

pjt_tree

Yen-Hsun Lin

2023-04-27

This document will explore tree methods on the training data, conduct CV and select best tuning variables, and finally calculate AUC for the best model

0. getting data

```
suppressMessages(library(data.table))
suppressMessages(library(ggplot2))
suppressMessages(library(rpart))
suppressMessages(library(rpart.plot))
suppressMessages(library(caret))
suppressMessages(library(randomForest))
suppressMessages(library(DescTools))
suppressMessages(library(gbm))
suppressMessages(library(plyr))

trn <- fread("loan_balanced_trn.csv", stringsAsFactors = TRUE)
tst <- fread("loan_balanced_tst.csv", stringsAsFactors = TRUE)

trn$TARGET <- factor(trn$TARGET)
tst$TARGET <- factor(tst$TARGET)

## doing this because the random forest predict method has some bug. It is
## sensitive to levels of factor
for (name in names(trn)[sapply(trn,class) == "factor"]){
  levels(tst[[name]]) <- levels(trn[[name]])
}

selected_fm1 <- TARGET ~ DAYS_EMPLOYED + OCCUPATION_TYPE + REGION_RATING_CLIENT_W_CITY +
  DAYS_LAST_PHONE_CHANGE + NAME_CONTRACT_TYPE + AMT_GOODS_PRICE +
  AMT_CREDIT + DAYS_BIRTH + NAME_EDUCATION_TYPE + FLAG_OWN_CAR +
  NAME_INCOME_TYPE + DAYS_ID_PUBLISH + CODE_GENDER + DAYS_REGISTRATION +
  FLAG_WORK_PHONE + AMT_REQ_CREDIT_BUREAU_YEAR + FLAG_OWN_REALTY +
  DEF_30_CNT_SOCIAL_CIRCLE + AMT_ANNUITY + AMT_REQ_CREDIT_BUREAU_HOUR

ctrl <- trainControl(method = "CV", number = 10)
```

```
calc_accu <- function(actual, pred){
  mean(actual == pred)
}
classifier <- function(prob, cutoff, pos = "1", neg = "0"){
  ifelse(prob > cutoff, pos, neg)
}
```

1. Single tree

Use 10-fold CV (the train chunk is not evaluate in RMD for times sake)

```
set.seed(432)
sing_tree_train <- train(selected_fml, data = trn, trControl = ctrl,
  method = "rpart",
  tuneGrid = data.frame(cp = seq(0.001,0.1,by = 0.001)))

plot(sing_tree_train)
sing_tree_train$bestTune

rpart.plot(sing_tree_train$finalModel)

sing_tree_train$bestTune
```

```
## best cp selected is 0.002
```

```
stree <- rpart(selected_fml, data = trn, cp = 0.002)
```

```
## testing accuracy
```

```
calc_accu(predict(stree, tst, type = "class"), tst$TARGET)
```

```
## [1] 0.607
```

2. Random forest

This chunk is for demonstration. It is not eval in RMD

```
set.seed(432)
rf_train <- train(selected_fml, data = trn, trControl = ctrl,
  method = "rf",
  tuneGrid = data.frame(mtry = 4:15) )

rf_train$results
plot(rf_train)
importance(RF4)
```

```
## the cv suggest selecting 12 predictors at each split gives the lowest CV
## error
```

```

set.seed(432)

best_RF <- randomForest(selected_fml, data = trn, trControl = ctrl,
  mtry = 12)

calc_accu(predict(best_RF, tst, type = "class"), tst$TARGET)

## [1] 0.6195

importance(best_RF)

```

```

##                               MeanDecreaseGini
## DAYS_EMPLOYED                  591.506352
## OCCUPATION_TYPE                407.797290
## REGION_RATING_CLIENT_W_CITY    109.506581
## DAYS_LAST_PHONE_CHANGE         475.614151
## NAME_CONTRACT_TYPE             33.364122
## AMT_GOODS_PRICE                323.426222
## AMT_CREDIT                    377.507610
## DAYS_BIRTH                     518.584319
## NAME_EDUCATION_TYPE            92.025656
## FLAG_OWN_CAR                   48.573066
## NAME_INCOME_TYPE               80.580310
## DAYS_ID_PUBLISH                507.558332
## CODE_GENDER                    42.628148
## DAYS_REGISTRATION              513.463771
## FLAG_WORK_PHONE                 62.231486
## AMT_REQ_CREDIT_BUREAU_YEAR     220.483741
## FLAG_OWN_REALTY                 45.293137
## DEF_30_CNT_SOCIAL_CIRCLE       73.209721
## AMT_ANNUITY                    471.834275
## AMT_REQ_CREDIT_BUREAU_HOUR     4.196389

```

3. Boosting

I use parallel running to reduce running time.

```

library(parallel)

train_gbm <- function(d){
  train(selected_fml, data = trn, trControl = ctrl,
    method = "gbm",
    tuneGrid = expand.grid(
      n.trees = c(500),
      interaction.depth = d,
      shrinkage = seq(0.01,0.5,by = 0.01),
      n.minobsinnode = 10
    ), verbose = FALSE)
}

```

```

clus <- makeCluster(10, type = "PSOCK")
clusterEvalQ(clus, library(gbm))
clusterEvalQ(clus, library(caret))
clusterEvalQ(clus, library(plyr))
clusterEvalQ(clus, set.seed(432))
clusterExport(clus, varlist = c("trn", "ctrl", "selected_fml", "train_gbm"))

boosting_trains <- parLapply(cl = clus, 1:10, train_gbm)

stopCluster(clus)

```

```

get_best_tune <- function(train_obj){
  best_idx <- as.numeric(rownames(train_obj$bestTune))
  print(train_obj$results[best_idx,])
}

```

```

get_best_tune(boosting_trains[[1]])
get_best_tune(boosting_trains[[2]])
get_best_tune(boosting_trains[[3]])
get_best_tune(boosting_trains[[4]])
get_best_tune(boosting_trains[[5]])
get_best_tune(boosting_trains[[6]])
get_best_tune(boosting_trains[[7]])
get_best_tune(boosting_trains[[8]])
get_best_tune(boosting_trains[[9]])
get_best_tune(boosting_trains[[10]])

```

```

test <- boosting_trains[[2]]$finalModel
## The best model is shrinkage = 0.05 with interaction.depth = 2

```

```

selected_fml1 <- as.character(TARGET) ~ DAYS_EMPLOYED + OCCUPATION_TYPE + REGION_RATING_CLIENT_W_CITY +
  DAYS_LAST_PHONE_CHANGE + NAME_CONTRACT_TYPE + AMT_GOODS_PRICE +
  AMT_CREDIT + DAYS_BIRTH + NAME_EDUCATION_TYPE + FLAG_OWN_CAR +
  NAME_INCOME_TYPE + DAYS_ID_PUBLISH + CODE_GENDER + DAYS_REGISTRATION +
  FLAG_WORK_PHONE + AMT_REQ_CREDIT_BUREAU_YEAR + FLAG_OWN_REALTY +
  DEF_30_CNT_SOCIAL_CIRCLE + AMT_ANNUITY + AMT_REQ_CREDIT_BUREAU_HOUR

```

```

best_boost <- gbm(selected_fml1, data = trn, n.trees = 500,
  interaction.depth = 2, shrinkage = 0.05,
  n.minobsinnode = 10,
)

```

```

## Distribution not specified, assuming bernoulli ...

```

```

pred_boost <- classifier(predict(best_boost, tst, type = "response"), 0.5)

```

```

## Using 500 trees...

```

```
calc_accu(pred_boost, tst$TARGET)
```

```
## [1] 0.6376
```