RFM Analysis

```
library(plyr)
library(dplyr)
library(ggplot2)
library(RColorBrewer)
library(data.table)
library(scales)

setwd("C:/Users/cherring/Documents")
```

Data Ingestion and Transformations

```
data <- read.csv("train_clubmahindra.csv")
data <- data[c(1,2,7,8,13,14,15,18,20,24)]
data$booking_date <- as.character(data$booking_date)
data$booking_date <-as.POSIXct(data$booking_date, format = "%d/%m/%y")

# Subset to 2017
data <- data[substr(data$booking_date,1,4) == "2017",]

# Calculate Total Amount Spent
data$total_amount_spent <- data$amount_spent_per_room_night_scaled * 100 *
data$roomnights

# Initialize customer data frame
customers <- as.data.frame(unique(data$memberid))
names(customers) <- "memberid"
```

Recency

```
# Calculate number of days since booking date
data$recency <- as.Date("2018-01-01") - as.Date(data$booking_date)

# Obtain number of days since most recent booking
data = data.table(data)
recency = data[,list(recency=min(recency)),by = 'memberid']

# Add recency to customer data
customers <- merge(customers, recency, by="memberid", all=TRUE, sort=TRUE)
remove(recency)
customers$recency <- as.numeric(customers$recency)
```

Frequency

```
# Obtain list of distinct invoices by customer
customer.invoices <- subset(data, select = c("memberid","reservation_id"))
customer.invoices <- customer.invoices[!duplicated(customer.invoices), ]
customer.invoices <- customer.invoices[order(customer.invoices$memberid),]
```

```
row.names(customer.invoices) <- NULL
customer.invoices$rescount <- 1

# Calculate frequency by taking sum of distinct invoices
frequency = customer.invoices[,list(frequency=sum(rescount)),by = 'memberid']

# Add frequency to customer data
customers <- merge(customers, frequency, by="memberid", all=TRUE, sort=TRUE)
remove(frequency)
customers$frequency <- as.numeric(customers$frequency)
```

Monetary

```
# Calculate monetary by taking sum of total amounts
monetary = data[,list(monetary=sum(total_amount_spent)),by = 'memberid']

# Add monetary value to customers dataset
customers <- merge(customers, monetary, by="memberid", all.x=TRUE, sort=TRUE)
remove(monetary)
customers$monetary <- as.numeric(customers$monetary)
```

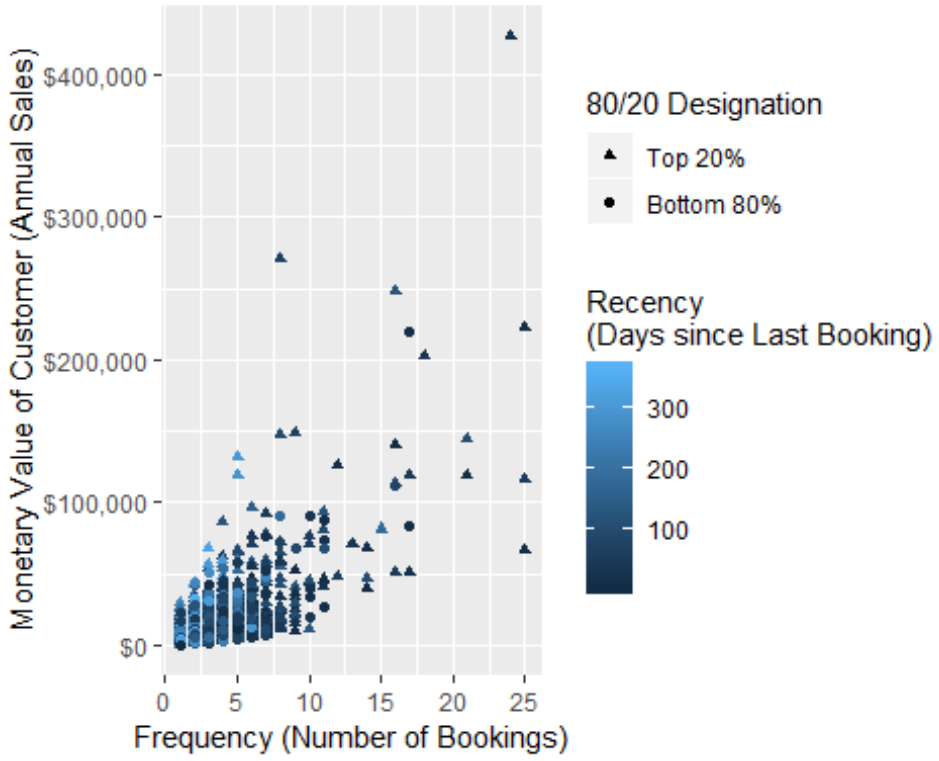
Apply Pareto Principle (80/20 rule)

```
pareto.cutoff <- 0.8 * sum(customers$monetary)
customers$pareto <- ifelse(cumsum(customers$monetary) <= pareto.cutoff, "Top
20%", "Bottom 80%")
customers$pareto <- factor(customers$pareto, levels=c("Top 20%", "Bottom
80%"), ordered=TRUE)
levels(customers$pareto)

## [1] "Top 20%"    "Bottom 80%"
```

