

Kaggle Competition - Grupo Bimbo Inventory Demand

loaded packages

```
library(markdown)
library(knitr)
library(DescTools)
library(data.table)
library(dplyr)
```

Data Exploration

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.

File descriptions

1. train.csv — the training set
2. test.csv — the test set
3. sample_submission.csv — a sample submission file in the correct format
4. cliente_tabla.csv — client names (can be joined with train/test on Cliente_ID)
5. producto_tabla.csv — product names (can be joined with train/test on Producto_ID)
6. town_state.csv — town and state (can be joined with train/test on Agencia_ID)

loaded data

```
train <- fread("train.csv", stringsAsFactors=TRUE, data.table = FALSE)
```

##

Read 0.0% of 74180464 rows

Read 4.1% of 74180464 rows

Read 8.1% of 74180464 rows

Read 12.0% of 74180464 rows

Read 15.9% of 74180464 rows

Read 19.9% of 74180464 rows

Read 23.8% of 74180464 rows

Read 27.7% of 74180464 rows

Read 31.7% of 74180464 rows

Read 35.7% of 74180464 rows

Read 39.6% of 74180464 rows

Read 43.5% of 74180464 rows

Read 47.3% of 74180464 rows

Read 51.1% of 74180464 rows

Read 54.9% of 74180464 rows

Read 58.5% of 74180464 rows

Read 62.4% of 74180464 rows

Read 66.3% of 74180464 rows

Read 70.3% of 74180464 rows

Read 74.1% of 74180464 rows

Read 78.0% of 74180464 rows

Read 81.9% of 74180464 rows

Read 85.6% of 74180464 rows

Read 89.4% of 74180464 rows

Read 93.2% of 74180464 rows

Read 97.0% of 74180464 rows

Read 74180464 rows and 11 (of 11) columns from 2.980 GB file in 00:00:32

```
test <- fread("test.csv", stringsAsFactors=TRUE, data.table = FALSE)
```

```
client <- fread("cliente_tabla.csv", stringsAsFactors=TRUE, data.table = FALSE)
```

```
product <- fread("producto_tabla.csv", stringsAsFactors=TRUE, data.table = FALSE)
```

```
sample.sub <- fread("sample_submission.csv", stringsAsFactors=TRUE, data.table = FALSE)
```

```
town.state <- fread("town_state.csv", stringsAsFactors=TRUE, data.table = FALSE)
```

Data Fields

1. Semana — Week number (From Thursday to Wednesday)
2. Agencia_ID — Sales Depot ID
3. Canal_ID — Sales Channel ID
4. Ruta_SAK — Route ID (Several routes = Sales Depot)
5. Cliente_ID — Client ID
6. NombreCliente — Client name
7. Producto_ID — Product ID
8. NombreProducto — Product Name
9. Venta_uni_hoy — Sales unit this week (integer)
10. Venta_hoy — Sales this week (unit: pesos)
11. Dev_uni_proxima — Returns unit next week (integer)
12. Dev_proxima — Returns next week (unit: pesos)
13. Demanda_uni_equil — Adjusted Demand (integer) (This is the target you will predict)

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.

There are duplicate Cliente_ID's in cliente_tabla, which means one Cliente_ID may have multiple NombreCliente that are very similar. This is due to the NombreCliente being noisy and not standardized in the raw data, so it is up to you to decide how to clean up and use this information.

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.

train data

```
dim(train)
```

```
## [1] 74180464    11
```

```
colnames(train) #data for train data set
```

```
## [1] "Semana"      "Agencia_ID"  "Canal_ID"
## [4] "Ruta_SAK"    "Cliente_ID"  "Producto_ID"
## [7] "Venta_uni_hoy" "Venta_hoy"   "Dev_uni_proxima"
## [10] "Dev_proxima" "Demanda_uni_equil"
```

```
head(train)
```

```
##  Semana Agencia_ID Canal_ID Ruta_SAK Cliente_ID Producto_ID Venta_uni_hoy
## 1    3    1110      7    3301    15766    1212         3
## 2    3    1110      7    3301    15766    1216         4
## 3    3    1110      7    3301    15766    1238         4
## 4    3    1110      7    3301    15766    1240         4
## 5    3    1110      7    3301    15766    1242         3
## 6    3    1110      7    3301    15766    1250         5
##  Venta_hoy Dev_uni_proxima Dev_proxima Demanda_uni_equil
## 1    25.14         0         0         3
## 2    33.52         0         0         4
## 3    39.32         0         0         4
## 4    33.52         0         0         4
## 5    22.92         0         0         3
## 6    38.20         0         0         5
```

