Predicting customer behavior using Machine Learning models

1 Break-Even Response Rate & ROI

```
cost_per_offer <- 1.5

amazon_prime_fee <- 8.99

avg_revenue <-40

COGS <- 0.7

shipping <- 6

profit_per_customer <- avg_revenue*(1-COGS) + amazon_prime_fee - shipping #We multiply the average

#revenue with the percentage that is not COGS, then add revenue generated by the prime membership

#and subtract the shipping cost supported by Amazon.

breakeven_response_rate <- cost_per_offer/profit_per_customer

# pls do not modify the codes below

# these are for TAs to check results

print(paste("cost_per_offer is ", cost_per_offer))

[1] "cost_per_offer is 1.5"
```

```
print(paste("profit_per_customer is", profit_per_customer))
   [1] "profit_per_customer is 14.99"
print(paste("breakeven_response_rate is", breakeven_response_rate))
   [1] "breakeven_response_rate is 0.10006671114076"
  sub_sum <- sum(data_full$subscribe == "yes", na.rm = TRUE) #Filtered and summed only</pre>
  #the customers who are subscribers (ignored the null values).
  total_costs_of_mailing_blanket <- cost_per_offer * 10000 ##The total cost of mailing
   #all 10000 customers. Whether they will subscribe or not, we still incur this cost.
  total_profit_blanket <- profit_per_customer * sub_sum #Determined the expected profit.
  ROI_blanket <- (total_profit_blanket-total_costs_of_mailing_blanket)/</pre>
    total_costs_of_mailing_blanket
  print(paste("total_costs_of_mailing_blanket is ", total_costs_of_mailing_blanket))
   [1] "total_costs_of_mailing_blanket is 15000"
print(paste("total_profit_blanket is ", total_profit_blanket))
   [1] "total_profit_blanket is 12561.62"
 print(paste("ROI_blanket is ", ROI_blanket))
   [1] "ROI_blanket is -0.162558666666667"
```

2 Unsupervised Learning for Segmentation and Targeting

```
# RFM variables

rfm <- data_full%>%

mutate(recency = last,  # days since last purchase

frequency = home + sports + clothes + health + books + digital + toys,

#total purchases across categories

monetary_value = electronics+nonelectronics  #total spending

nonetary_value = electronics+nonelectronics  #total spending

summary(rfm[c("recency", "frequency", "monetary_value")])
```

```
recency
                frequency
                             monetary_value
    : 1.00
                     : 1.00 Min.
                                  : 15.0
Min.
             Min.
1st Qu.: 7.00 1st Qu.: 1.00
                            1st Qu.:128.0
Median: 11.00 Median: 2.00 Median: 209.0
Mean
     :12.26 Mean : 3.85
                             Mean
                                   :208.2
3rd Qu.:15.00
              3rd Qu.: 6.00
                             3rd Qu.:284.0
      :35.00
              Max. :12.00
                             Max. :478.0
Max.
```

```
#Scaling data
data_kmeans <- rfm %>%
mutate(

recency = scale(recency),
frequency = scale(frequency),
monetary_value = scale(monetary_value)

#K-means clustering
data_kmeans <- data_kmeans %>%
select(recency, frequency, monetary_value) %>%
mutate(
```

```
recency = scale(recency),
frequency = scale(frequency),
monetary_value = scale(monetary_value)

)
```

```
# Determine the optimal number of clusters using the Silhouette method below
set.seed(888)

pacman::p_load(factoextra, cluster)

fviz_nbclust(data_kmeans, kmeans, method = "silhouette")
```

Optimal number of clusters 0.4 Upper 90.0 0.0 1 2 3 4 5 6 7 8 9 10 Number of clusters k

```
# implement k-means clustering below

# do not modify seeds

set.seed(888)

result_kmeans <- kmeans(data_kmeans,

centers = 2,

nstart = 10</pre>
```

```
)
# use broom::tidy() to check the clusters.
pacman::p_load(broom)
tidy(result_kmeans)
 # A tibble: 2 x 6
    recency frequency monetary_value size withinss cluster
      <dbl>
                <dbl>
                               <dbl> <int>
                                               <dbl> <fct>
 1 -0.00843
               -0.547
                              -0.344 7263
                                              13207. 1
 2 0.0224
                                               5712. 2
                1.45
                               0.912 2737
data_full <- data_full %>%
     mutate(subscribe = ifelse(subscribe == "yes", 1, 0))
 data_full <- data_full %>%
     mutate(segment = result_kmeans$cluster)
 data_full %>%
     group_by(segment) %>%
     summarise(avg_subscribe_rate = mean(subscribe, na.rm = T)) %>%
     ungroup()
 # A tibble: 2 x 2
   segment avg_subscribe_rate
                        <dbl>
     <int>
 1
         1
                       0.0680
 2
         2
                       0.126
# ROI for cluster 1 and 2
cluster2 <- sum(result_kmeans$cluster == 2, na.rm = TRUE)</pre>
total_costs_of_mailing_kmeans <- cost_per_offer*cluster2</pre>
total_profit_kmeans <- profit_per_customer*cluster2* 0.12568506</pre>
ROI_kmeans <- (total_profit_kmeans-total_costs_of_mailing_kmeans)/</pre>
   total_costs_of_mailing_kmeans
```

```
cluster1 <- sum(result_kmeans$cluster == 1, na.rm = TRUE)

total_costs_of_mailing_kmeans <- cost_per_offer*cluster1

total_profit_kmeans <- profit_per_customer*cluster1* 0.06801597

ROI_kmeans1 <- (total_profit_kmeans-total_costs_of_mailing_kmeans)/

total_costs_of_mailing_kmeans

[1] 0.2560127

ROI_kmeans1

[1] -0.3202937

print(paste("ROI_kmeans is ", ROI_kmeans))

[1] "ROI_kmeans is 0.2560126996"
```

