Project 5: Corporación Favorita Grocery Sales Forecasting - Group 1

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2017/12/4

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Background: Brick-and-mortar grocery stores are always in a delicate dance with purchasing and sales forecasting. Predict a little over, and grocers are stuck with overstocked, perishable goods. Guess a little under, and popular items quickly sell out, leaving money on the table and customers fuming.

The problem becomes more complex as retailers add new locations with unique needs, new products, ever transitioning seasonal tastes, and unpredictable product marketing. Corporación Favorita, a large Ecuadorian-based grocery retailer, knows this all too well. They operate hundreds of supermarkets, with over 200,000 different products on their shelves.

Corporación Favorita has challenged the Kaggle community to build a model that more accurately forecasts product sales. They currently rely on subjective forecasting methods with very little data to back them up and very little automation to execute plans. They're excited to see how machine learning could better ensure they please customers by having just enough of the right products at the right time.

Reference: Kaggle Website

Data: As the datasets on Kaggle are too large, to the nature of the method, we only implement our method on a subset of the data. We work on the training data to find the top 10 stores and top 200 items in terms of

observation frequency, and choose the subset of data related to these items and stores to use. We split our data into a training set(20140816-20160815) and a test set(20160816-20170815), and split the training set into a subtrain set (20140816-20160415) and a validation set(20160416-20160815).

Method:

Overall we use Stacking method. That is, we build two layers. In the first layer, we obtain the prediction results from each first-layer model and use these results as features in the second layer to get the final prediction values.

In the first layer, we take use of both Time Series models as well as supervised machine learning models. For Time Series models, we first train them on the subtrain set with different parameters and use the models on the validation set to compare the performance. Then we get the best model and use that to predict the sales on validation set and test set, and call these results as features_valid and features_test respectively. For machine learning models, we train the models using cross-validation on the whole training set and get the best model. Then we also use the best model to do the same thing on validation set and test set.

In the second layer, we use machine learning models (Random Forest) on the features_valid by cross-validation to find the best model. Then use the best model on feature_test to get the final predicted sales.

Evaluation: We use the same evaluation formula as on Kaggle evaluation formula.

Step 0: Load the packages, specify directories

```
packages.used=c("data.table","lubridate","dplyr","date","reshape2","forecast","doMC","foreach","xgboost
packages.needed=setdiff(packages.used, intersect(installed.packages()[,1], packages.used))
if(length(packages.needed)>0){
  install.packages(packages.needed, dependencies = TRUE)
}

library(data.table)
library(lubridate)
library(date)
library(reshape2)
library(forecast)
library(doMC)
library(foreach)
library(dplyr)
library(xgboost)
library(readr)
library(randomForest)
library(prophet)
library(caret)
library(mlr)
library(tseries)
library(doParallel)


setwd("~/Documents/GitHub/fall2017-project5-group1/doc")
```

Step 1: Load and process the data

As the train.csv on Kaggle is too large to upload on GitHub, you can download it from Kaggle_data, and save it togetehr with items.csv, oil.csv, and holidays_events.csv on local GitHub data/original data folder.

Then you can use the following code to preprocess the data.

```
run.pro = FALSE #if TRUE, preprocess the original data
if(run.pro){
  whole <- fread("../data/original data/train.csv")
  train <- whole[whole$date < "2016-08-16"&whole$date>="2014-08-15",]
  test <- whole[whole$date > "2016-08-15",]
  rm(whole)

  # chose top 10 stores and top 200 items with respect to observations
  store_tbl <- table(train$store_nbr)
  store_max <- store_tbl[order(store_tbl, decreasing = T)][1:10]
  item_tbl <- table(train$item_nbr)
  item_max <- item_tbl[order(item_tbl, decreasing = T)][1:200]

  store_test <- test$store_nbr[test$store_nbr %in% names(store_max)]
  item_test <- test$item_nbr[test$item_nbr %in% names(item_max)]
  store_test_perfm <- table(store_test)
  item_test_perfm <- table(item_test)

  train <- train[train$store_nbr %in% names(store_max) & train$item_nbr %in% names(item_max),]
  test <- test[test$store_nbr %in% names(store_max) & test$item_nbr %in% names(item_max),]

  train$date <- as.Date(parse_date_time(train$date,'%y-%m-%d'))
  train$store_item_nbr <- paste(train$store_nbr, train$item_nbr, sep="_")
  test$date <- as.Date(parse_date_time(test$date, '%y-%m-%d'))
  test$store_item_nbr <- paste(test$store_nbr, test$item_nbr, sep="_")

  write.csv(train,"../data/our_train.csv")
  write.csv(test, "../data/our_test.csv")

  ## combine with other useful variables
  items<-read.csv("../data/original data/items.csv",header=TRUE)
  holidays <- read.csv("../data/original data/holidays_events.csv",header = TRUE)
  oil <- read.csv("../data/original data/oil.csv",header=TRUE)

  train1 <- train %>%
    mutate(year = year(ymd(date)))  %>%
    mutate(month = month(ymd(date)))  %>%
    mutate(dayOfWeek = wday(date))  %>%
    mutate(day = day(ymd(date)))
  train1 <- merge(train1, items, by.x = "item_nbr", by.y = "item_nbr")

  holidaysNational = holidays %>%
    filter(type != "Work Day") %>%
    filter(locale == "National")
  holidaysNational <- holidaysNational%>%select(date,type,transferred)
  holidaysNational$celebrated <- ifelse(holidaysNational$transferred == "True", FALSE, TRUE)
  holidaysNational$date <- as.Date(parse_date_time(holidaysNational$date,'%y-%m-%d'))
  train_comb = left_join(train1,holidaysNational,by='date')

  oil$date <- as.Date(parse_date_time(oil$date,'%y-%m-%d'))
  train_comb <- left_join(train_comb, oil, by='date')
```

```
  write.csv(train_comb,"../output/combined_train.csv")

  test1 <- test %>%
    mutate(year = year(ymd(date)))  %>%
    mutate(month = month(ymd(date)))  %>%
    mutate(dayOfWeek = wday(date))  %>%
    mutate(day = day(ymd(date)))
  test1 <- merge(test1, items, by.x = "item_nbr", by.y = "item_nbr")

  test_comb = left_join(test1,holidaysNational,by='date')
  test_comb <- left_join(test_comb, oil, by='date')

  write.csv(test_comb,"../output/combined_test.csv")

  ## split train into subtrain and validation sets
  sub_train <- train%>%filter(date < "2016-04-16")
  valid_train <- train%>%filter(date > "2016-04-15")

  write.csv(sub_train,"../output/subtrain.csv")
  write.csv(valid_train,"../output/validation.csv")
}else{
  train <- fread("../output/combined_train.csv")
  test <- fread("../output/combined_test.csv")
  sub_train <- train%>%filter(date < "2016-04-16")
  valid_train <- train%>%filter(date > "2016-04-15")
}
```

```
##
Read 0.0% of 1428019 rows
Read 47.6% of 1428019 rows
Read 74.9% of 1428019 rows
Read 1428019 rows and 19 (of 19) columns from 0.141 GB file in 00:00:05
```

