Machine Learning project

Ale Goity

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#Summary We will analyzed the data using decision trees. I generated three models. Two models based in decision trees, the first using all the variables and a second model with only some variables. And a third model using parallel random forest (parRF). I alsp predicted the classe of the testing data using all the models. I compared the difference between the results obtain with the decision trees models and finally the prediction with the random forest model that predicted correctly all the testing predictions.

Read and cleaning the data

```
setwd("/Users/alegoity/Dropbox/Cursos/Coursera/R/Course8 (Machine Learning)/project/")
training<-read.csv("pml-training.csv")
testing<-read.csv("pml-testing.csv")
```

Remove columns with no information for the analysis. No variation in the column or NA values. Also, the information from columns 1 to 5. Doing this, we reduced variables to 54.

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.0.2
```

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

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

```
a<-nearZeroVar(training)
training<-training[,-a] #eliminate columns with no variation
training<-training[ , -(1:5)]
training<- training[,colSums(is.na(training))<nrow(training)-1000] #to eliminate columns with high numb

dim(training)
```

```
## [1] 19622    54
```

Use createDataPartition to generate training_data (70%) and testing_data (30%) group

```
set.seed(222)
inTrain<-createDataPartition(training$classe, p=0.7, list=FALSE)
training_data <- training[inTrain,]
testing_data <- training[-inTrain,]
```

Modelling

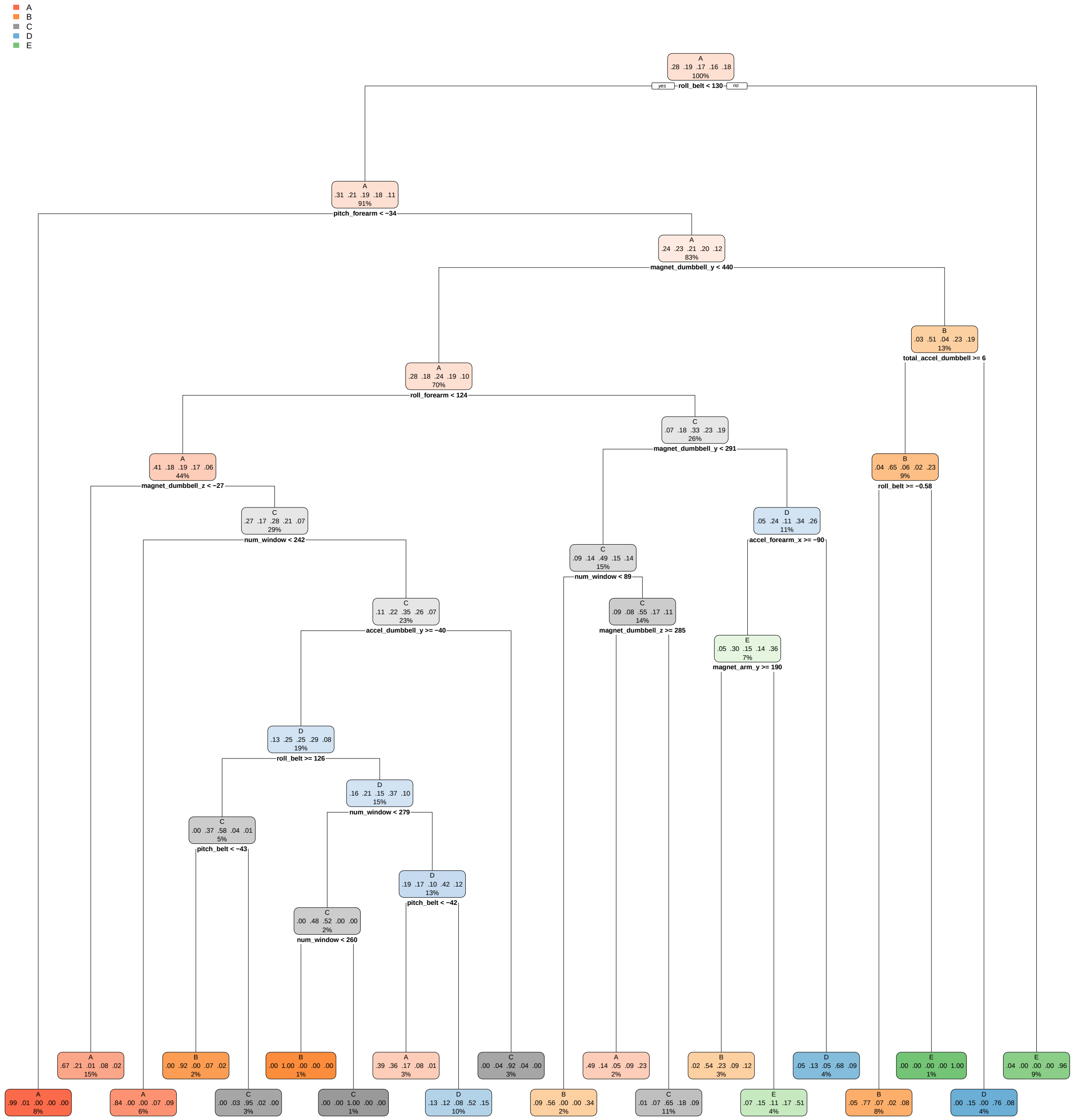
Create a decision tree model using all the variables

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

