CUSTOMER SEGMENTATION AND MARKET BASKET ANALYSIS FOR AN ONLINE RETAIL

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INTRODUCTION

Customer segmentation is the process of dividing the customers into different groups based on their behavior with the company. Using customer segments, the company can market their strategies to each group effectively.

Market Basket Analysis is a technique to identify the strength of association between pairs of products that are purchased together.
This technique is based on a concept that if a person buys a product A, how likely the person will buy a product B.

Customer Segmentation and Market Basket Analysis is to explore different types of customers and their granular purchase behavior patterns.

DATA SET

- Dataset contains the Business data, and this data set belongs to a UK-based registered non-store online retail.

- This Data set contains all the transactions data occurred between 01/12/2010 and 09/12/2011.

Number of Instances : 541909

Online Retail Dataset

Attribute	Description	Data Type
InvoiceNo	Invoice number	Character
StockCode	Product Code	Character
Description	Product Name	Character
Quantity	Quantity of each product per transaction	Number
InvoiceDate	Invoice Date and Time	Number
UnitPrice	Price of the Product per unit	Number
CustomerID	Customer Number	Number
Country	Country Name	Character

RESEARCH PROBLEMS

Identify the customers into different groups based on their behavior with the online retail. Identify the Loyal Customers.

Identify best 10 Association rules for the products purchased in the online retail.

PROPOSED SOLUTIONS

Identify the customers into different groups based on their behavior with the online retail.

RFM Analysis is the data-driven customer segmentation technique.

Recency : Number of days from the last purchase

Frequency : Number of visits

Monetary : Total amount spent

we use both K-means Clustering and Hierarchal clustering algorithms on RFM data for customer segmentation.

Identify best 10 Association rules for the products purchased in the online retail.

Group the products based on InvoiceNo and apply Apriori algorithm to find the association rules for the products.

Load the Data

```
# Load retail data into R session
install.packages("openxlsx")
library(openxlsx)
```

```
> data=read.xlsx("Online Retail.xlsx", 1)
>
> # Structure of the data
> str(data)
'data.frame':   541909 obs. of  8 variables:
 $ InvoiceNo  : chr  "536365" "536365" "536365" "536365" ...
 $ StockCode  : chr  "85123A" "71053" "84406B" "84029G" ...
 $ Description: chr  "WHITE HANGING HEART T-LIGHT HOLDER" "WHITE METAL LANTERN" "CREAM CUPID HEARTS COAT HANGER" "KNITTED UNION FLAG HOT WATER BOTTLE" ...
 $ Quantity   : num  6 6 8 6 6 2 6 6 6 32 ...
 $ InvoiceDate: num  40513 40513 40513 40513 40513 ...
 $ UnitPrice  : num  2.55 3.39 2.75 3.39 3.39 7.65 4.25 1.85 1.85 1.69 ...
 $ CustomerID : num  17850 17850 17850 17850 17850 ...
 $ Country    : chr  "United Kingdom" "United Kingdom" "United Kingdom" "United Kingdom" ...
> # Change the type of InvoiceDate
> data$InvoiceDate <- as.POSIXct(data$InvoiceDate * (60*60*24),
+                                origin="1899-12-30", tz="GMT")
> head(data)
  InvoiceNo StockCode                         Description Quantity         InvoiceDate UnitPrice CustomerID        Country
1    536365    85123A  WHITE HANGING HEART T-LIGHT HOLDER        6 2010-12-01 08:26:00      2.55      17850 United Kingdom
2    536365     71053                 WHITE METAL LANTERN        6 2010-12-01 08:26:00      3.39      17850 United Kingdom
3    536365    84406B      CREAM CUPID HEARTS COAT HANGER        8 2010-12-01 08:26:00      2.75      17850 United Kingdom
4    536365    84029G KNITTED UNION FLAG HOT WATER BOTTLE        6 2010-12-01 08:26:00      3.39      17850 United Kingdom
5    536365    84029E      RED WOOLLY HOTTIE WHITE HEART.        6 2010-12-01 08:26:00      3.39      17850 United Kingdom
6    536365     22752        SET 7 BABUSHKA NESTING BOXES        2 2010-12-01 08:26:00      7.65      17850 United Kingdom
```

- Observations = 541909
- Variables = 8

Change InvoiceDate type from Number to Date

Pre-Processing the Data

```
> # Check for the sum of Null values in all columns
> colSums(is.na(data))
  InvoiceNo   StockCode Description    Quantity InvoiceDate   UnitPrice  CustomerID     Country
          0           0        1454           0           0           0      135080           0
> # Omit the rows with Null values in CustomerID.
> library(tidyr)
> retail_data <- data %>%
+   drop_na(CustomerID)
>
> # Check for Null values
> colSums(is.na(retail_data))
  InvoiceNo   StockCode Description    Quantity InvoiceDate   UnitPrice  CustomerID     Country
          0           0           0           0           0           0           0           0
```

Handling Missing values

```
> # Summary of retail data
> summary(retail_data)
   InvoiceNo          StockCode         Description          Quantity          InvoiceDate                    UnitPrice          CustomerID      Country
 Length:406829      Length:406829      Length:406829      Min.   :-80995.00   Min.   :2010-12-01 08:26:00   Min.   :    0.00   Min.   :12346   Length:406829
 Class :character   Class :character   Class :character   1st Qu.:     2.00   1st Qu.:2011-04-06 15:02:00   1st Qu.:    1.25   1st Qu.:13953   Class :character
 Mode  :character   Mode  :character   Mode  :character   Median :     5.00   Median :2011-07-31 11:48:00   Median :    1.95   Median :15152   Mode  :character
                                                          Mean   :    12.06   Mean   :2011-07-10 16:30:57   Mean   :    3.46   Mean   :15288
                                                          3rd Qu.:    12.00   3rd Qu.:2011-10-20 13:06:00   3rd Qu.:    3.75   3rd Qu.:16791
                                                          Max.   : 80995.00   Max.   :2011-12-09 12:50:00   Max.   :38970.00   Max.   :18287
```

Remove return Transactions - Summary of data

```
> ## Remove unrelated and return transactions
> retail_data <- retail_data[retail_data$Quantity >= 0,]
> retail_data <- retail_data[retail_data$UnitPrice > 0,]
>
> summary(retail_data)
   InvoiceNo          StockCode         Description          Quantity          InvoiceDate                    UnitPrice          CustomerID      Country
 Length:397884      Length:397884      Length:397884      Min.   :    1.00   Min.   :2010-12-01 08:26:00   Min.   :    0.001   Min.   :12346   Length:397884
 Class :character   Class :character   Class :character   1st Qu.:    2.00   1st Qu.:2011-04-07 11:12:00   1st Qu.:    1.250   1st Qu.:13969   Class :character
 Mode  :character   Mode  :character   Mode  :character   Median :    6.00   Median :2011-07-31 14:39:00   Median :    1.950   Median :15159   Mode  :character
                                                          Mean   :   12.99   Mean   :2011-07-10 23:41:23   Mean   :    3.116   Mean   :15294
                                                          3rd Qu.:   12.00   3rd Qu.:2011-10-20 14:33:00   3rd Qu.:    3.750   3rd Qu.:16795
                                                          Max.   :80995.00   Max.   :2011-12-09 12:50:00   Max.   :8142.750   Max.   :18287
```

Customer Segmentation – Calculate RFM

Recency : Number of days since last Purchase.