Scatter Plots

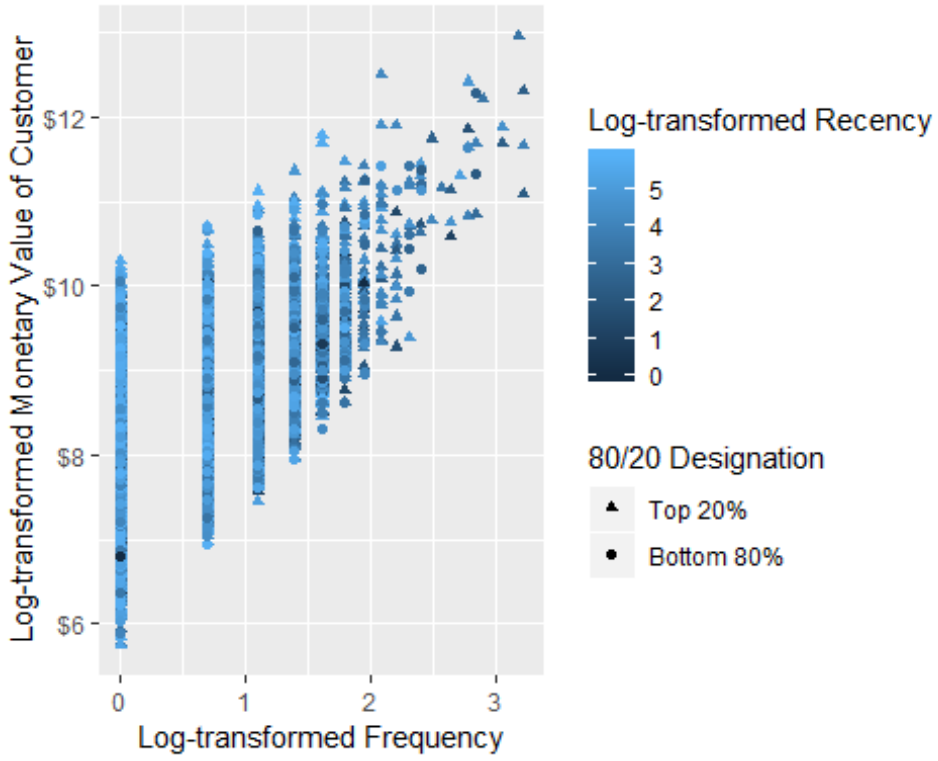
Raw Values

```
scatter.1 <- ggplot(customers, aes(x = frequency, y = monetary))
scatter.1 <- scatter.1 + geom_point(aes(colour = recency, shape = pareto))
scatter.1 <- scatter.1 + scale_shape_manual(name = "80/20 Designation",
values=c(17, 16))
scatter.1 <- scatter.1 + scale_colour_gradient(name="Recency\n(Days since
Last Booking)")
scatter.1 <- scatter.1 + scale_y_continuous(label=dollar)
scatter.1 <- scatter.1 + xlab("Frequency (Number of Bookings)")
scatter.1 <- scatter.1 + ylab("Monetary Value of Customer (Annual Sales)")
scatter.1
```



Log-transformed Values

```
scatter.1 <- ggplot(customers, aes(x = log(frequency), y = log(monetary)))
scatter.1 <- scatter.1 + geom_point(aes(colour = log(recency), shape =
pareto))
scatter.1 <- scatter.1 + scale_shape_manual(name = "80/20 Designation",
values=c(17, 16))
scatter.1 <- scatter.1 + scale_colour_gradient(name="Log-transformed
Recency")
scatter.1 <- scatter.1 + scale_y_continuous(label=dollar)
scatter.1 <- scatter.1 + xlab("Log-transformed Frequency")
scatter.1 <- scatter.1 + ylab("Log-transformed Monetary Value of Customer")
scatter.1
```



