Assignment 1.1 - Charles Book Club

The company is looking to target its customers more accurately. The company would like to use the information contained in their databases to identify who is most likely to be interested in a specific offer. This information enables them to design special programs carefully tailored to meet their customer segments' varying needs. In this use case, you will be applying multiple data mining techniques, including k-NN and logistic regression models.

The company two common membership programs: the continuity program, a reader signs up by accepting an offer of several books for just a few dollars (including shipping and handling) and an agreement to receive a shipment of one or two books each month thereafter at more-standard pricing. - common for childern's books - CON depends on the qulality of its selections

- the negative option plan, a reader receives a monthly announcement describing the book of the month. If the reader does not return the announcement by a specified date, the book is shipped and the reader is billed.
- common for adult books

NOTES:

- **Charles Book Club Overview:**
  - Established in 1986 with a focus on understanding customer preferences.
  - CBC offered specialty books through direct marketing channels (media advertising, mailing).
  - Built a database of 500,000 active members acquired through advertising in specialty magazines.
- **Problem Statement:**
  - Despite an increase in customer database and mailing volume, CBC's profits were declining.
  - Previous mailing strategies were untargeted, leading to inefficiencies in customer engagement and profitability.
- **Proposed Solution:**
  - CBC management decided to adopt database marketing techniques to improve targeting.
  - The goal was to identify the most profitable customers and design targeted campaigns.
  - A two-step process was proposed:
    1. Conduct a market test on 4000 customers to develop response models.
    2. Use response models to create a targeted customer list for promotional mailings.
- **Data Mining Techniques Utilized:**
  - **k-Nearest Neighbors (k-NN):** Used to classify customers based on purchasing behavior.
  - **Logistic Regression:** Applied to model response probabilities and predict customer behavior.
  - **RFM Segmentation (Recency, Frequency, Monetary):** Used to categorize customers into homogeneous segments based on past purchase behavior.
- **Assignment Goals:**
  - Analyze CBC's customer data using k-NN, logistic regression, and RFM segmentation.
  - Optimize promotional mailings by targeting the most responsive customer segments.
  - Provide data-driven recommendations to enhance CBC's marketing effectiveness and profitability.

```r
# load the data
cbc_data <- read.csv("/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 01/Assignment/CharlesBookClub.csv")

# display the structure of the dataset
str(cbc_data)
```

```
## 'data.frame':    4000 obs. of  24 variables:
##  $ Seq.            : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ ID.             : int  25 29 46 47 51 60 61 79 81 90 ...
##  $ Gender          : int  1 0 1 1 1 1 1 1 1 1 ...
##  $ M               : int  297 128 138 228 257 145 190 187 252 240 ...
##  $ R               : int  14 8 22 2 10 6 16 14 10 6 ...
##  $ F               : int  2 2 7 1 1 2 1 1 1 3 ...
##  $ FirstPurch      : int  22 10 56 2 10 12 16 14 10 20 ...
##  $ ChildBks        : int  0 0 2 0 0 0 0 1 0 0 ...
##  $ YouthBks        : int  1 0 1 0 0 0 0 0 0 0 ...
##  $ CookBks         : int  1 0 2 0 0 0 0 0 0 1 ...
##  $ DoItYBks        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ RefBks          : int  0 0 1 0 0 0 0 0 0 0 ...
##  $ ArtBks          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ GeogBks         : int  0 0 1 0 0 0 1 0 0 0 ...
##  $ ItalCook        : int  0 0 1 0 0 0 0 0 0 0 ...
##  $ ItalAtlas       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ ItalArt         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Florence        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Related.Purchase: int  0 0 2 0 0 0 1 0 0 0 ...
##  $ Mcode           : int  5 4 4 5 5 4 4 4 5 5 ...
##  $ Rcode           : int  4 3 4 1 3 2 4 4 3 2 ...
##  $ Fcode           : int  2 2 3 1 1 2 1 1 1 3 ...
##  $ Yes_Florence    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ No_Florence     : int  1 1 1 1 1 1 1 1 1 1 ...
```

```r
# display the summary statistics of the dataset
summary(cbc_data)
```

```
##       Seq.            ID.            Gender             M        
##  Min.   :   1   Min.   :   25   Min.   :0.0000   Min.   : 15.0  
##  1st Qu.:1001   1st Qu.: 8253   1st Qu.:0.0000   1st Qu.:129.0  
##  Median :2000   Median :16581   Median :1.0000   Median :208.0  
##  Mean   :2000   Mean   :16595   Mean   :0.7045   Mean   :208.1  
##  3rd Qu.:3000   3rd Qu.:24838   3rd Qu.:1.0000   3rd Qu.:283.0  
##  Max.   :4000   Max.   :32977   Max.   :1.0000   Max.   :479.0  
##        R               F            FirstPurch       ChildBks     
##  Min.   : 2.00   Min.   : 1.000   Min.   : 2.00   Min.   :0.0000  
##  1st Qu.: 8.00   1st Qu.: 1.000   1st Qu.:12.00   1st Qu.:0.0000  
##  Median :12.00   Median : 2.000   Median :20.00   Median :0.0000  
##  Mean   :13.39   Mean   : 3.833   Mean   :26.51   Mean   :0.6398  
##  3rd Qu.:16.00   3rd Qu.: 6.000   3rd Qu.:36.00   3rd Qu.:1.0000  
##  Max.   :36.00   Max.   :12.000   Max.   :99.00   Max.   :7.0000  
##     YouthBks         CookBks          DoItYBks          RefBks      
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000  
