

Clustering of UK Online Retail Dataset

by Sakib Bhuiyan

1. Introduction

In this Data Analysis Assignment, we performed K-means clustering and hierarchical clustering on a dataset that provides information on transactions from a UK-based online retail company. We found that the K-means clustering algorithm produced clusters that were noticeably different from those produced by the hierarchical clustering algorithm. In both methods, we found that the clusters produced were not incredibly homogenous and did not produce distinctively well-defined classes.

2. Data

The dataset provides information on transactions occurring between 1/12/2010 and 9/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique all-occasion gifts, and many of their customers are wholesalers. The original dataset contains 541,909 observations and 8 variables. A description of the 8 original variables are provided in Table 1.

Variable	Description
InvoiceNo	Nominal, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation.
StockCode	Product (item) code. Nominal, a 5-digit integral number uniquely assigned to each distinct product.
Description	Product (item) name. Nominal.
Quantity	The quantities of each product (item) per transaction. Numeric.
InvoiceDate	Invoice Date and time. Numeric, the day and time when each transaction was generated.
UnitPrice	Unit price. Numeric, Product price per unit in sterling.
CustomerID	Customer number. Nominal, a 5-digit integral number uniquely assigned to each customer.
Country	Country name. Nominal, the name of the country where each customer resides.

Table 1. Variables in the original dataset. Descriptions are sourced from <https://archive.ics.uci.edu/ml/datasets/Online%20Retail#>

The original dataset underwent the following clean-up steps prior to analysis:

1. Removed any observations for which Country was not specified.
2. Removed transactions that were returns or cancellations.
3. Aggregated all transactions for each customer in the dataset. This produced an aggregate amount spent per customer.
4. Determined the first month of customer interaction, as well as the last month of interaction. These two variables were used to calculate the duration of the customer's interaction with the company.

5. Calculated the Amount per Purchase, Purchases per Month, and Amount per Month for each customer.

All variables that were considered in the analysis are provided in Table 2.

Variable	Description
Country	Country name. Nominal; the name of the country where each customer resides.
Amount	Numeric; the total amount spent by customer.
LastMth	Nominal; the last month of customer interaction
Months	Numeric; the duration of the customer's interaction with the company
Purchases	Numeric; the number of purchased made by the customer during the time frame
Amount.per.Purchase	Numeric; Amount/Purchases
Purchases.per.Month	Numeric; Purchases/Months
Amount.per.Month	Numeric; Amount/Months

Table 2. Variables considered in the analysis.

2.1 Sources and References

The data used in this Data Analysis Assignment was obtained from Chen, et al. The source of the data and the references used are listed below:

Source

1. Daqing Chen, Sai Liang Sain, and Kun Guo, Data mining for the online retail industry: A case study of RFM model-based customer segmentation using data mining, Journal of Database Marketing and Customer Strategy Management, Vol. 19, No. 3, pp. 197-208, 2012 (Published online before print: 27 August 2012. doi: 10.1057/dbm.2012.17).

References

1. James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013) An Introduction to Statistical Learning with applications in R, www.StatLearning.com, Springer-Verlag, New York

3. Analyses, Plots, and Tables

We attempt to identify whether this online retail company's consumers can be segmented meaningfully by the recency and duration of their interaction with the company, the frequency of their purchases, and the amount they spent. We were also curious about whether we could segment the customers by their country of residence.

3.1 Exploratory Data Analysis

After the original dataset was cleaned using the steps described in Section 2, we explored whether there were any strong associations between the quantitative variables. The left panel of Figure 1 shows a correlation plot of all of the variables that were considered for inclusion in the analysis. We found strong associations between the following variables:

- Amount.per.Month and Amount.per.Purchase (positive association)
- FirstMth and Months (negative)
- Purchases and Purchases.per.Month (positive)

Based on the collinearity between the variables, we made the following decisions regarding which variables to include (or exclude) in the analysis:

- Exclude FirstMth.
- Exclude Purchases.
- Include LastMth. Despite the relatively strong association between LastMth and Months, the LastMth variable will serve as a measure of the recency of interaction between the customer and the online retailer.
- Include Amount. Despite the relatively strong associations between Amount and (1)Amount.per.Month and (2) Purchases, the Amount variable will serve as a measure of the volume of purchases by the customer.

Table 1 provides a description of the variables that were actually included in the analysis. The right panel of Figure 1 shows a correlation plot of these variables, and Table 3 provides summary statistics for these variables. We see that, with the exception of Amount.per.Month vs. Amount.per.Purchase, there are no Pearson correlation coefficients with magnitudes greater than 0.8 in the final dataset. Figure 2 provides histograms for the continuous variables in the dataset. We see that these variables all have right-skewed distributions.