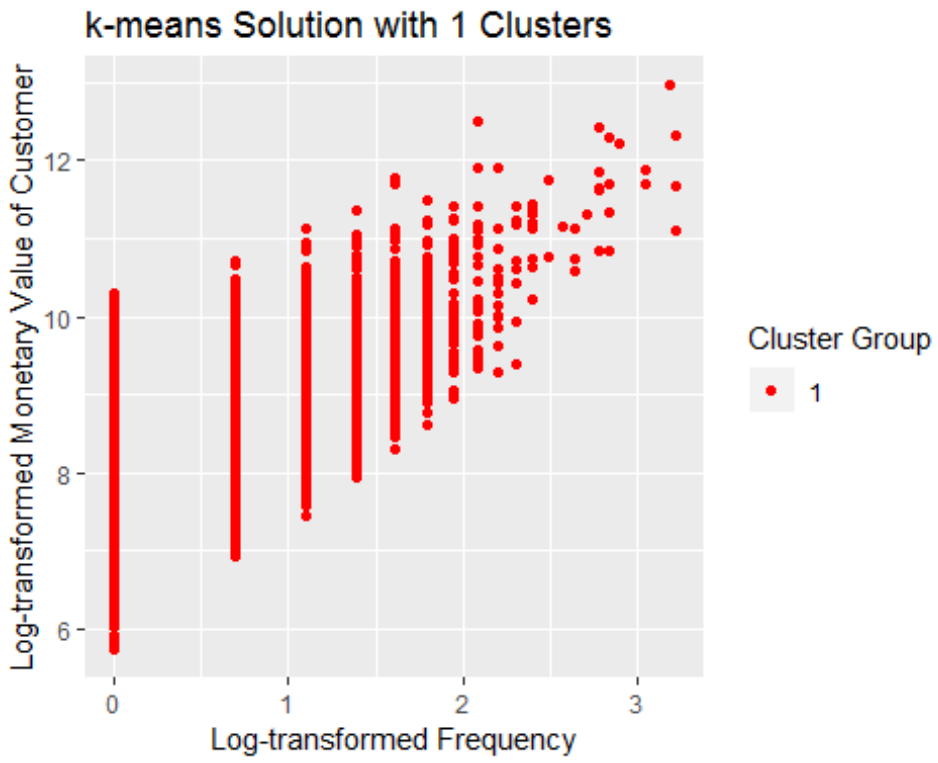
Modeling

Test number of clusters

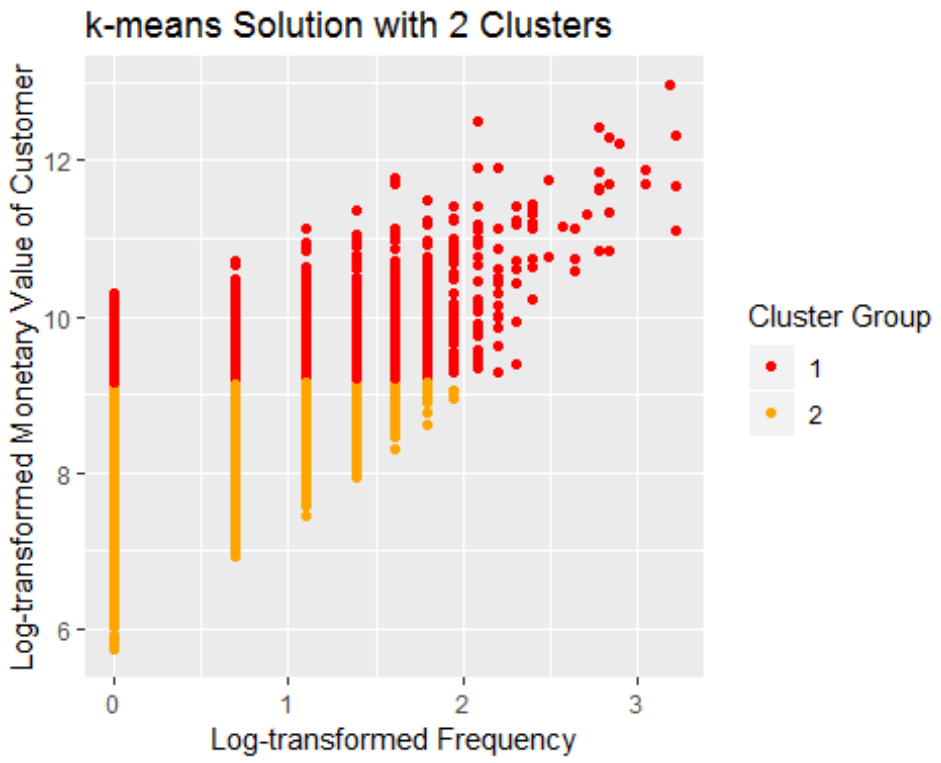
```
preprocessed <- customers[c(2:4)]
j <- 10 # maximum number of clusters

# Initiate model dataframe
models <- data.frame(k=integer(),
                     tot.withinss=numeric(),
                     betweenss=numeric(),
                     totss=numeric(),
                     rsquared=numeric())

# Add cluster membership to customers dataset
for (k in 1:j ) {

  print(k)

  # Run kmeans
  output <- kmeans(preprocessed, centers = k, nstart = 20)

  # Add cluster membership to customers dataset
  var.name <- paste("cluster", k, sep="_")
  customers[,(var.name)] <- output$cluster
  customers[,(var.name)] <- factor(customers[,(var.name)], levels = c(1:k))
```

```
  # Graph clusters
  cluster_graph <- ggplot(customers, aes(x = log(frequency), y =
log(monetary)))
  cluster_graph <- cluster_graph + geom_point(aes(colour =
customers[,(var.name)]))
  colors <-
c('red','orange','green3','deepskyblue','blue','darkorchid4','violet','pink1'
,'tan3','black')
  cluster_graph <- cluster_graph + scale_colour_manual(name = "Cluster
Group", values=colors)
  cluster_graph <- cluster_graph + xlab("Log-transformed Frequency")
  cluster_graph <- cluster_graph + ylab("Log-transformed Monetary Value of
Customer")
  title <- paste("k-means Solution with", k, sep=" ")
  title <- paste(title, "Clusters", sep=" ")
  cluster_graph <- cluster_graph + ggtitle(title)
  print(cluster_graph)

  # Cluster centers in original metrics
  print(title)
  cluster_centers <- ddply(customers, .(customers[,(var.name)]), summarize,
                           monetary=round(median(monetary),2),
frequency=round(median(frequency),1),
                           recency=round(median(recency), 0))
  names(cluster_centers)[names(cluster_centers)=="customers[, (var.name)]"]
<- "Cluster"
  print(cluster_centers)
  cat("\n")

  # Collect model information
  models[k,("k")] <- k
  models[k,("tot.withinss")] <- output$tot.withinss
  models[k,("betweenss")] <- output$betweenss
  models[k,("totss")] <- output$totss
  models[k,("rsquared")] <- round(output$betweenss/output$totss, 3)
  assign("models", models, envir = .GlobalEnv)
  remove(output, var.name, cluster_graph, cluster_centers, title, colors)
}
```