3 Decision Tree Analysis

```
data_tree <- rfm %>%
    select(-user_id) %>%
    select(-gender) %>%
    select(-city)

# set seed
set.seed(1314520)

data_tree <- rfm %>%
    mutate(subscribe = ifelse(subscribe == "yes", 1, 0))
n_rows_data_tree <- nrow(data_tree)</pre>
```

```
training_set_index <- sample(</pre>
      x = 1:n_rows_data_tree,
12
      size = 0.75*n_rows_data_tree,
13
      replace = FALSE
14
15
16
17
   # create data_training and data_test
18
   data_training <- data_tree %>%
      slice(training_set_index)
^{21}
   data_test <- data_tree %>%
      slice(-training_set_index)
```

```
# This is to print out first 5 customers
training_set_index[1:5]
```

[1] 3620 43 3574 4308 7387

```
pacman::p_load(rpart, rpart.plot)

# train model tree1 below

tree1 <- rpart(
formula = subscribe ~ recency + frequency + monetary_value, #subscribe is the

# wariable Tom tries to predict based on predictors

# (recency, frequency, monetary_value).

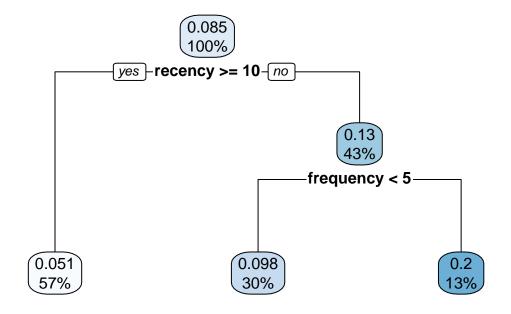
data = data_training, #training the model

method = "anova" #probabilities

)

# visualize tree1 below</pre>
```

```
rpart.plot(tree1)
```



```
# ROI for tree1
   prediction_from_decision_tree <- predict(tree1, data_test)</pre>
   data_test <- data_test %>%
       mutate(predicted_prob_decisiontree = prediction_from_decision_tree)
   data_test <- data_test %>%
       mutate(is_target_decisiontree = ifelse(predicted_prob_decisiontree >
                                                   breakeven_response_rate, 1, 0))
   total_costs_of_mailing_decisiontree <- cost_per_offer *</pre>
     sum(data_test$is_target_decisiontree)
   data_test_targeted_customers <- data_test %>%
10
       filter(is_target_decisiontree == 1)
11
   total_profit_decisiontree <- sum(data_test_targeted_customers$subscribe) *</pre>
12
     profit_per_customer
13
   # Compute ROI
```

```
ROI_decisiontree <-
(total_profit_decisiontree - total_costs_of_mailing_decisiontree)/
total_costs_of_mailing_decisiontree

ROI_decisiontree

ROI_decisiontree
```

[1] 0.7185987

4 Random Forest

```
pacman::p_load(ranger)
   set.seed(888)
   # train the random forest model below
   randomforest <- ranger(</pre>
     formula = subscribe ~ recency + frequency + monetary_value, #subscribe is the
     #variable Tom tries to predict based on predictors
     #(recency, frequency, monetary_value)
     data = data_training, # training the model
     probability = TRUE, #TRUE because we are interested in finding the probability
     #of a customer subscribing
     num.trees = 5000
11
12
13
   prediction_from_randomforest <- predict(randomforest, data_test)</pre>
   data_test <- data_test %>%
16
       mutate(predicted_prob_randomforest = prediction_from_randomforest$predictions[, 2])
17
18
   data_test <- data_test %>%
       mutate(is_target_randomforest = ifelse(predicted_prob_randomforest >
20
                                                  breakeven_response_rate, 1, 0))
21
```

```
22
   total_costs_of_mailing_randomforest <- cost_per_offer *</pre>
      sum(data_test$is_target_randomforest)
24
26
    data_responding_targeted_customers <- data_test %>%
27
        filter(is_target_randomforest == 1) %>%
28
        filter(subscribe == 1)
30
   # total profits from responding customers
31
   total_profit_randomforest <- nrow(data_responding_targeted_customers) * profit_per_customer</pre>
32
33
   # Compute ROI
   ROI_randomforest <-</pre>
      (total_profit_randomforest - total_costs_of_mailing_randomforest) /
36
      total_costs_of_mailing_randomforest
37
   ROI_randomforest
    [1] 0.4295828
```

```
print(paste("ROI_randomforest is ", ROI_randomforest))
```

[1] "ROI_randomforest is 0.429582760201743"