Practical Machine Learning

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Prediction Assignment

Background

Using devices such as JawboneUp, NikeFuelBand, and Fitbitit is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement - a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it.

In this project, the goal is 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. More information is available from the website: http://groupware.les.inf.puc-rio.br/har (http://groupware.les.inf.puc-rio.br/har) (see the section on the Weight Lifting Exercise Dataset).

Preparing the data and R packages

Load packages, set caching

```r
require(caret)
```

```
## Warning: package 'caret' was built under R version 3.6.3
```

```r
require(stats)
require(knitr)
require(ggplot2)
require(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 3.6.3
```

```r
require(Rtsne)
```

```
## Warning: package 'Rtsne' was built under R version 3.6.3
```

```r
require(xgboost)
```

```
## Warning: package 'xgboost' was built under R version 3.6.3
```

```
knitr::opts_chunk$set(cache=TRUE)
```

"XGBoost is an algorithm that has recently been dominating applied machine learning and Kaggle competitions for structured or tabular data. XGBoost is an implementation of gradient boosted decision trees designed for speed and performance." (*https://machinelearningmastery.com/gentle-introduction-xgboost-applied-machine-learning/ (https://machinelearningmastery.com/gentle-introduction-xgboost-applied-machine-learning/)*)

Getting Data

```
# URL of the training and testing data
train.url ="https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
test.url = "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
# file names
train.name = "./data/pml-training.csv"
test.name = "./data/pml-testing.csv"
# if directory does not exist, create new
if (!file.exists("./data")) {
  dir.create("./data")
}
# if files does not exist, download the files
if (!file.exists(train.name)) {
  download.file(train.url, destfile=train.name, method="curl")
}
if (!file.exists(test.name)) {
  download.file(test.url, destfile=test.name, method="curl")
}
# load the CSV files as data.frame
train = read.csv("./data/pml-training.csv")
test = read.csv("./data/pml-testing.csv")
dim(train)
```

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

```
dim(test)
```

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

The raw training data has 19,622 observations and 158 predictors. Column `X` is just the row numbers. We will be applying the model from the training data on the testing data, which has 20 rows and the same 158 features. The target outcome is named `classe`.

Data cleaning

First, extract target outcome (the activity quality) from training data, so now the training data contains only the predictors (the activity monitors).

```
# target outcome (label)
outcome.org = train[, "classe"]
outcome = outcome.org
levels(outcome)
```

```
## [1] "A" "B" "C" "D" "E"
```

Outcome has 5 levels in character format.
Because the XGBoost gradient booster only recognizes numeric data, we will convert the 'classe' levels to numeric.

```
# convert character levels to numeric
num.class = length(levels(outcome))
levels(outcome) = 1:num.class
head(outcome)
```

```
## [1] 1 1 1 1 1 1
## Levels: 1 2 3 4 5
```

The outcome column is removed from training data.

```
# remove outcome from train
train$classe = NULL
```

The assignment asks to use data from accelerometers on the `belt` , `forearm` , `arm` , and `dumbell` , we will match these keywords on the predictors and extract them for our model.

```
# filter columns on: belt, forearm, arm, dumbell
filter = grepl("belt|forearm|arm|dumbell", names(train))
train = train[, filter]
test = test[, filter]
```

Remove all columns with NA values.

```
# remove columns with NA
cols.without.na = colSums(is.na(test)) == 0
train = train[, cols.without.na]
test = test[, cols.without.na]
```

Preprocessing

Check for features's variance

Based on the PCA (principal component analysis), it is important that features have maximum variance for maximum uniqueness, so that each feature is as distant as possible (as orthogonal as possible) from the other features.

```
# check for zero variance
zero.var = nearZeroVar(train, saveMetrics=TRUE)
zero.var
```