test data

```
dim(test)
```

```
## [1] 6999251     7
```

```
colnames(test) #data for test data set
```

```
## [1] "id"      "Semana"  "Agencia_ID" "Canal_ID" "Ruta_SAK"
## [6] "Cliente_ID" "Producto_ID"
```

```
head(test)
```

```
## id Semana Agencia_ID Canal_ID Ruta_SAK Cliente_ID Producto_ID
## 1 0 11 4037 1 2209 4639078 35305
## 2 1 11 2237 1 1226 4705135 1238
## 3 2 10 2045 1 2831 4549769 32940
## 4 3 11 1227 1 4448 4717855 43066
## 5 4 11 1219 1 1130 966351 1277
## 6 5 11 1146 4 6601 1741414 972
```

common parameters between train and test

```
colnames(train)[colnames(train) %in% colnames(test)]
```

```
## [1] "Semana" "Agencia_ID" "Canal_ID" "Ruta_SAK" "Cliente_ID"
## [6] "Producto_ID"
```

town_state

Town and State data were added to train/test data.

Information about Town/State was stored as integer.

```
head(town.state)
```

```
## Agencia_ID      Town      State
## 1 1110 2008 AG. LAGO FILT MÉXICO, D.F.
## 2 1111 2002 AG. AZCAPOTZALCO MÉXICO, D.F.
## 3 1112 2004 AG. CUAUTITLAN ESTADO DE MÉXICO
## 4 1113 2008 AG. LAGO FILT MÉXICO, D.F.
## 5 1114 2029 AG. IZTAPALAPA 2 MÉXICO, D.F.
## 6 1116 2011 AG. SAN ANTONIO MÉXICO, D.F.
```

```
train$Town <- rep(NA,nrow(train))
loop <- length(town.state$Agencia_ID)

for (i in 1:loop){
  train$Town[which(train$Agencia_ID == town.state$Agencia_ID[i])] <- town.state$Town[town.state$Agencia_ID == town.state$Agencia_ID[i]]
}
gc()
```

```
##      used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 758474 40.6 1442291 77.1 940480 50.3
## Vcells 553950896 4226.4 958321926 7311.5 926312353 7067.3
```

```
test$Town <- rep(NA,nrow(test))
loop <- length(town.state$Agencia_ID)

for (i in 1:loop){
  test$Town[which(test$Agencia_ID == town.state$Agencia_ID[i])] <- town.state$Town[town.state$Agencia_ID == town.state$Agencia_ID[i]]
}
gc()
```

```
##      used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 758525 40.6 1442291 77.1 940480 50.3
## Vcells 557450591 4253.1 958321926 7311.5 957363879 7304.2
```

```
train$State <- rep(NA,nrow(train))
loop <- length(town.state$Agencia_ID)

for (i in 1:loop){
  train$State[which(train$Agencia_ID == town.state$Agencia_ID[i])] <- town.state$State[town.state$Agencia_ID == town.state$Agencia_ID[i]]
}
gc()
```

```
##      used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 758561 40.6 1442291 77.1 940480 50.3
## Vcells 594540867 4536.0 1150066311 8774.4 1115719761 8512.3
```

```
test$State <- rep(NA,nrow(test))
loop <- length(town.state$Agencia_ID)

for (i in 1:loop){
  test$State[which(test$Agencia_ID == town.state$Agencia_ID[i])] <- town.state$State[town.state$Agencia_ID == town.state$Agencia_ID[i]]
}
gc()
```

```
##      used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 758603 40.6 1442291 77.1 940480 50.3
## Vcells 598040563 4562.7 1150066311 8774.4 1148719651 8764.1
```

