954:534 Wish Project

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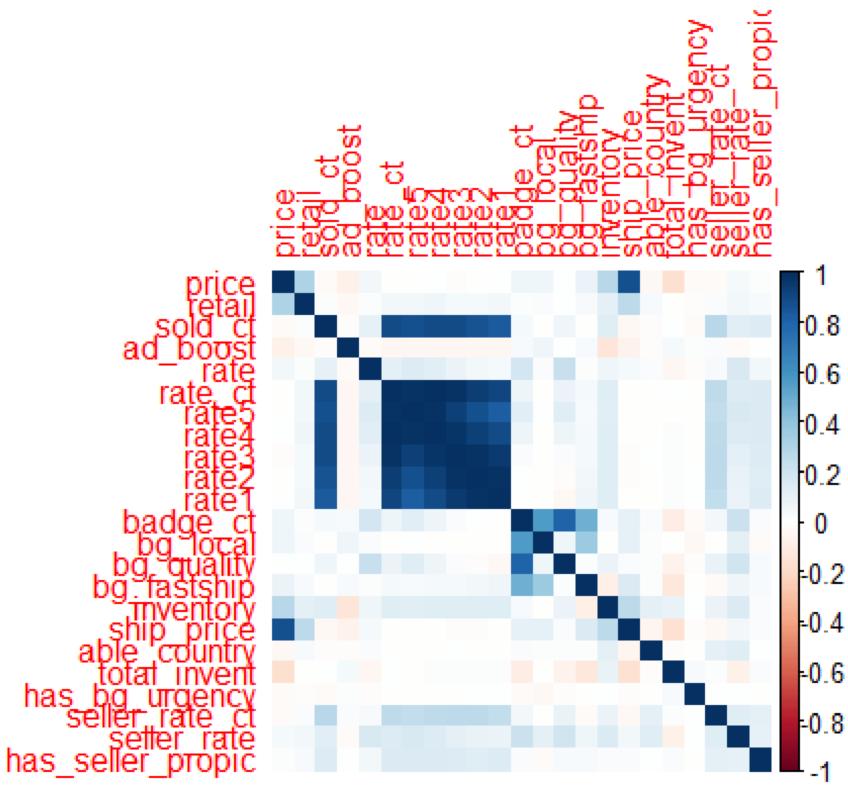
```
options(warn = -1)
library(dplyr)
library(tidyr)
#library(tidyverse)
library(GGally)
library(plotly)
library(cowplot)
library(ggcorrplot)
library(stringr)
```

Data pre-processing

```
wish <- read.csv('summer-products-with-rating-and-performance_2020-08.csv')

#dropping unnecessary columns
drops <- c('title', 'tags', 'crawl_month', 'theme', 'product_id', 'product_pi
cture', 'product_url', 'merchant_id', 'merchant_profile_picture', 'merchant_i
nfo_subtitle', 'merchant_name', 'merchant_title', 'urgency_text', 'title_orig
', 'shipping_option_name', 'currency_buyer')
wish <- wish[, !(names(wish) %in% drops)]

#convert NA to 0
wish$has_urgency_banner <- as.integer(wish$has_urgency_banner)
wish$has_urgency_banner[which(is.na(wish$has_urgency_banner))] <- 0
wish$rating_five_count[which(is.na(wish$rating_five_count))] <- 0
wish$rating_four_count[which(is.na(wish$rating_four_count))] <- 0
wish$rating_three_count[which(is.na(wish$rating_three_count))] <- 0
wish$rating_two_count[which(is.na(wish$rating_two_count))] <- 0
wish$rating_one_count[which(is.na(wish$rating_one_count))] <- 0
wish$rating[which(wish$rating_count == 0)] <- 0

# cleaning size and color option
wish <- wish %>%
  mutate(product_variation_size_id = tolower(product_variation_size_id)) %>%
  mutate(product_variation_size_id = gsub(pattern = '.', replacement = '',
                                          x = product_variation_size_id, fixe
d = TRUE)) %>%
  mutate(product_variation_size_id = gsub(pattern = '(size-*)|(size)', replac
ement = '',
                                          x = product_variation_size_id)) %>%
  mutate(product_variation_size_id = gsub(pattern = '.+[-]', replacement = ''
,
                                          x = product_variation_size_id)) %>%
```

```
  mutate(product_variation_size_id = ifelse(grepl(pattern = 'xl',product_vari
ation_size_id),
                                            'xl', product_variation_size_id))
%>%
  mutate(product_variation_size_id = ifelse(grepl(pattern = 'xs', product_var
iation_size_id),
                                            'xs', product_variation_size_id))
%>%
  mutate(product_variation_size_id = str_replace(product_variation_size_id, '
', '')) %>%
  mutate(product_variation_size_id = ifelse(product_variation_size_id %in% c(
's', 'xs', 'm', 'l', 'xl'),product_variation_size_id, 'One-sized'))
wish <- wish %>%
    mutate(product_color = tolower(product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'red|burgundy|claret|wine|j
asper', product_color),
                                  'red', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'blue|navy', product_color)
,
                                  'blue', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'white', product_color),
                                  'white', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'green|army', product_color
),
                                  'green', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'black', product_color),
                                  'black', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'yellow|leopard|gold', prod
uct_color),
                                  'yellow', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'pink|rose', product_color)
,
                                  'pink', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'grey|gray|silver', product
_color),
                                  'gray', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'purple|violet', product_co
lor),
                                  'purple', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'orange|apricot', product_c
olor),
                                  'orange', product_color)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'beige|nude|ivory|coffee|br
own|khaki|camel',
                                        product_color), 'khaki', product_colo
r)) %>%
    mutate(product_color = ifelse(grepl(pattern = 'floral|multicolor|camoufla
ge|rainbow|star',
                                        product_color), 'multicolor', product
_color))
```

```r
#name blank category
wish['product_color'][wish['product_color'] == ''] <- 'Not defined'
wish['origin_country'][wish['origin_country'] == ''] <- 'Not defined'

#shipping_is_express has too many zero, so we decided to exclude this column
wish <- select(wish, -c(shipping_is_express))

#Only 7 colors have more than 100 records so We decided to keep only 8 factor
s of color, i.e. black, white, blue, red, green, yellow, pink and others.
color_list <- c('black', 'white', 'blue', 'red', 'green', 'yellow', 'pink')
wish$product_color[!(wish$product_color %in% color_list)] <- 'others'

wish %>%
  group_by(product_color) %>%
  summarise(no_rows = length(product_color)) %>%
  arrange(desc(no_rows)) %>%
  filter(no_rows > 100)

#We decided to change origin to CN and others.
wish$origin_country <- as.character(wish$origin_country)
wish$origin_country[which(wish$origin_country != 'CN')] <- 'others'
wish$origin_country[is.na(wish$origin_country)] <- 'others'

wish %>%
  group_by(origin_country) %>%
  summarise(no_rows = length(origin_country)) %>%
  arrange(desc(no_rows))

#convert column name to short version
origin_colname <- colnames(wish)
colnames(wish) <- c('price', 'retail', 'sold_ct', 'ad_boost', 'rate', 'rate_c
t', 'rate5', 'rate4', 'rate3', 'rate2', 'rate1', 'badge_ct', 'bg_local', 'bg_
quality', 'bg_fastship', 'color', 'size', 'inventory', 'ship_price', 'able_co
untry', 'total_invent', 'has_bg_urgency', 'origin', 'seller_rate_ct', 'seller
_rate', 'has_seller_propic')

library(corrplot)

## corrplot 0.84 loaded

# finding correlation between numeric columns and charges

numeric.column <- sapply(wish, is.numeric)
corr <- cor(wish[, numeric.column]) #, use = 'pairwise.complete.obs'
corrplot(corr, method = 'color')
```



