Retail

November 7, 2023

0.1 Retail - PGP .

$ Course-end Project 1$

$ Description$ ## 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

[1]:
```
# Import th import libraries
```

[2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import matplotlib
warnings.filterwarnings('ignore')
```

Import several python libraries for graphs and understanding of data: * : This library provides functionality for generating profile reports from pandas DataFrame objects. These reports include statistics, data types, missing values, and more, making it useful for data exploration and analysis.

- : Plotly Express is a high-level interface for creating interactive visualizations using Plotly, a popular plotting library. It simplifies the process of creating complex visualizations with minimal code.

[3]:
```
!pip install pandas_profiling
!pip install plotly
!pip install kneed
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pandas_profiling in
/usr/local/lib/python3.7/site-packages (2.8.0)
Requirement already satisfied: ipywidgets>=7.5.1 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (7.6.5)
Requirement already satisfied: astropy>=4.0 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (4.0.1.post1)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (1.4.1)
Requirement already satisfied: missingno>=0.4.2 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (0.4.2)
Requirement already satisfied: joblib in /usr/local/lib/python3.7/site-packages
(from pandas_profiling) (0.14.1)
Requirement already satisfied: phik>=0.9.10 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (0.10.0)
Requirement already satisfied: requests>=2.23.0 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (2.23.0)
Requirement already satisfied: jinja2>=2.11.1 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (2.11.1)
Requirement already satisfied: tqdm>=4.43.0 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (4.62.3)
Requirement already satisfied: confuse>=1.0.0 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (1.3.0)
Requirement already satisfied: tangled-up-in-unicode>=0.0.6 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (0.0.6)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (1.21.5)
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (1.1.5)
Requirement already satisfied: visions[type_image_path]==0.4.4 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (0.4.4)
Requirement already satisfied: matplotlib>=3.2.0 in
/usr/local/lib/python3.7/site-packages (from pandas_profiling) (3.5.1)
Requirement already satisfied: htmlmin>=0.1.12 in /usr/local/lib/python3.7/site-
packages (from pandas_profiling) (0.1.12)
Requirement already satisfied: attrs>=19.3.0 in /usr/local/lib/python3.7/site-
packages (from visions[type_image_path]==0.4.4->pandas_profiling) (19.3.0)
Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.7/site-
packages (from visions[type_image_path]==0.4.4->pandas_profiling) (2.4)
Requirement already satisfied: imagehash in /usr/local/lib/python3.7/site-
packages (from visions[type_image_path]==0.4.4->pandas_profiling) (4.1.0)
Requirement already satisfied: Pillow in /usr/local/lib/python3.7/site-packages
```

```
(from visions[type_image_path]==0.4.4->pandas_profiling) (7.1.1)
Requirement already satisfied: pyyaml in /usr/local/lib/python3.7/site-packages
(from confuse>=1.0.0->pandas_profiling) (5.3.1)
Requirement already satisfied: ipykernel>=4.5.1 in
/usr/local/lib/python3.7/site-packages (from
ipywidgets>=7.5.1->pandas_profiling) (5.2.0)
Requirement already satisfied: traitlets>=4.3.1 in
/usr/local/lib/python3.7/site-packages (from
ipywidgets>=7.5.1->pandas_profiling) (5.1.1)
Requirement already satisfied: ipython>=4.0.0 in /usr/local/lib/python3.7/site-
packages (from ipywidgets>=7.5.1->pandas_profiling) (7.13.0)
Requirement already satisfied: widgetsnbextension~=3.5.0 in
/usr/local/lib/python3.7/site-packages (from
ipywidgets>=7.5.1->pandas_profiling) (3.5.1)
Requirement already satisfied: nbformat>=4.2.0 in /usr/local/lib/python3.7/site-
packages (from ipywidgets>=7.5.1->pandas_profiling) (5.0.5)
Requirement already satisfied: ipython-genutils~=0.2.0 in
/usr/local/lib/python3.7/site-packages (from
ipywidgets>=7.5.1->pandas_profiling) (0.2.0)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in
/usr/local/lib/python3.7/site-packages (from
ipywidgets>=7.5.1->pandas_profiling) (1.0.2)
Requirement already satisfied: MarkupSafe>=0.23 in
/usr/local/lib/python3.7/site-packages (from jinja2>=2.11.1->pandas_profiling)
(1.1.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/site-
packages (from matplotlib>=3.2.0->pandas_profiling) (0.10.0)
Requirement already satisfied: pyparsing>=2.2.1 in
/usr/local/lib/python3.7/site-packages (from
matplotlib>=3.2.0->pandas_profiling) (2.4.6)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/site-
packages (from matplotlib>=3.2.0->pandas_profiling) (21.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/site-packages (from
matplotlib>=3.2.0->pandas_profiling) (1.2.0)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.7/site-packages (from
matplotlib>=3.2.0->pandas_profiling) (2.8.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.7/site-packages (from
matplotlib>=3.2.0->pandas_profiling) (4.28.5)
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/site-packages
(from missingno>=0.4.2->pandas_profiling) (0.11.2)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/site-
packages (from pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3->pandas_profiling)
(2019.3)
Requirement already satisfied: numba>=0.38.1 in /usr/local/lib/python3.7/site-
packages (from phik>=0.9.10->pandas_profiling) (0.48.0)
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Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/site-packages (from requests>=2.23.0->pandas_profiling)
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Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/site-
packages (from requests>=2.23.0->pandas_profiling) (2.9)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.7/site-packages (from requests>=2.23.0->pandas_profiling)
(1.25.8)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/site-packages (from requests>=2.23.0->pandas_profiling)
(3.0.4)
Requirement already satisfied: six in /usr/local/lib/python3.7/site-packages
(from cycler>=0.10->matplotlib>=3.2.0->pandas_profiling) (1.14.0)
Requirement already satisfied: jupyter-client in /usr/local/lib/python3.7/site-
packages (from ipykernel>=4.5.1->ipywidgets>=7.5.1->pandas_profiling) (6.1.2)
Requirement already satisfied: tornado>=4.2 in /usr/local/lib/python3.7/site-
packages (from ipykernel>=4.5.1->ipywidgets>=7.5.1->pandas_profiling) (6.1)
Requirement already satisfied: jedi>=0.10 in /usr/local/lib/python3.7/site-
packages (from ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (0.16.0)
Requirement already satisfied: prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0 in
/usr/local/lib/python3.7/site-packages (from
ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (3.0.5)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.7/site-packages (from
ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (41.2.0)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.7/site-
packages (from ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (0.7.5)
Requirement already satisfied: pygments in /usr/local/lib/python3.7/site-
packages (from ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (2.6.1)
Requirement already satisfied: decorator in /usr/local/lib/python3.7/site-
packages (from ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (4.4.2)
Requirement already satisfied: backcall in /usr/local/lib/python3.7/site-
packages (from ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (0.1.0)
Requirement already satisfied: pexpect in /usr/local/lib/python3.7/site-packages
(from ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling) (4.8.0)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in
/usr/local/lib/python3.7/site-packages (from
nbformat>=4.2.0->ipywidgets>=7.5.1->pandas_profiling) (4.4.0)
Requirement already satisfied: jupyter-core in /usr/local/lib/python3.7/site-
packages (from nbformat>=4.2.0->ipywidgets>=7.5.1->pandas_profiling) (4.6.3)
Requirement already satisfied: llvmlite<0.32.0,>=0.31.0dev0 in
/usr/local/lib/python3.7/site-packages (from
numba>=0.38.1->phik>=0.9.10->pandas_profiling) (0.31.0)
Requirement already satisfied: notebook>=4.4.1 in /usr/local/lib/python3.7/site-
packages (from widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling)
(6.0.3)
Requirement already satisfied: PyWavelets in /usr/local/lib/python3.7/site-
packages (from imagehash->visions[type_image_path]==0.4.4->pandas_profiling)
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(1.1.1)
Requirement already satisfied: parso>=0.5.2 in /usr/local/lib/python3.7/site-
packages (from jedi>=0.10->ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling)
(0.6.2)
Requirement already satisfied: importlib-metadata in
/usr/local/lib/python3.7/site-packages (from
jsonschema!=2.5.0,>=2.4->nbformat>=4.2.0->ipywidgets>=7.5.1->pandas_profiling)
(1.6.0)
Requirement already satisfied: importlib-resources>=1.4.0 in
/usr/local/lib/python3.7/site-packages (from
jsonschema!=2.5.0,>=2.4->nbformat>=4.2.0->ipywidgets>=7.5.1->pandas_profiling)
(5.4.0)
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in
/usr/local/lib/python3.7/site-packages (from
jsonschema!=2.5.0,>=2.4->nbformat>=4.2.0->ipywidgets>=7.5.1->pandas_profiling)
(0.16.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/site-packages (from
jsonschema!=2.5.0,>=2.4->nbformat>=4.2.0->ipywidgets>=7.5.1->pandas_profiling)
(4.0.1)
Requirement already satisfied: terminado>=0.8.1 in
/usr/local/lib/python3.7/site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling)
(0.8.3)
Requirement already satisfied: pyzmq>=17 in /usr/local/lib/python3.7/site-
packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling)
(19.0.0)
Requirement already satisfied: nbconvert in /usr/local/lib/python3.7/site-
packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling)
(5.6.1)
Requirement already satisfied: prometheus-client in
/usr/local/lib/python3.7/site-packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling)
(0.7.1)
Requirement already satisfied: Send2Trash in /usr/local/lib/python3.7/site-
packages (from
notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling)
(1.5.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.7/site-packages
(from prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0->ipython>=4.0.0->ipywidgets>=
7.5.1->pandas_profiling) (0.1.9)
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.7/site-
packages (from pexpect->ipython>=4.0.0->ipywidgets>=7.5.1->pandas_profiling)
(0.6.0)
Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.7/site-
packages (from importlib-resources>=1.4.0->jsonschema!=2.5.0,>=2.4->nbformat>=4.
```

```
2.0->ipywidgets>=7.5.1->pandas_profiling) (3.1.0)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.7/site-
packages (from nbconvert->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets
>=7.5.1->pandas_profiling) (0.6.0)
Requirement already satisfied: entrypoints>=0.2.2 in
/usr/local/lib/python3.7/site-packages (from nbconvert->notebook>=4.4.1->widgets
nbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling) (0.3)
Requirement already satisfied: mistune<2,>=0.8.1 in
/usr/local/lib/python3.7/site-packages (from nbconvert->notebook>=4.4.1->widgets
nbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling) (0.8.4)
Requirement already satisfied: bleach in /usr/local/lib/python3.7/site-packages
(from nbconvert->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets>=7.5.1->
pandas_profiling) (3.1.4)
Requirement already satisfied: pandocfilters>=1.4.1 in
/usr/local/lib/python3.7/site-packages (from nbconvert->notebook>=4.4.1->widgets
nbextension~=3.5.0->ipywidgets>=7.5.1->pandas_profiling) (1.4.2)
Requirement already satisfied: testpath in /usr/local/lib/python3.7/site-
packages (from nbconvert->notebook>=4.4.1->widgetsnbextension~=3.5.0->ipywidgets
>=7.5.1->pandas_profiling) (0.4.4)
Requirement already satisfied: webencodings in /usr/local/lib/python3.7/site-
packages (from bleach->nbconvert->notebook>=4.4.1->widgetsnbextension~=3.5.0->ip
ywidgets>=7.5.1->pandas_profiling) (0.5.1)
WARNING: You are using pip version 22.0.3; however, version 23.3.1 is

available.

You should consider upgrading via the '/usr/local/bin/python3 -m pip install

--upgrade pip' command.

Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: plotly in /usr/local/lib/python3.7/site-packages
(5.5.0)
Requirement already satisfied: six in /usr/local/lib/python3.7/site-packages
(from plotly) (1.14.0)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.7/site-
packages (from plotly) (8.0.1)
WARNING: You are using pip version 22.0.3; however, version 23.3.1 is

available.

You should consider upgrading via the '/usr/local/bin/python3 -m pip install

--upgrade pip' command.

Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: kneed in ./.local/lib/python3.7/site-packages
(0.8.5)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/site-
```

```
packages (from kneed) (1.4.1)
Requirement already satisfied: numpy>=1.14.2 in /usr/local/lib/python3.7/site-
packages (from kneed) (1.21.5)
WARNING: You are using pip version 22.0.3; however, version 23.3.1 is
available.
You should consider upgrading via the '/usr/local/bin/python3 -m pip install
--upgrade pip' command.
```

[4]:
```
import pandas_profiling
import plotly.express as px
```

[5]:
```
# lets import the file online retail
retail_data =pd.read_excel("Online Retail.xlsx")
retail_data.head()
```

[5]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
```

1 Data Cleaning:

$ Project Task:$
$ Data Modeling :$

2 1. Perform a preliminary data inspection and data cleaning.

[6]:
```
retail_data.describe()
```

[6]:
```
            Quantity      UnitPrice     CustomerID
count  541909.000000  541909.000000  406829.000000
mean        9.552250       4.611114   15287.690570
```

```
std       218.081158      96.759853    1713.600303
min    -80995.000000  -11062.060000   12346.000000
25%         1.000000       1.250000   13953.000000
50%         3.000000       2.080000   15152.000000
75%        10.000000       4.130000   16791.000000
max     80995.000000   38970.000000   18287.000000
```

Interpretation : The quantiy that customer paid unit price approxamilty 9.552 that is around 18287 customer paid the unit price.

[7]:
```
retail_data.shape
```

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

[8]:
```
retail_data.columns
```

[8]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')
```

[9]:
```
retail_data.info()
```

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

[10]:
```
# Normally we can determine the missing data as given below:
retail_data.isnull().sum()
```

[10]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
```

```
Country              0
dtype: int64
```

$ Interpretation:$ we can observe that the Description and customer Id has around 1454 and 135080 null values. lets get rid of it as description and customer ID has no impact on quantity and unit price prediction

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

[11]:
```
# this code helps us to determine the missing values with the type of data and␣
↪column in a very formatted way:
columntype␣
↪=['Categorical','Categorical','Categorical','Descrete','Date','Continuous','Categorical','C
missingdf= pd.DataFrame({'Columns':retail_data.columns.to_list(),'Type of Data':
↪columntype,'Number of Missing Values':retail_data.isna().sum()})
def highlight_max(s):
    is_max=s
    return['background-color:pink' if v else ''for v in is_max]
missingdf.style.apply(highlight_max,subset=['Number of Missing Values'])
missingdf.style.hide_index()
```

[11]:
```
<pandas.io.formats.style.Styler at 0x7fa7f10f22d0>
```

[12]:
```
# Alternative way to find the data usinf profile_report which gives duplicate␣
↪,missing values and variable types:
retail_data.profile_report()
```

```
Summarize dataset:   0%|          | 0/22 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[12]:

$ Interpretation:$ 1. we have observed that description column has 1454 missing values and customerID has 135080 values, as the customer ID has no significance impact on the data, hence we can drop it.

2. The Description is Null will be automatically treated when discarding records while missing values of customer ID.

[13]:
```
print("Number of records before dropping customer ID columns")
print(len(retail_data))
retail_data.drop(retail_data[retail_data['CustomerID'].isna()].
 ↪index,inplace=True)
retail_data.reset_index(drop=True)
print("Number of records after dropping customr ID columns")
print(len(retail_data))
print("Is there any missing data in Description Column afterdropping the Null␣
 ↪CustomerID columns")
print(any(retail_data['Description'].isna()==True))
missingdf=pd.DataFrame({'Columns':retail_data.columns.to_list(),'Number of␣
 ↪Missing Values after cleaning':retail_data.isna().sum()})
missingdf.style.hide_index()
```

```
Number of records before dropping customer ID columns
541909
Number of records after dropping customr ID columns
406829
Is there any missing data in Description Column afterdropping the Null
CustomerID columns
False
```

[13]:
```
<pandas.io.formats.style.Styler at 0x7fa7f10a3d10>
```

$ Interpretation:$ Hence the value of missing data has been rectified.

3.1 b. Remove duplicate data records.

[14]:
```
print("Number of records before dropping the dupicate records")
print(len(retail_data))
retail_data.drop_duplicates(inplace=True)
retail_data.reset_index(drop=True)
print("Number of records after dropping the duplicate records")
print(len(retail_data))
```

```
Number of records before dropping the dupicate records
406829
Number of records after dropping the duplicate records
401604
```

[15]:
```
# lets remove the transaction of the last month in year 2011.
#as they have only data for 9 days.
import datetime
def get_month(x):
    return datetime.datetime(x.year,x.month,x.day)
print("Number of records before dropping the transaction of te last month")
```

```
print(len(retail_data))
```

```
Number of records before dropping the transaction of te last month
401604
```

[16]:
```
# lets create InvoiceMonth column
retail_data['InvoiceMonth']=retail_data['InvoiceDate'].apply(get_month)
retail_data[retail_data['InvoiceMonth']>datetime.datetime(2011,11,30)]
retail_data.drop(retail_data[retail_data['InvoiceMonth']>datetime.
↪datetime(2011,11,30)].index,inplace=True)
retail_data.reset_index(drop=True)
print("Number of records after dropping the transactions of the last ")
print(len(retail_data))
```