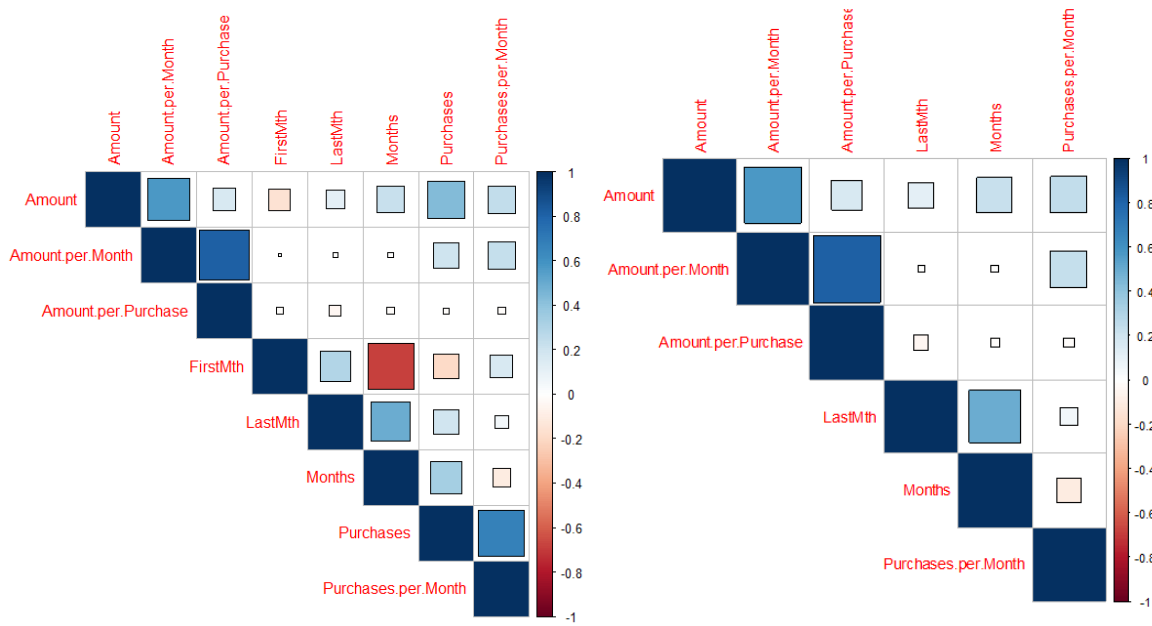


Figure 1. Left panel: Correlation plot of all variables that were considered for inclusion in the analysis. Right panel: Correlation plot of the variables that were, indeed, included in the analysis.

Amount		FirstMth		LastMth		Months	
Min. :	0.0	Min. :	1.00	Min. :	1.00	Min. :	1.00
1st Qu.:	303.9	1st Qu.:	2.00	1st Qu.:	8.00	1st Qu.:	1.00
Median :	656.6	Median :	5.00	Median :	11.00	Median :	4.00
Mean :	1952.1	Mean :	5.45	Mean :	9.47	Mean :	5.02
3rd Qu.:	1593.3	3rd Qu.:	9.00	3rd Qu.:	12.00	3rd Qu.:	9.00
Max. :	268478.0	Max. :	12.00	Max. :	12.00	Max. :	12.00
Purchases		Amount.per.Purchase		Purchases.per.Month		Amount.per.Month	
Min. :	1.00	Min. :	0.00	Min. :	0.1818	Min. :	0.0
1st Qu.:	17.00	1st Qu.:	12.34	1st Qu.:	6.6667	1st Qu.:	122.0
Median :	40.00	Median :	17.69	Median :	13.0000	Median :	221.5
Mean :	88.54	Mean :	54.56	Mean :	20.4697	Mean :	400.3
3rd Qu.:	97.00	3rd Qu.:	24.82	3rd Qu.:	24.0000	3rd Qu.:	388.4
Max. :	7376.00	Max. :	77183.60	Max. :	1145.5000	Max. :	77183.6

Table 3. Summary statistics of the quantitative variables considered in the analysis.