Step 2: The First Stack

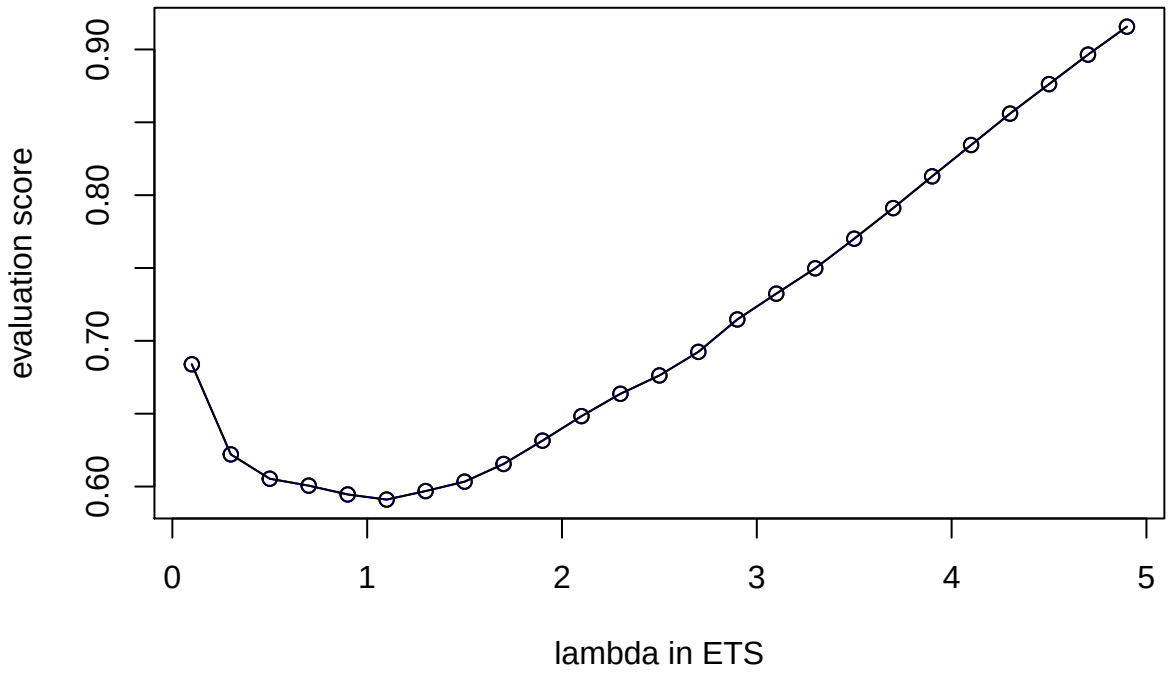
In the first stack, we use three Time Series models: ETS, ARIMA, and Prophet, as well as two machine learning models: XgBoost, and Random Forest.

Step 2.1 ETS (Exponential Smoothing State Space Model)

