In [1]:
```
#Importing libraries

import pandas as pd
import sqlite3

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [43]:
```
from IPython.display import HTML

HTML("<style>.container { width:100% !important; }</style>")
```

Out[43]:

In [3]:
```
#Importing dataset

data_retail = pd.read_excel('./OnlineRetail.xlsx')
```

In [4]:
```
#creating a copy
df = data_retail.copy()
print(df.shape)
```

```
(541909, 8)
```

In [5]:
```
#Creating database

conn = sqlite3.connect("dbsales")
cur = conn.cursor()
```

In [6]:
```
#Loading dataset to database

df.to_sql('dimsales', con=conn, if_exists='replace')
```

In [7]:
```
#checking if data loaded to table

pd.read_sql('SELECT * FROM dimsales', conn)
```

Out[7]:

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

	index	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
2	2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
...	...	...	...	...	...	...	...	...	...
541904	541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680.0	France
541905	541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680.0	France
541906	541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680.0	France
541907	541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680.0	France
541908	541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680.0	France

541909 rows × 9 columns

In [8]:

```
#Creating function to connect with database

def Q(sql):
    conn = sqlite3.connect("dbsales")
    Q = pd.read_sql_query("SELECT * from dimsales", con=conn)

    return pd.read_sql_query(sql ,conn)
```

In [9]:

```
#Checking data

Q("select * from dimsales")
```

Out[9]:

	index	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom

	index	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
3	3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
...	...	...	...	...	...	...	...	...	...
541904	541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680.0	France
541905	541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680.0	France
541906	541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680.0	France
541907	541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680.0	France
541908	541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680.0	France

541909 rows × 9 columns

In [10]:

```
#Getting table schema

Q("PRAGMA table_info('dimsales');")
```

Out[10]:

	cid	name	type	notnull	dflt_value	pk
0	0	index	INTEGER	0	None	0
1	1	InvoiceNo	TEXT	0	None	0
2	2	StockCode	TEXT	0	None	0
3	3	Description	TEXT	0	None	0
4	4	Quantity	INTEGER	0	None	0
5	5	InvoiceDate	TIMESTAMP	0	None	0
6	6	UnitPrice	REAL	0	None	0
7	7	CustomerID	REAL	0	None	0
8	8	Country	TEXT	0	None	0

In [11]:

```
#Counting number of records (rows)

Q("SELECT count (*) from dimsales",)
```

Out[11]:

count (*)

	count (*)
0	541909

In [12]:

```
#Counting number distinct inv.

Q("SELECT COUNT(DISTINCT InvoiceNo) as UniqueInvoices from dimsales;")
```

Out[12]:

	UniqueInvoices
0	25900

In [13]:

```
#Checking number of unique CustID's

Q("SELECT COUNT(DISTINCT CustomerID) as UniqueCustID from dimsales;")
```

Out[13]:

	UniqueCustID
0	4372

In [14]:

```
#Checking buyer countries

C = Q("SELECT distinct Country , \
      COUNT(DISTINCT CustomerID) as Customers,\
      Count(InvoiceNo) as Orders from dimsales \
      group by Country ORDER by InvoiceNo ASC ")