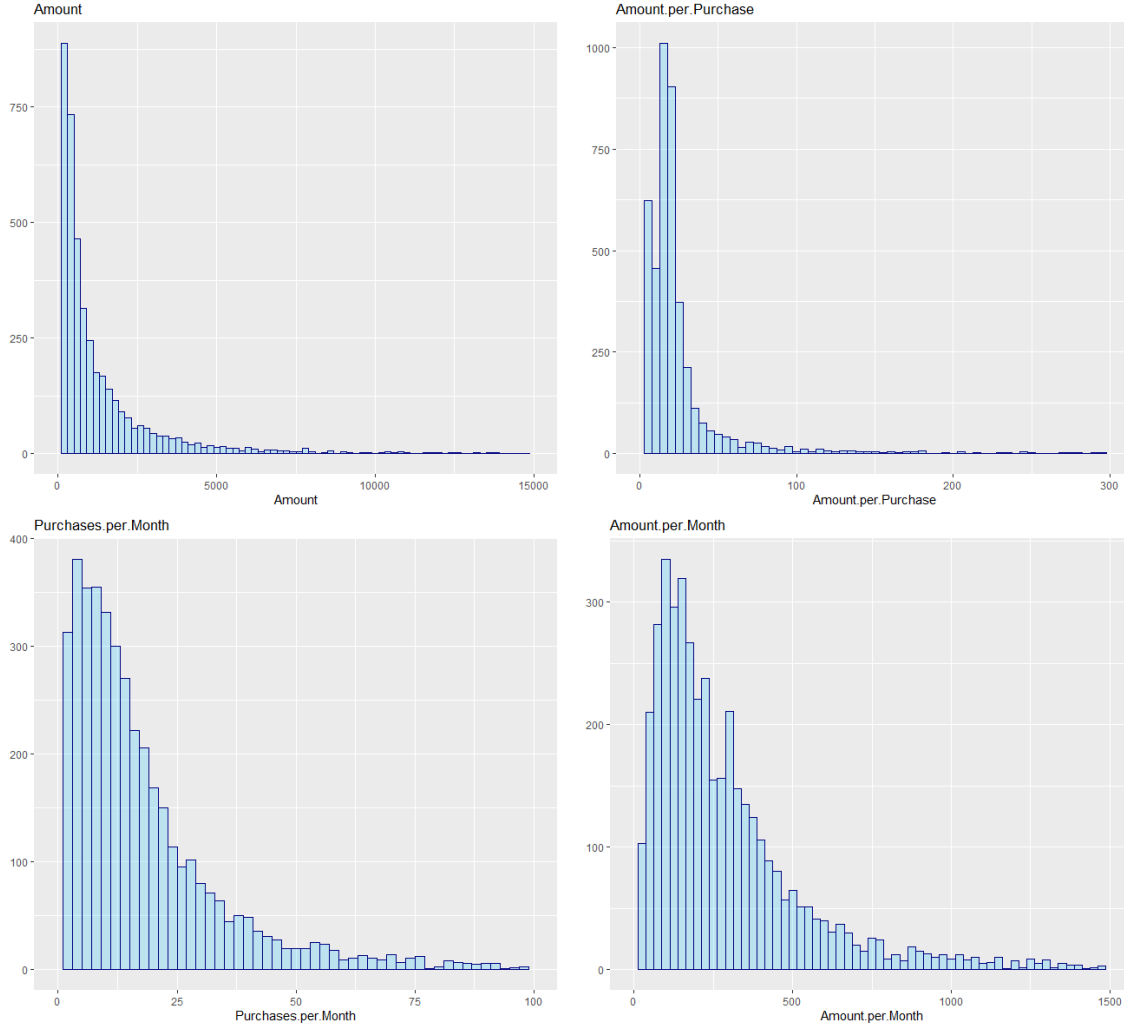


Figure 2. Histogram of the continuous variables included in the analysis.

3.2 K-Means Clustering

For both the K-means clustering and hierarchical clustering algorithms, the variables were scaled. The K-means algorithm was run with an nstart variable of 50 to obtain the local optimum. Values of K between 1 and 10 were considered. Country was not included in either clustering algorithm, considering it is a categorical factor. Calculating the Euclidean distance between categorical factors (even if they are treated as numerical) is not appropriate. Nevertheless, we consider Country after the K-means algorithm is run with the remaining numerical variables to determine if the algorithm found any patterns related to Country.

In Figure 3, we see an elbow in the value of the within cluster sum-of-squares at K=5. This determination is subjective, considering we could also conclude that the elbow exists at K=6. However, we proceeded with K=5, and fit the K-means clustering model to the dataset using 5 clusters.

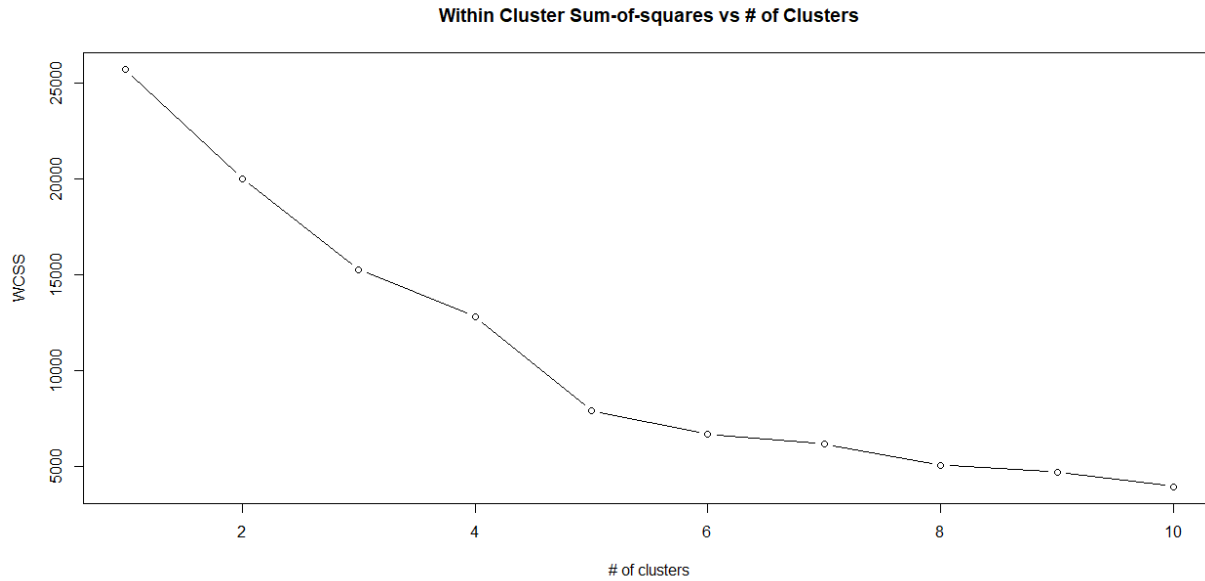


Figure 3. Plot of the within cluster sum-of-squares for each value of K between 1 and 10.

