

ML_project

Martin

8/15/2020

Executive Summary

Based on a dataset provide by HAR <http://groupware.les.inf.puc-rio.br/har>, I will try to train a predictive model to predict what exercise was performed using a dataset with 159 features.

I will use xgboost to train the model here. The final model have an accuracy of nearly 100 % on the training set, about 99% accuracy on validation set. It can predict all 20 cases correctly in the quiz when using the test set.

Downloading and reading data

```
trainURL <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
download.file(trainURL, "training.csv")

testURL <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"
download.file(testURL, "testing.csv")

training = read.csv("training.csv", na.strings=c("NA", "#DIV/0!", ""))
testing = read.csv("testing.csv", na.strings=c("NA", "#DIV/0!", ""))
```

Removing variables with NA values and variables that are not needed

```
n = NULL
for (i in names(training)){
  if(sum(is.na(training[,i]))/length(training[,i])<0.2){
    n= c(n,i)
  }
}
training2 <- training[,n]

rm = c("X", "user_name", "raw_timestamp_part_1", "raw_timestamp_part_2", "cvtd_timestamp", "new_window")
rm = which(names(training2) %in% rm)
training3 = training2[,-rm]
training3$classe = factor(training3$classe)
```

Convert all into integers, expect classe

```
classeLevels <- levels(training2$classe)
training4 <- data.frame(data.matrix(training3))
training4$classe <- factor(training4$classe)
str(training4)
```

```

## 'data.frame':    19622 obs. of  53 variables:
## $ roll_belt      : num  1.41 1.41 1.42 1.48 1.48 1.45 1.42 1.42 1.43 1.45 ...
## $ pitch_belt     : num  8.07 8.07 8.07 8.05 8.07 8.06 8.09 8.13 8.16 8.17 ...
## $ yaw_belt       : num -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 ...
## $ total_accel_belt : num  3 3 3 3 3 3 3 3 3 3 ...
## $ gyros_belt_x    : num  0 0.02 0 0.02 0.02 0.02 0.02 0.02 0.02 0.03 ...
## $ gyros_belt_y    : num  0 0 0 0 0.02 0 0 0 0 0 ...
## $ gyros_belt_z    : num -0.02 -0.02 -0.02 -0.03 -0.02 -0.02 -0.02 -0.02 -0.02 0 ...
## $ accel_belt_x    : num -21 -22 -20 -22 -21 -21 -22 -22 -20 -21 ...
## $ accel_belt_y    : num  4 4 5 3 2 4 3 4 2 4 ...
## $ accel_belt_z    : num  22 22 23 21 24 21 21 21 24 22 ...
## $ magnet_belt_x   : num -3 -7 -2 -6 -6 0 -4 -2 1 -3 ...
## $ magnet_belt_y   : num  599 608 600 604 600 603 599 603 602 609 ...
## $ magnet_belt_z   : num -313 -311 -305 -310 -302 -312 -311 -313 -312 -308 ...
## $ roll_arm        : num -128 -128 -128 -128 -128 -128 -128 -128 -128 -128 ...
## $ pitch_arm       : num  22.5 22.5 22.5 22.1 22.1 22 21.9 21.8 21.7 21.6 ...
## $ yaw_arm         : num -161 -161 -161 -161 -161 -161 -161 -161 -161 -161 ...
