1.1 Market Basket Analysis

An effective data mining technique to discover intriguing links and patterns in huge datasets is association rule mining. It entails recognizing popular item sets and creating rules that specify how multiple data items are related to one another. Association rule mining can be used to identify patterns that can be use in various industries and domains.

Industry/Domain	Use Case
Retail	Identifying customer behaviour patterns for optimised product placement, pricing, and promotional strategies.
Healthcare	Analysing patient data to improve outcomes and personalise treatments.
Finance	Analysing financial data to inform investment strategies and risk management.
Telecommunications	Analysing customer usage data to optimise network performance.
Manufacturing	Analysing production data to optimise processes.
Education	Analysing student performance data to develop personalised learning plans.
Transportation	Analysing traffic data to optimise routes and schedules.
Fraud detection	Identifying patterns of fraudulent activity in transactional data.
Supply chain management	Identifying patterns in inventory data to optimise supply chain processes.
Sports analytics	Identifying patterns in player performance data to develop optimal game strategies.
Social media	Analysing user behaviour patterns to inform targeted marketing campaigns.

The e-commerce retail sales conducted on an online platform are the subject of the online retail dataset used in this illustration. The discovery of common itemsets and the creation of rules to understand consumer purchase patterns are some potential advantages of association rule mining in this domain. Additionally, entails enhancing pricing strategies, upselling and cross-selling prospects and recommendations, as well as improving product suggestions, customer retention, and loyalty.

Association rule mining can discover and generate e-commerce platforms with valuable insights that can be utilized to improve the overall customer experience and increase revenue. As a example, if an existing customer comes to the platform with prior purchase history, we can suggest the most accurate product suggestions with the right pricing, and product specifications tailored to the customer’s expectations. Personalized product recommendations and promotions can be created based on customers' purchase histories and patterns. Pricing strategies can be optimized by bundling items that are frequently purchased together or offering discounts on complementary products. By identifying cross-selling and upselling opportunities, suggestions for additional products can be offered to customers to encourage them to make more purchases.

Retailers can also benefit from using association rule mining to better understand the needs, preferences, and behavior of their customers. Retailers can discover which products are popular among various consumer segments by analyzing transactional data, and they can identify patterns in customer behavior that could be influenced by marketing strategies and sales efforts.

Finally, the use of association rule mining in the e-commerce retail domain can lead to a range of benefits, including increased revenue and profitability, improved inventory management, and enhanced customer satisfaction and loyalty.

1.2

This "Online Retail II" dataset was downloaded from the UCI machine learning repository. The dataset contains transactional data from an online retailer based in the UK, with records spanning from 1st of December 2010 to 09th of December 2011.
All the data attributes are explained below.

Attribute	Description
InvoiceNo	A 6-digit integral number that is assigned to each transaction. If this code begins with the letter "c," a cancellation has occurred.(Nominal)
StockCode	Product (item) code. A 5-digit integral number is uniquely assigned to each distinct product. (Nominal)
Description	Product (item) name (Nominal)
Quantity	The quantities of each product (item) per transaction (Numeric)
InvoiceDate	Invoice date and time (Numeric)
UnitPrice	Product price per unit in sterling (Numeric)
CustomerID	Customer number.(Nominal)
Country	The name of the country where a customer resides. (Nominal)

All the data preprocessing is executed through R coding and RStudio.
First I uploaded the dataset to the RStudio environment analysed the missing values, data types, and null values. Then removed the null values and negative values.

```
#Loading the dataset
retail = read.csv("C:/Users/Gihan/Documents/Data mining course work/online_retail_II-2010-2011.csv", header = TRUE, stringsAsFactors = FALSE)
print(retail)

#Inspect the dataset to check for missing values, data types, and other issues
str(retail)
summary(retail)

#Remove missing values from the dataset
data <- retail[complete.cases(retail),]

#Remove rows with negative quantities or unit prices
data <- retail[retail$Quantity > 0,]
data <- retail[retail$UnitPrice > 0,]

#dropping null values
retail <- na.omit(retail)
```

After that we have to clear the rows which have errors and unrelated data in the dataset such as removing the cancelled orders, discounts, and postage fee transactions.

```
# Create a logical condition to identify the rows you want to remove
condition <- grepl("C", retail$Invoice)

# Use the condition to subset the data frame and remove the rows
retail <- retail[!condition, ]
print(retail)

# Create a logical condition to identify the rows you want to remove
condition <- grepl("DISCOUNT|POSTAGE", retail$Description, ignore.case = TRUE)

# Use the condition to subset the data frame and remove the rows
retail <- retail[!condition, ]
```