We did not find any overwhelmingly distinct segments in the clustering. First, we considered Months, which measures the duration of the customer's interaction with the online retailer. As summarized in Table 4, we can note a few findings:

- The majority of observations for which $\text{Months} \geq 6$ are in Cluster 1. This suggests that customers that have had a longer interaction time with the company have similar purchasing habits.
- Customers with lower values of Months ($\text{Months} < 5$) are typically found in Clusters 3, 4, and 5.
- Cluster 2 captures only 9 customers.

Months	Cluster					Sum
	1	2	3	4	5	
1		0.1%	45.6%	21.3%	33.0%	100.0%
2			61.2%	21.5%	17.4%	100.0%
3			61.0%	26.2%	12.9%	100.0%
4		0.6%	40.3%	46.1%	13.0%	100.0%
5	6.4%		37.8%	55.3%	0.5%	100.0%
6	62.8%		8.2%	29.0%		100.0%
7	84.2%			15.8%		100.0%
8	100.0%					100.0%
9	100.0%					100.0%
10	100.0%					100.0%
11	99.6%	0.4%				100.0%
12	98.2%	1.1%	0.7%			100.0%

Table 4. The Months variable (which had discrete values between 1 and 12) was referenced against the 5 clusters produced by the K-means clustering algorithm. Left Panel: Cluster 1 and Cluster 4 had the most observations. Cluster 2 had the fewest observations (9). Right Panel: The proportion of observations within each value of Months is referenced against the Cluster determined by the K-means clustering algorithm. For example, 45.6% of observations with $\text{Months}=1$ were classified in Cluster 3.

We also did not find any overwhelming segments when considering the recency of the customer's interaction with the company, which is measured by the LastMth variable. A larger value for LastMth indicates that the customer had a more recent interaction with the company. As summarized in Table 5, we can note a few findings:

- The majority of customers for which $\text{LastMth} \leq 5$ are in Cluster 5. This suggests that customers that have not had recent interactions with the online retailer have similar purchasing habits.
- The majority of customers for which $6 \leq \text{LastMth} \leq 8$ are in Cluster 4.
- Cluster 1 is composed of only customers for which $\text{LastMth} \geq 8$.

Lastmth	Cluster					Sum	Lastmth	Cluster					Sum
	1	2	3	4	5			1	2	3	4	5	
1					124	124	1					100.0%	100.0%
2		1			96	97	2		1.0%			99.0%	100.0%
3					113	113	3					100.0%	100.0%
4					174	174	4					100.0%	100.0%
5				20	125	145	5				13.8%	86.2%	100.0%
6				160	13	173	6				92.5%	7.5%	100.0%
7		1	4	185		190	7		0.5%	2.1%	97.4%		100.0%
8	26			17	151	194	8	13.4%		8.8%	77.8%		100.0%
9	78			29	125	232	9	33.6%		12.5%	53.9%		100.0%
10	194			162	87	443	10	43.8%		36.6%	19.6%		100.0%
11	355			380	3	738	11	48.1%		51.5%	0.4%		100.0%
12	1,062	7		594		1,663	12	63.9%	0.4%	35.7%			100.0%
Sum	1,715	9	1,186	731	645	4,286							

Table 5. Left Panel: The LastMth variable (which had discrete values between 1 and 12) was referenced against the 5 clusters produced by the K-means clustering algorithm. Right Panel: The proportion of observations within each value of LastMth is referenced against the Cluster. For example, 1.0% of observations with LastMth=2 were classified in Cluster 2.

Finally, we explored whether the clusters showed any patterns among the customers' countries of residence. We did not find much homogeneity in the clusters. However, we do note that for UK customers (which make up the largest customer base for the online retailer), 40.3% of customers fall within Cluster 1 and 27.4% fall within Cluster 3. This is summarized in Table 6.

Country	Cluster					Sum
	1	2	3	4	5	
Australia	57.1%	14.3%		14.3%	14.3%	100.0%
Austria	11.1%		22.2%	33.3%	33.3%	100.0%
Bahrain				100.0%		100.0%
Belgium	50.0%		13.6%	13.6%	22.7%	100.0%
Brazil					100.0%	100.0%
Canada			25.0%	50.0%	25.0%	100.0%
Channel Islands	33.3%		11.1%	33.3%	22.2%	100.0%
Cyprus	20.0%		40.0%		40.0%	100.0%
Czech Republic	100.0%					100.0%
Denmark	50.0%		33.3%	16.7%		100.0%
EIRE	33.3%	66.7%				100.0%
European Community				100.0%		100.0%
Finland	36.4%		54.5%		9.1%	100.0%
France	43.0%		29.1%	10.5%	17.4%	100.0%
Germany	39.8%		35.5%	12.9%	11.8%	100.0%
Greece				33.3%	66.7%	100.0%
Iceland	100.0%					100.0%
Israel			66.7%	33.3%		100.0%
Italy	28.6%		42.9%		28.6%	100.0%
Japan	37.5%		12.5%	25.0%	25.0%	100.0%
Lebanon					100.0%	100.0%
Lithuania					100.0%	100.0%
Malta	50.0%		50.0%			100.0%
Netherlands	44.4%	11.1%	11.1%	22.2%	11.1%	100.0%
Norway	30.0%		60.0%		10.0%	100.0%
Poland	33.3%			66.7%		100.0%
Portugal	26.3%		36.8%	10.5%	26.3%	100.0%
RSA			100.0%			100.0%
Saudi Arabia					100.0%	100.0%
Singapore	100.0%					100.0%
Spain	44.4%		29.6%	18.5%	7.4%	100.0%
Sweden	50.0%		12.5%	25.0%	12.5%	100.0%
Switzerland	21.1%		47.4%	10.5%	21.1%	100.0%
United Arab Emirates			50.0%		50.0%	100.0%
United Kingdom	40.3%	0.1%	27.4%	17.3%	14.8%	100.0%
USA			66.7%		33.3%	100.0%