```
## Warning: package 'rpart.plot' was built under R version 4.0.2
```

```r
set.seed(222)
model_DT1 <- rpart(classe ~., data = training_data, method = "class")

# Plot the trees
rpart.plot(model_DT1)
```




```r
testing_data$classe<-as.factor(testing_data$classe)
predict_tree <- predict(model_DT1, newdata= testing_data, type="class")
conMatrixtree <- confusionMatrix(testing_data$classe, predict_tree)
conMatrixtree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1491   38   10   87   48
##          B  251  643   63  153   29
##          C   50   71  822   54   29
##          D  107   38  132  647   40
##          E   98  104   63  120  697
##
## Overall Statistics
##
##                Accuracy : 0.7307
##                  95% CI : (0.7191, 0.742)
##     No Information Rate : 0.3393
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6573
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.7466   0.7192   0.7541   0.6098   0.8268
## Specificity            0.9529   0.9006   0.9575   0.9343   0.9236
## Pos Pred Value         0.8907   0.5645   0.8012   0.6712   0.6442
## Neg Pred Value         0.8798   0.9471   0.9448   0.9159   0.9696
## Prevalence             0.3393   0.1519   0.1852   0.1803   0.1432
## Detection Rate         0.2534   0.1093   0.1397   0.1099   0.1184
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.8498   0.8099   0.8558   0.7720   0.8752
```

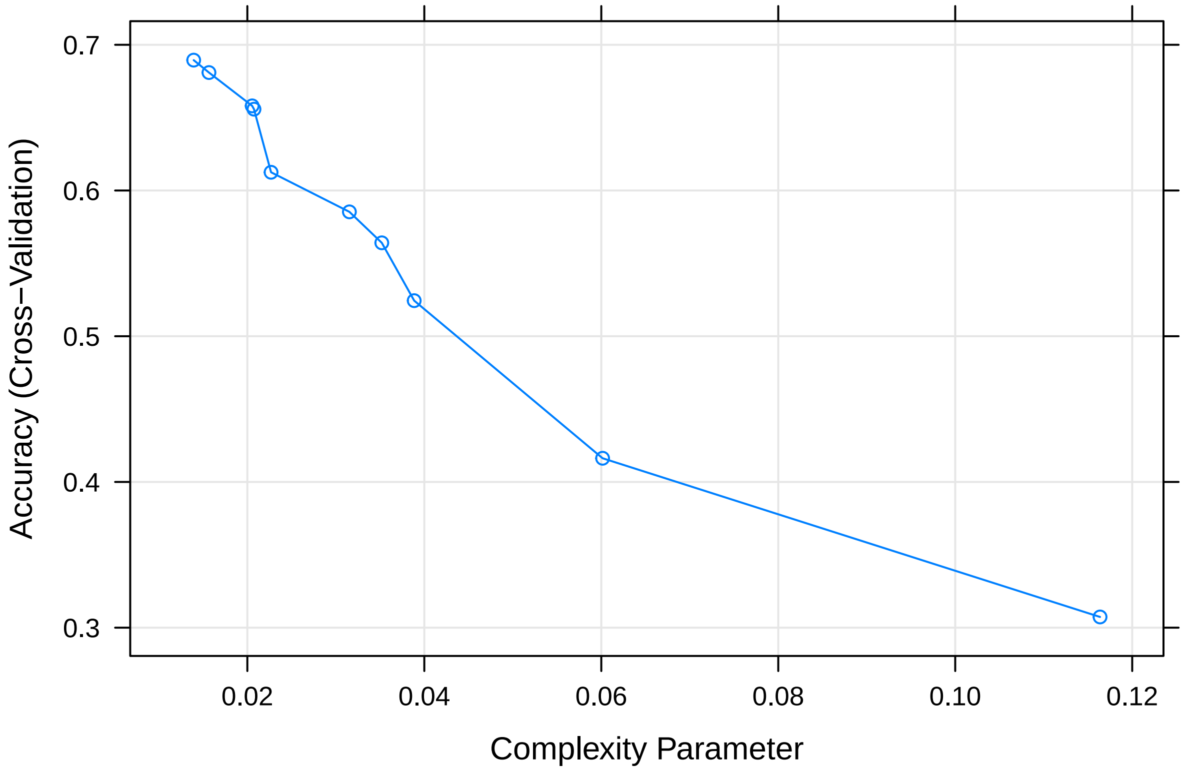
The accuracy of model_DT1 is 73.1%

Create a decision tree using cross validation to predict the accuracy of the model.

trControl is set to 10-fold cross validation and tuneLenght to 10