## $ total_accel_arm : num  34 34 34 34 34 34 34 34 34 34 ...
## $ gyros_arm_x     : num  0 0.02 0.02 0.02 0 0.02 0 0.02 0.02 0.02 ...
## $ gyros_arm_y     : num  0 -0.02 -0.02 -0.03 -0.03 -0.03 -0.03 -0.02 -0.03 -0.03 ...
## $ gyros_arm_z     : num -0.02 -0.02 -0.02 0.02 0 0 0 0 -0.02 -0.02 ...
## $ accel_arm_x     : num -288 -290 -289 -289 -289 -289 -289 -289 -288 -288 ...
## $ accel_arm_y     : num  109 110 110 111 111 111 111 111 109 110 ...
## $ accel_arm_z     : num -123 -125 -126 -123 -123 -122 -125 -124 -122 -124 ...
## $ magnet_arm_x    : num -368 -369 -368 -372 -374 -369 -373 -372 -369 -376 ...
## $ magnet_arm_y    : num  337 337 344 344 337 342 336 338 341 334 ...
## $ magnet_arm_z    : num  516 513 513 512 506 513 509 510 518 516 ...
## $ roll_dumbbell   : num  13.1 13.1 12.9 13.4 13.4 ...
## $ pitch_dumbbell  : num -70.5 -70.6 -70.3 -70.4 -70.4 ...
## $ yaw_dumbbell    : num -84.9 -84.7 -85.1 -84.9 -84.9 ...
## $ total_accel_dumbbell : num  37 37 37 37 37 37 37 37 37 37 ...
## $ gyros_dumbbell_x : num  0 0 0 0 0 0 0 0 0 0 ...
## $ gyros_dumbbell_y : num -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 -0.02 ...
## $ gyros_dumbbell_z : num  0 0 0 -0.02 0 0 0 0 0 0 ...
## $ accel_dumbbell_x : num -234 -233 -232 -232 -233 -234 -232 -234 -232 -235 ...
## $ accel_dumbbell_y : num  47 47 46 48 48 48 47 46 47 48 ...
## $ accel_dumbbell_z : num -271 -269 -270 -269 -270 -269 -270 -272 -269 -270 ...
## $ magnet_dumbbell_x : num -559 -555 -561 -552 -554 -558 -551 -555 -549 -558 ...
## $ magnet_dumbbell_y : num  293 296 298 303 292 294 295 300 292 291 ...
## $ magnet_dumbbell_z : num -65 -64 -63 -60 -68 -66 -70 -74 -65 -69 ...
## $ roll_forearm    : num  28.4 28.3 28.3 28.1 28 27.9 27.9 27.8 27.7 27.7 ...
## $ pitch_forearm   : num -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -63.9 -63.8 -63.8 ...
## $ yaw_forearm     : num -153 -153 -152 -152 -152 -152 -152 -152 -152 -152 ...
## $ total_accel_forearm : num  36 36 36 36 36 36 36 36 36 36 ...
## $ gyros_forearm_x  : num  0.03 0.02 0.03 0.02 0.02 0.02 0.02 0.02 0.03 0.02 ...
## $ gyros_forearm_y  : num  0 0 -0.02 -0.02 0 -0.02 0 -0.02 0 0 ...
## $ gyros_forearm_z  : num -0.02 -0.02 0 0 -0.02 -0.03 -0.02 0 -0.02 -0.02 ...
## $ accel_forearm_x  : num  192 192 196 189 189 193 195 193 193 190 ...
## $ accel_forearm_y  : num  203 203 204 206 206 203 205 205 204 205 ...
## $ accel_forearm_z  : num -215 -216 -213 -214 -214 -215 -215 -213 -214 -215 ...
## $ magnet_forearm_x : num -17 -18 -18 -16 -17 -9 -18 -9 -16 -22 ...
## $ magnet_forearm_y : num  654 661 658 658 655 660 659 660 653 656 ...
## $ magnet_forearm_z : num  476 473 469 469 473 478 470 474 476 473 ...
## $ classe          : Factor w/ 5 levels "1","2","3","4",...: 1 1 1 1 1 1 1 1 1 1 ...