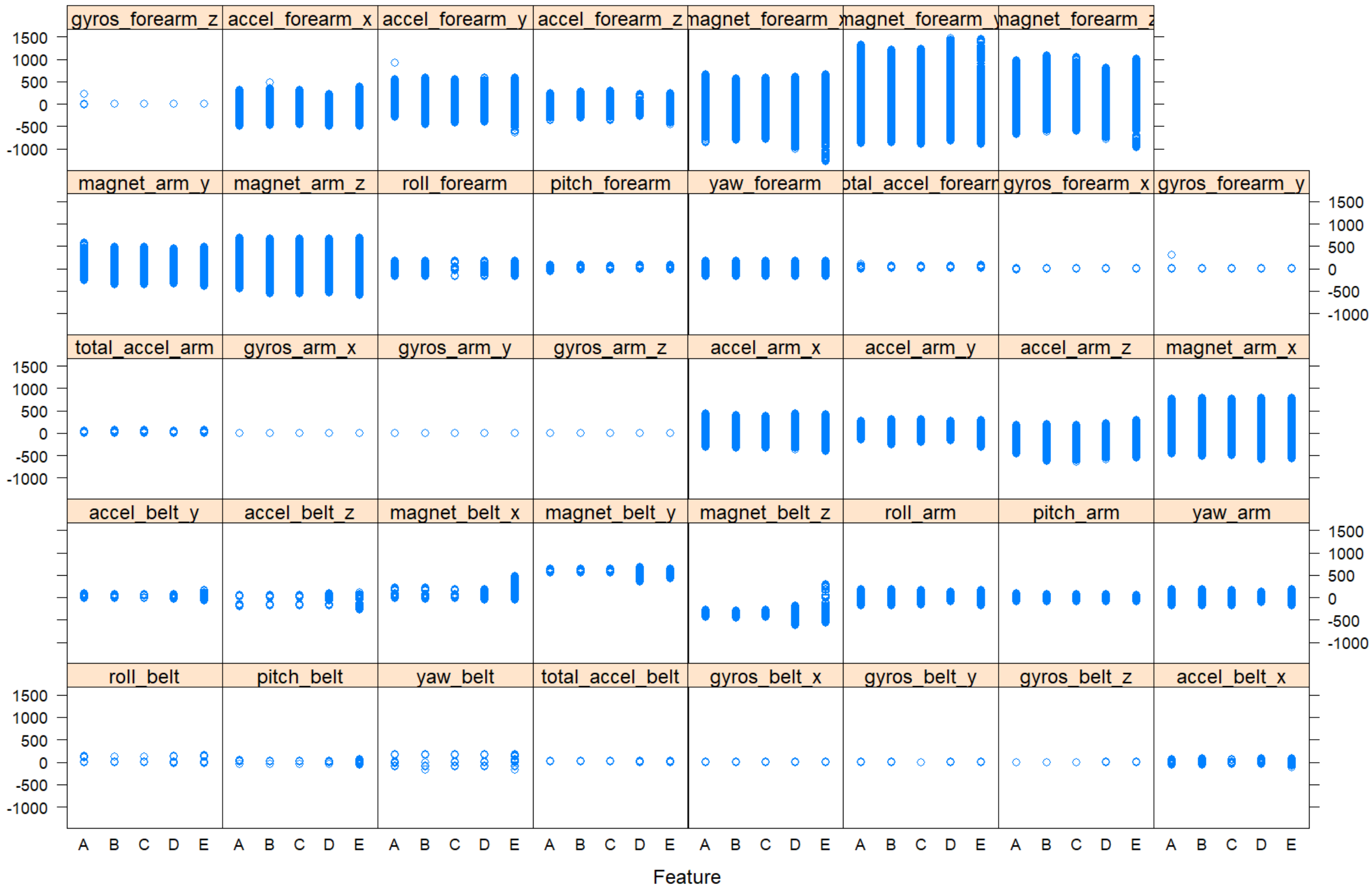
```
##                    freqRatio percentUnique zeroVar   nzv
## roll_belt           1.101904     6.7781062   FALSE FALSE
## pitch_belt          1.036082     9.3772296   FALSE FALSE
## yaw_belt            1.058480     9.9734991   FALSE FALSE
## total_accel_belt    1.063160     0.1477933   FALSE FALSE
## gyros_belt_x        1.058651     0.7134849   FALSE FALSE
## gyros_belt_y        1.144000     0.3516461   FALSE FALSE
## gyros_belt_z        1.066214     0.8612782   FALSE FALSE
## accel_belt_x        1.055412     0.8357966   FALSE FALSE
## accel_belt_y        1.113725     0.7287738   FALSE FALSE
## accel_belt_z        1.078767     1.5237998   FALSE FALSE
## magnet_belt_x       1.090141     1.6664968   FALSE FALSE
## magnet_belt_y       1.099688     1.5187035   FALSE FALSE
## magnet_belt_z       1.006369     2.3290184   FALSE FALSE
## roll_arm           52.338462    13.5256345   FALSE FALSE
## pitch_arm          87.256410    15.7323412   FALSE FALSE
## yaw_arm            33.029126    14.6570176   FALSE FALSE
## total_accel_arm     1.024526     0.3363572   FALSE FALSE
## gyros_arm_x         1.015504     3.2769341   FALSE FALSE
## gyros_arm_y         1.454369     