Practical Machine Learning Course Project

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Human Activity Recognition

We are using exercise tech data to try to classify different types of activities. In this dataset, six participants were asked to perform barbell lifts correctly and incorrectly in 5 different ways. We are tasked with cleaning and preprocessing this data in order to fit a machine learning model to predict which of the 5 different ways participants are performing the activity.

Reading in the Data

```
training = read.csv("~/Downloads/pml-training.csv")
testing = read.csv("~/Downloads/pml-testing.csv")
str(training, list.len=20)
```

```
## 'data.frame':    19622 obs. of  160 variables:
##  $ X                       : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ user_name               : Factor w/ 6 levels "adelmo","carlitos",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ raw_timestamp_part_1    : int  1323084231 1323084231 1323084231 1323084232 1323084232 1323084232
##  $ raw_timestamp_part_2    : int  788290 808298 820366 120339 196328 304277 368296 440390 484323 484
##  $ cvtd_timestamp          : Factor w/ 20 levels "02/12/2011 13:32",..: 9 9 9 9 9 9 9 9 9 9 ...
##  $ new_window              : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ num_window              : int  11 11 11 12 12 12 12 12 12 12 ...
##  $ 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        : int  3 3 3 3 3 3 3 3 3 3 ...
##  $ kurtosis_roll_belt      : Factor w/ 397 levels "","-0.016850",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ kurtosis_picth_belt     : Factor w/ 317 levels "","-0.021887",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ kurtosis_yaw_belt       : Factor w/ 2 levels "","#DIV/0!": 1 1 1 1 1 1 1 1 1 1 ...
##  $ skewness_roll_belt      : Factor w/ 395 levels "","-0.003095",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ skewness_roll_belt.1    : Factor w/ 338 levels "","-0.005928",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ skewness_yaw_belt       : Factor w/ 2 levels "","#DIV/0!": 1 1 1 1 1 1 1 1 1 1 ...
##  $ max_roll_belt           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_picth_belt          : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_yaw_belt            : Factor w/ 68 levels "","-0.1","-0.2",..: 1 1 1 1 1 1 1 1 1 1 ...
##   [list output truncated]
```

Data Cleaning

Here we output the structure of the first 20 columns of the training set. We use this command, along with summary and some histograms to see that many of the columns consist of values that are either mostly NA or " (empty strings). To clean the training set we remove these columns, along with removing the corresponding columns from the test set.

We also see that the first column is simply an index, so we don't need that. Furthermore, the 6th column, 'new_window', seems to not be useful for this classification problem.

```r
f1 <-  function(name) if((sum(is.na(training[name]))<19000)) {print(name)}
notNAnames <- unlist(lapply(names(training), f1))
training <- training[,notNAnames]
notNAnames.test <- notNAnames[-93]
testing <- testing[,notNAnames.test]

f2 <-  function(name) if((sum(training[name]=='')<19000)) {print(name)}
notEmptynames <- unlist(lapply(names(training), f2))
training <- training[,notEmptynames]
notEmptynames.test <- notEmptynames[-60]
testing <- testing[,notEmptynames.test]

training <- training[,-c(1,6)]
testing <- testing[,-c(1,6)]
```

```r
dim(training)
```

```
## [1] 19622    58
```

Preprocessing (PCA)

Here we see that the cleaning process has reduced the number of columns from 160 to only 58, which is still large. We can further reduce the number of features to use by performing a Principle Components Analysis. After some exploratory testing, we found that using the principle components that account for 80% of the variance is sufficient for this problem.

```r
suppressMessages(library(caret))
train_num <- data.frame(sapply(training, function(x) as.numeric(x)))
train_num$classe <- as.factor(train_num$classe)
preObj <- preProcess(train_num[,-58], method = "pca", thresh=0.8)
pca_training_preds <- predict(preObj, train_num[,-58])
dim(training)
```

```
## [1] 19622    58
```

```r
dim(pca_training_preds)
```

```
## [1] 19622    13
```

Here we see that only 13 principle components out of 57 (excluding the variable we are trying to predict) are necessary to account for 80% of the variance.

Model Selection

We tried a number of different classification algorithms, including Naive Bayes and Support Vector Machines, but found that a Random Forest does the best job (Also, using train(…,method='rf') took significantly longer than randomForest(…), so that's the method we use). Below we show 3 crossfolds from random forest models using the top 11 principle components. And since we aren't using train(), we can't use it's built-in cross-validations routines.

Cross Validation

```r
suppressMessages(library(caret))
suppressMessages(library(randomForest))

set.seed(39592)
fold1 <- createDataPartition(training$classe, p=0.8, list = F)
trainfold1 <- train_num[fold1,]
testfold1 <- train_num[-fold1,]
preObj1 <- preProcess(trainfold1[,-58], method = "pca", thresh=0.8)
pca_training_preds1 <- predict(preObj1, trainfold1[,-58])
pca_training_preds1$y <- trainfold1$classe
pca_testing_preds1 <- predict(preObj1, testfold1[,-58])
mod_rf_fold1 <- randomForest(y~.,data = pca_training_preds1)
pred_fold1 <- predict(mod_rf_fold1, pca_testing_preds1)
print(confusionMatrix(pred_fold1, testfold1$classe)$overall[1])
```

```
##  Accuracy
## 0.9722151
```

```r
set.seed(40639)
fold2 <- createDataPartition(training$classe, p=0.8, list = F)
trainfold2 <- train_num[fold2,]
testfold2 <- train_num[-fold2,]
preObj2 <- preProcess(trainfold2[,-58], method = "pca", thresh=0.8)
pca_training_preds2 <- predict(preObj2, trainfold2[,-58])
pca_training_preds2$y <- trainfold2$classe
pca_testing_preds2 <- predict(preObj2, testfold2[,-58])
mod_rf_fold2 <- randomForest(y~.,data = pca_training_preds2)
pred_fold2 <- predict(mod_rf_fold2, pca_testing_preds2)
print(confusionMatrix(pred_fold2, testfold2$classe)$overall[1])
```