```

Data Partitioning

splitting the data into training and validation sets. Test data will be our last data to predict on.

```
ind = createDataPartition(training4$classe,p=0.8,list = FALSE)
traindat = training4[ind,]
validation = training4[-ind,]
```

Training

We will use K fold cross validation with k=5. We will fit a model using XGBoost and use all variables as possible predictors for classe. These modeling may take a while...

```
control <- trainControl(method="cv", 5, allowParallel = TRUE)
modelXGB <- train(classe ~ ., data=traindat, method="xgbTree", trControl=control)
modelXGB
```

```
## eXtreme Gradient Boosting
##
## 15699 samples
##    52 predictor
##    5 classes: '1', '2', '3', '4', '5'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 12558, 12559, 12560, 12561, 12558
## Resampling results across tuning parameters:
##
##  eta  max_depth  colsample_bytree  subsample  nrounds  Accuracy  Kappa
##  0.3   1          0.6              0.50       50      0.8007516 0.7476521
##  0.3   1          0.6              0.50      100      0.8571254 0.8191130
##  0.3   1          0.6              0.50      150      0.8899301 0.8606188
##  0.3   1          0.6              0.75       50      0.7951468 0.7405415
##  0.3   1          0.6              0.75      100      0.8576364 0.8197888
##  0.3   1          0.6              0.75      150      0.8868093 0.8566746
##  0.3   1          0.6              1.00       50      0.7994788 0.7459445
##  0.3   1          0.6              1.00      100      0.8587821 0.8212219
##  0.3   1          0.6              1.00      150      0.8859179 0.8555476
##  0.3   1          0.8              0.50       50      0.8022171 0.7494763
##  0.3   1          0.8              0.50      100      0.8605654 0.8234282
##  0.3   1          0.8              0.50      150      0.8902489 0.8609998
##  0.3   1          0.8              0.75       50      0.8015813 0.7486400
##  0.3   1          0.8              0.75      100      0.8591010 0.8216134
##  0.3   1          0.8              0.75      150      0.8866188 0.8564299
##  0.3   1          0.8              1.00       50      0.7984600 0.7446760
##  0.3   1          0.8              1.00      100      0.8571268 0.8191468
##  0.3   1          0.8              1.00      150      0.8858544 0.8554790
##  0.3   2          0.6              0.50       50      0.9154743 0.8930604
##  0.3   2          0.6              0.50      100      0.9549022 0.9429393
##  0.3   2          0.6              0.50      150      0.9715270 0.9639781
##  0.3   2          0.6              0.75       50      0.9121613 0.8888438
##  0.3   2          0.6              0.75      100      0.9535643 0.9412488
##  0.3   2          0.6              0.75      150      0.9719734 0.9645442
##  0.3   2          0.6              1.00       50      0.9097423 0.8858102
##  0.3   2          0.6              1.00      100      0.9522904 0.9396508
##  0.3   2          0.6              1.00      150      0.9685969 0.9602743
```

