Customer Segmentation & Effective Cross Selling Project

Introduction

Mass marketing tactics have been used for years by many companies and it has given some good results for some of them. But, as this approach has been using companies resources in an inefficient way, it has been questioned for years and started to been seen as an expensive and time-consuming strategy.

So most companies already abonded this **‘one-size-fits-all’** approach. In order to use companies' resourses effectively and efficiently, they started to analyze their customers and tried to get some **segmentations** out of it.

Introduction

The main purpose of this analysis is **to cluster customer data** into groups sharing the same properties or behavioral characteristics. By clustering customers, companies will be able to drive dynamic content and personalization tactics for an effective marketing communications.

However, for segmentation to be used correctly, it needs to take into account that **different customers buy for different reasons**. And companies need to intelligently apply a number of considerations that could affect their purchasing decisions. A Harvard Business School professor even went as far to say that, of 30,000 new consumer products launches each year, 95% fail because of ineffective market segmentation.

Some of The Most Common Segment Descriptors?

1. **Demographic** – basic personal information .
2. **Geographic** – specific areas where customers or businesses are located,
3. **Behavioral** – how customers are using your products and what type of user they are.
4. **Loyalty** – For companies with loyalty programs, this can include customer activity and points earned/redeemed. Alternatively, it can be a recency, frequency, monetary (RFM) score.
5. **Time** - Customers who signed up for a product or service during a particular time frame
6. **Preference** – This can cover communication preference opt-ins, as well as which of your channels (such as online, through an app or in-store) they prefer and the time/day they are most responsive to your messages.
7. **Size** - The various sizes of customers who purchase company's products or services

In this project, we will use three of above mentioned methods in our analysis;

 # Behavior and Loyalty (Frequency, Recency and Tenure Analysis):** These cohorts are customers who purchased a product or subscribed to a service in the past. It groups customers by the type of product or service they signed up. Customers who signed up for basic level services might have different needs than those who signed up for advanced services. Understanding the needs of the various cohorts can help a company design custom-made services or products for particular segments.

> **In this project, we will use three of above mentioned methods in our analysis;**

> ****Time (Time Cohort Analysis)**:** Time cohorts are customers who signed up for a product or service during a particular time frame. Analyzing these cohorts shows the customers' behavior depending on the time they started using the company's products or services. The time may be monthly, quarterly, even daily.

> ****Size (Moneytary Value Analysis)**:** Size cohorts refer to the various sizes of customers who purchase company's products or services. This categorization can be based on the amount of spending in some period of time after acquisition, or the product type that the customer spent most of their order amount in some period of time.
****

Online Retail Transactions Dataset

The online retail transactions dataset is available from the UCI Machine Learning Repository (http://archive.ics.uci.edu/ml/datasets/online+retail). The dataset we will be using for our analysis contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. From the web site, we also learn that the company sells unique all-occasion gift items and a lot of customers of the organization are wholesalers.

Online Retail Transactions Dataset

The first thing you should notice about the dataset is its format. Unlike most of the datasets, it is not in a CSV format and instead comes as an Excel file. But, in python environment it is not a problem, we can read the dataset using the function read_excel provided by the pandas library.

In [3]:
```
# Read and save dataset as a dataframe:
from pandas import read_excel
df = read_excel('online_retail.xlsx')
```

Online Retail Transactions Dataset

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

> **So, here are the attributes of the dataset.**

- **InvoiceNo**: A unique identifier for the invoice. An invoice number shared across rows means that those transactions were performed in a single invoice (multiple purchases).
- **StockCode**: Identifier for items contained in an invoice.
- **Description**: Textual description of each of the stock item.
- **Quantity**: The quantity of the item purchased.
- **InvoiceDate**: Date of purchase.
- **UnitPrice**: Value of each item.
- **CustomerID**: Identifier for customer making the purchase.
- **Country**: Country of customer.

Online Retail Transactions Dataset

In [7]:
```
# Inspect how many total rows and columns we have.
df.shape
```

Out[7]:
```
(541909, 8)
```

In [8]:
```
# Count the features
print ('The total number of customers is: {}'. format(df.CustomerID.nunique()))
print ('The total number of invoices is: {}'. format(df.InvoiceNo.nunique()))
print ('The total number of dates is: {}'. format(df.InvoiceDate.nunique()))
print ('The total number of transactions is: {}'. format(len(df.index)))
```

```
The total number of customers is: 4372
The total number of invoices is: 25900
The total number of dates is: 23260
The total number of transactions is: 541909
```

> **Conclusion_1**:Although there are 541.909 transactions, there are only 4.372 customers and 25.900 invoices. This shows that multiple purchases are made by a single invoice and multiple invoices are taken by a single customer.

Data Wrangling

In [5]:
```
#In order to check whether column names have any white space...
df.columns
```

Out[5]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate', 'UnitPrice', 'CustomerID', 'Country'], dtype='object')
```

> Column Labels don't have any white space

Data Wrangling

```
# Inspect the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
InvoiceNo      541909 non-null object
StockCode      541909 non-null object
Description    540455 non-null object
Quantity       541909 non-null int64
InvoiceDate    541909 non-null datetime64[ns]
UnitPrice      541909 non-null float64
CustomerID     406829 non-null float64
Country        541909 non-null object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

> Quantity, UnitPrice and CustomerID are either integer or float numbers. InvoiceDate is datetime64 type. CustomerID and Description have missing values

Data Wrangling

```
# Drop missing values
df = df.dropna(subset=['CustomerID'])
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 406829 entries, 0 to 541908
Data columns (total 8 columns):
InvoiceNo      406829 non-null object
StockCode      406829 non-null object
Description    406829 non-null object
Quantity       406829 non-null int64
InvoiceDate    406829 non-null datetime64[ns]
UnitPrice      406829 non-null float64
CustomerID     406829 non-null float64
Country        406829 non-null object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 27.9+ MB
```

> So, after dropping missing values in CustomerID feature, we don't have any missing values anymore.

Data Wrangling

In [15]:
```
# Inspect the duplicate observations
df[df.duplicated(keep=False)].count()
```

Out[15]:
```
InvoiceNo      10062
StockCode      10062
Description    10062
Quantity       10062
InvoiceDate    10062
UnitPrice      10062
CustomerID     10062
Country        10062
dtype: int64
```

> There are quite a number of duplications. But we believe that it stems from the fact that the same customer can make several transactions in a single invoice (multiple purchases) or multiple invoices

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```
# Inspect two numerical attributes
df[['Quantity', 'UnitPrice']].describe()
```

	Quantity	UnitPrice
count	406829.000000	406829.000000
mean	12.061303	3.460471
std	248.693370	69.315162
min	-80995.000000	0.000000
25%	2.000000	1.250000
50%	5.000000	1.950000
75%	12.000000	3.750000
max	80995.000000	38970.000000

> As there are some negative values, we can assume that these are returns

EDA

Checking customer's profile

In [27]:
```
df.CustomerID.unique().shape
```

Out[27]:
```
(4372,)
```

In [33]:
```
(df.CustomerID.value_counts()/sum(df.CustomerID.value_counts())*100).head(13).cumsum()
```

Out[33]:
```
17841.0    1.962249
14911.0    3.413228
14096.0    4.673708
12748.0    5.814728
14606.0    6.498553
15311.0    7.110850
14646.0    7.623350
13089.0    8.079807
13263.0    8.492020
14298.0    8.895138
15039.0    9.265809
14156.0    9.614850
18118.0    9.930462
Name: CustomerID, dtype: float64
```

> **Conclusion:** Although there are 4,372 customers, 10% of all orders are made by 13 customers. So these 13 customers are very high value customers for the company.

EDA

Checking StockCode and Descriptions

In [34]:
```
df.StockCode.nunique()
```

Out[34]: 3684

In [35]:
```
df.Description.nunique()
```

Out[35]: 3896

> **Conclusion:** We have a mismatch in the number of StockCode and Description, as we can see that item descriptions are more than stock code values.This means that we have multiple descriptions for some of the stock codes. Let's try to understand why this happens.

In [47]:
```
cat_df = df.groupby(["StockCode","Description"]).count().reset_index()
```

In [51]:
```
cat_df.StockCode.value_counts()[cat_df.StockCode.value_counts()>1].reset_index().head()
```

Out[51]:

	index	StockCode
0	23196	4
1	23236	4
2	23413	3
3	23244	3
4	23209	3

In [61]:
```
df[df['StockCode'] ==cat_df.StockCode.value_counts()[cat_df.StockCode.value_counts()>1].reset_index()['index'][6]]['Description'].unique()
```

Out[61]:
```
array(['SET OF 4 KNICK KNACK TINS DOILEY ',
       'SET OF 4 KNICK KNACK TINS DOILY ',
       'SET OF 4 KNICK KNACK TINS  DOILEY '], dtype=object)
```

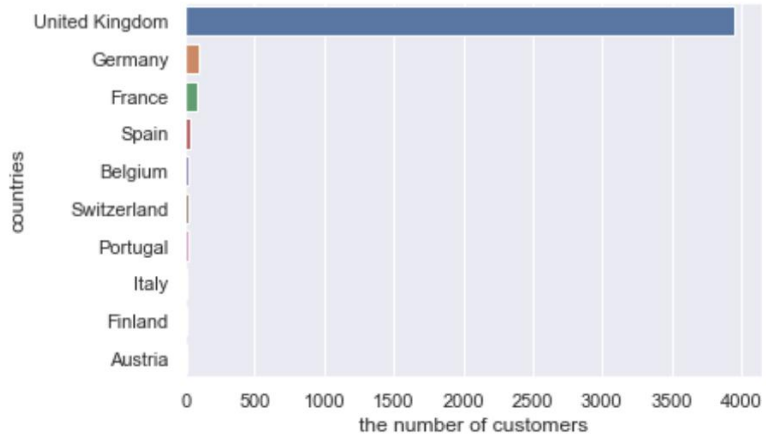
> **Conclusion:** We can see why there are multiple descriptions for some stock codes. Putting an extra white space or just some spelling errors can corrupt our dataset

EDA

In [16]:
```
# Checking the number of customers based on top 10 Countries
table = df.groupby('Country')['CustomerID'].nunique()
table_2 = table.sort_values(ascending = False).head(10)
```

In [17]:
```
# Set seaborn style
sns.set(color_codes=True)

