

Coursera Machine Learning Project

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I loaded the necessary libraries to do the machine learning.

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.0.3
```

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

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

```
library(dplyr)
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##   filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##   intersect, setdiff, setequal, union
```

```
library(ggplot2)
```

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

```
## Warning: package 'rpart.plot' was built under R version 4.0.3
```

```
## Loading required package: rpart
```

```
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.0.3
```

```
## corrplot 0.84 loaded
```

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.0.3
```

```
## randomForest 4.6-14
```

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

```
##
```

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

```
## The following object is masked from 'package:dplyr':
```

```
##
```

```
##      combine
```

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

```
##
```

```
##      margin
```

```
library(latexpdf)
```

The test and training data was loaded and I created an data partition where I then made training and test validation data sets based on the data partition.

```
train_data <- read.csv("pml-training.csv")
test_data <- read.csv("pml-testing.csv")
intrain <- createDataPartition(train_data$classe, p=0.7, list = FALSE)
train_valid <- train_data[intrain,]
test_valid <- train_data[-intrain,]
```

Get rid of variables with zero variables then removed NA data to make the training as efficient as possible.

```
near_zero <- nearZeroVar(train_valid)
train_valid <- train_valid[, -near_zero]
test_valid <- test_valid[, -near_zero]

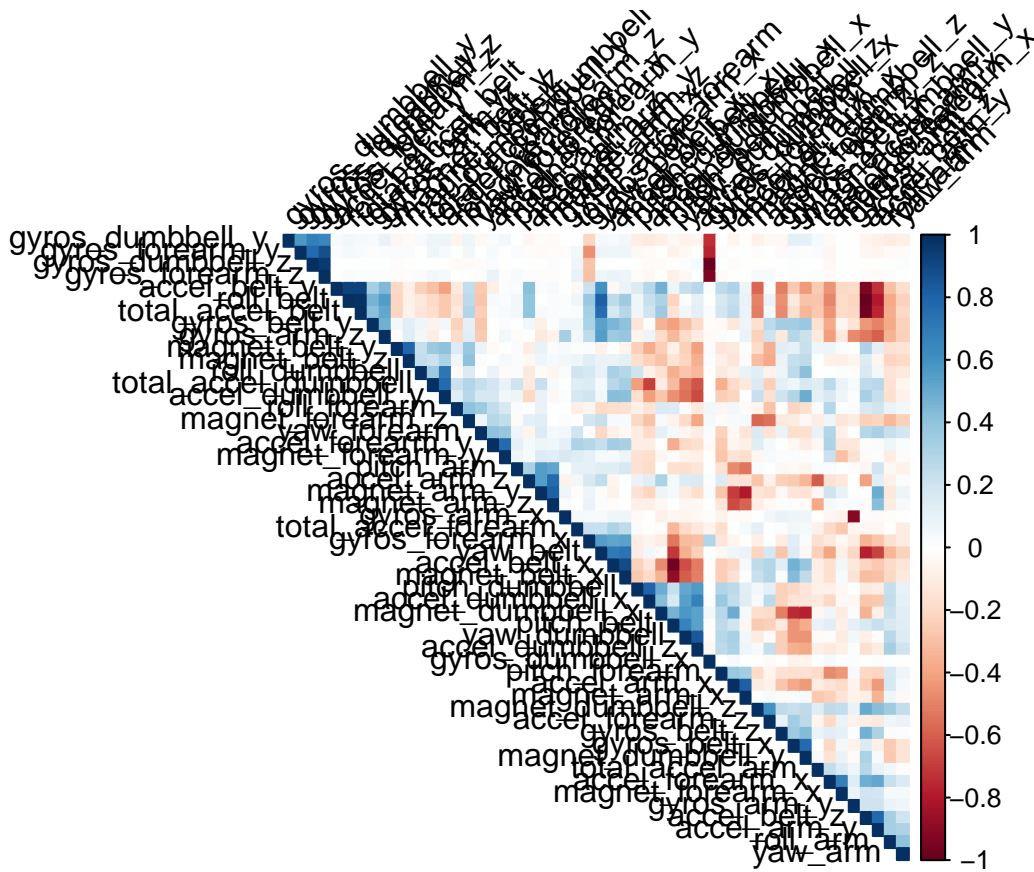
all_na <- sapply(train_valid, function(l) mean(is.na(l))) > 0.95
train_valid <- train_valid[, all_na == FALSE]
test_valid <- test_valid[, all_na == FALSE]
```

```
#Remove unnecessary variables
```

```
train_valid <- train_valid[, -c(1:6)]
test_valid <- test_valid[, -c(1:6)]
```