1.9162165   FALSE FALSE
## gyros_arm_z         1.110687     1.2638875   FALSE FALSE
## accel_arm_x         1.017341     3.9598410   FALSE FALSE
## accel_arm_y         1.140187     2.7367241   FALSE FALSE
## accel_arm_z         1.128000     4.0362858   FALSE FALSE
## magnet_arm_x        1.000000     6.8239731   FALSE FALSE
## magnet_arm_y        1.056818     4.4439914   FALSE FALSE
## magnet_arm_z        1.036364     6.4468454   FALSE FALSE
## roll_forearm       11.589286    11.0895933   FALSE FALSE
## pitch_forearm      65.983051    14.8557741   FALSE FALSE
## yaw_forearm        15.322835    10.1467740   FALSE FALSE
## total_accel_forearm  1.128928     0.3567424   FALSE FALSE
## gyros_forearm_x     1.059273     1.5187035   FALSE FALSE
## gyros_forearm_y     1.036554     3.7763735   FALSE FALSE
## gyros_forearm_z     1.122917     1.5645704   FALSE FALSE
## accel_forearm_x     1.126437     4.0464784   FALSE FALSE
## accel_forearm_y     1.059406     5.1116094   FALSE FALSE
## accel_forearm_z     1.006250     2.9558659   FALSE FALSE
## magnet_forearm_x    1.012346     7.7667924   FALSE FALSE
## magnet_forearm_y    1.246914     9.5403119   FALSE FALSE
## magnet_forearm_z    1.000000     8.5771073   FALSE FALSE
```