# Plot histogram
ax = sns.barplot(y= table_2.index, x=table_2.values)
ax.set(ylabel="countries")
ax.set(xlabel='the number of customers')
plt.show()
```



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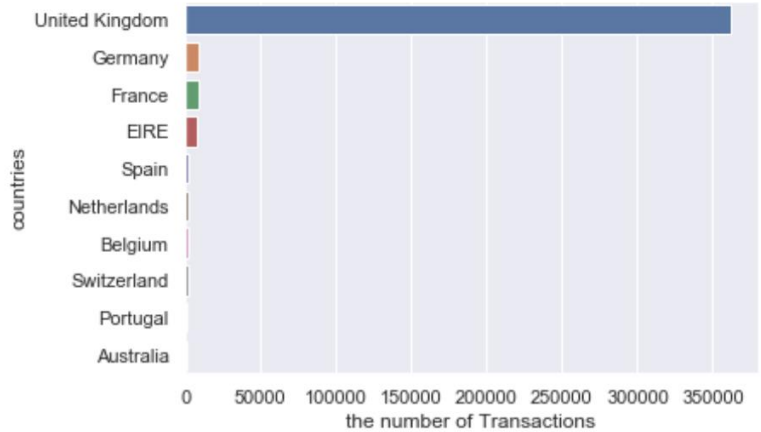
In [19]:
```
# Checking the top 10 countries the retailer is selling its items to, and the volumes of sales for those countries.
country_counts = df.Country.value_counts().head(10)

# Set seaborn style
sns.set(color_codes=True)

# Plot histogram
ax = sns.barplot(y= country_counts.index, x=country_counts.values)
ax.set(ylabel="countries")
ax.set(xlabel='the number of Transactions')
plt.show()
```



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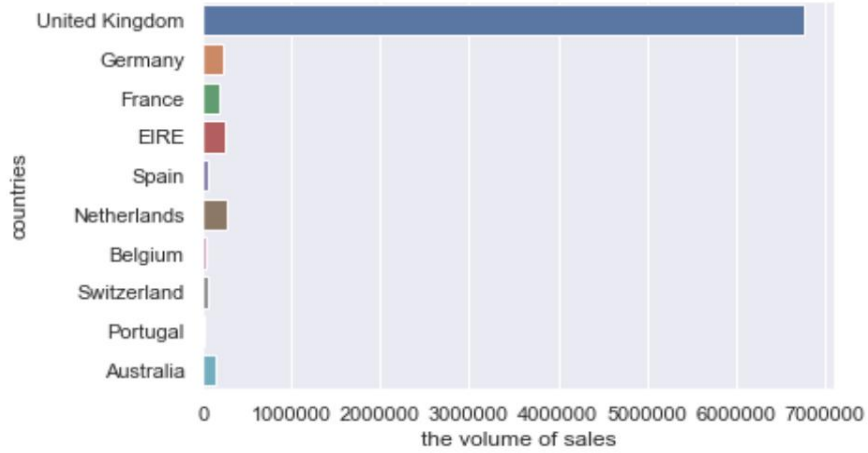
In [21]:
```
# Creating a loop in order to calculate the total amount sale to the top 10 countries
country_total = []
lst = []
for i in country_counts.index:
    country_total =df[df.Country ==i].Amount.sum()
    lst.append(country_total)

# Checking the Total Amount of sales for top countries.
country_counts = df.Country.value_counts().head(10)

# Plot histogram
ax = sns.barplot(y= country_counts.index, x=lst)
ax.set(ylabel="countries")
ax.set(xlabel="the volume of sales")
plt.show()
```



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In [22]:
```
# We categorize the unit price in order to check company's price portfolio
# So, we name the unit price 'low' if a number is in the interval [$0, $3],
# 'mid' for ($3, $7],
# 'mid_high' for ($7, $10],
# 'high' above $10.
category = pd.cut(df['UnitPrice'], bins=[0, 3, 7, 10, 100000], include_lowest=True, labels=['low', 'mid', 'mid_high', 'high'])
```

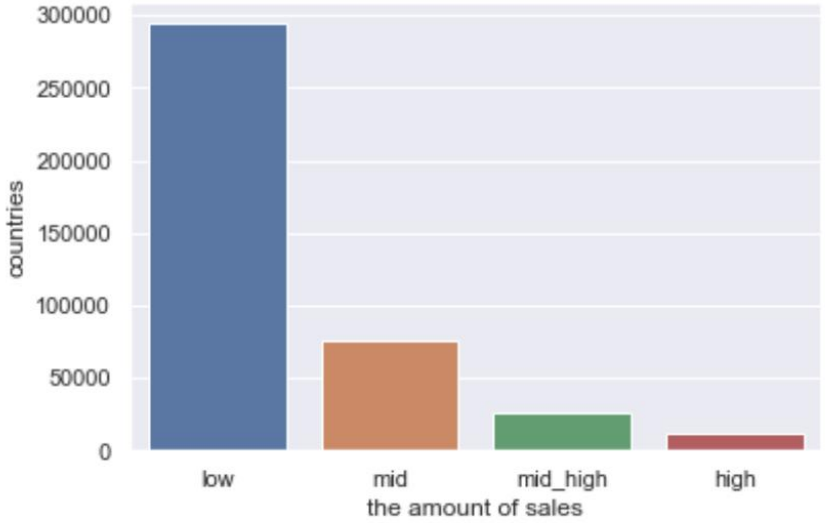
In [23]:
```
category.value_counts(normalize = True)
```

Out[23]:
```
low         0.723233
mid         0.184945
mid_high    0.062955
high        0.028867
Name: UnitPrice, dtype: float64
```

> Only 2.9% of the sales are more expensive than $10.

EDA