```
Number of records after dropping the transactions of the last
384222
```

4 c. Perform descriptive analytics on the given data.

Lets observe the countries that have most of the customers residing:

[17]:
```
retail_data.Country.value_counts(normalize=True).head(10).mul(100).round(2).
↪astype(str)+'%'
```

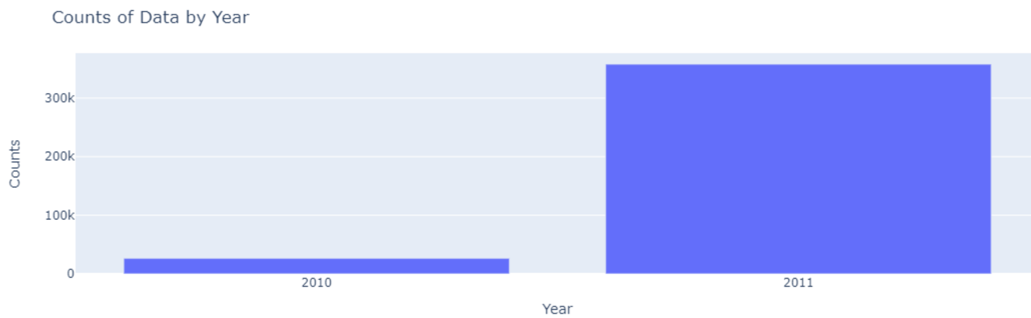
[17]:
```
United Kingdom    88.73%
Germany            2.38%
France             2.12%
EIRE               1.86%
Spain              0.64%
Netherlands        0.59%
Belgium            0.51%
Switzerland        0.49%
Portugal           0.36%
Australia          0.33%
Name: Country, dtype: object
```

Interpretation : UK has 88% customer has done more transaction than oher countries.

5 Lets Visualize the invoiceDate in 2010 and 2011

[18]:
```
import plotly.express as px

yearly_counts = retail_data['InvoiceDate'].dt.year.value_counts(sort=False)

fig = px.bar(x=yearly_counts.index, y=yearly_counts.values)
```

```
fig.update_layout(
    xaxis_title="Year",
    yaxis_title="Counts",
    title="Counts of Data by Year",
    xaxis=dict(tickmode='array', tickvals=list(yearly_counts.index),␣
 ↪ticktext=list(yearly_counts.index))
)

fig.show()
```



6 Lets Visualize the customer trend on monthly basis in the year 2011

[19]:
```
import plotly.express as px

# Create a DataFrame containing the data for the year 2011
data_2011= retail_data[retail_data.InvoiceDate.dt.year==2011]
# Calculate the counts of events for each month in 2011
monthly_counts =data_2011.InvoiceDate.dt.month.value_counts(sort=False)
# Define the colors for the bars
my_colors=[(x/10.0,x/20.0,0.75) for x in range (len(monthly_counts))]

# Create the bar chart using Plotly Express
fig =px.bar(
x=monthly_counts.index,#Monthly(x-axis)
y= monthly_counts.values,#counts(y-axis)
color=my_colors,#custom colors
labels={'x':'Month','y':'Event Count'},
title='Event Counts by Month in 2011')

# Rotate x-axis labels for better readability
fig.update_xaxes(tickangle=45)
```

```
# Show the plot
fig.show()
```

7 Visualize the items Contributing to maximum Price Value:

[20]:
```
import plotly.express as px

# Calculate TotalPrice
retail_data['TotalPrice'] = retail_data['Quantity'] * retail_data['UnitPrice']

# Sort and select the top 10 TotalPrice values
top_10_data = retail_data.sort_values(by='TotalPrice', ascending=False).head(10)

# Create a line plot using Plotly Express
fig = px.line(top_10_data, x='Description', y='TotalPrice', markers=True,␣
 ↪line_shape='linear', title='Line Plot Showing the Items Contributing to␣
 ↪Maximum Price Value')
fig.update_traces(marker=dict(color='cyan', size=8))
fig.update_layout(xaxis=dict(tickmode='array', tickvals=list(range(10)),␣
 ↪ticktext=top_10_data['Description']))

# Show the plot
fig.show()
```

$ Interpretation: $ item name medium Ceremic Top Storage Jar has highest retail approx 771836k.

Let us explore more data in retailing the item in countries.

[21]:
```
print("First Business transaction date is{}".format(retail_data.InvoiceDate.
 ↪min()))
print("Last Business transaction date is{}".format(retail_data.InvoiceDate.
 ↪max()))
```

```
First Business transaction date is2010-12-01 08:26:00
Last Business transaction date is2011-11-30 17:42:00
```

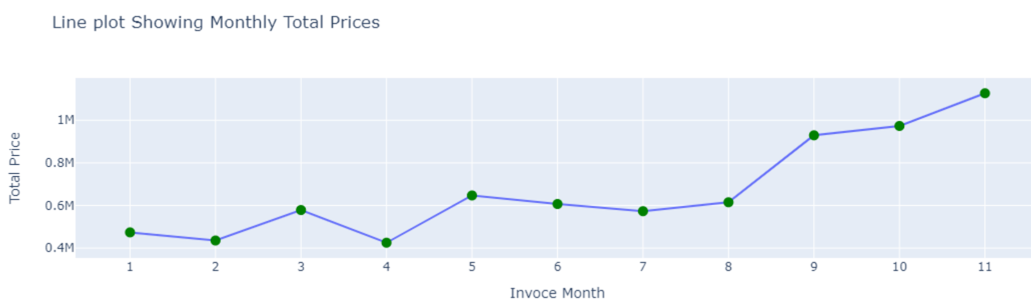
[22]:
```
monthly_gross =retail_data[retail_data.InvoiceDate.dt.year==2011].
 ↪groupby(retail_data.InvoiceDate.dt.month).TotalPrice.sum()
df =pd.DataFrame(monthly_gross)
df.index.name='Invoice Month'
df
```

[22]:

	TotalPrice
Invoice Month	
1	473731.900
2	435534.070
3	578576.210
4	425222.671
5	647011.670
6	606862.520
7	573112.321
8	615078.090
9	929356.232
10	973306.380
11	1126815.070

Interpretation : by the end of the year approximately we have 1126815.070 transactions that has happpend.

[23]:
```python
#Lets plot the above graph:
import plotly.express as px
# create a DataFrame
data =pd.DataFrame({'Invoice Month':monthly_gross.index,'Total Price':
 ↪monthly_gross.values})
# create the line plot using plotly express
fig=px.line(data,x='Invoice Month',y='Total Price',
            markers=True,line_shape='linear',title='Line plot Showing Monthly␣
 ↪Total Prices',
            labels={'Total Price':'Total Price','Invoice Month': 'Invoce Month'})
# Customize the Layout
fig.update_traces(marker=dict(color='green',size=10))
fig.update_xaxes(tickvals=list(range(1,13)))
fig.show();
```



Note: In this code:

We create a DataFrame (df) from your monthly_gross Pandas Series, with 'Invoice Month' as the column for months and 'Total Price' as the column for total prices.

We use Plotly Express to create the line plot. We specify the data, x-axis, y-axis, markers, line shape, title, and label names.

We customize the marker color to green, the marker size, and the x-axis tick values to match the months.

Finally, we show the plot using fig.show(). This code will produce a line plot similar to the one created with Seaborn and Matplotlib, but using Plotly Express.

Interpretation : There is a hike in the 11th month sales.

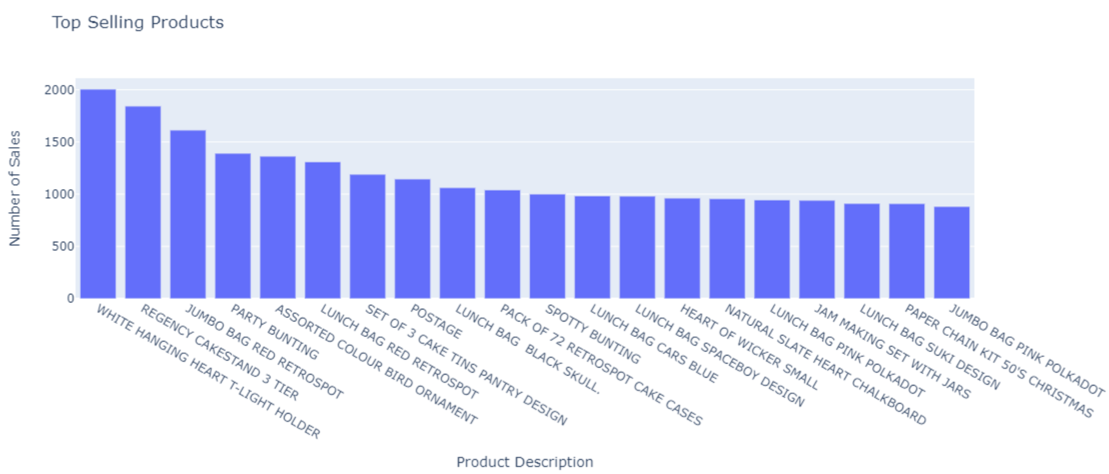
Lets Visualize some top product from the whole range:

[24]:
```python
retail_data.columns
```

[24]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'InvoiceMonth', 'TotalPrice'],
```

```
    dtype='object')
```

[25]:
```
import plotly.express as px
top_products =retail_data['Description'].value_counts()[:20]
# Create a DataFrame from the Pandas Series for Plotly Express
df = pd.DataFrame({'Product Description': top_products.index, 'Count':␣
 ↪top_products.values})

# Create the bar plot using Plotly Express
fig = px.bar(
    df, x='Product Description', y='Count',
    labels={'Count': 'Number of Sales', 'Product Description': 'Product␣
 ↪Description'},
    title='Top Selling Products',
)

# Set the size of the figure
fig.update_layout(width=800, height=500)

# Show the plot
fig.show()
```



$ Note:$In this code:

We create a DataFrame (df) from your top_products Pandas Series, with 'Product Description' as the column for product descriptions and 'Count' as the column for the number of sales.

We use Plotly Express to create the bar plot. We specify the data, x-axis, y-axis, labels, and title.

We set the size of the figure using fig.update_layout(width=800, height=500) to control the dimensions of the plot.

Finally, we show the plot using fig.show(). This code will produce a bar plot similar to the one created with Seaborn and Matplotlib, but using Plotly Express.

[26]:
```
pd.DataFrame(retail_data['Description'].value_counts())
```

[26]:

	Description
WHITE HANGING HEART T-LIGHT HOLDER	2005
REGENCY CAKESTAND 3 TIER	1843
JUMBO BAG RED RETROSPOT	1613
PARTY BUNTING	1391
ASSORTED COLOUR BIRD ORNAMENT	1363
…	…
CAT WITH SUNGLASSES BLANK CARD	1
GLASS AND PAINTED BEADS BRACELET OL	1
WALL ART , THE MAGIC FOREST	1
BLACK VINT ART DEC CRYSTAL BRACELET	1
FIRE POLISHED GLASS BRACELET BLACK	1

[3887 rows x 1 columns]

Visualize the entire data

[27]:
```
retail_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 384222 entries, 0 to 516383
Data columns (total 10 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   InvoiceNo     384222 non-null  object
 1   StockCode     384222 non-null  object
 2   Description   384222 non-null  object
 3   Quantity      384222 non-null  int64
 4   InvoiceDate   384222 non-null  datetime64[ns]
 5   UnitPrice     384222 non-null  float64
 6   CustomerID    384222 non-null  float64
 7   Country       384222 non-null  object
 8   InvoiceMonth  384222 non-null  datetime64[ns]
 9   TotalPrice    384222 non-null  float64
dtypes: datetime64[ns](2), float64(3), int64(1), object(4)
memory usage: 42.2+ MB
```

lets check the outliers using interquartile range rule: 1. Calculate the interquartile range for the data. 2. Multiply the interquartile range (IQR) by 1.5 (a constant used to discrete outliers) 3. Add 1.5 x(IQR) to the third quartile.Any number greater than this is a suspected outlier. 4. Subtract 1.5x(IQR) from the first quartile. Any number less than this is a suspected outlier.

[28]:
```python
def outlier_treatment(col):
    sorted(col)
    Q1,Q3 = np.percentile(col , [25,75])
    IQR = Q3 - Q1
    lower_range = Q1 - (1.5 * IQR)
    upper_range = Q3 + (1.5 * IQR)
    return lower_range,upper_range

lower_range,upper_range = outlier_treatment(retail_data['TotalPrice'])
print("Lower Range:",lower_range)
print("Upper Range:",upper_range)
```

```
Lower Range: -19.074999999999996
Upper Range: 43.12499999999999
```

[29]:
```python
lower_retail_df = retail_data[retail_data['TotalPrice'].values < lower_range]
lower_retail_df
```

[29]:
```
       InvoiceNo StockCode                          Description  Quantity  \
141      C536379         D                             Discount        -1
235      C536391     22556       PLASTERS IN TIN CIRCUS PARADE        -12
239      C536391     21484          CHICK GREY HOT WATER BOTTLE        -12
240      C536391     22557     PLASTERS IN TIN VINTAGE PAISLEY        -12
241      C536391     22553               PLASTERS IN TIN SKULLS        -24
…            …         …                                    …        …
516180   C579878     23542             WALL ART 70'S ALPHABET          -3
516221   C579884         D                             Discount        -1
516376   C579886     23460                SWEETHEART WALL TIDY         -2
516377   C579886     23458              DOLLY CABINET 3 DRAWERS         -2
516378   C579886     22170  PICTURE FRAME WOOD TRIPLE PORTRAIT         -3

               InvoiceDate  UnitPrice  CustomerID         Country  \
141    2010-12-01 09:41:00      27.50     14527.0  United Kingdom
235    2010-12-01 10:24:00       1.65     17548.0  United Kingdom
239    2010-12-01 10:24:00       3.45     17548.0  United Kingdom
240    2010-12-01 10:24:00       1.65     17548.0  United Kingdom
241    2010-12-01 10:24:00       1.65     17548.0  United Kingdom
…                        …          …           …               …
516180 2011-11-30 17:12:00       8.25     17340.0  United Kingdom
516221 2011-11-30 17:34:00      20.53     14527.0  United Kingdom
516376 2011-11-30 17:39:00       9.95     15676.0  United Kingdom
516377 2011-11-30 17:39:00      14.95     15676.0  United Kingdom
516378 2011-11-30 17:39:00       6.75     15676.0  United Kingdom

       InvoiceMonth  TotalPrice
141      2010-12-01      -27.50
235      2010-12-01      -19.80
```

```
239       2010-12-01      -41.40
240       2010-12-01      -19.80
241       2010-12-01      -39.60
…               …         …
516180    2011-11-30      -24.75
516221    2011-11-30      -20.53
516376    2011-11-30      -19.90
516377    2011-11-30      -29.90
516378    2011-11-30      -20.25

[1837 rows x 10 columns]
```

[30]:
```python
upper_retail_df = retail_data[retail_data['TotalPrice'].values > upper_range]
upper_retail_df
```

[30]:
```
       InvoiceNo StockCode                      Description  Quantity  \
9         536367     84879    ASSORTED COLOUR BIRD ORNAMENT        32
26        536370     22728        ALARM CLOCK BAKELIKE PINK        24
27        536370     22727         ALARM CLOCK BAKELIKE RED        24
28        536370     22726       ALARM CLOCK BAKELIKE GREEN        12
33        536370     21035  SET/2 RED RETROSPOT TEA TOWELS         18
…            …         …                              …       …
516207    579881     22727         ALARM CLOCK BAKELIKE RED        12
516208    579881     22730       ALARM CLOCK BAKELIKE IVORY        24
516213    579881     82582        AREA PATROLLED METAL SIGN        36
516214    579881     21175      GIN + TONIC DIET METAL SIGN        48
516216    579881     22728        ALARM CLOCK BAKELIKE PINK        24

               InvoiceDate  UnitPrice  CustomerID         Country  \
9      2010-12-01 08:34:00       1.69     13047.0  United Kingdom
26     2010-12-01 08:45:00       3.75     12583.0          France
27     2010-12-01 08:45:00       3.75     12583.0          France
28     2010-12-01 08:45:00       3.75     12583.0          France
33     2010-12-01 08:45:00       2.95     12583.0          France
…                        …        …           …             …
516207 2011-11-30 17:22:00       3.75     12429.0         Denmark
516208 2011-11-30 17:22:00       3.75     12429.0         Denmark
516213 2011-11-30 17:22:00       2.10     12429.0         Denmark
516214 2011-11-30 17:22:00       2.08     12429.0         Denmark
516216 2011-11-30 17:22:00       3.75     12429.0         Denmark

       InvoiceMonth  TotalPrice
9        2010-12-01       54.08
26       2010-12-01       90.00
27       2010-12-01       90.00
28       2010-12-01       45.00
33       2010-12-01       53.10
```

```
…          …          …
516207   2011-11-30      45.00
516208   2011-11-30      90.00
516213   2011-11-30      75.60
516214   2011-11-30      99.84
516216   2011-11-30      90.00

[29749 rows x 10 columns]
```

[31]:
```
lower_outliers = lower_retail_df.value_counts().sum(axis=0)
upper_outliers = upper_retail_df.value_counts().sum(axis=0)
total_outliers = lower_outliers + upper_outliers

print("Total Number of Outliers:",total_outliers)
```

```
Total Number of Outliers: 31586
```

7.0.1 Let us list down the row numbers that contain outliers:

lower_index = list(retail_data[retail_data['TotalPrice'] < lower_range].index)

upper_index = list(retail_data[retail_data['TotalPrice'] > upper_range].index)

total_index = list(lower_index + upper_index)

print(total_index)

$Interpretation: $ THe total outliers in the dataset is 31586.

