Project 3 - Example Main Script

Chengliang Tang, Tian Zheng

In your final repo, there should be an R markdown file that organizes **all computational steps** for evaluating your proposed image classification framework.

This file is currently a template for running evaluation experiments of image analysis (or any predictive modeling). You should update it according to your codes but following precisely the same structure.

```
if(!require("EBImage")){
  source("https://bioconductor.org/biocLite.R")
  biocLite("EBImage")
}
```

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

```
if(!require("gbm")){
  install.packages("gbm")
}
```

```
## Loading required package: gbm
```

```
## Loaded gbm 2.1.5
```

```
library("EBImage")
library("gbm")
```

Step 0: specify directories.

Set the working directory to the image folder. Specify the training and the testing set. For data without an independent test/validation set, you need to create your own testing data by random subsampling. In order to obain reproducible results, set.seed() whenever randomization is used.

```
set.seed(2018)
# use relative path for reproducibility
```

Provide directories for training images. Low-resolution (LR) image set and High-resolution (HR) image set will be in different subfolders.

```
train_dir <- "../data/train/" # This will be modified for different data sets.
train_LR_dir <- paste(train_dir, "LR/", sep="")
train_HR_dir <- paste(train_dir, "HR/", sep="")
train_label_path <- paste(train_dir, "label.csv", sep="")
```

Step 1: set up controls for evaluation experiments.

In this chunk, we have a set of controls for the evaluation experiments.

- (T/F) cross-validation on the training set
- (number) K, the number of CV folds
- (T/F) process features for training set
- (T/F) run evaluation on an independent test set
- (T/F) process features for test set

```
run.cv=FALSE # run cross-validation on the training set
K <- 5  # number of CV folds
run.feature.train=T # process features for training set
run.test=TRUE # run evaluation on an independent test set
run.feature.test=TRUE # process features for test set
```

Using cross-validation or independent test set evaluation, we compare the performance of models with different specifications. In this example, we use GBM with different `depth`. In the following chunk, we list, in a vector, setups (in this case, `depth`) corresponding to models that we will compare. In your project, you might compare very different classifiers. You can assign them numerical IDs and labels specific to your project.

```
model_values <- seq(3, 11, 2)
model_labels = paste("GBM with depth =", model_values)
```

Step 2: import training images class labels.

We provide extra information of image label: car (0), flower (1), market (2). These labels are not necessary for your model.

```
extra_label <- read.csv(train_label_path, colClasses=c("NULL", NA, NA))
```

Step2.5 split the training/test set according to lables

```
ts<-c()#index of test set
l<-unique(extra_label$Label)
label<-extra_label$Label
for(i in l){
  train_sub<-which(label==i)
  ts<-c(ts,sample(train_sub,length(train_sub)/5))
}
train_ind<-setdiff(1:1500,ts)#index of training set
```

Step 3: construct features and responses

`feature.R` should be the wrapper for all your feature engineering functions and options. The function `feature( )` should have options that correspond to different scenarios for your project and produces an R object that contains features and responses that are required by all the models you are going to evaluate later. + `feature.R` + Input: a path for low-resolution images. + Input: a path for high-resolution images. + Output: an RData file that contains extracted features and corresponding responses

```
source("../lib/feature.R")
tm_feature_train <- NA
if(run.feature.train){
  tm_feature_train <- system.time(dat_train <- feature(train_LR_dir, train_HR_dir,index=train_ind))
  feat_train <- dat_train$feature
  label_train <- dat_train$label
  save(dat_train, file="../output/feature_train.RData")
}


load("../output/feature_train.RData")
```

```
feat_train=dat_train$feature
label_train=dat_train$label
```

Step 4: Train a regression model with training features and responses

Call the train model and test model from library.