```
a= category.value_counts()
# Plot histogram
ax = sns.barplot(x= a.index, y=a.values)
ax.set(ylabel="countries")
ax.set(xlabel="the amount of sales")
plt.show()
```



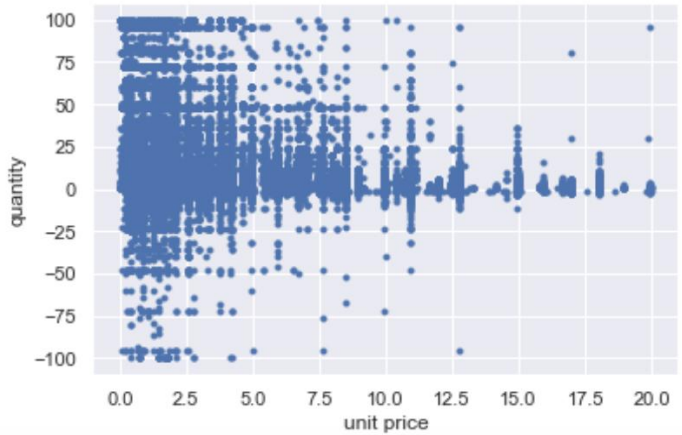
90 % of the items price are equal to or less than $7.

EDA

In order to better visualize the scatterplot, we drop the outliers in UnitPrice and Quantity features

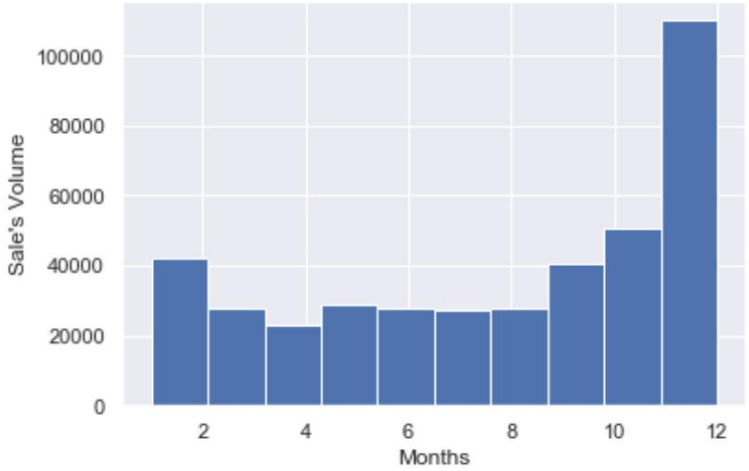
[63]:
```
df_normalized = df[(df['UnitPrice'] <= 20) & (df['Quantity'] <= 100) & (df['Quantity'] >= -100)]
```

[64]:
```
# Make a scatter plot in order to check whether there is a correlation between unit price and quantity.
plt.plot(df_normalized.UnitPrice, df_normalized.Quantity, marker='.', linestyle='none')

# Label the axes
plt.xlabel('unit price')
plt.ylabel('quantity')

# Show the result
plt.show()
```



EDA

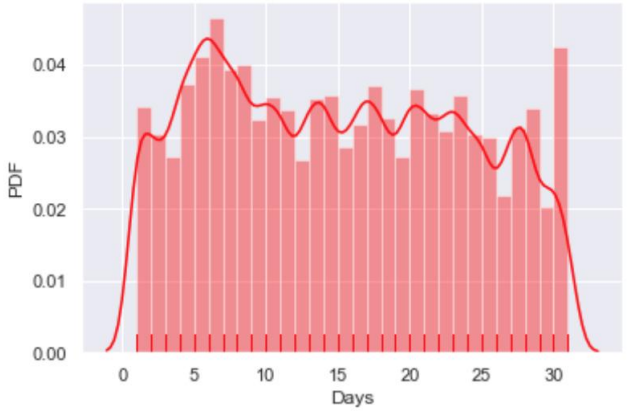
```
# Check on which month there are more sales.

plt.hist(df.InvoiceMonth)
plt.xlabel('Months')
plt.ylabel("Sale's Volume")
plt.show()
```



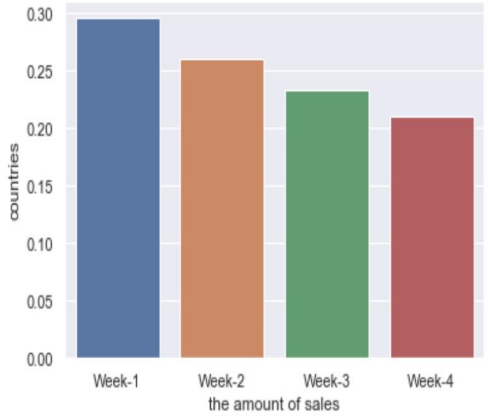
> **Conclusion_3:** There are more sales in December, most probably due to Christmass Shoppings.

EDA

```
# Check on which days there are more sales

j = df.InvoiceDay
sns.distplot(j, rug='True', bins=30, color = 'red')
plt.xlabel('Days')
plt.ylabel('PDF')
plt.show()
```



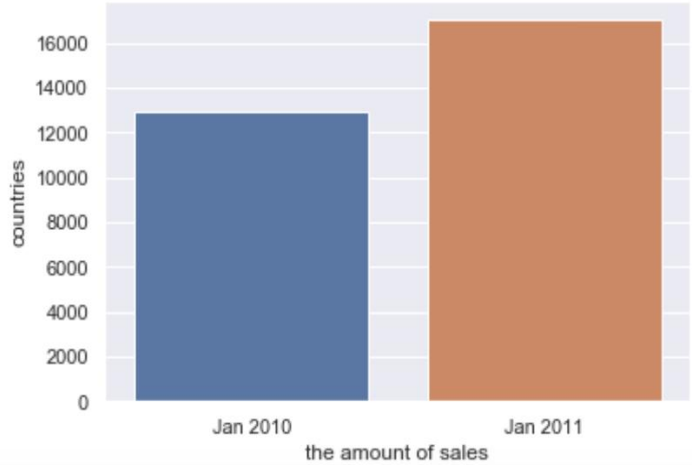

```
# Check in which weeks are there more sales.

lst3 = df.InvoiceDay.value_counts(normalize=True, sort=True, bins = 4)
lst4 = ['Week-1','Week-2','Week-3','Week-4']

# Plot histogram
ax = sns.barplot(x= lst4, y=lst3.values)
ax.set(ylabel="countries")
ax.set(xlabel="the amount of sales")
plt.show()
```



Conclusion_4: There are more sales in the first weeks of the months as most people get their pay checks at on first or second day of each month.

EDA

```
# Compare the overlaping period of 2011 and 2010

grouping2 = df[(df.InvoiceYear ==2010) & (df.InvoiceMonth ==12)&(df.InvoiceDay <9)]['Quantity'].count()
grouping3 = df[(df.InvoiceYear ==2011) & (df.InvoiceMonth ==12)&(df.InvoiceDay <9)]['Quantity'].count()

lst1 = [grouping2,grouping3]
lst2 = ['Jan 2010','Jan 2011']

# Plot histogram
ax = sns.barplot(x= lst2, y=lst1)
ax.set(ylabel="countries")
ax.set(xlabel="the amount of sales")
plt.show()
```



EDA

In [80]:
```
# Check the rate of item returns

return_rate = df[df.Quantity<0].Quantity.sum() / df[df.Quantity>0].Quantity.sum()
print (f"The return rate of items: {(return_rate.round(2))}")
```

```
The return rate of items: -0.05
```

> **Conclusion_6**: Their average return rate for the Top 500 merchants is 4.96%. As this company's return rate is 5%, it is around the average.

Hypothesis Testing

Hypothesis Testing

Testing whether UK and Other countries have different mean for the average sale (Amount divided by the number of Customers).

(The null hypothesis) Ho: UK and other countries have mean difference = 0 (Ho: $\mu 1 = \mu 2$)

(The alternative hypothesis) Ha: UK and other countries have mean difference $\neq 0$ (H1: $\mu 1 \neq \mu 2$)

Hypothesis Testing

```
## Z-test statistics

# Find the average sale of customers (for UK and other countries)

UK_mean = UK_sample['Amount'].sum()/customer_counts_UK
Others_mean = Others_sample['Amount'].sum()/customer_counts_Others

# Find the variance for low and high capacity
UK_var = UK_sample['Amount'].var()
Others_var = Others_sample['Amount'].var()

UK_ln = len(UK_sample['Amount'])
Others_ln = len(Others_sample['Amount'])

z = (UK_mean - Others_mean) / np.sqrt(UK_var/UK_ln + Others_var/Others_ln)
print ('Z-score: {}'.format(z))
```

```
Z-score: -733.7805627736338
```

```
p = stats.norm.cdf(-z)*2
print ('p-value:{}'.format(p))
```

```
p-value:2.0
```

> **Conclusion_7:** P-value is greater than 0.05, so we fail to reject Null Hypoyhesis, which means that UK and Other countries' average sale aren't statistically different. (Even though UK is the major destions for most transactions)

Hypothesis Testing

T-Test

```
#Calculate the T-test for the means of two independent samples of scores.

t, p = stats.ttest_ind(UK_sample['Amount'], Others_sample['Amount'])
print('t-statistic:', t)
print('p-value:', p)
```

> **Conclusion_8**: P-value is greater than 0.05, so we fail to reject Null Hypoyhesis, which means that UK and Other countries' average sale aren't statistically different.

Creating Customer Cohorts

Elements of Cohort Analysis

- **Pivot Table:**

The cohort analysis data is typically formatted as a pivot table.

- **Assigned cohort in rows:**

The row values represent the cohort. In our example, it is the month of the first purchase and customers are pooled into these groups based on their first ever purchase

- **Cohort index in columns:**

The column values represent months since acquisition.

- **Metrics in the table:**

Here, we have the count of active customers.

Step-1 Extracting year, month and day from InvoiceDate column

Now, we will create a function that truncates a given date object to a first day of the month. In another word, create a function by passing a datetime object extracting year, month and day from x

```
def get_month(x): return dt.datetime(x.year, x.month,1)
```

Then we apply it to the InvoiceDate and create an InvoiceMonth column

```
df['InvoiceMonthWhole'] = df['InvoiceDate'].apply(get_month)
```

```
df.head(1)
```

We create a groupby() object with CustomerID and use the InvoiceMonth column for the further manipulation. (Group by CustomerID and select the InvoiceMonth value)

```
grouping = df.groupby('CustomerID')['InvoiceMonthWhole']
```

We use transform( ) together with a min( ) function to assign the smallest InvoiceMonth value to each customer.