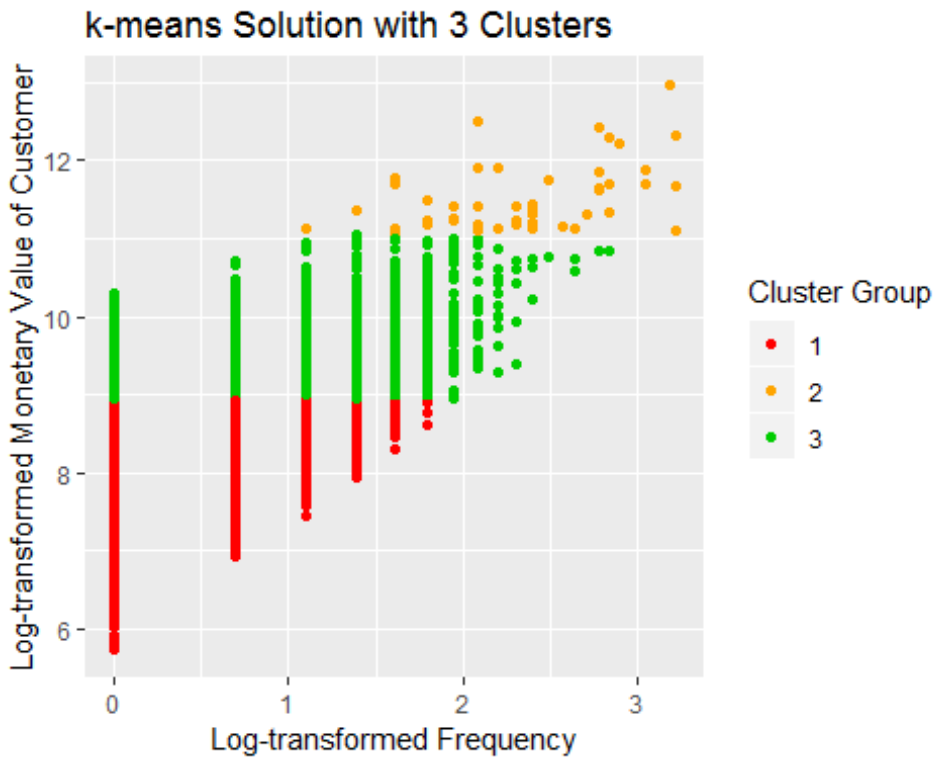
```
## [1] 1
```




```
## [1] "k-means Solution with 1 Clusters"
##   Cluster monetary frequency recency
## 1       1  3502.98         1     158
##
## [1] 2
```

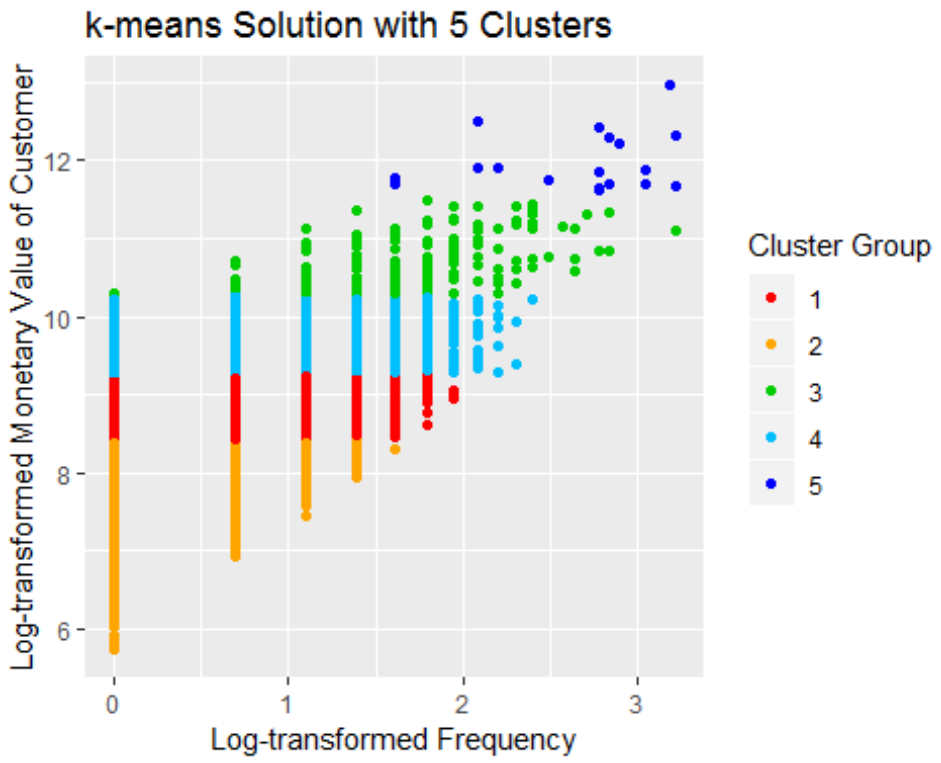



```
## [1] "k-means Solution with 2 Clusters"
##   Cluster monetary frequency recency
## 1       1 12392.48         3     119
## 2       2  3276.98         1     164
##
## [1] 3
```