7.1 $ Data Transformation:$

8 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.

Note: A cohort is a group of subjects who share a defining characteristic. We can observe how a cohort behaves across time and compare it to other cohorts. Cohorts are used in medicine, psychology, econometrics, ecology and many other areas to perform a cross-section (compare difference across subjects) at intervals through time.

9 Types of cohorts:

1. 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 or quarterly even daily.

2. Behaovior 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. Understaning the needs of the various cohorts can help a company design custom-made services or products for particular segments.
3. 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 periodic time after acquisition or the product type that the customer spent most of their order amount in some period of time.

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

For cohort analysis, there are a few labels that we have to create:

- Invoice period: A string representation of the year and month of a single transaction/invoice.
- Cohort group:A string representation of the the year and month of a customer's first purchase. This label is common across all invoices for a particular customer.
- Cohort period / Cohort Index:A integer representation a customer's stage in its "lifetime". The number represents the number of months passed since the first purchase.

[32]:
```
cohort= retail_data.copy()
cohort.head()
```

[32]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country InvoiceMonth  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom   2010-12-01
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom   2010-12-01
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01

   TotalPrice
0       15.30
1       20.34
2       22.00
3       20.34
4       20.34
```

[33]:
```
cohort.columns
```

[33]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'InvoiceMonth', 'TotalPrice'],
      dtype='object')
```

[34]:
```python
# define the get month function that will prase(resolve) the date
import datetime
def get_month(x):
    return datetime.datetime(x.year,x.month,1)
```

[35]:
```python
# Create theInvoiceMonth column
cohort['InvoiceMonth']=cohort['InvoiceDate'].apply(get_month)
```

[36]:
```python
#Groupby customer ID and select the InvoiceMonth value
grouping =cohort.groupby('CustomerID')['InvoiceMonth']
```

[37]:
```python
#Assigning a minimum InvoiceMonth value to the dataset
cohort['CohortMonth']=grouping.transform('min')
cohort.head()
```

[37]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country InvoiceMonth  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom   2010-12-01
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom   2010-12-01
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01

   TotalPrice CohortMonth
0       15.30  2010-12-01
1       20.34  2010-12-01
2       22.00  2010-12-01
3       20.34  2010-12-01
4       20.34  2010-12-01
```

Interpretation : we can see the minimum month is 2010.

- Calculate the time offset in months
- Calculating time offset for each transaction allows you to report the metrics for each cohort in a comparable fashion.
- lets create some varialbes that capture the integer value of years and months for invoice and cohort date using the get_int() fuction.

[38]:
```
def get_date_int(cohort,column):
    year =cohort[column].dt.year
    month=cohort[column].dt.month
    #day=cohort[column].dt.day
    return year,month
```

[39]:
```
# Get the integers for date parts from the InvoiceMonth column
invoice_year,invoice_month =get_date_int(cohort,'InvoiceMonth')
```

[40]:
```
# Get the integers for date parts from the 'CohortMonth' column
cohort_year,cohort_month = get_date_int(cohort,'CohortMonth')
```

[41]:
```
print("Unique terms for Cohort Year is {}".format(cohort_year.unique()))
print("Unique terms for Cohort Month is {}".format(cohort_month.unique()))
print("Unique terms for Invoice Year is {}".format(invoice_year.unique()))
print("Unique terms for Invoice Month is {}".format(invoice_month.unique()))
```

```
Unique terms for Cohort Year is [2010 2011]
Unique terms for Cohort Month is [12  1  2  3  4  5  6  7  8  9 10 11]
Unique terms for Invoice Year is [2010 2011]
Unique terms for Invoice Month is [12  1  2  3  4  5  6  7  8  9 10 11]
```

[42]:
```
# Calculate the difference in years
year_diff =invoice_year-cohort_year
# calculate difference in months
month_diff =invoice_month -cohort_month
#Extract the difference in months from all previous values
cohort['CohortIndex'] =year_diff*12+month_diff +1
cohort.head()
```

[42]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country InvoiceMonth  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom   2010-12-01
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom   2010-12-01
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01

   TotalPrice CohortMonth  CohortIndex
0       15.30  2010-12-01            1
1       20.34  2010-12-01            1
```

```
2        22.00   2010-12-01           1
3        20.34   2010-12-01           1
4        20.34   2010-12-01           1
```

Interpretation : This Cohort Index gives us an idea on the time difference in months between the customer's first purchase and the customer's current purchase.

[43]:
```
cohort['CohortIndex'].unique()
```

[43]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12])
```

11 b. Analyze the retention rate of customers.

- Calculate the retention rate (Customer retention) is a very uselfulmetric to understand how many of all the customer are still active. it gives the percentage of active customers compared to the total number of customers.

[44]:
```
grouping =cohort.groupby(['CohortMonth','CohortIndex'])
```

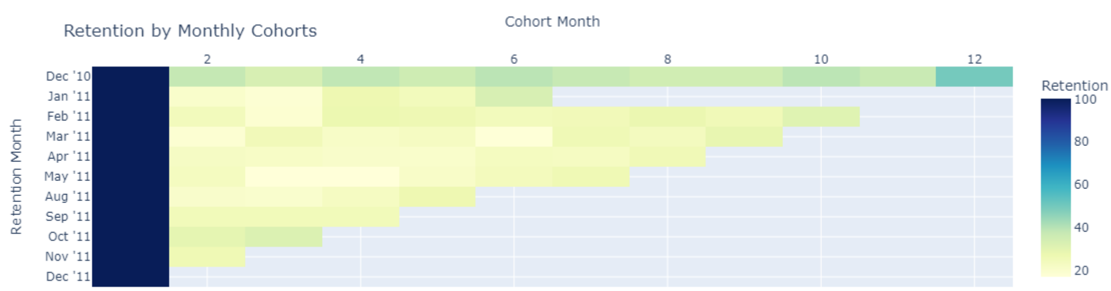
[45]:
```
#Count the number of unique values per customer ID
cohort_data =grouping['CustomerID'].apply(pd.Series.nunique).reset_index()
```

[46]:
```
#create a pivot
cohort_counts= cohort_data.
↪pivot(index='CohortMonth',columns='CohortIndex',values ='CustomerID')
# Select the first column and store it to cohort_sizes
cohort_sizes =cohort_counts.iloc[:,0]
#Divide the cohort count by cohort sizes along the rows
retention =cohort_counts.divide(cohort_sizes,axis=0)*100
print (cohort[cohort['CohortMonth']=='2011-12-01']['CustomerID'].nunique())
#Verifies 41 against this month
cohort_sizes
retention.index =retention.index.date
```

```
0
```

[47]:
```
import plotly.express as px
import pandas as pd

month_list = ["Dec '10", "Jan '11", "Feb '11", "Mar '11", "Apr '11",
              "May '11", "Jan '11", "Aug '11", "Sep '11",
              "Oct '11", "Nov '11", "Dec '11"]

# Assuming you have 'retention' as a Pandas DataFrame containing the data

# Create the heatmap using Plotly Express
```

```python
fig = px.imshow(
    retention,
    labels=dict(x="Cohort Month", y="Retention Month", color="Retention"),
    x=retention.columns,
    y=month_list,
    color_continuous_scale="YlGnBu",
)

# Customize the color scale and annotation
fig.update_xaxes(side="top")
fig.update_coloraxes(colorbar_title="Retention")
fig.update_traces(showscale=True)
fig.update_layout(
    title="Retention by Monthly Cohorts",
    xaxis_nticks=len(retention.columns),
)

# Show the plot
fig.show()
```



12 Calculating average price per cohort:

- Calculate the average price metric and analyze if there are any differences in shopping patterns across time and across cohorts.

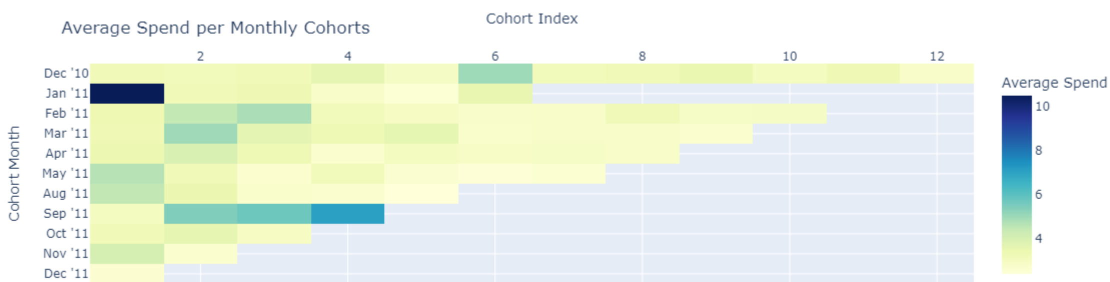
[48]:
```python
# create a groupby object and pass the monthly cohort and cohort index
grouping =cohort.groupby(['CohortMonth','CohortIndex'])
# Calculate the average of the unit price column
cohort_data =grouping['UnitPrice'].mean()
#Reset the index of cohort_data
cohort_data =cohort_data.reset_index()
# create a pivot
```

```
average_price =cohort_data.
 ↪pivot(index='CohortMonth',columns='CohortIndex',values='UnitPrice')
#average_price.round(1)
#average_price.index =average_price.index.date
average_price
#cohort_data
#cohort
```

[48]:
```
CohortIndex          1         2         3         4         5         6   \
CohortMonth
2010-12-01    3.216682  3.182040  3.207467  3.603758  2.937803  4.996508
2011-01-01    3.505492  3.653572  3.069534  8.439024  3.157803  3.172919
2011-02-01    3.355968  4.469638  4.824106  3.150045  2.987616  2.792577
2011-03-01    3.302802  4.990095  3.655094  3.289768  3.616562  2.758381
2011-04-01    3.431172  3.958074  3.300128  2.673439  3.028297  2.867185
2011-05-01    4.662054  3.243691  2.652761  3.167391  2.667158  2.495751
2011-06-01   10.490030  3.205283  3.343994  2.835952  2.553037  3.550657
2011-07-01    4.493676  3.480495  2.752121  2.701985  2.403989       NaN
2011-08-01    3.028246  5.425904  5.714033  7.046410       NaN       NaN
2011-09-01    3.235116  3.584834  2.957893       NaN       NaN       NaN
2011-10-01    4.053162  2.678140       NaN       NaN       NaN       NaN
2011-11-01    2.641554       NaN       NaN       NaN       NaN       NaN

CohortIndex         7         8         9         10        11        12
CohortMonth
2010-12-01   3.184572  3.235695  3.511560  3.035982  3.309705  2.835557
2011-01-01   2.918498  2.749649  2.641686  5.489040  2.886220       NaN
2011-02-01   2.812985  3.214380  2.894988  2.946092       NaN       NaN
2011-03-01   2.843273  2.809136  2.707846       NaN       NaN       NaN
2011-04-01   2.902668  2.812492       NaN       NaN       NaN       NaN
2011-05-01   2.615408       NaN       NaN       NaN       NaN       NaN
2011-06-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-07-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-08-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-09-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-10-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-11-01        NaN       NaN       NaN       NaN       NaN       NaN
```

[49]:
```
import plotly.express as px


# Create the heatmap using Plotly Express
fig = px.imshow(
    average_price,
    labels=dict(x="Cohort Index", y="Cohort Month", color="Average Spend"),
    x=average_price.columns,
    y=month_list,
```

```
    color_continuous_scale="YlGnBu",
)

# Customize the color scale and annotation
fig.update_xaxes(side="top")
fig.update_coloraxes(colorbar_title="Average Spend")
fig.update_traces(showscale=True)
fig.update_layout(
    title='Average Spend per Monthly Cohorts',
    xaxis_nticks=len(average_price.columns),
)

# Show the plot
fig.show()
```



- Calculate average quantity per cohort *Calculate the average quantity metric and anayze if there are any differences in shopping patterns across cohorts.

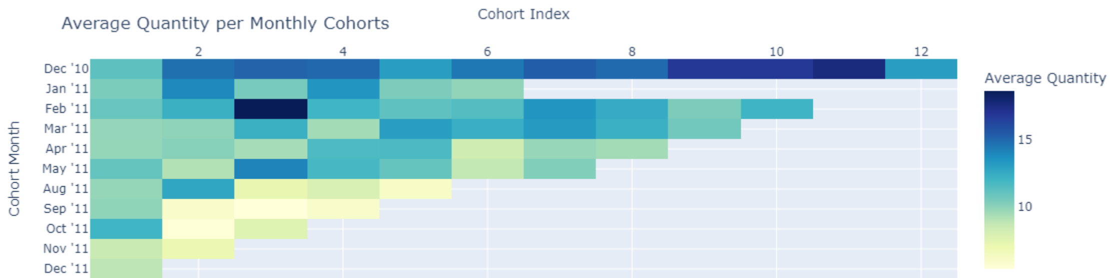
[50]:
```
# Create a groupby object and pass the monthly cohort and cohort index as list
grouping =cohort.groupby(['CohortMonth','CohortIndex'])
# Calculate the average of the Quantity column
cohort_data =grouping['Quantity'].mean()
# Reset the index of cohort_data
cohort_data =cohort_data.reset_index()
#Create a pivot
average_quantity =cohort_data.
 ↪pivot(index='CohortMonth',columns='CohortIndex',values='Quantity')
average_quantity.round(1)
average_quantity.index =average_quantity.index.date
average_quantity
```

[50]:
```
CohortIndex         1          2          3          4          5          6    \
2010-12-01  11.200463  14.691852  15.108447  14.954097  13.054649  14.416287
2011-01-01  10.127231  12.704190  12.429557  11.032382  12.288608  15.006101
```

```
2011-02-01   10.924450  12.251366  18.563808  12.018144  11.167271  11.476727
2011-03-01    9.818050   9.972109  12.249296   9.483094  13.037510  12.369617
2011-04-01    9.803935  10.130252   9.432453  11.622102  11.645560   8.315994
2011-05-01   10.977360   9.138087  14.023864  11.805435  10.973613   8.740725
2011-06-01   10.411028  13.859783  10.509642  13.384102  10.360800   9.901184
2011-07-01    9.804225  12.700952   7.229385   7.929151   6.101961        NaN
2011-08-01    9.941459   5.983114   5.371409   5.972992        NaN        NaN
2011-09-01   12.003023   5.551129   7.657590        NaN        NaN        NaN
2011-10-01    8.553545   7.056196        NaN        NaN        NaN        NaN
2011-11-01    8.901297        NaN        NaN        NaN        NaN        NaN

CohortIndex          7          8          9         10         11         12
2010-12-01   15.306910  14.879447  16.764934  16.809158  17.528956  13.019471
2011-01-01   14.302480  14.519414  11.451025   9.982762   9.256968        NaN
2011-02-01   13.378526  12.448602  10.381961  12.043074        NaN        NaN
2011-03-01   13.221102  12.263293  10.662973        NaN        NaN        NaN
2011-04-01    9.777895   9.480778        NaN        NaN        NaN        NaN
2011-05-01   10.275862        NaN        NaN        NaN        NaN        NaN
2011-06-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-07-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-08-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-09-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-10-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-11-01         NaN        NaN        NaN        NaN        NaN        NaN
```

[51]:
```
import plotly.express as px

# Assuming you have 'average_quantity' as a Pandas DataFrame containing the data
# and 'month_list' as a list of month labels

# Create the heatmap using Plotly Express
fig = px.imshow(
    average_quantity,
    labels=dict(x="Cohort Index", y="Cohort Month", color="Average Quantity"),
    x=average_quantity.columns,
    y=month_list,
    color_continuous_scale="YlGnBu",  # Use a valid predefined colorscale
)

# Customize the color scale and annotation
fig.update_xaxes(side="top")
fig.update_coloraxes(colorbar_title="Average Quantity")
fig.update_traces(showscale=True)
fig.update_layout(
    title='Average Quantity per Monthly Cohorts',
    xaxis_nticks=len(average_quantity.columns),
)
```