cliente_tabla

```
head(client)
```

```
## Cliente_ID      NombreCliente
## 1      0      SIN NOMBRE
## 2      1      OXXO XINANTECATL
## 3      2      SIN NOMBRE
## 4      3      EL MORENO
## 5      4 SDN SER DE ALIM CUERPO SA CIA DE INT
## 6      4 SDN SER DE ALIM CUERPO SA CIA DE INT
```

```
counts <- client %>% group_by(NombreCliente) %>% summarise(Count = length(Cliente_ID))
counts <- counts[order(-counts$Count),]
head(counts,10)
```

```
## Source: local data frame [10 x 2]
##
##   NombreCliente Count
##   (fctr) (int)
## 1 NO IDENTIFICADO 281670
## 2 LUPITA 4863
## 3 MARY 3016
## 4 LA PASADITA 2426
## 5 LA VENTANITA 2267
## 6 LA GUADALUPANA 1299
## 7 ROSY 1245
## 8 ALEX 1242
## 9 GABY 1238
## 10 LA ESCONDIDA 1216
```

```
sum(counts$Count[counts$Count == 1])/nrow(client) # the percentage of not duplicated name
```

```
## [1] 0.294888
```

About 70 % of client ID was duplicated. It will be better to remove client ID as a predictor variable.

producto_tabla

```
head(product)
```

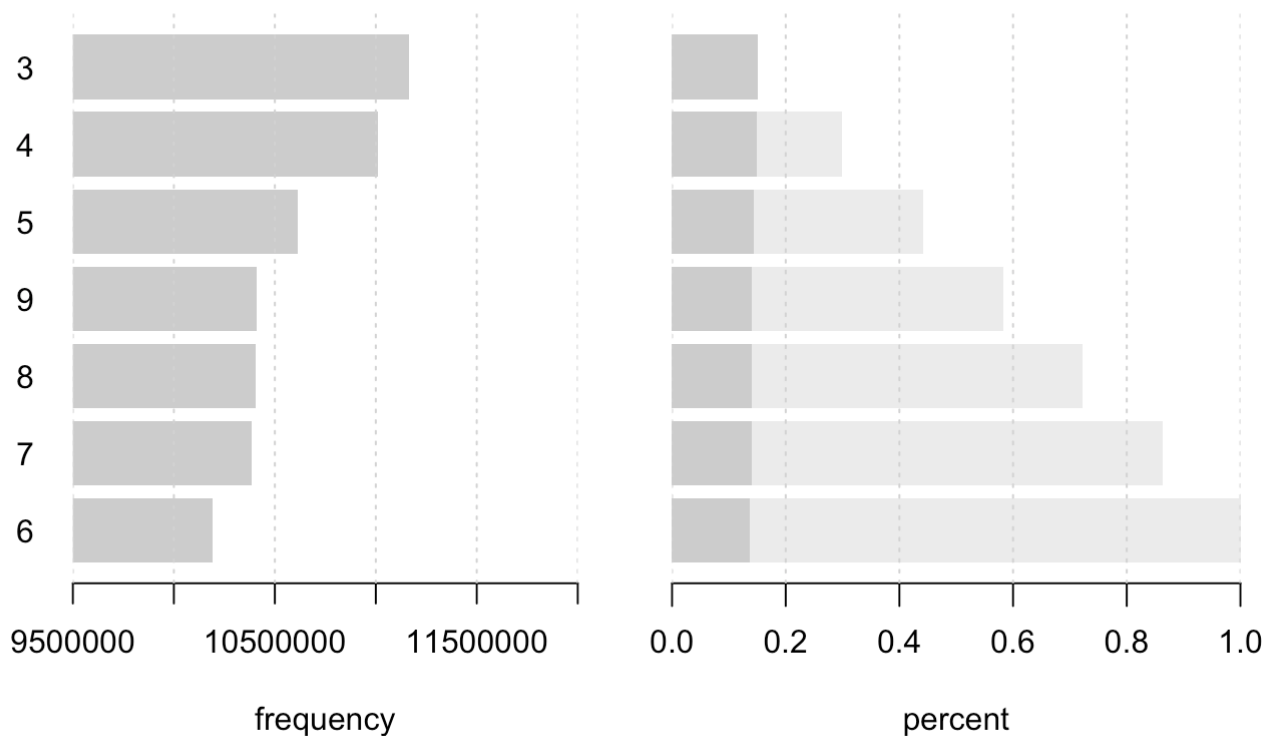
```
## Producto_ID      NombreProducto
## 1      0      NO IDENTIFICADO 0
## 2      9      Capuccino Moka 750g NES 9
## 3     41 Bimbollos Ext sAjonjoli 6p 480g BIM 41
## 4     53      Burritos Sincro 170g CU LON 53
## 5     72      Div Tira Mini Doradita 4p 45g TR 72
## 6     73      Pan Multigrano Linaza 540g BIM 73
```