Frequency: Number of visits.

Monetary: Total amount spent.

```
> ## Recency
> max_date <- max(retail_data$InvoiceDate)
> max_date
[1] "2011-12-09 12:49:59 GMT"
>
> # Difference between the InvoiceDate and max_date
> retail_data$time_delta <- as.numeric(difftime(as.Date(max_date), as.Date(retail_data$InvoiceDate), units="days"))
> head(retail_data$time_delta, 2)
[1] 373 373
> # minimum time_delta (maxdate - recent InvoiceDate) of every customer
> Recency <- retail_data %>%
+               select(CustomerID, time_delta) %>%
+               group_by(CustomerID) %>%
+               slice(which.min(time_delta))
```

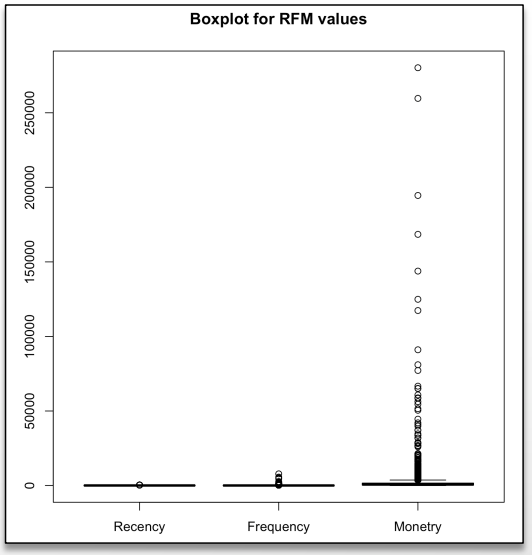
```
> # Frequency
> # Group the data by customerId and get the count of invoiceNo
> Frequency <- retail_data %>%
+                 select(CustomerID, InvoiceNo) %>%
+                 group_by(CustomerID) %>%
+                 summarize(count = n())
`summarise()` ungrouping output (override with `.groups` argument)
>
> ## Monetry
> # Group the data by CustomerID and get the sum of amount spent
> # Calculate total price i.e., quantity*unitprice
> retail_data$Total_Price <- (retail_data$Quantity)*(retail_data$UnitPrice)
>
> Monetry <- retail_data %>%
+                 select(CustomerID, Total_Price) %>%
+                 group_by(CustomerID) %>%
+                 summarize(Total = sum(Total_Price))
`summarise()` ungrouping output (override with `.groups` argument)
```

```
> RF <- merge(Recency, Frequency, by='CustomerID')
> RFM <- merge(RF, Monetry, by='CustomerID')
> colnames(RFM) <- c('CustomerID', 'Recency', 'Frequency', 'Monetry')
>
> str(RFM)
'data.frame':   4338 obs. of  4 variables:
 $ CustomerID: num  12346 12347 12348 12349 12350 ...
 $ Recency   : num  325 2 75 18 310 36 204 232 214 22 ...
 $ Frequency : int  1 182 31 73 17 85 4 58 13 59 ...
 $ Monetry   : num  77184 4310 1797 1758 334 ...
> head(RFM)
  CustomerID Recency Frequency  Monetry
1      12346     325         1 77183.60
2      12347       2       182  4310.00
3      12348      75        31  1797.24
4      12349      18        73  1757.55
5      12350     310        17   334.40
6      12352      36        85  2506.04
> summary(RFM)
   CustomerID       Recency         Frequency         Monetry
 Min.   :12346   Min.   :  0.00   Min.   :   1.00   Min.   :     3.75
 1st Qu.:13813   1st Qu.: 17.00   1st Qu.:  17.00   1st Qu.:   307.42
 Median :15300   Median : 50.00   Median :  41.00   Median :   674.48
 Mean   :15300   Mean   : 92.06   Mean   :  91.72   Mean   :  2054.27
 3rd Qu.:16779   3rd Qu.:141.75   3rd Qu.: 100.00   3rd Qu.:  1661.74
 Max.   :18287   Max.   :373.00   Max.   :7847.00   Max.   :280206.02
```

RFM data Pre-Processing

```
> ## RFM data re-processing ###################################################
>
> # Check for outliers
> boxplot(RFM[-1], main="Boxplot for RFM values")
>
> # Remove outliers
> Recency_outliers <- boxplot(RFM$Recency, plot=FALSE)$out
> RFM_data <- RFM[-which(RFM$Recency %in% Recency_outliers),]
>
> Frequency_outliers <- boxplot(RFM$Frequency, plot=FALSE)$out
> RFM_data <- RFM[-which(RFM$Frequency %in% Frequency_outliers),]
>
> Monetry_outliers <- boxplot(RFM$Monetry, plot=FALSE)$out
> RFM_data <- RFM[-which(RFM$Monetry %in% Monetry_outliers),]
>
> # Structure of RFM_data
> str(RFM_data)
'data.frame':   3911 obs. of  4 variables:
 $ CustomerID: num  12348 12349 12350 12352 12353 ...
 $ Recency   : num  75 18 310 36 204 232 214 22 1 52 ...
 $ Frequency : int  31 73 17 85 4 58 13 59 19 129 ...
 $ Monetry   : num  1797 1758 334 2506 89 ...
```

Removing Outliers




```
> # Scale the Numerical Variables
> vars <- c('Recency','Frequency','Monetry')
> Clust_Data <- data.frame(RFM_data[-1])
> Clust_Data[vars] <- lapply(RFM_data[vars], scale)
> head(Clust_Data)
     Recency   Frequency    Monetry
3 -0.2403706 -0.39472592  1.0990271
4 -0.8015356  0.14852823  1.0511234
5  2.0732046 -0.57581063 -0.6665412
6 -0.6243256  0.30374370  1.9545102
7  1.0296345 -0.74396072 -0.9627256
8  1.3052945 -0.04549111  0.2326333
```