```
# Show the plot
fig.show()
```



13 Project Task:

14 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.

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

15 What is RFM?

RFM is a method used to analyze customer value. RFM stands for RECENCY, Frequency, and Monetary. RECENCY: How recently did the customer visit our website or how recently did a customer purchase? Frequency: How often do they visit or how often do they purchase? Monetary: How much revenue we get from their visit or how much do they spend when they purchase? For example, if we see the sales data in the last 12 months, the RFM will look something like below

16 Why is it needed?

RFM Analysis is a marketing framework that is used to understand and analyze customer behaviour based on the above three factors RECENCY, Frequency, and Monetary.

16.0.1 RFM Analysis

RFM analysis is a customer segmentation technique that uses past purchase behavior to divide customers into groups. RFM helps divide customers into various categories or clusters to identify customers who are more likely to respond to promotions and also for future personalization services.

Recency (R): Time since last purchase

Frequency (F): Total number of purchases

Monetary (M): Total purchase value

Benefits of RFM analysis Increased customer retention Increased response rate Increased conversion rate Increased revenue

To perform RFM analysis, we divide customers into four equal groups according to the distribution of values for recency, frequency, and monetary value. Four equal groups across three variables create 64 (4x4x4) different customer segments, which is a manageable number.

For example, let's look at a customer who: is within the group who purchased most recently (R=4), is within the group who purchased most quantity (F=4), is within the group who spent the most (M=4) This customer belongs to RFM segment 4-4-4 (Best Customers), (R=4, F=4, M=4)

[52]:
```
Segment =  ['Platinum Customers',
                     'Big Spenders',
                     'High Spend New Customers',
                     'Lowest-Spending Active Loyal Customers',
                     'Recent Customers',
                     'Good Customers Almost Lost',
                     'Churned Best Customers',
                     'Lost Cheap Customers ']
RFM = [
                ['444', '443'],
                ['114', '124', '134', '144', '214', '224', '234', '244', '314',␣
 ↪'324', '334', '344', '414', '424', '434', '444'],
                ['413', '314', '313', '414'],
                ['331', '341', '431', '441'],
                ['422', '423', '424', '432', '433', '434', '442', '443', '444'],
                ['244', '234', '243', '233'],
                ['144', '134', '143', '133'],
```

```
                ['122', '111', '121', '112', '221', '212', '211']
                ]
# Create a dictionary for each segment to map them against each customer
Description = ['Customers who bought most recently, most often and spend the␣
 ↪most',
                'Customers who spend the most',
                'New Customers who spend the most',
                'Active Customers who buy very often but spend less ',
                'Customers who have purchased recently',
                'Customers who were frequent and good spenders who are becoming␣
 ↪very inactive',
                'Customers who were frequent and good spenders who are lost␣
 ↪contributing to attrition',
                'Customers who purchased long ago , less frequent and very␣
 ↪little']

Marketing = ['No price incentives, New products and Loyalty Programs',
                       'Market your most expensive products',
                       'Price Incentives',
                       'Promote economical cost effective products in daily use',
                       'Discounts and promote a variety of product sells',
                       'Aggressive Price Incentives',
                       'Monitor close communication with customers with constant␣
 ↪feedback and rework ',
                       'Dont spend too much time to re-acquire',
                       ]
rfm_segments = pd.DataFrame({'Segment': Segment , 'RFM' : RFM , 'Description':␣
 ↪Description, 'Marketing': Marketing})
rfm_segments
```

[52]:

```
                                  Segment  \
0                      Platinum Customers
1                            Big Spenders
2                 High Spend New Customers
3   Lowest-Spending Active Loyal Customers
4                        Recent Customers
5                Good Customers Almost Lost
6                   Churned Best Customers
7                      Lost Cheap Customers

                                                      RFM  \
0                                              [444, 443]
1  [114, 124, 134, 144, 214, 224, 234, 244, 314, …
2                                    [413, 314, 313, 414]
3                                    [331, 341, 431, 441]
4      [422, 423, 424, 432, 433, 434, 442, 443, 444]
```

```
5                               [244, 234, 243, 233]
6                               [144, 134, 143, 133]
7                [122, 111, 121, 112, 221, 212, 211]

                                         Description  \
0  Customers who bought most recently, most often…
1                     Customers who spend the most
2                 New Customers who spend the most
3  Active Customers who buy very often but spend …
4              Customers who have purchased recently
5  Customers who were frequent and good spenders …
6  Customers who were frequent and good spenders …
7  Customers who purchased long ago , less freque…

                                           Marketing
0  No price incentives, New products and Loyalty …
1                Market your most expensive products
2                                   Price Incentives
3  Promote economical cost effective products in …
4   Discounts and promote a variety of product sells
5                         Aggressive Price Incentives
6  Monitor close communication with customers wit…
7              Dont spend too much time to re-acquire
```

The RFM values can be grouped in several ways:

- 1.Percentiles e.g. quantiles
- 2.Pareto 80/20 cut
- 3.Custom - based on business knowledge

We are going to implement percentile-based grouping.

Process of calculating percentiles:

Sort customers based on that metric Break customers into a pre-defined number of groups of equal size Assign a label to each group

[53]:
```
retail_data.columns
```

[53]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'InvoiceMonth', 'TotalPrice'],
      dtype='object')
```

[54]:
```
retail_data['Total Sum']= retail_data['UnitPrice']*retail_data['Quantity']
```

[55]:
```
# Data Preparation
import datetime as dt
```

```python
print('Min Invoice Date:',retail_data.InvoiceDate.dt.date.min(),'Max Invoice␣
↪Date:',
    retail_data.InvoiceDate.dt.date.max())
retail_data.head()
```

```
Min Invoice Date: 2010-12-01 Max Invoice Date: 2011-11-30
```

[55]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country InvoiceMonth  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom   2010-12-01
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom   2010-12-01
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01

   TotalPrice  Total Sum
0       15.30      15.30
1       20.34      20.34
2       22.00      22.00
3       20.34      20.34
4       20.34      20.34
```

Note :In the real world, we would be working with the most recent snapshot of the data of today or yesterday.

[56]:
```python
retail_data.columns
```

[56]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'InvoiceMonth', 'TotalPrice',
       'Total Sum'],
      dtype='object')
```

[57]:
```python
cohort.columns
```

[57]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'InvoiceMonth', 'TotalPrice',
       'CohortMonth', 'CohortIndex'],
      dtype='object')
```

[58]:
```python
# lets set this date as the today"s date for further analysis
current_date =dt.date(2011,11,30)
```

```
current_date
```

[58]:
```
datetime.date(2011, 11, 30)
```

[59]:
```
# lets create a date column fr date values only
retail_data['Purchase_Date']=retail_data.InvoiceDate.dt.date
retail_data
```

[59]:
```
       InvoiceNo StockCode                         Description  Quantity  \
0         536365    85123A  WHITE HANGING HEART T-LIGHT HOLDER         6
1         536365     71053                 WHITE METAL LANTERN         6
2         536365    84406B      CREAM CUPID HEARTS COAT HANGER         8
3         536365    84029G KNITTED UNION FLAG HOT WATER BOTTLE         6
4         536365    84029E      RED WOOLLY HOTTIE WHITE HEART.         6
…           …        …                                   …       …
516379   C579886     22197                      POPCORN HOLDER        -1
516380   C579886     23146      TRIPLE HOOK ANTIQUE IVORY ROSE        -1
516381   C579887     84946        ANTIQUE SILVER T-LIGHT GLASS        -1
516382   C579887     85048 15CM CHRISTMAS GLASS BALL 20 LIGHTS        -1
516383   C579887     23490     T-LIGHT HOLDER HANGING LOVE BIRD        -3

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2      2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
…                      …          …          …              …
516379 2011-11-30 17:39:00       0.85     15676.0  United Kingdom
516380 2011-11-30 17:39:00       3.29     15676.0  United Kingdom
516381 2011-11-30 17:42:00       1.25     16717.0  United Kingdom
516382 2011-11-30 17:42:00       7.95     16717.0  United Kingdom
516383 2011-11-30 17:42:00       3.75     16717.0  United Kingdom

       InvoiceMonth  TotalPrice  Total Sum Purchase_Date
0        2010-12-01       15.30      15.30    2010-12-01
1        2010-12-01       20.34      20.34    2010-12-01
2        2010-12-01       22.00      22.00    2010-12-01
3        2010-12-01       20.34      20.34    2010-12-01
4        2010-12-01       20.34      20.34    2010-12-01
…             …          …          …            …
516379   2011-11-30       -0.85      -0.85    2011-11-30
516380   2011-11-30       -3.29      -3.29    2011-11-30
516381   2011-11-30       -1.25      -1.25    2011-11-30
516382   2011-11-30       -7.95      -7.95    2011-11-30
516383   2011-11-30      -11.25     -11.25    2011-11-30
```

```
[384222 rows x 12 columns]
```

[60]:
```
snapshot_date = retail_data['InvoiceDate'].max() + dt.timedelta(days=1)
snapshot_date
```

[60]:
```
Timestamp('2011-12-01 17:42:00')
```

Note : The last day of purchase in total is 09 DEC, 2011. To calculate the day periods, * let's set one day after the last one,or * 10 DEC as a snapshot_date. We will cound the diff days with snapshot_date.

17 2.Calculate RFM metrics

Alternatively rfm =cohort.groupby(['CustomerID']).agg({'InvoiceDate':lambda x:(snapshot_date-x.max()).days, 'InvoiceNo':'count','Total Sum':'sum'}) #Function Lambda: it gives the number of days between hypothetical today and the last transaction #Rename columns rfm.rename(columns={'InvoiceDate':'Recency','InvoiceNo':'Frequency','Total Sum':'Monetary Value'} ,inplace= True)

18 Final RFM values

rfm.head()

19 Recency

¶ Recency is about when was the last order of a customer. It means the number of days since a customer made the last purchase. If it's a case for a website or an app, this could be interpreted as the last visit day or the last login time.

[61]:
```
recency =retail_data.groupby('CustomerID')['Purchase_Date'].max().reset_index()
recency
```

[61]:

	CustomerID	Purchase_Date
0	12346.0	2011-01-18
1	12347.0	2011-10-31
2	12348.0	2011-09-25
3	12349.0	2011-11-21
4	12350.0	2011-02-02
…	…	…
4326	18280.0	2011-03-07
4327	18281.0	2011-06-12
4328	18282.0	2011-08-09
4329	18283.0	2011-11-30
4330	18287.0	2011-10-28

```
[4331 rows x 2 columns]
```

[62]:
```
# creating a separate column for this date.
recency = recency.assign(Current_Date =current_date)
recency
```

[62]:
```
      CustomerID Purchase_Date Current_Date
0        12346.0    2011-01-18   2011-11-30
1        12347.0    2011-10-31   2011-11-30
2        12348.0    2011-09-25   2011-11-30
3        12349.0    2011-11-21   2011-11-30
4        12350.0    2011-02-02   2011-11-30
…          …             …            …
4326     18280.0    2011-03-07   2011-11-30
4327     18281.0    2011-06-12   2011-11-30
4328     18282.0    2011-08-09   2011-11-30
4329     18283.0    2011-11-30   2011-11-30
4330     18287.0    2011-10-28   2011-11-30

[4331 rows x 3 columns]
```

[63]:
```
#Compute the Number of days since last purchase
recency['Recency']=recency.Purchase_Date.apply(lambda x:(current_date-x).days)
current_date
```

[63]:
```
datetime.date(2011, 11, 30)
```

[64]:
```
recency.head()
```

[64]:
```
   CustomerID Purchase_Date Current_Date  Recency
0     12346.0    2011-01-18   2011-11-30      316
1     12347.0    2011-10-31   2011-11-30       30
2     12348.0    2011-09-25   2011-11-30       66
3     12349.0    2011-11-21   2011-11-30        9
4     12350.0    2011-02-02   2011-11-30      301
```

[65]:
```
# Drop the irrelevant Date Columns
recency.drop(['Purchase_Date','Current_Date'],axis=1,inplace=True)
recency
```

[65]:
```
      CustomerID  Recency
0        12346.0      316
1        12347.0       30
2        12348.0       66
3        12349.0        9
4        12350.0      301
```

```
…           …        …
4326      18280.0      268
4327      18281.0      171
4328      18282.0      113
4329      18283.0        0
4330      18287.0       33

[4331 rows x 2 columns]
```

20 Frequency

Frequency is about the number of purchase in a given period. It could be 3 months, 6 months or 1 year. So we can understand this value as for how often or how many a customer used the product of a company. The bigger the value is, the more engaged the customers are. Could we say them as our VIP? Not necessary. Cause we also have to think about how much they actually paid for each purchase, which means monetary value.

[66]:
```
retail_data.columns
```

[66]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'InvoiceMonth', 'TotalPrice',
       'Total Sum', 'Purchase_Date'],
      dtype='object')
```

[67]:
```
frequency =retail_data.groupby('CustomerID').InvoiceNo.nunique().reset_index().
 ↪rename(columns={'InvoiceNo':'Frequency'})
frequency.max()
```

[67]:
```
CustomerID    18287.0
Frequency       238.0
dtype: float64
```

21 Monetary

Monetary is the total amount of money a customer spent in that given period. Therefore big spenders will be differentiated with other customers such as MVP or VIP.

[68]:
```
# Create a separate  column for Total Cost Uit Purchased
retail_data['Total_cost']= retail_data.Quantity *retail_data.UnitPrice
retail_data
```

[68]:
```
       InvoiceNo StockCode                          Description  Quantity  \
0         536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1         536365     71053                  WHITE METAL LANTERN         6
```

```
2         536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3         536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4         536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6
…           …         …                                  …     …
516379   C579886     22197                       POPCORN HOLDER        -1
516380   C579886     23146       TRIPLE HOOK ANTIQUE IVORY ROSE        -1
516381   C579887     84946         ANTIQUE SILVER T-LIGHT GLASS        -1
516382   C579887     85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        -1
516383   C579887     23490     T-LIGHT HOLDER HANGING LOVE BIRD        -3

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2      2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
…                      …        …         …             …
516379 2011-11-30 17:39:00       0.85     15676.0  United Kingdom
516380 2011-11-30 17:39:00       3.29     15676.0  United Kingdom
516381 2011-11-30 17:42:00       1.25     16717.0  United Kingdom
516382 2011-11-30 17:42:00       7.95     16717.0  United Kingdom
516383 2011-11-30 17:42:00       3.75     16717.0  United Kingdom

       InvoiceMonth  TotalPrice  Total Sum Purchase_Date  Total_cost
0        2010-12-01       15.30      15.30    2010-12-01       15.30
1        2010-12-01       20.34      20.34    2010-12-01       20.34
2        2010-12-01       22.00      22.00    2010-12-01       22.00
3        2010-12-01       20.34      20.34    2010-12-01       20.34
4        2010-12-01       20.34      20.34    2010-12-01       20.34
…                 …         …        …           …          …
516379   2011-11-30       -0.85      -0.85    2011-11-30       -0.85
516380   2011-11-30       -3.29      -3.29    2011-11-30       -3.29
516381   2011-11-30       -1.25      -1.25    2011-11-30       -1.25
516382   2011-11-30       -7.95      -7.95    2011-11-30       -7.95
516383   2011-11-30      -11.25     -11.25    2011-11-30      -11.25

[384222 rows x 13 columns]
```

[69]:
```python
monetary =retail_data.groupby('CustomerID').Total_cost.sum().reset_index().
 ↪rename(columns={'Total_cost':'Monetary'})
monetary.head()
```

[69]:

	CustomerID	Monetary
0	12346.0	0.00
1	12347.0	4085.18
2	12348.0	1797.24
3	12349.0	1757.55

```
4     12350.0    334.40
```

[70]:
```
# Lets combine all three to form an aggregated RFM Table
rf= recency.merge(frequency,on='CustomerID')
rfm = rf.merge(monetary, on ='CustomerID')
```

[71]:
```
rfm.set_index('CustomerID',inplace=True)
rfm.head()
```

[71]:

CustomerID	Recency	Frequency	Monetary
12346.0	316	2	0.00
12347.0	30	6	4085.18
12348.0	66	4	1797.24
12349.0	9	1	1757.55
12350.0	301	1	334.40

NoteThat : * We will rate "Recency" customer who have been active more recently better than the less recent customer,because each company wants its customers to be recent.

- We will rate "Frequency" and "Monetary Value" higher label because we want Customer to spend more money and visit more often(that is different order than recency).