`train.R` and `test.R` should be wrappers for all your model training steps and your classification/prediction steps. + `train.R` + Input: a path that points to the training set features and responses. + 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 classifier. + Output: an R object of response 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")
```

Model selection with cross-validation

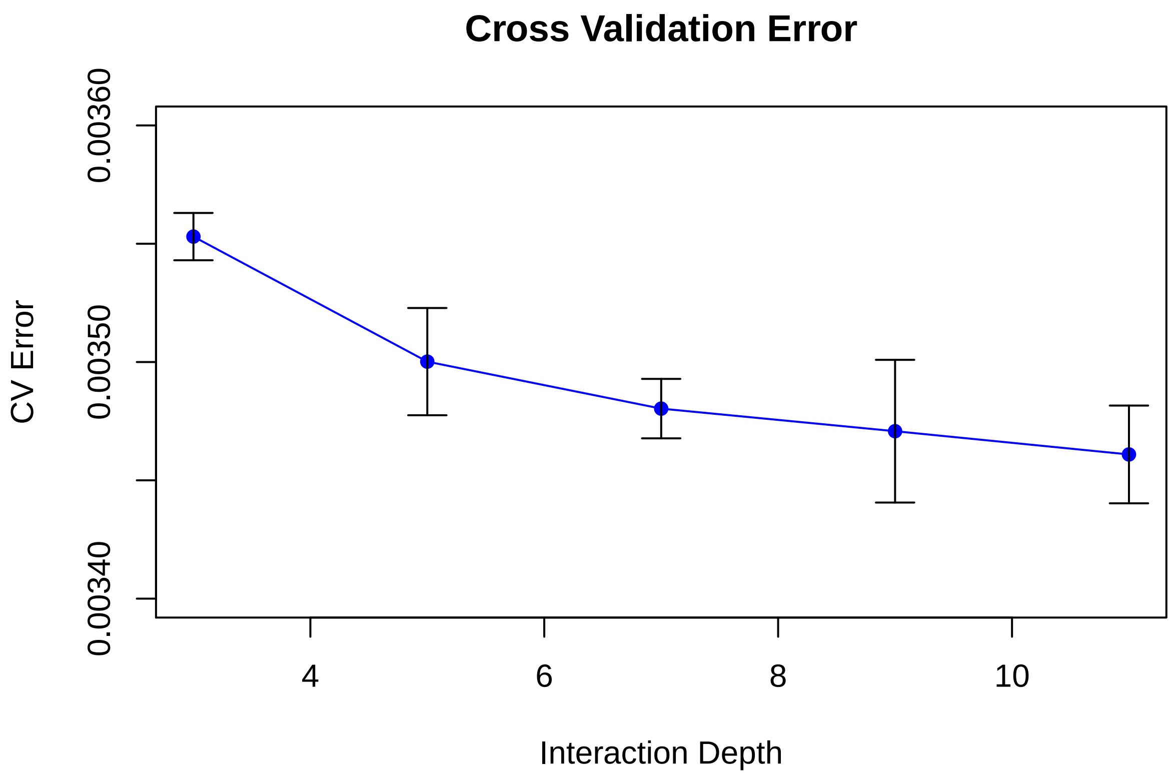
- Do model selection by choosing among different values of training model parameters, that is, the interaction depth for GBM in this example.

```
source("../lib/cross_validation.R")

if(run.cv){
  err_cv <- array(dim=c(length(model_values), 2))
  for(k in 1:length(model_values)){
    cat("k=", k, "\n")
    err_cv[k,] <- cv.function(feat_train, label_train, model_values[k], K)
  }
  save(err_cv, file="../output/err_cv.RData")
}
```

Visualize cross-validation results.