##	0.3	2	0.8	0.50	50	0.9152185	0.8927263
##	0.3	2	0.8	0.50	100	0.9594883	0.9487451
##	0.3	2	0.8	0.50	150	0.9747123	0.9680088
##	0.3	2	0.8	0.75	50	0.9142642	0.8915325
##	0.3	2	0.8	0.75	100	0.9566216	0.9451244
##	0.3	2	0.8	0.75	150	0.9719734	0.9645438
##	0.3	2	0.8	1.00	50	0.9127991	0.8896803
##	0.3	2	0.8	1.00	100	0.9545198	0.9424643
##	0.3	2	0.8	1.00	150	0.9699985	0.9620463
##	0.3	3	0.6	0.50	50	0.9641380	0.9546285
##	0.3	3	0.6	0.50	100	0.9850948	0.9811451
##	0.3	3	0.6	0.50	150	0.9914008	0.9891225
##	0.3	3	0.6	0.75	50	0.9613988	0.9511642
##	0.3	3	0.6	0.75	100	0.9845216	0.9804197
##	0.3	3	0.6	0.75	150	0.9912735	0.9889613
##	0.3	3	0.6	1.00	50	0.9598699	0.9492371
##	0.3	3	0.6	1.00	100	0.9830561	0.9785673
##	0.3	3	0.6	1.00	150	0.9905727	0.9880752
##	0.3	3	0.8	0.50	50	0.9623545	0.9523768
##	0.3	3	0.8	0.50	100	0.9852218	0.9813062
##	0.3	3	0.8	0.50	150	0.9920377	0.9899286
##	0.3	3	0.8	0.75	50	0.9638197	0.9542320
##	0.3	3	0.8	0.75	100	0.9858588	0.9821108
##	0.3	3	0.8	0.75	150	0.9912098	0.9888817
##	0.3	3	0.8	1.00	50	0.9622269	0.9522113
##	0.3	3	0.8	1.00	100	0.9849034	0.9809033
##	0.3	3	0.8	1.00	150	0.9915283	0.9892842
##	0.4	1	0.6	0.50	50	0.8259773	0.7797382
##	0.4	1	0.6	0.50	100	0.8817144	0.8502160
##	0.4	1	0.6	0.50	150	0.9097405	0.8857359
##	0.4	1	0.6	0.75	50	0.8270599	0.7810960
##	0.4	1	0.6	0.75	100	0.8799926	0.8480098
##	0.4	1	0.6	0.75	150	0.9057908	0.8807268
##	0.4	1	0.6	1.00	50	0.8244487	0.7777284
##	0.4	1	0.6	1.00	100	0.8788477	0.8465867
##	0.4	1	0.6	1.00	150	0.9044536	0.8790125
##	0.4	1	0.8	0.50	50	0.8297354	0.7843995
##	0.4	1	0.8	0.50	100	0.8826688	0.8514311
##	0.4	1	0.8	0.50	150	0.9090397	0.8848514
##	0.4	1	0.8	0.75	50	0.8263606	0.7801716
##	0.4	1	0.8	0.75	100	0.8806953	0.8489578
##	0.4	1	0.8	0.75	150	0.9064282	0.8815316
##	0.4	1	0.8	1.00	50	0.8254686	0.7790887
##	0.4	1	0.8	1.00	100	0.8804400	0.8486352
##	0.4	1	0.8	1.00	150	0.9042624	0.8787897
##	0.4	2	0.6	0.50	50	0.9321617	0.9141573
##	0.4	2	0.6	0.50	100	0.9668133	0.9580111
##	0.4	2	0.6	0.50	150	0.9792984	0.9738142
##	0.4	2	0.6	0.75	50	0.9307615	0.9123987
##	0.4	2	0.6	0.75	100	0.9675782	0.9589834
##	0.4	2	0.6	0.75	150	0.9807636	0.9756658
##	0.4	2	0.6	1.00	50	0.9271938	0.9079131
##	0.4	2	0.6	1.00	100	0.9658581	0.9568057
##	0.4	2	0.6	1.00	150	0.9791710	0.9736511

```
## 0.4 2 0.8 0.50 50 0.9354750 0.9183552
## 0.4 2 0.8 0.50 100 0.9694890 0.9614018
## 0.4 2 0.8 0.50 150 0.9810181 0.9759886
## 0.4 2 0.8 0.75 50 0.9337547 0.9161873
## 0.4 2 0.8 0.75 100 0.9678331 0.9593065
## 0.4 2 0.8 0.75 150 0.9815911 0.9767142
## 0.4 2 0.8 1.00 50 0.9327349 0.9148918
## 0.4 2 0.8 1.00 100 0.9659854 0.9569642
## 0.4 2 0.8 1.00 150 0.9805722 0.9754257
## 0.4 3 0.6 0.50 50 0.9727379 0.9655145
## 0.4 3 0.6 0.50 100 0.9894901 0.9867068
## 0.4 3 0.6 0.50 150 0.9922926 0.9902508
## 0.4 3 0.6 0.75 50 0.9730558 0.9659150
## 0.4 3 0.6 0.75 100 0.9899993 0.9873503
## 0.4 3 0.6 0.75 150 0.9936941 0.9920238
## 0.4 3 0.6 1.00 50 0.9711450 0.9634966
## 0.4 3 0.6 1.00 100 0.9888531 0.9858995
## 0.4 3 0.6 1.00 150 0.9929297 0.9910568
## 0.4 3 0.8 0.50 50 0.9752856 0.9687334
## 0.4 3 0.8 0.50 100 0.9903820 0.9878344
## 0.4 3 0.8 0.50 150 0.9929935 0.9911378
## 0.4 3 0.8 0.75 50 0.9735650 0.9665585
## 0.4 3 0.8 0.75 100 0.9899356 0.9872693
## 0.4 3 0.8 0.75 150 0.9937576 0.9921039
## 0.4 3 0.8 1.00 50 0.9733739 0.9663213
## 0.4 3 0.8 1.00 100 0.9899357 0.9872700
## 0.4 3 0.8 1.00 150 0.9933116 0.9915401
##
## Tuning parameter 'gamma' was held constant at a value of 0
## Tuning parameter 'min_child_weight' was held constant at
## a value of 1
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were nrounds = 150, max_depth = 3, eta = 0.4, gamma = 0, colsamp
## 0.8, min_child_weight = 1 and subsample = 0.75.
```