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000  
##  Median :0.0000   Median :0.0000   Median :0.0000   Median :0.0000  
##  Mean   :0.3048   Mean   :0.7312   Mean   :0.3508   Mean   :0.2562  
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.0000  
##  Max.   :5.0000   Max.   :7.0000   Max.   :5.0000   Max.   :4.0000  
##      ArtBks         GeogBks          ItalCook        ItalAtlas     
##  Min.   :0.000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000  
##  1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000  
##  Median :0.000   Median :0.0000   Median :0.0000   Median :0.0000  
##  Mean   :0.289   Mean   :0.3875   Mean   :0.1253   Mean   :0.0375  
```

```
##  3rd Qu.:0.000   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :5.000   Max.   :6.0000   Max.   :3.0000   Max.   :2.0000
##     ItalArt          Florence      Related.Purchase     Mcode
##  Min.   :0.00000   Min.   :0.0000   Min.   :0.000    Min.   :1.000
##  1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.000    1st Qu.:4.000
##  Median :0.00000   Median :0.0000   Median :0.000    Median :5.000
##  Mean   :0.04575   Mean   :0.0845   Mean   :0.885    Mean   :4.281
##  3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:1.000    3rd Qu.:5.000
##  Max.   :2.00000   Max.   :1.0000   Max.   :8.000    Max.   :5.000
##      Rcode          Fcode         Yes_Florence     No_Florence
##  Min.   :1.00   Min.   :1.000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:3.00   1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:1.0000
##  Median :3.00   Median :2.000   Median :0.0000   Median :1.0000
##  Mean   :3.17   Mean   :2.086   Mean   :0.0845   Mean   :0.9155
##  3rd Qu.:4.00   3rd Qu.:3.000   3rd Qu.:0.0000   3rd Qu.:1.0000
##  Max.   :4.00   Max.   :3.000   Max.   :1.0000   Max.   :1.0000
```

```r
# display the first few rows of the dataset
head(cbc_data)
```

```
##   Seq. ID. Gender   M  R F FirstPurch ChildBks YouthBks CookBks DoItYBks RefBks
## 1    1  25      1 297 14 2         22        0        1       1        0      0
## 2    2  29      0 128  8 2         10        0        0       0        0      0
## 3    3  46      1 138 22 7         56        2        1       2        0      1
## 4    4  47      1 228  2 1          2        0        0       0        0      0
## 5    5  51      1 257 10 1         10        0        0       0        0      0
## 6    6  60      1 145  6 2         12        0        0       0        0      0
##   ArtBks GeogBks ItalCook ItalAtlas ItalArt Florence Related.Purchase Mcode
## 1      0       0        0         0       0        0                0     5
## 2      0       0        0         0       0        0                0     4
## 3      0       1        1         0       0        0                2     4
## 4      0       0        0         0       0        0                0     5
## 5      0       0        0         0       0        0                0     5
## 6      0       0        0         0       0        0                0     4
##   Rcode Fcode Yes_Florence No_Florence
## 1     4     2            0           1
## 2     3     2            0           1
## 3     4     3            0           1
## 4     1     1            0           1
## 5     3     1            0           1
## 6     2     2            0           1
```

```r
set.seed(1)  # Set seed for reproducibility
trainIndex <- createDataPartition(cbc_data$Florence, p = 0.6, list = FALSE)
train_data <- cbc_data[trainIndex, ]
validation_data <- cbc_data[-trainIndex, ]

# question 1.1 Calculate response reate for the training data and RFM combinations.

# over response rate for training data
overall_response_rate <- mean(train_data$Florence)
print(paste("Overall Response Rate for Training Data:", overall_response_rate))
```

```
## [1] "Overall Response Rate for Training Data: 0.0870833333333333"
```

```r
# This response rate indicates that around 8.7% of the customers in the training data have purchased "Th

# calculate response rates for each RFM category
rfm_response_rate <- train_data %>%
  group_by(R, F, M) %>%
  summarize(response_rate = mean(Florence))
```

```
## `summarise()` has grouped output by 'R', 'F'. You can override using the
## `.groups` argument.
```

```r
# Find combinations with above-average response rates
above_average_combinations <- rfm_response_rate %>%
  filter(response_rate > overall_response_rate)

print(above_average_combinations)
```

```
## # A tibble: 206 x 4
## # Groups:   R, F [91]
##        R     F     M response_rate
##    <int> <int> <int>         <dbl>
##  1     2     1   131           1
##  2     2     1   140           1
##  3     2     1   148           1
##  4     2     1   152           0.5
##  5     2     1   230           1
##  6     2     1   297           1
##  7     2     1   299           1
##  8     2     2    43           1
##  9     2     2   203           0.5
## 10     2     2   274           1
## # i 196 more rows
```

```r
### Question 1.2: Compute the response rate for validation data using "above-average" RFM combinations
```

```r
# Filter validation data based on above-average RFM combinations
validation_selected <- validation_data %>%
  semi_join(above_average_combinations, by = c("R", "F", "M"))

# Compute response rate for validation data
validation_response_rate <- mean(validation_selected$Florence)
print(paste("Validation response rate for above-average combinations:", validation_response_rate))
```

```
## [1] "Validation response rate for above-average combinations: 0.15"
```