Find what data is correlated with one another and used a cutoff of 0.7 to determine the best correlation

```
corr_train <- cor(train_valid[, -53], use = "pairwise.complete.obs")
corr_high <- findCorrelation(corr_train, cutoff = 0.7)
#corrplot doesn't help much
corrplot(corr_train, order = "hclust" , method = "color" , type = "upper", tl.col="black", tl
```



Train the necessary prediction models and compare the accuracy of the separate prediction models to find the best model to use.

```
control <- trainControl(method = "cv", number = 3, verboseIter=FALSE)
metric <- "Accuracy"
```

```

#Prediction models
#Random Forest
set.seed(13)
fit.rf <- train(classe~., data=train_valid, method="rf", metric=metric, trControl=control)
#Classification Tree
set.seed(13)
fit.ct <- train(classe~., data=train_valid, method="rpart", trControl=control)
#Linear Algorithms
set.seed(13)
fit.la <- train(classe~., data=train_valid, method="lda", metric = metric, trControl=control)

#Rpart
set.seed(13)
fit.cart <- train(classe~., data=train_valid, method="rpart", metric=metric, trControl=control)

#Gradient Boosting method
set.seed(13)
fit.gbm <- train(classe~., data=train_valid, method="gbm", metric=metric, trControl=control)

```

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1255
##	2	1.5243	nan	0.1000	0.0833
##	3	1.4669	nan	0.1000	0.0687
##	4	1.4209	nan	0.1000	0.0553
##	5	1.3854	nan	0.1000	0.0442
##	6	1.3564	nan	0.1000	0.0444
##	7	1.3273	nan	0.1000	0.0410
##	8	1.3021	nan	0.1000	0.0336
##	9	1.2804	nan	0.1000	0.0315
##	10	1.2586	nan	0.1000	0.0296
##	20	1.1049	nan	0.1000	0.0156
##	40	0.9300	nan	0.1000	0.0084
##	60	0.8232	nan	0.1000	0.0062
##	80	0.7422	nan	0.1000	0.0044
##	100	0.6787	nan	0.1000	0.0028
##	120	0.6269	nan	0.1000	0.0026
##	140	0.5824	nan	0.1000	0.0014
##	150	0.5625	nan	0.1000	0.0023
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1904
##	2	1.4885	nan	0.1000	0.1267
##	3	1.4050	nan	0.1000	0.1025
##	4	1.3391	nan	0.1000	0.0844
##	5	1.2842	nan	0.1000	0.0682
##	6	1.2408	nan	0.1000	0.0606
##	7	1.2020	nan	0.1000	0.0573
##	8	1.1639	nan	0.1000	0.0513
##	9	1.1306	nan	0.1000	0.0501
##	10	1.0987	nan	0.1000	0.0453
##	20	0.8917	nan	0.1000	0.0203
##	40	0.6787	nan	0.1000	0.0086
##	60	0.5513	nan	0.1000	0.0064