Replacement will be not needed. No duplicate ID was found.

```
Desc(train$Semana, plotit = TRUE, digits=7)
```

```
## -----
## train$Semana (factor)
##
## length    n  NAs unique levels  dupes
## 7e+07 7e+07    0 7e+00 7e+00    y
##
## level freq    perc cumfreq    cumperc
## 1    3 1e+07 15.0514116% 1e+07 15.0514116%
## 2    4 1e+07 14.8416340% 2e+07 29.8930457%
## 3    5 1e+07 14.3102327% 3e+07 44.2032784%
## 4    9 1e+07 14.0316095% 4e+07 58.2348878%
## 5    8 1e+07 14.0291223% 5e+07 72.2640101%
## 6    7 1e+07 13.9967431% 6e+07 86.2607532%
## 7    6 1e+07 13.7392468% 7e+07 100.0000000%
```

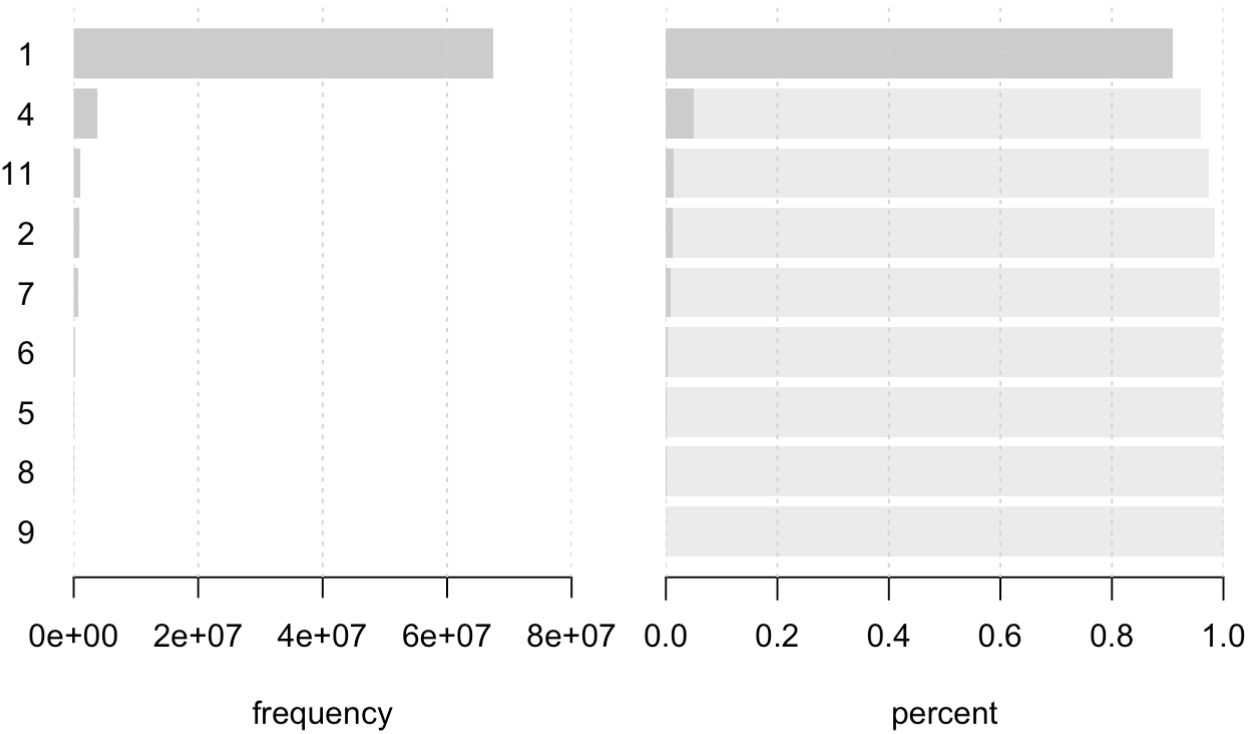
train\$Semana (factor)



```
Desc(train$Canal_ID, plotit = TRUE, digits=9)
```

```
## -----
## train$Canal_ID (factor)
##
## length    n  NAs unique levels  dupes
## 7e+07 7e+07    0 9e+00 9e+00    y
##
## level freq      perc cumfreq      cumperc
## 1 1 7e+07 90.906976532% 7e+07 90.906976532%
## 2 4 4e+06 5.065717842% 7e+07 95.972694374%
## 3 11 1e+06 1.324196354% 7e+07 97.296890729%
## 4 2 8e+05 1.131694188% 7e+07 98.428584917%
## 5 7 7e+05 0.904723378% 7e+07 99.333308295%
## 6 6 3e+05 0.379330332% 7e+07 99.712638627%
## 7 5 1e+05 0.196571971% 7e+07 99.909210598%
## 8 8 7e+04 0.090279834% 7e+07 99.999490432%
## 9 9 4e+02 0.000509568% 7e+07 100.000000000%
```

