Problem Statement

It is a critical requirement for business to understand the value derived from a customer. RFM is a method used for analyzing customer value.

Customer segmentation is the practice of segregating the customer base into groups of individuals based on some common characteristics such as age, gender, interests, and spending habits

Perform customer segmentation using RFM analysis. The resulting segments can be ordered from most valuable (highest recency, frequency, and value) to least valuable (lowest recency, frequency, and value).

Dataset Description

This is a transnational data set which contains all the transactions that occurred between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique and all-occasion gifts.

Variables Description

InvoiceNo Invoice number. Nominal, a six 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 five 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 six digit integral number uniquely assigned to each customer

Country Country name. Nominal, the name of the country where each customer resides

Project Task: 1

Data Cleaning:

1. Perform a preliminary data inspection and data cleaning.

a. Check for missing data and formulate an apt strategy to treat them.

b. Remove duplicate data records.

c. Perform descriptive analytics on the given data.

Data Transformation:

2. Perform cohort analysis (a cohort is a group of subjects that share a defining characteristic). Observe how a cohort behaves across time and compare it to other cohorts.

a. Create month cohorts and analyze active customers for each cohort.

b. Analyze the retention rate of customers.

```
#importing required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

```
df = pd.read_excel('/content/Online Retail.xlsx')
```

```
df.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0

```
df.shape
```

```
(541909, 8)
```

```
#missing value treatment

df.isna().sum()
```

```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

Missing description of product won't effect our analysis. We drop this column any way.

```
df['InvoiceNo'].nunique()
```

```
25900
```

There are Total 25900 unique invoice numbers

```
df['CustomerID'].nunique()
```

```
4372
```

There are total 4372 customers consisting total 541909 orders

```
second_df= df[df['CustomerID'].isnull()]
```

```
second_df.head(10)
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Customer
622	536414	22139	NaN	56	2010-12-01 11:52:00	0.00	Na
1443	536544	21773	DECORATIVE ROSE BATHROOM BOTTLE	1	2010-12-01 14:32:00	2.51	Na
1444	536544	21774	DECORATIVE CATS BATHROOM BOTTLE	2	2010-12-01 14:32:00	2.51	Na
1445	536544	21786	POLKADOT RAIN HAT	4	2010-12-01 14:32:00	0.85	Na
1446	536544	21787	RAIN PONCHO RETROSPOT	2	2010-12-01 14:32:00	1.66	Na

```
second_df.shape
```

```
(135080, 8)
```

```
df2 = second_df.groupby(['InvoiceNo'])
df2.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Custome
622	536414	22139	NaN	56	2010-12-01 11:52:00	0.00	
1443	536544	21773	DECORATIVE ROSE BATHROOM BOTTLE	1	2010-12-01 14:32:00	2.51	
1444	536544	21774	DECORATIVE CATS BATHROOM BOTTLE	2	2010-12-01 14:32:00	2.51	
1445	536544	21786	POLKADOT RAIN HAT	4	2010-12-01 14:32:00	0.85	
1446	536544	21787	RAIN PONCHO	2	2010-12-01	1.66	

```
second_df['InvoiceNo'].nunique()
```

```
3710
```

As we see after our analysis, 3710 InvoiceNo don't have a customerID. and 3710 is comparitively very less the total InvoiceNo 25900. Data without customerID is no Use. so we drop this.

```
 df.dropna(subset=['CustomerID'], inplace=True )
```

```
df.isnull().sum()
```

```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

```
#remove duplicates

df.duplicated().sum()
```

```
5225
```

```
df = df.drop_duplicates()
```

```
df.duplicated().sum()
```

```
0
```

```
#descriptive analysis

df['Country'].nunique()
```

```
37
```

There are total 37 countries

```
#customer country wise

df3 = pd.DataFrame(df.groupby('Country')['CustomerID'].nunique())
```

```
ccw = pd.DataFrame(df3).sort_values(by='CustomerID', ascending=False)
ccw
```

	CustomerID
Country	
United Kingdom	3950
Germany	95
France	87
Spain	31
Belgium	25
Switzerland	21
Portugal	19