Scale the data

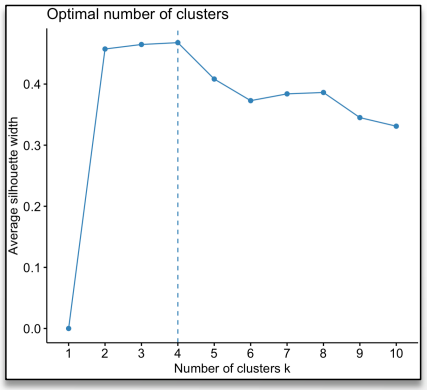
K-Means Clustering – K with Silhouette Method

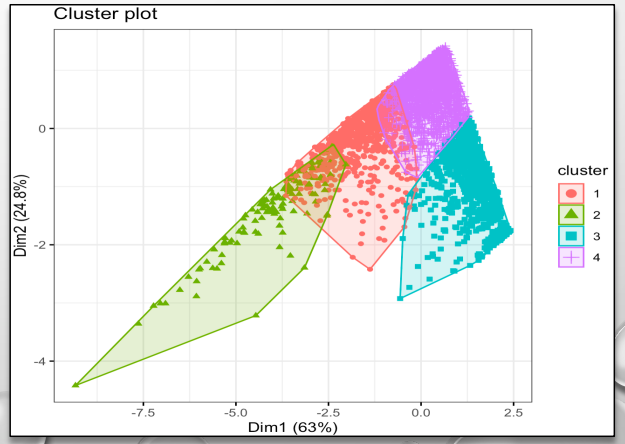
- Silhouette Method
- Silhouette Score is a measure of how similar an object is to its own cluster. Ranges from -1 to +1

```
> # Silhouette Score
> set.seed(123)
> fviz_nbclust(Clust_Data, kmeans, method = "silhouette")
> # From the silhouette method, the optimal number of clusters is 4
```

```
> # Compute K-Means with k as 4
> set.seed(101)
> KM_Model1 <- kmeans(Clust_Data, 4, nstart = 25)
> # nstart=25 will generate 25 random centroids and choose the best one for algorithm.
>
> fviz_cluster(KM_Model1, data=Clust_Data,
+              geom="point",
+              ellipse.type = "convex",
+              ggtheme = theme_bw())
>
> # Size of Clusters
> KM_Model1$size
[1]  786  119  985 2021
> # Center of clusters
> KM_Model1$centers
     Recency  Frequency     Monetry
1 -0.5719567  0.7426322  1.4600967
2 -0.7496632  4.0453278  1.8326463
3  1.5205852 -0.4883279 -0.6109894
4 -0.4745218 -0.2890153 -0.3779794
```

K = 4



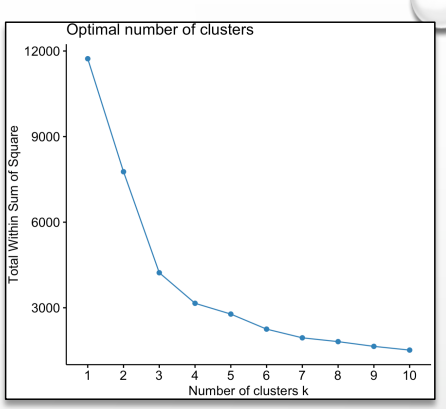


K-Means Clustering – K with Elbow Method

Elbow Method

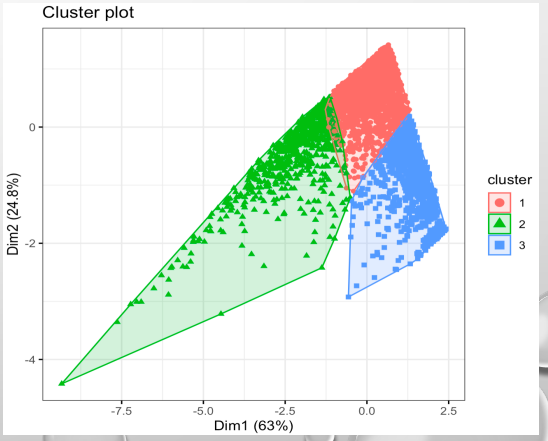
- Elbow Method gives the total Within Sum of Squared Errors for different values of K.

```
> # Elbow method
> set.seed(123)
> fviz_nbclust(Clust_Data, kmeans, method='wss')
> # From the elbow method, at k=3, the total within sum of squares will be less.
```



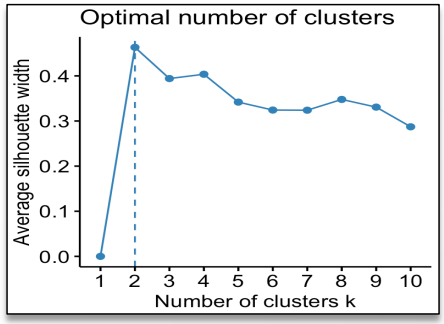
K = 3

```
> # Compute K-Means with k as 3
> set.seed(101)
> KM_Model2 <- kmeans(Clust_Data, 3, nstart = 25)
> # nstart=25 will generate 25 random centroids and choose the best one for algorithm.
>
> fviz_cluster(KM_Model2, data=Clust_Data,
+              geom="point",
+              ellipse.type = "convex",
+              ggtheme = theme_bw())
>
> # Size of Clusters
> KM_Model2$size
[1] 2154  758  999
> # Center of clusters
> KM_Model2$centers
     Recency  Frequency    Monetry
1 -0.4781634 -0.2581498 -0.3034692
2 -0.6310794  1.3699627  1.6535819
3  1.5098321 -0.4828600 -0.6003427
```