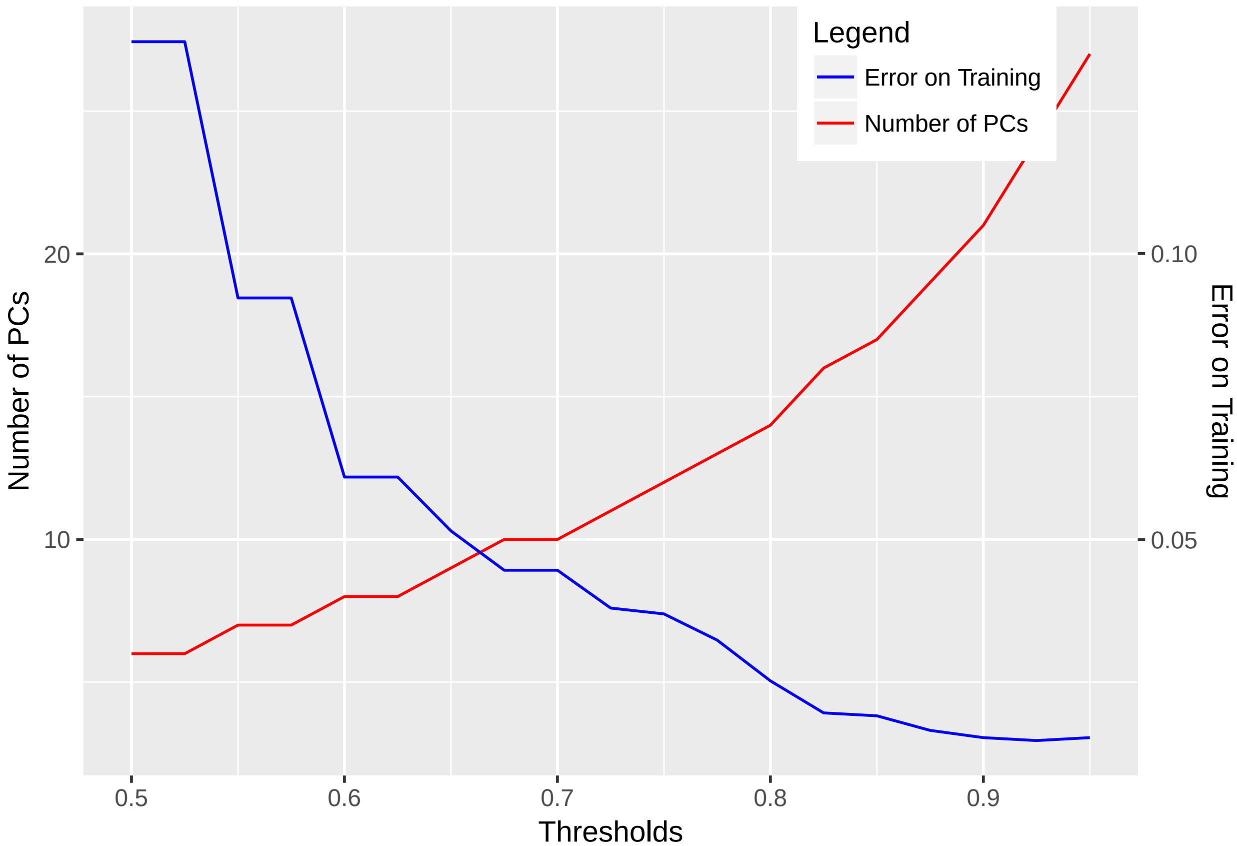
```
##  Accuracy
## 0.9696661
```

```r
set.seed(94823)
fold3 <- createDataPartition(training$classe, p=0.8, list = F)
trainfold3 <- train_num[fold3,]
testfold3 <- train_num[-fold3,]
preObj3 <- preProcess(trainfold3[,-58], method = "pca", thresh=0.8)
pca_training_preds3 <- predict(preObj3, trainfold3[,-58])
pca_training_preds3$y <- trainfold3$classe
pca_testing_preds3 <- predict(preObj3, testfold3[,-58])
mod_rf_fold3 <- randomForest(y~.,data = pca_training_preds3)
pred_fold3 <- predict(mod_rf_fold3, pca_testing_preds3)
print(confusionMatrix(pred_fold3, testfold3$classe)$overall[1])
```

```
##  Accuracy
## 0.9709406
```

Dependence on PCA Threshold

Here we plot the change in the number of PCs used and the error (1-accuracy) in a test set as we change the variation threshold for PCs. As the threshold increases, the necessary number of PC increases, but the error decreases.



Test Set Predictions

```
test_num <- data.frame(sapply(testing, function(x) as.numeric(x)))
pca_testing_preds <- predict(preObj, test_num)

pca_training_preds$y <- training$classe
mod_rf_full <- randomForest(y~.,data = pca_training_preds)
pred <- predict(mod_rf_full, pca_testing_preds)
pred
```

```
##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
##  A  A  A  A  A  E  D  B  A  A  B  C  B  A  E  E  A  B  B  B
## Levels: A B C D E
```

Since the model does well consistently on the cross-validation folds, and because we used PCA, I think the model will do quite well on unseen data, probably >90% (out of sample error <10%).