train\$Canal_ID (factor)

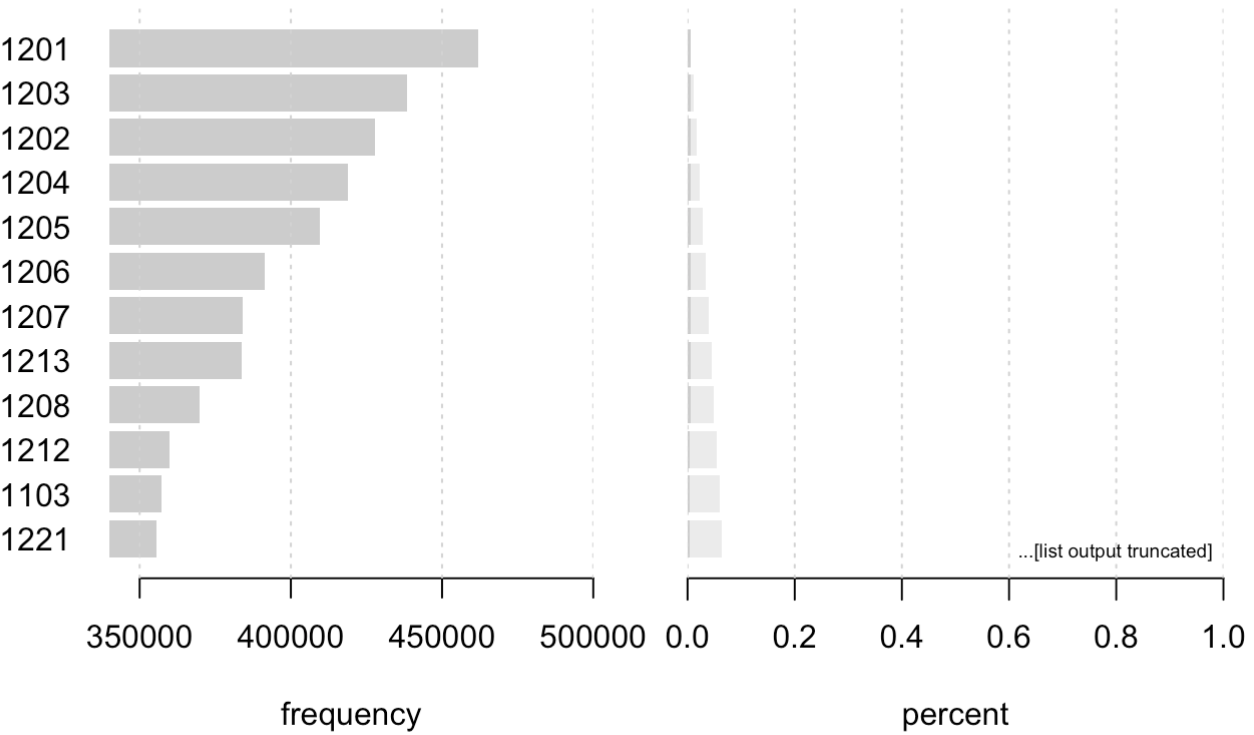


```
Desc(train$Ruta_SAK, plotit = TRUE)
```



```
## -----
## train$Ruta_SAK (factor)
##
## length    n  NAs unique levels dupes
## 7e+07 7e+07  0 4e+03 4e+03    y
##
## level freq perc cumfreq cumperc
## 1  1201 5e+05 0.6% 5e+05 0.6%
## 2  1203 4e+05 0.6% 9e+05 1.2%
## 3  1202 4e+05 0.6% 1e+06 1.8%
## 4  1204 4e+05 0.6% 2e+06 2.4%
## 5  1205 4e+05 0.6% 2e+06 2.9%
## 6  1206 4e+05 0.5% 3e+06 3.4%
## 7  1207 4e+05 0.5% 3e+06 4.0%
## 8  1213 4e+05 0.5% 3e+06 4.5%
## 9  1208 4e+05 0.5% 4e+06 5.0%
## 10 1212 4e+05 0.5% 4e+06 5.5%
## 11 1103 4e+05 0.5% 4e+06 5.9%
## 12 1221 4e+05 0.5% 5e+06 6.4%
## ... etc.
## [list output truncated]
```