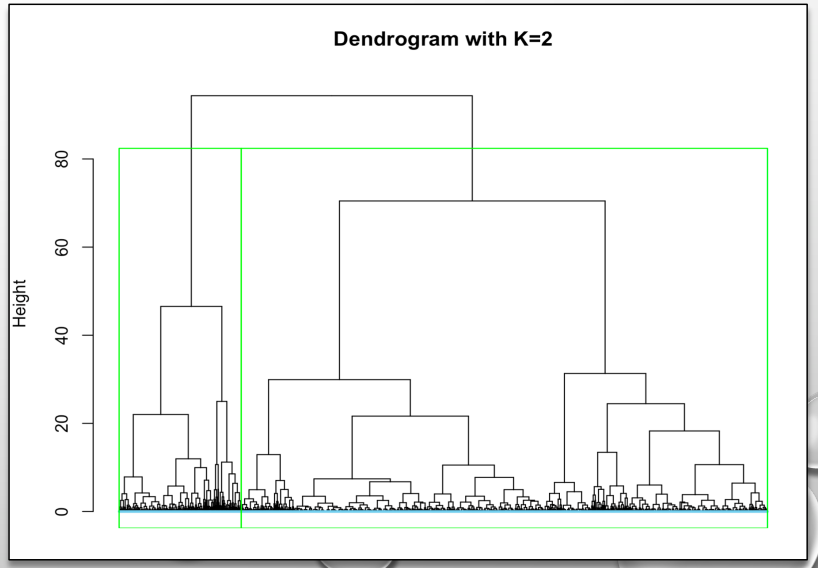


Hierarchical Clustering – K with Silhouette Method

```
> ## Hierarchical Clustering ##############################################
>
> # Silhouette Score
> set.seed(123)
> fviz_nbclust(Clust_Data, hcut, method = "silhouette")
> # From the silhouette method, the optimal number of clusters is 2
>
> # calculate distance between vectors of Clust_Data
> d <- dist(Clust_Data, method='euclidean')
> HC_model1 <- hclust(d, method='ward.D2')
>
> # Dendrogram, customizing the plot to remove labels
> HC_model1_d <- as.dendrogram(HC_model1)
> nodePar <- list(lab.cex = 0.6, pch = c(NA, 19),
+                 cex = 0.2, col = "skyblue")
> plot(HC_model1_d, ylab = "Height", nodePar = nodePar, leaflab = "none",
+      main = "Dendrogram with K=2")
> rect.hclust(HC_model1, k=2, border="green")
>
> groups <- cutree(HC_model1, k=2)
> HC_data1 <- data.frame(Clust_Data, groups)
> head(HC_data1, 1)
     Recency  Frequency  Monetry groups
3 -0.2403706 -0.3947259 1.099027      1
>
> # size of groups
> HC_data1 %>%
+   group_by(groups) %>%
+   summarise(count=n())
`summarise()` ungrouping output (override with `.groups` argument)
# A tibble: 2 x 2
  groups count
   <int> <int>
1      1  3174
2      2   737
```

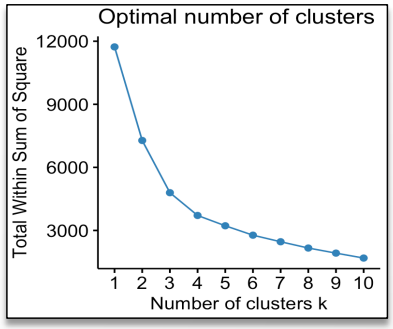


Considering
K = 2

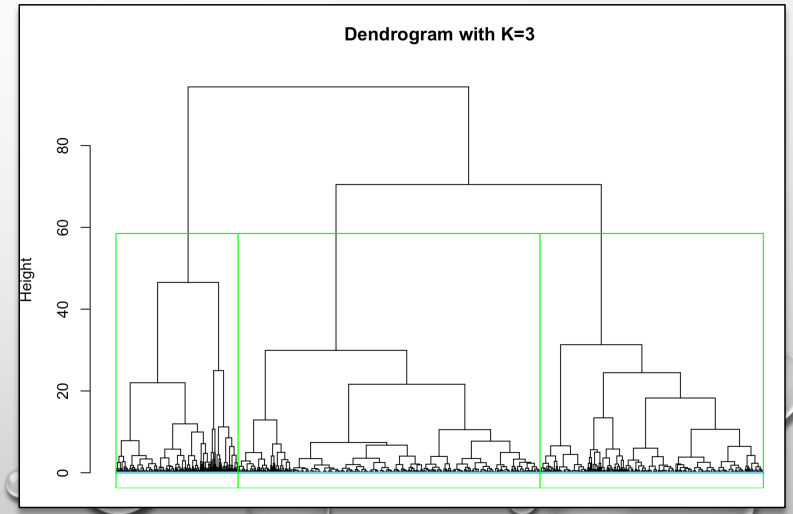


Hierarchical Clustering - K with Elbow method

```
> # Elbow method
> set.seed(123)
> fviz_nbclust(Clust_Data, hcut, method='wss')
> # From the elbow method, at k=3, the total within sum of squares will be less.
>
> HC_model2 <- hclust(d, method='ward.D2')
>
> # Dendrogram, customizing the plot to remove labels
> HC_model1_d <- as.dendrogram(HC_model1)
> nodePar <- list(lab.cex = 0.6, pch = c(NA, 19),
+                 cex = 0.2, col = "skyblue")
> plot(HC_model1_d, ylab = "Height", nodePar = nodePar, leaflab = "none",
+      main = "Dendrogram with K=3")
> rect.hclust(HC_model1, k=3, border="green")
>
> groups <- cutree(HC_model2, k=3)
> HC_data2 <- data.frame(Clust_Data, groups)
> head(HC_data2, 1)
     Recency  Frequency  Monetry groups
3 -0.2403706 -0.3947259 1.099027      1
>
> # size of groups
> HC_data2 %>%
+   group_by(groups) %>%
+   summarise(count=n())
`summarise()` ungrouping output (override with `.groups` argument)
# A tibble: 3 x 2
  groups count
   <int> <int>
1      1  1349
2      2   737
3      3  1825
```



Considering
K = 3



Clustering - Evaluation

Using Internal validation measures

Connectivity : Degree of connectedness of the clusters determined by KNN. This should be minimum.

Silhouette width: Measures the compactness of the clusters.

$$S_i = \frac{(b_i - a_i)}{max(a_i, b_i)}$$

a_i is the average distance of object i from all other objects of same cluster.

b_i is the average distance of object i from all other objects of different cluster.

The range of S_i is [-1,1].