Table 6. Left Panel: The Country variable was referenced against the 5 clusters produced by the K-means clustering algorithm. Right Panel: the proportion of observations within each Country is referenced against the Cluster. For example, 57.1% of the observations with Country=Australia were classified in Cluster 1.

To visualize the clusters, we projected the observations onto the plane created by the first two principal components of the dataset. These two principal components explain 61.89% of the variation. In Figure 4, we can see that Cluster 2 is the least dense, and is obviously separate from the other four clusters. Clusters 1, 3, 4, and 5 are extremely close to each other in this space. We can see a distinct separation between Clusters 1 and 5. However, there is overlap between Clusters 1, 3, and 4. There is also overlap between Clusters 3, 4, and 5.

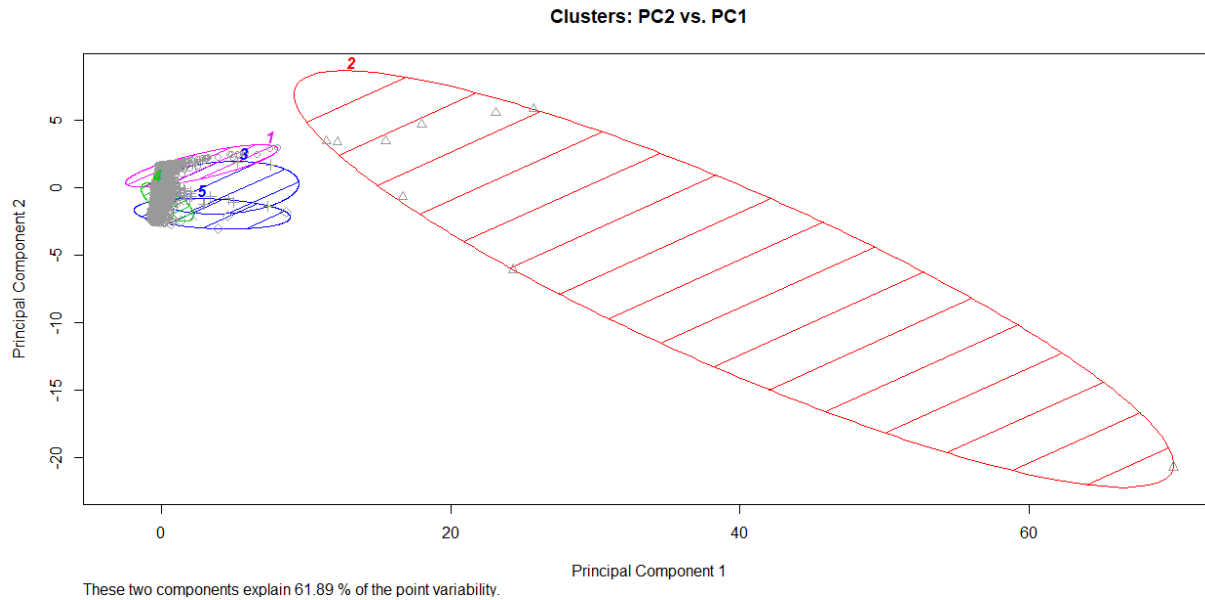


Figure 4. Visualization of the clusters, with observations projected onto the plane created by the first two principal components of the dataset. The gray points represent observations projected onto this plane. This plot was produced using the `clusplot()` function within the `cluster` library.

3.3 Hierarchical Clustering

The variables were also scaled before proceeding with the hierarchical clustering algorithm. We first observed the differences in the dendrogram between the complete linkage, average linkage, and single linkage methods. We found that the complete linkage method produced the most distinct clusters (as shown in

Figure 5), and proceeded with this method. Using the length of the branches in the dendrogram, we subjectively decided to use 4 clusters to fit the model.

