Project 3: Main Script

Ka Heng (Helen) Lo

March 24, 2017

This file firstly details the model selection process for an advanced binary classification model, that takes in images and classifies them as either a labradoodle ("1") or fried chicken ("0") - simply referred to as the Advanced Model. Secondly, it runs evaluation experiments to compare the Baseline Model - gradient boosting model (gbm) with parameters tuned on the original SIFT features - with our Advanced Model.

```r
#Load (and install if necessary) required packages
if(!require("EBImage")){
  source("https://bioconductor.org/biocLite.R")
  biocLite("EBImage")
}
```

```
## Loading required package: EBImage
```

```r
needed <- setdiff(c("gbm", "data.table", "e1071", "class", "adabag","caret", "xgboost"),
                  rownames(installed.packages()))
if (length(needed) > 0 ){
  install.packages(needed)
}
library(EBImage)
library(gbm)
```

```
## Loading required package: survival

## Loading required package: lattice

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.1
```

```r
library(data.table)
```

```
##
## Attaching package: 'data.table'

## The following object is masked from 'package:EBImage':
##
##     transpose
```

```r
library(e1071)
library(class)
library(adabag)
```

```
## Loading required package: rpart

## Loading required package: mlbench

## Loading required package: caret

## Loading required package: ggplot2

##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:survival':
##
##     cluster
```

```
library(caret)
library(xgboost)
```

Import class labels for training images

We code labradoodles as "1" and fried chicken as "0" for binary classification.

```
label_train <- read.csv("../data/train/labels.csv")
label_train <- as.matrix(label_train)[,1]
#some of our models require labels to be numeric in [0,1], so we keep the labels as 0's and 1's
#for any model that requires labels to be factors we pass the labels to the tune or train function
#specific to the model as numeric values and coerce them inside the function to be factors
```

Selecting the Advanced Model:

Model selection with provided SIFT features of training images

Import the SIFT features of the set of 2000 training images

```
train_sift <- read.csv("../data/train/sift_features.csv")
train_sift <- t(as.matrix(train_sift))
```

Tune parameters of each model via cross-validation

Set up control for tuning models under consideration based on the provided SIFT features of the training images.
+ (T/F) tune models under consideration based on provided SIFT features

```
###### T/F to reproduce the tuning process for all models considered ######
run.tune.sift = FALSE
```

- Parameter-tuning process:

```
#get summary tables of best tuned parameters for each model considered, i.e. lowest cv error
#6 columns: "Model", "Best_Param_1", "Best_Param_2", "Best_Param_3",
#            "Best_Error", "Training_Time"
#  - NA values for Best_Param_2 and/or Best_Param_3 if model has less than 3 params
############################################################################################


#source("../lib/xgboost.R")
#source("../lib/svm.R")
#source("../lib/knn.R")
#source("../lib/AdaBag_AdaBoost.R")
#source("../lib/blgbm.R")

if(run.tune.sift) {
  source("../lib/xgboost.R")
  source("../lib/svm.R")
  source("../lib/knn.R")
```

```r
  source("../lib/AdaBag_AdaBoost.R")
  source("../lib/blgbm.R")

  summary.xgb <- tune.xgb(train_sift,label_train)
  #save(summary.xgb, file="output/summary_best_xgb.RData")

  summary.svm.lin <- tune.svm.lin(train_sift,label_train)
  #save(summary.svm.lin, file="output/summary_best_svm_lin.Rdata")

  summary.svm.rad <- tune.svm.rad(train_sift,label_train)
  #save(summary.svm.rad,file="output/summary_best_svm_rad.Rdata")

  summary.knn <- tune.knn(train_sift,label_train)
  #save(summary.knn, file="output/summary_best_knn.Rdata")

  summary.AdaBag <- tune.AdaBag(train_sift,label_train)
  #save(summary.AdaBag,file="output/summary_best_AdaBag2.Rdata")

  summary.AdaBoost.M1 <- tune.AdaBoost.M1(train_sift,label_train)
  #save(summary.AdaBoost.M1,file="output/summary_best_AdaBoost.M1.Rdata")

  summary.AdaBoost_SAMME <- tune.AdaBoost_SAMME(train_sift,label_train)
  #save(summary.AdaBoost_SAMME,file="output/summary_best_AdaBoost_SAMME.Rdata")

  summary.bl<- tune.bl(train_sift, label_train)
  #save(summary.bl,file="output/summary_best_blgbm.RData")
}
```