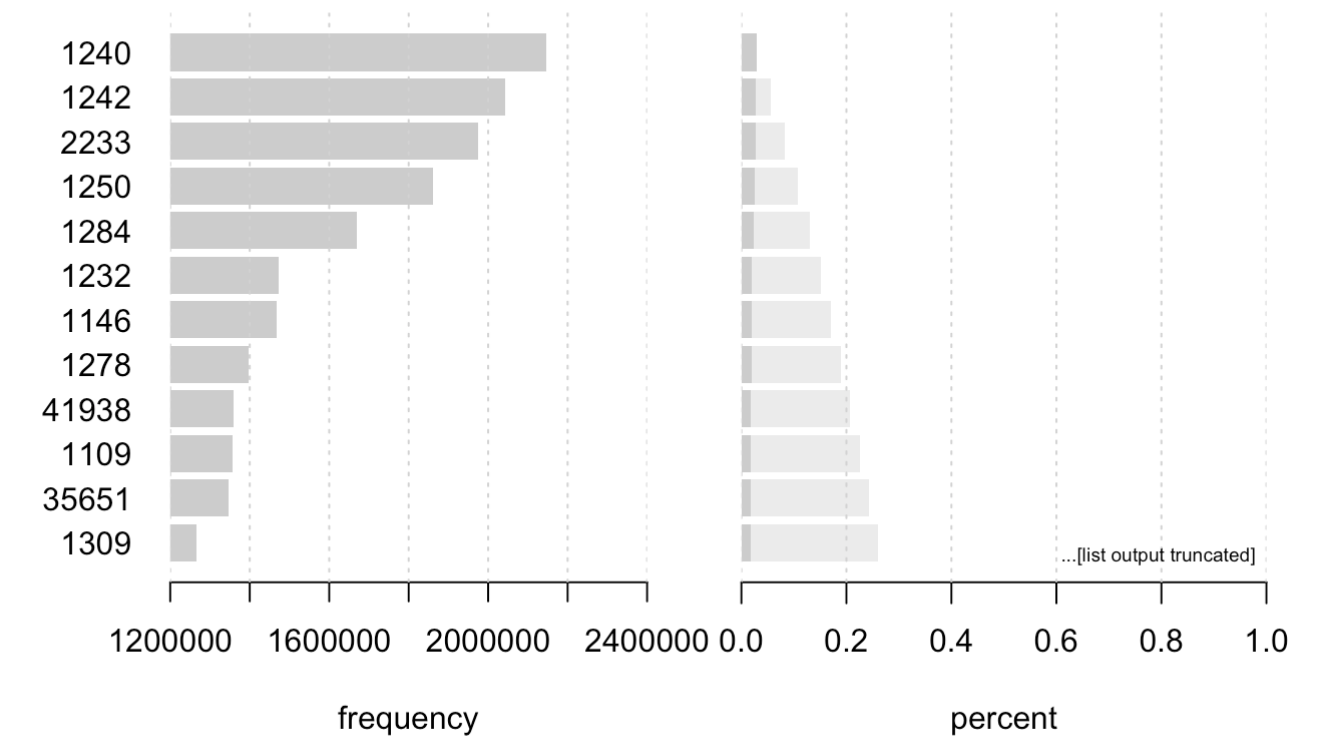
train\$Ruta_SAK (factor)



```
Desc(train$Producto_ID, plotit = TRUE)
```

```
## -----
## train$Producto_ID (factor)
##
## length    n  NAs unique levels dupes
## 7e+07 7e+07  0 2e+03 2e+03    y
##
## level freq perc cumfreq cumperc
## 1  1240 2e+06 2.9% 2e+06 2.9%
## 2  1242 2e+06 2.8% 4e+06 5.6%
## 3  2233 2e+06 2.7% 6e+06 8.3%
## 4  1250 2e+06 2.5% 8e+06 10.8%
## 5  1284 2e+06 2.3% 1e+07 13.1%
## 6  1232 1e+06 2.0% 1e+07 15.1%
## 7  1146 1e+06 2.0% 1e+07 17.0%
## 8  1278 1e+06 1.9% 1e+07 18.9%
## 9  41938 1e+06 1.8% 2e+07 20.8%
## 10 1109 1e+06 1.8% 2e+07 22.6%
## 11 35651 1e+06 1.8% 2e+07 24.4%
## 12 1309 1e+06 1.7% 2e+07 26.1%
## ... etc.
## [list output truncated]
```