In this model, we tune the parameter lambda of Box-Cox Transformation, as other parameters in this model can be automatically estimated by the ets() function in R.

```
run.ets = FALSE #if TRUE, run train-validation process on ETS model and run the prediction on test usin

if(run.ets){
  train_valid <- valid_train
  train_sub <- sub_train[, c('date','store_item_nbr', 'unit_sales')]
  train_sub_wide <- dcast(train_sub, store_item_nbr ~ date, mean, value.var = "unit_sales", fill = 0)
  train_ts <- ts(train_sub_wide, frequency = 7)
```

```
  fcst_intv = length(unique(train_valid$date))  # number of days of forecast in the validation set
  fcst_matrix <- matrix(NA, nrow=nrow(train_ts), ncol=fcst_intv)

  # train the models by forecasting sales in validation set
  lam.ranges <- seq(0.1, 5, by = 0.2)
  valid_score <- rep(NA, length(lam.ranges))
  for (i in 1:length(lam.ranges)){
    lam <- lam.ranges[i]
    registerDoMC(detectCores()-1)
    fcst_matrix <- foreach(i=1:nrow(train_ts),.combine=rbind, .packages=c("forecast")) %dopar% {
      fcst_matrix <- forecast(ets(train_ts[i,], lambda = lam),h=fcst_intv)$mean
    }
    colnames(fcst_matrix) <- as.character(seq(from = as.Date("2016-04-16"),
                                              to = as.Date("2016-08-15"),
                                              by = 'day'))
    fcst_df <- as.data.frame(cbind(train_sub_wide[, 1], fcst_matrix))
    colnames(fcst_df)[1] <- "store_item_nbr"

    fcst_df_long <- melt(fcst_df, id = 'store_item_nbr',
                                  variable.name = "fcst_date",
                                  value.name = 'unit_sales')
    fcst_df_long$store_item_nbr <- as.character(fcst_df_long$store_item_nbr)
    fcst_df_long$fcst_date <- as.Date(parse_date_time(fcst_df_long$fcst_date,'%y-%m-%d'))
    fcst_df_long$unit_sales <- as.numeric(fcst_df_long$unit_sales)
    colnames(fcst_df_long)[3] <- "sales_pred"

    train_valid$date <- as.Date(parse_date_time(train_valid$date, '%y-%m-%d'))
    train_comb <- left_join(train_valid, fcst_df_long,
                            c("store_item_nbr" = "store_item_nbr", 'date' = 'fcst_date'))
    train_comb$sales_pred[train_comb$sales_pred < 0] <- 0
    train_comb$unit_sales[train_comb$unit_sales < 0] <- 0

    train_save <- train_comb[,c(1:6,8,ncol(train_comb))]
    save(train_save, file = paste0("../output/ets/ets_lambda_",lam.ranges[i],".RData"))
    # calculate the score of accuracy prediction on validation set
    w <- ifelse(train_comb$perishable == 0, 1, 1.25)
    valid_score[i] <- sqrt(sum(w * (log(train_comb$sales_pred + 1) - log(train_comb$unit_sales + 1))^2),
  }
  save(valid_score, file = "../output/valid_score.RData")
}else{
  load("../output/ets/valid_score.RData")
  lam.ranges <- seq(0.1, 5, by = 0.2)
}

# the best parameter lambda
plot(lam.ranges, valid_score, col="blue", xlab="lambda in ETS", ylab="evaluation score",type="o")
points(lam.ranges,valid_score,type="o")
```




```
ets.par <- lam.ranges[which.min(valid_score)]
print(paste0("the best lambda in ETS is ", ets.par))
```

```
## [1] "the best lambda in ETS is 1.1"
```

```
# the features_valid corresponding to ets.par
load(paste0("../output/ets/ets_lambda_",ets.par,".RData"))
valid_ets <- train_save%>%select(V1, id, sales_pred)
colnames(valid_ets)[3] <- "ets_pred"

# the features_test corresponding to ets.par
if(run.ets){
  # performance on test dataset
  test$date <- as.Date(parse_date_time(test$date,'%y-%m-%d'))

  train_sub_wide <- dcast(train, store_item_nbr ~ date, mean, value.var = "unit_sales", fill = 0)
  train_ts <- ts(train_sub_wide, frequency = 7)

  fcst_intv = 365  # number of days of forecast in the test set
  fcst_matrix <- matrix(NA,nrow=nrow(train_ts),ncol=fcst_intv)

  # forecast the sales in test set use the best ets.par
  registerDoMC(detectCores()-1)
  fcst_matrix <- foreach(i=1:nrow(train_ts),.combine=rbind, .packages=c("forecast")) %dopar% {
  fcst_matrix <- forecast(ets(train_ts[i,], lambda = ets.par), h=fcst_intv)$mean
  }
  colnames(fcst_matrix) <- as.character(seq(from = as.Date("2016-08-16"),
                                            to = as.Date("2017-08-15"),
                                            by = 'day'))
  fcst_df <- as.data.frame(cbind(train_sub_wide[, 1], fcst_matrix))
  colnames(fcst_df)[1] <- "store_item_nbr"
```

```
  fcst_df_long <- melt(fcst_df, id = 'store_item_nbr',
                               variable.name = "fcst_date",
                               value.name = 'unit_sales')
  fcst_df_long$store_item_nbr <- as.character(fcst_df_long$store_item_nbr)
  fcst_df_long$fcst_date <- as.Date(parse_date_time(fcst_df_long$fcst_date,'%y-%m-%d'))
  fcst_df_long$unit_sales <- as.numeric(fcst_df_long$unit_sales)
  colnames(fcst_df_long)[3] <- "sales_pred"

  test_comb <- left_join(test, fcst_df_long,
                         c("store_item_nbr" = "store_item_nbr", 'date' = 'fcst_date'))
  test_comb$sales_pred[test_comb$sales_pred < 0] <- 0
  test_comb$unit_sales[test_comb$unit_sales < 0] <- 0

  save(test_comb, file = "../output/ets/test_comb.RData")
}else{
  load("../output/ets/test_comb.RData")
}
test_ets <- test_comb%>%select(V1, id, sales_pred)
colnames(test_ets)[3] <- "ets_pred"
```