```
df['CohortMonthWhole'] = grouping.transform('min')
```

Step-2 Calculating the time offset

Now, we will calculate the number of months between any transaction and the first transaction for each customer. We will use InvoiceMonth and CohortMonth values to do this. We will start by creating two object with year and month integer values from each of the InvoiceMonth and CohortMonth variables.

```
CohortYear, CohortMonth, _=get_date_int(df, 'CohortMonthWhole')
```

```
# Create an CohortYear, CohortMonth column

df['CohortYear']= CohortYear
df['CohortMonth']= CohortMonth
```

Next, we will calculate the differences in years and months between them.

```
years_diff = df.InvoiceYear - df.CohortYear
months_diff = df.InvoiceMonth - df.CohortMonth
```

Defining a cohort is the first step to cohort analysis. We will now create monthly cohorts based on the month each customer has made their first transaction.

```
# Calculate the number of months for the CohortIndex (12 months in a year)
# Create a new column (CohortIndex)

df['CohortIndex'] = years_diff * 12 + months_diff + 1 # +1 is added, as we want to start the index with 1.
```

Cohorts Table

```
# Rows are first activity (month of acquisition)
# Columns are time since first activity
cohort_counts
```

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12	13
CohortMonthWhole													
2010-12-01	948.0	362.0	317.0	367.0	341.0	376.0	360.0	336.0	336.0	374.0	354.0	474.0	260.0
2011-01-01	421.0	101.0	119.0	102.0	138.0	126.0	110.0	108.0	131.0	146.0	155.0	63.0	NaN
2011-02-01	380.0	94.0	73.0	106.0	102.0	94.0	97.0	107.0	98.0	119.0	35.0	NaN	NaN
2011-03-01	440.0	84.0	112.0	96.0	102.0	78.0	116.0	105.0	127.0	39.0	NaN	NaN	NaN
2011-04-01	299.0	68.0	66.0	63.0	62.0	71.0	69.0	78.0	25.0	NaN	NaN	NaN	NaN
2011-05-01	279.0	66.0	48.0	48.0	60.0	68.0	74.0	29.0	NaN	NaN	NaN	NaN	NaN
2011-06-01	235.0	49.0	44.0	64.0	58.0	79.0	24.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	191.0	40.0	39.0	44.0	52.0	22.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	167.0	42.0	42.0	42.0	23.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	298.0	89.0	97.0	36.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

The first column with cohort index "one" represents the total number of customers in that cohort.

Let's look at the table- we can see that the first cohort was acquired in December 2010, there are 948 customers in it.

Step-4: Calculate Cohort Metrics (customer retention rate table and the average purchase quantity table)

Retention

Retention: It measures how many customers from each of the cohort returned in the subsequent months.

Retention Rate: The ratio of how many customers came back in the subsequent months.

```
# Divide all values in the cohort_counts table by cohort_sizes
retention = cohort_counts.divide(cohort_sizes, axis=0)
```

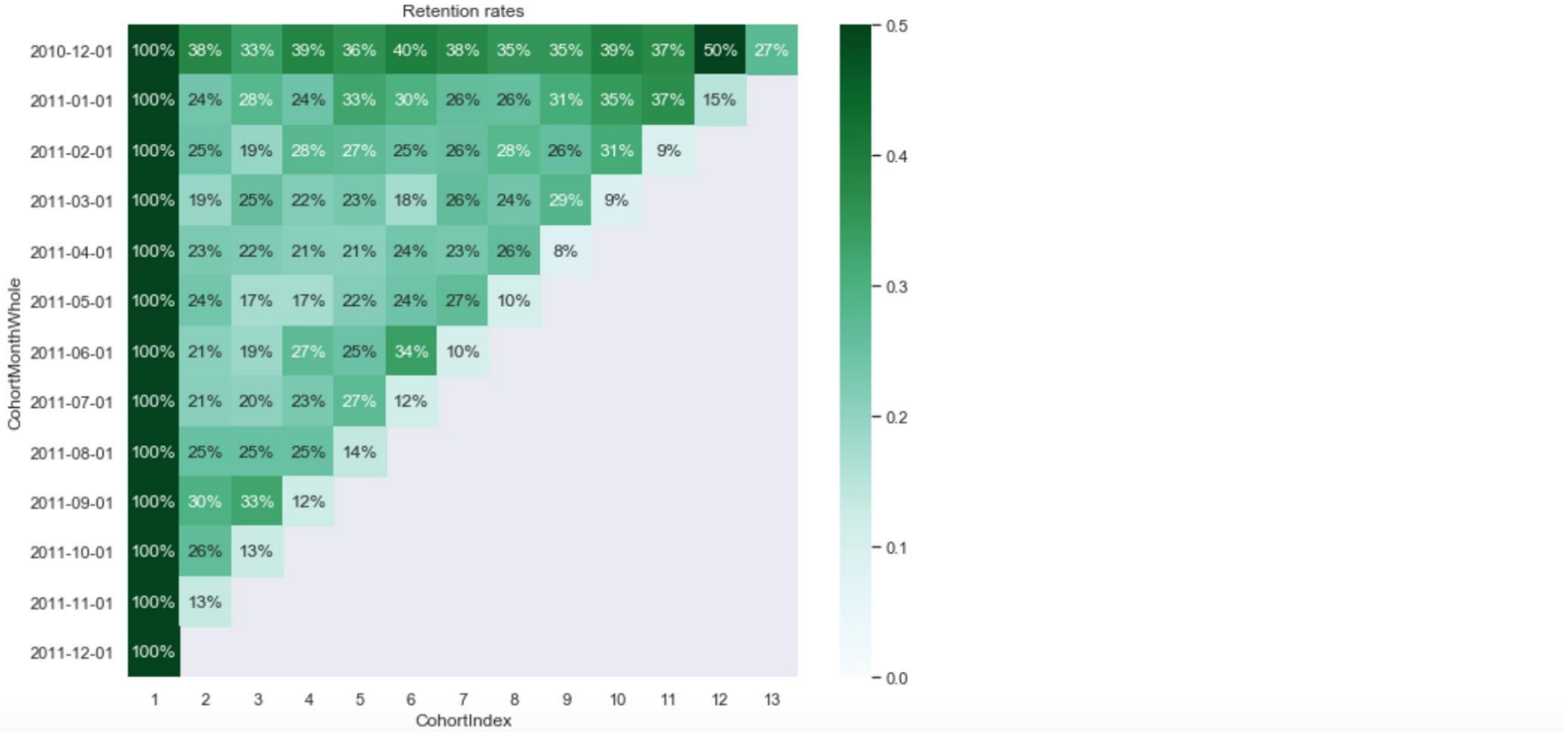
```
# Review the retention table (All numbers below shows % percent)
retention.round(3) * 100
```

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12	13
CohortMonthWhole													
2010-12-01	100.0	38.2	33.4	38.7	36.0	39.7	38.0	35.4	35.4	39.5	37.3	50.0	27.4
2011-01-01	100.0	24.0	28.3	24.2	32.8	29.9	26.1	25.7	31.1	34.7	36.8	15.0	NaN
2011-02-01	100.0	24.7	19.2	27.9	26.8	24.7	25.5	28.2	25.8	31.3	9.2	NaN	NaN
2011-03-01	100.0	19.1	25.5	21.8	23.2	17.7	26.4	23.9	28.9	8.9	NaN	NaN	NaN
2011-04-01	100.0	22.7	22.1	21.1	20.7	23.7	23.1	26.1	8.4	NaN	NaN	NaN	NaN
2011-05-01	100.0	23.7	17.2	17.2	21.5	24.4	26.5	10.4	NaN	NaN	NaN	NaN	NaN
2011-06-01	100.0	20.9	18.7	27.2	24.7	33.6	10.2	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	100.0	20.9	20.4	23.0	27.2	11.5	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	100.0	25.1	25.1	25.1	13.8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	100.0	29.9	32.6	12.1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	100.0	26.4	13.1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	100.0	13.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	100.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Now, we can examine our retention table. As you can see, the first column has a 100% retention rate for all cohorts, as expected. We can compare the retention rate over time and across cohorts to evaluate the health of our customer's shopping habits

Retention Rates