```
set.seed(222)
model_DT2<- train(classe~., data = training_data, method = "rpart", trControl = trainControl("cv", numbe

plot(model_DT2)
```



To

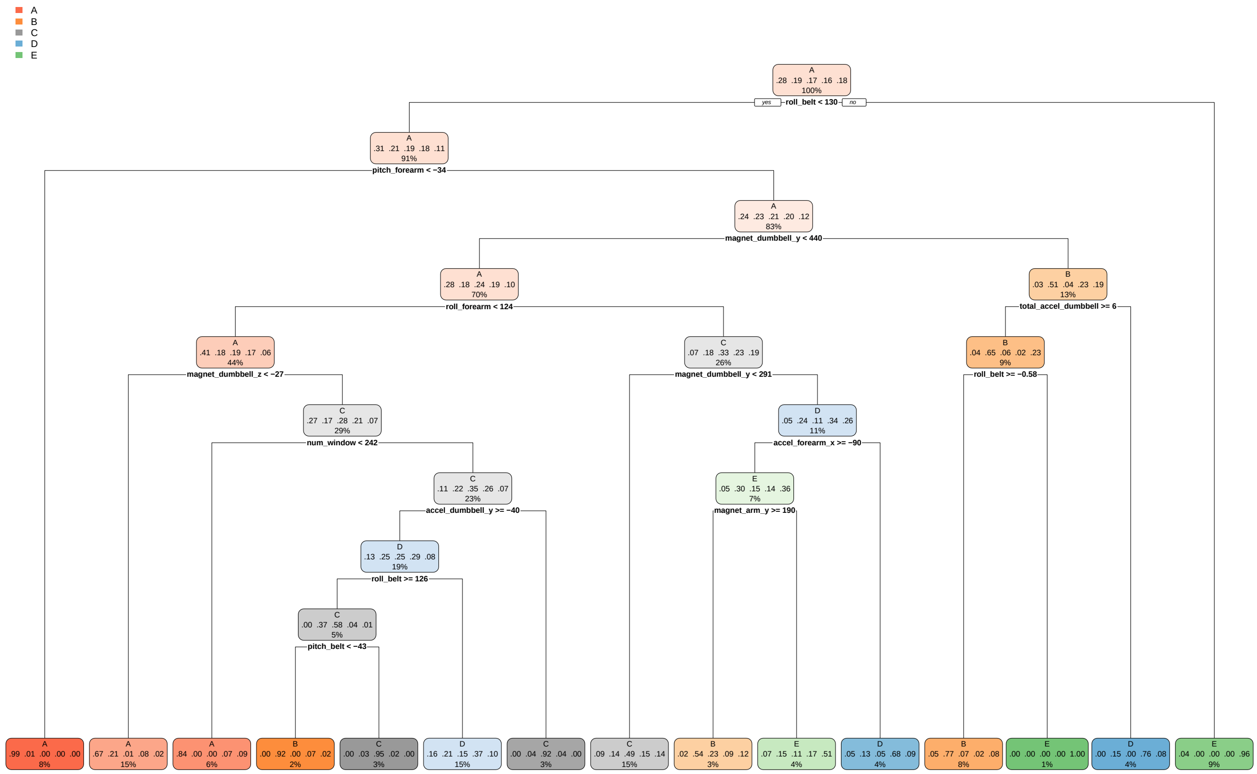
determing the cp at which is obtained the best model accuracy