Summary Table: parameter-tuning process on original SIFT features

Summary table of *best* models (i.e. models with *best* parameters) tuned on original SIFT features of the training set via cross-validation, sorted by CV Error.

```r
library(data.table)
#load already produced summary tables for best tuned parameters for each model considered
load("../output/summary_best_xgb.RData")
load("../output/summary_best_svm_lin.Rdata")
load("../output/summary_best_svm_rad.Rdata")
load("../output/summary_best_knn.Rdata")

load("../output/summary_best_AdaBag2.Rdata")

load("../output/summary_best_AdaBoost.M1.Rdata")
load("../output/summary_best_AdaBoost_SAMME.Rdata")

load("../output/summary_best_blgbm.Rdata")

#6 columns: "Model", "Best_Param_1", "Best_Param_2", "Best_Param_3",
#             "Best_Error", "Training_Time"
#  - NA values for Best_Param_2 and/or Best_Param_3 if model has less than 3 params
summary1 <- rbind(summary.xgb, summary.svm.lin,
                  summary.svm.rad,
                  summary.AdaBag2, summary.AdaBoost.M1,
                  summary.AdaBoost_SAMME,
```

```
                  summary.knn,summary.bl)

#sort table by Best_Error in ascending order
summary1 <- summary1[order(summary1$Best_Error)]

#add column for feature set models are tuned on
(summary1 <- data.table(summary1[,1], Features = rep("Original SIFT",8), summary1[,2:6]))
```

```
##                      Model      Features     Best_Param_1 Best_Param_2
## 1:                 XGBoost Original SIFT    max_depth = 5    eta = 0.5
## 2:                  BL GBM Original SIFT shrinkage = 0.16   ntrees= 64
## 3: SVM with linear kernel Original SIFT      cost = 5000           NA
## 4:                  AdaBag Original SIFT     mfinal = 100           NA
## 5:             AdaBoost.M1 Original SIFT      mfinal = 15           NA
## 6:          AdaBoost_SAMME Original SIFT      mfinal = 15           NA
## 7:                     KNN Original SIFT            k = 1           NA
## 8: SVM with Radial Kernel Original SIFT       cost = 500    gamma = 2
##     Best_Param_3   Best_Error Training_Time
## 1: nrounds = 169 5.267342e-05      49.148 s
## 2:            NA 2.365000e-01      15.234 s
## 3:            NA 2.520000e-01      73.452 s
## 4:            NA 2.915000e-01    1780.513 s
## 5:            NA 3.095000e-01     239.031 s
## 6:            NA 3.190000e-01     249.718 s
## 7:            NA 3.735000e-01            NA
## 8:            NA 4.020000e-01      73.638 s
```

```
save(summary1,file="../output/summary_best_models1.Rdata")
```

Model selection with new visual features

Import sets of new visual features

```
#import the three csv files - the three new sets of visual features
new_train_feat1 <- read.csv("../data/train/sift_features_resize+adaptive.csv")
new_train_feat1 <- t(as.matrix(new_train_feat1))

new_train_feat2 <- read.csv("../data/train/sift_features_resize.csv")
new_train_feat2 <- t(as.matrix(new_train_feat2))

new_train_feat3 <- read.csv("../data/train/sift_features_adaptive.csv")
new_train_feat3 <- t(as.matrix(new_train_feat3))
```

Tune parameters of each model via cross-validation

- Set up control for tuning models under consideration based on three new sets of features of the training images.
- (T/F) tune models under consideration based on three new sets of visual features

```
###### T/F to reproduce the tuning process for all models considered ######
run.tune.new = FALSE
```