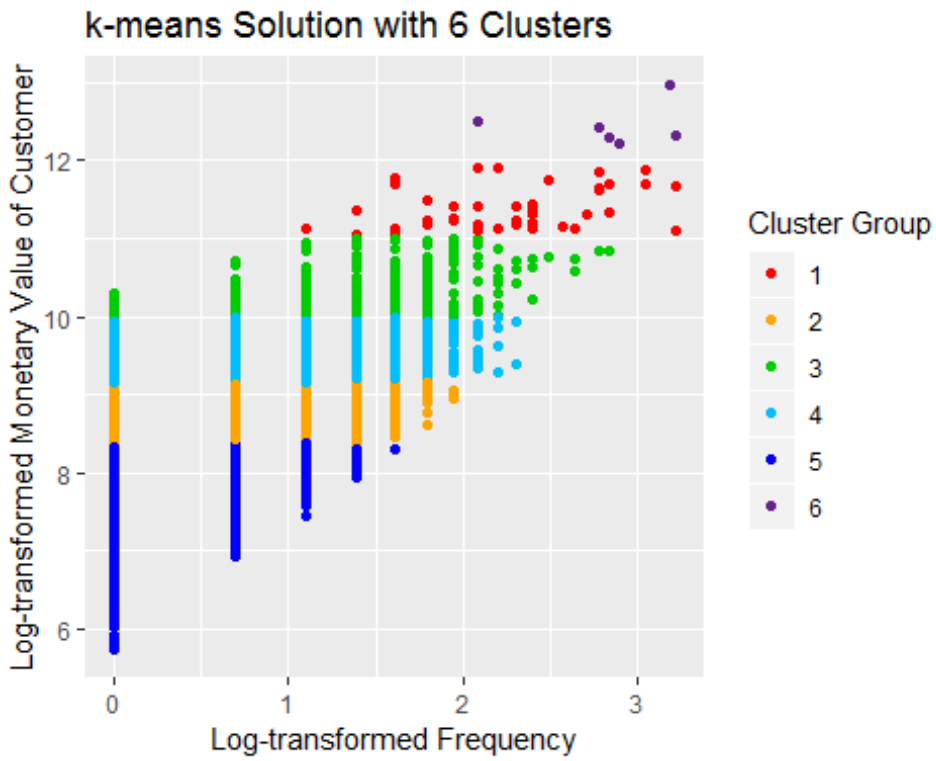



```
## [1] "k-means Solution with 3 Clusters"
##   Cluster monetary frequency recency
## 1       1  3121.59         1     167
## 2       2 87261.93        10      60
## 3       3 10089.68         3     121
##
## [1] 4
```

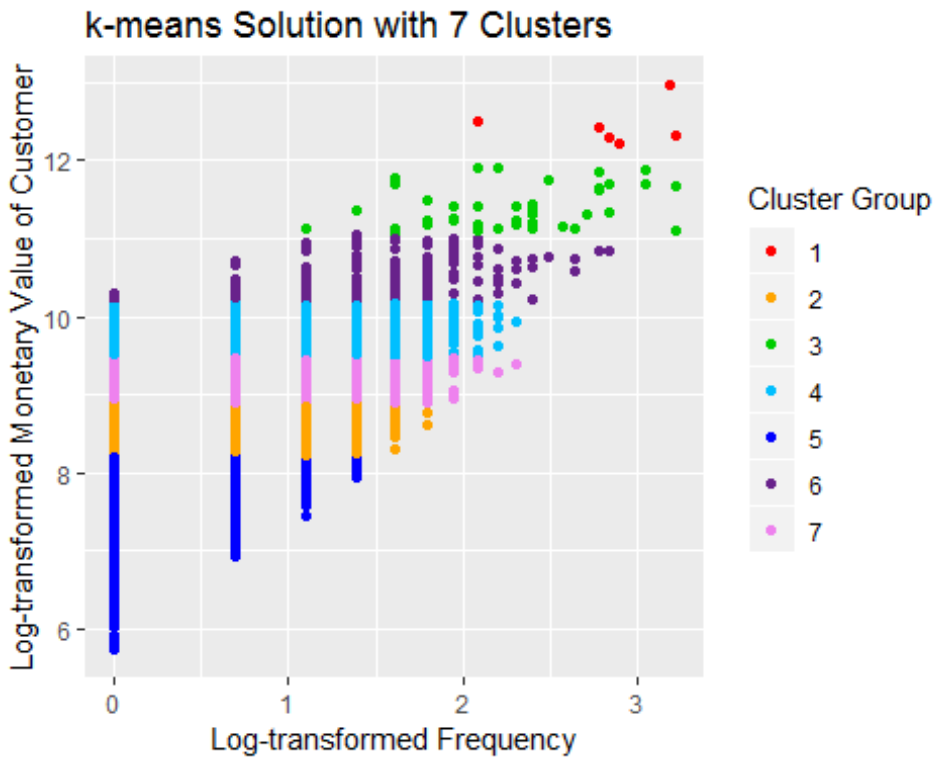

```
## [1] "k-means Solution with 4 Clusters"
##   Cluster  monetary frequency recency
## 1       1   8634.10         2     122
## 2       2 142114.32        16      60
## 3       3  30841.91         4      92
## 4       4   2917.07         1     171
##
## [1] 5
```