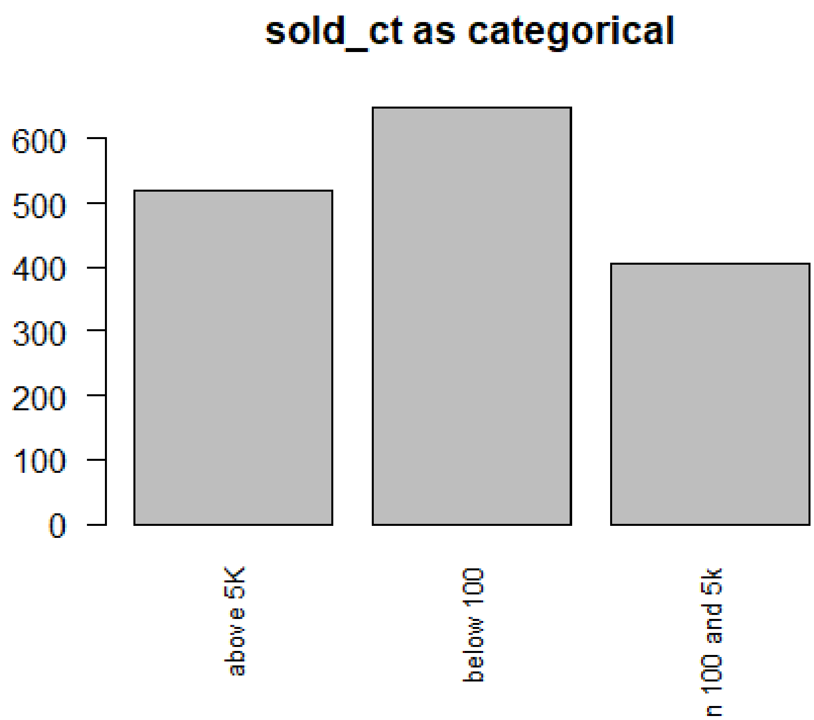

```
#convert the y (sold_ct) to categorical. Also since it is unbalanced we group
some category together.
table(wish['sold_ct']) # very unbalaned
```

```
##
##      1      2      3      6      7      8     10     50    100   1000    50
00
##      3      2      2      1      2      4     49     76    509    405     2
17
##  10000  20000  50000 100000
##    177    103     17      6
```

```
wish_cate <- wish
wish_cate$sold_ct_cate <- wish_cate$sold_ct
wish_cate$sold_ct_cate[which(wish_cate$sold_ct <= 100)] <- 'below 100'
wish_cate$sold_ct_cate[which(wish_cate$sold_ct >= 5000)] <- 'above 5K'
wish_cate$sold_ct_cate[which(wish_cate$sold_ct > 100 & wish_cate$sold_ct < 50
00)] <- 'between 100 and 5k'
wish_cate <- select(wish_cate, -sold_ct)
wish_cate$sold_ct_cate <- as.factor(wish_cate$sold_ct_cate)
wish_cate$color <- as.factor(wish_cate$color)
wish_cate$size <- as.factor(wish_cate$size)
wish_cate$origin <- as.factor(wish_cate$origin)
table(wish_cate$sold_ct_cate) # much better
```

```
##
##           above 5K          below 100 between 100 and 5k
##                520                648                405
```

```
x1 <- factor(wish_cate$sold_ct_cate)
tb <- table(x1)
barplot(tb, names.arg = row.names(tb), cex.names = 0.8, main = "sold_ct as ca
tegorical", las = 2)
```




```
#percentage of each rate count
wish_cate$rate5_pct <- wish_cate$rate5/wish_cate$rate_ct
wish_cate$rate4_pct <- wish_cate$rate4/wish_cate$rate_ct
wish_cate$rate3_pct <- wish_cate$rate3/wish_cate$rate_ct
wish_cate$rate2_pct <- wish_cate$rate2/wish_cate$rate_ct
wish_cate$rate1_pct <- wish_cate$rate1/wish_cate$rate_ct

drops <- c('rate_ct', 'rate5', 'rate4', 'rate3', 'rate2', 'rate1')
wish_cate <- wish_cate[, !(names(wish_cate) %in% drops)]

wish_cate <- wish_cate %>% drop_na(rate5_pct)
wish_cate <- wish_cate %>% drop_na(price)

summary(wish_cate)
```

```
##      price            retail           ad_boost          rate
##  Min.   : 1.000   Min.   :  1.00   Min.   :0.0000   Min.   :1.000
##  1st Qu.: 5.830   1st Qu.:  7.00   1st Qu.:0.0000   1st Qu.:3.530
```

```
##  Median : 8.000   Median : 10.00   Median :0.0000   Median :3.830
##  Mean   : 8.335   Mean   : 23.27   Mean   :0.4332   Mean   :3.786
##  3rd Qu.:11.000   3rd Qu.: 26.00   3rd Qu.:1.0000   3rd Qu.:4.090
##  Max.   :49.000   Max.   :252.00   Max.   :1.0000   Max.   :5.000
##
##     badge_ct         bg_local          bg_quality        bg_fastship
##  Min.   :0.0000   Min.   :0.00000   Min.   :0.00000   Min.   :0.00000
##  1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.00000
##  Median :0.0000   Median :0.00000   Median :0.00000   Median :0.00000
##  Mean   :0.1086   Mean   :0.01898   Mean   :0.07657   Mean   :0.01309
##  3rd Qu.:0.0000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.00000
##  Max.   :3.0000   Max.   :1.00000   Max.   :1.00000   Max.   :1.00000
##
##      color              size        inventory       ship_price
##  black  :304   l        : 53   Min.   : 1.00   Min.   : 1.000
##  others :278   m        :204   1st Qu.: 6.00   1st Qu.: 2.000
##  white  :268   One-sized: 87   Median :50.00   Median : 2.000
##  blue   :167   s        :669   Mean   :33.22   Mean   : 2.345
##  red    :150   xl       : 56   3rd Qu.:50.00   3rd Qu.: 3.000
##  green  :138   xs       :459   Max.   :50.00   Max.   :12.000
##  (Other):223
##   able_country     total_invent   has_bg_urgency     origin
##  Min.   :  6.00   Min.   : 1.00   Min.   :0.000   CN    :1472
##  1st Qu.: 31.00   1st Qu.:50.00   1st Qu.:0.000   others:  56
##  Median : 40.00   Median :50.00   Median :0.000
##  Mean   : 40.45   Mean   :49.82   Mean   :0.301
##  3rd Qu.: 43.00   3rd Qu.:50.00   3rd Qu.:1.000
##  Max.   :140.00   Max.   :50.00   Max.   :1.000
##
##  seller_rate_ct     seller_rate    has_seller_propic             sold_ct_c
ate
##  Min.   :      3   Min.   :2.941   Min.   :0.0000    above 5K           :52
0
##  1st Qu.:   2116   1st Qu.:3.919   1st Qu.:0.0000    below 100          :60
3
##  Median :   8194   Median :4.041   Median :0.0000    between 100 and 5k:40
5
##  Mean   :  26667   Mean   :4.033   Mean   :0.1466
##  3rd Qu.:  24616   3rd Qu.:4.160   3rd Qu.:0.0000
##  Max.   :2174765   Max.   :4.578   Max.   :1.0000
##
##    rate5_pct        rate4_pct        rate3_pct        rate2_pct
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.00000
##  1st Qu.:0.3889   1st Qu.:0.1603   1st Qu.:0.1082   1st Qu.:0.04147
##  Median :0.4715   Median :0.1879   Median :0.1429   Median :0.06667
##  Mean   :0.4680   Mean   :0.1861   Mean   :0.1406   Mean   :0.07467
##  3rd Qu.:0.5537   3rd Qu.:0.2143   3rd Qu.:0.1693   3rd Qu.:0.09140
##  Max.   :1.0000   Max.   :0.6667   Max.   :0.5000   Max.   :1.00000
##
##    rate1_pct
```

```
##  Min.   :0.00000
##  1st Qu.:0.07021
##  Median :0.11073
##  Mean   :0.13069
##  3rd Qu.:0.16874
##  Max.   :1.00000
##
```

```r
str(wish_cate)
```

```
## 'data.frame':    1528 obs. of  25 variables:
##  $ price            : num  16 8 8 8 2.72 3.92 7 12 11 5.78 ...
##  $ retail           : int  14 22 43 8 3 9 6 11 84 22 ...
##  $ ad_boost         : int  0 1 0 1 1 0 0 0 1 0 ...
##  $ rate             : num  3.76 3.45 3.57 4.03 3.1 5 3.84 3.76 3.47 3.6 ..
.
##  $ badge_ct         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bg_local         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bg_quality       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bg_fastship      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ color            : Factor w/ 8 levels "black","blue",..: 7 3 8 1 8 2 7
2 1 4 ...
##  $ size             : Factor w/ 6 levels "l","m","One-sized",..: 2 6 6 2 4
6 6 2 2 4 ...
##  $ inventory        : int  50 50 1 50 1 1 50 50 50 50 ...
##  $ ship_price       : int  4 2 3 2 1 1 2 3 2 2 ...
##  $ able_country     : int  34 41 36 41 35 40 31 139 36 33 ...
##  $ total_invent     : int  50 50 50 50 50 50 50 50 50 50 ...
##  $ has_bg_urgency   : num  1 1 1 0 1 0 0 0 1 0 ...
##  $ origin           : Factor w/ 2 levels "CN","others": 1 1 1 1 1 1 1 1 1
1 ...
##  $ seller_rate_ct   : int  568 17752 295 23832 14482 65 10194 342 330 5534
...
##  $ seller_rate      : num  4.13 3.9 3.99 4.02 4 ...
##  $ has_seller_propic: int  0 0 0 0 0 0 1 0 0 0 ...
##  $ sold_ct_cate     : Factor w/ 3 levels "above 5K","below 100",..: 2 1 2
1 2 2 1 3 2 1 ...
##  $ rate5_pct        : num  0.481 0.37 0.357 0.509 0.3 ...
##  $ rate4_pct        : num  0.148 0.167 0.286 0.206 0.2 ...
##  $ rate3_pct        : num  0.185 0.182 0.143 0.15 0.1 ...
##  $ rate2_pct        : num  0.0185 0.105 0 0.0725 0.1 ...
##  $ rate1_pct        : num  0.1667 0.1756 0.2143 0.0622 0.3 ...
```