- Parameter-tuning process:

```r
if (run.tune.new){
  source("../lib/xgboost.R")
  source("../lib/blgbm.R")

  ###******* Tune for xgBoost
  #  1)tune on the first set of new visual features for the training images
  summary.xgb.new1 <- tune.xgb(new_train_feat1,label_train)
  #save(summary.xgb.new1,file="../output/summary_best_xgb_new1.Rdata")

  #  2)tune on the second set of new visual features for the training images
  summary.xgb.new2 <- tune.xgb(new_train_feat2,label_train)
  #save(summary.xgb.new2,file="../output/summary_best_xgb_new2.Rdata")

  #  3)tune on the third set of new visual features for the training images
  summary.xgb.new3 <- tune.xgb(new_train_feat3,label_train)
  #save(summary.xgb.new3,file="../output/summary_best_xgb_new3.Rdata")


  ###******* Tune for gbm
  #  1)tune on the first set of new visual features for the training images
  summary.gbm.new1 <- bl.tune(new_train_feat1,label_train)
  #save(summary.gbm.new1,file="../output/summary_best_gbm_new1.Rdata")

  #  2)tune on the second set of new visual features for the training images
  summary.gbm.new2 <- bl.tune(new_train_feat2,label_train)
  #save(summary.gbm.new2,file="../output/summary_best_gbm_new2.Rdata")

  #  3)tune on the third set of new visual features for the training images
  summary.gbm.new3 <- bl.tune(new_train_feat3,label_train)
  #save(summary.gbm.new3,file="../output/summary_best_gbm_new3.Rdata")

}
```

Summary Table: parameter-tuning process on new features

```r
#load Rdata files
load("../output/summary_best_xgb_new1.Rdata")
load("../output/summary_best_xgb_new2.Rdata")
load("../output/summary_best_xgb_new3.Rdata")
load("../output/summary_best_gbm_new1.Rdata")
load("../output/summary_best_gbm_new2.Rdata")
load("../output/summary_best_gbm_new3.Rdata")

summary2 <- rbind(summary.xgb.new1, summary.xgb.new2,
                  summary.xgb.new3, summary.gbm.new1,
                  summary.gbm.new2, summary.gbm.new3)
#sort table by Best_Error in ascending order
summary2 <- summary2[order(summary2$Best_Error)]

#add column for feature set models are tuned on
(summary2 <- data.table(summary2[,1], Features = c("SIFT- resize+adaptive","SIFT- resize",
                                                   "SIFT- adaptive", "SIFT- resize+adaptive",
                                                   "SIFT- resize", "SIFT- adaptive"),
```

```
                        summary2[,2:6]))
```

```
##      Model               Features     Best_Param_1 Best_Param_2
## 1: XGBoost SIFT- resize+adaptive    max_depth = 7    eta = 0.5
## 2:  BL GBM           SIFT- resize shrinkage = 0.21   ntrees= 48
## 3: XGBoost         SIFT- adaptive    max_depth = 7    eta = 0.2
## 4:  BL GBM SIFT- resize+adaptive shrinkage = 0.16  ntrees= 127
## 5:  BL GBM           SIFT- resize shrinkage = 0.21   ntrees= 46
## 6: XGBoost         SIFT- adaptive    max_depth = 7    eta = 0.2
##    Best_Param_3 Best_Error Training_Time
## 1: nrounds = 45     0.1890      19.032 s
## 2:           NA     0.1900      11.324 s
## 3: nrounds = 62     0.1905      26.374 s
## 4:           NA     0.1935      23.067 s
## 5:           NA     0.2470      12.802 s
## 6: nrounds = 44     0.2575      20.311 s
```

```
save(summary2,file="../output/summary_best_models2.Rdata")
```

Convolutional Neural Network (CNN)

Tune CNN model on set of raw training images via cross-validation

- Set up control for tuning CNN on set of raw images
- (T/F) tune CNN

```
###### T/F to reproduce the tuning process for all models considered ######
run.tune.cnn = FALSE
```

