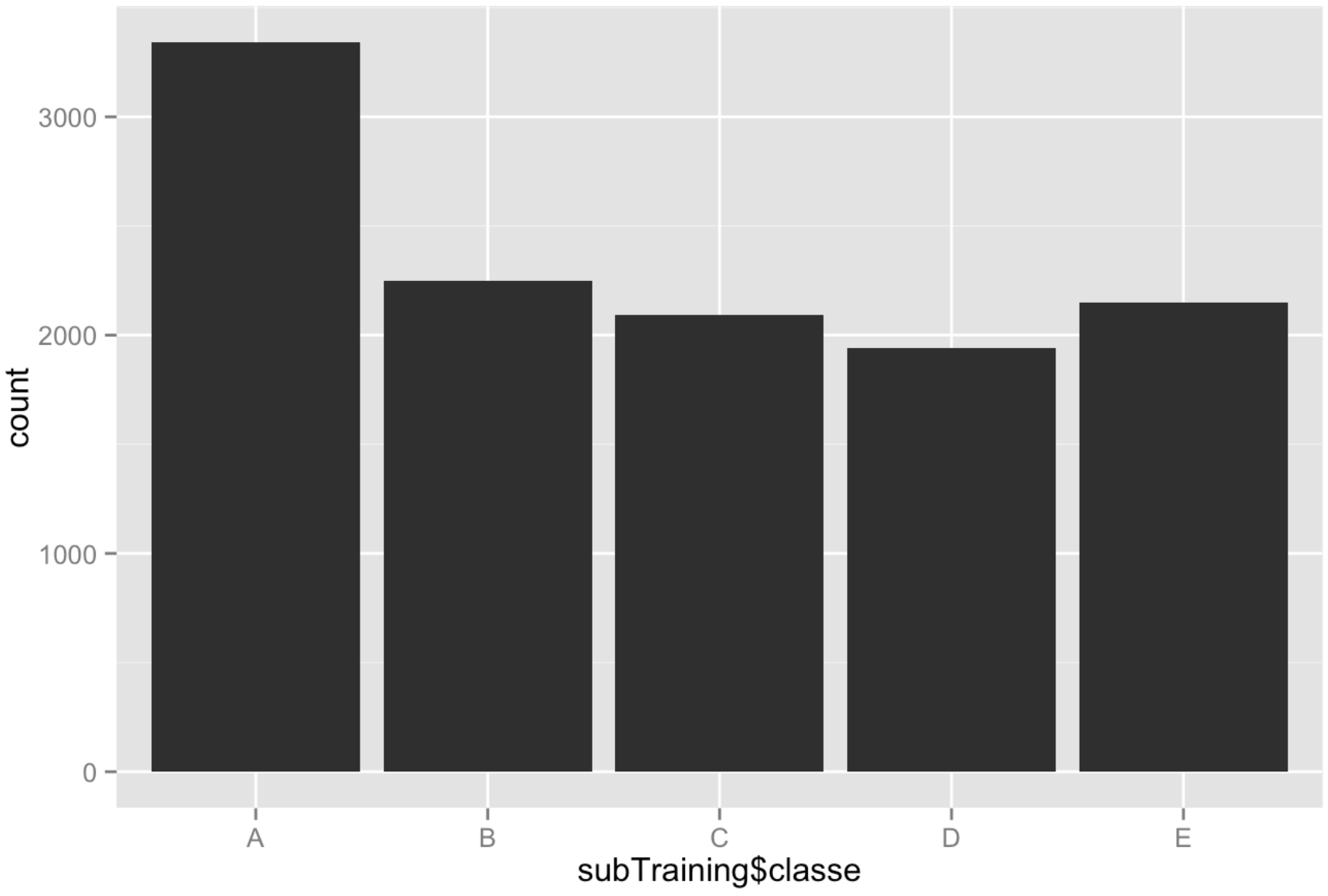
```
library("caret")
```

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

```
summary(subTraining$classe)
```

```
##    A    B    C    D    E
## 3340 2249 2092 1943 2149
```

```
qplot(subTraining$classe,
        main="Levels of the variable classe")
```