Methodology

80:20 split for train and test set

```r
set.seed(123)

train_rows <- sample(1:nrow(wish), 0.8 * nrow(wish))
```

```r
wish.train <- wish_cate[train_rows, ] # wish training set
wish.test <- wish_cate[-train_rows, ]

wish.train <- wish.train %>% drop_na(price)
```

Multinomial Regression

```r
set.seed(123)
library(nnet)
multinomial.mod <- multinom(sold_ct_cate ~ ., data = wish.train) #, na.action
= na.roughfix

## # weights:  108 (70 variable)
## initial  value 1339.208380
## iter  10 value 1255.977483
## iter  20 value 1189.343320
## iter  30 value 1164.442293
## iter  40 value 1161.648181
## iter  50 value 1160.944105
## iter  60 value 1160.541882
## iter  70 value 1159.267178
## iter  80 value 1158.778710
## final  value 1158.151626
## converged

summary(multinomial.mod)

## Call:
## multinom(formula = sold_ct_cate ~ ., data = wish.train)
##
## Coefficients:
##                      (Intercept)      price      retail   ad_boost     rate
## below 100               61.52575 0.05993473 0.007125439 0.02511886 52.47417
## between 100 and 5k     162.13209 0.05669671 0.006771135 0.19507681  8.30567
##                         badge_ct   bg_local  bg_quality bg_fastship   colorb
lue
## below 100            -0.09765252 -1.0448405 -0.07811868  1.02530663 -0.17996
180
## between 100 and 5k    0.01625992 -0.2818895  0.24682887  0.05132056 -0.03807
248
##                      colorgreen  colorothers  colorpink  colorred  colorwhit
e
## below 100             0.2602755 -0.187931448 -0.0856353 0.1882070 -0.2789398
1
## between 100 and 5k    0.3371423 -0.000843693  0.4433978 0.6170049 -0.0426730
5
##                      coloryellow      sizem sizeOne-sized      sizes      siz
exl
## below 100              0.9822648  0.1970586     1.5743267 0.41382825  0.8979
739
```

```
## between 100 and 5k   1.2630431 -0.3892427     0.5845379 0.01774944 -0.3659
442
##                        sizexs    inventory  ship_price able_country total_i
nvent
## below 100          1.3233542 -0.011385347 -0.17951453   0.01114518    -4.4
93798
## between 100 and 5k 0.5343495 -0.006466085 -0.05803779   0.01434421    -4.3
65661
##                    has_bg_urgency originothers seller_rate_ct seller_rate
## below 100              0.09241284    1.0077496  -1.677742e-05  -1.6910850
## between 100 and 5k     0.17423052    0.1463904  -1.292792e-05  -0.5705007
##                    has_seller_propic rate5_pct rate4_pct rate3_pct rate2_p
ct
## below 100                 -0.33584439 -93.12020 -40.06576  8.845931  65.005
29
## between 100 and 5k         0.07444447  15.54658  24.04949 32.023675  39.895
97
##                    rate1_pct
## below 100          120.86049
## between 100 and 5k  50.61638
##
## Std. Errors:
##                     (Intercept)        price      retail     ad_boost
## below 100          8.607617e-05 0.0005094232 0.002561476 5.506705e-05
## between 100 and 5k 9.088986e-05 0.0006262238 0.002580111 6.270339e-05
##                            rate     badge_ct     bg_local   bg_quality
## below 100          0.0003177981 4.290554e-06 1.452266e-06 5.115773e-06
## between 100 and 5k 0.0003372213 9.832451e-06 3.080471e-06 8.086474e-06
##                     bg_fastship    colorblue   colorgreen  colorothers
## below 100          1.197296e-06 6.700695e-06 1.170119e-05 2.473794e-05
## between 100 and 5k 8.439712e-07 6.012753e-06 1.348777e-05 2.312286e-05
##                       colorpink     colorred   colorwhite  coloryellow
## below 100          7.596063e-06 1.558492e-05 2.029067e-05 1.036194e-05
## between 100 and 5k 8.749608e-06 1.770766e-05 1.659566e-05 1.452224e-05
##                           sizem sizeOne-sized        sizes       sizexl
## below 100          9.245807e-06  4.306001e-06 2.445879e-05 2.957718e-06
## between 100 and 5k 4.759126e-06  6.895911e-06 3.000295e-05 1.796344e-06
##                          sizexs   inventory   ship_price able_country
## below 100          8.797572e-05 0.003763135 0.0001556580  0.004116648
## between 100 and 5k 8.126724e-05 0.004002453 0.0001837391  0.004186555
##                    total_invent has_bg_urgency originothers seller_rate_ct
## below 100           0.004305804   2.088730e-05 2.187938e-06   2.664673e-06
## between 100 and 5k  0.004542852   2.247189e-05 1.212141e-06   2.407260e-06
##                     seller_rate has_seller_propic    rate5_pct    rate4_pc
t
## below 100          0.0003359766      1.283221e-05 3.756664e-05 1.633464e-0
5
## between 100 and 5k 0.0003572466      2.017580e-05 3.987934e-05 1.703798e-0
5
##                       rate3_pct    rate2_pct    rate1_pct
```

```
## below 100          1.258024e-05 7.464148e-06 1.229044e-05
## between 100 and 5k 1.458081e-05 6.645865e-06 1.281971e-05
##
## Residual Deviance: 2316.303
## AIC: 2448.303
```

```
multinomial.pred_train <- predict(multinomial.mod, wish.train)
multinomial.pred_test <- predict(multinomial.mod, wish.test)
# training error
print("Misclassification rate on the training set:")
```

```
## [1] "Misclassification rate on the training set:"
```

```
mean(as.character(multinomial.pred_train) != as.character(wish.train$sold_ct_
cate))
```

```
## [1] 0.4577523
```

```
# test error
print("Misclassification rate on the test set:")
```

```
## [1] "Misclassification rate on the test set:"
```

```
mean(as.character(multinomial.pred_test) != as.character(wish.test$sold_ct_ca
te))
```

```
## [1] 0.4854369
```

```
confusion.matrix <- table(wish.test$sold_ct_cate, multinomial.pred_test)
print(confusion.matrix)
```

```
##                       multinomial.pred_test
##                        above 5K below 100 between 100 and 5k
##   above 5K                   61        28                 15
##   below 100                  27        90                  7
##   between 100 and 5k         26        47                  8
```

```
accuracy.percent <- 100*sum(diag(confusion.matrix))/sum(confusion.matrix)
above5k.precent <- 100*confusion.matrix[1,1]/sum(confusion.matrix[1,])
print(paste("Test accuracy:",accuracy.percent,"%"))
```

```
## [1] "Test accuracy: 51.4563106796116 %"
```

```
print(paste("Above 5k accuracy:",above5k.precent,"%"))
```

```
## [1] "Above 5k accuracy: 58.6538461538462 %"
```