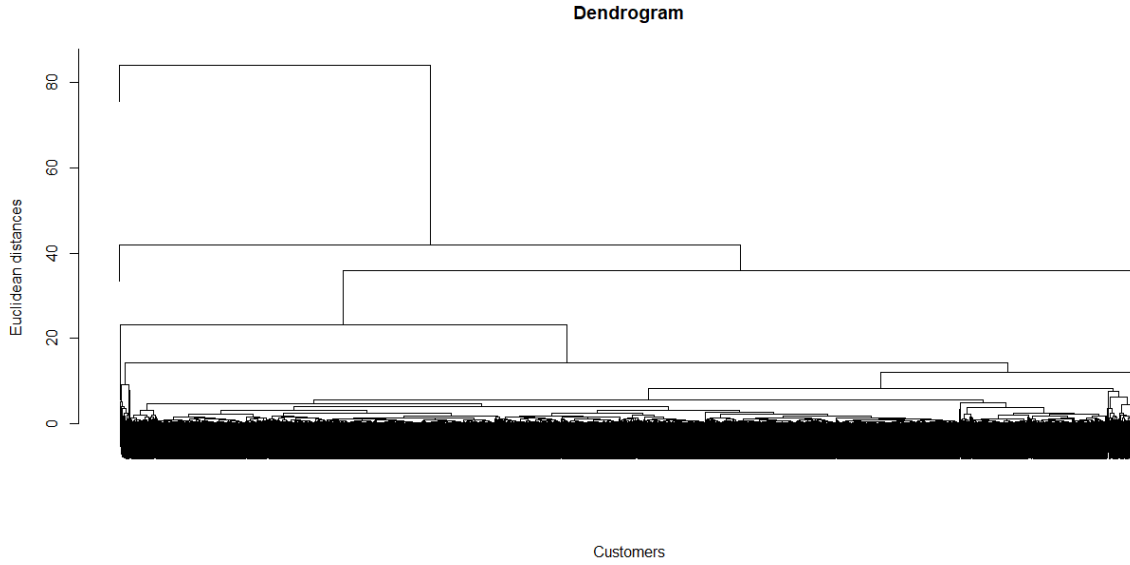


Figure 5. Dendrogram produced by hierarchical clustering using complete linkage.

Just as in the K-means clustering discussed in Section 3.2, we considered the value of Months against the clusters produced by the hierarchical clustering algorithm. In Table 7, we see that Cluster 2 captures 99% of the observations. In fact, only customers for which $\text{Months} \in \{1, 4, 11, 12\}$ were found in the other clusters.

Months	Cluster				Sum
	1	2	3	4	
1	1	1,690	1		1,692
2		219			219
3		210			210
4		153		1	154
5		188			188
6		207			207
7		215			215
8		221			221
9		252			252
10		233			233
11		251	1		252
12		439	4		443
Sum	1	4,278	6	1	4,286

Table 7. The Months variable was referenced against the 4 clusters produced by the hierarchical clustering algorithm. Left Panel: Cluster 2 had 99% of all observations. Right Panel: The proportion of observations within each value of Months is referenced against the Cluster.

In Table 8, we see a similar pattern when referencing the value of LastMth against the Cluster produced by hierarchical clustering.

Lastmth	Cluster				Sum
	1	2	3	4	
1		124			124
2	1	96			97
3		113			113
4		174			174
5		145			145
6		173			173
7		189	1		190
8		194			194
9		232			232
10		443			443
11		738			738
12		1,657	5	1	1,663
Sum	1	4,278	6	1	4,286

Table 8. Left Panel: The LastMth variable was referenced against the 4 clusters produced by the hierarchical clustering algorithm. Right Panel: The proportion of observations within each value of LastMth is referenced against the Cluster.

In Table 9, we see that only customers from Australia, EIRE, Netherlands, and the UK were found outside of Cluster 2.

Country	Cluster				Sum
	1	2	3	4	
Australia		6	1		7
Austria		9			9
Bahrain		2			2
Belgium		22			22
Brazil		1			1
Canada		4			4
Channel Islands		9			9
Cyprus		5			5
Czech Republic		1			1
Denmark		6			6
EIRE		2	1		3
European Community		1			1
Finland		11			11
France		86			86
Germany		93			93
Greece		3			3
Iceland		1			1
Israel		3			3
Italy		14			14
Japan		8			8
Lebanon		1			1
Lithuania		1			1
Malta		2			2
Netherlands		8	1		9
Norway		10			10
Poland		6			6
Portugal		19			19
RSA		1			1
Saudi Arabia		1			1
Singapore		1			1
Spain		27			27
Sweden		8			8
Switzerland		19			19
United Arab Emirates		2			2
United Kingdom	1	3,882	3	1	3,887
USA		3			3
Sum	1	4,278	6	1	4,286

Table 9. Left Panel: The Country variable was referenced against the 4 clusters produced by the hierarchical clustering algorithm. Right Panel: The proportion of observations within each Country is referenced against the Cluster.

To visualize the clusters, we again projected the observations onto the plane created by the first two principal components of the dataset. In Figure 6, we see that Cluster 2 is the most dense. There is some overlap between Clusters 2 and 3. In this space, Cluster 4 is within Cluster 3. Cluster 1 is distinctly different from the remaining three clusters, considering it is far from the other clusters in this space. We can see that the clusters produced by hierarchical clustering using complete linkage are incredibly different from the ones produced by K-means clustering using K=5.