##	80	0.4617	nan	0.1000	0.0048
##	100	0.3963	nan	0.1000	0.0025
##	120	0.3439	nan	0.1000	0.0023
##	140	0.3052	nan	0.1000	0.0017
##	150	0.2864	nan	0.1000	0.0021
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2304
##	2	1.4605	nan	0.1000	0.1557
##	3	1.3612	nan	0.1000	0.1258
##	4	1.2812	nan	0.1000	0.1045
##	5	1.2161	nan	0.1000	0.0881
##	6	1.1589	nan	0.1000	0.0795
##	7	1.1091	nan	0.1000	0.0628
##	8	1.0682	nan	0.1000	0.0618
##	9	1.0285	nan	0.1000	0.0648
##	10	0.9876	nan	0.1000	0.0513
##	20	0.7514	nan	0.1000	0.0210
##	40	0.5300	nan	0.1000	0.0135
##	60	0.4004	nan	0.1000	0.0070
##	80	0.3179	nan	0.1000	0.0036
##	100	0.2603	nan	0.1000	0.0028
##	120	0.2169	nan	0.1000	0.0021
##	140	0.1831	nan	0.1000	0.0017
##	150	0.1695	nan	0.1000	0.0014
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1254
##	2	1.5236	nan	0.1000	0.0830
##	3	1.4671	nan	0.1000	0.0669
##	4	1.4238	nan	0.1000	0.0489
##	5	1.3905	nan	0.1000	0.0514
##	6	1.3569	nan	0.1000	0.0474
##	7	1.3276	nan	0.1000	0.0411
##	8	1.3017	nan	0.1000	0.0349
##	9	1.2795	nan	0.1000	0.0339
##	10	1.2572	nan	0.1000	0.0309
##	20	1.0996	nan	0.1000	0.0146
##	40	0.9251	nan	0.1000	0.0081
##	60	0.8149	nan	0.1000	0.0053
##	80	0.7358	nan	0.1000	0.0059
##	100	0.6696	nan	0.1000	0.0034
##	120	0.6196	nan	0.1000	0.0023
##	140	0.5745	nan	0.1000	0.0025
##	150	0.5528	nan	0.1000	0.0030
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1807
##	2	1.4891	nan	0.1000	0.1247
##	3	1.4075	nan	0.1000	0.1071
##	4	1.3386	nan	0.1000	0.0872
##	5	1.2829	nan	0.1000	0.0760
##	6	1.2346	nan	0.1000	0.0573
##	7	1.1959	nan	0.1000	0.0620

##	8	1.1570	nan	0.1000	0.0561
##	9	1.1214	nan	0.1000	0.0446
##	10	1.0933	nan	0.1000	0.0541
##	20	0.8835	nan	0.1000	0.0257
##	40	0.6715	nan	0.1000	0.0126
##	60	0.5422	nan	0.1000	0.0068
##	80	0.4599	nan	0.1000	0.0059
##	100	0.3925	nan	0.1000	0.0034
##	120	0.3404	nan	0.1000	0.0035
##	140	0.2985	nan	0.1000	0.0012
##	150	0.2818	nan	0.1000	0.0022

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2381
##	2	1.4580	nan	0.1000	0.1548
##	3	1.3589	nan	0.1000	0.1262
##	4	1.2777	nan	0.1000	0.1069
##	5	1.2095	nan	0.1000	0.0953
##	6	1.1493	nan	0.1000	0.0737
##	7	1.1010	nan	0.1000	0.0686
##	8	1.0549	nan	0.1000	0.0631
##	9	1.0146	nan	0.1000	0.0557
##	10	0.9784	nan	0.1000	0.0544
##	20	0.7463	nan	0.1000	0.0289
##	40	0.5219	nan	0.1000	0.0122
##	60	0.3918	nan	0.1000	0.0053
##	80	0.3132	nan	0.1000	0.0040
##	100	0.2568	nan	0.1000	0.0031
##	120	0.2148	nan	0.1000	0.0019
##	140	0.1835	nan	0.1000	0.0015
##	150	0.1692	nan	0.1000	0.0009