```
plt.figure(figsize=(10, 8))
plt.title('Retention rates')
sns.heatmap(data = retention, annot = True, fmt = '.0%', yticklabels = [item.date() for item in cohort_sizes.index.tolist()])
plt.show()
```



Average Quantity

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12	13
CohortMonthWhole													
2010-12-01	11.0	14.6	15.0	14.8	12.9	14.3	15.2	14.8	16.7	16.7	17.3	12.8	14.8
2011-01-01	10.0	12.6	12.3	10.9	12.2	14.9	14.2	14.4	11.4	9.9	9.1	9.5	NaN
2011-02-01	10.8	12.1	18.6	12.0	11.1	11.4	13.3	12.4	10.3	11.9	12.6	NaN	NaN
2011-03-01	9.8	9.9	12.2	9.5	13.6	12.3	13.2	12.2	10.5	8.9	NaN	NaN	NaN
2011-04-01	9.8	10.1	9.4	11.6	11.5	8.2	9.7	9.3	7.3	NaN	NaN	NaN	NaN
2011-05-01	10.9	9.0	13.9	11.8	10.9	8.7	10.1	7.4	NaN	NaN	NaN	NaN	NaN
2011-06-01	10.3	13.7	10.5	13.3	10.2	9.8	9.3	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	9.7	12.7	7.1	7.8	6.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	9.9	6.0	5.3	6.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	11.9	5.5	7.6	8.8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	8.4	6.9	8.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	8.7	9.3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	14.5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

> **Conclusion_10**: Decembers and January cohorts have higher average quantity, which means that they shop more than other cohorts.

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12	13
CohortMonthWhole													
2010-12-01	3.2	3.2	3.2	3.6	2.9	5.0	3.2	3.2	3.5	3.0	3.3	2.8	2.8
2011-01-01	3.5	3.7	3.1	8.4	3.2	3.2	2.9	2.7	2.6	5.5	2.9	2.6	NaN
2011-02-01	3.3	4.4	4.8	3.1	3.0	2.8	2.8	3.2	2.9	2.9	3.2	NaN	NaN
2011-03-01	3.3	5.0	3.7	3.3	3.6	2.8	2.8	2.8	2.7	2.5	NaN	NaN	NaN
2011-04-01	3.4	4.0	3.3	2.7	3.0	2.9	2.9	2.8	2.6	NaN	NaN	NaN	NaN
2011-05-01	4.6	3.2	2.6	3.2	2.7	2.5	2.6	2.5	NaN	NaN	NaN	NaN	NaN
2011-06-01	10.4	3.2	3.3	2.8	2.6	3.5	2.3	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	4.5	3.5	2.7	2.7	2.4	2.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	3.0	5.4	5.7	7.0	6.8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	3.2	3.6	2.9	2.6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	4.0	2.7	2.6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	2.6	2.3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	2.3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

> **Conclusion_11**: The average price for all cohorts are between 2 and 5 dollars.

Behavior Cohort Analysis

Behavioral customer segmentation based on identified metrics:

> RFM (Recency, Frequency, Monetary Value) Segmentation

> RFMT(Recency, Frequency, Monetary Value, Tenure) Segmenation

> RFMTS(Recency, Frequency, Monetary Value, Tenure, Send Back) Segmenation

a. Recency (R):

**How recent was each customer's last purchase,

b. Frequency (F):

**How many purchases the customer has done in the last 12 months

c. Monetary Value (M):

** How much has the customer spent in the last 12 months.

d. Tenure (T):

** When did customer make his/her first purchase.

e. Send Back (S):

** How satisfied is the customer (High return rate (in terms of monetary value) shows higher dissatisfaction)

Creating RFMT and RFMTS Tables

```
# Aggregate data on a customer level

datamart= df.groupby(['CustomerID']).agg({
    'InvoiceDate': lambda x: (snapshot_date - x.max()).days,
    'InvoiceNo': 'count',
    'Amount': 'sum',
    'InvoiceMonthWhole': lambda x: (snapshot_date - x.min()).days})

# Rename columns for easier interpretation
datamart.rename(columns = {'InvoiceDate': 'Recency',
                           'InvoiceNo': 'Frequency',
                           'Amount': 'MonetaryValue',
                           'InvoiceMonthWhole': 'Tenure'}, inplace=True)
```

```
datamart['MonetaryValue'] = datamart['MonetaryValue'].round(2)
```

```
datamart.head()
```

CustomerID	Recency	Frequency	MonetaryValue	Tenure
12346.0	326	2	0.00	343
12347.0	2	182	4310.00	374
12348.0	75	31	1797.24	374
12349.0	19	73	1757.55	39
12350.0	310	17	334.40	312

Creating Recency Quartile

```
# Let's create a list of labels-only this time the values are reversed as lower recency is rated higher.
r_labels = range(4, 0, -1)
r_quartiles = pd.qcut(datamart['Recency'], 4, labels = r_labels)
datamart = datamart.assign(R = r_quartiles.values)
```

```
datamart.head()
```

CustomerID	Recency	Frequency	MonetaryValue	Tenure	R
12346.0	326	2	0.00	343	1
12347.0	2	182	4310.00	374	4
12348.0	75	31	1797.24	374	2
12349.0	19	73	1757.55	39	3
12350.0	310	17	334.40	312	1

Creating Frequency and Monetary Quartiles

```
f_labels = range(1,5)
m_labels = range(1,5)

f_quartiles = pd.qcut(datamart['Frequency'], 4, labels = f_labels)
m_quartiles = pd.qcut(datamart['MonetaryValue'], 4, labels = m_labels)

datamart = datamart.assign(F = f_quartiles.values)
datamart = datamart.assign(M = m_quartiles.values)
```

Creating Tenure Quartile

```
t_labels = range(1,5)

t_quartiles = pd.qcut(datamart['Tenure'], 4, labels = t_labels)

datamart = datamart.assign(T = t_quartiles.values)
```

```
datamart.head()
```

CustomerID	Recency	Frequency	MonetaryValue	Tenure	R	F	M	T
12346.0	326	2	0.00	343	1	1	1	3
12347.0	2	182	4310.00	374	4	4	4	4
12348.0	75	31	1797.24	374	2	2	4	4

Creating Send Back Quartile

]:
```
#df['Amount'][df.Amount<0].value_counts().sort_index()
```

]:
```
s_quartiles = pd.cut(datamart['MonetaryValue'],[-np.inf,-100,-10,0,np.inf],right=False, labels = range(1,5))

datamart = datamart.assign(S = s_quartiles.values)
```

]:
```
datamart.head()
```

]:

CustomerID	Recency	Frequency	MonetaryValue	Tenure	R	F	M	T	S
12346.0	326	2	0.00	343	1	1	1	3	4
12347.0	2	182	4310.00	374	4	4	4	4	4
12348.0	75	31	1797.24	374	2	2	4	4	4

Building RFM Segment and RFM Score

> Concatenate RFM quartile values to RFM_Segment

> Sum RFM quartiles values to RFM_Score

:
```
def join_rfm(x): return str(x['R']) + str(x['F']) + str(x['M'])
datamart['RFM_Segment'] = datamart.apply(join_rfm, axis=1)
datamart['RFM_Score'] = datamart[['R','F','M']].sum(axis=1)
```

:
```
datamart.head()
```

:

CustomerID	Recency	Frequency	MonetaryValue	Tenure	R	F	M	T	S	RFM_Segment	RFM_Score
12346.0	326	2	0.00	343	1	1	1	3	4	111	3.0
12347.0	2	182	4310.00	374	4	4	4	4	4	444	12.0
12348.0	75	31	1797.24	374	2	2	4	4	4	224	8.0
12349.0	19	73	1757.55	39	3	3	4	1	4	334	10.0
12350.0	310	17	334.40	312	1	1	2	3	4	112	4.0

Analyzing RFM segments

Largest RFM segments

```
#datamart.groupby('RFM_Segment').size()
```

```
datamart.groupby('RFM_Segment').size().sort_values(ascending=False)[:10]
```

```
RFM_Segment
444    471
111    392
122    209
344    206
211    181
333    176
222    173
233    164
433    156
322    126
dtype: int64
```

> **Conclusion_12:** The largest RFM segment is 444, which means they are frequent and recent customers and also they have higher spending habit. So, the number of people belonging to this group is 471, which is 10% of total population. And also beacuse of their shopping pattern, this group of people is our primary target group.

Summary metrics per RFM Score

```
datamart.groupby('RFM_Score').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count'] }).round(1)
```

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
RFM_Score				
3.0	264.8	7.8	109.1	392
4.0	174.5	13.9	227.1	391
5.0	153.0	21.2	346.8	517
6.0	94.3	28.5	491.8	468
7.0	78.8	39.7	724.2	447
8.0	62.7	57.0	974.7	467
9.0	44.2	79.0	1369.6	411
10.0	31.3	115.3	1894.0	440
11.0	20.5	193.9	3845.7	368
12.0	6.7	371.8	8850.7	471

Grouping into named segments

Use RFM score to group customers into Gold, Silver and Bronze segments.