Step 2.2 ARIMA

```
run.arima = FALSE #if TRUE, train ARIMA model and predict using ARIMA model on main.Rmd
if(run.arima){
  subtrain1 = subtrain[ ,c("date","store_item_nbr","unit_sales")]
  subtrain1$Date = as.Date(subtrain$date)
  validation = valid_train[ ,c("date","store_item_nbr","unit_sales","perishable")]

  train_sub = dcast(subtrain1, store_item_nbr ~ Date, mean, value.var = "unit_sales", fill = 0)
  a = seq(from=as.Date("2016-04-16"), to=as.Date("2016-08-15"),by = 'day')
  wide = length(a)

  #Predict ARIMA(Try several times here is the best parameters)
  fc.wiki = foreach(i=1:nrow(train_sub), .combine=rbind, .packages="forecast") %dopar% {
  y = tsclean(as.ts(unlist(train_sub[i, -1])))
  forecast(auto.arima(y, max.p=2, max.d=2, max.q=1), h=wide)$mean
  }

  colnames(fc.wiki) = as.character(seq(from = as.Date("2016-04-16"),
                                       to = as.Date("2016-08-15"),
                                       by = 'day'))

  train_result = cbind(train_sub[, 1], fc.wiki)
  rownames(train_result) = rownames(train_sub)
  colnames(train_result) [1] = "store_item_nbr"
  subtrain_result = as.data.frame(train_result)

  #Reshaped the predict dataset again
  train_result_long = melt(subtrain_result, id = "store_item_nbr", variable.name = "Date", value.name =
                             "sales_pred")
  train_result_long$Date = as.Date(train_result_long$Date)
```

```
  train_result_long $sales_pred = as.numeric(train_result_long$sales_pred)
  #Get the final results dataframe and save as RData
  train_comb = left_join(validation, train_result_long,
                         c("store_item_nbr" = "store_item_nbr",'date' = 'Date'))
  train_comb$sales_pred[train_comb$sales_pred < 0] = 0
  train_comb$unit_sales[train_comb$unit_sales < 0] = 0
  save(train_comb, file = "ARIMA Feature validate.RData")

  #Used the trainning result to the test set
  wide = length(unique(test$date))
  fc.wiki = foreach(i=1:nrow(train_sub), .combine=rbind,
                    .packages="forecast") %dopar% {
    y = tsclean(as.ts(unlist(train_sub[i, -1])))
    forecast(auto.arima(y, max.p=2, max.d=2, max.q=1), h=wide)$mean
  }
  colnames(fc.wiki) = as.character(unique(test$date))
  test_result = cbind(train_sub[, 1], fc.wiki)
  colnames(test_result) [1] = "store_item_nbr"
  test_result = as.data.frame(test_result)

  test_result_long = melt(test_result, id = "store_item_nbr", variable.name = "Date", value.name =
                            "sales_pred")
  test_result_long$Date = as.Date(test_result_long$Date)

  test_result_long$sales_pred = as.numeric(test_result_long$sales_pred)
  test$date = as.Date(test $ date)
  test_comb = left_join(test, test_result_long,
                        c("store_item_nbr" =
                            "store_item_nbr",'date' = 'Date'))

  save(test_comb, file = "ARIMA Feature test.RData")
}else{
  load("../output/ARIMA Feature validate.RData")
  load("../output/ARIMA Feature Test.RData")
}
valid_arima <- train_comb[,c(2,4,21)]
colnames(valid_arima)[3] <- "arima_pred"
test_arima <- test_comb[,c(1:3, 8, 9)]
colnames(test_arima)[5] <- "arima_pred"
```

Step 2.3 Prophet

Prophet is an open-source modeling framework developed at Facebook used to provide automated forecasting specificly aimed at solving problems regarding effecient allocation of resources over time for capacity planning. Due to the nature of how the automated forecasting is structured, the function tunes the parameters, so no parameter selection is needed from us.

```
run.prophet = FALSE #if TRUE, run train process on Prophet model and run the prediction on test using b

load(paste0("../output/prophet_changepoint_0.1.RData"))
valid_prophet <- train_save%>%select(V1, id, sales_pred)
colnames(valid_prophet)[3] <- "prophet_pred"
```

```
# the features_test corresponding to ets.par
if(run.prophet){
  # performance on test dataset
  test$date <- as.Date(parse_date_time(test$date,'%y-%m-%d'))

  train_sub_wide <- dcast(train, store_item_nbr ~ date, mean, value.var = "unit_sales", fill = 0)
  train_ts <- ts(train_sub_wide, frequency = 7)

  fcst_intv = 365  # number of days of forecast in the test set
  fcst_matrix <- matrix(NA,nrow=nrow(train_ts),ncol=fcst_intv)

  # forecast the sales in test set use the best ets.par
  registerDoMC(detectCores()-1)
  fcst_matrix <- foreach(i=1:nrow(train_ts),.combine=rbind, .packages=c("forecast")) %dopar% {
tmp = data.frame(ds = colnames(train_ts),
                     y = train_ts[i,])
    m <- prophet(tmp, changepoint.prior.scale = 0.1)
    future <- make_future_dataframe(m, periods = fcst_intv,freq = "day")

    fcst_matrix1 <- tail(predict(m, future)$yhat,fcst_intv)
    }
  colnames(fcst_matrix) <- as.character(seq(from = as.Date("2016-08-16"),
                                            to = as.Date("2017-08-15"),
                                            by = 'day'))
  fcst_df <- as.data.frame(cbind(train_sub_wide[, 1], fcst_matrix))
  colnames(fcst_df)[1] <- "store_item_nbr"

  fcst_df_long <- melt(fcst_df, id = 'store_item_nbr',
                               variable.name = "fcst_date",
                               value.name = 'unit_sales')
  fcst_df_long$store_item_nbr <- as.character(fcst_df_long$store_item_nbr)
  fcst_df_long$fcst_date <- as.Date(parse_date_time(fcst_df_long$fcst_date,'%y-%m-%d'))
  fcst_df_long$unit_sales <- as.numeric(fcst_df_long$unit_sales)
  colnames(fcst_df_long)[3] <- "sales_pred"

  test_comb <- left_join(test, fcst_df_long,
                         c("store_item_nbr" = "store_item_nbr", 'date' = 'fcst_date'))
  test_comb$sales_pred[test_comb$sales_pred < 0] <- 0
  test_comb$unit_sales[test_comb$unit_sales < 0] <- 0

  save(test_comb, file = "../output/prophet_test_comb.RData")
}
load("../output/prophet_test_comb.RData")
test_prophet <- test_comb%>%select(V1, id, sales_pred)
colnames(test_prophet)[3] <- "prophet_pred"
```