Question 2: k-NN classification

```r
### Question 2: k-NN classification

# Normalize relevant variables using mutate(across())
normalize <- function(x) {
  return((x - min(x)) / (max(x) - min(x)))
}

train_data_norm <- train_data %>%
  mutate(across(c(R, F, M, FirstPurch, Related.Purchase), normalize))
```

```r
validation_data_norm <- validation_data %>%
  mutate(across(c(R, F, M, FirstPurch, Related.Purchase), normalize))
```

```r
# Prepare input and output for k-NN
train_x <- train_data_norm %>% select(R, F, M, FirstPurch, Related.Purchase)
train_y <- train_data_norm$Florence

validation_x <- validation_data_norm %>% select(R, F, M, FirstPurch, Related.Purchase)
validation_y <- validation_data_norm$Florence

# Perform k-NN for k = 1 to 11
k_values <- 1:11
accuracy_results <- data.frame(k = k_values, accuracy = NA)

for (i in seq_along(k_values)) {
  knn_pred <- knn(train_x, validation_x, train_y, k = k_values[i])
  accuracy_results$accuracy[i] <- mean(knn_pred == validation_y)
}

# Display the accuracy for each k
accuracy_results
```

```
##     k accuracy
## 1   1 0.856250
## 2   2 0.866875
## 3   3 0.908750
## 4   4 0.905625
## 5   5 0.915000
## 6   6 0.913125
## 7   7 0.918125
## 8   8 0.917500
## 9   9 0.917500
## 10 10 0.917500
## 11 11 0.918125
```

```r
# Find the best k
best_k <- accuracy_results[which.max(accuracy_results$accuracy), "k"]
print(paste("Best k:", best_k))
```

```
## [1] "Best k: 7"
```