All features have enough variability, FALSE for zeroVar. So we will keep these features.

Plot of relationship between features and outcome

Plot the relationship between features and outcome. From the plot below, each feature has relatively the same distribution among the 5 outcome levels (A, B, C, D, E).

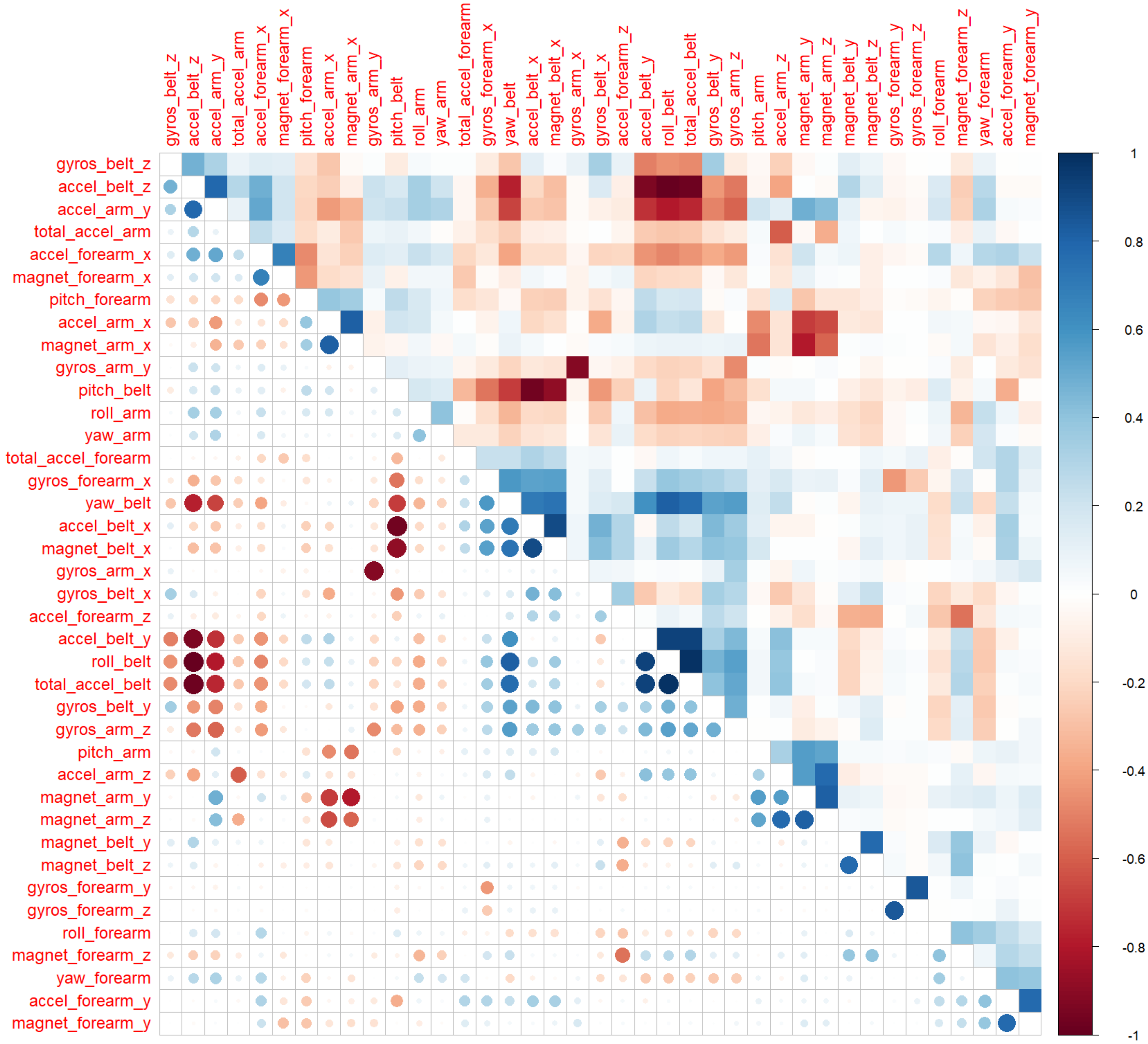
```
featurePlot(train, outcome.org, "strip")
```