- Parameter-tuning process

```
if (run.tune.cnn) {
  img_train_dir <- "../data/train/raw_images"
  source("../lib/CNN.R")
  source("../lib/CNNcv.R")

  #first resize the raw images and then split into test set(200) and train set(1800)
  data_list <- to.resize.split(img_train_dir,label_train)


  #cross-validation on the resized train set (1800 images)
  iter <- seq(60,100,by=10) #iter is the range of the tune parameters
  #get best num.rounds
  best_num.rounds <- CNNcv(data_list$train_data,iter)

  #retrain data (1800 images) ; get run.time; and test error using test set(200 images)
  cnn.output <- CNN(data_list$train_data,data_list$test_data)

  summary.cnn <- data.table(Model = "CNN", Features = NA,
           Best_Param_1 = paste("num.rounds =",best_num.rounds),
           Best_Param_2 = NA,
           Best_Param_3 = NA,
           Best_Error = cnn.output$test_err,
           Training_Time = paste(cnn.output$train_time, "s"))
```

```
  #save(summary.cnn, file="output/summary_best_cnn.RData")

}
```

Selecting the *best* Advanced Model

Summary Table of best models tuned on various feature sets (original SIFT & new) + CNN

```
#load Rdata files
load("../output/summary_best_models1.Rdata")
load("../output/summary_best_models2.Rdata")

load("../output/summary_best_cnn.Rdata")

summary3 <- rbind(summary1,summary2,summary.cnn)
(summary3 <- summary3[order(summary3$Best_Error)])
```

```
##                       Model              Features     Best_Param_1
##  1:                 XGBoost         Original SIFT    max_depth = 5
##  2:                     CNN                    NA   num.round = 60
##  3:                 XGBoost SIFT- resize+adaptive    max_depth = 7
##  4:                  BL GBM          SIFT- resize shrinkage = 0.21
##  5:                 XGBoost        SIFT- adaptive    max_depth = 7
##  6:                  BL GBM SIFT- resize+adaptive shrinkage = 0.16
##  7:                  BL GBM         Original SIFT shrinkage = 0.16
##  8:                  BL GBM          SIFT- resize shrinkage = 0.21
##  9: SVM with linear kernel         Original SIFT      cost = 5000
## 10:                 XGBoost        SIFT- adaptive    max_depth = 7
## 11:                  AdaBag         Original SIFT     mfinal = 100
## 12:             AdaBoost.M1         Original SIFT      mfinal = 15
## 13:          AdaBoost_SAMME         Original SIFT      mfinal = 15
## 14:                     KNN         Original SIFT            k = 1
## 15: SVM with Radial Kernel         Original SIFT       cost = 500
##     Best_Param_2  Best_Param_3   Best_Error Training_Time
##  1:    eta = 0.5 nrounds = 169 5.267342e-05      49.148 s
##  2:           NA            NA 1.355000e-01    321.5955 s
##  3:    eta = 0.5  nrounds = 45 1.890000e-01      19.032 s
##  4:   ntrees= 48            NA 1.900000e-01      11.324 s
##  5:    eta = 0.2  nrounds = 62 1.905000e-01      26.374 s
##  6:  ntrees= 127            NA 1.935000e-01      23.067 s
##  7:   ntrees= 64            NA 2.365000e-01      15.234 s
##  8:   ntrees= 46            NA 2.470000e-01      12.802 s
##  9:           NA            NA 2.520000e-01      73.452 s
## 10:    eta = 0.2  nrounds = 44 2.575000e-01      20.311 s
## 11:           NA            NA 2.915000e-01    1780.513 s
## 12:           NA            NA 3.095000e-01     239.031 s
## 13:           NA            NA 3.190000e-01     249.718 s
## 14:           NA            NA 3.735000e-01            NA
## 15:    gamma = 2            NA 4.020000e-01      73.638 s
```

```
save(summary3,file="../output/summary_best_models3.Rdata")
save(summary3,file="../output/summary_best_models3.Rdata")
```

In the summary table, the models under consideration are ranked by best (min) error. The Baseline Model