Then created a subset of the dataset to categorise the transactions that only occurred in the United Kingdom. This is because my objective is to discover the rules only from the United Kingdom.

```
#creating rows corresponding to transactions in the United Kingdom
retail <- retail[retail$Country == "United Kingdom", ]
print(retail)
```

After that I have dropped the columns which are not important to my analysis.

```
#drop columns such as StockCode, Price, Country, InvoiceDate,  and Quantity
retail <- retail[, !(names(retail) %in% c("StockCode", "Price", "Country", "Quantity",
"InvoiceDate"))]
print(retail)
```

In order to generate meaningful association rules, it is important to ensure that the dataset is clean, relevant, and contains only the necessary information. This involves making certain choices in data preprocessing, such as removing missing values and negative quantities or unit prices. By doing so, the remaining data becomes more accurate and reliable, which is crucial for generating meaningful insights. Additionally, dropping irrelevant columns helps to reduce the dimensionality of the data, which makes it easier to focus on the most relevant information for association rule mining. Ultimately, these choices help to ensure that the resulting association rules are more useful and actionable for e-commerce platforms.

After conducting all the data preprocessing tasks, I created a summary of the subset from the main dataset.

```
summary(retail)
```

Invoice		**Description**		**Customer.ID**	
Length Class Mode	354302 Character Character	Length Class Mode	354302 Character Character	Min 1st Qu. Median Mean 3rd Qu. Max	12346 14194 15522 15522 16931 18287

1.3

I have explained the association rule mining with examples and use cases in the previous sections. We can utilize the ‘arules’ package in R to carry out association rule mining. To begin the process we need to convert preprocessed data into the transactional format with using the ‘transactions( )’ function.

The Apriori algorithm can be used to find association rules based on minimum support and confidence level.

The support and confidence levels are set using the parameter argument, and the association rules are found using the apriori() function. Then, using the inspect() function, we can see the top rules according to a selected metric, such lift or confidence.

We can visualise the association rules on a plot using the ‘(arulesViz)’ library.

The plot() function can be used to create a scatter plot of the rules based on a provided metric, such as minimum support and confidence level. This allows us to see the rules in action.

Changing the parameter setting and algorithm will change the quality and number of rules discovered through the dataset. It also affects the processing power and processing time varies according to each parameter setting. By doing repetitive trial and testing to fine-tune the quality of rules generated. We can perform multiple times of testing cycles with parameter settings based on the previous results to identify and discover new quality rules for improvement.

```
# load the arules package
library(arules)
library(arulesViz)

# convert the preprocessed data into a transaction format
transactions <- transactions(split(retail[,"Description"],retail[,"Invoice"]))
print(transactions)

# find association rules using Apriori algorithm
rules <- apriori(transactions, parameter = list(support = 0.02, confidence = 0.7))

# inspect the top 150 rules by confidence
inspect(head(sort(rules, by = "lift"), n = 150))

#Plotting the rules in  Scatter plot
plot(rules)
```