```
model_DT2$bestTune
```

```
##            cp
## 1 0.01393551
```

plot the best decision tree obtained

```
rpart.plot(model_DT2$finalModel)
```



Decisions rules the model

```
model_DT2$finalModel
```

```
## n= 13737
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
##   1) root 13737 9831 A (0.28 0.19 0.17 0.16 0.18)
##     2) roll_belt< 129.5 12499 8640 A (0.31 0.21 0.19 0.18 0.11)
##       4) pitch_forearm< -33.65 1097   12 A (0.99 0.011 0 0 0) *
##       5) pitch_forearm>=-33.65 11402 8628 A (0.24 0.23 0.21 0.2 0.12)
##        10) magnet_dumbbell_y< 439.5 9640 6920 A (0.28 0.18 0.24 0.19 0.1)
##          20) roll_forearm< 123.5 6026 3573 A (0.41 0.18 0.19 0.17 0.055)
##            40) magnet_dumbbell_z< -27.5 2060  672 A (0.67 0.21 0.012 0.079 0.023) *
##            41) magnet_dumbbell_z>=-27.5 3966 2873 C (0.27 0.17 0.28 0.21 0.072)
##              82) num_window< 241.5 875  139 A (0.84 0.0011 0 0.072 0.086) *
##              83) num_window>=241.5 3091 1998 C (0.11 0.22 0.35 0.26 0.068)
##               166) accel_dumbbell_y>=-40.5 2629 1857 D (0.13 0.25 0.25 0.29 0.08)
##                 332) roll_belt>=125.5 625  261 C (0 0.37 0.58 0.038 0.0064)
##                   664) pitch_belt< -42.75 243   20 B (0 0.92 0 0.066 0.016) *
##                   665) pitch_belt>=-42.75 382   18 C (0 0.026 0.95 0.021 0) *
##                 333) roll_belt< 125.5 2004 1256 D (0.16 0.21 0.15 0.37 0.1) *
##               167) accel_dumbbell_y< -40.5 462   35 C (0 0.039 0.92 0.037 0) *
##          21) roll_forearm>=123.5 3614 2412 C (0.074 0.18 0.33 0.23 0.19)
##            42) magnet_dumbbell_y< 290.5 2105 1074 C (0.09 0.14 0.49 0.15 0.14) *
##            43) magnet_dumbbell_y>=290.5 1509  992 D (0.052 0.24 0.11 0.34 0.26)
##              86) accel_forearm_x>=-90.5 945  609 E (0.051 0.3 0.15 0.14 0.36)
##               172) magnet_arm_y>=189.5 372  172 B (0.019 0.54 0.23 0.094 0.12) *
```

```
##              173) magnet_arm_y< 189.5 573  283 E (0.072 0.15 0.11 0.17 0.51) *
##             87) accel_forearm_x< -90.5 564  179 D (0.053 0.13 0.046 0.68 0.089) *
##        11) magnet_dumbbell_y>=439.5 1762  869 B (0.031 0.51 0.044 0.23 0.19)
##          22) total_accel_dumbbell>=5.5 1255  439 B (0.043 0.65 0.06 0.018 0.23)
##            44) roll_belt>=-0.58 1053  237 B (0.051 0.77 0.071 0.021 0.082) *
##            45) roll_belt< -0.58 202    0 E (0 0 0 0 1) *
##          23) total_accel_dumbbell< 5.5 507  120 D (0 0.15 0.0039 0.76 0.081) *
##     3) roll_belt>=129.5 1238   47 E (0.038 0 0 0 0.96) *
```

Make predictions on the test data

```
testing_data$classe<-as.factor(testing_data$classe)
predicted_classe <-predict(model_DT2, testing_data)
```

Compute model accuracy rate on test data

```
mean(predicted_classe == testing_data$classe)
```

```
## [1] 0.6880204
```

The accuracy of model_DT2 is 68.8%

Predict testing cases

Based on the accuracy of the models we will use model_DT1 (use all variables to make the prediction).

```
testing_prediction1<-predict(model_DT1, newdata = testing, type="class")
testing_prediction1
```

```
##  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  C  D  D  A  A  C  B  A  A  E  D  A  A  A  B
## Levels: A B C D E
```

EXTRA

We will compare the predictions obtain using model_DT1 and model_DT2.

Prediction using model_DT2

```
testing_prediction2<-predict(model_DT2, newdata = testing)
testing_prediction2
```

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

Compare how many equal predictions we obtain using model_DT1 or model_DT2