Dicision Tree Models

```
library(tree)
```

```
## Registered S3 method overwritten by 'tree':
##   method     from
##   print.tree cli
```

```
set.seed(123)

tree.wish <- tree(sold_ct_cate ~ ., data = wish.train)
summary(tree.wish)
```

```
##
## Classification tree:
## tree(formula = sold_ct_cate ~ ., data = wish.train)
## Variables actually used in tree construction:
## [1] "rate2_pct"      "seller_rate_ct" "rate3_pct"      "rate4_pct"
## Number of terminal nodes:  10
## Residual mean deviance:  1.418 = 1715 / 1209
## Misclassification error rate: 0.3158 = 385 / 1219
```

```
tree.pred <- predict(tree.wish, wish.test, type = "class")

# table(tree.pred, wish.test$sold_ct_cate)

# print("Misclassification error rate on test set: ")

confusion.matrix <- table(wish.test$sold_ct_cate, tree.pred)
print(confusion.matrix)
```

```
##                      tree.pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  88         5                 11
##   below 100                 13        98                 13
##   between 100 and 5k        42        20                 19
```

```
accuracy.percent <- 100*sum(diag(confusion.matrix))/sum(confusion.matrix)
above5k.precent <- 100*confusion.matrix[1,1]/sum(confusion.matrix[1,])
print(paste("Test accuracy:",accuracy.percent,"%"))
```

```
## [1] "Test accuracy: 66.3430420711974 %"
```

```
print(paste("Above 5k accuracy:",above5k.precent,"%"))
```

```
## [1] "Above 5k accuracy: 84.6153846153846 %"
```

Bagging

```
library(randomForest)
```

```
## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

## The following object is masked from 'package:dplyr':
##
##     combine
```

```
set.seed(123)

bag.wish <- randomForest(sold_ct_cate ~ ., data = wish.train, mtry = length(w
ish.train) - 1, importance = TRUE, na.action = na.roughfix)
bag.wish
```

```
##
## Call:
##  randomForest(formula = sold_ct_cate ~ ., data = wish.train, mtry = length
(wish.train) -      1, importance = TRUE, na.action = na.roughfix)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 24
##
##         OOB estimate of  error rate: 27.07%
## Confusion matrix:
##                     above 5K below 100 between 100 and 5k class.error
## above 5K                 329        10                 77   0.2091346
## below 100                 20       419                 40   0.1252610
## between 100 and 5k       122        61                141   0.5648148
```

```
bag.pred <- predict(bag.wish, wish.test)

confusion.matrix <- table(wish.test$sold_ct_cate, bag.pred)
print(confusion.matrix)
```

```
##                      bag.pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  84         3                 17
##   below 100                  3       111                 10
##   between 100 and 5k        24        12                 45
```

```
accuracy.percent <- 100*sum(diag(confusion.matrix))/sum(confusion.matrix)
above5k.precent <- 100*confusion.matrix[1,1]/sum(confusion.matrix[1,])
print(paste("Test accuracy:",accuracy.percent,"%"))
```

```
## [1] "Test accuracy: 77.6699029126214 %"
```

```
print(paste("Above 5k accuracy:",above5k.precent,"%"))
```

```
## [1] "Above 5k accuracy: 80.7692307692308 %"
```

Random forest

```
set.seed(123)

rf.wish <- randomForest(sold_ct_cate ~ ., data = wish.train, mtry = (length(w
ish.train) - 1) / 3, importance = TRUE, na.action = na.roughfix)
rf.wish

##
## Call:
##  randomForest(formula = sold_ct_cate ~ ., data = wish.train, mtry = (lengt
h(wish.train) -      1)/3, importance = TRUE, na.action = na.roughfix)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 8
##
##         OOB estimate of  error rate: 27.24%
## Confusion matrix:
##                     above 5K below 100 between 100 and 5k class.error
## above 5K                 331        13                 72   0.2043269
## below 100                 23       419                 37   0.1252610
## between 100 and 5k       122        65                137   0.5771605

rf.pred <- predict(rf.wish, wish.test)


confusion.matrix <- table(wish.test$sold_ct_cate, rf.pred)
print(confusion.matrix)

##                      rf.pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  83         2                 19
##   below 100                  4       108                 12
##   between 100 and 5k        23        12                 46

accuracy.percent <- 100*sum(diag(confusion.matrix))/sum(confusion.matrix)
above5k.precent <- 100*confusion.matrix[1,1]/sum(confusion.matrix[1,])
print(paste("Test accuracy:",accuracy.percent,"%"))

## [1] "Test accuracy: 76.6990291262136 %"

print(paste("Above 5k accuracy:",above5k.precent,"%"))

## [1] "Above 5k accuracy: 79.8076923076923 %"
```