Plot of correlation matrix

Plot a correlation matrix between features.
A good set of features is when they are highly uncorrelated (orthogonal). The plot below shows average of correlation is not too high, so there isn't a need to perform further PCA preprocessing.

```
corrplot.mixed(cor(train), lower="circle", upper="color",
               tl.pos="lt", diag="n", order="hclust", hclust.method="complete")
```

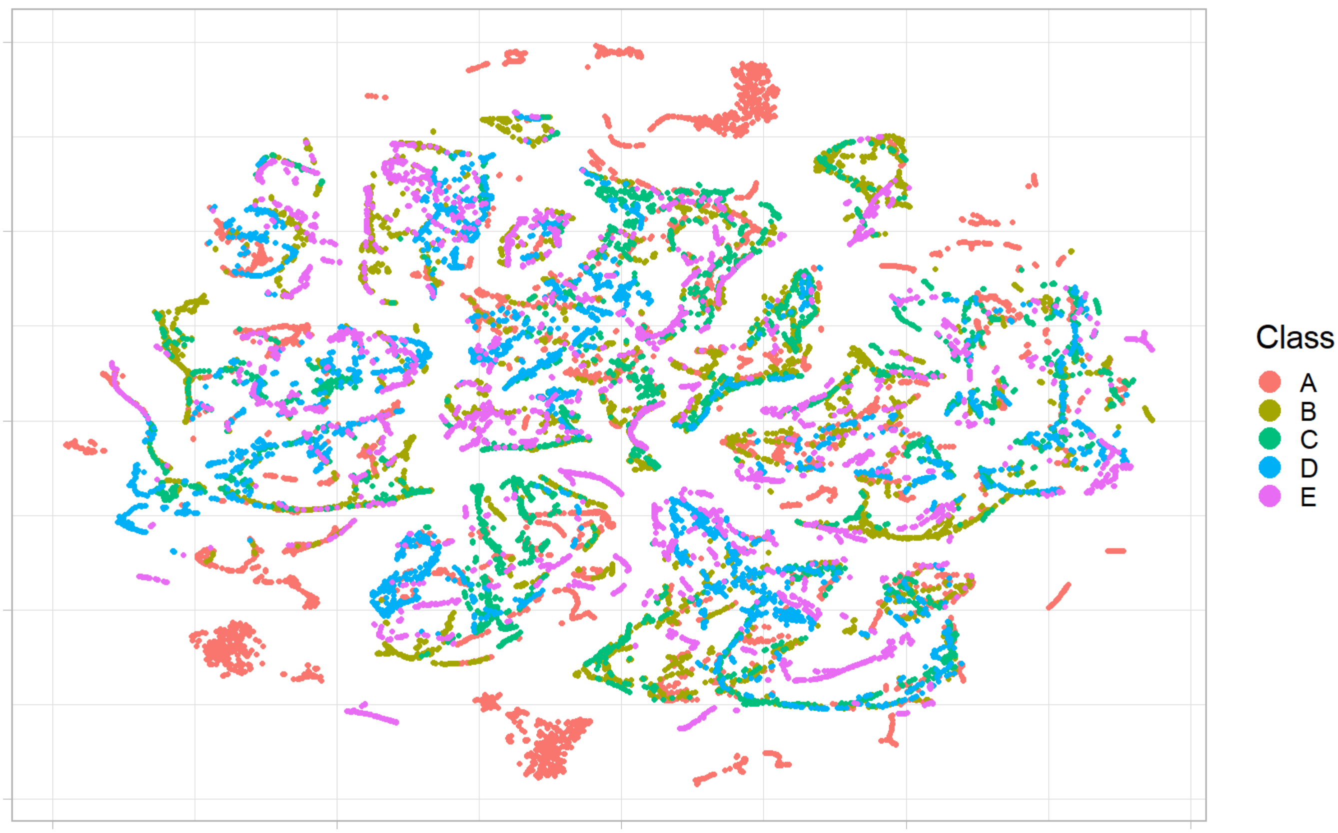


tSNE plot

A tSNE (t-Distributed Stochastic Neighbor Embedding) visualization is a 2D plot of multidimensional features. In the tSNE plot below there is no clear separation of clustering of the 5 levels of outcome (A, B, C, D, E). This indicates a need for robust machine learning to make our predictions.

```
# t-Distributed Stochastic Neighbor Embedding
tsne = Rtsne(as.matrix(train), check_duplicates=FALSE, pca=TRUE,
              perplexity=30, theta=0.5, dims=2)
embedding = as.data.frame(tsne$Y)
embedding$Class = outcome.org
g = ggplot(embedding, aes(x=V1, y=V2, color=Class)) +
  geom_point(size=1.25) +
  guides(colour=guide_legend(override.aes=list(size=6))) +
  xlab("") + ylab("") +
  ggtitle("t-SNE 2D Embedding of 'Classe' Outcome") +
  theme_light(base_size=20) +
  theme(axis.text.x=element_blank(),
        axis.text.y=element_blank())
print(g)
```

t-SNE 2D Embedding of 'Classe' Outcome



Build machine learning model

Now build a machine learning model to predict activity quality (`classe` outcome) from the activity monitors (the features or predictors) by using XGBoost extreme gradient boosting algorithm.

XGBoost data

XGBoost supports only numeric matrix data.

```
# convert data to matrix
train.matrix = as.matrix(train)
mode(train.matrix) = "numeric"
test.matrix = as.matrix(test)
mode(test.matrix) = "numeric"
# convert outcome from factor to numeric matrix
# XGBoost takes multi-labels in [0, numOfClass)
y = as.matrix(as.integer(outcome)-1)
```

XGBoost parameters

Set XGBoost parameters for cross validation and training.
Set a multiclass classification objective as the gradient boosting's learning function.
Set evaluation metric to `merror`, multiclass error rate.

```
# XGBoost parameters
param <- list("objective" = "multi:softprob",    # multiclass classification
              "num_class" = num.class,    # number of classes
              "eval_metric" = "merror",    # evaluation metric
              "nthread" = 8,   # number of threads to be used
              "max_depth" = 16,    # maximum depth of tree
              "eta" = 0.3,    # step size shrinkage
              "gamma" = 0,    # minimum loss reduction
              "subsample" = 1,    # part of data instances to grow tree
              "colsample_bytree" = 1,  # subsample ratio of columns when constructing each tree
              "min_child_weight" = 12  # minimum sum of instance weight needed in a child
              )
```

Expected error rate

Expected error rate is less than `1%` for a good classification. Do cross validation to estimate the error rate using 4-fold cross validation, with 200 epochs to reach the expected error rate of less than `1%`.