```
def segment_me(df):
    if df['RFM_Score'] >= 9:
        return '1.Gold'
    elif (df['RFM_Score'] >= 5) and (df['RFM_Score'] < 9):
        return '2.Silver'
    else:
        return '3.Bronze'
```

```
datamart['General_Segment'] = datamart.apply(segment_me, axis=1)
```

```
datamart.groupby('General_Segment').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean','sum', 'count']
}).round(1)
```

	Recency	Frequency	MonetaryValue		
	mean	mean	mean	sum	count
General_Segment					
1.Gold	25.2	195.1	4130.3	6980190.8	1690
2.Silver	98.9	36.1	625.8	1188323.3	1899
3.Bronze	219.7	10.9	168.0	131551.7	783

> **Conclusion_13:** The largest segment is our Gold customers. Their spending is almost 90% of total amount and their average spending is 7 times more than Silver Customers and 20 times more than Bronze customers. So Gold segment would be the primary target for our promotions and advertisements.

	Recency	Frequency	MonetaryValue		Tenure	
	mean	mean	mean	count	mean	count
RFMT_Score						
5.0	166.0	8.3	129.8	346	183.5	346
6.0	156.5	12.8	214.8	443	184.0	443
7.0	154.2	20.9	316.2	568	193.8	568
8.0	129.4	29.9	486.0	426	195.1	426
9.0	100.3	41.3	727.8	395	198.9	395
10.0	81.4	53.8	924.2	399	228.7	399
11.0	56.7	73.0	1265.3	390	238.9	390
12.0	50.3	103.7	1652.1	319	264.5	319
13.0	34.0	163.9	2395.5	328	292.3	328
14.0	23.9	180.9	3567.6	272	316.0	272
15.0	15.0	250.3	5127.9	224	357.9	224
16.0	6.5	440.2	12182.8	262	374.0	262

	Recency	Frequency	MonetaryValue		Tenure	
	mean	mean	mean	sum	mean	count
General_Segment						
1.Gold	25.2	195.1	4130.3	6980190.8	278.8	1690
2.Silver	98.9	36.1	625.8	1188323.3	198.2	1899
3.Bronze	219.7	10.9	168.0	131551.7	253.0	783

> **Conclusion_14:** Quiet interestingly, the number of people (1.690) in Gold segment hasn't changed. So our primary target segment for our promotions and advertisements stays the same

```
datamart['General_Segment_3'] = datamart.apply(segment_me, axis=1)
```

```
datamart.groupby('General_Segment').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count'],
    'Tenure': ['mean','count'],
    'S': ['count']
}).round(1)
```

	Recency	Frequency	MonetaryValue		Tenure		S
	mean	mean	mean	count	mean	count	count
General_Segment							
1.Gold	25.2	195.1	4130.3	1690	278.8	1690	1690
2.Silver	98.9	36.1	625.8	1899	198.2	1899	1899
3.Bronze	219.7	10.9	168.0	783	253.0	783	783

> **Conclusion_15:** Again, the number of people (1.690) in Gold segment hasn't changed. So our primary target segment for our promotions and advertisements stays the same

Preprocessing for Machine Learning Part

Assumptions of K-Means

1. Equal average values of variables
2. Equal standard deviation of variables
3. Symmetrical distribution of variables

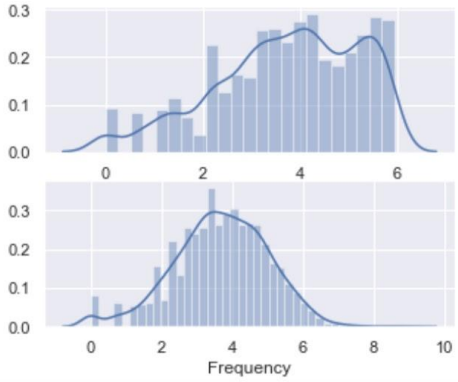
Sequence

1. Unskew the data - log transformation
2. Standardize to the same average values
3. Scale to the same standard deviation
4. Store as a separate array to be used for clustering

Data Transformations for Skewness

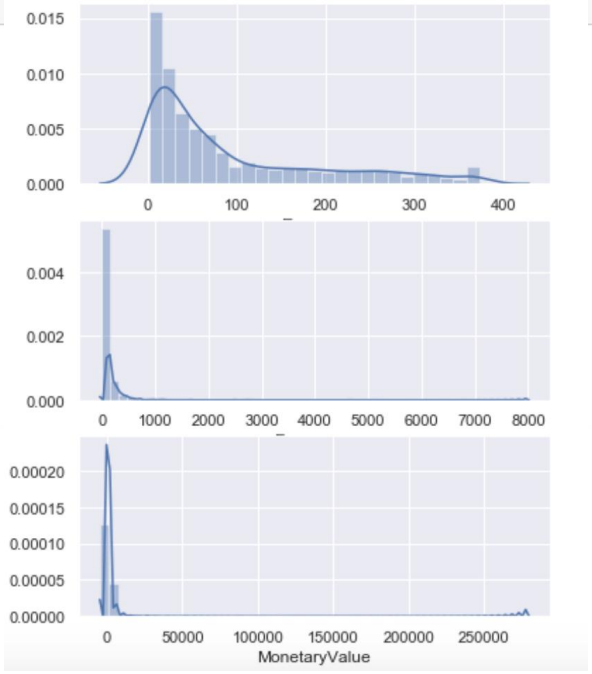
The easiest way to unskew the data is applying logarithmic transformation but it only works for positive values. There are other approaches like Box-Cox transformation but for sake of simplicity, logarithmic transformation is used here.

```
]: plt.figure(figsize=(5, 4))

recency_log = np.log(datamart['Recency'])
frequency_log = np.log(datamart['Frequency'])

plt.subplot(2, 1, 1); sns.distplot(recency_log)
plt.subplot(2, 1, 2); sns.distplot(frequency_log)

plt.show()
```



After

Before



```
datamart['MonetaryValue'].min()
```

```
-4287.63
```

Dealing with Negative Numbers

1. Adding a constant before log transformation:

This method is to add a constant number for each variables. The choice of value is arbitrary but the best practice is to add the absolute value of the lowest negative value to each observation and then a small constant like 1, to force the variables to be strictly positive

2. Cube root transformation:

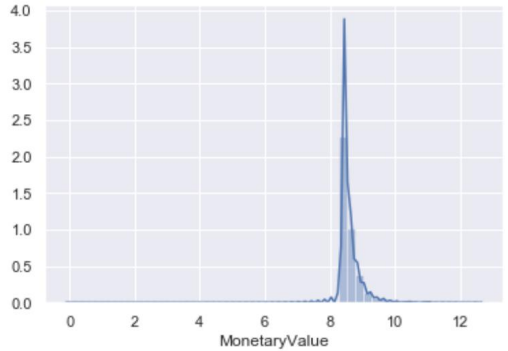
This method is calculating a cube root works well in some cases. The fortunate thing about customer behavior data is that it almost always positive, so we don't have to worry about this.