```
sum(testing_prediction1 == testing_prediction2)
```

```
## [1] 18
```

We obtain equal results in 18 of 20 cases using any of the two models. Observing differences in two cases were model_DT1 should have a better performance.

Model random forest

Create a random forest model with cross validation to predict the accuracy of the model.

To diminish calculation time it was set to 3-fold cross validation and 100 trees. And parallele random forest (parRF) was used.

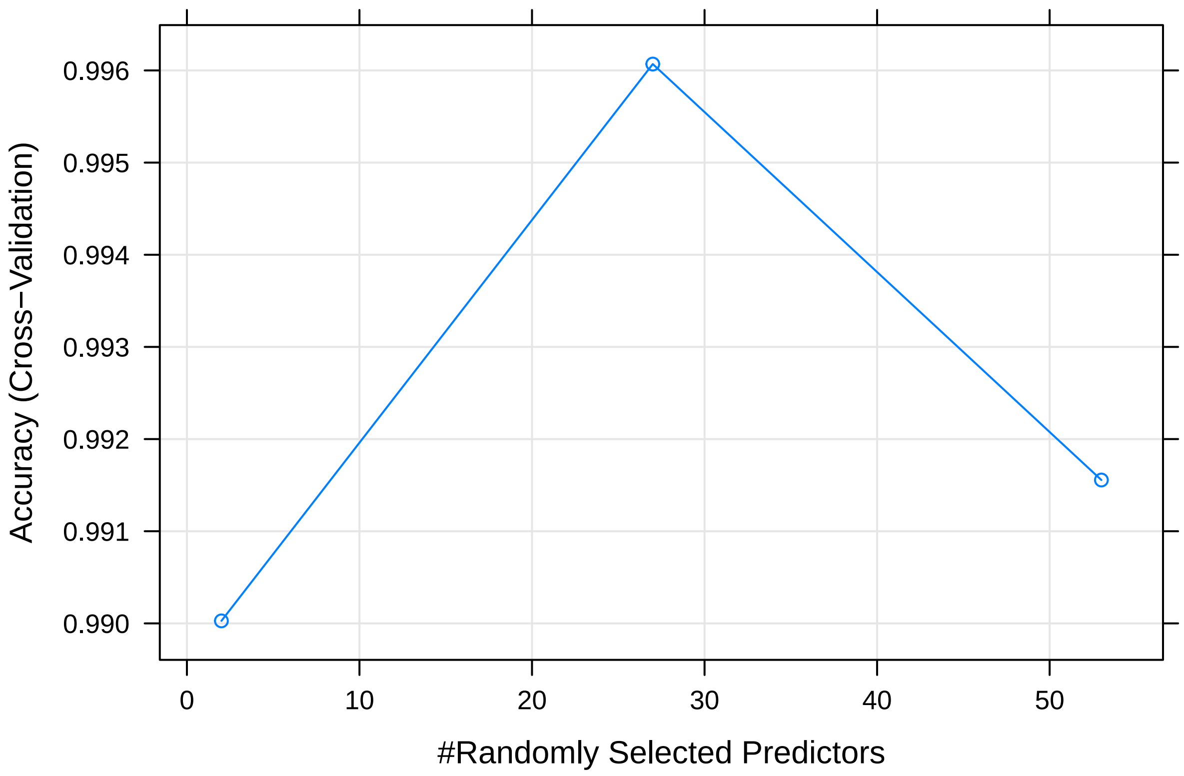
```
library(doParallel)
```

```
## Warning: package 'doParallel' was built under R version 4.0.2
## Loading required package: foreach
## Warning: package 'foreach' was built under R version 4.0.2
## Loading required package: iterators
## Warning: package 'iterators' was built under R version 4.0.2
## Loading required package: parallel
```

```
model_RF<- train(classe~., data = training_data, method = "parRF",  trControl = trainControl("cv", numbe
```

```
## Warning: executing %dopar% sequentially: no parallel backend registered
```

```
plot(model_RF)
```



To evaluate the values of the model_RF

```
model_RF$finalModel
```

```
##
## Call:
##  randomForest(x = "x", y = "y", ntree = 100, mtry = 27, ntrees = 100)
```

```
##                Type of random forest: classification
##                      Number of trees: 100
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.31%
## Confusion matrix:
##      A    B    C    D    E  class.error
## A 3904    1    0    0    1 0.0005120328
## B   10 2645    3    0    0 0.0048908954
## C    0    7 2387    2    0 0.0037562604
## D    0    0   14 2236    2 0.0071047957
## E    0    2    0    1 2522 0.0011881188
```

Error rate is 0.25%

Make predictions on the test data

```
testing_data$classe<-as.factor(testing_data$classe)
predicted_classe <-predict(model_RF, testing_data)
```

Compute model accuracy rate on test data

```
mean(predicted_classe == testing_data$classe)
```

```
## [1] 0.9976211
```

The accuracy of model_DT2 is 99.8%

Predict testing cases

Based on the accuracy of the models we will use model_DT1 (use all variables to make the prediction).

```
testing_prediction_RF<-predict(model_RF, newdata = testing)
testing_prediction_RF
```

```
##  [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
```

Using random forest we were able to predict correctly a 100% of the predictions