```
  load("../output/err_cv.RData")
  plot(model_values, err_cv[,1], xlab="Interaction Depth", ylab="CV Error",
       main="Cross Validation Error", type="n", ylim=c(0.0034, 0.0036))
  points(model_values, err_cv[,1], col="blue", pch=16)
  lines(model_values, err_cv[,1], col="blue")
  arrows(model_values, err_cv[,1]-err_cv[,2], model_values, err_cv[,1]+err_cv[,2],
        length=0.1, angle=90, code=3)
```



- Choose the “best”" parameter value

```
model_best=model_values[1]
if(run.cv){
  model_best <- model_values[which.min(err_cv[,1])]
}
#Using the one standard error rule, the best depth is 7 instead of 11
par_best <- list(depth=7)
```

- Train the model with the entire training set using the selected model (model parameter) via cross-validation.

```
tm_train=NA
tm_train <- system.time(fit_train <- train(feat_train, label_train, par_best))
```

```
## OOB generally underestimates the optimal number of iterations although predictive performance is reas
## OOB generally underestimates the optimal number of iterations although predictive performance is reas
## OOB generally underestimates the optimal number of iterations although predictive performance is reas
## OOB generally underestimates the optimal number of iterations although predictive performance is reas
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```

```
save(fit_train, file="../output/fit_train.RData")
```

Step 5: Super-resolution for test images

Feed the final training model with the completely holdout testing data. + `superResolution.R` + Input: a path that points to the folder of low-resolution test images. + Input: a path that points to the folder (empty) of high-resolution test images. + Input: an R object that contains tuned predictors. + Output: construct high-resolution versions for each low-resolution test image.

```
source("../lib/superResolution.R")
test_dir <- "../data/train/" # This will be modified for different data sets.
test_LR_dir <- paste(test_dir, "LR/", sep="")
test_HR_dir <- paste(test_dir, "HR/", sep="")

tm_test=NA
if(run.test){
  load(file="../output/fit_train.RData")
  tm_test <- system.time(performance<-superResolution(train_LR_dir, train_HR_dir,fit_train,index=ts))
}
```

Summarize the test MSE and PSNR

```
#test mse
performance[1]
```

```
## [1] 0.003390449
```

```
#test psnr
performance[2]
```

```
## [1] 24.69743
```

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.

```
cat("Time for constructing training features=", tm_feature_train[1], "s \n")
```

```
## Time for constructing training features= 70.87 s
```

```
cat("Time for training model=", tm_train[1], "s \n")
```

```
## Time for training model= 5680.271 s
```

```
cat("Time for super-resolution=", tm_test[1], "s \n")
```

```
## Time for super-resolution= 1481.813 s
```

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```

Step2.5 split the training/test set according to lables

```
ts<-c()#index of test set
l<-unique(extra_label$Label)
label<-extra_label$Label
for(i in l){
  train_sub<-which(label==i)
  ts<-c(ts,sample(train_sub,length(train_sub)/5))
}
train_ind<-setdiff(1:1500,ts)#index of training set
```

Step 3: construct features and responses

```
load("../output/feature_train.RData")
feat_train=dat_train$feature
label_train=dat_train$label
```

Step 4: Train a regression model with training features and responses

Call the train model and test model from library.

`train.R` and `test.R` should be wrappers for all your model training steps and your classification/prediction steps. + `train.R` + Input: a path that points to the training set features and responses. + 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 classifier. + Output: an R object of response predictions on the test set. If there are multiple classifiers under evaluation, there should be multiple sets of label predictions.

```
source("../lib/trainXGboost.R")
source("../lib/testXGboost.R")
```

Model selection with cross-validation

- Do model selection by choosing among different values of training model parameters, that is, the interaction depth for GBM in this example.

```
# source("../lib/cross_validationXGboost.R")
#
# if(run.cv){
#   err_cv <- array(dim=c(length(model_values), 2))
#   for(k in 1:length(model_values)){
#     cat("k=", k, "\n")
#     err_cv[k,] <- cv.functionXG(feat_train, label_train, model_values[k], K)
#   }
#   save(err_cv, file="../output/err_cvXGboost.RData")
# }
```