Dunn Index: Measures the separation of clusters.

$$D = \frac{min.separation}{max.diameter}$$

This should be maximum.

```
> ## Clustering Validation
> library(clValid)
> # Internal
> internal <- clValid(as.matrix(Clust_Data), nClust = 2:4,
+                     clMethods = c("hierarchical","kmeans"),
+                    validation = "internal")

The number of items to be clustered is larger than 'maxitems'
The memory and time required may be excessive, do you wish to continue?
(y to continue, any other character to exit)
y
> summary(internal)

Clustering Methods:
 hierarchical kmeans

Cluster sizes:
 2 3 4

Validation Measures:
                                    2        3        4

hierarchical Connectivity    3.0290  15.8480  26.2401
             Dunn            0.2803   0.0540   0.0540
             Silhouette      0.8232   0.6360   0.4251
kmeans       Connectivity  153.5032 255.6778 276.3798
             Dunn            0.0024   0.0031   0.0041
             Silhouette      0.4574   0.4648   0.4688

Optimal Scores:

             Score  Method       Clusters
Connectivity 3.0290 hierarchical 2
Dunn         0.2803 hierarchical 2
Silhouette   0.8232 hierarchical 2
```

Clustering - Evaluation

Manual evaluation using centers of Clusters

Centers of 4 clusters with K-Means

```
> # Centers of clusters from K-means Model with K= 4
> KM_Model1$centers
     Recency  Frequency   Monetary
1 -0.5719567  0.7426322  1.4600967
2 -0.7496632  4.0453278  1.8326463
3  1.5205852 -0.4883279 -0.6109894
4 -0.4745218 -0.2890153 -0.3779794
```

Centers of 3 clusters with K-Means

```
> # Centers of clusters from K-means Model with K= 3
> KM_Model2$centers
     Recency  Frequency   Monetary
1 -0.4781634 -0.2581498 -0.3034692
2 -0.6310794  1.3699627  1.6535819
3  1.5098321 -0.4828600 -0.6003427
```

Centers of 2 clusters with Hierarchical

```
> # Centers of clusters from Hierarchical clustering with K = 2
> apply (Clust_Data, 2, function (x) tapply (x, groups2, mean))
     Recency  Frequency   Monetary
1  0.1508643 -0.2854663 -0.4000176
2 -0.6497195  1.2294028  1.7227353
```

Centers of 3 clusters with Hierarchical

```
> # Centers of clusters from Hierarchical clustering with K = 3
> apply (Clust_Data, 2, function (x) tapply (x, groups3, mean))
     Recency  Frequency   Monetary
1  1.1628303 -0.4485738 -0.4882853
2 -0.6497195  1.2294028  1.7227353
3 -0.5971588 -0.1649007 -0.3347721
```

Customer Segmentation - Conclusion

```
> customers_1 <- head(RFM_data$CustomerID[RFM_data$Cluster == 1])
> filter(RFM_data, RFM_data$CustomerID %in% customers_1)
  CustomerID Recency Frequency Monetry Cluster
1      12348      75        31 1797.24       1
2      12350     310        17  334.40       1
3      12353     204         4   89.00       1
4      12354     232        58 1079.40       1
5      12355     214        13  459.40       1
6      12358       1        19 1168.06       1
```

Cluster 1 is of the customers who are either with More Recency or Less Frequency or Less Monetary in the online Retail.

```
> customers_2 <- head(RFM_data$CustomerID[RFM_data$Cluster == 2])
> filter(RFM_data, RFM_data$CustomerID %in% customers_2)
  CustomerID Recency Frequency Monetry Cluster
1      12349      18        73 1757.55       2
2      12352      36        85 2506.04       2
3      12356      22        59 2811.43       2
4      12360      52       129 2662.06       2
5      12370      51       167 3545.69       2
6      12371      44        63 1887.96       2
```

Cluster 2 is of the customers who are Recent, Frequent and spent more amount in the online Retail.

Customers in Cluster 2 are **Loyal Customers**.

Market Basket Analysis – Association rules

Pre-Processing the data

```
> # Pre-Processing ################################################################
> colSums(is.na(data))
  InvoiceNo   StockCode Description    Quantity InvoiceDate   UnitPrice  CustomerID     Country
          0           0        1454           0           0           0      135080           0
> library(tidyr)
>
> # Remove rows with Description as Null
> rules_data <- data %>%
+               drop_na(Description)
```

Handle Missing values

```
> #remove the unrelated and return transactions
> rules_data <- rules_data[rules_data$Quantity >= 0,]
> rules_data <- rules_data[rules_data$UnitPrice > 0,]
>
> # str(rules_data)
>
> length(unique(rules_data$StockCode))
[1] 3922
> length(unique(rules_data$Description))
[1] 4026
>
> head(rules_data$Description, 3)
[1] "WHITE HANGING HEART T-LIGHT HOLDER" "WHITE METAL LANTERN"                "CREAM CUPID HEARTS COAT HANGER"
>
> # trim the Description
> library(stringr)
> rules_data$Description <- str_trim(rules_data$Description)
> # Check for Special characters
> rules_data[grepl('[!#$%&*+;<=>?@[]^`|~]', rules_data$Description),]
[1] InvoiceNo   StockCode   Description Quantity    InvoiceDate UnitPrice   CustomerID  Country
<0 rows> (or 0-length row.names)
```

- Removed return transactions
- Trim the description
- Check for special characters in the description
- Check for the number of unique stock codes and unique descriptions

Market Basket Analysis – Pre-Processing the data

```
> # Check for Description in lower case
> head(rules_data[grepl('[:lower:]', rules_data$Description),])
     InvoiceNo StockCode                      Description Quantity         InvoiceDate UnitPrice CustomerID        Country
2060    536557     22686     FRENCH BLUE METAL DOOR SIGN No        1 2010-12-01 14:41:00      1.25      17841 United Kingdom
2231    536569         M                           Manual        1 2010-12-01 15:35:00      1.25      16274 United Kingdom
2242    536569         M                           Manual        1 2010-12-01 15:35:00     18.95      16274 United Kingdom
2558    536592     21594      Dr. Jam's Arouzer Stress Ball        1 2010-12-01 17:06:00      4.21         NA United Kingdom
3296    536620     22965 3 TRADITIONAl BISCUIT CUTTERS  SET        6 2010-12-02 10:27:00      2.10      14135 United Kingdom
3400    536626     22965 3 TRADITIONAl BISCUIT CUTTERS  SET        6 2010-12-02 10:46:00      2.10      13418 United Kingdom
> # Remove the data with description as Manual
> rules_data <- rules_data[rules_data$Description != 'Manual',]
> # Identify the StockCodes having two descriptions and use the descriptions to process the multi descriptions
> df <- data.frame(rules_data %>%
+   select(StockCode, Description) %>%
+   group_by(StockCode, Description) %>%
+   count(StockCode, Description))
>
> x <- df$StockCode[duplicated(df$StockCode)]
> sort(df$Description[df$StockCode %in% x])
  [1] "16 PC CUTLERY SET PANTRY DESIGN"     "16 PIECE CUTLERY SET PANTRY DESIGN"  "3 DRAWER ANTIQUE WHITE WOOD CABINET" "3 TRADITIONAl BISCUIT CUTTERS  SET"
  [5] "3 TRADITIONAL COOKIE CUTTERS  SET"   "36 DOILIES DOLLY GIRL"               "36 DOILIES VINTAGE CHRISTMAS"        "50'S CHRISTMAS GIFT BAG LARGE"
  [9] "60 CAKE CASES VINTAGE CHRISTMAS"     "70'S ALPHABET WALL ART"              "72 CAKE CASES VINTAGE CHRISTMAS"     "ACRYLIC JEWEL SNOWFLAKE,PINK"
 [13] "ADULT APRON APPLE DELIGHT"           "ALUMINIUM HEART"                     "ALUMINIUM STAMPED HEART"             "ANIMALS AND NATURE WALL ART"
```