(GBM with original SIFT) is ranked 7th with cross-validation estimated prediction error of .2365 and training time of 15.234 seconds. Model 1 in the table (XGBoost with original SIFT) has the lowest estimated prediction error of 5.267342e-05 (<<.2365), but it has a higher training time of 49.148 seconds (>15.234 seconds). Model 2 in the table (CNN with 1800 of the 2000 raw images) has an test error (testing with the remaining 200 of the 2000 raw images) of .1355, but it has a really large training time of 321.5955 seconds (>>15.234 seconds). Model 3 in the table (XGBoost with SIFT- resize+adaptive) has a decently low cross-validation estimated prediction error of .189 (<.2365) and a decently low training time of 19.032 seconds (only slightly larger, but comparable to 15.234 seconds). Thus, we chose Model 3 (XGBoost with SIFT- resize+adaptive) to be our advanced model, as it seems the best compromise between a low estimated prediction error and a small training time.

Comparing the Baseline Model and the Advanced Model

Set up controls for evaluation experiments: Baseline Model vs. Advanced Model

- (T/F) train Baseline Model and Advanced Model
- (T/F) process features for training set
- (T/F) run evaluation on an independent test set for both Baseline Model and Advanced Model
- (T/F) process features for test set

```
run.train=TRUE # train 'best' model
run.feature.train=TRUE # process features for training set
run.test=FALSE # run evaluation on an independent test set
run.feature.test=FALSE # process features for test set
```

Import given SIFT features new visual features of the test set

We construct the new visual features outside of R/Rstudio, so we just import the .csv files with the new feature data.

```
#Recall for the training set we imported the .csv files before
if (run.feature.train){
  #dat_train_sift <- read.csv("../data/train/sift_features.csv")
  #dat_train_sift <- t(as.matrix(dat_train_sift))
  dat_train_sift <- train_sift
  save(dat_train_sift,file="../output/dat_train_sift.Rdata")

  #dat_train_new <- read.csv("../data/train/sift_features_resize+adaptive.csv")
  #dat_train_new <- t(as.matrix(dat_train_new))
  dat_train_new <- new_train_feat1 #we selected new feature set 1: SIFT- resize+adaptive
  save(dat_train_new,file="../output/dat_train_new.Rdata")
}

##Now for the test set:
if (run.feature.test){
  #Import the provide SIFT features of the test set
  dat_test_sift <- read.csv("../data/test/sift_features_test.csv")
  dat_test_sift <- t(as.matrix(dat_test_sift))
  save(dat_test_sift,file="../output/dat_test_sift.Rdata")
  #Import the set of new visual features (constructed outside of R)
  dat_test_new <- read.csv("../data/test/sift_features_resize+adaptive.csv")  # ***or other file name
  dat_test_new <- t(as.matrix(dat_test_new))
  save(dat_test_new,file="../output/dat_test_new.Rdata")
```

```
}

#tm_feature_test = NA
```

Train a classification model with training images

`train.R` and `test.R` should be wrappers for all your model training steps and your classification/prediction steps. + `train.R` + Input: an R object that contains processed training set features. + Input: an R object of training sample labels. + Output: an RData file that contains trained classifiers in the forms of R objects: models/settings/links to external trained configurations. + `test.R` + Input: a path that points to the test set features. + Input: an R object that contains a trained classifiers. + Output: an R object of class label predictions on the test set. If there are multiple classifiers under evaluation, there should be multiple sets of label predictions.

```
source("../lib/train.R")
source("../lib/test.R")
```

Train Baseline Model and Advanced Model

Here we call the `train()` function in `train.R`. We fit the entire set of constructed visual features of the training images to the Baseline Model and the Advanced Model.

```
#Here, we call train() from train.R
#   -note that train() returns a list of two model objects: list(baseline_fit,advanced_fit)
tm_train=NA ; tm_train_base=NA ; tm_train_adv=NA
if(run.train){
  load(file="../output/dat_train_sift.Rdata")
  load(file="../output/dat_train_new.Rdata")
  tm_train <- system.time(fit_train <- train(dat_train_base = dat_train_sift,
                                             dat_train_adv = dat_train_new,
                                             label_train=label_train))
  save(fit_train, file="../output/fit_train.Rdata")

  #individual times for training base model and advanced model
  tm_train_base <- system.time(fit_train_base <- train(dat_train_base = dat_train_sift,
                                                       label_train=label_train, model="base"))
  tm_train_adv <- system.time(fit_train_adv <- train(dat_train_adv = dat_train_new,
                                                     label_train=label_train,model="advanced"))
}
```