4-fold cross validation

```
# set random seed, for reproducibility
set.seed(3333)
# k-fold cross validation, with timing
nround.cv = 200
system.time( bst.cv <- xgb.cv(param=param, data=train.matrix, label=y,
              nfold=4, nrounds=nround.cv, prediction=TRUE, verbose=FALSE) )
```

```
##    user  system elapsed
##  325.58   17.78   65.38
```

Elapsed time is around 65 seconds.

```
tail(bst.cv$evaluation_log)
```

```
##    iter train_merror_mean train_merror_std test_merror_mean test_merror_std
## 1:  195                 0                0       0.00530000    0.0009667083
## 2:  196                 0                0       0.00535075    0.0010326598
## 3:  197                 0                0       0.00535075    0.0010818152
## 4:  198                 0                0       0.00535075    0.0010326598
## 5:  199                 0                0       0.00535075    0.0010818152
## 6:  200                 0                0       0.00535075    0.0010818152
```

From the cross validation, choose index with minimum multiclass error rate.
Index will be used in the model training to fulfill expected minimum error rate of `< 1%`.

```
# index of minimum merror
min.merror.idx = which.min(bst.cv$evaluation_log[, test_merror_mean])
min.merror.idx
```

```
## [1] 181
```

```
# minimum merror
bst.cv$evaluation_log[min.merror.idx,]
```

```
##    iter train_merror_mean train_merror_std test_merror_mean test_merror_std
## 1:  181                 0                0         0.005198    0.0009394174
```

Best cross-validation's minimum error rate `test_merror_mean` is around 0.006 (0.6%), happened at 181st iteration.

Confusion matrix

Tabulates the cross-validation's predictions of the model against the truths.

```
# get CV's prediction decoding
pred.cv = matrix(bst.cv$pred, nrow=length(bst.cv$pred)/num.class, ncol=num.class)
pred.cv = max.col(pred.cv, "last")
# confusion matrix
confusionMatrix(factor(y+1), factor(pred.cv))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    1    2    3    4    5
##          1 5571    7    2    0    0
##          2   10 3775   12    0    0
##          3    0   32 3380   10    0
##          4    0    0   19 3194    3
##          5    0    1    1    8 3597
##
## Overall Statistics
##
##                Accuracy : 0.9946
##                  95% CI : (0.9935, 0.9956)
##     No Information Rate : 0.2844
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9932
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity            0.9982   0.9895   0.9900   0.9944   0.9992
## Specificity            0.9994   0.9986   0.9974   0.9987   0.9994
## Pos Pred Value         0.9984   0.9942   0.9877   0.9932   0.9972
## Neg Pred Value         0.9993   0.9975   0.9979   0.9989   0.9998
## Prevalence             0.2844   0.1944   0.1740   0.1637   0.1835
## Detection Rate         0.2839   0.1924   0.1723   0.1628   0.1833
## Detection Prevalence   0.2844   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy      0.9988   0.9941   0.9937   0.9965   0.9993
```

Confusion matrix shows concentration of correct predictions is on the diagonal, as expected.

The average accuracy is `99.46%`, with error rate is `0.54%`. So, expected error rate of less than `1%` is fulfilled.

Model training

Fit the XGBoost gradient boosting model on all of the training data.

```
# real model fit training, with full data
system.time( bst <- xgboost(param=param, data=train.matrix, label=y,
                           nrounds=min.merror.idx, verbose=0) )
```

```
##    user  system elapsed
##  101.08    4.76   19.92
```

Time elapsed is around 17 seconds.

Predicting the testing data

```
# xgboost predict test data using the trained model
pred <- predict(bst, test.matrix)
head(pred, 10)
```

```
##  [1] 4.265299e-04 9.977400e-01 1.414487e-03 1.428610e-04 2.761256e-04
##  [6] 9.993364e-01 5.164818e-04 1.322326e-04 3.265377e-06 1.159673e-05
```

