Practical Machine Learning Course Project

Patihe Suip

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Project Executive Summary

This project goal 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. Then we perform barbell lifts correctly and incorrectly in 5 different ways. It will then predict the manner in which they did the exercise. It was the the "classe" variable in the training set. This report will describe how we built our model, how we used cross validation, what we think the expected out of sample error is, and why we made the choices.

We will also use your prediction model to predict 20 different test cases. As below request:-

-Submission should consist of a link to a Github repo with your R markdown and compiled HTML file describing your analysis. Please constrain the text of the writeup to < 2000 words and the number of figures to be less than 5. It will make it easier for the graders if you submit a repo with a gh-pages branch so the HTML page can be viewed online (and you always want to make it easy on graders.

- And apply your machine learning algorithm to the 20 test cases available in the test data above. Please submit your predictions in appropriate format to the programming assignment for automated grading. See the programming assignment for additional details.

Setting-up The Environment

setwd("D:\Data Scientist\Machine Learning\Machine Project")

Splitting the Data

The data is already been splitted into the testing set and training set, both the files are loaded separately. As we can see, there are 19622 rows and 160 columns of data available form the training data set and 20 rows and 160 columns of testing data set.

```
testingori <- read.csv("pml-testing.csv", na.strings=c("NA",""), strip.white=T)
training <- read.csv("pml-training.csv", na.strings=c("NA",""), strip.white=T)
dim(training)
```

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

```
dim(testingori)
```

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

Trimming Variable

In the 160 variables, there are a lot of variables that will not contribute to the analysis. In this section, we are removing all those columns that contain "NA" and has no numeric value from the training data set. This leaves us with only 60 variables to review.

```
training2 <- training[ , colSums(is.na(training)) == 0]
dim(training2)
```

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

After we review the variables, the first 7 variables are information that are not significant for our analysis. Thus we are removing those 7 non-relevant variables. This process will reduce the variables further to 53 variables with the last variable being classe, the variable that we are predicting.

```
training3<-training2[,-c(1:7)]
dim(training3)
```

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

After last step in preparing the baseline training data is to look at the correlations between the variables in our dataset. We may want to remove highly correlated predictors from our analysis and replace them with weighted combinations of predictors. This may allow a more complete capture of the information available.

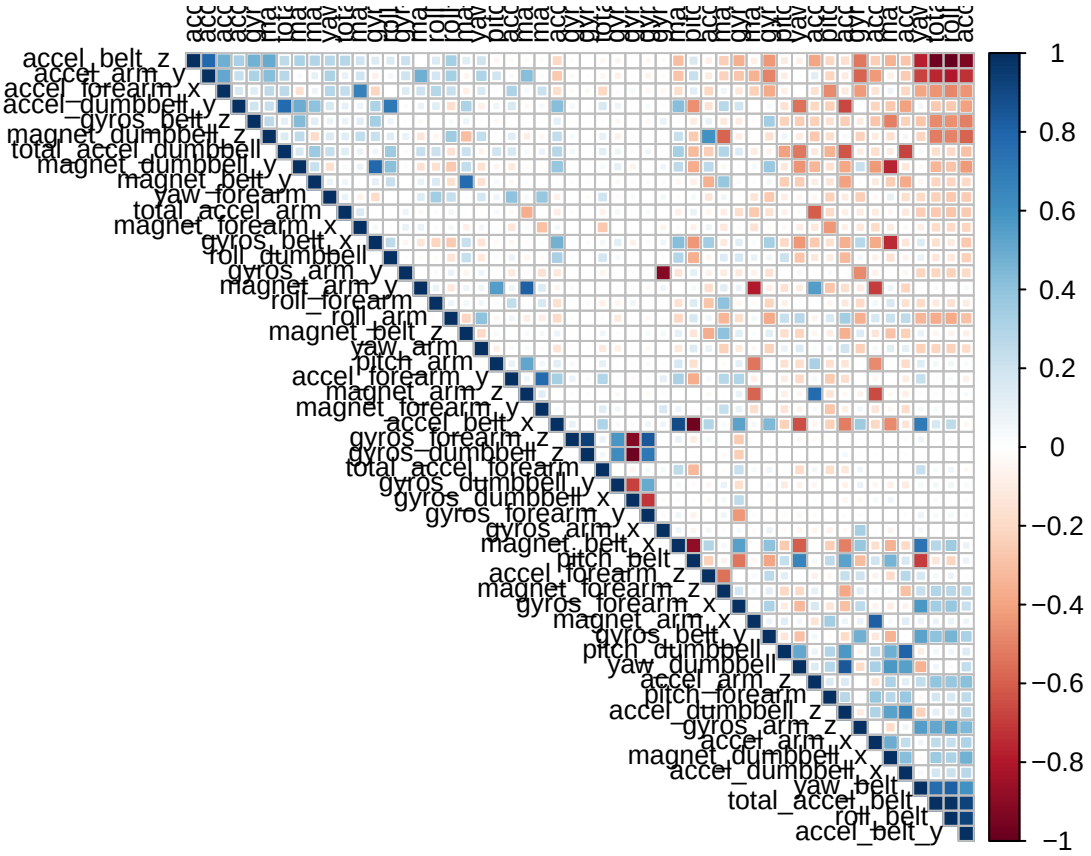
```
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 3.2.3
```

```
corrmatrix<- cor(na.omit(training3[sapply(training3, is.numeric)]))
dim(corrmatrix)
```

```
## [1] 52 52
```

```
corrplot(corrmatrix, order = "FPC", method = "square", type = "upper", tl.cex = 0.8, tl.col = rgb(0, 0,
```