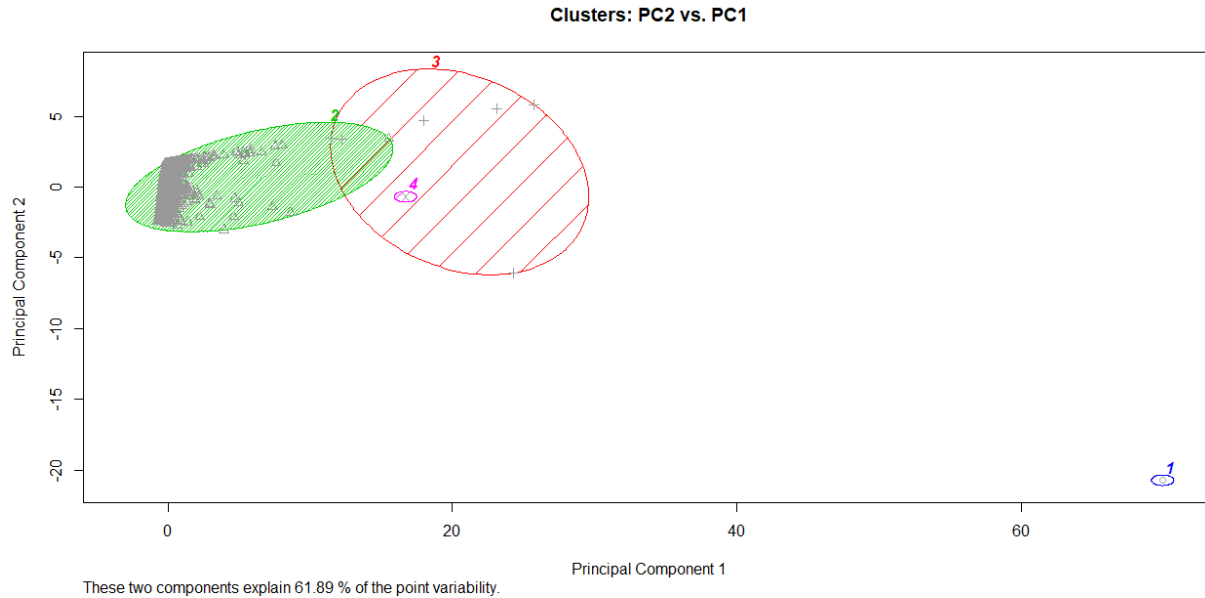


Figure 6. Visualization of the clusters, with observations projected onto the plane created by the first two principal components of the dataset. The gray points represent observations projected onto this plane.

4. Conclusion

In this Data Analysis Assignment, we found that the K-means clustering algorithm and hierarchical clustering algorithm produced significantly different clusters for the UK online retailer dataset. We found more distinct segmentation in the K-means clustering. However, this segmentation did not provide us much meaningful, intuitive information about the customers. We noticed loose trends related to the duration and recency of the customer's interaction with the retailer. However, we also saw a large amount of overlap between the clusters. This illustrates that, in real-world practice, clusters are often not homogenous and it is rare to find very well- defined classes.

5. Appendix – R Code

```
#####
# Data Analysis Assignment
# Week 11
#
#####

RNGkind(sample.kind="Rounding")

library(corrplot)
library(cluster)
library(ggplot2)
library(ClassDiscovery)

dev.new(width=8, height=12, unit="in")
```

```
#####
# Clean up the dataset & get it ready
# for analysis.
# The below code is sourced from Canvas.
#
#####

library(readxl) # you may need to
install the 'readxl' package first
eretail = read_excel("Online Retail.xlsx")
dim(eretail)
names(eretail)

eretail = eretail[eretail$Country != "Unspecified",] # remove 'unspecified'
country
eretail = eretail[eretail$Quantity > 0,] # remove
returns/cancellations

IDtab = table(eretail$Country, eretail$CustomerID) # crosstab country by
customer ID
IDtab = apply(IDtab > 0, 2, sum) # is any customer ID
duplicated across countries?
duplicateIDs = names(IDtab[IDtab > 1]) # duplicate IDs to clean
up
eretail = eretail[!is.element(eretail$CustomerID, duplicateIDs),]
rm(IDtab)

eretail$InvoiceMth = substr(eretail$InvoiceDate, 1, 7) # extract
month of invoice
eretail = eretail[as.vector(eretail$InvoiceMth) != "2011-12",] # remove
December 2011 as it only covers first week

eretail$Amount = eretail$Quantity * eretail$UnitPrice # compute
amount per invoice item

eaggr = aggregate(Amount~Country+CustomerID, data=eretail, sum) # compute
aggregate amount spent per customer
row.names(eaggr) = eaggr$CustomerID
eaggr = eaggr[, -2]
eaggr = cbind(eaggr, aggregate(InvoiceMth~CustomerID, data=eretail, min)[, -
1]) # 1st month of customer interaction
names(eaggr)[3] = "FirstMth"
eaggr = cbind(eaggr, aggregate(InvoiceMth~CustomerID, data=eretail, max)[, -
1]) # last month of cust. interaction
names(eaggr)[4] = "LastMth"

# relabel months and compute duration of customer interaction
levels(eaggr$FirstMth) = 1:12
levels(eaggr$LastMth) = 1:12
eaggr$FirstMth = as.numeric(as.vector(eaggr$FirstMth))
eaggr$LastMth = as.numeric(as.vector(eaggr$LastMth))
eaggr$Months = eaggr$LastMth - eaggr$FirstMth + 1
```

```

eaggr = cbind(eaggr, apply( table(eretail$CustomerID, eretail$InvoiceMth) ,
1, sum ) )
names(eaggr)[6] = "Purchases"

# Some useful statistics (which you may or may not decide to use)
eaggr$Amount.per.Purchase = eaggr$Amount / eaggr$Purchases
eaggr$Purchases.per.Month = eaggr$Purchases / eaggr$Months
eaggr$Amount.per.Month = eaggr$Amount / eaggr$Months

eaggr[1:30,]

# Export data frames to CSV
write.csv(eretail, "eretail.csv")
write.csv(eaggr, "eaggr.csv")

#####
# Exploratory Data Analysis
#
#####

eaggr_quant = eaggr[, -1]

# Convert to numeric variables
eaggr_quant$Purchases = as.numeric(eaggr_quant$Purchases)
str(eaggr_quant)

# Correlation plot of eaggr data frame (quantitative variables )
corr = cor(eaggr_quant, method = "pearson")

# Correlation plot
corrplot(corr,
         type = "upper",
         method = "square",
         outline = T,
         order = "alphabet")

# Create data frame that will be considered in clustering algorithms
X = eaggr[, c(1, 2, 4, 5, 7:9)]

#Convert Country to factor
X$Country = as.factor(X$Country)
str(X)

#Correlation Plot
X.corr = cor(X[, -1], method = "pearson")
corrplot(X.corr,
         type = "upper",
         method = "square",
         outline = T,
         order = "alphabet")

# Scale the variables