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1297
##	2	1.5205	nan	0.1000	0.0837
##	3	1.4617	nan	0.1000	0.0679
##	4	1.4166	nan	0.1000	0.0532
##	5	1.3820	nan	0.1000	0.0445
##	6	1.3514	nan	0.1000	0.0470
##	7	1.3220	nan	0.1000	0.0415
##	8	1.2961	nan	0.1000	0.0299
##	9	1.2755	nan	0.1000	0.0340
##	10	1.2525	nan	0.1000	0.0301
##	20	1.0947	nan	0.1000	0.0154
##	40	0.9174	nan	0.1000	0.0083
##	60	0.8098	nan	0.1000	0.0059
##	80	0.7314	nan	0.1000	0.0044
##	100	0.6682	nan	0.1000	0.0023
##	120	0.6168	nan	0.1000	0.0025
##	140	0.5744	nan	0.1000	0.0022
##	150	0.5569	nan	0.1000	0.0016

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.1854

##	2	1.4867	nan	0.1000	0.1332
##	3	1.4002	nan	0.1000	0.1041
##	4	1.3338	nan	0.1000	0.0790
##	5	1.2822	nan	0.1000	0.0726
##	6	1.2366	nan	0.1000	0.0675
##	7	1.1921	nan	0.1000	0.0634
##	8	1.1517	nan	0.1000	0.0449
##	9	1.1215	nan	0.1000	0.0459
##	10	1.0930	nan	0.1000	0.0386
##	20	0.8874	nan	0.1000	0.0254
##	40	0.6783	nan	0.1000	0.0084
##	60	0.5489	nan	0.1000	0.0088
##	80	0.4603	nan	0.1000	0.0053
##	100	0.3927	nan	0.1000	0.0020
##	120	0.3419	nan	0.1000	0.0022
##	140	0.2999	nan	0.1000	0.0023
##	150	0.2815	nan	0.1000	0.0016

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2402
##	2	1.4537	nan	0.1000	0.1603
##	3	1.3495	nan	0.1000	0.1250
##	4	1.2698	nan	0.1000	0.1008
##	5	1.2046	nan	0.1000	0.0840
##	6	1.1500	nan	0.1000	0.0807
##	7	1.0989	nan	0.1000	0.0586
##	8	1.0600	nan	0.1000	0.0604
##	9	1.0223	nan	0.1000	0.0580
##	10	0.9859	nan	0.1000	0.0514
##	20	0.7474	nan	0.1000	0.0248
##	40	0.5277	nan	0.1000	0.0140
##	60	0.4025	nan	0.1000	0.0058
##	80	0.3242	nan	0.1000	0.0041
##	100	0.2614	nan	0.1000	0.0031
##	120	0.2204	nan	0.1000	0.0018
##	140	0.1860	nan	0.1000	0.0018
##	150	0.1707	nan	0.1000	0.0010