SVM

Linear

```
library(e1071)
# summary(wish.train)
```

```r
# summary(wish.test)

set.seed(123)

tuned <- tune(svm, sold_ct_cate ~ ., data = wish.train, kernel = "linear", ra
nges = list(cost = append(seq(0.01, 10, by = 0.5), 10)))
summary(tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##   8.51
##
## - best performance: 0.4814862
##
## - Detailed performance results:
##     cost     error dispersion
## 1   0.01 0.5053109 0.04242946
## 2   0.51 0.4839385 0.04506527
## 3   1.01 0.4839656 0.04133876
## 4   1.51 0.4839724 0.04068346
## 5   2.01 0.4814998 0.03790904
## 6   2.51 0.4815066 0.03637876
## 7   3.01 0.4814998 0.04201858
## 8   3.51 0.4831459 0.03843672
## 9   4.01 0.4831391 0.04081346
## 10  4.51 0.4839588 0.04090609
## 11  5.01 0.4847785 0.04098030
## 12  5.51 0.4831324 0.04218639
## 13  6.01 0.4847853 0.03975657
## 14  6.51 0.4839520 0.04349467
## 15  7.01 0.4831256 0.04569449
## 16  7.51 0.4831324 0.04340741
## 17  8.01 0.4839520 0.04434453
## 18  8.51 0.4814862 0.04346441
## 19  9.01 0.4823127 0.04347480
## 20  9.51 0.4814862 0.04380657
## 21 10.00 0.4831324 0.04357905
```

```r
print("The best cost:")
```

```
## [1] "The best cost:"
```

```r
tuned$best.parameter$cost
```

```
## [1] 8.51
```

```
lin.svm <- svm(sold_ct_cate ~ ., kernel = "linear", type = "C-class", data =
wish.train, cost = tuned$best.parameter$cost)

train_pred <- predict(lin.svm, wish.train, na.action = na.exclude)
table <- table(wish.train$sold_ct_cate, train_pred)

print(paste("accuracy with cost =", tuned$best.parameter$cost, "for train: ")
)

## [1] "accuracy with cost = 8.51 for train: "

1-(sum(table)-sum(diag(table))) / (sum(table))

## [1] 0.5348646

test_pred <- predict(lin.svm, wish.test)
table <- table(wish.test$sold_ct_cate, test_pred)

print(paste("accuracy with cost =", tuned$best.parameter$cost, "for test: "))

## [1] "accuracy with cost = 8.51 for test: "

1-(sum(table)-sum(diag(table))) / (sum(table))

## [1] 0.5048544

print(paste("above 5k group - accuracy with cost =", tuned$best.parameter$cos
t, ": "))

## [1] "above 5k group - accuracy with cost = 8.51 : "

sum(table[1,1]) /sum(table[1,])

## [1] 0.5384615

# we cannot plot SVM classification plot since we have more than 2 columns
table(wish.test$sold_ct_cate, test_pred)

##                      test_pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  56        35                 13
##   below 100                 18        91                 15
##   between 100 and 5k        26        46                  9
```

Radial

```
# names(wish.train)
set.seed(123)

tuned <- tune(svm, sold_ct_cate ~ ., data = wish.train, kernel = "radial", ra
nges = list(cost = append(seq(0.01, 15, by = 0.5), 10)))
summary(tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##    cost
##   12.01
##
## - best performance: 0.3675112
##
## - Detailed performance results:
##      cost     error dispersion
## 1    0.01 0.6070519 0.04260201
## 2    0.51 0.4298537 0.03659364
## 3    1.01 0.4159193 0.03849578
## 4    1.51 0.4077293 0.03480182
## 5    2.01 0.3995258 0.03606130
## 6    2.51 0.3970532 0.03736618
## 7    3.01 0.3904891 0.04562588
## 8    3.51 0.3921284 0.04731593
## 9    4.01 0.3863907 0.04793160
## 10   4.51 0.3822924 0.03879900
## 11   5.01 0.3814862 0.03992683
## 12   5.51 0.3823059 0.03877121
## 13   6.01 0.3814795 0.03870461
## 14   6.51 0.3781940 0.03609755
## 15   7.01 0.3790137 0.03875255
## 16   7.51 0.3814659 0.03912204
## 17   8.01 0.3839249 0.03433190
## 18   8.51 0.3822788 0.03786632
## 19   9.01 0.3781872 0.03880695
## 20   9.51 0.3749085 0.03738736
## 21  10.01 0.3757282 0.03752909
## 22  10.51 0.3699837 0.03683100
## 23  11.01 0.3683376 0.03636024
## 24  11.51 0.3683308 0.03789495
## 25  12.01 0.3675112 0.03489759
## 26  12.51 0.3691505 0.03202574
## 27  13.01 0.3716095 0.03338185
## 28  13.51 0.3732557 0.03371330
## 29  14.01 0.3691573 0.03347686
## 30  14.51 0.3675180 0.03184827
## 31  10.00 0.3749085 0.03718716
```

```r
print("The best cost:")
```

```
## [1] "The best cost:"
```

```r
tuned$best.parameter$cost
```

```
## [1] 12.01

rad.svm <- svm(sold_ct_cate ~ ., kernel = "radial", data = wish.train, cost =
tuned$best.parameter$cost)

train_pred <- predict(rad.svm, wish.train, na.action = na.exclude)
table <- table(wish.train$sold_ct_cate, train_pred)

print(paste("accuracy with cost =", tuned$best.parameter$cost, "for train: ")
)

## [1] "accuracy with cost = 12.01 for train: "

1-(sum(table)-sum(diag(table))) / (sum(table))

## [1] 0.8630025

test_pred <- predict(rad.svm, wish.test)
table <- table(wish.test$sold_ct_cate, test_pred)

print(paste("accuracy with cost =", tuned$best.parameter$cost, "for test: "))

## [1] "accuracy with cost = 12.01 for test: "

1-(sum(table)-sum(diag(table))) / (sum(table))

## [1] 0.6343042

print(paste("above 5k group - accuracy with cost =", tuned$best.parameter$cos
t, ": "))

## [1] "above 5k group - accuracy with cost = 12.01 : "

sum(table[1,1]) /sum(table[1,])

## [1] 0.6730769

table(wish.test$sold_ct_cate, test_pred)

##                      test_pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  70         8                 26
##   below 100                 11        93                 20
##   between 100 and 5k        36        12                 33
```

The result shows that there is overfitting issue. (traing error is getting low, but test error is getting higher)

Polynomial

```
set.seed(123)
tune.poly <- tune(svm, sold_ct_cate ~ ., data = wish.train, kernel = "poly",
```

```r
degree = 3, ranges = list(cost = append(seq(0.01, 15, by = 0.5), 10)))
summary(tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##  12.01
##
## - best performance: 0.3675112
##
## - Detailed performance results:
##     cost     error dispersion
## 1   0.01 0.6070519 0.04260201
## 2   0.51 0.4298537 0.03659364
## 3   1.01 0.4159193 0.03849578
## 4   1.51 0.4077293 0.03480182
## 5   2.01 0.3995258 0.03606130
## 6   2.51 0.3970532 0.03736618
## 7   3.01 0.3904891 0.04562588
## 8   3.51 0.3921284 0.04731593
## 9   4.01 0.3863907 0.04793160
## 10  4.51 0.3822924 0.03879900
## 11  5.01 0.3814862 0.03992683
## 12  5.51 0.3823059 0.03877121
## 13  6.01 0.3814795 0.03870461
## 14  6.51 0.3781940 0.03609755
## 15  7.01 0.3790137 0.03875255
## 16  7.51 0.3814659 0.03912204
## 17  8.01 0.3839249 0.03433190
## 18  8.51 0.3822788 0.03786632
## 19  9.01 0.3781872 0.03880695
## 20  9.51 0.3749085 0.03738736
## 21 10.01 0.3757282 0.03752909
## 22 10.51 0.3699837 0.03683100
## 23 11.01 0.3683376 0.03636024
## 24 11.51 0.3683308 0.03789495
## 25 12.01 0.3675112 0.03489759
## 26 12.51 0.3691505 0.03202574
## 27 13.01 0.3716095 0.03338185
## 28 13.51 0.3732557 0.03371330
## 29 14.01 0.3691573 0.03347686
## 30 14.51 0.3675180 0.03184827
## 31 10.00 0.3749085 0.03718716
```

```r
print("The best cost:")
```