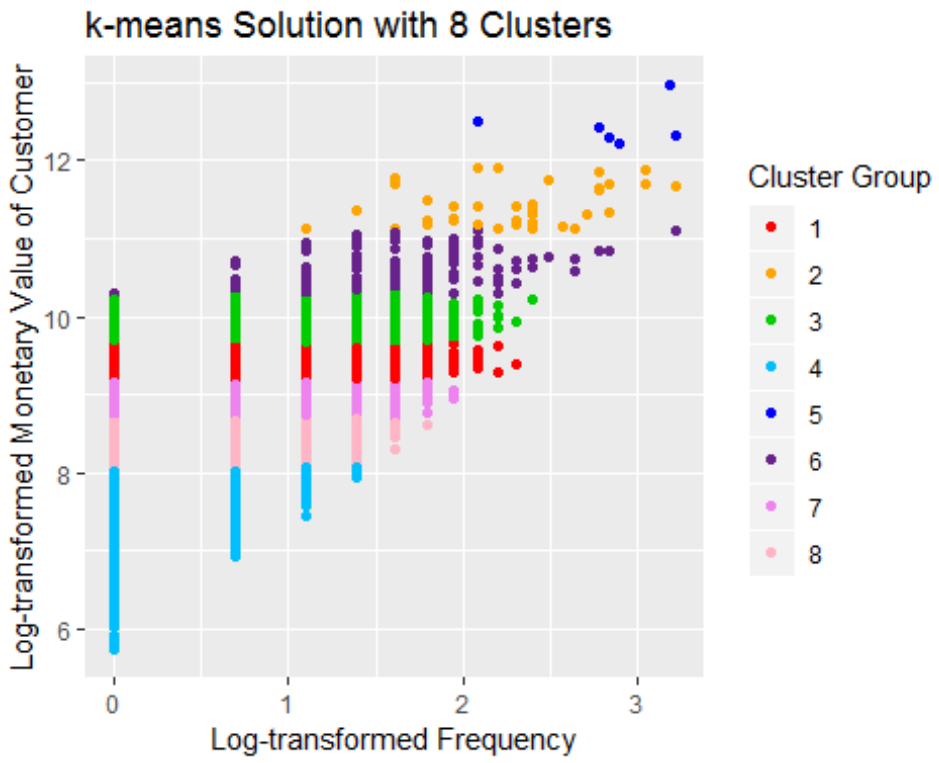

```
## [1] "k-means Solution with 5 Clusters"
##   Cluster  monetary frequency recency
## 1       1   6137.99         2     142
## 2       2   2453.98         1     178
## 3       3  38273.84         5      92
## 4       4  12931.55         3     118
## 5       5 142114.32        16      60
##
## [1] 6
```



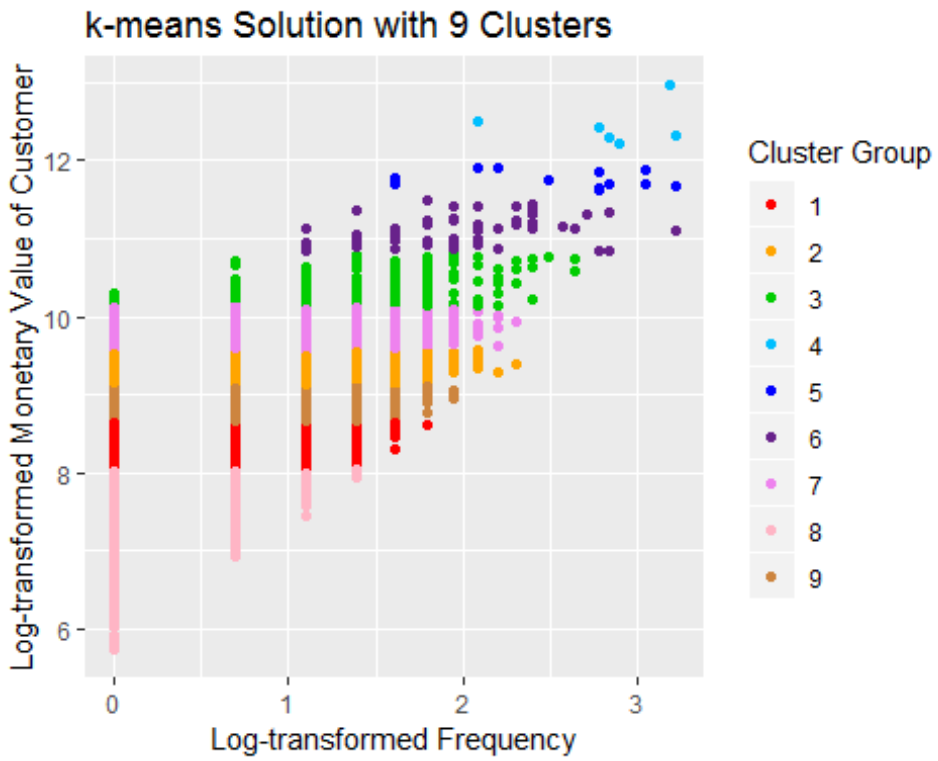

```
## [1] "k-means Solution with 6 Clusters"
##   Cluster  monetary frequency recency
## 1       1  81232.30       9.5      63
## 2       2   5843.51       2.0     142
## 3       3  28220.45       4.0     100
## 4       4  11868.87       3.0     121
## 5       5   2420.40       1.0     179
## 6       6 234831.18      17.5      30
##
## [1] 7
```