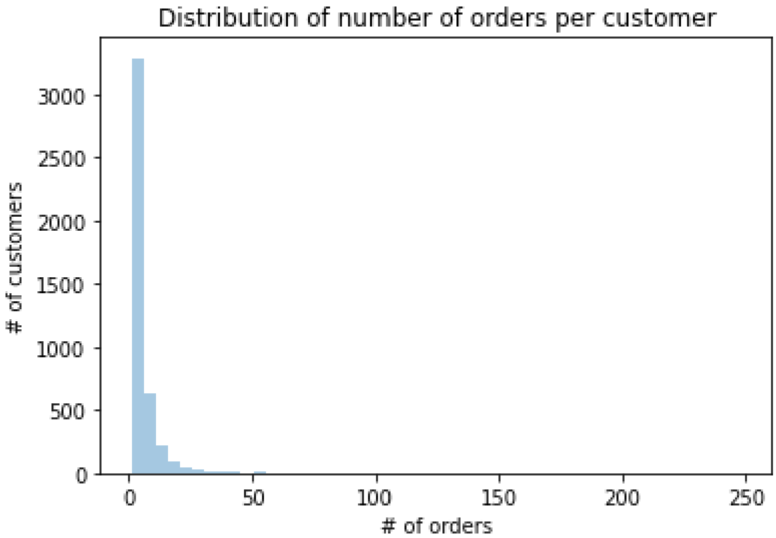
```
#customer order more than once
orders = df.groupby(['CustomerID'])['InvoiceNo'].nunique()
order_perc = np.sum(orders>1)/df['CustomerID'].nunique()
print(f'{100 * order_perc:.2f}% of customers ordered more than one item.')
```

```
69.97% of customers ordered more than one item.
```

Netherlands	9

```
#ploting number of orders
ax = sns.distplot(orders, kde=False, hist=True)
ax.set(title='Distribution of number of orders per customer', xlabel='# of orders', y
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning:
  warnings.warn(msg, FutureWarning)
```



Malta	2

```
import datetime as dt
from operator import attrgetter
```

```
#cohort analysis
df['order_month']=df['InvoiceDate'].dt.to_period('M')
```

```
df['cohort']=df.groupby('CustomerID')['InvoiceDate'].transform('min').dt.to_period('M
```

```
df.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0

```
df_cohort=pd.DataFrame(df.groupby(['cohort','order_month']).agg(n_customers=('Custome
```

```
#active customers in each cohort
df_cohort['period_number']= (df_cohort.order_month - df_cohort.cohort).apply(attrgett
df_cohort
```

	cohort	order_month	n_customers	period_number
0	2010-12	2010-12	948	0
1	2010-12	2011-01	362	1
2	2010-12	2011-02	317	2
3	2010-12	2011-03	367	3
4	2010-12	2011-04	341	4
...	...	...	...	...
86	2011-10	2011-11	93	1
87	2011-10	2011-12	46	2
88	2011-11	2011-11	321	0
89	2011-11	2011-12	43	1
90	2011-12	2011-12	41	0

91 rows × 4 columns

```
cohort_pivot= df_cohort.pivot_table(index='cohort', values='n_customers', columns='pe
cohort_pivot
```

period_number	0	1	2	3	4	5	6	7	8	9	1
cohort											
2010-12	948.0	362.0	317.0	367.0	341.0	376.0	360.0	336.0	336.0	374.0	354.
2011-01	421.0	101.0	119.0	102.0	138.0	126.0	110.0	108.0	131.0	146.0	155.
2011-02	380.0	94.0	73.0	106.0	102.0	94.0	97.0	107.0	98.0	119.0	35.
2011-03	440.0	84.0	112.0	96.0	102.0	78.0	116.0	105.0	127.0	39.0	Na
2011-04	299.0	68.0	66.0	63.0	62.0	71.0	69.0	78.0	25.0	NaN	Na
2011-05	279.0	66.0	48.0	48.0	60.0	68.0	74.0	29.0	NaN	NaN	Na
2011-06	235.0	49.0	44.0	64.0	58.0	79.0	24.0	NaN	NaN	NaN	Na
2011-07	191.0	40.0	39.0	44.0	52.0	22.0	NaN	NaN	NaN	NaN	Na
2011-08	167.0	42.0	42.0	42.0	23.0	NaN	NaN	NaN	NaN	NaN	Na