Question 2.1: Create a lift curve for the best k-NN model

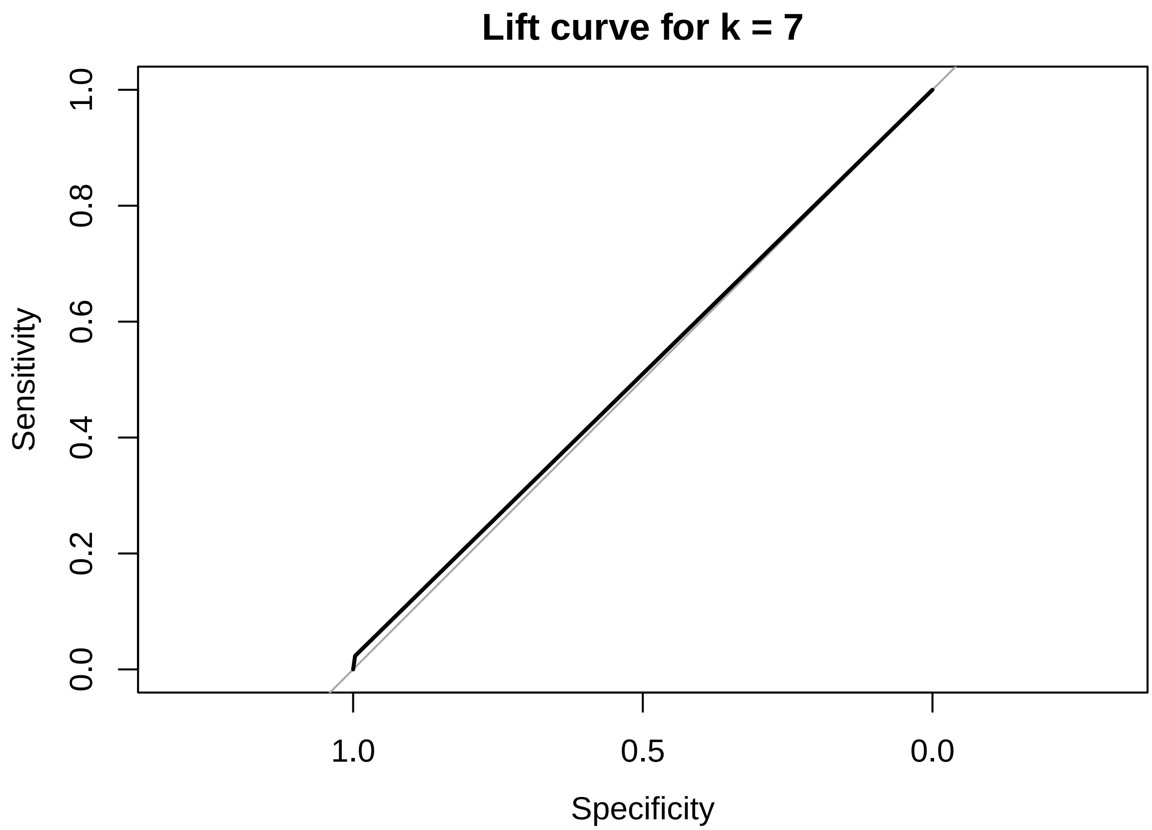
```r
# Run k-NN with the best k
knn_best_pred <- knn(train_x, validation_x, train_y, k = best_k)

# Create a lift curve
roc_obj <- roc(validation_y, as.numeric(knn_best_pred))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
plot(roc_obj, main = paste("Lift curve for k =", best_k))
```