```
# Adding the absolute value of lowest negative number (4287.63) and a small constant (1). Total is 4288.63
datamart['MonetaryValue'] += 4288.63
```

```
monetary_value_log = np.log(datamart.MonetaryValue)
```

```
sns.distplot(monetary_value_log)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a353e99b0>
```



Choosing the number of clusters

There are three Methods:

> **1. Visual methods - elbow criterion:**

- Plot the number of clusters against within-cluster sum-of-squared-errors (SSE) - sum of squared distances from every data point to their cluster center
- Identify an "elbow" in the plot
- Elbow - a point representing an "optimal" number of clusters

> **2. Mathematical methods - silhouette coefficient:**

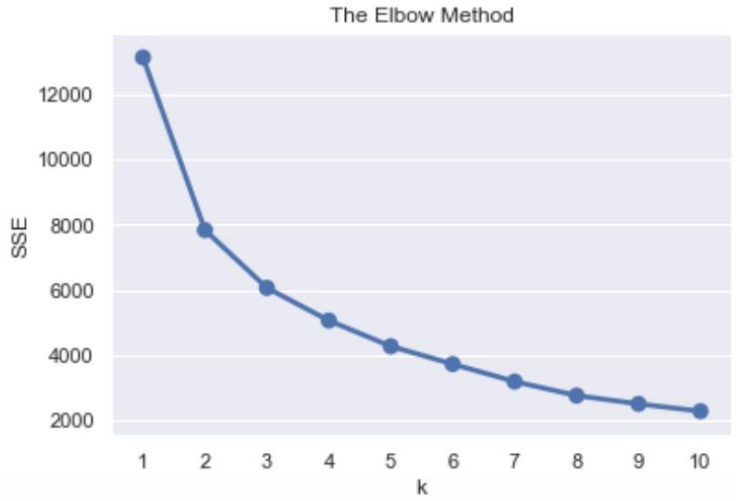
> **3. Experimentation and interpretation (analyzing segments):**

- Build clustering at and around elbow solution
- Analyze their properties - average RFM values
- Compare against each other and choose one which makes most business sense

Visual methods - Elbow Method:

```
# Fit KMeans and calculate SSE for each *k*
sse = {}
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=1)
    kmeans.fit(datamart_normalized)
    sse[k] = kmeans.inertia_ # sum of squared distances to closest cluster center
```

```
# Plot SSE for each *k*
plt.title('The Elbow Method')
plt.xlabel('k'); plt.ylabel('SSE')
sns.pointplot(x=list(sse.keys()), y=list(sse.values()))
plt.show()
```



Run KMeans

n_clusters = 2

```
# Import KMeans
from sklearn.cluster import KMeans

# Initialize KMeans
kmeans = KMeans(n_clusters = 2, random_state = 1)

# Fit k-means clustering on the normalized data set
kmeans.fit (datamart_normalized)
```

```
# Extract cluster labels
cluster_labels_2 = kmeans.labels_
```

```
# Create a DataFrame by adding a new cluster label column
datamart_rfm_k2 = datamart_rfm.assign(Cluster=cluster_labels_2)

# Group the data by cluster
grouped_2 = datamart_rfm_k2.groupby(['Cluster'])

# Calculate average RFM values and segment sizes per cluster value
grouped_2.agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count','sum']
  }).round(1)
```

	Recency	Frequency	MonetaryValue		
	mean	mean	mean	count	sum
Cluster					
0	22.4	191.3	8322.1	1728	14380643.9
1	137.6	28.9	4791.7	2644	12669312.3

n_clusters = 3

```
# Initialize KMeans
kmeans = KMeans(n_clusters = 3, random_state = 1)

# Fit k-means clustering on the normalized data set
kmeans.fit (datamart_normalized)

# Extract cluster labels
cluster_labels_3 = kmeans.labels_
```

```
# Create a DataFrame by adding a new cluster label column
datamart_rfm_k3 = datamart_rfm.assign(Cluster=cluster_labels_3)

# Group the data by cluster
grouped_3 = datamart_rfm_k3.groupby(['Cluster'])

# Calculate average RFM values and segment sizes per cluster value
grouped_3.agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count', 'sum']
  }).round(1)
```

	Recency	Frequency	MonetaryValue		
	mean	mean	mean	count	sum
Cluster					
0	33.4	97.9	5647.5	1912	10798112.4
1	163.1	22.1	4718.3	2042	9634806.7
2	13.1	417.6	15830.2	418	6617037.0

Profile and interpret segments

Approaches to build customer personas

1. Summary statistics for each cluster e.g. average RFM values
2. Snake plots (from market research)
3. Relative importance of cluster attributes compared to population

Summary statistics for 2 clusters ¶

```
# Calculate average RFM values and segment sizes per cluster value- For 2 Clusters
grouped_2.agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count', 'sum']
  }).round(1)
```

	Recency	Frequency	MonetaryValue		
	mean	mean	mean	count	sum
Cluster					
0	22.4	191.3	8322.1	1728	14380643.9
1	137.6	28.9	4791.7	2644	12669312.3

Summary statistics for 3 clusters

```
# Calculate average RFM values and segment sizes per cluster value
grouped_3.agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count', 'sum']
  }).round(1)
```

	Recency	Frequency	MonetaryValue		
	mean	mean	mean	count	sum
Cluster					
0	33.4	97.9	5647.5	1912	10798112.4
1	163.1	22.1	4718.3	2042	9634806.7
2	13.1	417.6	15830.2	418	6617037.0

Conclusion:

> We just compare these two clusters. As we can see fromm the above tables, there are some inherent differences between 2-cluster and 3-cluster solutions. While 2-cluster solution is simplier, 3-cluster gives more insight. But 2-cluster solution is more in line with our RFM analysis solution (in Gold segment, we have 1.690 customers, in 2-cluster segment, we have 1.728 customers. And these segments' total monetary valeu are almost the same, which is 14 million $)

2. Snake plots

We use snake plots to understand and compare segments. Snake plots are a market research technique plotting different segments and their RFM Values on a line chart. But we need to normalize the data (center and scale) so that the values would be comparable. Finally we plot each cluster's average values on a line plot.

First, we create a DataFrame from our normalized NumPy array.

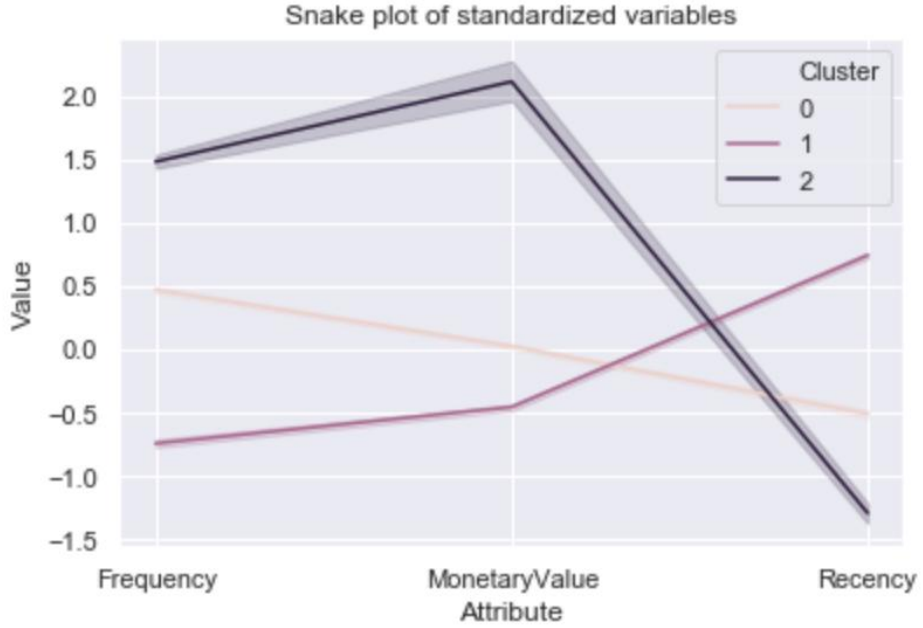
```
# Transform datamart_normalized as DataFrame and add a Cluster column

# We will pass it to the pandas DataFrame function, and use the index and columns from the original datamart_rfm

datamart_normalized = pd.DataFrame(datamart_normalized,
                                   index=datamart_rfm.index,
                                   columns=datamart_rfm.columns)
datamart_normalized['Cluster'] = datamart_rfm_k3['Cluster']
```

For easier plotting, we will melt the data into a long form format so RFM values and metric names are stored in 1 column each.