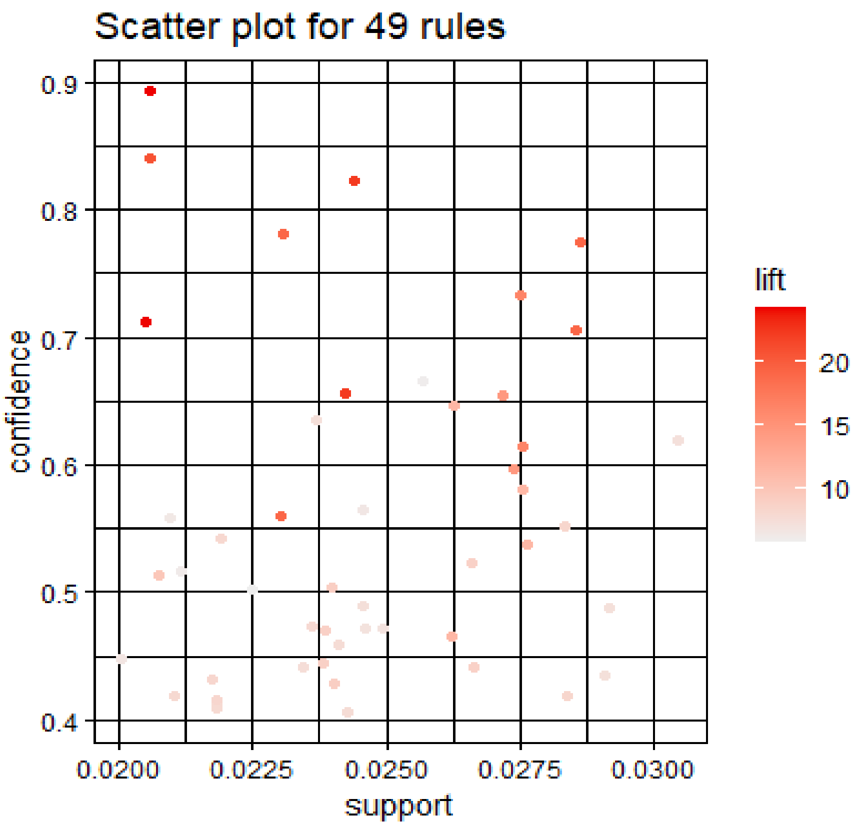
1.4

In this section I will test and trial four cycles until we can find satisfied itemset rules.

Testing 01

```
# find association rules using Apriori algorithm
rules <- apriori(transactions, parameter = list(support = 0.02, confidence = 0.4))
```

- In this testing cycle we set the parameter settings support as 0.02 and confidence level as 0.4. We got 49 rules sorted according to the highest lift and highest confidence level.



	Rules	Support	Confidence	Coverage	Lift	Count
1	**{PINK REGENCY TEACUP AND SAUCER,ROSES REGENCY TEACUP AND SAUCER } => {GREEN REGENCY TEACUP AND SAUCER}**	**0.0205027**	**0.8903394**	**0.0230279**	**24.196283**	**341**
2	**{GREEN REGENCY TEACUP AND SAUCER,PINK REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }**	**0.0205027**	**0.8440594**	**0.0242905**	**20.705599**	**341**
3	**{PINK REGENCY TEACUP AND SAUCER} => {GREEN REGENCY TEACUP AND SAUCER}**	**0.0242905**	**0.8194726**	**0.0296417**	**22.270373**	**404**
4	**{GREEN REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }**	**0.0286195**	**0.7777778**	**0.0367965**	**19.079646**	**476**
5	**{PINK REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }**	**0.0230279**	**0.7768763**	**0.0296417**	**19.057531**	**383**
6	**{GARDENERS KNEELING PAD CUP OF TEA } => {GARDENERS KNEELING PAD KEEP CALM }**	**0.0275373**	**0.7304625**	**0.0376984**	**16.373386**	**458**
7	**{GREEN REGENCY TEACUP AND SAUCER,ROSES REGENCY TEACUP AND SAUCER } => {PINK REGENCY TEACUP AND SAUCER}**	**0.0205027**	**0.7163866**	**0.0286195**	**24.168238**	**341**
8	**{ROSES REGENCY TEACUP AND SAUCER } => {GREEN REGENCY TEACUP AND SAUCER}**	**0.0286195**	**0.7020649**	**0.0407648**	**19.079646**	**476**
9	**{RED HANGING HEART T-LIGHT HOLDER} => {WHITE HANGING HEART T-LIGHT HOLDER}**	**0.0257335**	**0.6666667**	**0.0386003**	**5.88535**	**428**
10	**{GREEN REGENCY TEACUP AND SAUCER} => {PINK REGENCY TEACUP AND SAUCER}**	**0.0242905**	**0.6601307**	**0.0367965**	**22.270373**	**404**
11	{ALARM CLOCK BAKELIKE GREEN} => {ALARM CLOCK BAKELIKE RED }	0.0272968	0.657971	0.0414863	14.437169	454
12	{PAPER CHAIN KIT VINTAGE CHRISTMAS} => {PAPER CHAIN KIT 50S CHRISTMAS }	0.0262747	0.6454948	0.0407047	11.360709	437
13	{JUMBO BAG STRAWBERRY} => {JUMBO BAG RED RETROSPOT}	0.0237494	0.6350482	0.0373978	7.299324	395
14	{JUMBO BAG PINK POLKADOT} => {JUMBO BAG RED RETROSPOT}	0.0304233	0.6231527	0.0488216	7.162596	506
15	{GARDENERS KNEELING PAD KEEP CALM } => {GARDENERS KNEELING PAD CUP OF TEA }	0.0275373	0.6172507	0.0446128	16.373386	458
16	{ALARM CLOCK BAKELIKE RED } => {ALARM CLOCK BAKELIKE GREEN}	0.0272968	0.5989446	0.0455748	14.437169	454
17	{WOODEN FRAME ANTIQUE WHITE } => {WOODEN PICTURE FRAME WHITE FINISH}	0.0275373	0.5841837	0.0471381	11.377216	458
18	{JUMBO STORAGE BAG SUKI} => {JUMBO BAG RED RETROSPOT}	0.024531	0.5666667	0.04329	6.513338	408
19	{ROSES REGENCY TEACUP AND SAUCER } => {PINK REGENCY TEACUP AND SAUCER}	0.0230279	0.5648968	0.0407648	19.057531	383