```
#retention rate of customers
cohort_size = cohort_pivot.iloc[:,0]
retention_matrix = cohort_pivot.divide(cohort_size, axis=0)
```

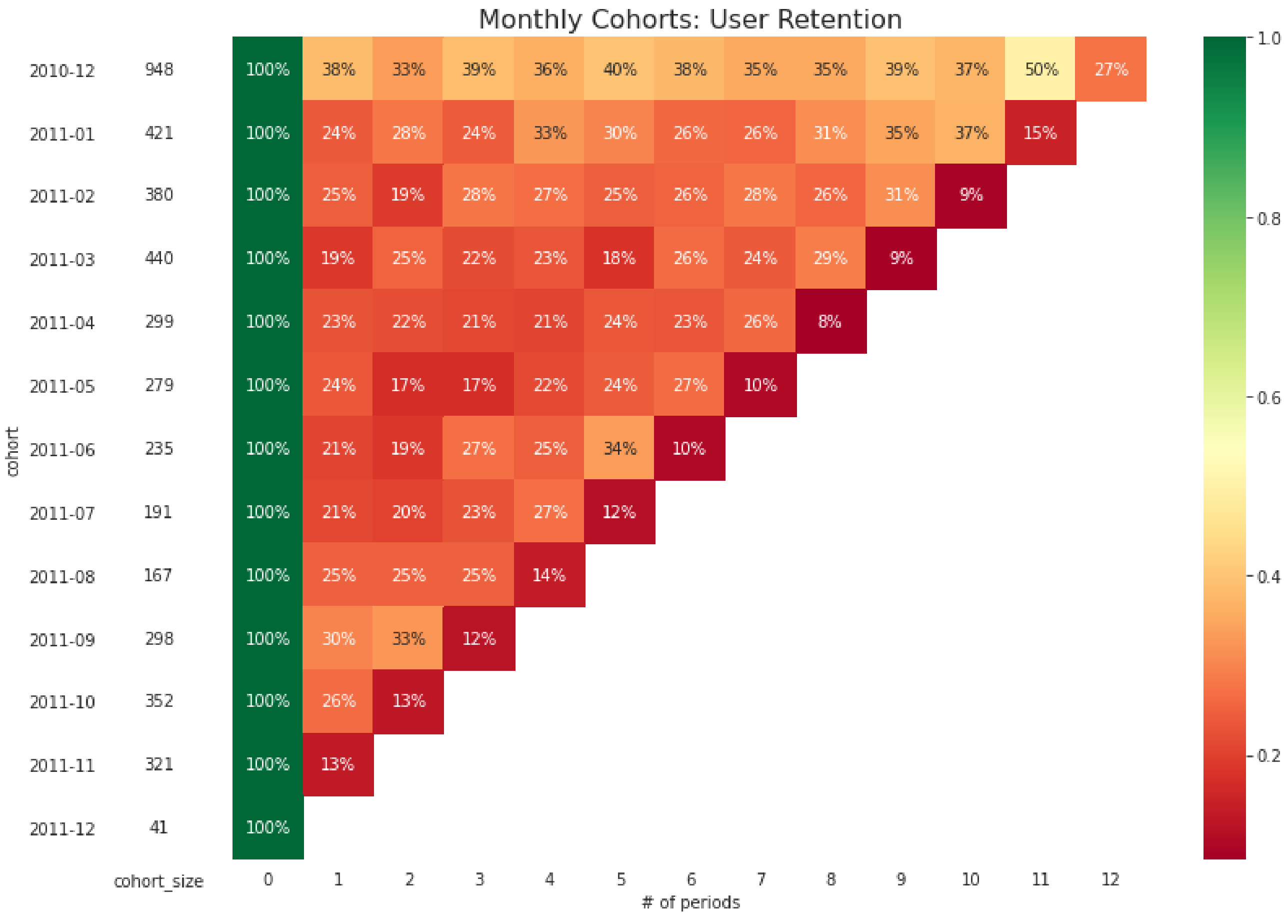
```
retention_matrix
```

period_number	0	1	2	3	4	5	6	7
cohort								
2010-12	1.0	0.381857	0.334388	0.387131	0.359705	0.396624	0.379747	0.35443
2011-01	1.0	0.239905	0.282660	0.242280	0.327791	0.299287	0.261283	0.25653
2011-02	1.0	0.247368	0.192105	0.278947	0.268421	0.247368	0.255263	0.28157
2011-03	1.0	0.190909	0.254545	0.218182	0.231818	0.177273	0.263636	0.23863
2011-04	1.0	0.227425	0.220736	0.210702	0.207358	0.237458	0.230769	0.26087
2011-05	1.0	0.236559	0.172043	0.172043	0.215054	0.243728	0.265233	0.10394
2011-06	1.0	0.208511	0.187234	0.272340	0.246809	0.336170	0.102128	Na
2011-07	1.0	0.209424	0.204188	0.230366	0.272251	0.115183	NaN	Na
2011-08	1.0	0.251497	0.251497	0.251497	0.137725	NaN	NaN	Na
2011-09	1.0	0.298658	0.325503	0.120805	NaN	NaN	NaN	Na
2011-10	1.0	0.264205	0.130682	NaN	NaN	NaN	NaN	Na
2011-11	1.0	0.133956	NaN	NaN	NaN	NaN	NaN	Na
2011-12	1.0	NaN	NaN	NaN	NaN	NaN	NaN	Na