22 RFM Table integrity Check

Lets Check wheter he RFM table attributes are in conjuction with the original values:

[72]:
```
rfm.index[1]
```

[72]: 12347.0

[73]:
```
# Fetch the records corressponding to the first customer id in above table
retail_data[retail_data.CustomerID== rfm.index[1]]
```

[73]:

	InvoiceNo	StockCode	Description	Quantity \
14938	537626	85116	BLACK CANDELABRA T-LIGHT HOLDER	12
14939	537626	22375	AIRLINE BAG VINTAGE JET SET BROWN	4
14940	537626	71477	COLOUR GLASS. STAR T-LIGHT HOLDER	12
14941	537626	22492	MINI PAINT SET VINTAGE	36
14942	537626	22771	CLEAR DRAWER KNOB ACRYLIC EDWARDIAN	12
…	…	…	…	…
428999	573511	22196	SMALL HEART MEASURING SPOONS	24
429000	573511	22195	LARGE HEART MEASURING SPOONS	24
429001	573511	20719	WOODLAND CHARLOTTE BAG	10
429002	573511	23162	REGENCY TEA STRAINER	8
429003	573511	22131	FOOD CONTAINER SET 3 LOVE HEART	6

```
                InvoiceDate  UnitPrice  CustomerID  Country InvoiceMonth  \
14938   2010-12-07 14:57:00       2.10     12347.0  Iceland   2010-12-07
14939   2010-12-07 14:57:00       4.25     12347.0  Iceland   2010-12-07
14940   2010-12-07 14:57:00       3.25     12347.0  Iceland   2010-12-07
14941   2010-12-07 14:57:00       0.65     12347.0  Iceland   2010-12-07
14942   2010-12-07 14:57:00       1.25     12347.0  Iceland   2010-12-07
…                     …         …           …        …            …
428999 2011-10-31 12:25:00       0.85     12347.0  Iceland   2011-10-31
429000 2011-10-31 12:25:00       1.65     12347.0  Iceland   2011-10-31
429001 2011-10-31 12:25:00       0.85     12347.0  Iceland   2011-10-31
429002 2011-10-31 12:25:00       3.75     12347.0  Iceland   2011-10-31
429003 2011-10-31 12:25:00       1.95     12347.0  Iceland   2011-10-31

        TotalPrice  Total Sum Purchase_Date  Total_cost
14938         25.2       25.2    2010-12-07        25.2
14939         17.0       17.0    2010-12-07        17.0
14940         39.0       39.0    2010-12-07        39.0
14941         23.4       23.4    2010-12-07        23.4
14942         15.0       15.0    2010-12-07        15.0
…                …          …             …           …
428999        20.4       20.4    2011-10-31        20.4
429000        39.6       39.6    2011-10-31        39.6
429001         8.5        8.5    2011-10-31         8.5
429002        30.0       30.0    2011-10-31        30.0
429003        11.7       11.7    2011-10-31        11.7

[171 rows x 13 columns]
```

Check if the number difference of days from the purchase date in original record is same as shown in rfm dataset

[74]:
```
(current_date-retail_data[retail_data.CustomerID==rfm.index[0]].iloc[0].
 ↪Purchase_Date).days==rfm.iloc[0,0]
```

[74]:
```
True
```

23 Customer segments with RFM Model

The simplest way to create customers segments from RFM Model is to use Quantiles. We assign a score from 1 to 4 to Recency, Frequency and Monetary. Four is the best/highest value, and one is the lowest/worst value. A final RFM score is calculated simply by combining individual RFM score numbers.

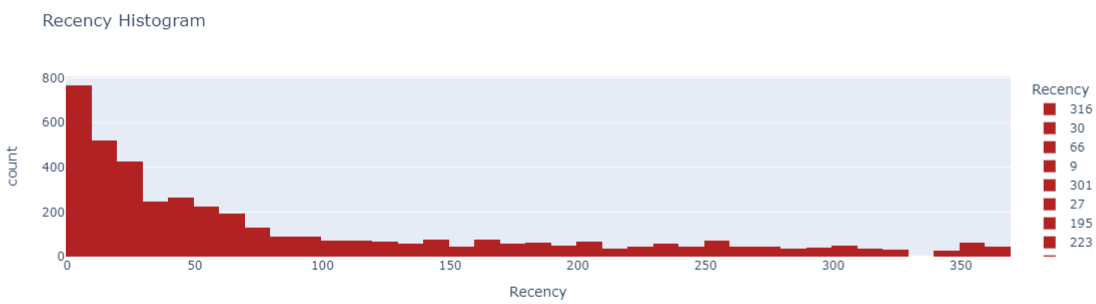
[75]:
```
# RFM Quantiles
quantile =rfm.quantile(q=[0.25,0.5,0.75])
quantile
```

[75]:
```
      Recency  Frequency  Monetary
0.25     15.0        1.0   288.755
0.50     48.0        3.0   628.780
0.75    144.0        5.0  1545.905
```

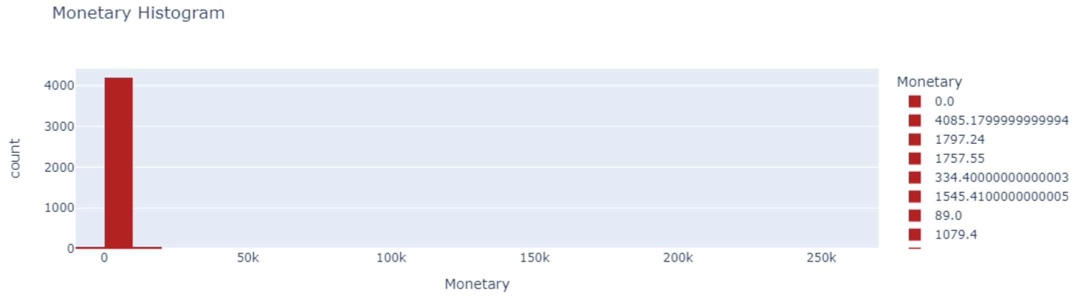
[76]:
```
# lets convert quartile information into a dictionary so that cutoff can be␣
↪picked up.
quantile=quantile.to_dict()
quantile
rfm
```

[76]:
```
            Recency  Frequency  Monetary
CustomerID
12346.0         316          2      0.00
12347.0          30          6   4085.18
12348.0          66          4   1797.24
12349.0           9          1   1757.55
12350.0         301          1    334.40
…              …        …        …
18280.0         268          1    180.60
18281.0         171          1     80.82
18282.0         113          2     98.76
18283.0           0         15   1837.53
18287.0          33          3   1837.28

[4331 rows x 3 columns]
```

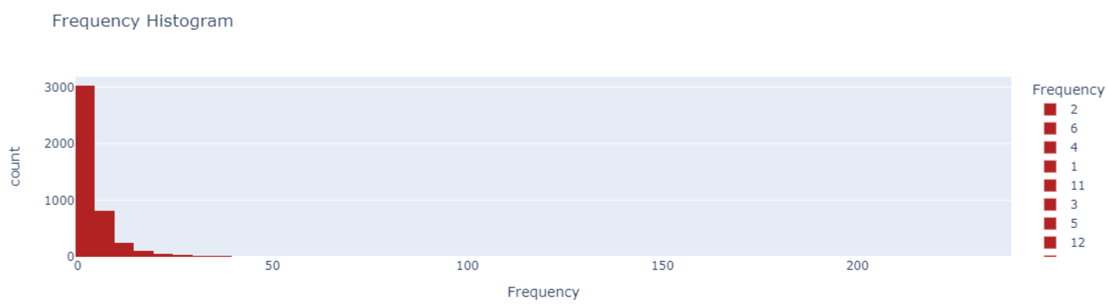
[77]:
```
# Let us visualize the histogram charts for Recency Frequency and Monetary
import plotly.express as px

fig = px.histogram(rfm, x="Recency", nbins=50, color="Recency", title="Recency␣
↪Histogram")
fig.update_traces(marker=dict(color='firebrick'))
fig.update_xaxes(title="Recency")
fig.show()
```



[78]:
```
import plotly.express as px

fig = px.histogram(rfm, x="Monetary", nbins=50, color="Monetary",␣
 ↪title="Monetary Histogram")
fig.update_traces(marker=dict(color='firebrick'))
fig.update_xaxes(title="Monetary")
fig.show()
```



[79]:
```
import plotly.express as px

fig = px.histogram(rfm, x="Frequency", nbins=50, color="Frequency",␣
 ↪title="Frequency Histogram")
fig.update_traces(marker=dict(color='firebrick'))
fig.update_xaxes(title="Frequency")
fig.show()
```



Interpretation : Hence from the graph we can observe that highest recency (recently purchase around) is 3, monetary is 786 around 1 count and frequnecy 3 around 488.

24 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.

For analysis it is critical to combine the scores to create a single score. There are few approaches. One approach is to just concatenate the scores to create a 3 digit number between 111 and 444. Here the drawback is too many categories (4x4x4).

[80]:
```
# Arguments (x = value, p = recency, monetary_value, frequency, d = quantiles␣
↪dict)
def RScore(x,p,d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1
# Arguments (x = value, p = recency, monetary_value, frequency, k = quantiles␣
↪dict)
def FMScore(x,p,d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.50]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4
rfm_segment = rfm.copy()
rfm_segment['R_Quartile'] = rfm_segment['Recency'].apply(RScore,␣
↪args=('Recency',quantile,))
rfm_segment['F_Quartile'] = rfm_segment['Frequency'].apply(FMScore,␣
↪args=('Frequency',quantile,))
rfm_segment['M_Quartile'] = rfm_segment['Monetary'].apply(FMScore,␣
↪args=('Monetary',quantile,))
```

[81]:
```
rfm_segment.head()
```

[81]:
```
            Recency  Frequency  Monetary  R_Quartile  F_Quartile  M_Quartile
CustomerID
12346.0         316          2      0.00           1           2           1
12347.0          30          6   4085.18           3           4           4
```

```
12348.0           66          4   1797.24           2            3            4
12349.0            9          1   1757.55           4            1            4
12350.0          301          1    334.40           1            1            2
```

[82]:
```
rfm_segment[rfm_segment.Monetary==rfm_segment.Monetary.max()]
rfm_segment
```

[82]:
```
            Recency  Frequency  Monetary  R_Quartile  F_Quartile  M_Quartile
CustomerID
12346.0         316          2      0.00           1           2           1
12347.0          30          6   4085.18           3           4           4
12348.0          66          4   1797.24           2           3           4
12349.0           9          1   1757.55           4           1           4
12350.0         301          1    334.40           1           1           2
…             …       …       …        …           …           …
18280.0         268          1    180.60           1           1           1
18281.0         171          1     80.82           1           1           1
18282.0         113          2     98.76           2           2           1
18283.0           0         15   1837.53           4           4           4
18287.0          33          3   1837.28           3           2           4

[4331 rows x 6 columns]
```

Interpretation : 4331 rows has monetry range as maximum.

Note : for analysis it is critical to combine the scores to create a single score. there are few apporoches. * one is to just concatenate the score to create 3 digit number between 111 and 444. * second take the mean of recancy, frequency and monetary and define the ratings range accordingly using pd.qcut which is use to determine discrete values based on quantile.

here, i will be using 1st method but the drawback is many categries will be there (4x4x4)

25 B1. Combine three ratings to get a RFM segment (as strings)

[83]:
```
rfm_segment['RFMScore'] =rfm_segment.R_Quartile.map(str)\
+rfm_segment.F_Quartile.map(str)\
+ rfm_segment.M_Quartile.map(str)
rfm_segment.head()
```

[83]:
```
            Recency  Frequency  Monetary  R_Quartile  F_Quartile  M_Quartile  \
CustomerID
12346.0         316          2      0.00           1           2           1
12347.0          30          6   4085.18           3           4           4
12348.0          66          4   1797.24           2           3           4
12349.0           9          1   1757.55           4           1           4
12350.0         301          1    334.40           1           1           2
```

```
            RFMScore
CustomerID
12346.0          121
12347.0          344
12348.0          234
12349.0          414
12350.0          112
```

Interpretation : henece we combined the recency quartile, frequence quartile and monetary quartile and name the new column RFMScore.

1.Best Recency score = 4 (most recently purchase)

2.Best Frequency score = 4 (most frequently purchase)

3.Best Monetary score = 4 (who spent the most)

26 RFM Segment Allocation.

Lets define the customer segment best to our Knowledge basis RFM score and assign them to each customer respectively.

[84]:
```
# Reset the index to create a customer_ID column
rfm_segment.reset_index(inplace=True)
```

[85]:
```
import itertools
```

[86]:
```
# Highest frequency as well as monetary value with least recencycy
platinium_customers =['444','443']
print("Platinium Customers:{}".format(platinium_customers))
# Get all combinations of [1,2,3,4] and length 2
big_spenders_combination =itertools.product([1,2,3,4],repeat=2)
#Print the obtained Combinations
big_spenders=[]
for i in list(big_spenders_combination):
    item =(list(i))
    item.append(4)
    big_spenders.append(("".join(map(str,item))))
print("Big Spenders:{}".format(big_spenders))
#High Spending New Customers-This group consists of those customers in 1-4-1␣
 ↪and 1-4-2.
#These are customers who transacted only once,but very recently and  they spent␣
 ↪a lot
high_spend_new_customers =['413','314','313','414']
print("High Spend New Customers:{}".format(high_spend_new_customers))
print("High Spend New Customers:{}".format(high_spend_new_customers))
```

```
lowest_spending_active_loyal_customers_comb= itertools.product([3,4],repeat=2)
lowest_spending_active_loyal_customers =[]
for i in list (lowest_spending_active_loyal_customers_comb):
    item=(list(i))
    item.append(1)
    lowest_spending_active_loyal_customers.append(("".join(map(str,item))))
print ("Lowest Spending Active Loyal Customers : {}".
 ↪format(lowest_spending_active_loyal_customers))

recent_customers_comb =  itertools.product([ 2,3,4], repeat = 2)
recent_customers = []
for i in list(recent_customers_comb):
    item = (list(i))
    item.insert(0,4)
    recent_customers.append( ("".join(map(str,item))))
print ("Recent Customers: {}".format(recent_customers))




almost_lost = ['244', '234', '243', '233']        #  Low R - Customer's␣
 ↪shopping less often now who used to shop a lot
print ("Good Customers Almost Lost: {}".format(almost_lost))

churned_best_customers = ['144', '134' ,'143','133']
print ("Churned Best Customers: {}".format(churned_best_customers))


lost_cheap_customers = ['122','111' ,'121','112','221','212' ,'211'] #␣
 ↪Customer's shopped long ago but with less frequency and monetary value
print ("Lost Cheap Customers: {}".format(lost_cheap_customers))
```

```
Platinium Customers:['444', '443']
Big Spenders:['114', '124', '134', '144', '214', '224', '234', '244', '314',
'324', '334', '344', '414', '424', '434', '444']
High Spend New Customers:['413', '314', '313', '414']
High Spend New Customers:['413', '314', '313', '414']
Lowest Spending Active Loyal Customers : ['331', '341', '431', '441']
Recent Customers: ['422', '423', '424', '432', '433', '434', '442', '443',
'444']
Good Customers Almost Lost: ['244', '234', '243', '233']
Churned Best Customers: ['144', '134', '143', '133']
Lost Cheap Customers: ['122', '111', '121', '112', '221', '212', '211']
```

[87]:
```
# Create a dictionary for each segment to map them against each customer
segment_dict = {
    'Platinum Customers':platinium_customers,
```

```
    'Big Spenders':      big_spenders,
    'High Spend New Customers':high_spend_new_customers,
    'Lowest-Spending Active Loyal Customers' :␣
↪lowest_spending_active_loyal_customers ,
    'Recent Customers': recent_customers,
    'Good Customers Almost Lost':almost_lost,
    'Churned Best Customers':   churned_best_customers,
    'Lost Cheap Customers ': lost_cheap_customers,
}
```

[88]:
```
# Allocate  segment to each customer as per the RFM score mapping
def find_key(value):
    for k,v in segment_dict.items():
        if value in v:
            return k
rfm_segment['Segment'] = rfm_segment.RFMScore.map(find_key)

# Allocate all remaining customers to others segment category
rfm_segment.Segment.fillna('others', inplace=True)
rfm_segment.sample(10)
```

[88]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
2133     15258.0      159          2    623.16           1           2
2505     15758.0       15          1    205.25           4           1
3231     16763.0      176          2    594.90           1           2
888      13534.0       23         42   5255.88           3           4
3443     17053.0      119          2    496.38           2           2
2957     16384.0       80          2    584.50           2           2
1431     14298.0       21         43  50889.70           3           4
2378     15594.0        6          6   1767.53           4           4
3854     17631.0      128          2    416.50           2           2
1963     15042.0      190          1    135.93           1           1