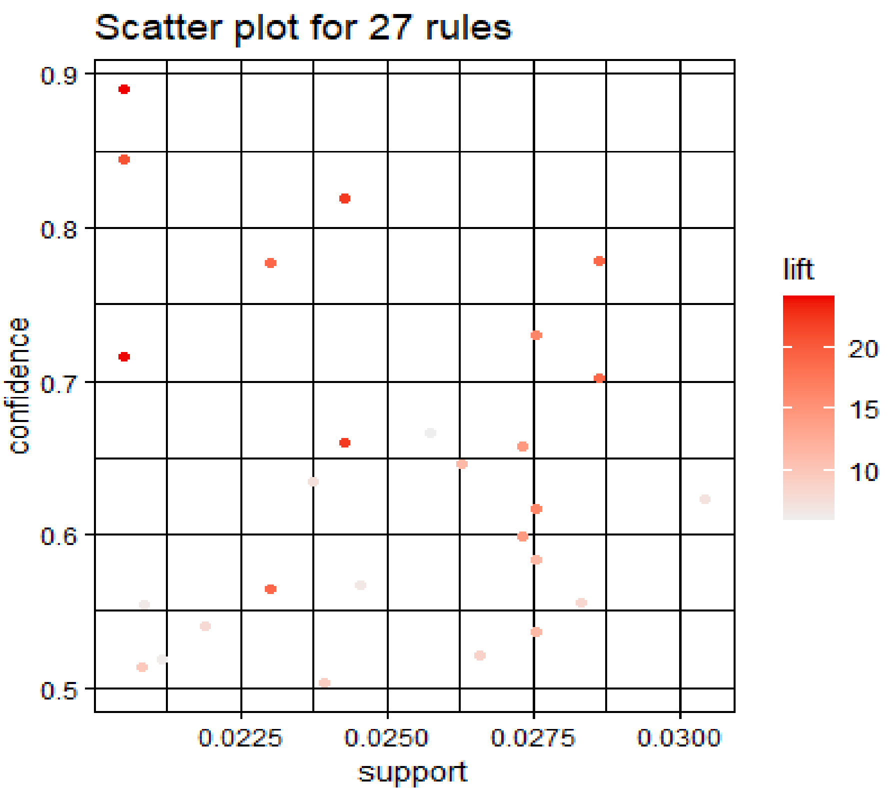
20	{LUNCH BAG PINK POLKADOT} => {LUNCH BAG RED RETROSPOT}	0.0283189	0.5554245	0.0509861	8.248054	471
21	{JUMBO BAG BAROQUE BLACK WHITE} => {JUMBO BAG RED RETROSPOT}	0.0208634	0.5543131	0.0376383	6.371344	347
22	{LUNCH BAG WOODLAND} => {LUNCH BAG RED RETROSPOT}	0.0218855	0.5400593	0.0405243	8.019881	364
23	{WOODEN PICTURE FRAME WHITE FINISH} => {WOODEN FRAME ANTIQUE WHITE }	0.0275373	0.5362998	0.0513468	11.377216	458
24	{LUNCH BAG PINK POLKADOT} => {LUNCH BAG BLACK SKULL.}	0.0265753	0.5212264	0.0509861	8.703853	442
25	{ROSES REGENCY TEACUP AND SAUCER } => {REGENCY CAKESTAND 3 TIER}	0.021164	0.519174	0.0407648	6.124044	352
26	{LUNCH BAG WOODLAND} => {LUNCH BAG SPACEBOY DESIGN }	0.0208033	0.5133531	0.0405243	9.780171	346
27	{HEART OF WICKER LARGE} => {HEART OF WICKER SMALL}	0.0239298	0.5031606	0.0475589	9.017852	398
28	{JUMBO SHOPPER VINTAGE RED PAISLEY} => {JUMBO BAG RED RETROSPOT}	0.0224267	0.4979973	0.0450337	5.724044	373
29	{LUNCH BAG SUKI DESIGN } => {LUNCH BAG RED RETROSPOT}	0.0246513	0.4904306	0.0502646	7.282895	410
30	{LUNCH BAG BLACK SKULL.} => {LUNCH BAG RED RETROSPOT}	0.0291005	0.4859438	0.0598846	7.216265	484
31	{LUNCH BAG SUKI DESIGN } => {LUNCH BAG BLACK SKULL.}	0.0236292	0.4700957	0.0502646	7.850032	393
32	{LUNCH BAG SPACEBOY DESIGN } => {LUNCH BAG RED RETROSPOT}	0.0246513	0.4696449	0.0524892	6.974227	410
33	{LUNCH BAG CARS BLUE} => {LUNCH BAG RED RETROSPOT}	0.0248317	0.468254	0.0530303	6.953571	413
34	{LUNCH BAG PINK POLKADOT} => {LUNCH BAG CARS BLUE}	0.0238095	0.4669811	0.0509861	8.80593	396
35	{PAPER CHAIN KIT 50S CHRISTMAS } => {PAPER CHAIN KIT VINTAGE CHRISTMAS}	0.0262747	0.4624339	0.0568182	11.360709	437
36	{LUNCH BAG CARS BLUE} => {LUNCH BAG BLACK SKULL.}	0.0241703	0.4557823	0.0530303	7.611015	402
37	{LUNCH BAG CARS BLUE} => {LUNCH BAG PINK POLKADOT}	0.0238095	0.4489796	0.0530303	8.80593	396
38	{LUNCH BAG APPLE DESIGN} => {LUNCH BAG RED RETROSPOT}	0.0200217	0.4463807	0.0448533	6.628753	333
39	{LUNCH BAG SPACEBOY DESIGN } => {LUNCH BAG BLACK SKULL.}	0.0233887	0.4455899	0.0524892	7.440815	389
40	{LUNCH BAG BLACK SKULL.} => {LUNCH BAG PINK POLKADOT}	0.0265753	0.4437751	0.0598846	8.703853	442