Correlation Analysis

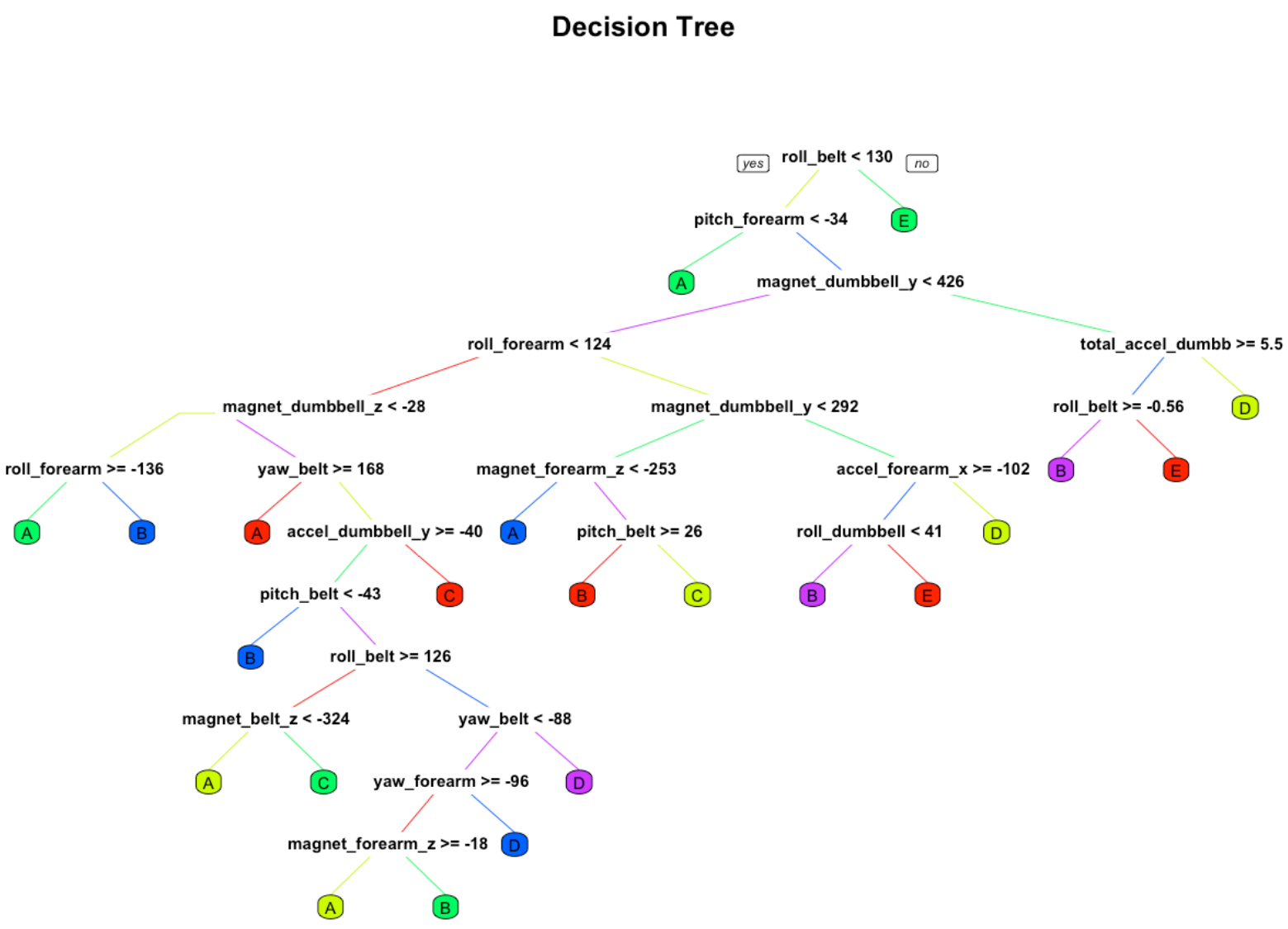
```
correlation <- findCorrelation(cor(subTraining[, 1:ncol(subTraining)-1]), cutoff=0
.8)
names(subTraining)[correlation]
```

```
##  [1] "accel_belt_z"     "roll_belt"        "accel_belt_y"
##  [4] "accel_dumbbell_z" "accel_belt_x"     "pitch_belt"
##  [7] "accel_dumbbell_x" "accel_arm_x"      "magnet_arm_y"
## [10] "gyros_arm_x"
```