      M_Quartile RFMScore               Segment
2133           2      122  Lost Cheap Customers
2505           1      411                others
3231           2      122  Lost Cheap Customers
888            4      344          Big Spenders
3443           2      222                others
2957           2      222                others
1431           4      344          Big Spenders
2378           4      444     Platinum Customers
3854           2      222                others
1963           1      111  Lost Cheap Customers
```

Interpretation : each rows based on the data has been segregated into quantile r,f,m and srting segments

Let's visualize different customer segments records in general to answers these questions for the retail business. Who are my best customers? Who are the biggest spenders? Which customers are at the verge of churning? Who are lost customers that you don't need to pay much attention to? Who are your loyal customers? Which customers you must retain? Who has the potential to be converted in more profitable customers? Which group of customers is most likely to respond to your current campaign?

[89]:
```
# Best Customers who's recency, frequency as well as monetary attribute is␣
↪highest.
rfm_segment[rfm_segment.RFMScore=='444'].sort_values('Monetary',␣
↪ascending=False).head()
```

[89]:
```
      CustomerID  Recency  Frequency   Monetary  R_Quartile  F_Quartile  \
1685     14646.0        7         74  267761.00           4           4
4193     18102.0        2         59  244952.95           4           4
3722     17450.0        1         54  185759.77           4           4
1876     14911.0        0        238  125482.36           4           4
54       12415.0       15         26  123725.45           4           4

      M_Quartile RFMScore             Segment
1685           4      444  Platinum Customers
4193           4      444  Platinum Customers
3722           4      444  Platinum Customers
1876           4      444  Platinum Customers
54             4      444  Platinum Customers
```

[90]:
```
# Biggest spenders
rfm_segment[rfm_segment.RFMScore=='334'].sort_values('Monetary',␣
↪ascending=False).head()
```

[90]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
2765     16126.0       20          4   6287.77           3           3
12       12359.0       48          5   6274.23           3           3
727      13316.0       28          5   5570.69           3           3
2894     16303.0       16          4   5305.83           3           3
2868     16258.0       36          5   5203.51           3           3

      M_Quartile RFMScore       Segment
2765           4      334  Big Spenders
12             4      334  Big Spenders
727            4      334  Big Spenders
2894           4      334  Big Spenders
2868           4      334  Big Spenders
```

[91]:
```
# customers that you must retain are those whose monetary and frequency was␣
↪high but recency reduced quite a lot recently
```

```
rfm_segment[rfm_segment.RFMScore=='244'].sort_values('Monetary',␣
↪ascending=False).head()
```

[91]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
457      12939.0       55          8  11581.80           2           4
49       12409.0       69          7  11056.93           2           4
2807     16180.0       91         10  10217.48           2           4
1776     14769.0       68          9  10041.86           2           4
3215     16745.0       77         18   7157.10           2           4

      M_Quartile RFMScore      Segment
457            4      244  Big Spenders
49             4      244  Big Spenders
2807           4      244  Big Spenders
1776           4      244  Big Spenders
3215           4      244  Big Spenders
```

[92]:
```
rfm_segment.to_excel('RFM Segment.xlsx')
```

[93]:
```
rfm_segment.Segment.value_counts()
rfm_segment.Recency
```

[93]:
```
0       316
1        30
2        66
3         9
4       301
       …
4326    268
4327    171
4328    113
4329      0
4330     33
Name: Recency, Length: 4331, dtype: int64
```

27 Summary metrics per RFM Score

[94]:
```
rfm.columns
```

[94]:
```
Index(['Recency', 'Frequency', 'Monetary'], dtype='object')
```

[95]:
```
rfm_rfm = rfm[['Recency','Frequency','Monetary']]
print(rfm_rfm.describe())
```

```
           Recency     Frequency       Monetary
```

```
count  4331.000000  4331.000000    4331.000000
mean     90.277303     4.910875    1832.597551
std      99.389069     9.025901    7944.283177
min       0.000000     1.000000   -4287.630000
25%      15.000000     1.000000     288.755000
50%      48.000000     3.000000     628.780000
75%     144.000000     5.000000    1545.905000
max     364.000000   238.000000  267761.000000
```

28 Project Task-3

1. Create clusters using k-means clustering algorithm.

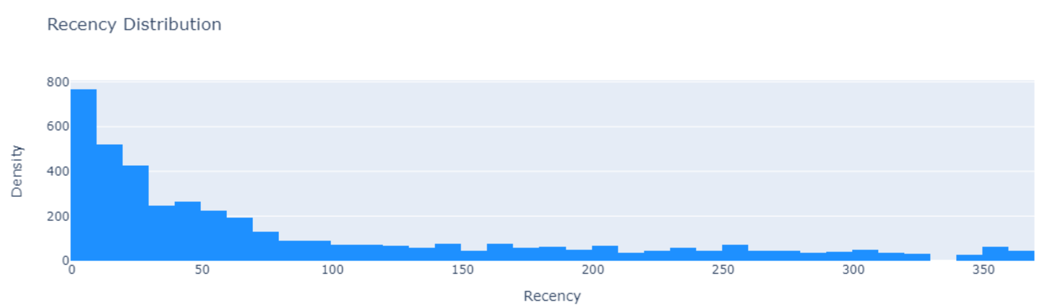
- a. Prepare the data for the algorithm. If the data is asymmetrically distributed, manage the skewness with appropriate transformation. Standardize the data.
- b. Decide the optimum number of clusters to be formed.
- c. Analyze these clusters and comment on the results.

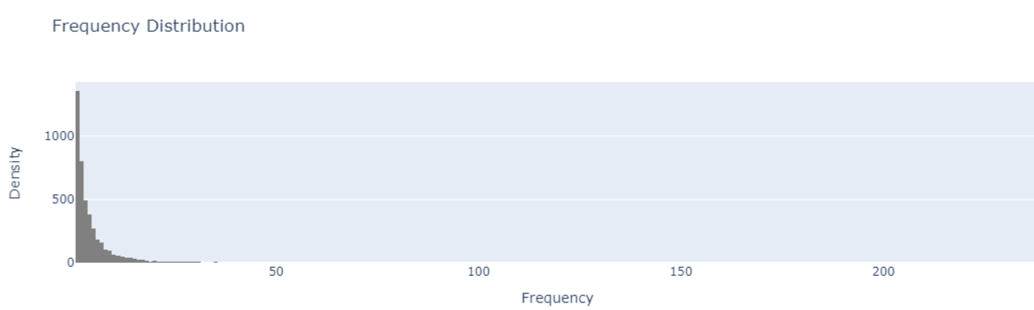
29 1. Create clusters using k-means clustering algorithm.

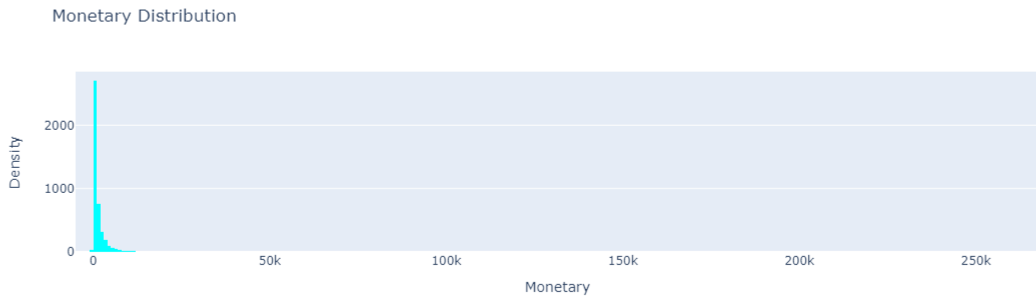
30 a. Prepare the data for the algorithm. If the data is asymmetrically distributed, manage the skewness with appropriate transformation. Standardize the data.

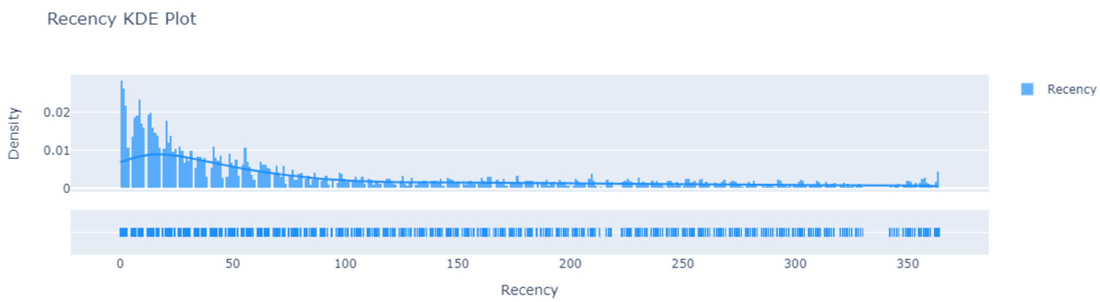
[96]:
```python
import plotly.express as px
import plotly.figure_factory as ff

# Histograms
histogram_recency = px.histogram(rfm, x="Recency", title="Recency Distribution", color_discrete_sequence=["dodgerblue"])
histogram_recency.update_xaxes(title_text="Recency")
histogram_recency.update_yaxes(title_text="Density")

histogram_frequency = px.histogram(rfm, x="Frequency", title="Frequency Distribution", color_discrete_sequence=["grey"])
histogram_frequency.update_xaxes(title_text="Frequency")
histogram_frequency.update_yaxes(title_text="Density")

histogram_monetary = px.histogram(rfm, x="Monetary", title="Monetary Distribution", color_discrete_sequence=["cyan"])
histogram_monetary.update_xaxes(title_text="Monetary")
histogram_monetary.update_yaxes(title_text="Density")
```

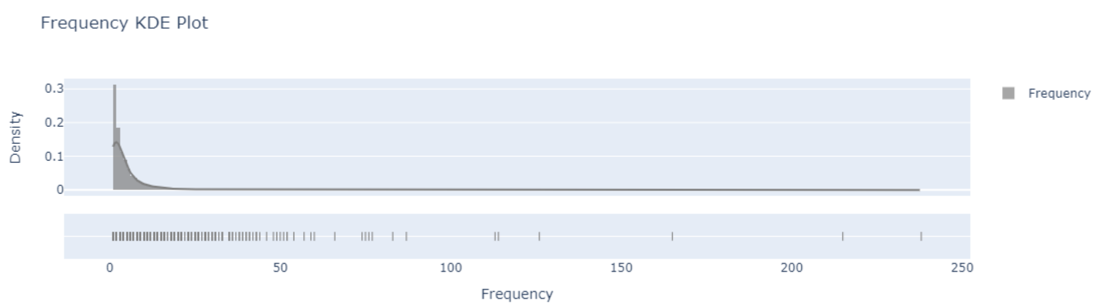
```
# KDE Plots
kde_recency = ff.create_distplot([rfm["Recency"]], group_labels=["Recency"], colors=["dodgerblue"])
kde_recency.update_layout(title="Recency KDE Plot", xaxis_title="Recency", yaxis_title="Density")

kde_frequency = ff.create_distplot([rfm["Frequency"]], group_labels=["Frequency"], colors=["grey"])
kde_frequency.update_layout(title="Frequency KDE Plot", xaxis_title="Frequency", yaxis_title="Density")

kde_monetary = ff.create_distplot([rfm["Monetary"]], group_labels=["Monetary"], colors=["cyan"])
kde_monetary.update_layout(title="Monetary KDE Plot", xaxis_title="Monetary", yaxis_title="Density")

# Show the plots
histogram_recency.show()
histogram_frequency.show()
histogram_monetary.show()
kde_recency.show()
kde_frequency.show()
kde_monetary.show()
```

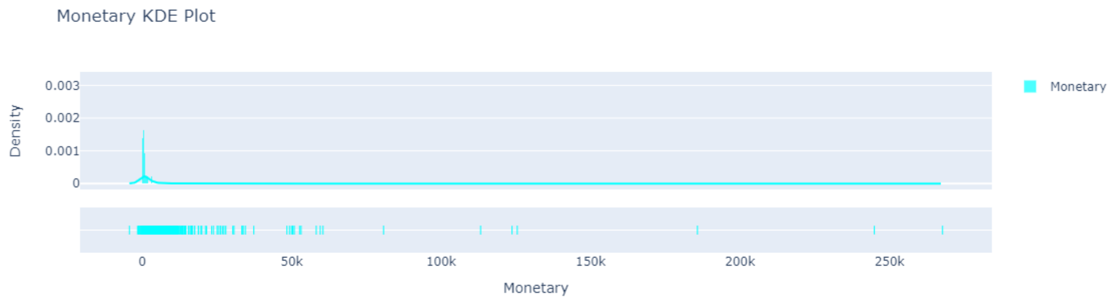





Monetary Distribution
Density
2000
1000
0
0
50k
100k
150k
200k
250k
Monetary


Recency KDE Plot
Density
0.02
0.01
0
Recency
0
50
100
150
200
250
300
350
Recency


Frequency KDE Plot
Density
0.3
0.2
0.1
0
Frequency
0
50
100
150
200
250
Frequency



Interpretation : Here we obsevered the data is highly skewed so we have to transform and scale the data first because K-Means assumes that the variables should have a symmetric distribution (not skewed) and they should have same average values as well as same variance.

[97]:
```
# Let's describe the table to see if there are any negative values
rfm.describe()
```

[97]:

	Recency	Frequency	Monetary
count	4331.000000	4331.000000	4331.000000
mean	90.277303	4.910875	1832.597551
std	99.389069	9.025901	7944.283177
min	0.000000	1.000000	-4287.630000
25%	15.000000	1.000000	288.755000
50%	48.000000	3.000000	628.780000
75%	144.000000	5.000000	1545.905000
max	364.000000	238.000000	267761.000000

$ Interpretation:$ We can observe that Monetary contains negative values. So first we need to make sure that minimum range of value starts from 1 otherwise log transformation may lead to errors in graph plotting as well as K-Means clustering. After that we will utilize log transformation and scaling to make data available for for K-Means clustering.

[98]:
```
# create a copy of rfm
rfm_scaled =rfm.copy()
# shift all the values in the column by adding absolute of minimum value to␣
↪each value, thereby making each value positive
rfm_scaled.Monetary =rfm_scaled.Monetary + abs(rfm_scaled.Monetary.min()) +1
rfm_scaled.Recency =rfm_scaled.Recency + abs(rfm_scaled.Recency.min())+1

# check the summary of the new values
rfm_scaled.describe()
```

[98]:

	Recency	Frequency	Monetary
count	4331.000000	4331.000000	4331.000000
mean	91.277303	4.910875	6121.227551

```
std      99.389069    9.025901    7944.283177
min       1.000000    1.000000       1.000000
25%      16.000000    1.000000    4577.385000
50%      49.000000    3.000000    4917.410000
75%     145.000000    5.000000    5834.535000
max     365.000000  238.000000  272049.630000
```

Interpretation : Hence we can observe that the minimum value converted to 1.

[99]:
```
# Transform the data before K-Means Clustering
from sklearn.preprocessing import StandardScaler
# Taking log first because normalization forces data for negative values
log_df =np.log(rfm_scaled)
# Normalize the data for uniform averages and means in the distributions.
scaler =StandardScaler()
normal_df =scaler.fit_transform(log_df)
normal_df =pd.DataFrame(data=normal_df,index=rfm.index,columns=rfm.columns)
```

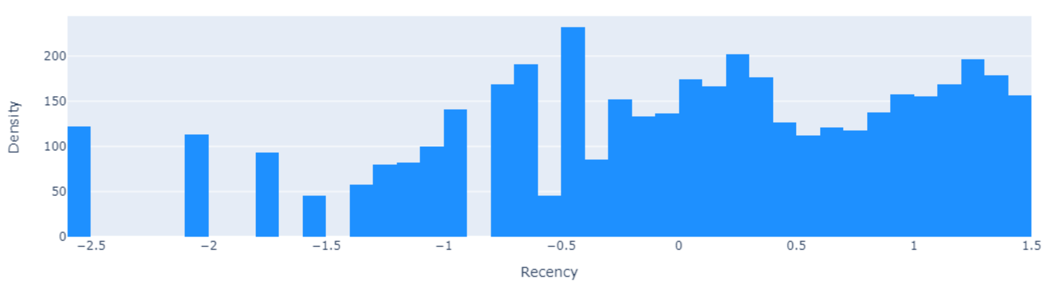
[100]:
```
normal_df
```

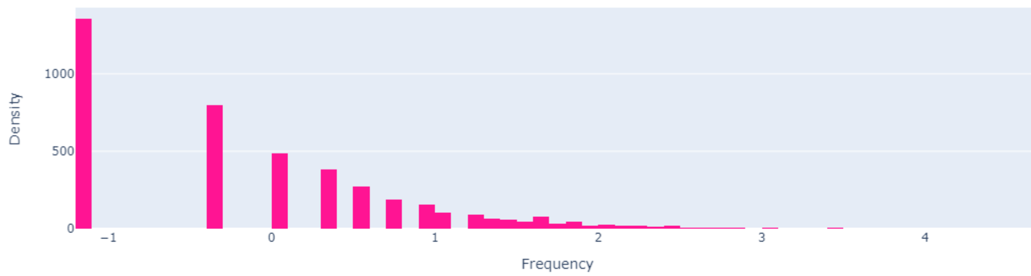
[100]:
```
             Recency  Frequency  Monetary
CustomerID
12346.0     1.386976  -0.369465 -0.687546
12347.0    -0.198501   0.790665  1.180610
12348.0     0.327082   0.362496  0.289615
12349.0    -0.970062  -1.101426  0.271348
12350.0     1.353919  -1.101426 -0.477924
…                …          …         …
18280.0     1.275007  -1.101426 -0.572384
18281.0     0.970027  -1.101426 -0.635422
18282.0     0.689543  -0.369465 -0.623983
18283.0    -2.540311   1.758265  0.308037
18287.0    -0.135507   0.058705  0.307923