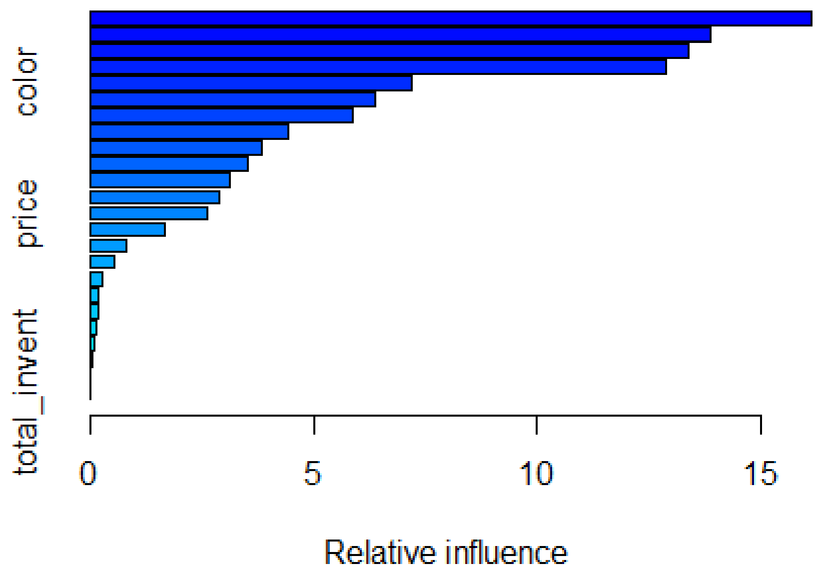
```
## [1] "The best cost:"

tuned$best.parameter$cost

## [1] 12.01

poly.svm <- svm(sold_ct_cate ~ ., kernel = "poly", data = wish.train, degree
= 3, cost = tuned$best.parameter$cost)

train_pred <- predict(poly.svm, wish.train, na.action = na.exclude)
table <- table(wish.train$sold_ct_cate, train_pred)

print(paste("accuracy with cost =", tuned$best.parameter$cost, "for train: ")
)

## [1] "accuracy with cost = 12.01 for train: "

1-(sum(table)-sum(diag(table))) / (sum(table))

## [1] 0.733388

test_pred <- predict(poly.svm, wish.test)
table <- table(wish.test$sold_ct_cate, test_pred)

print(paste("accuracy with cost =", tuned$best.parameter$cost, "for test: "))

## [1] "accuracy with cost = 12.01 for test: "

1-(sum(table)-sum(diag(table))) / (sum(table))

## [1] 0.5566343

print(paste("above 5k group - accuracy with cost =", tuned$best.parameter$cos
t, ": "))

## [1] "above 5k group - accuracy with cost = 12.01 : "

sum(table[1,1]) /sum(table[1,])

## [1] 0.8461538

table(wish.test$sold_ct_cate, test_pred)

##                      test_pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  88         5                 11
##   below 100                 35        74                 15
##   between 100 and 5k        59        12                 10
```

GBM

```
library(gbm)
```

```
## Loaded gbm 2.1.8
```

```r
boost.wish = gbm(sold_ct_cate ~ ., data = wish.train, distribution = "multinomial", n.trees = 10000, shrinkage = 0.01, interaction.depth = 4)
summary(boost.wish)
```




```
##                                 var    rel.inf
## rate2_pct                 rate2_pct 16.12485958
## rate4_pct                 rate4_pct 13.86494973
## rate3_pct                 rate3_pct 13.34848772
## seller_rate_ct       seller_rate_ct 12.84795272
## color                         color  7.17406831
## rate1_pct                 rate1_pct  6.38769545
## seller_rate             seller_rate  5.85917016
## rate5_pct                 rate5_pct  4.41883467
## retail                       retail  3.84763373
## able_country           able_country  3.50756573
## rate                           rate  3.14135646
## size                           size  2.90831988
## price                         price  2.64017935
## inventory                 inventory  1.67281080
## ship_price               ship_price  0.82420334
## ad_boost                   ad_boost  0.53543846
## has_bg_urgency       has_bg_urgency  0.26273503
## bg_quality               bg_quality  0.18791776
## badge_ct                   badge_ct  0.17240086
## has_seller_propic has_seller_propic  0.12808411
```

```
## origin                        origin  0.08833278
## bg_local                    bg_local  0.05700338
## bg_fastship              bg_fastship  0.00000000
## total_invent            total_invent  0.00000000

boost.predP <- predict(boost.wish, wish.test, n.trees = 10000, type = 'respon
se')

classification <- c("above 5K", "below 100", "between 100 and 5k")
boost.pred <- apply(boost.predP, 1, which.max)
boost.pred <- classification[boost.pred]
confusion.matrix <- table(wish.test$sold_ct_cate, boost.pred)
print(confusion.matrix)

##                      boost.pred
##                       above 5K below 100 between 100 and 5k
##   above 5K                  82         3                 19
##   below 100                  4       108                 12
##   between 100 and 5k        20        10                 51

accuracy.percent <- 100*sum(diag(confusion.matrix))/sum(confusion.matrix)
above5k.precent <- 100*confusion.matrix[1,1]/sum(confusion.matrix[1,])
print(paste("Test accuracy:",accuracy.percent,"%"))

## [1] "Test accuracy: 77.9935275080906 %"

print(paste("Above 5k accuracy:",above5k.precent,"%"))

## [1] "Above 5k accuracy: 78.8461538461538 %"
```