Step 2.4 XGBoost

XGBoost is a popular boosting algorithm that has been used to use a lot of Kaggle competitions. It is an implementation of a gradient boosting machine. XGBoost is relative fast to train and does well with large datasets, and requires some hyperparameter tuning to achieve the best results.

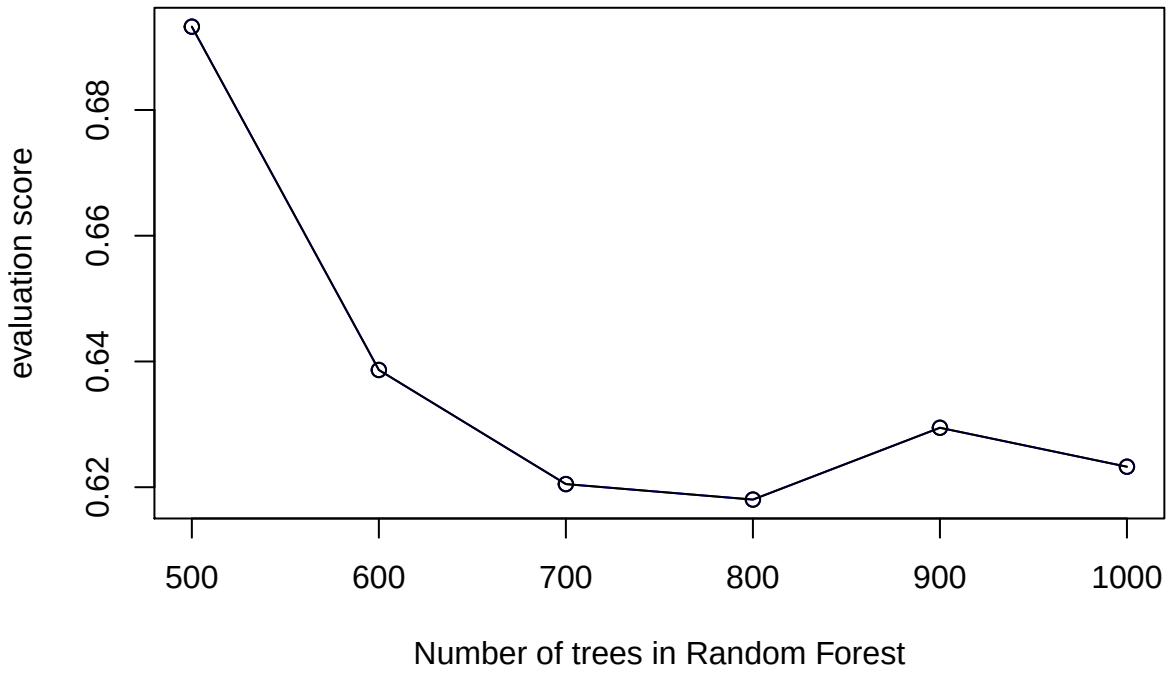
```
run.xgboost = FALSE #if TRUE, run all the processing, cross-validation, and prediction process on XgBoo

# process data function
df_format <- function(df){
  df$onpromotion[df$onpromotion == FALSE] <- 0
  df$onpromotion[df$onpromotion == TRUE] <- 1

  df$unit_sales[df$unit_sales < 0] <- 0
  df$log_sales <- log(df$unit_sales + 1)
return(df)
}

if(run.xgboost){
  # set core number and seed
  registerDoMC(cores=4)
  set.seed(6)
  # process data for XgBoost
  combined_train <- df_format(train)
  combined_test <- df_format(test)
  combined_valid <- df_format(valid_train)

  features <- c('item_nbr', 'id', 'store_nbr', 'onpromotion', 'year', 'month', 'dayOfWeek', 'class',
                'perishable', 'dcoilwtico')

  dtrain <- xgb.DMatrix(data = as.matrix(combined_train[, features]), label = combined_train$log_sales)
  dtest <- xgb.DMatrix(data = as.matrix(combined_test[, features]), label = combined_test$log_sales)
  dvalid <- xgb.DMatrix(data = as.matrix(combined_valid[, features]), label = combined_valid$log_sales)

  # watchlist, when training we can see the performance on both train and test sets
  watchlist <- list(train=dtrain, test = dtest)

  # gridsearch parameters, when tuning you can specify a list of values to test for
  # each parameter. The current parameters in this grid represent the best values
  # for our training set
  searchGridSubCol <- expand.grid(subsample = c(0.7),
                                  colsample_bytree = c(0.7),
                                  max_depth = c(8),
                                  # min_child = c(1, 5, 10),
                                  min_child = c(10),
                                  eta = c(0.7),
                                  # gamma = c(0.1, 1, 10)
                                  gamma = c(1))

  ntrees <- 40

    rmseErrorsHyperparameters <- apply(searchGridSubCol, 1, function(parameterList){

      #Extract Parameters to test
      currentGamma <- parameterList[["gamma"]]