[4331 rows x 3 columns]
```

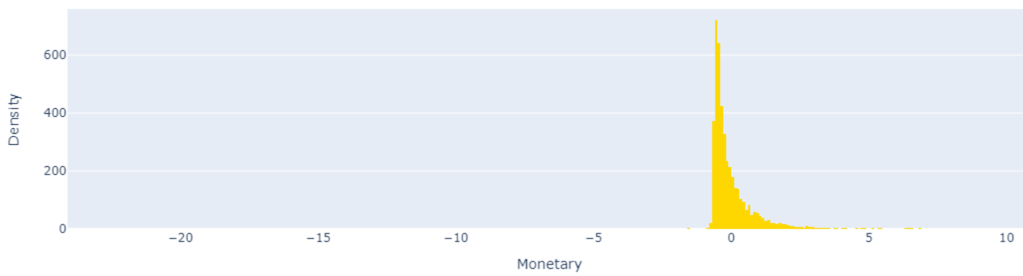
Visualize the data after applying lograthmic transformation on the scaled data. observe that the skewness is reduced.

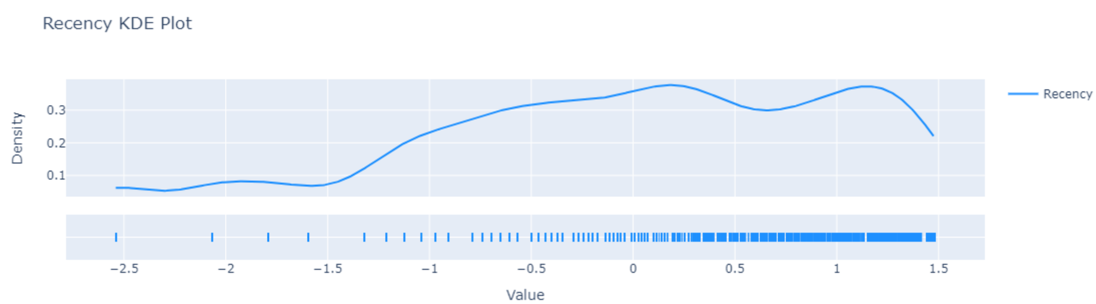
[101]:
```
import plotly.express as px
import plotly.figure_factory as ff

# Create histograms
fig1 = px.histogram(normal_df, x="Recency",␣
 ↪color_discrete_sequence=["dodgerblue"])
fig1.update_xaxes(title_text="Recency")
fig1.update_yaxes(title_text="Density")
```

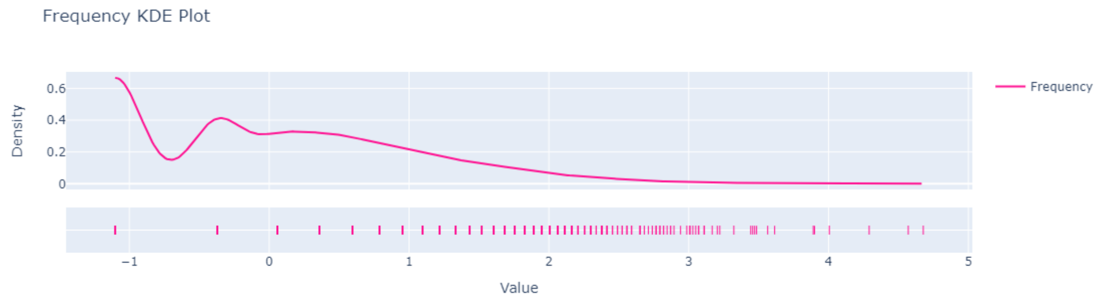
```
fig2 = px.histogram(normal_df, x="Frequency",␣
↪color_discrete_sequence=["deeppink"])
fig2.update_xaxes(title_text="Frequency")
fig2.update_yaxes(title_text="Density")

fig3 = px.histogram(normal_df, x="Monetary", color_discrete_sequence=["gold"])
fig3.update_xaxes(title_text="Monetary")
fig3.update_yaxes(title_text="Density")

# Create KDE plots
kde_fig1 = ff.create_distplot([normal_df["Recency"]], ["Recency"],␣
↪colors=["dodgerblue"], show_hist=False)
kde_fig1.update_layout(title="Recency KDE Plot", xaxis_title="Value",␣
↪yaxis_title="Density")

kde_fig2 = ff.create_distplot([normal_df["Frequency"]], ["Frequency"],␣
↪colors=["deeppink"], show_hist=False)
kde_fig2.update_layout(title="Frequency KDE Plot", xaxis_title="Value",␣
↪yaxis_title="Density")

kde_fig3 = ff.create_distplot([normal_df["Monetary"]], ["Monetary"],␣
↪colors=["gold"], show_hist=False)
kde_fig3.update_layout(title="Monetary KDE Plot", xaxis_title="Value",␣
↪yaxis_title="Density")

# Show the plots
fig1.show()
fig2.show()
fig3.show()
kde_fig1.show()
kde_fig2.show()
kde_fig3.show()
```

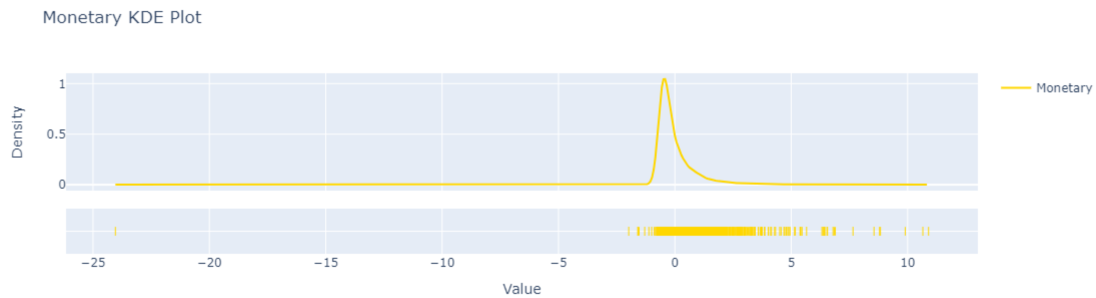



Density
1000
500
0
−1
0
1
2
3
4
Frequency


Density
600
400
200
0
−20
−15
−10
−5
0
5
10
Monetary


Recency KDE Plot
Density
0.3
0.2
0.1
Recency
−2.5
−2
−1.5
−1
−0.5
0
0.5
1
1.5
Value





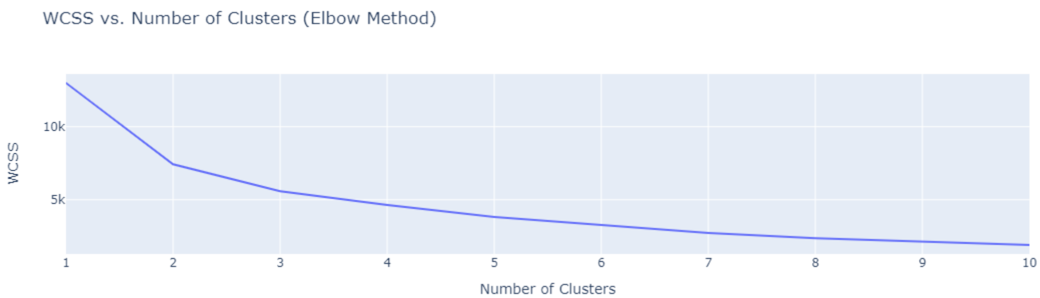
Interpretation : we can observe that the means and averages are approximately uniformed now in each distribution. Now the data is apt for unsupervised algorithm i.e. K-Means.Lets try to find number of appropriate clusters to divide customers as per there spending pattern with elbow method first.

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

32 b.1. WCSS-Within Cluster Sum of Squares(WCSS).

[102]:
```
import plotly.express as px
from sklearn.cluster import KMeans

wcss = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++')
    kmeans.fit(normal_df)
    wcss.append(kmeans.inertia_)
```

```
fig = px.line(x=range(1, 11), y=wcss, title="WCSS vs. Number of Clusters (Elbow␣
↪Method)")
fig.update_traces(marker=dict(symbol="circle", size=10))
fig.update_layout(
    xaxis_title="Number of Clusters",
    yaxis_title="WCSS",
    showlegend=False
)
fig.show()
```



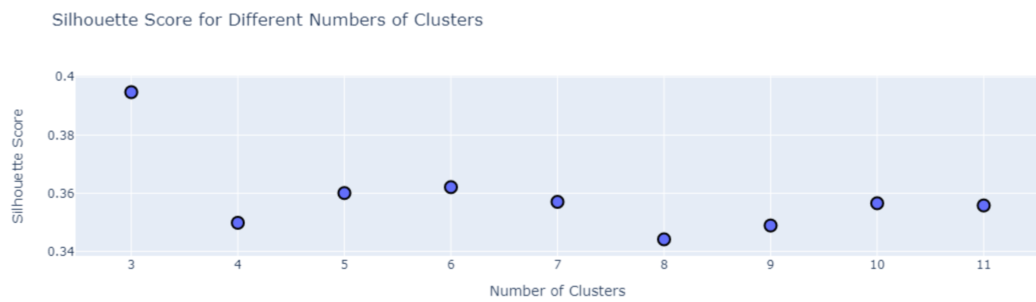
[103]:
```
ElbowPlot =pd.DataFrame({'Cluster':range(1,11),'SSE':wcss})
ElbowPlot.to_excel('Elbow Plot Data.xlsx')
```

33 b2.Silhouette Score

[104]:
```
from sklearn.metrics import silhouette_score
wcss_silhouette=[]
for i in range(3,12):
    km=KMeans(n_clusters =i, random_state =0,init ='k-means++').fit(normal_df)
    preds= km.predict(normal_df)
    silhouette= silhouette_score(normal_df,preds)
    wcss_silhouette.append(silhouette)
print("Silhouette score for number of cluster(s){}:{}".format(i,silhouette))

df = pd.DataFrame({"Number of Clusters": range(3, 12), "Silhouette Score":␣
↪wcss_silhouette})

fig = px.scatter(df, x="Number of Clusters", y="Silhouette Score",␣
↪title="Silhouette Score for Different Numbers of Clusters")
fig.update_traces(marker=dict(size=12, line=dict(width=2, color='Black')))
fig.update_layout(
    xaxis_title="Number of Clusters",
```

```
    yaxis_title="Silhouette Score",
    showlegend=False,
)
fig.show()
```

```
Silhouette score for number of cluster(s)11:0.3557950595147287
```



Interpretation : Here we can clearly see that optimum number of cluster should be 4 not 2 or 3.Because that is the only point after which the mean cluster distance looks to be plateaued after a steep downfall. So we will assume the 4 number of clusters as best for grouping of customer segments.

Now let's apply K-Means on 4 clusters to segregate the customer base.

[105]:
```
kmeans= KMeans(n_clusters=4,random_state =1,init='k-means++')
kmeans.fit(normal_df)
cluster_labels =kmeans.labels_
kmeans
```

[105]:
```
KMeans(n_clusters=4, random_state=1)
```

[106]:
```
print(f"Shape of cluster label array is {cluster_labels.shape}")
print(f"Shape of RFM segment dataframe is{rfm_segment.shape}")
```

```
Shape of cluster label array is (4331,)
Shape of RFM segment dataframe is(4331, 9)
```

34 c. Analyze these clusters and comment on the results.

[107]:
```
# Assign the Clusters as column to each customer
Cluster_table =rfm_segment.assign(Cluster =cluster_labels)
```

[108]:
```python
# Check counts of records assigned to different clusters
Cluster_table.Cluster.value_counts()
```

[108]:
```
2    1941
3    1187
0    1013
1     190
Name: Cluster, dtype: int64
```

Interpretation : Here we see that most of the customers belong to 0,2 and 3 cluster, wheras very less number of customers assigned to 1 cluster, may be possible that those are some of the best customers out of the pool or worst customers,lets checkout the pattern.

[109]:
```python
Cluster_table.sample(10)
```

[109]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
3345     16917.0      267          1    391.52           1           1
4088     17951.0       30          4    990.84           3           3
3098     16584.0       71          3    908.03           2           2
260      12668.0        2          5   3772.35           4           3
4174     18077.0       24         10   2329.07           3           4
3277     16823.0      218          1    358.38           1           1
2587     15867.0       13         14   3524.56           4           4
3609     17298.0       92          2    498.42           2           2
914      13576.0        1         20   6703.30           4           4
2707     16049.0       31          3   1074.81           3           2

      M_Quartile RFMScore               Segment  Cluster
3345           2      112  Lost Cheap Customers        2
4088           3      333                others        0
3098           3      223                others        2
260            4      434           Big Spenders        3
4174           4      344           Big Spenders        3
3277           2      112  Lost Cheap Customers        2
2587           4      444     Platinum Customers        3
3609           2      222                others        2
914            4      444     Platinum Customers        1
2707           3      323                others        0
```

[110]:
```python
print ("Platinum customers belong to cluster  : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Platinum␣
 ↪Customers']['Cluster'].unique()))
print ("Big Spenders belong to cluster  : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Big Spenders']['Cluster'].
 ↪unique()))
```

```
print ("High Spend new Customers belong to cluster  : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='High Spend New␣
 ↪Customers']['Cluster'].unique()))
print ("Lowest-Spending Active Loyal Customers belong to cluster: {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Lowest-Spending Active Loyal␣
 ↪Customers']['Cluster'].unique()))
print ("Recent Customers belong to cluster  : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Recent␣
 ↪Customers']['Cluster'].unique()))
print ("Good Customers Almost Lost belong to cluster : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Good Customers Almost␣
 ↪Lost']['Cluster'].unique()))
print ("Churned Best Customers belong to cluster : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Churned Best␣
 ↪Customers']['Cluster'].unique()))
print ("Lost Cheap customers belong to cluster  : {} ".
 ↪format(Cluster_table[Cluster_table['Segment']=='Lost Cheap Customers␣
 ↪']['Cluster'].unique()))
```

```
Platinum customers belong to cluster  : [3 1]
Big Spenders belong to cluster  : [3 0 2 1]
High Spend new Customers belong to cluster  : [0 2]
Lowest-Spending Active Loyal Customers belong to cluster: [0 3]
Recent Customers belong to cluster  : [0 3]
Good Customers Almost Lost belong to cluster : [2 3 0]
Churned Best Customers belong to cluster : [2 3]
Lost Cheap customers belong to cluster  : [2 0]
```

Interpretation : Here we can observe that RFM score is very low for customers in 0 & 3 cluster. Comparetivey, customers in 1&2 clusters have high RFM scores along with above average Recency and frequency values.

Let's checkout customers in each cluster more closely

[111]:
```
Cluster_table[Cluster_table.Cluster==3].sample(5)
```

[111]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile	\
3905	17696.0	29	14	2201.05	3	4	
387	12840.0	134	6	2714.27	2	4	
2660	15984.0	62	8	2050.71	2	4	
2652	15974.0	30	8	3429.55	3	4	
2334	15532.0	16	6	1500.88	3	4	

	M_Quartile	RFMScore	Segment	Cluster
3905	4	344	Big Spenders	3
387	4	244	Big Spenders	3
2660	4	244	Big Spenders	3
2652	4	344	Big Spenders	3

```
2334             3      343         others        3
```

Interpretation : Here it can be seen that the RFM score for Cluster 3 customers with low recency,good frequency and high monetary value.These are the loyal customers to the firm.

[112]:
```
Cluster_table[Cluster_table.Cluster==2].sample(5)
```

[112]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile	\
1330	14155.0	257	1	118.75	1	1	
584	13120.0	229	1	30.60	1	1	
2752	16112.0	134	4	195.74	2	3	
3009	16451.0	78	1	266.97	2	1	
865	13507.0	89	3	2022.79	2	2	

	M_Quartile	RFMScore	Segment	Cluster
1330	1	111	Lost Cheap Customers	2
584	1	111	Lost Cheap Customers	2
2752	1	231	others	2
3009	1	211	Lost Cheap Customers	2
865	4	224	Big Spenders	2

Interpretation : Cluster 2 contains the highest number of customers who accounts for lowest value to the firm because there RFM values are lowest. Most of them are in the lost segment or on the verge of churning out.