```
import matplotlib.colors as mcolors
```

```
with sns.axes_style('white'):
```

```
fig, ax=plt.subplots(1,2,figsize=(12,8), sharey=True, gridspec_kw={'width_ratios':[


#retention matrix
sns.heatmap(retention_matrix,
            mask=retention_matrix.isnull(),
            annot=True,
            fmt='.0%',
            cmap='RdYlGn',
            ax=ax[1])
ax[1].set_title('Monthly Cohorts: User Retention', fontsize=16)
ax[1].set(xlabel='# of periods', ylabel='')

#cohort size
cohort_size_df = pd.DataFrame(cohort_size).rename(columns={0:'cohort_size'})
white_cmap = mcolors.ListedColormap(['white'])
sns.heatmap(cohort_size_df,
            annot=True,
            cbar=False,
            fmt='g',
            cmap=white_cmap,
            ax=ax[0])

fig.tight_layout()
```



Project Task:2

Data Modeling :

1. Build a RFM (Recency Frequency Monetary) model. Recency means the number of days since a customer made the last purchase. Frequency is the number of purchase in a given period. It could be 3 months, 6 months or 1 year. Monetary is the total amount of money a customer spent in that given period. Therefore, big spenders will be differentiated among other customers such as MVP (Minimum Viable Product) or VIP.
2. Calculate RFM metrics.
3. Build RFM Segments. Give recency, frequency, and monetary scores individually by dividing them into quartiles.

b1. Combine three ratings to get a RFM segment (as strings).

b2. Get the RFM score by adding up the three ratings.

b3. Analyze the RFM segments by summarizing them and comment on the findings.

Note: Rate “recency" for customer who has been active more recently higher than the less recent customer, because each company wants its customers to be recent.

Note: Rate “frequency" and “monetary" higher, because the company wants the customer to visit more often and spend more money

Methodology

To get the RFM score of a customer, we need to first calculate the R, F and M scores on a scale from 1 (worst) to 5 (best).

1. calculate Recency = number of days since last purchase
2. calculate Freqency = number of purchases during the studied period (usually one year)
3. calculate Monetary = total amount of purchases made during the studied period
4. find quintiles for each of these dimensions
5. give a grade to each dimension depending in which quintiles it stands
6. combine R, F and M scores to get the RFM score
7. map RF scores to segments

```
df['Price'] = df['Quantity']*df['UnitPrice']
```

```
#combine InvoiceNo

new_df = df.groupby(['InvoiceNo', 'InvoiceDate', 'CustomerID']).agg({'Price': lambda
new_df.head()
```

	InvoiceNo	InvoiceDate	CustomerID	Price
0	536365	2010-12-01 08:26:00	17850.0	139.12
1	536366	2010-12-01 08:28:00	17850.0	22.20
2	536367	2010-12-01 08:34:00	13047.0	278.73
3	536368	2010-12-01 08:34:00	13047.0	70.05
4	536369	2010-12-01 08:35:00	13047.0	17.85

```
from datetime import timedelta
```

```
#create a refdate to calculate the Recency score

refdate = new_df['InvoiceDate'].max() + timedelta(days=1)
refdate
```

```
Timestamp('2011-12-10 12:50:00')
```

```
#to study the data over a period of one year
period = 365
```

```
#to calculate recency: add a column with the number of days between the purchase and

new_df['daysincelastorder']= new_df['InvoiceDate'].apply(lambda x: (refdate - x).days
```