      currentSubsampleRate <- parameterList[["subsample"]]
      currentColsampleRate <- parameterList[["colsample_bytree"]]
      currentDepth <- parameterList[["max_depth"]]
      currentEta <- parameterList[["eta"]]
```

```
      currentMinChild <- parameterList[["min_child"]]

      xgboostModelCV <- xgb.cv(data =  dtrain, nrounds = ntrees, nfold = 2, showsd = TRUE,
                               metrics = "rmse", verbose = TRUE, "eval_metric" = "rmse",
                               "objective" = "reg:linear", "max.depth" = currentDepth, "eta" = currentEta
                               "subsample" = currentSubsampleRate, "colsample_bytree" = currentColsample
                               , print_every_n = 10, "min_child_weight" = currentMinChild, "gamma" =
                                 currentGamma,
                               booster = "gbtree",
                               early_stopping_rounds = 10)

      xvalidationScores <- as.data.frame(xgboostModelCV$evaluation_log)
      rmse <- tail(xvalidationScores$test_rmse_mean, 1)
      trmse <- tail(xvalidationScores$train_rmse_mean,1)
      output <- return(c(rmse, trmse, currentSubsampleRate, currentColsampleRate, currentDepth, current
                         currentMinChild, currentGamma))

    })

  #
  output <- as.data.frame(t(rmseErrorsHyperparameters))
  varnames <- c("TestRMSE", "TrainRMSE", "SubSampRate", "ColSampRate", "Depth", "eta", "currentMinChild
                "Gammma")
  names(output) <- varnames
  save(output, file = "../output/xgboost/cverror.RData")

  bst <- xgb.train(data=dtrain, eta=0.7, gamma = 1, max_depth = 8,
                min_child_weight = 10, subsample = 0.7, colsample_bytree = 0.7,
                nrounds=40, watchlist=watchlist, nthread = 4, objective = "reg:linear")


  features_test <- predict(bst, dtest)
  features_test <- exp(features_test) - 1
  save(features_test, file = "../output/xgboost/features_test.RData")

  features_valid <- predict(bst, dvalid)
  features_valid <- exp(features_valid) - 1
  save(features_valid, file = "../output/xgboost/features_valid.RData")
}else{
  load("../output/xgboost/features_test.RData")
  load("../output/xgboost/features_valid.RData")
}

valid_xgboost <- features_valid
test_xgboost <- features_test
```