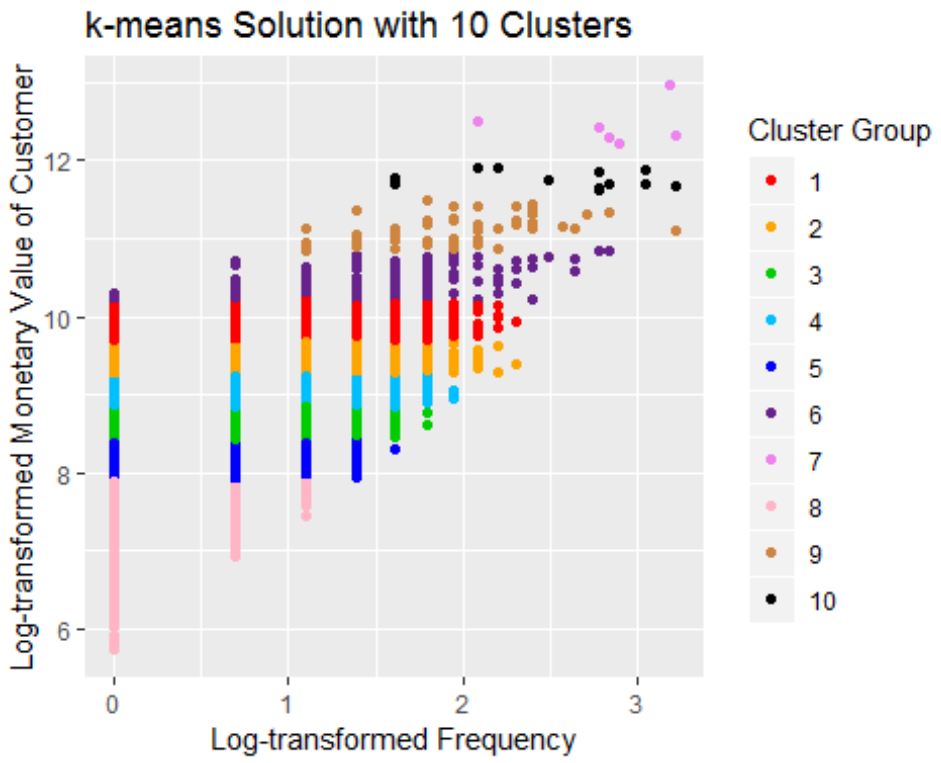

```
## [1] "k-means Solution with 7 Clusters"
##   Cluster  monetary frequency recency
## 1       1 234831.18      17.5      30
## 2       2   5081.29       2.0     150
## 3       3  81572.21      10.0      66
## 4       4  15667.49       3.0     116
## 5       5   2320.75       1.0     181
## 6       6  34051.75       4.0     108
## 7       7   8898.02       2.0     121
##
## [1] 8
```




```
## [1] "k-means Solution with 8 Clusters"
##   Cluster  monetary frequency recency
## 1       1  11490.82       3.0     121
## 2       2  84928.00      10.0      63
## 3       3  18533.49       3.0     101
## 4       4   2176.37       1.0     182
## 5       5 234831.18      17.5      30
## 6       6  36191.01       4.0     106
## 7       7   7309.24       2.0     128
## 8       8   4431.70       2.0     153
##
## [1] 9
```