Make predictions

Here we call the `test()` function in `test.R`. Feed the Baseline Model and the Advanced Model with the completely holdout testing data.

```
#####################################################################################################
#to test the test() function, get predictions on training data for base model and advanced model
load(file="../output/fit_train.Rdata")
load(file="../output/dat_train_sift.Rdata")
load(file="../output/dat_train_new.Rdata")
(pred_train <- test(fit_train = fit_train, dat_test_base = dat_train_sift,
                    dat_test_adv = dat_train_new))
```

```
## $baseline_pred
##    [1] 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0
##   [35] 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 1 1 0 0 1 0 0 0 0 0
##   [69] 0 0 1 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0
##  [103] 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0 1 0 0 0 0 0 0
##  [137] 0 0 0 1 1 0 1 0 1 0 0 1 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0
##  [171] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 0 1 0 0 0 0 0 0 0 0 1
##  [205] 0 0 0 1 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 1 1 0 0 1 0 1 0 0 0 1 0
##  [239] 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 1 0 0 1 0 0 0 0
##  [273] 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 1 0 0
##  [307] 0 1 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0
##  [341] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 0 1
##  [375] 0 1 0 1 1 0 0 0 0 0 0 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1
##  [409] 0 0 0 0 0 1 1 1 0 0 0 0 0 1 0 0 0 0 0 1 0 1 1 0 0 1 0 0 0 0 1 0 0 0
##  [443] 1 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0
##  [477] 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0
##  [511] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 1 0 1 0
##  [545] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
##  [579] 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 1
##  [613] 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
##  [647] 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0
##  [681] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0
##  [715] 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
##  [749] 0 0 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 1 1 0 1 0 0 0 1 1 0 0 0 1
##  [783] 1 0 0 0 0 0 0 0 0 1 1 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 1 0 0
##  [817] 1 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [851] 0 0 0 1 1 0 0 1 1 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0
##  [885] 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0
##  [919] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0
##  [953] 0 0 0 1 0 1 0 1 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0
##  [987] 0 1 0 0 0 0 0 1 0 0 1 0 0 0 1 0 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 1
## [1021] 1 1 1 0 1 0 1 1 0 1 1 1 0 1 1 1 1 1 1 0 1 1 1 0 1 1 1 1 1 0 1 0 0 1
## [1055] 0 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 0 1 1 0 1 1 1 1 1 0 0 1 1 1 1
## [1089] 1 1 0 1 0 1 0 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1
## [1123] 1 1 0 1 1 0 0 1 1 1 1 1 1 0 0 1 0 1 1 0 1 1 0 0 1 0 0 1 1 1 1 0 0 1
## [1157] 1 0 1 1 1 0 1 1 0 1 1 1 0 0 1 0 1 1 1 1 1 1 0 1 1 0 0 0 0 1 0 0 1 1
## [1191] 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 0
## [1225] 1 0 0 1 0 1 1 1 0 0 0 0 0 1 0 1 0 1 1 1 0 1 1 1 1 0 1 1 1 0 1 0 1 0
## [1259] 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 0 0 1 1 1 1 1
## [1293] 1 1 1 1 1 1 1 1 1 1 0 0 0 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 0 0 1 1
## [1327] 0 1 1 0 0 1 0 1 1 0 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 0 1 0 1 1 1
## [1361] 1 1 0 0 0 0 1 1 1 0 0 1 0 1 0 0 1 1 1 0 1 0 1 1 1 0 0 1 1 1 1 1 1 1
## [1395] 0 0 1 0 1 1 1 0 1 1 1 0 0 1 0 1 1 1 1 0 1 1 0 1 1 0 0 1 1 1 0 0 0 0
## [1429] 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1 1 0 1 1 1 0 1 1 1 0 0 1 1
## [1463] 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 0 0 1 0
## [1497] 1 1 1 1 0 1 0 0 1 1 1 1 1 0 0 1 1 0 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 0
## [1531] 0 1 1 0 1 1 1 1 1 0 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1
## [1565] 1 1 0 1 1 0 1 1 0 0 1 0 0 1 1 1 0 0 1 1 0 1 1 0 0 0 0 0 1 1 1 1 1 1
## [1599] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 1 1 1 1 0 1 1 1 1 1 1 1
## [1633] 1 0 1 1 1 1 0 1 0 1 1 0 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1667] 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1
## [1701] 1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 0 1 0 1 1 0 0 1 1 1 1
## [1735] 1 1 0 1 0 1 1 1 1 1 0 1 0 1 1 1 1 1 1 0 1 1 1 0 1 1 0 0 1 1 1 1 1 1
## [1769] 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 1 1 1 1
```

```
## [1803] 1 1 1 1 0 0 0 0 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1837] 1 1 0 1 0 1 0 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 0 0 1 1 0 1 1 0 0 1 1 0
## [1871] 1 0 0 0 1 1 0 0 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1 1 0 1 1 1 0 1 0 1 1 1
## [1905] 1 1 1 1 1 1 1 1 1 0 1 1 0 1 0 1 1 1 1 1 1 1 0 1 1 1 0 0 1 0 1 1 1 1
## [1939] 1 1 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1
## [1973] 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
##
## $advanced_pred
##    [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [35] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [69] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [103] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [137] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [171] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [205] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [239] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [273] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [307] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [341] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [375] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [409] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [443] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [477] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [511] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [545] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [579] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [613] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [647] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [681] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [715] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [749] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [783] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [817] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [851] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [885] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [919] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [953] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [987] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1021] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1055] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1089] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1123] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1157] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1191] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1225] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1259] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1293] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1327] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1361] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1395] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1429] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1463] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1497] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1531] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