```
#creating dataframe for receny (number of days since last order) and frequency (total

aggr = {'daysincelastorder': lambda x:x.min(),
        'InvoiceDate' : lambda x:len([d for d in x if d>= refdate - timedelta(days=pe

rfm = new_df.groupby('CustomerID').agg(aggr).reset_index()
rfm.rename(columns={'daysincelastorder':'Recency', 'InvoiceDate':'Frequency'}, inplac
rfm.head()
```

	CustomerID	Recency	Frequency
0	12346.0	326	2
1	12347.0	2	6
2	12348.0	75	4
3	12349.0	19	1
4	12350.0	310	1

```
#add the Monetary value of each customer by adding sales over the last year

rfm['Monetary']=rfm['CustomerID'].apply(lambda x:new_df[(new_df['CustomerID']==x) & (
rfm.head()
```

	CustomerID	Recency	Frequency	Monetary
0	12346.0	326	2	0.00
1	12347.0	2	6	3598.21
2	12348.0	75	4	1797.24
3	12349.0	19	1	1757.55
4	12350.0	310	1	334.40

```
#finding quintiles for each parameter

quintiles = rfm[['Recency','Frequency','Monetary']].quantile([.2,.4,.6,.8]).to_dict()
quintiles
```

```
{'Frequency': {0.2: 1.0, 0.4: 2.0, 0.6: 3.0, 0.8: 6.0},
 'Monetary': {0.2: 214.45600000000002,
  0.4: 439.26200000000006,
  0.6: 869.3879999999999,
  0.8: 1897.4440000000002},
 'Recency': {0.2: 11.0, 0.4: 32.0, 0.6: 71.0, 0.8: 178.80000000000018}}
```

```
#assign rank from 1 to 5. A smaller Recency value is better whereas higher Frequency

def r_score(x):
  if x <= quintiles['Recency'][.2]:
    return 5
  elif x <= quintiles['Recency'][.4]:
    return 4
  elif x <= quintiles['Recency'][.6]:
    return 3
  elif x <= quintiles['Recency'][.8]:
    return 2
  else:
    return 1


```

```
def fm_score(x,c):
  if x <= quintiles[c][.2]:
    return 1
  elif x <= quintiles[c][.4]:
    return 2
  elif x <= quintiles[c][.6]:
    return 3
  elif x <= quintiles[c][.8]:
    return 4
  else:
    return 5
```

```
#calculate R, F and M score
```

```
rfm['R']=rfm['Recency'].apply(lambda x: r_score(x))
rfm['F']=rfm['Frequency'].apply(lambda x: fm_score(x, 'Frequency'))
rfm['M']=rfm['Monetary'].apply(lambda x: fm_score(x, 'Monetary'))
```

```
#combine RFM score
rfm['RFM Score'] = rfm['R'].map(str) + rfm['F'].map(str) + rfm['M'].map(str)
rfm.head()
```

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFM Score
0	12346.0	326	2	0.00	1	2	1	121
1	12347.0	2	6	3598.21	5	4	5	545
2	12348.0	75	4	1797.24	2	4	4	244
3	12349.0	19	1	1757.55	4	1	4	414
4	12350.0	310	1	334.40	1	1	2	112

RFM score give us 125 segmennts which is not east to deal. We divide them into 10 segmensts based on R and F score.

Segment : Description

---

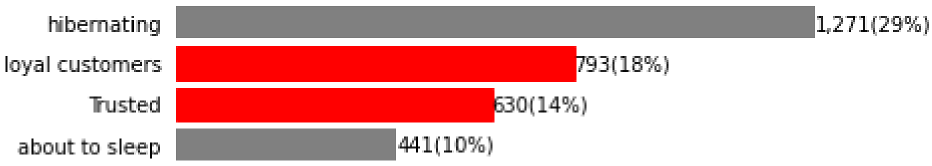
1. Trusted : Bought recently, buy often and spend the most
2. Loyal Customers : Buy on a regular basis. Responsive to promotions.
3. Potential Loyalist : Recent customers with average frequency.
4. Recent Customers : Bought most recently, but not often.
5. Promising : Recent shoppers, but haven’t spent much.
6. Customers Needing Attention : Above average recency, frequency and monetary values. May not have bought very recently though.
7. About To Sleep : Below average recency and frequency. Will lose them if not reactivated.
8. At Risk : Purchased often but a long time ago. Need to bring them back!
9. Can’t Lose Them : Used to purchase frequently but haven’t returned for a long time.
10. Hibernating : Last purchase was long back and low number of orders. May be lost.