Post-processing

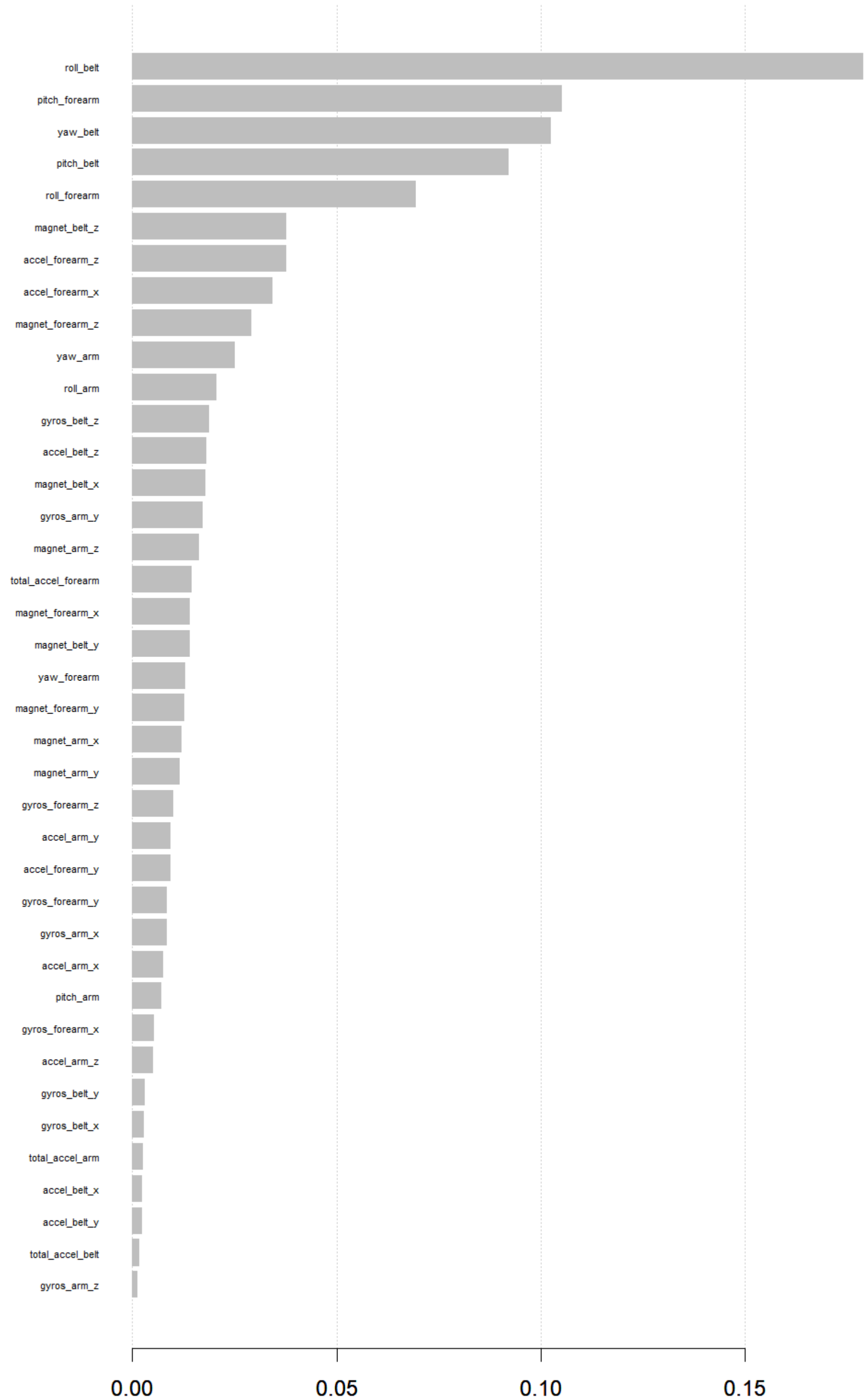
Output of prediction is the predicted probability of the 5 levels (columns) of outcome.
Decode the quantitative 5 levels of outcomes to qualitative letters (A, B, C, D, E).

```
# decode prediction
pred = matrix(pred, nrow=num.class, ncol=length(pred)/num.class)
pred = t(pred)
pred = max.col(pred, "last")
pred.char = toupper(letters[pred])
```

(*The prediction result `pred.char` is not displayed intentionally due to Honour Code, because it is the answer of the "project submission" part.*)

Feature importance

```
# get the trained model
model = xgb.dump(bst, with_stats=TRUE)
# get the feature real names
names = dimnames(train.matrix)[[2]]
# compute feature importance matrix
importance_matrix = xgb.importance(names, model=bst)
# plot
gp = xgb.plot.importance(importance_matrix)
```