XGBoost

```
library(xgboost)
# Create numeric labels with one-hot encoding
set.seed(123)
train_labs <- as.numeric(wish.train$sold_ct_cate) - 1
val_labs <- as.numeric(wish.test$sold_ct_cate) - 1

# options(na.action='na.pass')
new_train <- model.matrix(~ . + 0, data = subset(wish.train, select = -sold_c
t_cate))
new_val <- model.matrix(~ . + 0, data = subset(wish.test, select = -sold_ct_c
ate))

# Prepare matrices
xgb_train <- xgb.DMatrix(data = new_train, label = train_labs)
xgb_val <- xgb.DMatrix(data = new_val, label = val_labs)

params <- list(booster = "gbtree", objective = "multi:softprob", num_class =
4, eval_metric = "mlogloss")
```

```r
# Calculate # of folds for cross-validation
xgbcv <- xgb.cv(params = params, data = xgb_train, nrounds = 100, nfold = 5,
showsd = TRUE, stratified = TRUE, print_every_n = 10, early_stop_round = 20,
maxiimize = FALSE, prediction = TRUE)
```

```
## [1]  train-mlogloss:1.128172+0.005632    test-mlogloss:1.169920+0.009762
## [11] train-mlogloss:0.433942+0.010224    test-mlogloss:0.684675+0.038885
## [21] train-mlogloss:0.230444+0.008175    test-mlogloss:0.632566+0.043106
## [31] train-mlogloss:0.140213+0.007266    test-mlogloss:0.634191+0.042982
## [41] train-mlogloss:0.088632+0.005966    test-mlogloss:0.638861+0.046647
## [51] train-mlogloss:0.060192+0.003827    test-mlogloss:0.654579+0.053184
## [61] train-mlogloss:0.042890+0.002283    test-mlogloss:0.673031+0.057878
## [71] train-mlogloss:0.032716+0.001623    test-mlogloss:0.691112+0.056010
## [81] train-mlogloss:0.025648+0.001521    test-mlogloss:0.707691+0.058055
## [91] train-mlogloss:0.020897+0.001250    test-mlogloss:0.723342+0.062724
## [100]    train-mlogloss:0.017756+0.001176    test-mlogloss:0.734206+0.0604
95
```

```r
# Function to compute classification error
classification_error <- function(conf_mat) {
  conf_mat = as.matrix(conf_mat)

  error = 1 - sum(diag(conf_mat)) / sum(conf_mat)

  return (error)
}

# Mutate xgb output to deliver hard predictions
xgb_train_preds <- data.frame(xgbcv$pred) %>% mutate(max = max.col(., ties.me
thod = "last"), label = train_labs + 1)

# Examine output
head(xgb_train_preds)
```

```
##             X1          X2           X3           X4 max label
## 1 2.557963e-01 0.394735545 3.491999e-01 2.682663e-04   2     3
## 2 9.978531e-01 0.001962732 1.680852e-04 1.610581e-05   1     1
## 3 8.626200e-05 0.999510407 4.009536e-04 2.427827e-06   2     2
## 4 1.106577e-04 0.997806489 2.068996e-03 1.382771e-05   2     2
## 5 3.321923e-02 0.934673190 3.199683e-02 1.107415e-04   2     3
## 6 8.847255e-06 0.999940276 5.025148e-05 6.239600e-07   2     2
```

```r
xgb_conf_mat <- table(true = train_labs + 1, pred = xgb_train_preds$max)

# Error
cat("XGB Training Classification Error Rate:", classification_error(xgb_conf_
mat), "\n")
```

```
## XGB Training Classification Error Rate: 0.2657916
```

```r
# predicting / testing on test dataset
xgb_model <- xgb.train(params = params, data = xgb_train, nrounds = 100)

# Predict for validation set
xgb_val_preds <- predict(xgb_model, newdata = xgb_val)

xgb_val_out <- matrix(xgb_val_preds, nrow = 4, ncol = length(xgb_val_preds) /
4) %>%
               t() %>%
               data.frame() %>%
               mutate(max = max.col(., ties.method = "last"), label = val_lab
s + 1)

# Confustion Matrix
xgb_val_conf <- table(true = val_labs + 1, pred = xgb_val_out$max)

cat("XGB Validation Classification Error Rate:", 1-classification_error(xgb_v
al_conf), "\n")

## XGB Validation Classification Error Rate: 0.7508091

cat("XGB Validation Classification Error Rate - above 5k:", xgb_val_conf[1,1]
/sum(xgb_val_conf[1,]), "\n")

## XGB Validation Classification Error Rate - above 5k: 0.8076923
```

Stacked Ensembles

```r
# we already have gbm.wish for GBM, now build RF model
# https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/stacked-ensembl
es.html
# Stacked Ensemble model's performance is not so different from those of base
learners'
library(h2o)

##
## ----------------------------------------------------------------------
##
## Your next step is to start H2O:
##     > h2o.init()
##
## For H2O package documentation, ask for help:
##     > ??h2o
##
## After starting H2O, you can use the Web UI at http://localhost:54321
## For more information visit https://docs.h2o.ai
##
## ----------------------------------------------------------------------

##
## Attaching package: 'h2o'
```

```
## The following objects are masked from 'package:stats':
##
##     cor, sd, var

## The following objects are masked from 'package:base':
##
##     %*%, %in%, &&, ||, apply, as.factor, as.numeric, colnames,
##     colnames<-, ifelse, is.character, is.factor, is.numeric, log,
##     log10, log1p, log2, round, signif, trunc

h2o.init()

##  Connection successful!
##
## R is connected to the H2O cluster:
##     H2O cluster uptime:         14 minutes 33 seconds
##     H2O cluster timezone:       America/New_York
##     H2O data parsing timezone:  UTC
##     H2O cluster version:        3.32.0.1
##     H2O cluster version age:    2 months and 7 days
##     H2O cluster name:           H2O_started_from_R_maxmo_plv200
##     H2O cluster total nodes:    1
##     H2O cluster total memory:   7.00 GB
##     H2O cluster total cores:    12
##     H2O cluster allowed cores:  12
##     H2O cluster healthy:        TRUE
##     H2O Connection ip:          localhost
##     H2O Connection port:        54321
##     H2O Connection proxy:       NA
##     H2O Internal Security:      FALSE
##     H2O API Extensions:         Amazon S3, Algos, AutoML, Core V3, TargetE
ncoder, Core V4
##     R Version:                  R version 3.6.2 (2019-12-12)

wish.train.h2o <- as.h2o(wish.train)

##   |
|                                                                      |   0%
|
|======================================================================| 100%

wish.test.h2o <- as.h2o(wish.test)

##   |
|                                                                      |   0%
|
|======================================================================| 100%

predictors <- c(colnames(wish.train)[1:length(wish.train) - 1])
response <- "sold_ct_cate"

set.seed(123)
```

```
gbm.wish <- h2o.gbm(x = predictors,
                    y = response,
                    nfolds = 5,
                    distribution = "multinomial",
                    keep_cross_validation_predictions = TRUE,
                    training_frame = wish.train.h2o, seed=1)

##   |
|                                                                      |   0%
|
|===============                                                       |  22%
|
|======================================================================| 100%

rf.wish <- h2o.randomForest(x = predictors,
                          y = response,
                          training_frame = wish.train.h2o,
                          ntrees = 50,
                          nfolds = 5,
                          keep_cross_validation_predictions = TRUE,
                          seed = 1)

##   |
|                                                                      |   0%
|
|==========                                                            |  14%
|
|============================================================          |  85%
|
|======================================================================| 100%

ensemble <- h2o.stackedEnsemble(x = predictors,
                                y = response,
                                training_frame = wish.train.h2o,
                                base_models = list(gbm.wish, rf.wish))

##   |
|                                                                      |   0%
|
|======================================================================| 100%

perf <- h2o.performance(ensemble, newdata = wish.test.h2o)

# Compare to base learner performance on the test set
perf_gbm_test <- h2o.performance(gbm.wish, newdata = wish.test.h2o)
perf_rf_test <- h2o.performance(rf.wish, newdata = wish.test.h2o)
baselearner_best_auc_test <- max(h2o.auc(perf_gbm_test), h2o.auc(perf_rf_test
))
ensemble_auc_test <- h2o.auc(perf)
print(sprintf("Best Base-learner Test AUC:  %s", baselearner_best_auc_test))
```

```
## [1] "Best Base-learner Test AUC:  -Inf"
```

```r
print(sprintf("Ensemble Test AUC:  %s", ensemble_auc_test))
```

```
## character(0)
```

```r
perf
```

```
## H2OMultinomialMetrics: stackedensemble
##
## Test Set Metrics:
## =====================
##
## MSE: (Extract with `h2o.mse`) 0.1869437
## RMSE: (Extract with `h2o.rmse`) 0.4323699
## Logloss: (Extract with `h2o.logloss`) 0.5548341
## Mean Per-Class Error: 0.2670902
## Null Deviance: (Extract with `h2o.nulldeviance`) 669.9311
## Residual Deviance: (Extract with `h2o.residual_deviance`) 342.8875
## AIC: (Extract with `h2o.aic`) NaN
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>, <data>)`)
## =========================================================================
## Confusion Matrix: Row labels: Actual class; Column labels: Predicted class
##                      above 5K below 100 between 100 and 5k  Error       Rate
## above 5K                   85         2                 17 0.1827 = 19 / 104
## below 100                   4       107                 13 0.1371 = 17 / 124
## between 100 and 5k         29        10                 42 0.4815 =  39 / 81
## Totals                    118       119                 72 0.2427 = 75 / 309
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>, <data>)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.757282
## 2 2  0.961165
## 3 3  1.000000
```

```r
perf_gbm_test
```

```
## H2OMultinomialMetrics: gbm
##
## Test Set Metrics:
## =====================
##
## MSE: (Extract with `h2o.mse`) 0.2065348
## RMSE: (Extract with `h2o.rmse`) 0.454461
## Logloss: (Extract with `h2o.logloss`) 0.6037602
## Mean Per-Class Error: 0.2878935
## R^2: (Extract with `h2o.r2`) 0.6518089
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>, <data>)`)
## =========================================================================
```

```
## Confusion Matrix: Row labels: Actual class; Column labels: Predicted class
##                     above 5K below 100 between 100 and 5k  Error       Rate
## above 5K                  87         2                 15 0.1635 = 17 / 104
## below 100                  3       103                 18 0.1694 = 21 / 124
## between 100 and 5k        30        13                 38 0.5309 =  43 / 81
## Totals                   120       118                 71 0.2621 = 81 / 309
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>, <data>)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.737864
## 2 2  0.948220
## 3 3  1.000000
```

```
perf_rf_test
```

```
## H2OMultinomialMetrics: drf
##
## Test Set Metrics:
## =====================
##
## MSE: (Extract with `h2o.mse`) 0.2127525
## RMSE: (Extract with `h2o.rmse`) 0.461251
## Logloss: (Extract with `h2o.logloss`) 0.6123574
## Mean Per-Class Error: 0.3100205
## R^2: (Extract with `h2o.r2`) 0.6413268
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>, <data>)`)
## =========================================================================
## Confusion Matrix: Row labels: Actual class; Column labels: Predicted class
##                     above 5K below 100 between 100 and 5k  Error       Rate
## above 5K                  84         4                 16 0.1923 = 20 / 104
## below 100                  4       106                 14 0.1452 = 18 / 124
## between 100 and 5k        33        15                 33 0.5926 =  48 / 81
## Totals                   121       125                 63 0.2783 = 86 / 309
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>, <data>)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.721683
## 2 2  0.948220
## 3 3  1.000000
```

```
# Generate predictions on a test set
pred <- h2o.predict(ensemble, newdata = wish.test.h2o)
```

```
##   |
|                                                                      |   0%
|
|======================================================================| 100%
```