- Handle data with no valid Description
- Handle data with typo errors in Description

```
> rules_data$Description <- ifelse(rules_data$Description == "WALL ART BICYCLE SAFTEY", "WALL ART BICYCLE SAFETY",
+ ifelse(rules_data$Description == "WALL ART,ONLY ONE PERSON", "WALL ART ONLY ONE PERSON",
+ ifelse(rules_data$Description == "WHITE WIRE PLANT POT HOLDER", "WHITE HEARTS WIRE PLANT POT HOLDER",
+ ifelse(rules_data$Description == "WHITE METAL LANTERN", "WHITE MOROCCAN METAL LANTERN",
+ ifelse(rules_data$Description == "WOODLAND MINI RUCKSACK", "WOODLAND MINI BACKPACK",
+ ifelse(rules_data$Description == "WRAP RED DOILEY", "WRAP RED VINTAGE DOILY"  ,
+ ifelse(rules_data$Description == "WRAP VINTAGE PETALS  DESIGN", "WRAP VINTAGE LEAF DESIGN",
+ ifelse(rules_data$Description == "ZINC PLANT POT HOLDER" ,"ZINC HEARTS PLANT POT HOLDER",
+ ifelse(rules_data$Description == "ZINC  STAR T-LIGHT HOLDER", "ZINC STAR T-LIGHT HOLDER",
+ ifelse(rules_data$Description == "ZINC T-LIGHT HOLDER STAR LARGE", "ZINC T-LIGHT HOLDER STARS LARGE", rules_data$Description ))))))))))
```

Market Basket Analysis – Format the data

```
> # Use ddply function to get all the items bought together in a row separated by ,.
> # To get the items bought together, get Description by grouping the data on InvoiceNo.
> Association_data <- ddply(rules_data,c("InvoiceNo"),
+                           function(x)paste(x$Description,
+                           collapse = ","))
> str(Association_data)
'data.frame':   19868 obs. of  2 variables:
 $ InvoiceNo: chr  "536365" "536366" "536367" "536368" ...
 $ V1       : chr  "WHITE HANGING HEART T-LIGHT HOLDER,WHITE MOROCCAN METAL LANTERN,CREAM CUPID HEARTS COAT HANGER,
R RED POLKA DOT" "ASSORTED COLOUR BIRD ORNAMENT,POPPY'S PLAYHOUSE BEDROOM,POPPY'S PLAYHOUSE KITCHEN,FELTCRAFT PRINC
ACK PARIS FASHION,YELLOW COAT RACK PARIS FASHION,BLUE COAT RACK PARIS FASHION" ...
>
> Association_data$InvoiceNo <- NULL
> colnames(Association_data) <- c("items")
> Association_data$items <- as.factor(Association_data$items)
>
> str(Association_data)
'data.frame':   19868 obs. of  1 variable:
 $ items: Factor w/ 18926 levels "10 COLOUR SPACEBOY PEN,BLUE CALCULATOR RULER,ASSORTED TUTTI FRUTTI PEN,PAINT YOUR
 7575 1380 685 10606 6441 17919 17121 ...
>
> # To view the transactional_data in the better format
> write.csv(Association_data, "transactional_data.csv", quote=FALSE, row.names = FALSE)
```

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	items													
2	WHITE HANG	WHITE MOR	CREAM CUPI	KNITTED UN	RED WOOLL	SET 7 BABUS	GLASS STAR	FROSTED T-LIGHT HOLDER						
3	HAND WARM	HAND WARMER RED POLKA DOT												
4	ASSORTED C	POPPY'S PLA	POPPY'S PLA	FELTCRAFT F	IVORY KNITT	BOX OF 6 AS	BOX OF VINT	BOX OF VINT	HOME BUILD	LOVE BUILDI	RECIPE BOX	DOORMAT NEW ENGLAND		
5	JAM MAKING	RED COAT R	YELLOW COA	BLUE COAT RACK PARIS FASHION										
6	BATH BUILDING BLOCK WORD													

Association Rules – Apriori Algorithm

```
> transactional_data <- read.transactions('transactional_data.csv', format = 'basket', sep=',', quote="")
Warning message:
In asMethod(object) : removing duplicated items in transactions
```

```
> # Association rules
> rules.1 <- apriori(transactional_data, parameter=list(support=0.1, confidence = 0.1))
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen maxlen target  ext
        0.1    0.1    1 none FALSE            TRUE       5     0.1      1     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 1986

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[3938 item(s), 19869 transaction(s)] done [0.40s].
sorting and recoding items ... [3 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 done [0.00s].
writing ... [3 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].
```

With min.confidence 0.1 and min.support 0.1
- 3 Association Rules

```
> rules.05 <- apriori(transactional_data, parameter=list(support=0.05, confidence = 0.1))
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen maxlen target  ext
        0.1    0.1    1 none FALSE            TRUE       5    0.05      1     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 993

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[3938 item(s), 19869 transaction(s)] done [0.19s].
sorting and recoding items ... [34 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 done [0.00s].
writing ... [3 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].
```