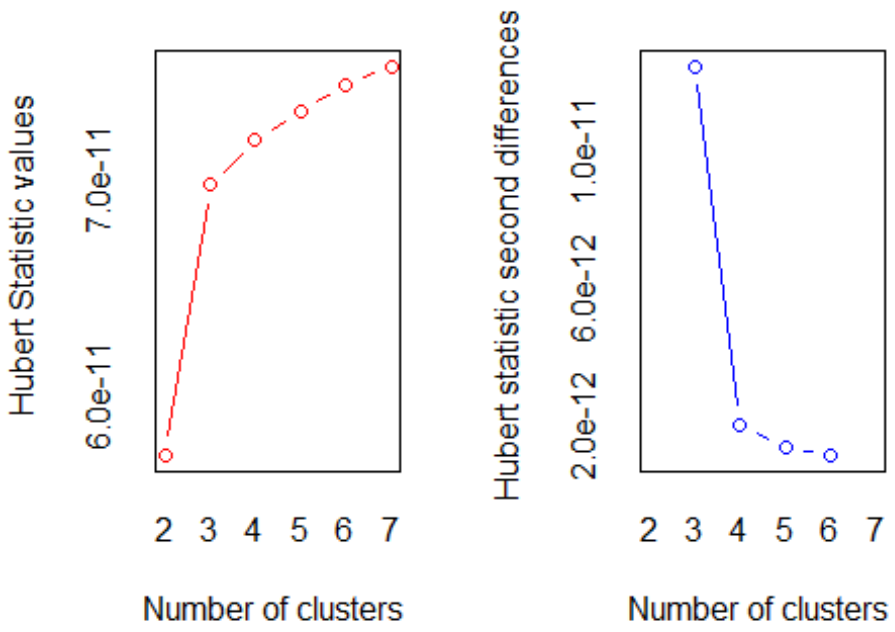

```
## [1] "k-means Solution with 9 Clusters"
##   Cluster  monetary frequency recency
## 1       1   4279.77       2.0     155
## 2       2  10872.55       3.0     121
## 3       3  31032.26       4.0     102
## 4       4 234831.18      17.5      30
## 5       5 122884.97      16.0      72
## 6       6  66076.84       7.0      61
## 7       7  17037.38       3.0     111
## 8       8   2129.94       1.0     183
## 9       9   7066.82       2.0     131
##
## [1] 10
```



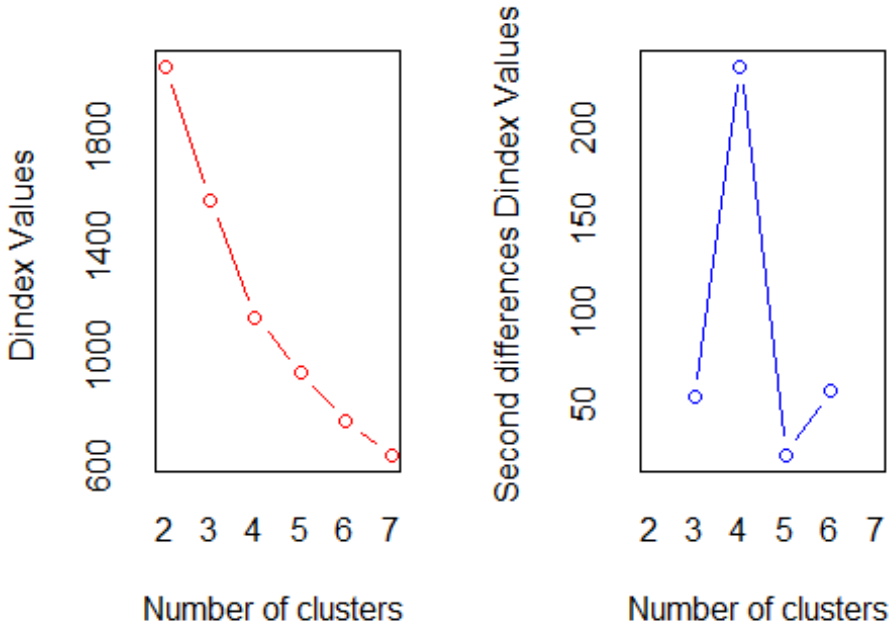

```
## [1] "k-means Solution with 10 Clusters"
##    Cluster  monetary frequency recency
## 1        1  18618.24       3.0     100
## 2        2  12254.72       3.0     121
## 3        3   5411.39       2.0     150
## 4        4   8189.38       2.0     122
## 5        5   3481.92       1.0     165
## 6        6  33396.71       4.0     107
## 7        7 234831.18      17.5      30
## 8        8   1862.77       1.0     183
## 9        9  67292.57       7.0      72
## 10      10 122884.97      16.0      72
```

```
# Use NBClust to determine optimal number of clusters
library(NbClust)
set.seed(1)
nc <- NbClust(preprocessed[sample(nrow(preprocessed), 1000),], min.nc=2,
max.nc=7, method="kmeans")
```

```
## [1] "Frey index : No clustering structure in this data set"
```




```
## *** : The Hubert index is a graphical method of determining the number of
clusters.
##                 In the plot of Hubert index, we seek a significant knee
that corresponds to a
##                 significant increase of the value of the measure i.e the
significant peak in Hubert
##                 index second differences plot.
##
```




```
## *** : The D index is a graphical method of determining the number of
clusters.
##                 In the plot of D index, we seek a significant knee (the
significant peak in Dindex
##                 second differences plot) that corresponds to a significant
increase of the value of
##                 the measure.
##
## *******************************************************************
## * Among all indices:
## * 5 proposed 2 as the best number of clusters
## * 9 proposed 3 as the best number of clusters
## * 2 proposed 4 as the best number of clusters
## * 2 proposed 5 as the best number of clusters
## * 3 proposed 6 as the best number of clusters
## * 2 proposed 7 as the best number of clusters
##
##                     ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is  3
##
##
## *******************************************************************

barplot(table(nc$Best.n[1,]),
        xlab="Number of Clusters", ylab="Number of Criteria",
        main="Number of Clusters Chosen by Criteria",
```

```
        cex.axis = .8,
        cex.names = .8)
```

ber of Clusters Chosen by