Prediction model 1: Decision Tree

```
library("rpart")
model1 <- rpart(classe ~ .,
                subTraining,
                method="class")
#model1

predictions1<-predict(model1, subTesting,type ="class")
cols=rainbow(5)
library("rpart.plot")
rpart.plot(model1, main="Decision Tree",box.col=cols, branch.col=cols)
```




```
confusionMatrix(predictions1, subTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1956  246   23   57   31
##          B  103  982  131  103  193
##          C   67  122 1016  184  167
##          D   91  107   87  856  120
##          E   23   91   73   73  947
##
## Overall Statistics
##
##                Accuracy : 0.7335
##                  95% CI : (0.7235, 0.7432)
##     No Information Rate : 0.2854
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6625
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.8732   0.6344   0.7639   0.6724   0.6495
## Specificity            0.9364   0.9159   0.9172   0.9384   0.9593
## Pos Pred Value         0.8457   0.6495   0.6530   0.6788   0.7846
## Neg Pred Value         0.9487   0.9107   0.9501   0.9367   0.9231
## Prevalence             0.2854   0.1972   0.1694   0.1622   0.1858
## Detection Rate         0.2492   0.1251   0.1294   0.1091   0.1207
## Detection Prevalence   0.2947   0.1926   0.1982   0.1607   0.1538
## Balanced Accuracy      0.9048   0.7751   0.8405   0.8054   0.8044
```

Prediction model 2: Random Forest

```
library("randomForest")
model2<- randomForest(classe ~ .,
                      subTraining,
                      method="class")
model2
```

```
##
## Call:
##  randomForest(formula = classe ~ ., data = subTraining, method = "class")
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 7
##
##         OOB estimate of  error rate: 0.59%
## Confusion matrix:
##      A    B    C    D    E class.error
## A 3335    5    0    0    0 0.001497006
## B   13 2231    5    0    0 0.008003557
## C    0    9 2081    2    0 0.005258126
## D    0    0   24 1918    1 0.012866701
## E    0    0    2    8 2139 0.004653327
```

```
predictions2<-predict(model2, subTesting,type="class")
confusionMatrix(predictions2, subTesting$classe)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 2239    8    0    0    0
##          B    0 1535   10    0    0
##          C    0    5 1319   14    0
##          D    0    0    1 1259    6
##          E    1    0    0    0 1452
##
## Overall Statistics
##
##                Accuracy : 0.9943
##                  95% CI : (0.9923, 0.9958)
##     No Information Rate : 0.2854
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9927
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9996   0.9916   0.9917   0.9890   0.9959
## Specificity            0.9986   0.9984   0.9971   0.9989   0.9998
## Pos Pred Value         0.9964   0.9935   0.9858   0.9945   0.9993
## Neg Pred Value         0.9998   0.9979   0.9983   0.9979   0.9991
## Prevalence             0.2854   0.1972   0.1694   0.1622   0.1858
## Detection Rate         0.2853   0.1956   0.1680   0.1604   0.1850
## Detection Prevalence   0.2863   0.1968   0.1705   0.1613   0.1851
## Balanced Accuracy      0.9991   0.9950   0.9944   0.9940   0.9979
```

Predictions for both models

```
predict(model1, testing,type="class")
```

```
##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
##  B  A  E  D  A  C  D  B  A  A  C  E  C  A  E  D  A  B  B  B
## Levels: A B C D E
```

```
predict(model2, testing,type="class")
```

```
##  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
```

Decision about one of the two prediction model

Accuracy for Random Forest model - 0.9943 (95% CI : (0.9923, 0.9958)).

Accuracy for Decision Tree model - 0.7335 (95% CI: (0.7235, 0.7432)).

The Random Forests model is better.