41	{LUNCH BAG SUKI DESIGN } => {LUNCH BAG CARS BLUE}	0.0218254	0.4342105	0.0502646	8.18797	363
42	{LUNCH BAG RED RETROSPOT} => {LUNCH BAG BLACK SKULL.}	0.0291005	0.4321429	0.0673401	7.216265	484
43	{HEART OF WICKER SMALL} => {HEART OF WICKER LARGE}	0.0239298	0.4288793	0.0557961	9.017852	398
44	{LUNCH BAG RED RETROSPOT} => {LUNCH BAG PINK POLKADOT}	0.0283189	0.4205357	0.0673401	8.248054	471
45	{LUNCH BAG SUKI DESIGN } => {LUNCH BAG SPACEBOY DESIGN }	0.0209235	0.4162679	0.0502646	7.930548	348
46	{LUNCH BAG SPACEBOY DESIGN } => {LUNCH BAG CARS BLUE}	0.0218254	0.4158076	0.0524892	7.840943	363
47	{LUNCH BAG CARS BLUE} => {LUNCH BAG SUKI DESIGN }	0.0218254	0.4115646	0.0530303	8.18797	363
48	{LUNCH BAG CARS BLUE} => {LUNCH BAG SPACEBOY DESIGN }	0.0218254	0.4115646	0.0530303	7.840943	363
49	{LUNCH BAG BLACK SKULL.} => {LUNCH BAG CARS BLUE}	0.0241703	0.4036145	0.0598846	7.611015	402

Testing 02

```
# find association rules using Apriori algorithm
rules <- apriori(transactions, parameter = list(support = 0.02, confidence = 0.5))
```

- In this testing cycle we set the parameter settings support as 0.02 and confidence level as 0.5. We got 27 rules sorted according to the highest lift and highest confidence level.