```
# We basically melt the three RFM columns and create one called attribute.
datamart_melt = pd.melt(datamart_normalized.reset_index(),
                    id_vars=['CustomerID', 'Cluster'],
                    value_vars=['Recency', 'Frequency', 'MonetaryValue'],
                    var_name='Attribute',
                    value_name='Value')
```

```
# Visualize the snake plot. It makes it very easy and intuitive to interpr
plt.title('Snake plot of standardized variables')
sns.lineplot(x="Attribute", y="Value", hue='Cluster', data=datamart_melt)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a344b14e0>
```



Effective Cross selling (using the FP growth algorithm)

Cross selling is the ability to sell more products to a customer by analyzing the customer's shopping trends and the general shopping trends.

> **Itemset** is just a collection of one or more items that occur together in a transaction. For example, {milk, bread} is example of an itemset.

> **Support** is defined as number of times an itemset appears in the dataset.

> **Confidence** is a measure of the times the number of times a rule is found to exist in the dataset.

> **Lift** is defined as the ratio of observed support to the support expected in the case the elements of the rule were independent.

> **Frequent itemsets** are itemsets whose support is greater than a user defined support threshold.

Loading and Filtering Dataset

]:
```
import csv
import matplotlib.pyplot as plt
import Orange
from Orange.data import Domain, DiscreteVariable, ContinuousVariable
from orangecontrib.associate.fpgrowth import *

%matplotlib inline
```

We have created a function (**prune_dataset**) which will help us reduce the size of our dataset (we reduce the size of the items) based on our requirements. The function can be used for performing two types of pruning:

> • Pruning based on percentage of total sales: The parameter **total_sales_perc** will help us select the number of items that will explain the required percentage of sales. The default value is 50% or 0.5.

> • Pruning based on ranks of items: Another way to perform the pruning is to specify the starting (**start_item**) and the ending rank (**end_item**) of the items for which we want to prune our dataset.

length_trans: by default, we will only look for transactions which have at least two items,

Building Transaction Dataset

```
items = list(df.Description.unique())
grouped = df.groupby('InvoiceNo')
transaction_level_df = grouped.aggregate(lambda x: tuple(x)).reset_index()
[['InvoiceNo','Description']]
```

```
[['InvoiceNo', 'Description']]
```

```
transaction_dict = {item:0 for item in items}
output_dict = dict()
temp = dict()
for rec in transaction_level_df.to_dict('records'):
    invoice_num = rec['InvoiceNo']
    items_list = rec['Description']
    transaction_dict = {item:0 for item in items}
    transaction_dict.update({item:1 for item in items if item in items_list})
    temp.update({invoice_num:transaction_dict})
new = [v for k,v in temp.items()]
tranasction_df = pd.DataFrame(new)
del(tranasction_df[tranasction_df.columns[0]])
```

```
tranasction_df.shape
```

```
(22190, 3895)
```

```
tranasction_df.head(5)
```

	50'S CHRISTMAS GIFT BAG LARGE	DOLLY GIRL BEAKER	I LOVE LONDON MINI BACKPACK	I LOVE LONDON MINI RUCKSACK	NINE DRAWER OFFICE TIDY	OVAL WALL MIRROR DIAMANTE	RED SPOT GIFT BAG LARGE	SET 2 TEA TOWELS I LOVE LONDON	SPACEBOY BABY GIFT SET	TOADSTOOL BEDSIDE LIGHT	TRELLIS COAT RACK	10 COLOUR SPACEBOY PEN	12 COLOURED PARTY BALLOONS	12 DAISY PEGS IN WOOD BOX	12 EGG HOUSE PAINTED WOOD	12 HANGING EGGS HAND PAINTED	12 IVORY ROSE PEG PLACE SETTINGS
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5 rows x 3895 columns

The following code will help us reduce the number of features from 3895 to 15. We just pick 15 as a common sense number.

The following code will help us reduce the number of features from 3895 to 15. We just pick 15 as a common sense number.

```
output_df_n, item_counts_n = prune_dataset(input_df=tranasction_df, length_trans=2, start_item=0, end_item=15)
print(output_df_n.shape)
```

```
(4724, 15)
```

So we find out that we have only 15 items responsible for 50% of sales and 4724 transactions that have those items along with other items and we can also see what those items are. The next step is to convert this selected data into the required Table data structure.

```
output_df_n.head()
```

	WHITE HANGING HEART T-LIGHT HOLDER	REGENCY CAKESTAND 3 TIER	JUMBO BAG RED RETROSPOT	PARTY BUNTING	ASSORTED COLOUR BIRD ORNAMENT	LUNCH BAG RED RETROSPOT	SET OF 3 CAKE TINS PANTRY DESIGN	POSTAGE	LUNCH BAG BLACK SKULL.	PACK OF 72 RETROSPOT CAKE CASES	SPOTTY BUNTING	LUNCH BAG SPACEBOY DESIGN	PAPER CHAIN KIT 50'S CHRISTMAS	LUNCH BAG CARS BLUE	NATURAL SLATE HEART CHALKBOARD
13	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
23	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0
33	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0
36	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0

Association Rule Mining with FP Growth¶

```
input_assoc_rules = output_df_n
domain_transac = Domain([DiscreteVariable.make(name=item,values=['0', '1']) for item in input_assoc_rules.columns])
data_tran = Orange.data.Table.from_numpy(domain=domain_transac,  X=input_assoc_rules.as_matrix(),Y= None)
data_tran_en, mapping = OneHot.encode(data_tran, include_class=True)
```

The last line above is required for coding our input so that the entire domain is represented as binary variables. This will complete all the parsing and data manipulation required for our rule-mining.

The final step is creating our rules. We need to specify two pieces of information for generating our rules: **support and confidence**. An important piece of information is to start with a higher support, as lower support will mean a higher number of frequent itemsets and hence a longer execution time. We will specify a min- **support** of 0.01—47 transactions at least—and see the number of frequent itemsets that we get before we specify confidence and generate our rules.

```
support = 0.01
print("num of required transactions = ", int(input_assoc_rules.shape[0]*support))
num_trans = input_assoc_rules.shape[0]*support
itemsets = dict(frequent_itemsets(data_tran_en, support))
```

```
num of required transactions =  47
```

```
len(itemsets)
```

```
661348
```

```
support = 0.01
print("num of required transactions = ", int(input_assoc_rules.shape[0]*support))
num_trans = input_assoc_rules.shape[0]*support
itemsets = dict(frequent_itemsets(data_tran_en, support))
```

```
num of required transactions =  47
```

```
len(itemsets)
```

```
661348
```

So we get a **661,348 itemsets for a support of only 1%!** This will increase exponentially if we decrease the support or if we increase the number of items in our dataset. Next, we will specify a confidence value and generate our rules. The code below will take a confidence value and generate the rules that fulfill our specific support and confidence criteria.

These rules are decoded using the mapping and variable names. Orange3-Associate also provides a helper function that will help us extract metrics about each of these rules.

The code below will perform rule generation and decoding of rules, and then compile it all in a dataframe that we can use for further analysis.

Sort and display rules

```
dw = pd.options.display.max_colwidth
pd.options.display.max_colwidth = 100
(pruned_rules_df[['antecedent','consequent',
                  'support','confidence','lift']].groupby('consequent')
                                                 .max()
                                                 .reset_index()
                                                 .sort_values(['lift', 'support','confidence'],
                                                              ascending=False)).head()
```

	consequent	antecedent	support	confidence	lift
4	LUNCH BAG SPACEBOY DESIGN	WHITE HANGING HEART T-LIGHT HOLDER, LUNCH BAG RED RETROSPOT, LUNCH BAG CARS BLUE	257	0.675676	3.643712
2	LUNCH BAG CARS BLUE	WHITE HANGING HEART T-LIGHT HOLDER, LUNCH BAG SPACEBOY DESIGN	263	0.657895	3.511745
1	LUNCH BAG BLACK SKULL.	WHITE HANGING HEART T-LIGHT HOLDER, LUNCH BAG SPACEBOY DESIGN , LUNCH BAG CARS BLUE	263	0.692308	3.501565
3	LUNCH BAG RED RETROSPOT	WHITE HANGING HEART T-LIGHT HOLDER, LUNCH BAG SPACEBOY DESIGN , LUNCH BAG CARS BLUE	263	0.818182	3.239808
6	SPOTTY BUNTING	WHITE HANGING HEART T-LIGHT HOLDER, PARTY BUNTING	78	0.478571	2.733702

Let's interpret the first rule, which states that: {WHITE HANGING HEART T-LIGHT HOLDER, LUNCH BAG RED RETROSPOT, LUNCH BAG CARS BLUE -->LUNCH BAG SPACEBOY DESIGN} The first rule means that people who bought white hanging heart t-light holder, lunch bag red retrospot and lunch bag cars blue tend to lunch bag spacebiy desing.

> Let's interpret the first rule, which states that: {WHITE HANGING HEART T-LIGHT HOLDER, LUNCH BAG RED RETROSPOT, LUNCH BAG CARS BLUE -->LUNCH BAG SPACEBOY DESIGN} The first rule means that people who bought white hanging heart t-light holder, lunch bag red retrospot and lunch bag cars blue tend to lunch bag spacebiy desing.

> Let's try to understand the metrics.

> **Support** of the rule is 257, which means, all the items together appear in 257 transactions in the dataset.

> **Confidence** of the rule is 67%, which means that 67% of the time the antecedent items occurred we also had the consequent in the transaction (i.e. 67% of times, customers who bought the left side items also bought lunch bag spacebiy design).

> **Lift** means that the probability of finding consequent in the transactions which have antecendent is greater than the normal probability. So the higher the lift, the better it is. the main idea is that we are looking for greater lifts.

Conclusion: This analysis is very important for sellers' perspective, as they can bundle specific products like these (antecendent and consequent) together or run a marketing scheme that offers discount on buying them together. It is also very useful input for web designers as they can put those related items close to each other.