```

```

X.scale = X
X.scale[, -1] = scale(X.scale[, -1])
str(X.scale)

# Summary statistics of eaggr data frame
summary(eaggr)

# Histograms
hist.Amount = qplot(X$Amount,
                     geom="histogram",
                     binwidth = 200,
                     main = "Amount",
                     xlab = "Amount",
                     fill=I("deepskyblue"),
                     col=I("navy"),
                     alpha=I(.2),
                     xlim = c(0, 15000))

hist.AmountperPurchase = qplot(X$Amount.per.Purchase,
                                geom="histogram",
                                binwidth = 5,
                                main = "Amount.per.Purchase",
                                xlab = "Amount.per.Purchase",
                                fill=I("deepskyblue"),
                                col=I("navy"),
                                alpha=I(.2),
                                xlim = c(0, 300))

hist.PurchasesperMonth = qplot(X$Purchases.per.Month,
                                geom="histogram",
                                binwidth = 2,
                                main = "Purchases.per.Month",
                                xlab = "Purchases.per.Month",
                                fill=I("deepskyblue"),
                                col=I("navy"),
                                alpha=I(.2),
                                xlim = c(0, 100))

hist.AmountperMonth = qplot(X$Amount.per.Month,
                             geom="histogram",
                             binwidth = 25,
                             main = "Amount.per.Month",
                             xlab = "Amount.per.Month",
                             fill=I("deepskyblue"),
                             col=I("navy"),
                             alpha=I(.2),
                             xlim = c(0, 1500))

hist.Amount
hist.AmountperPurchase
hist.PurchasesperMonth
hist.AmountperMonth

```



```
#####
# K-means clustering
#
#####

# Use the elbow method to find the optimal number of clusters
set.seed(1234)
wcss = vector()

# For loop to test different values of "K"
for (i in 1:10) wcss[i] = sum(kmeans(X.scale[, -1], i, nstart = 50)$withinss)
# Exclude Country from k-means algorithm b/c it is categorical
plot(1:10,
     wcss,
     type = 'b',
     main = paste('Within Cluster Sum-of-squares vs # of Clusters'),
     xlab = '# of clusters',
     ylab = 'WCSS')

# Fitting K-Means to the dataset
set.seed(1234)
kmeans = kmeans(x = X.scale[, -1], centers = 5)
y_kmeans = kmeans$cluster
X$Cluster = y_kmeans
table(X$Months, X$Cluster)
table(X$LastMth, X$Cluster)
table(X$Country, X$Cluster)

# Visualising the clusters using Principal Components
set.seed(1234)
clusplot(X.scale[, -1],
         y_kmeans,
         lines = 0,
         shade = TRUE,
         color = TRUE,
         labels = 4,
         plotchar = TRUE,
         span = TRUE,
         col.p = "gray60",
         xlab = "Principal Component 1",
         ylab = "Principal Component 2",
         main = "Clusters: PC2 vs. PC1"
        )

#####
# Hierarchical clustering
#
#####

# Using the dendrogram to find the optimal number of clusters
```

```

dendrogram = hclust(d = dist(X.scale[, -1], method = 'euclidean'), method =
'complete')
plot(dendrogram,
     main = paste('Dendrogram'),
     xlab = 'Customers',
     ylab = 'Euclidean distances',
     labels = F,
     sub="")

# Fitting Hierarchical Clustering to the dataset
set.seed(1234)
hc = hclust(d = dist(X.scale[, -1], method = 'euclidean'), method =
'complete')

# Cut the dendrogram to 4 clusters
y_hc = cutree(hc, 4)

X$Cluster.HC = y_hc
table(X$Months, X$Cluster.HC)
table(X$LastMth, X$Cluster.HC)
table(X$Country, X$Cluster.HC)

# Visualising the clusters using Principal Components
set.seed(1234)
clusplot(X.scale[, -1],
        y_hc,
        lines = 0,
        shade = TRUE,
        color = TRUE,
        labels = 4,
        plotchar = TRUE,
        span = TRUE,
        col.p = "gray60",
        xlab = "Principal Component 1",
        ylab = "Principal Component 2",
        main = "Clusters: PC2 vs. PC1"
)

```