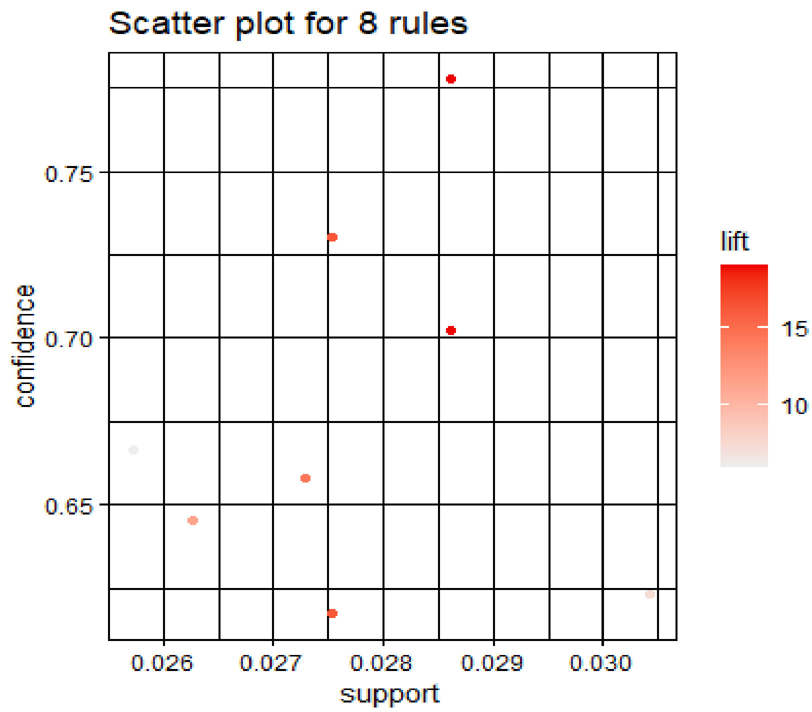
	Rules	Support	Confidence	Coverage	Lift	Count
1	**{PINK REGENCY TEACUP AND SAUCER,ROSES REGENCY TEACUP AND SAUCER } => {GREEN REGENCY TEACUP AND SAUCER}**	**0.02050265**	**0.8903394**	**0.0230279**	**24.196283**	**341**
2	**{GREEN REGENCY TEACUP AND SAUCER,PINK REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }**	**0.02050265**	**0.8440594**	**0.02429052**	**20.705599**	**341**
3	**{PINK REGENCY TEACUP AND SAUCER} => {GREEN REGENCY TEACUP AND SAUCER}**	**0.02429052**	**0.8194726**	**0.02964165**	**22.270373**	**404**
4	**{GREEN REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }**	**0.02861953**	**0.7777778**	**0.03679654**	**19.079646**	**476**
5	**{PINK REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }**	**0.0230279**	**0.7768763**	**0.02964165**	**19.057531**	**383**
6	**{GARDENERS KNEELING PAD CUP OF TEA } => {GARDENERS KNEELING PAD KEEP CALM }**	**0.02753728**	**0.7304625**	**0.03769841**	**16.373386**	**458**
7	**{GREEN REGENCY TEACUP AND SAUCER,ROSES REGENCY TEACUP AND SAUCER } => {PINK REGENCY TEACUP AND SAUCER}**	**0.02050265**	**0.7163866**	**0.02861953**	**24.168238**	**341**
8	**{ROSES REGENCY TEACUP AND SAUCER } => {GREEN REGENCY TEACUP AND SAUCER}**	**0.02861953**	**0.7020649**	**0.04076479**	**19.079646**	**476**
9	**{RED HANGING HEART T-LIGHT HOLDER} => {WHITE HANGING HEART T-LIGHT HOLDER}**	**0.02573353**	**0.6666667**	**0.03860029**	**5.88535**	**428**
10	**{GREEN REGENCY TEACUP AND SAUCER} => {PINK REGENCY TEACUP AND SAUCER}**	**0.02429052**	**0.6601307**	**0.03679654**	**22.270373**	**404**
11	{ALARM CLOCK BAKELIKE GREEN} => {ALARM CLOCK BAKELIKE RED }	0.02729678	0.657971	0.04148629	14.437169	454
12	{PAPER CHAIN KIT VINTAGE CHRISTMAS} => {PAPER CHAIN KIT 50S CHRISTMAS }	0.02627465	0.6454948	0.04070467	11.360709	437
13	{JUMBO BAG STRAWBERRY} => {JUMBO BAG RED RETROSPOT}	0.0237494	0.6350482	0.03739779	7.299324	395
14	{JUMBO BAG PINK POLKADOT} => {JUMBO BAG RED RETROSPOT}	0.03042328	0.6231527	0.04882155	7.162596	506
15	{GARDENERS KNEELING PAD KEEP CALM } => {GARDENERS KNEELING PAD CUP OF TEA }	0.02753728	0.6172507	0.04461279	16.373386	458
16	{ALARM CLOCK BAKELIKE RED } => {ALARM CLOCK BAKELIKE GREEN}	0.02729678	0.5989446	0.0455748	14.437169	454
17	{WOODEN FRAME ANTIQUE WHITE } => {WOODEN PICTURE FRAME WHITE FINISH}	0.02753728	0.5841837	0.04713805	11.377216	458
18	{JUMBO STORAGE BAG SUKI} => {JUMBO BAG	0.02453102	0.5666667	0.04329004	6.513338	408