roll_belt
pitch_forearm
yaw_belt
pitch_belt
roll_forearm
magnet_belt_z
accel_forearm_z
accel_forearm_x
magnet_forearm_z
yaw_arm
roll_arm
gyros_belt_z
accel_belt_z
magnet_belt_x
gyros_arm_y
magnet_arm_z
total_accel_forearm
magnet_forearm_x
magnet_belt_y
yaw_forearm
magnet_forearm_y
magnet_arm_x
magnet_arm_y
gyros_forearm_z
accel_arm_y
accel_forearm_y
gyros_forearm_y
gyros_arm_x
accel_arm_x
pitch_arm
gyros_forearm_x
accel_arm_z
gyros_belt_y
gyros_belt_x
total_accel_arm
accel_belt_x
accel_belt_y
total_accel_belt
gyros_arm_z
0.00
0.05
0.10
0.15

```
print(gp)
```

```
##                Feature        Gain       Cover   Frequency  Importance
##  1:          roll_belt 0.179057707 0.120097267 0.056619211 0.179057707
##  2:      pitch_forearm 0.105141254 0.092985416 0.060301096 0.105141254
##  3:           yaw_belt 0.102448144 0.094514105 0.090083456 0.102448144
##  4:         pitch_belt 0.092215619 0.071465888 0.067419408 0.092215619
##  5:       roll_forearm 0.069428911 0.065032294 0.055637375 0.069428911
##  6:       magnet_belt_z 0.037723818 0.039839979 0.029209622 0.037723818
##  7:     accel_forearm_z 0.037688164 0.026391486 0.033382425 0.037688164
##  8:     accel_forearm_x 0.034375825 0.027384627 0.020536737 0.034375825
##  9:    magnet_forearm_z 0.029180977 0.026468668 0.031418753 0.029180977
## 10:             yaw_arm 0.024995436 0.019883334 0.022254950 0.024995436
## 11:            roll_arm 0.020557171 0.023435712 0.039764359 0.020557171
## 12:        gyros_belt_z 0.018697278 0.037166835 0.019063983 0.018697278
## 13:        accel_belt_z 0.018208177 0.021996129 0.026182294 0.018208177
## 14:       magnet_belt_x 0.017813906 0.021368382 0.025855016 0.017813906
## 15:         gyros_arm_y 0.017248175 0.024119822 0.025200458 0.017248175
## 16:        magnet_arm_z 0.016254872 0.023685193 0.023154966 0.016254872
## 17: total_accel_forearm 0.014544365 0.010644756 0.010554737 0.014544365
## 18:    magnet_forearm_x 0.014176442 0.017694504 0.022009491 0.014176442
## 19:       magnet_belt_y 0.014042048 0.020447426 0.020536737 0.014042048
## 20:         yaw_forearm 0.012856769 0.011098825 0.023236786 0.012856769
## 21:    magnet_forearm_y 0.012624463 0.017038763 0.022582229 0.012624463
## 22:        magnet_arm_x 0.012103689 0.006709258 0.012191131 0.012103689
## 23:        magnet_arm_y 0.011551818 0.019498390 0.020782196 0.011551818
## 24:     gyros_forearm_z 0.010115423 0.013062272 0.014400262 0.010115423
## 25:         accel_arm_y 0.009452266 0.012916091 0.017509409 0.009452266
## 26:     accel_forearm_y 0.009304977 0.012935878 0.023564065 0.009304977
## 27:     gyros_forearm_y 0.008419790 0.013989208 0.025527737 0.008419790
## 28:         gyros_arm_x 0.008348822 0.015574663 0.023073147 0.008348822
## 29:         accel_arm_x 0.007613398 0.015901336 0.019963999 0.007613398
## 30:           pitch_arm 0.007070270 0.011915215 0.023809524 0.007070270
## 31:     gyros_forearm_x 0.005336731 0.008955171 0.016118475 0.005336731
## 32:         accel_arm_z 0.005103130 0.008305321 0.018163967 0.005103130
## 33:        gyros_belt_y 0.003080351 0.014936202 0.008591065 0.003080351
## 34:        gyros_belt_x 0.002892846 0.009363722 0.014891180 0.002892846
## 35:     total_accel_arm 0.002491270 0.004030219 0.009000164 0.002491270
## 36:        accel_belt_x 0.002429069 0.007239348 0.009818360 0.002429069
## 37:        accel_belt_y 0.002344086 0.006046993 0.005072820 0.002344086
## 38:    total_accel_belt 0.001707466 0.001913906 0.003109147 0.001707466
## 39:         gyros_arm_z 0.001355075 0.003947397 0.009409262 0.001355075
##                Feature        Gain       Cover   Frequency  Importance
```

Feature importance plot is useful to select only best features with highest correlation to the outcome(s). To improve model fitting performance (time or overfitting), less important features can be removed.