With min.confidence 0.1 and Support 0.05
- 3 Association Rules

Inspect Association Rules

```
> rules.029 <- apriori(transactional_data, parameter=list(support=0.0293, confidence = 0.1, minlen=2))
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen maxlen target  ext
        0.1    0.1    1 none FALSE            TRUE       5  0.0293      2     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 582

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[3938 item(s), 19869 transaction(s)] done [0.21s].
sorting and recoding items ... [139 item(s)] done [0.00s].
creating transaction tree ... done [0.01s].
checking subsets of size 1 2 3 done [0.00s].
writing ... [20 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].
> inspect(sort(rules.029, by='confidence'))
     lhs                                    rhs                                    support    confidence coverage   lift      count
[1]  {PINK REGENCY TEACUP AND SAUCER}    => {GREEN REGENCY TEACUP AND SAUCER}    0.03180834 0.8261438  0.03850219 16.203999 632
[2]  {PINK REGENCY TEACUP AND SAUCER}    => {ROSES REGENCY TEACUP AND SAUCER}    0.03009714 0.7816993  0.03850219 14.583647 598
[3]  {GREEN REGENCY TEACUP AND SAUCER}   => {ROSES REGENCY TEACUP AND SAUCER}    0.03860285 0.7571570  0.05098394 14.125776 767
[4]  {ROSES REGENCY TEACUP AND SAUCER}   => {GREEN REGENCY TEACUP AND SAUCER}    0.03860285 0.7201878  0.05360109 14.125776 767
[5]  {JUMBO BAG PINK POLKADOT}           => {JUMBO BAG RED RETROSPOT}           0.04152197 0.6773399  0.06130152  6.442349 825
[6]  {ALARM CLOCK BAKELIKE GREEN}        => {ALARM CLOCK BAKELIKE RED}          0.03221098 0.6530612  0.04932307 12.346026 640
[7]  {JUMBO  BAG BAROQUE BLACK WHITE}    => {JUMBO BAG RED RETROSPOT}           0.02944285 0.6270096  0.04695757  5.963645 585
[8]  {GREEN REGENCY TEACUP AND SAUCER}   => {PINK REGENCY TEACUP AND SAUCER}    0.03180834 0.6238894  0.05098394 16.203999 632
[9]  {JUMBO STORAGE BAG SUKI}            => {JUMBO BAG RED RETROSPOT}           0.03643867 0.6114865  0.05959032  5.816000 724
[10] {ALARM CLOCK BAKELIKE RED}          => {ALARM CLOCK BAKELIKE GREEN}        0.03221098 0.6089439  0.05289647 12.346026 640
[11] {JUMBO SHOPPER VINTAGE RED PAISLEY} => {JUMBO BAG RED RETROSPOT}           0.03422417 0.5787234  0.05913735  5.504383 680
[12] {ROSES REGENCY TEACUP AND SAUCER}   => {PINK REGENCY TEACUP AND SAUCER}    0.03009714 0.5615023  0.05360109 14.583647 598
[13] {LUNCH BAG PINK POLKADOT}           => {LUNCH BAG RED RETROSPOT}           0.03049977 0.5559633  0.05485933  7.058425 606
[14] {LUNCH BAG  BLACK SKULL.}           => {LUNCH BAG RED RETROSPOT}           0.03226131 0.5035350  0.06406966  6.392803 641
[15] {LUNCH BAG RED RETROSPOT}           => {LUNCH BAG  BLACK SKULL.}           0.03226131 0.4095847  0.07876592  6.392803 641
[16] {JUMBO BAG RED RETROSPOT}           => {JUMBO BAG PINK POLKADOT}           0.04152197 0.3949258  0.10513866  6.442349 825
[17] {LUNCH BAG RED RETROSPOT}           => {LUNCH BAG PINK POLKADOT}           0.03049977 0.3872204  0.07876592  7.058425 606
[18] {JUMBO BAG RED RETROSPOT}           => {JUMBO STORAGE BAG SUKI}            0.03643867 0.3465773  0.10513866  5.816000 724
[19] {JUMBO BAG RED RETROSPOT}           => {JUMBO SHOPPER VINTAGE RED PAISLEY} 0.03422417 0.3255146  0.10513866  5.504383 680
[20] {JUMBO BAG RED RETROSPOT}           => {JUMBO  BAG BAROQUE BLACK WHITE}    0.02944285 0.2800383  0.10513866  5.963645 585
```

Prune Redundant Association Rules

```
> # Prune the Redundant Rules ################################################
>
> # Check for the rules which are subset of other rules
> subset_matrix <- is.subset(rules,rules)
>
> # Assigning FALSE to diagonal line (as every rule is a subset of it's own, neglect diagonal positions)
> subset_matrix[lower.tri(subset_matrix, diag=T)] <- F
>
> # Check the item sets which are redudant and which are not
> redundant <- apply(subset_matrix, 2, any)
>
> rules.pruned <- rules[!redundant]
>
> # Inspect the pruned rules
> inspect(rules.pruned)
     lhs                                  rhs                                  support    confidence coverage   lift      count
[1]  {PINK REGENCY TEACUP AND SAUCER}     => {GREEN REGENCY TEACUP AND SAUCER} 0.03180834 0.8261438  0.03850219 16.203999 632
[2]  {PINK REGENCY TEACUP AND SAUCER}     => {ROSES REGENCY TEACUP AND SAUCER} 0.03009714 0.7816993  0.03850219 14.583647 598
[3]  {GREEN REGENCY TEACUP AND SAUCER}    => {ROSES REGENCY TEACUP AND SAUCER} 0.03860285 0.7571570  0.05098394 14.125776 767
[4]  {JUMBO BAG PINK POLKADOT}            => {JUMBO BAG RED RETROSPOT}         0.04152197 0.6773399  0.06130152  6.442349 825
[5]  {ALARM CLOCK BAKELIKE GREEN}         => {ALARM CLOCK BAKELIKE RED}        0.03221098 0.6530612  0.04932307 12.346026 640
[6]  {JUMBO  BAG BAROQUE BLACK WHITE}     => {JUMBO BAG RED RETROSPOT}         0.02944285 0.6270096  0.04695757  5.963645 585
[7]  {JUMBO STORAGE BAG SUKI}             => {JUMBO BAG RED RETROSPOT}         0.03643867 0.6114865  0.05959032  5.816000 724
[8]  {JUMBO SHOPPER VINTAGE RED PAISLEY}  => {JUMBO BAG RED RETROSPOT}         0.03422417 0.5787234  0.05913735  5.504383 680
[9]  {LUNCH BAG PINK POLKADOT}            => {LUNCH BAG RED RETROSPOT}         0.03049977 0.5559633  0.05485933  7.058425 606
[10] {LUNCH BAG  BLACK SKULL.}            => {LUNCH BAG RED RETROSPOT}         0.03226131 0.5035350  0.06406966  6.392803 641
```