Visualize cross-validation results.

```
# if(run.cv){
#   load("../output/err_cvXGboost.RData")
#   plot(model_values, err_cv[,1], xlab="Interaction Depth", ylab="CV Error",
#        main="Cross Validation Error", type="n", ylim=c(0, 0.01))
#   points(model_values, err_cv[,1], col="blue", pch=16)
#   lines(model_values, err_cv[,1], col="blue")
#   arrows(model_values, err_cv[,1]-err_cv[,2], model_values, err_cv[,1]+err_cv[,2],
#         length=0.1, angle=90, code=3)
# }
```

- Choose the “best”" parameter value

```
# model_best=model_values[1]
# if(run.cv){
#   model_best <- model_values[which.min(err_cv[,1])]
# }
#
# par_best <- list(nr=model_best)
par_best <- list(nr=11)
```

- Train the model with the entire training set using the selected model (model parameter) via cross-validation.

```
tm_train=NA
tm_train <- system.time(fit_train <- trainXG(feat_train, label_train, par_best))
```

```
## Loading required package: BayesTree

## Loading required package: iRF

## iRF 2.0.0

## 
## Attaching package: 'iRF'

## The following object is masked from 'package:EBImage':
## 
##     combine

## Loading required package: rpart

## Loading required package: xgboost
## [1]  train-rmse:0.254926
## [2]  train-rmse:0.135891
## [3]  train-rmse:0.082520
## [4]  train-rmse:0.062244
## [5]  train-rmse:0.055931
## [6]  train-rmse:0.054168
## [7]  train-rmse:0.053649
## [8]  train-rmse:0.053487
## [9]  train-rmse:0.053417
## [10] train-rmse:0.053379
## [11] train-rmse:0.053353
## [1]  train-rmse:0.254776
## [2]  train-rmse:0.135613
## [3]  train-rmse:0.082089
## [4]  train-rmse:0.061705
## [5]  train-rmse:0.055363
## [6]  train-rmse:0.053606
## [7]  train-rmse:0.053100
## [8]  train-rmse:0.052949
## [9]  train-rmse:0.052890
## [10] train-rmse:0.052859
## [11] train-rmse:0.052839
## [1]  train-rmse:0.255005
## [2]  train-rmse:0.135868
## [3]  train-rmse:0.082385
## [4]  train-rmse:0.062050
## [5]  train-rmse:0.055736
## [6]  train-rmse:0.053994
## [7]  train-rmse:0.053498
## [8]  train-rmse:0.053356
## [9]  train-rmse:0.053302
## [10] train-rmse:0.053275
## [11] train-rmse:0.053258
## [1]  train-rmse:0.255041
## [2]  train-rmse:0.135808
## [3]  train-rmse:0.082261
## [4]  train-rmse:0.061863
## [5]  train-rmse:0.055502
## [6]  train-rmse:0.053732
## [7]  train-rmse:0.053221
## [8]  train-rmse:0.053068
## [9]  train-rmse:0.053009
## [10] train-rmse:0.052979
## [11] train-rmse:0.052961
## [1]  train-rmse:0.254716
## [2]  train-rmse:0.135284
## [3]  train-rmse:0.081419
## [4]  train-rmse:0.060744
## [5]  train-rmse:0.054244
## [6]  train-rmse:0.052417
## [7]  train-rmse:0.051876
## [8]  train-rmse:0.051707
## [9]  train-rmse:0.051636
## [10] train-rmse:0.051595
## [11] train-rmse:0.051569
## [1]  train-rmse:0.254535
## [2]  train-rmse:0.134970
## [3]  train-rmse:0.080944
## [4]  train-rmse:0.060150
## [5]  train-rmse:0.053613
## [6]  train-rmse:0.051792
## [7]  train-rmse:0.051265
## [8]  train-rmse:0.051108
## [9]  train-rmse:0.051047
## [10] train-rmse:0.051016
## [11] train-rmse:0.050995
## [1]  train-rmse:0.254812
## [2]  train-rmse:0.135280
## [3]  