	RED RETROSPOT}					
19	{ROSES REGENCY TEACUP AND SAUCER } => {PINK REGENCY TEACUP AND SAUCER}	0.0230279	0.5648968	0.04076479	19.057531	383
20	{LUNCH BAG PINK POLKADOT} => {LUNCH BAG RED RETROSPOT}	0.0283189	0.5554245	0.05098605	8.248054	471
21	{JUMBO BAG BAROQUE BLACK WHITE} => {JUMBO BAG RED RETROSPOT}	0.0208634	0.5543131	0.03763829	6.371344	347
22	{LUNCH BAG WOODLAND} => {LUNCH BAG RED RETROSPOT}	0.02188552	0.5400593	0.04052429	8.019881	364
23	{WOODEN PICTURE FRAME WHITE FINISH} => {WOODEN FRAME ANTIQUE WHITE }	0.02753728	0.5362998	0.0513468	11.377216	458
24	{LUNCH BAG PINK POLKADOT} => {LUNCH BAG BLACK SKULL.}	0.02657528	0.5212264	0.05098605	8.703853	442
25	{ROSES REGENCY TEACUP AND SAUCER } => {REGENCY CAKESTAND 3 TIER}	0.02116402	0.519174	0.04076479	6.124044	352
26	{LUNCH BAG WOODLAND} => {LUNCH BAG SPACEBOY DESIGN }	0.02080327	0.5133531	0.04052429	9.780171	346
27	{HEART OF WICKER LARGE} => {HEART OF WICKER SMALL}	0.02392977	0.5031606	0.04755892	9.017852	398

Testing 03

```
# find association rules using Apriori algorithm
rules <- apriori(transactions, parameter = list(support = 0.025, confidence = 0.6))
```

- In this testing cycle we set the parameter settings support as 0.025 and confidence level as 0.6. We got 08 rules sorted according to the highest lift and highest confidence level.