```
segmentation = {
    r'[1-2][1-2]': 'hibernating',
    r'[1-2][3-4]': 'at risk',
    r'[1-2]5': "can't loose",
    r'3[1-2]': 'about to sleep',
    r'33': 'need attention',
    r'[3-4][4-5]': 'loyal customers',
    r'41': 'promising'
```

```
    r'41': 'promising',
    r'51': 'new customers',
    r'[4-5][2-3]': 'potential loyalists',
    r'5[4-5]': 'Trusted',
}

rfm['Segment']=rfm['R'].map(str) + rfm['F'].map(str)
rfm['Segment']=rfm['Segment'].replace(segmentation, regex=True)
rfm.head()
```

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFM Score	Segment
0	12346.0	326	2	0.00	1	2	1	121	hibernating
1	12347.0	2	6	3598.21	5	4	5	545	Trusted
2	12348.0	75	4	1797.24	2	4	4	244	at risk
3	12349.0	19	1	1757.55	4	1	4	414	promising
4	12350.0	310	1	334.40	1	1	2	112	hibernating

```
# count of number of customers in each segment

seg_counts = rfm['Segment'].value_counts().sort_values(ascending=True)

fig, ax = plt.subplots()

bars = ax.barh(range(len(seg_counts)), seg_counts, color='grey')
ax.set_frame_on(False)
ax.tick_params(left=False, bottom=False, labelbottom=False)
ax.set_yticks(range(len(seg_counts)))
ax.set_yticklabels(seg_counts.index)

for i, bar in enumerate(bars):
  value = bar.get_width()
  if seg_counts.index[i] in ['Trusted','loyal customers']:
    bar.set_color('red')
  ax.text(value,
          bar.get_y() + bar.get_height()/2,
          '{:,}({:}%)'.format(int(value),
                              int(value*100/seg_counts.sum())),
          va='center',
          ha='left'
          )

plt.show()
```



Project Task: 3

Data Modeling :

1. Create clusters using k-means clustering algorithm.

a. Prepare the data for the algorithm. If the data is asymmetrically distributed, manage the skewness with appropriate transformation. Standardize the data.

b. Decide the optimum number of clusters to be formed.

c. Analyze these clusters and comment on the results.

```
cluster = rfm
cluster = cluster.reset_index(level=0).iloc[:,[3,4]].values

pd.DataFrame(cluster)
```

	0	1
0	2.0	0.00
1	6.0	3598.21
2	4.0	1797.24
3	1.0	1757.55
4	1.0	334.40
...	...	...
4367	1.0	180.60
4368	1.0	80.82
4369	3.0	176.60
4370	16.0	2045.53
4371	3.0	1837.28

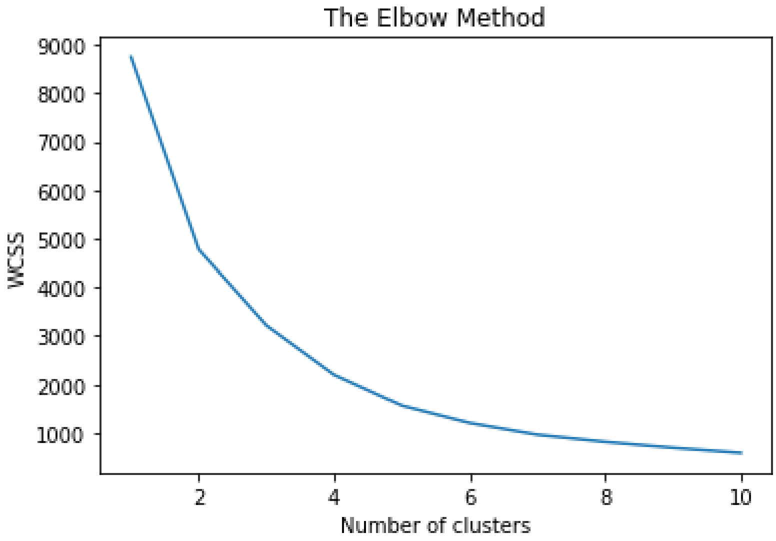
4372 rows × 2 columns