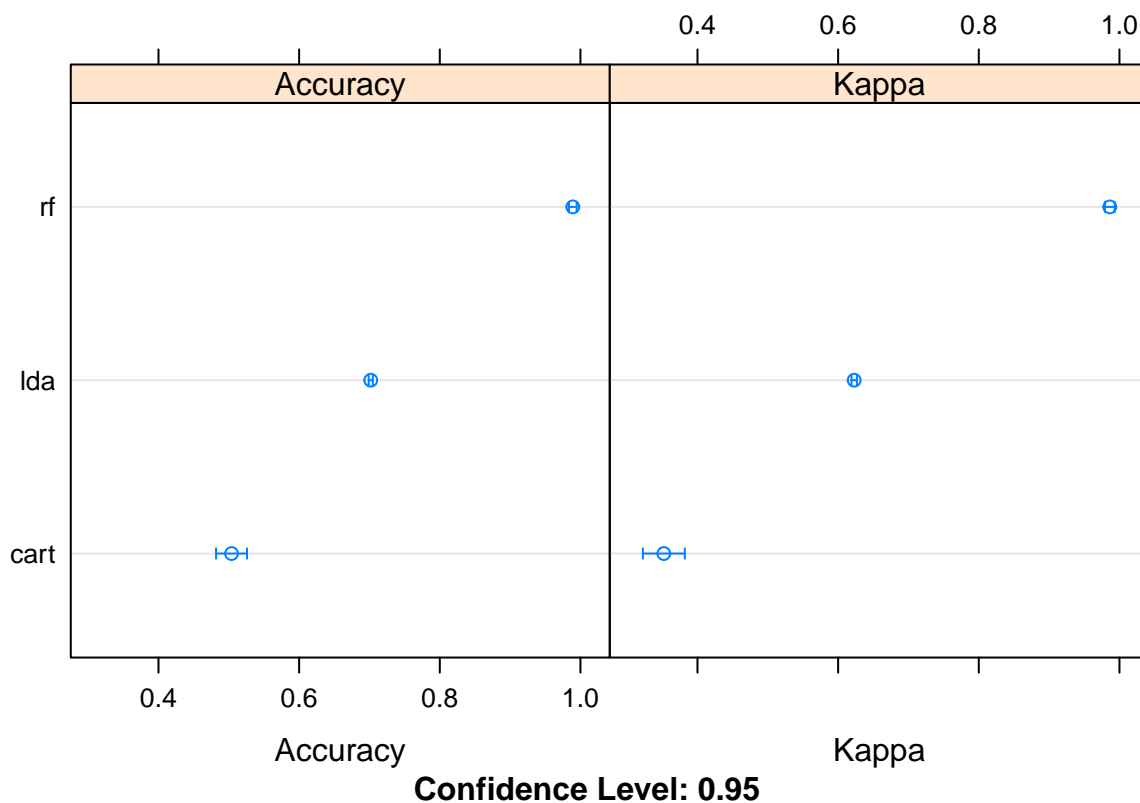
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.6094	nan	0.1000	0.2338
##	2	1.4595	nan	0.1000	0.1600
##	3	1.3568	nan	0.1000	0.1215
##	4	1.2797	nan	0.1000	0.1062
##	5	1.2138	nan	0.1000	0.0977
##	6	1.1532	nan	0.1000	0.0786
##	7	1.1030	nan	0.1000	0.0706
##	8	1.0591	nan	0.1000	0.0522
##	9	1.0250	nan	0.1000	0.0641
##	10	0.9841	nan	0.1000	0.0557
##	20	0.7483	nan	0.1000	0.0210
##	40	0.5223	nan	0.1000	0.0135
##	60	0.4029	nan	0.1000	0.0083
##	80	0.3198	nan	0.1000	0.0051
##	100	0.2648	nan	0.1000	0.0021

```
##      120      0.2228      nan      0.1000      0.0016
##      140      0.1887      nan      0.1000      0.0015
##      150      0.1741      nan      0.1000      0.0014
```

```
results <- resamples(list(lda=fit.la, cart=fit.ct, rf=fit.rf))
summary(results)
```

```
##
## Call:
## summary.resamples(object = results)
##
## Models: lda, cart, rf
## Number of resamples: 3
##
## Accuracy
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max. NA's
## lda  0.7005242 0.7013213 0.7021184 0.7018270 0.7024784 0.7028384    0
## cart 0.4936681 0.5012028 0.5087374 0.5038957 0.5090095 0.5092815    0
## rf   0.9871123 0.9879885 0.9888646 0.9891533 0.9901737 0.9914829    0
##
## Kappa
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max. NA's
## lda  0.6211090 0.6221066 0.6231041 0.6227853 0.6236235 0.6241429    0
## cart 0.3382773 0.3486582 0.3590391 0.3521455 0.3590796 0.3591201    0
## rf   0.9836938 0.9848030 0.9859123 0.9862776 0.9875696 0.9892268    0
```

```
dotplot(results)
```

We found that the random forest model is the most accurate according to the boxplot.

Use predict function to test the random forest model

```
end_result <- predict(fit.rf, newdata = test_data)
summary(end_result)
```

```
## A B C D E
## 7 8 1 1 3
```

```
end_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
```