Question 3: Logistic Regression

```r
# Model with all 16 predictors
logit_model_full <- glm(Florence ~ ., data = train_data, family = "binomial")
```

```
## Warning: glm.fit: algorithm did not converge
```

```r
# Model with a subset of predictors
logit_model_subset <- glm(Florence ~ R + F + M + FirstPurch + Related.Purchase, data = train_data, famil

# Summary of the models
summary(logit_model_full)
```

```
##
## Call:
## glm(formula = Florence ~ ., family = "binomial", data = train_data)
##
## Coefficients: (2 not defined because of singularities)
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -2.657e+01  6.333e+04   0.000    1.000
## Seq.              1.131e-14  4.982e+02   0.000    1.000
## ID.              -1.380e-15  6.067e+01   0.000    1.000
## Gender            6.247e-14  1.597e+04   0.000    1.000
## M                -7.372e-16  1.573e+02   0.000    1.000
## R                 3.761e-14  1.889e+03   0.000    1.000
## F                -1.215e-13  8.393e+03   0.000    1.000
## FirstPurch       -1.481e-14  1.240e+03   0.000    1.000
## ChildBks          2.552e-13  1.158e+04   0.000    1.000
```

```
## YouthBks          9.027e-14  1.577e+04   0.000    1.000
## CookBks           3.005e-13  1.144e+04   0.000    1.000
## DoItYBks          3.424e-13  1.439e+04   0.000    1.000
## RefBks            2.811e-13  1.636e+04   0.000    1.000
## ArtBks           -4.944e-13  1.271e+04   0.000    1.000
## GeogBks          -5.774e-14  1.118e+04   0.000    1.000
## ItalCook          1.611e-13  1.919e+04   0.000    1.000
## ItalAtlas         4.916e-14  3.681e+04   0.000    1.000
## ItalArt          -2.741e-13  3.302e+04   0.000    1.000
## Related.Purchase         NA         NA      NA       NA
## Mcode             8.518e-14  1.605e+04   0.000    1.000
## Rcode            -5.550e-13  1.378e+04   0.000    1.000
## Fcode            -1.038e-13  1.470e+04   0.000    1.000
## Yes_Florence      5.313e+01  2.638e+04   0.002    0.998
## No_Florence              NA         NA      NA       NA
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1.4195e+03  on 2399  degrees of freedom
## Residual deviance: 1.3924e-08  on 2378  degrees of freedom
## AIC: 44
##
## Number of Fisher Scoring iterations: 25
```

```r
summary(logit_model_subset)
```

```
##
## Call:
## glm(formula = Florence ~ R + F + M + FirstPurch + Related.Purchase,
##     family = "binomial", data = train_data)
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -2.174e+00  2.133e-01 -10.192  < 2e-16 ***
## R                -4.046e-02  1.526e-02  -2.650  0.00804 **
## F                 5.916e-02  5.064e-02   1.168  0.24273
## M                -4.459e-05  8.561e-04  -0.052  0.95846
## FirstPurch       -8.124e-03  1.056e-02  -0.769  0.44185
## Related.Purchase  2.815e-01  5.814e-02   4.842 1.29e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1419.5  on 2399  degrees of freedom
## Residual deviance: 1363.9  on 2394  degrees of freedom
## AIC: 1375.9
##
## Number of Fisher Scoring iterations: 5
```

```r
# Predict probabilities for validation data
pred_probs_full <- predict(logit_model_full, validation_data, type = "response")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases
```

```r
pred_probs_subset <- predict(logit_model_subset, validation_data, type = "response")

# Apply 30% cutoff for validation data
cutoff <- 0.3
targeted_customers_full <- ifelse(pred_probs_full > cutoff, 1, 0)
targeted_customers_subset <- ifelse(pred_probs_subset > cutoff, 1, 0)

# Count the number of buyers in the targeted set
buyers_full <- sum(validation_data$Florence[targeted_customers_full == 1])
buyers_subset <- sum(validation_data$Florence[targeted_customers_subset == 1])

print(paste("Number of buyers (full model):", buyers_full))
```

```
## [1] "Number of buyers (full model): 129"
```

```r
print(paste("Number of buyers (subset model):", buyers_subset))
```

```
## [1] "Number of buyers (subset model): 4"
```

3.3 Briefly explain, in two to three paragraphs, the business objective, the data mining models used, why they were used, the model results, and your recommendations to your non-technical stakeholder team. The business objective of this assignment is to help Charles Book Club (CBC) improve its marketing effectiveness and profitability by targeting the most responsive customer segments. To achieve this goal, we utilized data mining techniques such as k-Nearest Neighbors (k-NN) and Logistic Regression to analyze CBC's customer data and predict customer behavior. The k-NN model was used to classify customers based on purchasing behavior, while the Logistic Regression model was applied to model response probabilities and predict customer behavior. Additionally, we used RFM Segmentation (Recency, Frequency, Monetary) to categorize customers into homogeneous segments based on past purchase behavior.