bimbo features.R

gquai

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# DATA SCIENCE ACADEMY
# Big Data Analytics com R e Microsoft Azure Machine Learning
# Model to accurately predict inventory demand based on data sales histories
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# In this competition, you will forecast the demand of a product for a given week, at a
# particular store.
# The dataset you are given consists of 9 weeks of sales transactions in Mexico. Every week,
# there are delivery
# trucks that deliver products to the vendors. Each transaction consists of sales and returns.
# Returns are the products that are unsold and expired. The demand for a product in a certain
# week is defined as the sales this week subtracted by the return next week.
#
# The train and test dataset are split based on time, as well as the public and private
# leaderboard dataset split.
# Things to note:
# There may be products in the test set that don't exist in the train set. This is the expected
# behavior of inventory data,
# since there are new products being sold all the time. Your model should be able to accommodate
# this.
# The adjusted demand (Demanda_uni_equil) is always >= 0 since demand should be either 0 or a
# positive value. The reason that Venta_uni_hoy - Dev_uni_proxima
# sometimes has negative values is that the returns records sometimes carry over a few weeks.
# File descriptions
# train.csv - the training set
\# test.csv - the test set
# sample_submission.csv - a sample submission file in the correct format
# cliente_tabla.csv - client names (can be joined with train/test on Cliente_ID)
# producto_tabla.csv - product names (can be joined with train/test on Producto_ID)
# town_state.csv - town and state (can be joined with train/test on Agencia_ID)
# Data fields
# Semana - Week number (From Thursday to Wednesday)
# Agencia_ID - Sales Depot ID
# Canal_ID - Sales Channel ID
# Ruta_SAK - Route ID (Several routes = Sales Depot)
# Cliente_ID - Client ID
# NombreCliente - Client name
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# Producto_ID - Product ID
# NombreProducto - Product Name
# Venta_uni_hoy - Sales unit this week (integer)
# Venta_hoy - Sales this week (unit: pesos)
# Dev_uni_proxima - Returns unit next week (integer)
# Dev_proxima - Returns next week (unit: pesos)
# Demanda_uni_equil - Adjusted Demand (integer) (This is the target you will predict)
setwd('D:/Github/DSA_BIMBO_INVENTORY')
library(data.table)
library(caTools)
library(caret)
## Loading required package: lattice
## Loading required package: ggplot2
library(corrplot)
## corrplot 0.84 loaded
library(lares)
## Registered S3 method overwritten by 'xts':
##
    method
               from
     as.zoo.xts zoo
##
## Registered S3 method overwritten by 'quantmod':
##
   method
                      from
    as.zoo.data.frame zoo
##
## Registered S3 methods overwritten by 'forecast':
##
    method
                       from
##
   fitted.fracdiff fracdiff
    residuals.fracdiff fracdiff
library(MASS)
v_c_file_train <- "dataset/train_clean.csv"</pre>
v_c_file_out <- "dataset/train_features.csv"</pre>
gc()
             used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 2716138 145.1 4102610 219.2 4102610 219.2
## Vcells 4310940 32.9 10146329 77.5 7140074 54.5
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# TRAIN DATASET
train <- data.table::fread(file = v_c_file_train)</pre>
# Balance by product and customer
df <- train[, list(prod_cust_balance = median(Demanda_uni_equil), prod_cust_bal_mean = mean(Demanda_uni
train <- merge(x = train, y = df, all.x = TRUE, by.x = c("Cliente_ID", "Producto_ID"), by.y = c("Client
# Balance by route and product
df <- train[, list(prod_rout_balance = median(Demanda_uni_equil)), by = list(Ruta_SAK, Producto_ID)]</pre>
train <- merge(x = train, y = df, all.x = TRUE, by.x = c("Ruta_SAK", "Producto_ID"), by.y = c("Ruta_SAK")
# Balance by route and customer
df <- train[, list(cust_rout_balance = median(Demanda_uni_equil)), by = list(Ruta_SAK, Cliente_ID)]
train <- merge(x = train, y = df, all.x = TRUE, by.x = c("Ruta_SAK", "Cliente_ID"), by.y = c("Ruta_SAK"
# Route Size
df1 <- train[ , list(rout_sum = sum(Demanda_uni_equil)), by = list(Ruta_SAK)]</pre>
# Product proportion at the route (when we not know the customer this may be useful)
df <- train[ , list(prod_sum = sum(Demanda_uni_equil)), by = list(Ruta_SAK, Producto_ID)]
df <- merge(x = df, y = df1, all.x = TRUE, by.x = c("Ruta_SAK"), by.y = c("Ruta_SAK"))
df[rout_sum > 0, prod_rout_prop := prod_sum / rout_sum]
train <- merge(x = train, y = df[,list(Ruta_SAK, Producto_ID, prod_rout_prop)], all.x = TRUE, by.x = c(</pre>
# Customer proportion at the route (when we not know the product this may be useful)
df <- train[ , list(cust_sum = sum(Demanda_uni_equil)), by = list(Ruta_SAK, Cliente_ID)]
df \leftarrow merge(x = df, y = df1, all.x = TRUE, by.x = c("Ruta_SAK"), by.y = c("Ruta_SAK"))
df[rout_sum > 0, cust_rout_prop := cust_sum / rout_sum]
train <- merge(x = train, y = df[,list(Ruta_SAK, Cliente_ID, cust_rout_prop)], all.x = TRUE, by.x = c(".
remove(df1)
remove(df)
# Order by Cliente_ID, Producto_ID, Semana
train <- data.table::setorder(x = train, Cliente_ID, Producto_ID, Semana)</pre>
# Get the balance from previous line
train[,last_week_balance := shift(x = Demanda_uni_equil, n = 1)]
train[!(Cliente_ID == shift(Cliente_ID, n = 1) & Producto_ID == shift(Producto_ID, n = 1)), last_week_b
train[is.na(last_week_balance), last_week_balance := 0]
train[, Agencia_ID := NULL]
train[, Canal_ID := NULL]
train[, Venta_uni_hoy := NULL]
train[, Venta_hoy := NULL]
train[, Dev_uni_proxima := NULL]
train[, Dev_proxima := NULL]
train[, previous_week_balance := NULL]
## Warning in `[.data.table`(train, , `:=`(previous_week_balance, NULL)): Column
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'previous_week_balance' does not exist to remove

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train[, unit_price := NULL]
train[, dev_unit_price := NULL]

fwrite(x = train, file = v_c_file_out)

rm(list=ls())
gc()
```

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## used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 2753804 147.1 4102610 219.2 4102610 219.2
## Vcells 67912979 518.2 1711818331 13060.2 2139665969 16324.4
```