Step 2.5 Random Forest

As the dataset is quite large, it takes over several hours to train Random Forest on the train set for one cross-validation iteration. So we used resampling method here: randomly sampling the data in K folds. Every time, we choose two folds, one for training Random Forest model, and one for evaluation. After doing this for all the values of ntree, we can get the best Random Forest model. Although this method may have some bias when training the models, it can help obtain a reasonable model in a short time.

```r
run.rf = FALSE #if TRUE, run RF on the samples from the whole train set and predict sales on validation

n_trees <- seq(500, 1000, 100)
if(run.rf){
  # process the whole train data so they can be used in RF smoothly
  train$onpromotion <- ifelse(train$onpromotion == TRUE, 1, 0)
  train$unit_sales[train$unit_sales < 0] <- 0

  train.rf <- train[,-c(1,3,4,8,16,17,19)]
  train.rf$celebrated[is.na(train.rf$celebrated)] <- FALSE
  train.rf$family <- factor(train.rf$family)
  train.rf$celebrated <- factor(train.rf$celebrated)

  set.seed(2)
  n_train <- nrow(train.rf)
  K <- 100 #sample the data into 100 folds
  n.fold <- floor(n_train/K)
  s <- sample(rep(1:K, c(rep(n.fold, K-1), n_train-(K-1)*n.fold)))

  score.rf <- rep(NA, length(n_trees))
  opt.mtry <- rep(NA, length(n_trees)) #optimal mtry for a certain n_tree value

  # run the RF on random sampled data
  for (i in 1:length(n_trees)){
    train.data <- train.rf[s == i,]
    test.data <- train.rf[s == 100-i,]

    fit <- tuneRF(train.data[,-"unit_sales"], train.data$unit_sales,
                  ntreeTry = n_trees[i],
                  doBest = TRUE)

    # Get the 'mtry' for trained model
    opt.mtry[i] <- fit$mtry
    pred <- predict(fit, test.data[,-c("unit_sales")])
    w <- ifelse(test.data$perishable == 0, 1, 1.25)
    score.rf[i] <- sqrt(sum(w * (log(pred + 1) - log(test.data$unit_sales + 1))^2)/sum(w))
    save(fit, file=paste0("../output/RF_ntree",n_trees[i],".RData"))
  }
  save(score.rf, file="../output/RF_score100.RData")
  save(opt.mtry, file="../output/RF_mtry.RData")
}else{
  load("../output/RF_score100.RData")
  #load("../output/RF_mtry.RData")
}

# the best parameter ntree
plot(n_trees, score.rf, col="blue", xlab="Number of trees in Random Forest", ylab="evaluation score",ty
points(n_trees,score.rf,type="o")
```




```
rf.par <- n_trees[which.min(score.rf)]
print(paste0("the best ntree in Random Forest is ", rf.par))
```

```
## [1] "the best ntree in Random Forest is 800"
```

```
load(paste0("../output/RF_ntree",rf.par,".RData"))
if(run.rf){
  # predict on validation set
  valid_rf <- valid_train
  valid_rf$onpromotion <- ifelse(valid_rf$onpromotion == TRUE, 1, 0)
  valid_rf$unit_sales[valid_rf$unit_sales < 0] <- 0

  valid_rf <- valid_rf[,-c(1,3,4,8,16,17,19)]
  valid_rf$celebrated[is.na(valid_rf$celebrated)] <- FALSE
  valid_rf$family <- factor(valid_rf$family)
  valid_rf$celebrated <- factor(valid_rf$celebrated)

  rf_pred <- predict(fit, valid_rf[,-which(colnames(valid_rf) == "unit_sales")])
  save(rf_pred, file=paste0("../output/RF_validion.RData"))
  # predict on test set
  test_rf <- test
  test_rf$onpromotion <- ifelse(test_rf$onpromotion == TRUE, 1, 0)
  test_rf$unit_sales[test_rf$unit_sales < 0] <- 0

  test_rf <- test_rf[,-c(1,3,4,8,16,17,19)]
  test_rf$celebrated[is.na(test_rf$celebrated)] <- FALSE
  test_rf$family <- factor(test_rf$family)
  test_rf$celebrated <- factor(test_rf$celebrated)

  del.row <- which(colnames(test_rf) == "unit_sales") # that is 3 here
  rf_pred1 <- predict(fit, test_rf[,-3])
```

```
  save(rf_pred1, file=paste0("../output/RF_test.RData"))
}else{
  load("../output/RF_validion.RData")
  load("../output/RF_test.RData")
}
valid_rf <- rf_pred
test_rf <- rf_pred1
```

Step 2.6 Combine Features

```
run.merge = FALSE #if TRUE, combine the features from the first Stack in main.Rmd
if(run.merge){
  # Combine features on validation set
  comb_valid <- merge(valid_ets, valid_prophet, by.x = c("V1","id"), by.y = c("V1", "id"))
  valid_train$rf_pred <- valid_rf
  valid_train$xgboost_pred <- valid_xgboost
  comb_valid <- merge(valid_train[,c(1:6, 8, 15, 20, 21)], comb_valid, by.x = c("V1", "id"), by.y = c("
                                                                                                      "
  comb_valid <- merge(comb_valid, valid_arima, by.x=c("V1", "id"), by.y = c("V1", "id"))
  save(comb_valid, file="../output/comb_validFeatures.RData")

  # Combine feature on test set
  comb_test <- merge(test_ets, test_prophet, by.x = c("V1","id"), by.y = c("V1", "id"))
  test$rf_pred <- test_rf
  test$xgboost_pred <- test_xgboost
  comb_test <- merge(test[,c(1:6, 8, 15, 20, 21)], comb_test, by.x = c("V1", "id"), by.y = c("V1", "id"
  comb_test <- merge(comb_test, test_arima, by.x = "id", by.y ="id")
  comb_test <- comb_test[,-c(13:15)]
  save(comb_test, file="../output/comb_testFeatures.RData")
}else{
  load("../output/comb_validFeatures.RData")
  load("../output/comb_testFeatures.RData")
}
```

Step 3: The Second Stack

In the second Stack, we train Models on the validation set use the features from 1st Stack.

3.1 Average-Feature Prediction

First of all, we just use the mean of our test features obtained from 1st Stack models as the predictions of sales on test set, call this Average-Feature Prediction method, and see the performance.

```
mean_pred = rowMeans(comb_test[,9:13])
w = ifelse(comb_test$perishable == 0, 1, 1.25)
actual_sales = ifelse(comb_test$unit_sales < 0, 0, comb_test$unit_sales)

avg_kaggle_score = sqrt(sum(w * (log(mean_pred + 1) - log(actual_sales + 1))^2)/sum(w))

print(paste0("the score for Average-Feature Prediction method is ", avg_kaggle_score))
```

```
## [1] "the score for Average-Feature Prediction method is 0.656219466969189"
```

We could see that the performance of the Average-Feature Prediction method is not very good.