train-rmse:0.081302
## [4]  train-rmse:0.060567
## [5]  train-rmse:0.054065
## [6]  train-rmse:0.052261
## [7]  train-rmse:0.051745
## [8]  train-rmse:0.051596
## [9]  train-rmse:0.051541
## [10] train-rmse:0.051513
## [11] train-rmse:0.051496
## [1]  train-rmse:0.254827
## [2]  train-rmse:0.135182
## [3]  train-rmse:0.081125
## [4]  train-rmse:0.060314
## [5]  train-rmse:0.053759
## [6]  train-rmse:0.051926
## [7]  train-rmse:0.051392
## [8]  train-rmse:0.051235
## [9]  train-rmse:0.051175
## [10] train-rmse:0.051145
## [11] train-rmse:0.051125
## [1]  train-rmse:0.255514
## [2]  train-rmse:0.136536
## [3]  train-rmse:0.083414
## [4]  train-rmse:0.063391
## [5]  train-rmse:0.057214
## [6]  train-rmse:0.055502
## [7]  train-rmse:0.055006
## [8]  train-rmse:0.054856
## [9]  train-rmse:0.054794
## [10] train-rmse:0.054760
## [11] train-rmse:0.054739
## [1]  train-rmse:0.255383
## [2]  train-rmse:0.136298
## [3]  train-rmse:0.083064
## [4]  train-rmse:0.062973
## [5]  train-rmse:0.056782
## [6]  train-rmse:0.055078
## [7]  train-rmse:0.054596
## [8]  train-rmse:0.054457
## [9]  train-rmse:0.054405
## [10] train-rmse:0.054379
## [11] train-rmse:0.054362
## [1]  train-rmse:0.255647
## [2]  train-rmse:0.136573
## [3]  train-rmse:0.083360
## [4]  train-rmse:0.063300
## [5]  train-rmse:0.057126
## [6]  train-rmse:0.055435
## [7]  train-rmse:0.054960
## [8]  train-rmse:0.054829
## [9]  train-rmse:0.054780
## [10] train-rmse:0.054758
## [11] train-rmse:0.054744
## [1]  train-rmse:0.255690
## [2]  train-rmse:0.136527
## [3]  train-rmse:0.083281
## [4]  train-rmse:0.063189
## [5]  train-rmse:0.056985
## [6]  train-rmse:0.055272
## [7]  train-rmse:0.054785
## [8]  train-rmse:0.054645
## [9]  train-rmse:0.054593
## [10] train-rmse:0.054568
## [11] train-rmse:0.054553
```

```r
save(fit_train, file="../output/fit_trainXG.RData")
```

Step 5: Super-resolution for test images

Feed the final training model with the completely holdout testing data. + `superResolution.R` + Input: a path that points to the folder of low-resolution test images. + Input: a path that points to the folder (empty) of high-resolution test images. + Input: an R object that contains tuned predictors. + Output: construct high-resolution versions for each low-resolution test image.

```r
source("../lib/superResolutionXG.R")
test_dir <- "../data/train/" # This will be modified for different data sets.
test_LR_dir <- paste(test_dir, "LR/", sep="")
test_HR_dir <- paste(test_dir, "HR/", sep="")

tm_test=NA
if(run.test){
  load(file="../output/fit_trainXG.RData")
  tm_test <- system.time(performance<-superResolutionXG(train_LR_dir, train_HR_dir,fit_train,index=ts))
}
```

Summarize the test MSE and PSNR

```r
#test mse
performance[1]
```

```
## [1] 0.002909522
```

```
#test psnr
performance[2]
```

```
## [1] 25.36178
```

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.

```
cat("Time for training model=", tm_train[1], "s \n")
```

```
## Time for training model= 37.258 s
```

```
cat("Time for super-resolution=", tm_test[1], "s \n")
```

```
## Time for super-resolution= 304.293 s
```