Neural network

```
library(neuralnet)

##
## Attaching package: 'neuralnet'

## The following object is masked from 'package:dplyr':
##
##     compute

library(nnet)
y_index = grep("sold_ct_cate", names(wish.train))
nn.train = cbind(wish.train[, -y_index], wish.train[, y_index])
names(nn.train)[names(nn.train) == 'wish.train[, y_index]'] <- 'sold_ct_cate'


nn.train = cbind(nn.train[, 1:8],class.ind(as.factor(nn.train$color)),nn.trai
n[, 11:15],nn.train[17:24],class.ind(as.factor(nn.train$size)),class.ind(as.f
actor(nn.train$origin)), class.ind(as.factor(nn.train$sold_ct_cate)))
#normalized by scaling data
scl <- function(x){ (x - min(x))/(max(x) - min(x)) }
nn.train[, 1:29] <- data.frame(lapply(nn.train[, 1:29], scl))

names(nn.train)[names(nn.train) == 'One-sized'] <- 'one_sized'
names(nn.train)[names(nn.train) == 'above 5K'] <- 'above_5k'
names(nn.train)[names(nn.train) == 'below 100'] <- 'below_100'
names(nn.train)[names(nn.train) == 'between 100 and 5k'] <- 'btw_100_5k'

name <- names(nn.train)
f <- as.formula(paste("above_5k + below_100 + btw_100_5k ~", paste(name[!name
%in% c("above_5k","below_100","btw_100_5k")], collapse = " + ")))
f

## above_5k + below_100 + btw_100_5k ~ price + retail + ad_boost +
##     rate + badge_ct + bg_local + bg_quality + bg_fastship + black +
##     blue + green + others + pink + red + white + yellow + inventory +
##     ship_price + able_country + total_invent + has_bg_urgency +
##     seller_rate_ct + seller_rate + has_seller_propic + rate5_pct +
##     rate4_pct + rate3_pct + rate2_pct + rate1_pct + l + m + one_sized +
##     s + xl + xs + CN + others

set.seed(123)
nn <- neuralnet(f,
                data = nn.train,
                hidden = c(37, 15,3),
                act.fct = "logistic",
                linear.output = FALSE,stepmax = 3000)

plot(nn)
```

```r
nn.test = cbind(wish.test[, -y_index], wish.test[, y_index])
names(nn.test)[names(nn.test) == 'wish.test[, y_index]'] <- 'sold_ct_cate'

nn.test = cbind(nn.test[, 1:8], class.ind(as.factor(nn.test$color)), nn.test[
, 11:15], nn.test[17:24], class.ind(as.factor(nn.test$size)), class.ind(as.fa
ctor(nn.test$origin)), class.ind(as.factor(nn.test$sold_ct_cate)))
#normalized by scaling data
scl <- function(x){ (x - min(x))/(max(x) - min(x)) }
nn.test[, 1:29] <- data.frame(lapply(nn.test[, 1:29], scl))

names(nn.test)[names(nn.test) == 'One-sized'] <- 'one_sized'
names(nn.test)[names(nn.test) == 'above 5K'] <- 'above_5k'
names(nn.test)[names(nn.test) == 'below 100'] <- 'below_100'
names(nn.test)[names(nn.test) == 'between 100 and 5k'] <- 'btw_100_5k'

#train accuracy
nn.train_pred <- compute(nn, nn.train[, 1:37])
nn.train_pred <- nn.train_pred$net.result
true_y.train <- max.col(nn.train[, 38:40])
predicted_y.train <- max.col(nn.train_pred)

#test accuracy
nn.test_pred <- compute(nn, nn.test[, 1:37])
nn.test_pred <- nn.test_pred$net.result
true_y.test <- max.col(nn.test[, 38:40])
predicted_y.test <- max.col(nn.test_pred)

table.train <- table(true_y.train, predicted_y.train)
table.test <- table(true_y.test, predicted_y.test)


print("accuracy for train: ")

## [1] "accuracy for train: "

print(1-(sum(table.train)-sum(diag(table.train))) / (sum(table.train)))

## [1] 0.9589828

print("accuracy for test: ")

## [1] "accuracy for test: "

print(1-(sum(table.test)-sum(diag(table.test))) / (sum(table.test)))

## [1] 0.5210356

print("above 5k group accuracy:")

## [1] "above 5k group accuracy:"
```

```r
sum(table.test[1,1]) /sum(table.test[1,])
```

```
## [1] 0.6153846
```