3.2 Linear Regression

Here we use ridge regression for the second stack, as it allows for some variable/feature selection/importance via shrinkage, while not necessarily shrinking the coefficients to 0 (since we believe that all of the models will have some predictive power still).

```
run_linear_stack2 = FALSE
if (run_linear_stack2) {

  train_x = comb_valid[,-c(1,3,4,5,6)]
  train_y = comb_valid[,6]

  train_x$linear_stack_pred = NA

  test = comb_test[,c(1,7,6,8,9,10,11,12,13)]
  test$linear_stack_pred = NA

  lambdas <- 10^seq(3, -2, by = -.5)

  unique_combos = unique(train_x$store_item_nbr)

  for (i in 1:length(unique_combos)) {
    print(i)

    indices_train = which(train_x$store_item_nbr == unique_combos[i])
    x = train_x[indices_train,-c(1,2,3,9)]
    y = train_y[indices_train]

    indices_test = which(test$store_item_nbr.x == unique_combos[i])
    test_sub = test[indices_test,]
    test_x = test_sub[,c(5:9)]

    cv_fit <- cv.glmnet(model.matrix( ~ ., x), y, alpha = 0, lambda = lambdas)
    opt_lambda <- cv_fit$lambda.min
    fit <- cv_fit$glmnet.fit

    ytest_predicted <- predict(fit, s = opt_lambda, newx = model.matrix(~ . , test_x))
    ytrain_predicted <- predict(fit, s = opt_lambda, newx = model.matrix(~ . , x))

    train_x$linear_stack_pred[indices_train] = ytrain_predicted
    test$linear_stack_pred[indices_test] = ytest_predicted
  }

  w = ifelse(test$perishable == 0, 1, 1.25)

  test$linear_stack_pred[test$linear_stack_pred < 0 | is.na(test$linear_stack_pred)]<- 0
  test$unit_sales[test$unit_sales < 0] <- 0

  save(train_x,test,file="../output/stack2_linear.RData")
```

```
} else {
  load("../output/stack2_linear.RData")
  w = ifelse(test$perishable == 0, 1, 1.25)
}

linear_kaggle_score = sqrt(sum(w * (log(test$linear_stack_pred + 1) - log(test$unit_sales + 1))^2)/sum(w
print(paste0("the score for Linear Regression in stack 2 is ", linear_kaggle_score))
```

```
## [1] "the score for Linear Regression in stack 2 is 0.869774354620931"
```

We can see from the results that Linear Regression performs even worse than the Average-Feature Prediction method.

3.3 Random Forest

Still this time, as the dataset too large (over 200,000 observations in validation set), we use sampling method to train Random Forest model, which is the same as in the 1st Stack.

```
run_rf_stack2 = FALSE

n_tree2 <- seq(500, 1000, 100)
if(run_rf_stack2){
  train_rf <- comb_valid[,c("date","store_item_nbr","unit_sales","rf_pred","xgboost_pred","ets_pred","pr
  train_rf$unit_sales[train_rf$unit_sales < 0] <- 0
  set.seed(2)
  n1 <- nrow(train_rf)
  K <- 20 #divide into 20 folds
  n.fold <- floor(n1/K)
  s <- sample(rep(1:K, c(rep(n.fold, K-1), n1-(K-1)*n.fold)))

  score.tree <- rep(NA, length(n_tree2))
  mtry.tree <- rep(NA, length(n_tree2))

  # run the RF on random sampled data
  for (i in 1:length(n_tree2)){
    train.data <- train_rf[s == i,]
    test.data <- train_rf[s == 20 - i,]

    fit <- tuneRF(train.data[,4:8], train.data$unit_sales,
                  ntreeTry = n_tree2[j],
                  doBest = TRUE)
    save(fit, file=paste0("../output/RF2/fit_",n_tree2[i],"ntree.RData"))

    # Get the 'mtry' for trained model
    mtry.tree[i] <- fit$mtry

    pred <- predict(fit, test.data[,4:8])
    w <- ifelse(test.data$perishable == 0, 1, 1.25)
    score.tree[i] <- sqrt(sum(w * (log(pred + 1) - log(test.data$unit_sales + 1))^2)/sum(w))
  }

  save(score.tree, file="../output/RF2/score_tree.RData")
```

```
}else{
  load("../output/RF2/score_tree.RData")
}
best_tree <- n_tree2[which.min(score.tree)]
names(score.tree) <- as.character(n_tree2)
score.tree
```

```
##       500       600       700       800       900      1000
## 0.5344506 0.5233278 0.5310558 0.5233710 0.5279626 0.5278661
```

```
print(paste0("Best ntree parameter is ",best_tree,"."))
```

```
## [1] "Best ntree parameter is 600."
```

```
if(run_rf_stack2){
  test_rf <- comb_test[,c("unit_sales","rf_pred","xgboost_pred","ets_pred","prophet_pred","arima_pred",
  test_rf$unit_sales[test_rf$unit_sales < 0] <- 0

  load(paste0("../output/RF2/fit_",best_tree,"ntree.RData"))
  pred <- predict(fit, test_rf[,2:6])
  save(pred, file="../output/RF2/test_pred.RData")
  w <- ifelse(test_rf$perishable == 0, 1, 1.25)
  score_rf<- sqrt(sum(w * (log(pred + 1) - log(test_rf$unit_sales + 1))^2)/sum(w))
  print(paste0("the score for RF in stack 2 is", score_rf))
}else{
  load("../output/RF2/test_pred.RData")
  test_rf <- comb_test
  test_rf$unit_sales[test_rf$unit_sales < 0] <- 0
  w <- ifelse(test_rf$perishable == 0, 1, 1.25)
  score_rf<- sqrt(sum(w * (log(pred + 1) - log(test_rf$unit_sales + 1))^2)/sum(w))
  print(paste0("the score for RF in stack 2 is ", score_rf))
}
```

```
## [1] "the score for RF in stack 2 is 0.597965460665963"
```

We can see that Random Forest performs better than Average-Feature Prediction as it reduces the error score by over 8% (= 1-score_rf/avg_kaggle_score).