Association rules Evaluation

$$\boldsymbol{Support}\ (\{\boldsymbol{X}\} \rightarrow \{\boldsymbol{Y}\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Total\ Transactions}$$

$$\boldsymbol{Confidence}\ (\{\boldsymbol{X}\} \rightarrow \{\boldsymbol{Y}\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Transactions\ containing\ X}$$

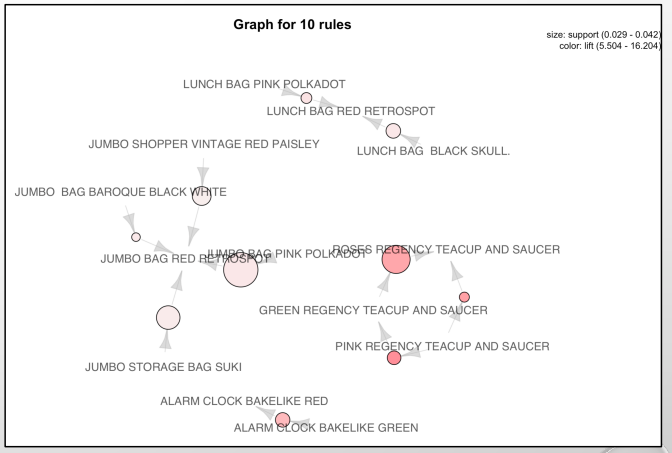
```
> # We evaluate the association rules with support, confidence, lift values
> interestMeasure(rules.pruned, c("support", "confidence", "lift"), transactional_data)
      support confidence      lift
1  0.03180834  0.8261438 16.203999
2  0.03009714  0.7816993 14.583647
3  0.03860285  0.7571570 14.125776
4  0.04152197  0.6773399  6.442349
5  0.03221098  0.6530612 12.346026
6  0.02944285  0.6270096  5.963645
7  0.03643867  0.6114865  5.816000
8  0.03422417  0.5787234  5.504383
9  0.03049977  0.5559633  7.058425
10 0.03226131  0.5035350  6.392803
```

$$\boldsymbol{Lift}\ (\{\boldsymbol{X}\} \rightarrow \{\boldsymbol{Y}\}) = \frac{(Transactions\ containing\ both\ X\ and\ Y)/(Transactions\ containing\ X)}{Fraction\ of\ transcations\ containingY}$$

Best 10 Association rules

```
> # Inspect the pruned rules ordered by confidence
> inspect(sort(rules.pruned, by='confidence'))
     lhs                                  rhs                                 support    confidence coverage   lift      count
[1]  {PINK REGENCY TEACUP AND SAUCER}     => {GREEN REGENCY TEACUP AND SAUCER} 0.03180834 0.8261438  0.03850219 16.203999 632
[2]  {PINK REGENCY TEACUP AND SAUCER}     => {ROSES REGENCY TEACUP AND SAUCER} 0.03009714 0.7816993  0.03850219 14.583647 598
[3]  {GREEN REGENCY TEACUP AND SAUCER}    => {ROSES REGENCY TEACUP AND SAUCER} 0.03860285 0.7571570  0.05098394 14.125776 767
[4]  {JUMBO BAG PINK POLKADOT}            => {JUMBO BAG RED RETROSPOT}         0.04152197 0.6773399  0.06130152  6.442349 825
[5]  {ALARM CLOCK BAKELIKE GREEN}         => {ALARM CLOCK BAKELIKE RED}        0.03221098 0.6530612  0.04932307 12.346026 640
[6]  {JUMBO  BAG BAROQUE BLACK WHITE}     => {JUMBO BAG RED RETROSPOT}         0.02944285 0.6270096  0.04695757  5.963645 585
[7]  {JUMBO STORAGE BAG SUKI}             => {JUMBO BAG RED RETROSPOT}         0.03643867 0.6114865  0.05959032  5.816000 724
[8]  {JUMBO SHOPPER VINTAGE RED PAISLEY}  => {JUMBO BAG RED RETROSPOT}         0.03422417 0.5787234  0.05913735  5.504383 680
[9]  {LUNCH BAG PINK POLKADOT}            => {LUNCH BAG RED RETROSPOT}         0.03049977 0.5559633  0.05485933  7.058425 606
[10] {LUNCH BAG  BLACK SKULL.}            => {LUNCH BAG RED RETROSPOT}         0.03226131 0.5035350  0.06406966  6.392803 641
```

```
> library(grid)
> library(arulesViz)
>
> plot(rules.pruned, method="graph")
```



CONCLUSION

Identify the customers into different groups based on their behavior with the online retail. Identify the Loyal Customers.

Customers of online-retail have been segmented into two groups using their Recency, Frequency and Monetary values.
Group 1 – either with More Recency or Less Frequency or Less Monetary.
Group 2 – Less Recency, More Frequency and More Monetary.
Group 2 customers are identified as Loyal Customers.

Identify best 10 Association rules for the products purchased in the online retail.

Best 10 Association rules ordered by confidence

```
{PINK REGENCY TEACUP AND SAUCER}     => {GREEN REGENCY TEACUP AND SAUCER}
{PINK REGENCY TEACUP AND SAUCER}     => {ROSES REGENCY TEACUP AND SAUCER}
{GREEN REGENCY TEACUP AND SAUCER}    => {ROSES REGENCY TEACUP AND SAUCER}
{JUMBO BAG PINK POLKADOT}            => {JUMBO BAG RED RETROSPOT}
{ALARM CLOCK BAKELIKE GREEN}         => {ALARM CLOCK BAKELIKE RED}
{JUMBO  BAG BAROQUE BLACK WHITE}     => {JUMBO BAG RED RETROSPOT}
{JUMBO STORAGE BAG SUKI}             => {JUMBO BAG RED RETROSPOT}
{JUMBO SHOPPER VINTAGE RED PAISLEY}  => {JUMBO BAG RED RETROSPOT}
{LUNCH BAG PINK POLKADOT}            => {LUNCH BAG RED RETROSPOT}
{LUNCH BAG  BLACK SKULL.}            => {LUNCH BAG RED RETROSPOT}
```

FUTURE WORK

- Use Gap-Statistic Method to find the optimal number of clusters for clustering.
- Use Density based and K-mediods clustering algorithms for Customer segmentation.
- Inspect Association rules with confidence levels 0.8, 0.7 and so.. .Business can use these rules in designing lossless promotional offers for the products.


THANK YOU