```
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
cluster = sc.fit_transform(cluster)
```

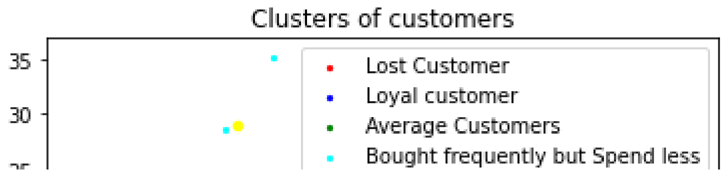
```
from sklearn.cluster import KMeans
wcss= []
```

```

for i in range(1,11):
  kmeans = KMeans(n_clusters = i , init = 'k-means++')
  kmeans.fit(cluster)
  wcss.append(kmeans.inertia_)
plt.plot(range(1,11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



Optimum number of clusters to be formed is 4

```
kmeans = KMeans(n_clusters=4, init='k-means++')
y_kmeans = kmeans.fit_predict(cluster)

plt.scatter(cluster[y_kmeans == 0, 0], cluster[y_kmeans == 0, 1], s = 5, c = 'red', l
plt.scatter(cluster[y_kmeans == 1, 0], cluster[y_kmeans == 1, 1], s = 5, c = 'blue',
plt.scatter(cluster[y_kmeans == 2, 0], cluster[y_kmeans == 2, 1], s = 5, c = 'green',
plt.scatter(cluster[y_kmeans == 3, 0], cluster[y_kmeans == 3, 1], s = 5, c = 'cyan',
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 20, c =
plt.title('Clusters of customers')
plt.xlabel('Total Spending')
plt.ylabel('Buying Frequency')
plt.legend()
plt.show()
```



Project Task: 4

Data Reporting:

1. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

a. Country-wise analysis to demonstrate average spend. Use a bar chart to show the monthly figures

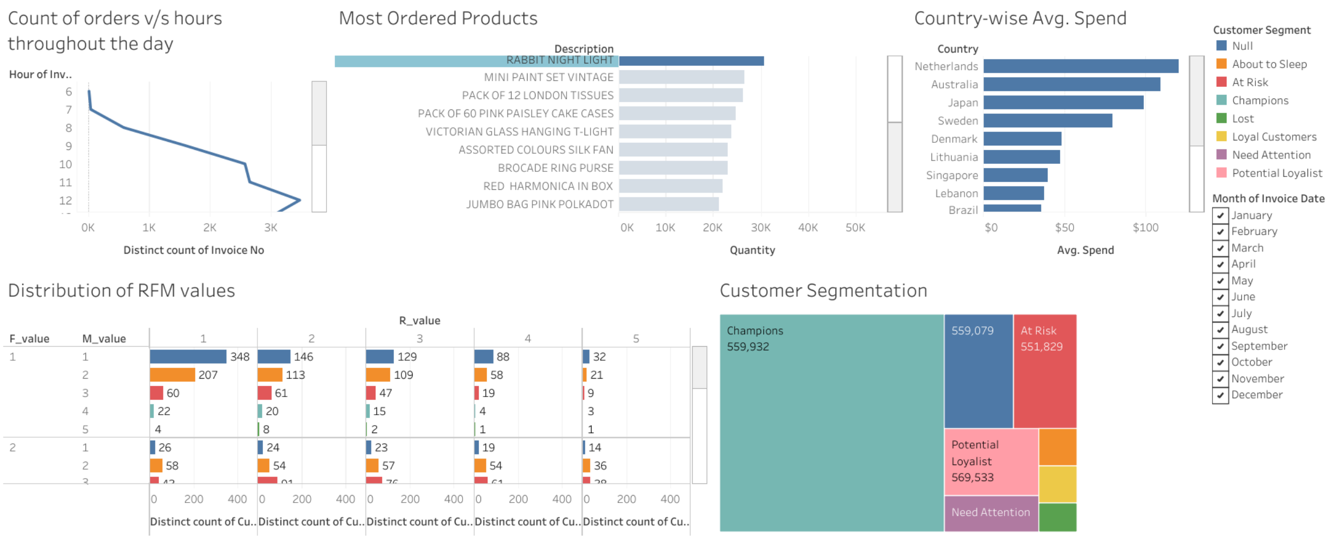
b. Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold

c. Bar graph to show the count of orders vs. hours throughout the day

d. Plot the distribution of RFM values using histogram and frequency charts

e. Plot error (cost) vs. number of clusters selected

f. Visualize to compare the RFM values of the clusters using heatmap



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