Plotting Correlation

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.2.2
```

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

```
## Warning: package 'ggplot2' was built under R version 3.2.1
```

The grid shows the correlation between pairs of the predictors in our dataset. From a high-level perspective darker blue and darker red squares indicate high positive and high negative correlations, respectively. Those that are highly correlated will be be removed with a a cutoff determined at 90%.Removing the highly correlated variable (90% and above)

```
removecor = findCorrelation(corrmatrix, cutoff = .99, verbose = TRUE)
```

```
## Compare row 10  and column  1 with corr  0.992
##   Means:  0.27 vs 0.168 so flagging column 10
## All correlations <= 0.99
```

```
training5 = training3[,-removecor]
dim(training5)
```

```
## [1] 19622    52
```

Now we split the updated training dataset into a training dataset (70% of the observations) and a validation dataset (30% of the observations). This validation dataset will allow us to perform cross validation when designing our model.

Cross Validation

```
inTrain <- createDataPartition(y=training5$classe, p=0.7, list=FALSE)
training <- training5[inTrain,]
testing <- training5[-inTrain,]
dim(training);dim(testing)
```

```
## [1] 13737    52
```

```
## [1] 5885   52
```

Random Forest Model & Cross Validation Testing

Train a model using a random forest approach on the smaller training dataset.

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.2.2
```

```
## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.
```

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

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1674    0    0    0    0
##          B    4 1133    2    0    0
##          C    0    7 1016    3    0
##          D    0    0   10  954    0
##          E    0    0    0    0 1082
##
## Overall Statistics
```

```
##
##                Accuracy : 0.9956
##                  95% CI : (0.9935, 0.9971)
##     No Information Rate : 0.2851
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9944
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9976   0.9939   0.9883   0.9969   1.0000
## Specificity            1.0000   0.9987   0.9979   0.9980   1.0000
## Pos Pred Value         1.0000   0.9947   0.9903   0.9896   1.0000
## Neg Pred Value         0.9991   0.9985   0.9975   0.9994   1.0000
## Prevalence             0.2851   0.1937   0.1747   0.1626   0.1839
## Detection Rate         0.2845   0.1925   0.1726   0.1621   0.1839
## Detection Prevalence   0.2845   0.1935   0.1743   0.1638   0.1839
## Balanced Accuracy      0.9988   0.9963   0.9931   0.9974   1.0000
```

Accuracy and Out-of-Sample Error Estimate

The Random forest trees were generated for the training dataset using cross-validation. Then the generated algorithm was examnined under the partitioned training set to examine the accuracy and estimated error of prediction. By using 52 predictors for five classes using cross-validation an accuracy of 0.9958 with a 95% CI [(0.9937, 0.9972)] was achieved accompanied by a Kappa value of 0.9946. Thus the The estimated accuracy of the model is 99.58% and the estimated out-of-sample error based on our fitted model applied to the cross validation dataset is 0.42%.

Predicted Results

Lastly we then run our model against the testing dataset and display the predicted results

```
testingori<-testingori[,names(training[,-52])]
predictionsB2<-predict(modFitB1,testingori, type="class")
predictionsB2
```

```
##  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
```