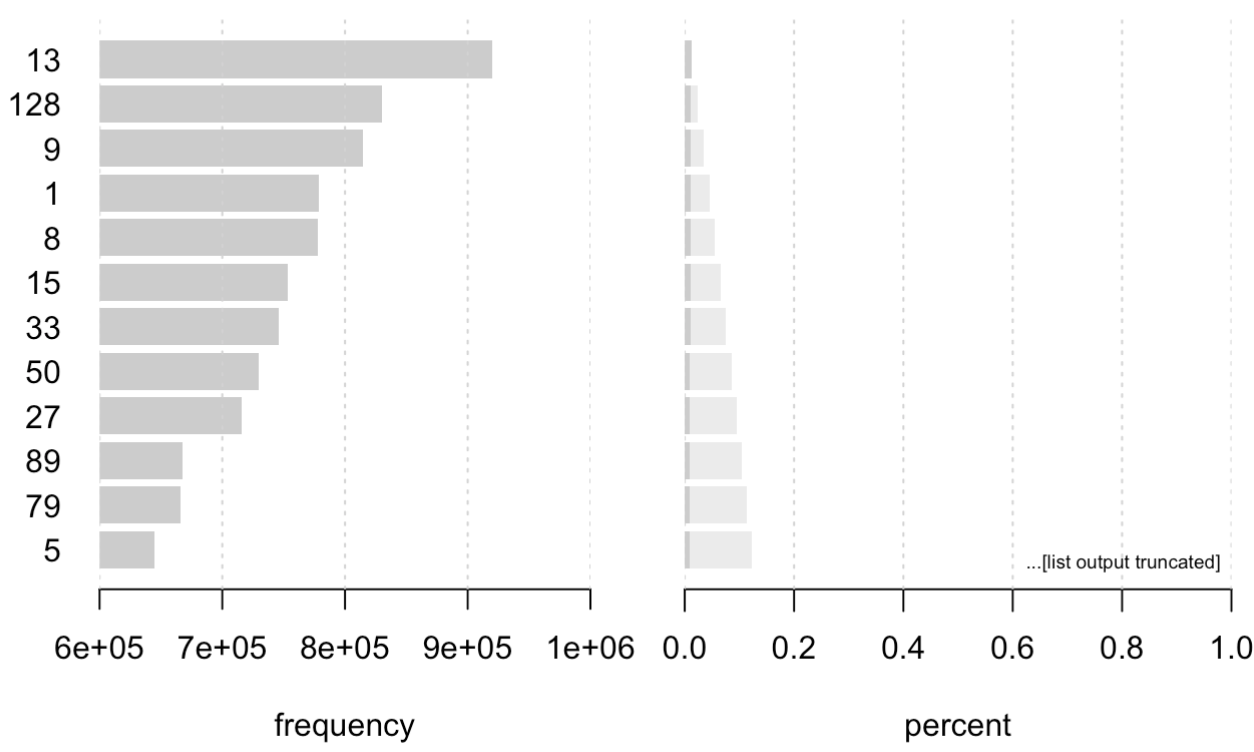
train\$Producto_ID (factor)



```
Desc(train$Town, plotit = TRUE)
```

```
## -----
## train$Town (factor)
##
## length    n  NAs unique levels dupes
## 7e+07 7e+07  0 3e+02 3e+02    y
##
## level freq perc cumfreq cumperc
## 1    13 9e+05 1.2% 9e+05 1.2%
## 2    128 8e+05 1.1% 2e+06 2.4%
## 3     9 8e+05 1.1% 3e+06 3.5%
## 4     1 8e+05 1.0% 3e+06 4.5%
## 5     8 8e+05 1.0% 4e+06 5.6%
## 6    15 8e+05 1.0% 5e+06 6.6%
## 7    33 7e+05 1.0% 6e+06 7.6%
## 8    50 7e+05 1.0% 6e+06 8.6%
## 9    27 7e+05 1.0% 7e+06 9.5%
## 10   89 7e+05 0.9% 8e+06 10.4%
## 11   79 7e+05 0.9% 8e+06 11.3%
## 12    5 6e+05 0.9% 9e+06 12.2%
## ... etc.
## [list output truncated]
```

train\$Town (factor)



```
Desc(train$State, plotit = TRUE)
```

```
## -----
## train$State (factor)
##
## length    n  NAs unique levels dupes
## 7e+07 7e+07  0 3e+01 3e+01    y
##
## level freq  perc cumfreq cumperc
## 1    10 1e+07 14.7% 1e+07 14.7%
## 2    17 8e+06 10.4% 2e+07 25.1%
## 3    14 6e+06  8.7% 3e+07 33.8%
## 4    21 4e+06  5.9% 3e+07 39.6%
## 5    31 4e+06  5.5% 3e+07 45.2%
## 6    11 4e+06  5.3% 4e+07 50.5%
## 7    19 4e+06  4.8% 4e+07 55.3%
## 8    15 3e+06  4.5% 4e+07 59.8%
## 9    13 2e+06  3.1% 5e+07 62.9%
## 10   29 2e+06  3.0% 5e+07 65.8%
## 11    6 2e+06  2.5% 5e+07 68.3%
## 12    2 2e+06  2.4% 5e+07 70.7%
## ... etc.
## [list output truncated]
```

train\$State (factor)