[113]:
```
Cluster_table[Cluster_table.Cluster==1].sample(5)
```

[113]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile	\
1110	13854.0	15	28	7722.74	4	4	
848	13488.0	8	17	8910.61	4	4	
3215	16745.0	77	18	7157.10	2	4	
1193	13969.0	7	17	7879.72	4	4	
3914	17706.0	35	21	9321.53	3	4	

	M_Quartile	RFMScore	Segment	Cluster
1110	4	444	Platinum Customers	1
848	4	444	Platinum Customers	1
3215	4	244	Big Spenders	1
1193	4	444	Platinum Customers	1
3914	4	344	Big Spenders	1

Interpretation : Cluster 1 with very high monetary value along with good frequency and recency values. These are the most valuable customers to the firm. They should be looked after periodically to access there concerns.

[114]:
```
Cluster_table[Cluster_table.Cluster == 0].sample(5)
```

[114]:

```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
2592     15877.0        8          1    239.31           4           1
347      12784.0        0          2    532.82           4           2
684      13258.0        2          3    672.83           4           2
2225     15385.0       31          1    316.88           3           1
3512     17155.0        8          2    251.70           4           2

      M_Quartile RFMScore           Segment  Cluster
2592           1      411            others        0
347            2      422  Recent Customers        0
684            3      423  Recent Customers        0
2225           2      312            others        0
3512           1      421            others        0
```

[115]:

```
Cluster_table.head()
```

[115]:

```
   CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0     12346.0      316          2      0.00           1           2
1     12347.0       30          6   4085.18           3           4
2     12348.0       66          4   1797.24           2           3
3     12349.0        9          1   1757.55           4           1
4     12350.0      301          1    334.40           1           1

   M_Quartile RFMScore               Segment  Cluster
0           1      121  Lost Cheap Customers        2
1           4      344          Big Spenders        3
2           4      234          Big Spenders        3
3           4      414          Big Spenders        0
4           2      112  Lost Cheap Customers        2
```

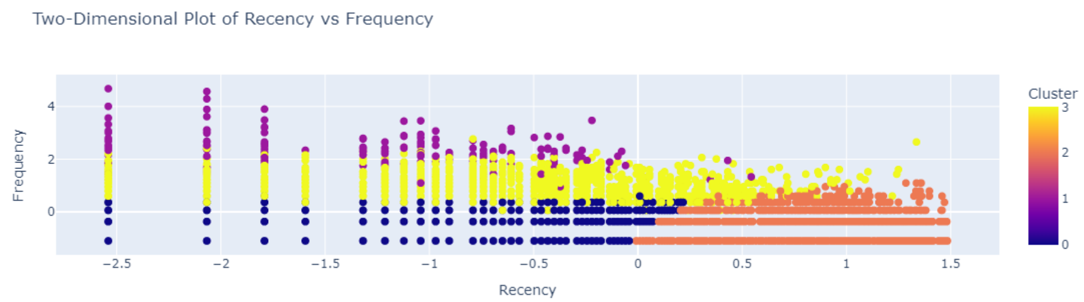
Interpretaion : Cluster 0 is somewhat average collectively can respond to the targeted campaigns.

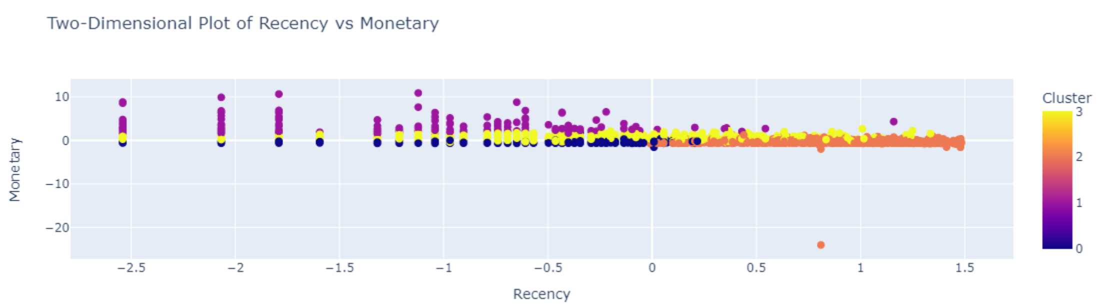
Scatter Plot to visualize the division of customers into different segments based on the RFM atributes.

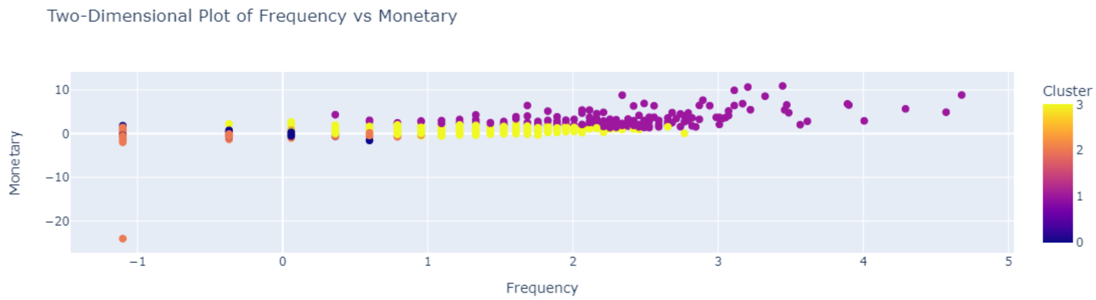
[116]:

```
# Plotting two dimesional plots of each attributes respectively.
import plotly.express as px
X = normal_df.iloc[:, 0:3].values

cluster_labels = kmeans.labels_

attribute_names = normal_df.columns[:3]

for i in range(3):
    for j in range(i + 1, 3):
        df = pd.DataFrame({
            attribute_names[i]: X[:, i],
```

```
            attribute_names[j]: X[:, j],
            'Cluster': cluster_labels
        })

        fig = px.scatter(df, x=attribute_names[i], y=attribute_names[j],␣
↪color='Cluster',
                          title=f'Two-Dimensional Plot of {attribute_names[i]}␣
↪vs {attribute_names[j]}')

        fig.update_traces(marker=dict(size=8))
        fig.update_layout(showlegend=True)
        fig.show()
```








```
[118]: Cluster_table.to_excel('RFMSegment.xlsx')
```

Let's try to visualize this pattern through the help Clusters.

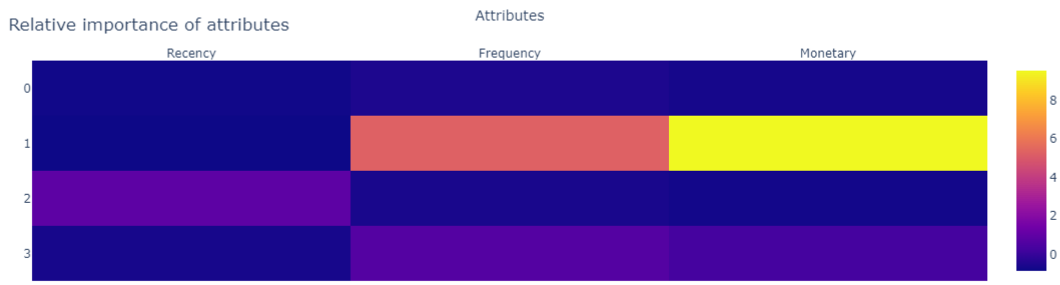
Heat Map We will utilize heat map to visualize the relative importance of each attributes in all four customer segments i.e. clusters. It calculates importance score by dividing them and subtracting 1 (ensures 0 is returned when cluster average equals population average).

The farther a ratio is from 0, the more important that attribute is for a segment relative to the total population.

```
[119]: # Assign Cluster labels to RFM table
rfm_table_cluster = rfm.assign(Cluster = cluster_labels)

# Average attributes for each cluster
cluster_avg = rfm_table_cluster.groupby(['Cluster']).mean()

# Calculate the population average
population_avg = rfm.mean()

# Calculate relative importance of attributes by
relative_imp = cluster_avg / population_avg - 1
```

```
[120]: import plotly.express as px
import numpy as np

# Assuming you have a DataFrame named relative_imp
# This DataFrame should contain your data

fig = px.imshow(relative_imp.values, x=relative_imp.columns, y=relative_imp.
 ↪index)
fig.update_xaxes(side="top")  # To have the x-axis labels at the top
fig.update_layout(
    title="Relative importance of attributes",
```

```
    xaxis_title="Attributes",
    yaxis_title="",
    yaxis=dict(tickmode='array', tickvals=np.arange(len(relative_imp.index)),
               ticktext=relative_imp.index),
)
fig.update_traces(text=relative_imp.values, colorbar=dict(title='Colorbar␣
↪Title'))
fig.show()
```



34.0.1 TABLEAU

Project Task: Week4

35 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

[121]:
```
retail_data.to_excel("Retail_data_Tableau.xlsx")
```

[122]:
```
retail_data.head()
```

[122]:

```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country InvoiceMonth  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom   2010-12-01
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom   2010-12-01
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom   2010-12-01

   TotalPrice  Total Sum Purchase_Date  Total_cost
0       15.30      15.30    2010-12-01       15.30
1       20.34      20.34    2010-12-01       20.34
2       22.00      22.00    2010-12-01       22.00
3       20.34      20.34    2010-12-01       20.34
4       20.34      20.34    2010-12-01       20.34
```

[Click Here for Tableau dashboard]https://public.tableau.com/app/profile/zeba.khan6011/viz/StoryRetail/RETAI

35.1 User Interactive Online Retail Story Board for UK Retail Store

1. Retail Dashboard a. Country Wise Analysis b. Top Products by Sales c. Top Products by Count d. Monthly Figures e.Count of orders Vs Hours Throughout the Day f. Elbow Plot -Error Cost against the no of clusters g. Recency Histogram h. Customer Segments i.FM Heat Map j. RM HEat Map

2. RFM Cluster Analysis Dashboard a. Geaographical Viz b. Cost Vs No of clusters c. Frequency Sum Vs Clusters d. RF Heat Map e. RF Plot f. FM Plot g. RM Plot h. Cluster View

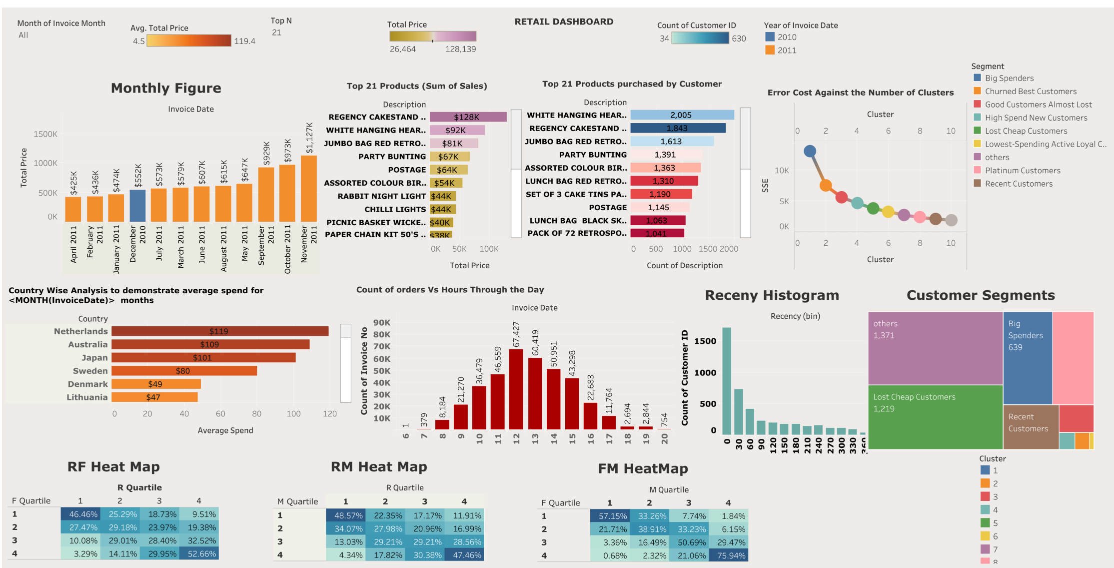
[2]:

```
!pip install Pillow
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: Pillow in /usr/local/lib/python3.7/site-packages
(7.1.1)
WARNING: You are using pip version 22.0.3; however, version 23.3.1 is
available.
You should consider upgrading via the '/usr/local/bin/python3 -m pip install
--upgrade pip' command.
```

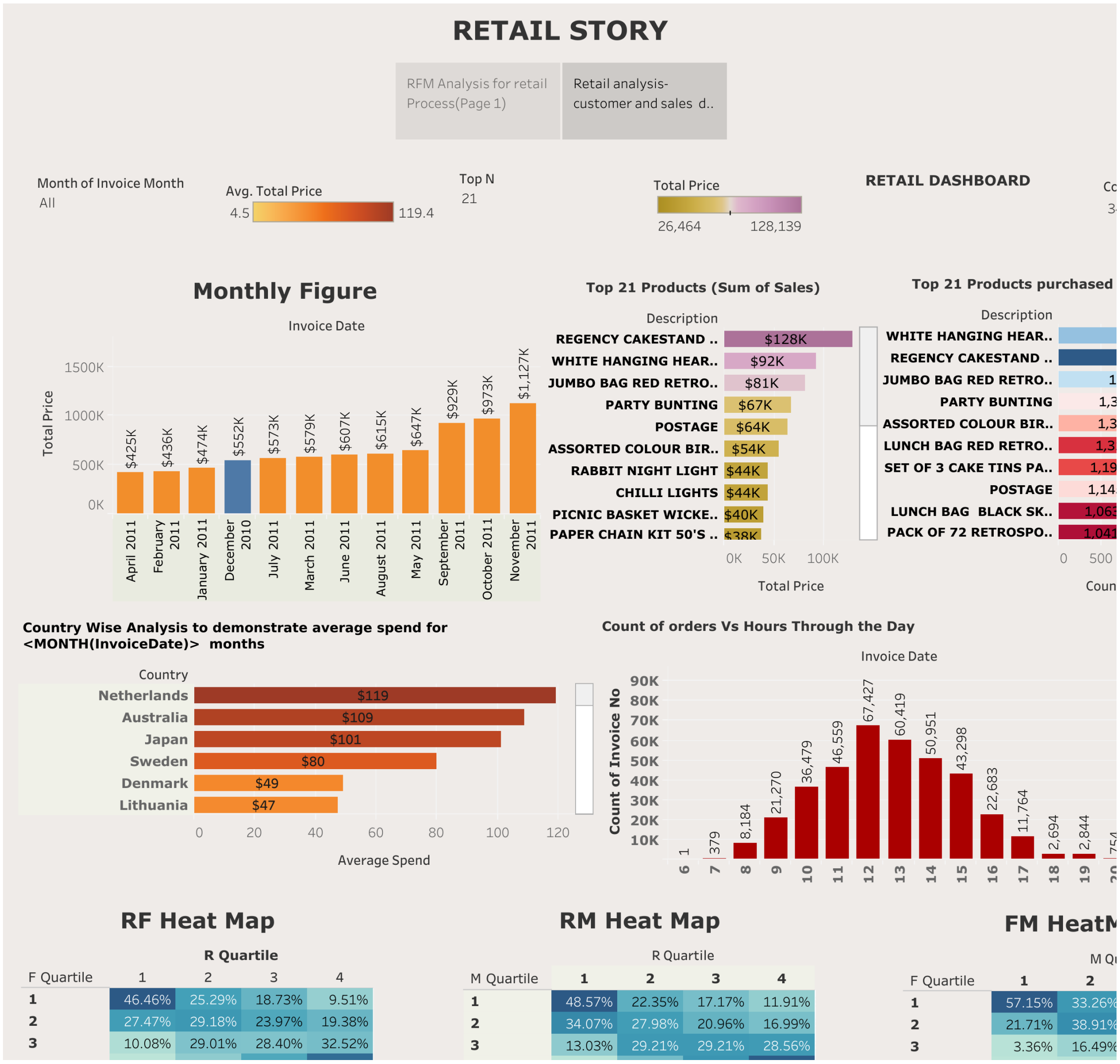
$ Note:$ installing the pilow function to download and upload the image png file.

[3]:
```python
from PIL import Image
from IPython.display import display  # This is for Jupyter Notebook/Colab, you␣
↪can skip it if not using these environments

# Open the PNG image
image1 = Image.open('RETAIL DASHBOARD.png')  # open the image Retail Dashboard␣
↪with the path to your PNG file
image2 =Image.open('RETAIL STORY (1).png')
image3 =Image.open('RETAIL STORY.png')

# Display the image (for Jupyter Notebook/Colab)
display(image1)

# If not in a Jupyter environment, you can simply show the image using:
# image.show()
```



[4]:
```python
display(image2)
```


```
[5]: display(image3)
```




```
[ ]:
```

```
[ ]:
```

35.1.1 Conclusion:

It i critical requirement for business to understand the value derived from a customer. RFM and cohort analysis is a method used for analyzing customer value. Business optimisation can be achieved with the above RFM customer segmentation with having segregated the customer base into groups of individuals based on well defined characteristics and traits. Visualization is added to implement the user story with relevant charts. Necessary promotion campaigns with agressive price incentives and discounts can help monitor customer attrition.

-Zeba Khan

```
[ ]:
```