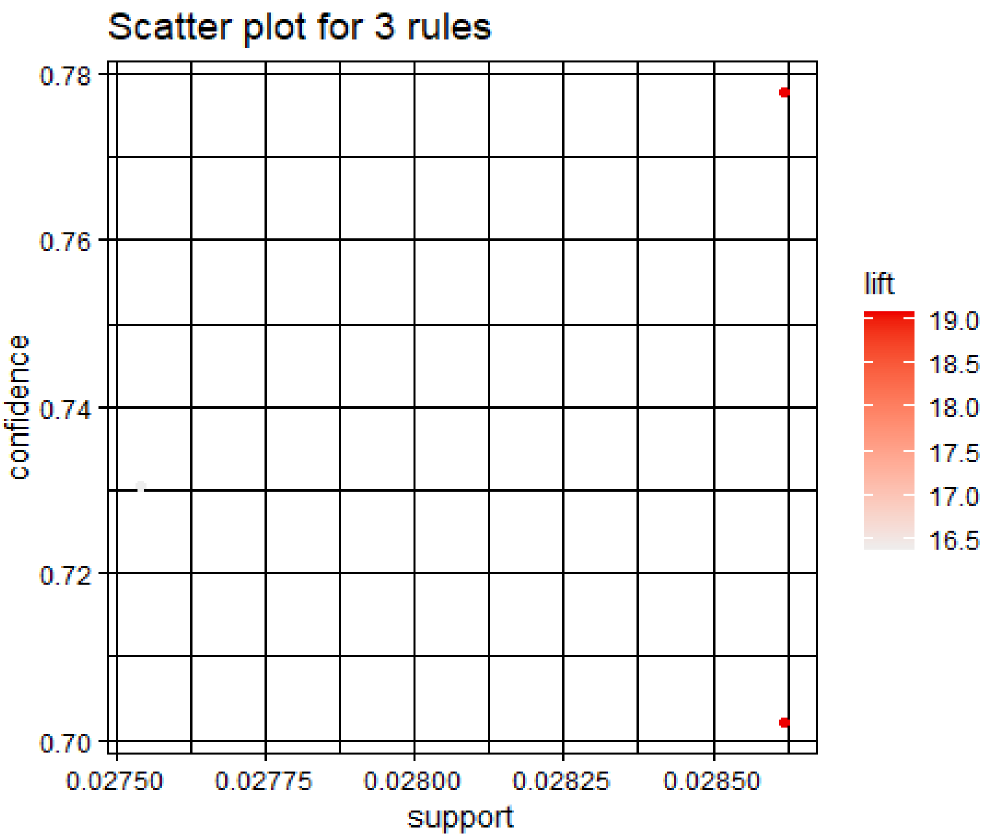


	Rules	Support	Confidence	Coverage	Lift	Count
1	{GREEN REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }	0.02861953	0.7777778	0.03679654	19.079646	476
2	{GARDENERS KNEELING PAD CUP OF TEA } => {GARDENERS KNEELING PAD KEEP CALM }	0.02753728	0.7304625	0.03769841	16.373386	458
3	{ROSES REGENCY TEACUP AND SAUCER } => {GREEN REGENCY TEACUP AND SAUCER}	0.02861953	0.7020649	0.04076479	19.079646	476
4	{RED HANGING HEART T-LIGHT HOLDER} => {WHITE HANGING HEART T-LIGHT HOLDER}	0.02573353	0.6666667	0.03860029	5.88535	428
5	{ALARM CLOCK BAKELIKE GREEN} => {ALARM CLOCK BAKELIKE RED }	0.02729678	0.657971	0.04148629	14.437169	454
6	{PAPER CHAIN KIT VINTAGE CHRISTMAS} => {PAPER CHAIN KIT 50S CHRISTMAS }	0.02627465	0.6454948	0.04070467	11.360709	437
7	{JUMBO BAG PINK POLKADOT} => {JUMBO BAG RED RETROSPOT}	0.03042328	0.6231527	0.04882155	7.162596	506
8	{GARDENERS KNEELING PAD KEEP CALM } => {GARDENERS KNEELING PAD CUP OF TEA }	0.02753728	0.6172507	0.04461279	16.373386	458

Testing 04

```
# find association rules using Apriori algorithm
rules <- apriori(transactions, parameter = list(support = 0.025, confidence = 0.7))
```

- In this testing cycle we set the parameter settings support as 0.025 and confidence level as 0.7. We got 03 rules sorted according to the highest lift and highest confidence level.



	Rules	Support	Confidence	Coverage	Lift	Count
1	{GREEN REGENCY TEACUP AND SAUCER} => {ROSES REGENCY TEACUP AND SAUCER }	0.02861953	0.7777778	0.03679654	19.07965	476
2	{GARDENERS KNEELING PAD CUP OF TEA } => {GARDENERS KNEELING PAD KEEP CALM }	0.02753728	0.7304625	0.03769841	16.37339	458
3	{ROSES REGENCY TEACUP AND SAUCER } => {GREEN REGENCY TEACUP AND SAUCER}	0.02861953	0.7020649	0.04076479	19.07965	476

- After analysing four cycles of testing above 3 rules are the best association rules discovered from the online retail dataset. As we did data preprocessing, these transactions were filtered only from the United Kingdom. We can target a promotional campaign targeting the United Kingdom household demographics in online Ads platforms such as Google and social media. This will help boost sales further.

- With a lift value of 19.07965, the first rule says that consumers who buy the "GREEN REGENCY TEACUP AND SAUCER" are very likely to buy the "ROSES REGENCY TEACUP AND SAUCER" as well. This suggests that the two things have a significant favorable association. As a result, the client might want to think about marketing both products simultaneously, perhaps by giving consumers a discount if they buy both at once. With that in mind, develop the product placement on the webpage together.
- Also client can promote if those items are bought together, the buyer will get a discount or discount coupon for the next purchase.