```
## [1565] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1599] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1633] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1667] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1701] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1735] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1769] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1803] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1837] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1871] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1905] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1939] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [1973] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

```r
################################################################################################
#Make predictions and record the time it takes
tm_test=NA
if(run.test){
  load(file="../output/dat_test_sift.Rdata")
  load(file="../output/dat_test_new.Rdata")
  load(file="../output/fit_train.Rdata")
  tm_test <- system.time(pred_test <- test(fit_train = fit_train,
                                           dat_test_base = dat_test_sift,
                                           dat_test_adv = dat_test_new))
  save(pred_test, file="../output/pred_test.RData")

  #individual times for making predictions using base model and advanced model
  tm_test_base <- system.time(pred_test_base <- test(fit_train = fit_train_base,
                                                     dat_test_base = dat_test_sift,
                                                     model="base"))
  tm_test_adv <- system.time(pred_test_adv <- test(fit_train = fit_train_adv,
                                                   dat_test_adv = dat_test_new,
                                                   model="advanced"))
}
```

Summarize Running Time

Prediction performance matters, so does the running times for constructing features and for training the model, especially when the computation resource is limited.

```r
if(run.feature.train){
  load("../output/tm_new_feature_train.Rdata")   #tm_new_feature_train
  cat("Time for constructing new training features=", tm_new_feature_train[1], "s \n")
}
```

```
## Time for constructing new training features= 1163.52 s
```

```r
if (run.feature.test){
load("../output/tm_new_feature_test.Rdata")   #tm_new_feature_test
cat("Time for constructing new testing features=", tm_new_feature_test[1], "s \n")
}
if (run.train){
cat("Time for training models (Baseline + Advanced)=", tm_train[1], "s \n")
cat("Time for training Baseline Model=", tm_train_base[1], "s \n")
cat("Time for training Advanced Model=", tm_train_adv[1], "s \n")
```

```
}
```

```
## Time for training models (Baseline + Advanced)= 30.587 s
## Time for training Baseline Model= 10.421 s
## Time for training Advanced Model= 19.095 s
```

```
if(run.test){
cat("Time for making predictions (Baseline + Advanced)=", tm_test[1], "s \n")
cat("Time for making predictions with Baseline Model=", tm_test_base[1], "s \n")
cat("Time for making predictions with Advanced Model=", tm_test_adv[1], "s \n")
}
```