Predictions and performance of model on train and validation data

```
predict1 <- predict(modelXGB, traindat)
confusionMatrix(traindat$classe, predict1)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    1    2    3    4    5
##           1 4464    0    0    0    0
##           2    0 3038    0    0    0
##           3    0    0 2738    0    0
##           4    0    0    0 2573    0
##           5    0    0    0    0 2886
##
## Overall Statistics
##
##           Accuracy : 1
##           95% CI : (0.9998, 1)
```

```
##      No Information Rate : 0.2843
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 1
##
##      McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##              Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity          1.0000   1.0000   1.0000   1.0000   1.0000
## Specificity          1.0000   1.0000   1.0000   1.0000   1.0000
## Pos Pred Value       1.0000   1.0000   1.0000   1.0000   1.0000
## Neg Pred Value       1.0000   1.0000   1.0000   1.0000   1.0000
## Prevalence           0.2843   0.1935   0.1744   0.1639   0.1838
## Detection Rate       0.2843   0.1935   0.1744   0.1639   0.1838
## Detection Prevalence 0.2843   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy     1.0000   1.0000   1.0000   1.0000   1.0000
```

```
predict2 <- predict(modelXGB, validation)
confusionMatrix(validation$classe, predict2)
```

```
## Confusion Matrix and Statistics
```

```
##
##      Reference
## Prediction   1    2    3    4    5
##      1 1113    0    3    0    0
##      2    1  755    3    0    0
##      3    0    2  677    5    0
##      4    0    0    6  637    0
##      5    0    0    1    0  720
```

```
## Overall Statistics
```

```
##
##      Accuracy : 0.9946
##      95% CI : (0.9918, 0.9967)
##      No Information Rate : 0.284
##      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          0.9991   0.9974   0.9812   0.9922   1.0000
## Specificity          0.9989   0.9987   0.9978   0.9982   0.9997
## Pos Pred Value       0.9973   0.9947   0.9898   0.9907   0.9986
## Neg Pred Value       0.9996   0.9994   0.9960   0.9985   1.0000
## Prevalence           0.2840   0.1930   0.1759   0.1637   0.1835
## Detection Rate       0.2837   0.1925   0.1726   0.1624   0.1835
## Detection Prevalence 0.2845   0.1935   0.1744   0.1639   0.1838
## Balanced Accuracy     0.9990   0.9980   0.9895   0.9952   0.9998
```

We can see that model is doing well both on training and validation data. On training set it achieved more than 99% accuracy and on validation accuracy is also more than 99%.

Predicting Test Data

In the first column are the predictions for the given test set. 1=A , 2=B and so on.

```
predicttest <- predict(modelXGB, testing)
testpred = cbind(predicttest)
testpred
```

```
##      predicttest
## [1,]           2
## [2,]           1
## [3,]           2
## [4,]           1
## [5,]           1
## [6,]           5
## [7,]           4
## [8,]           2
## [9,]           1
## [10,]          1
## [11,]          2
## [12,]          3
## [13,]          2
## [14,]          1
## [15,]          5
## [16,]          5
## [17,]          1
## [18,]          2
## [19,]          2
## [20,]          2
```