C
```

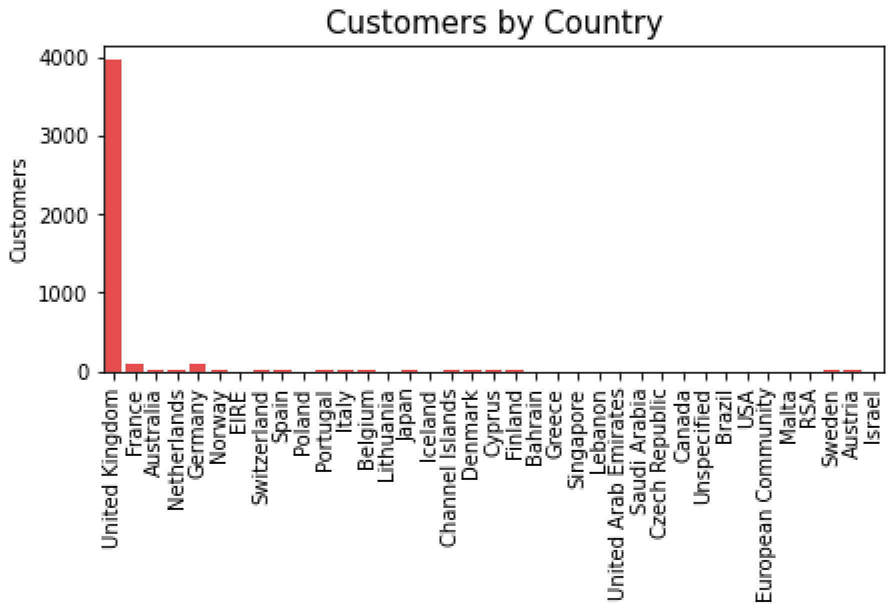
Out[14]:

	Country	Customers	Orders
0	United Kingdom	3950	495478
1	France	87	8557
2	Australia	9	1259
3	Netherlands	9	2371
4	Germany	95	9495
5	Norway	10	1086
6	EIRE	3	8196
7	Switzerland	21	2002
8	Spain	31	2533
9	Poland	6	341
10	Portugal	19	1519
11	Italy	15	803
12	Belgium	25	2069
13	Lithuania	1	35
14	Japan	8	358
15	Iceland	1	182

	Country	Customers	Orders
16	Channel Islands	9	758
17	Denmark	9	389
18	Cyprus	8	622
19	Finland	12	695
20	Bahrain	2	19
21	Greece	4	146
22	Hong Kong	0	288
23	Singapore	1	229
24	Lebanon	1	45
25	United Arab Emirates	2	68
26	Saudi Arabia	1	10
27	Czech Republic	1	30
28	Canada	4	151
29	Unspecified	4	446
30	Brazil	1	32
31	USA	4	291
32	European Community	1	61
33	Malta	2	127
34	RSA	1	58
35	Sweden	8	462
36	Austria	11	401
37	Israel	4	297

In [15]:

```
# Checking (visualisation ) how many customers by Country

Contr = C[C['Customers']>0]
Contry_cust = Contr.groupby('Country')['Customers'].count().sort_values(ascending=False).r

plt.figure(figsize=(7,3))
sns.barplot(x= Contr['Country'], y=Contr['Customers'], color="red", alpha=0.8)
plt.title("Customers by Country", size=15)
plt.xticks(rotation=90)
plt.xlabel(" ")
plt.show()
```



In [16]:

```
#Checking for Nulls %

df_nulls = Q("select * from dimsales")

df_nulls.isnull().sum() * 100 / len(df_nulls)
```

Out[16]:

```
index           0.000000
InvoiceNo       0.000000
StockCode       0.000000
Description     0.268311
Quantity        0.000000
InvoiceDate     0.000000
UnitPrice       0.000000
CustomerID     24.926694
Country         0.000000
dtype: float64
```

In [17]:

```
#Changing data type to datetime

df_nulls['InvoiceDate']=pd.to_datetime(df_nulls['InvoiceDate'])

df_nulls.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 9 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   index        541909 non-null  int64
 1   InvoiceNo    541909 non-null  object
 2   StockCode    541909 non-null  object
 3   Description  540455 non-null  object
 4   Quantity     541909 non-null  int64
 5   InvoiceDate  541909 non-null  datetime64[ns]
 6   UnitPrice    541909 non-null  float64
 7   CustomerID   406829 non-null  float64
 8   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(2), object(4)
memory usage: 37.2+ MB
```

In [18]:

```
#Getting statistics summary
```

```
df_nulls.describe()
```

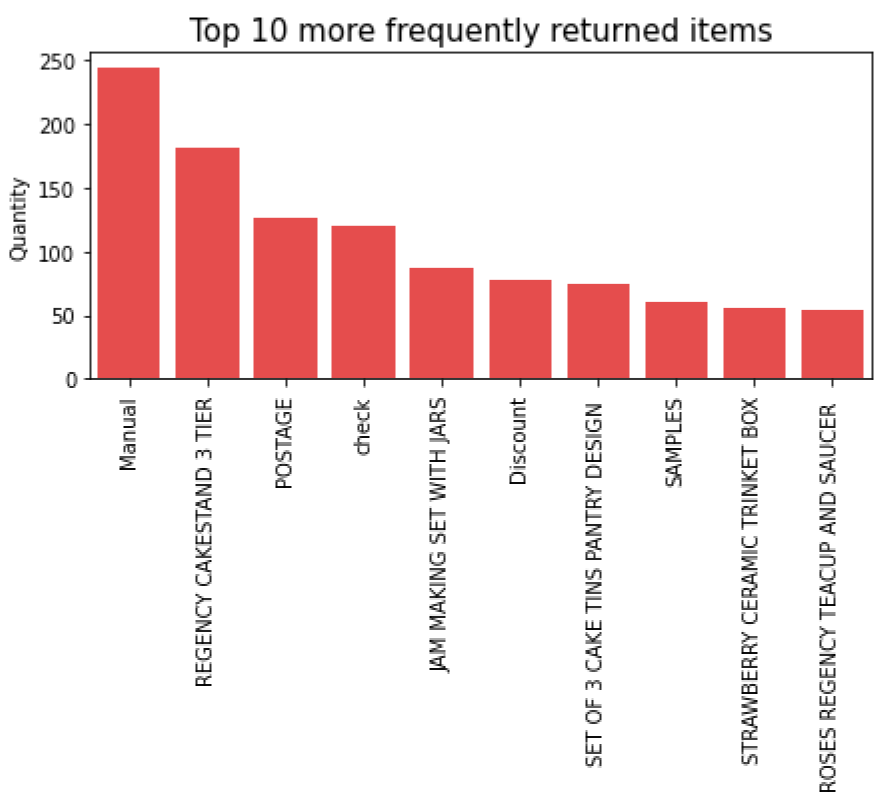
Out[18]:

	index	Quantity	UnitPrice	CustomerID
count	541909.00000	541909.000000	541909.000000	406829.000000
mean	270954.00000	9.552250	4.611114	15287.690570
std	156435.79785	218.081158	96.759853	1713.600303
min	0.00000	-80995.000000	-11062.060000	12346.000000
25%	135477.00000	1.000000	1.250000	13953.000000
50%	270954.00000	3.000000	2.080000	15152.000000
75%	406431.00000	10.000000	4.130000	16791.000000
max	541908.00000	80995.000000	38970.000000	18287.000000

Note: There are many negative numbers which may be cancelled items or returns

In [19]:

```
#checking for most frequently returned items

refunds = df_nulls[df_nulls['Quantity']<0]
refunds = refunds.groupby('Description')['Quantity'].count().sort_values(ascending=False).

plt.figure(figsize=(7,3))
sns.barplot(x= refunds['Description'], y=refunds['Quantity'], color="red", alpha=0.8)
plt.title("Top 10 more frequently returned items", size=15)
plt.xticks(rotation=90)
plt.xlabel(" ")
plt.show()
```



In [20]:

```
#Checking reason for high values as per descriptive analysis

df_nulls[df_nulls['UnitPrice']>1000].head(20)
```

Out[20]:

	index	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
15016	15016	C537630	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:04:00	13541.33	NaN	United Kingdom
15017	15017	537632	AMAZONFEE	AMAZON FEE	1	2010-12-07 15:08:00	13541.33	NaN	United Kingdom
16232	16232	C537644	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:34:00	13474.79	NaN	United Kingdom
16313	16313	C537647	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:41:00	5519.25	NaN	United Kingdom
16356	16356	C537651	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:49:00	13541.33	NaN	United Kingdom
16357	16357	C537652	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:51:00	6706.71	NaN	United Kingdom
28994	28994	C538682	M	Manual	-1	2010-12-13 17:14:00	1130.90	NaN	United Kingdom
41448	41448	539856	M	Manual	1	2010-12-22 14:41:00	1298.40	NaN	United Kingdom
43702	43702	C540117	AMAZONFEE	AMAZON FEE	-1	2011-01-05 09:55:00	16888.02	NaN	United Kingdom
43703	43703	C540118	AMAZONFEE	AMAZON FEE	-1	2011-01-05 09:57:00	16453.71	NaN	United Kingdom
45622	45622	C540271	M	Manual	-1	2011-01-06 11:51:00	1126.00	12503.0	Spain
64570	64570	C541651	M	Manual	-1	2011-01-20 11:48:00	1283.80	NaN	United Kingdom
64573	64573	C541653	BANK CHARGES	Bank Charges	-1	2011-01-20 11:50:00	1050.15	NaN	United Kingdom
73446	73446	C542348	M	Manual	-1	2011-01-27 12:09:00	1715.85	12539.0	Spain
90557	90557	C544047	M	Manual	-1	2011-02-15 12:36:00	1435.79	NaN	United Kingdom
96844	96844	C544587	AMAZONFEE	AMAZON FEE	-1	2011-02-21 15:07:00	5575.28	NaN	United Kingdom
96845	96845	C544589	AMAZONFEE	AMAZON FEE	-1	2011-02-21 15:11:00	5258.77	NaN	United Kingdom
117052	117052	C546325	M	Manual	-1	2011-03-11 10:15:00	1687.17	14911.0	EIRE
117053	117053	C546327	M	Manual	-1	2011-03-11 10:18:00	1687.17	14911.0	EIRE
117054	117054	546328	M	Manual	1	2011-03-11 10:19:00	1687.17	14911.0	EIRE

In [21]:

```
# Printing the details of the dataset

maxdate = df_nulls['InvoiceDate'].dt.date.max()
mindate = df_nulls['InvoiceDate'].dt.date.min()
unique_cust = df_nulls['CustomerID'].nunique()
unique_stocks = df_nulls['StockCode'].nunique()
```

```
tot_quantity = df_nulls['Quantity'].sum()
tot_sales = df_nulls['Quantity'].multiply(df_nulls['UnitPrice']).sum()

print(f"The Time range of transactions is: {mindate} to {maxdate}")
print(f"Total number of unique customers: {unique_cust}")
print(f"Total number of unique stocks: {unique_stocks}")
print(f"Total Quantity Sold: {tot_quantity}")
print(f"Total Sales for the period: {tot_sales}")
```

```
The Time range of transactions is: 2010-12-01 to 2011-12-09
Total number of unique customers: 4372
Total number of unique stocks: 4070
Total Quantity Sold: 5176450
Total Sales for the period: 9747747.933999998
```

DATA PREPROCESSING and EDA

In [22]:

```
# Cleaning the dataset SQL - removing cancelled, not orders, and negative transactions

dataretail = Q("SELECT * FROM dimsales WHERE StockCode NOT like '%[0-9]%'\
         AND StockCode NOT like '%A%'\
         AND StockCode NOT like '%B%' \
         AND StockCode NOT like '%G%'\
         AND StockCode NOT like '%E%' \
         AND StockCode NOT like '%M%'\
         AND StockCode NOT like '%D%' \
         AND StockCode NOT like '%gift_0001_20%'\
         AND StockCode NOT like '%gift_0001_10%'\
         AND StockCode NOT like '%gift_0001_30%'\
         AND StockCode NOT like '%22467%'\
         AND StockCode NOT like'%C%' \
         AND StockCode NOT like '%S%' \
         AND StockCode NOT like '%W%' \
         AND StockCode NOT like '%L%' \
         AND StockCode NOT like '%F%' \
         AND StockCode NOT like '%P%' \
         AND StockCode NOT like '%J%' \
         AND StockCode NOT like '%21319%' \
         AND StockCode NOT like '%17109D%' \
         AND StockCode NOT like '%21621%' \
         AND StockCode NOT like '%DCGS0057%' \
         AND StockCode NOT like '%21181%'\
         AND StockCode NOT like '%23444%'\
         AND StockCode NOT like '%84929%'\
         AND StockCode NOT like '%23343%'\
         AND StockCode NOT like '%20713%'\
         AND StockCode NOT like '%23595%'\
         AND StockCode NOT like '%21829%'\
         AND StockCode NOT like '%21915%'\
         AND StockCode NOT like '%20832%'\
         AND StockCode NOT like '%23157%'\
         AND StockCode NOT like '%85107%'\
         AND StockCode NOT like '%CRUK%'\
         AND StockCode NOT like '%POST%'\
         AND StockCode NOT like '%AMAZONFEE%'\
         AND StockCode NOT like '%BANK CHARGES%'\
         AND InvoiceNo NOT LIKE '%C%'\
         AND Description NOT LIKE '%?%'\
         AND CustomerID IS NOT NULL\
         AND Description IS NOT NULL\
         AND Quantity >0 \
         AND UnitPrice >0 ")

cur.close()
```

In [23]:

```
#Checking for nulls and data types

dataretail.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 360728 entries, 0 to 360727
Data columns (total 9 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   index        360728 non-null  int64  
 1   InvoiceNo    360728 non-null  object 
 2   StockCode    360728 non-null  object 
 3   Description  360728 non-null  object 
 4   Quantity     360728 non-null  int64  
 5   InvoiceDate  360728 non-null  object 
 6   UnitPrice    360728 non-null  float64
 7   CustomerID   360728 non-null  float64
 8   Country      360728 non-null  object 
dtypes: float64(2), int64(2), object(5)
memory usage: 24.8+ MB
```

In [24]:

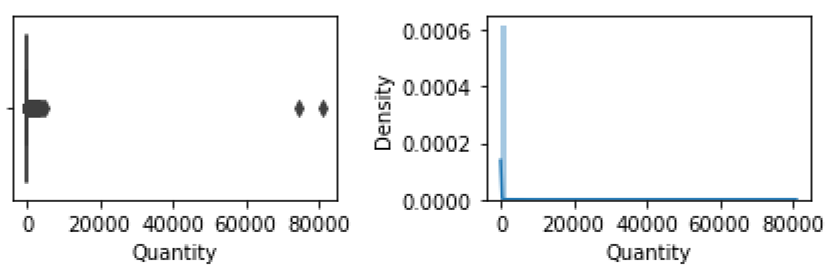
```
#Checking null values

dataretail.isnull().sum() * 100 / len(dataretail)
```

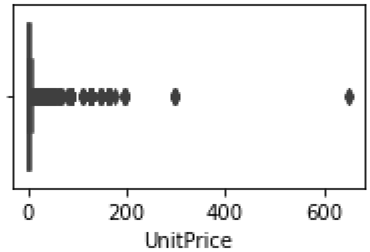
Out[24]:

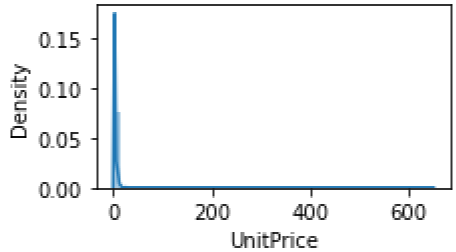
```
index          0.0
InvoiceNo      0.0
StockCode      0.0
Description    0.0
Quantity       0.0
InvoiceDate    0.0
UnitPrice      0.0
CustomerID     0.0
Country        0.0
dtype: float64
```

In [25]:

```
#Visualizing Quantity and UnitPrice distributions and outliers

#Note: Metrics are positively skewed/right skewed.

columns = ['Quantity','UnitPrice']

for i in columns:
    fig,axes = plt.subplots(1,2,figsize=(6,2))
    sns.boxplot(x=dataretail[i],orient = 'v',ax = axes[0])
    sns.distplot(dataretail[i],ax = axes[1])
    fig.tight_layout()
```







In [26]:

```
#Identifying upper & lower limits-Quantile-based hard edges

upper_limit = dataretail.iloc[:,[4,6]].quantile(0.99)
lower_limit = dataretail.iloc[:,[4,6]].quantile(0.01)


print("Highest allowed",upper_limit, '\n ')
print("Lowest allowed",lower_limit, '\n ')


print(dataretail[["Quantity"]].skew())
print(dataretail[["UnitPrice"]].skew())
```

```
Highest allowed Quantity     120.00
UnitPrice     12.75
Name: 0.99, dtype: float64

Lowest allowed Quantity     1.00
UnitPrice    0.21
Name: 0.01, dtype: float64

Quantity    393.047101
dtype: float64
UnitPrice    36.298725
dtype: float64
```

Note: There are many outliers on the dataset, however; since this is a whole sale store only extremely values will be removed (1%)

In [27]:

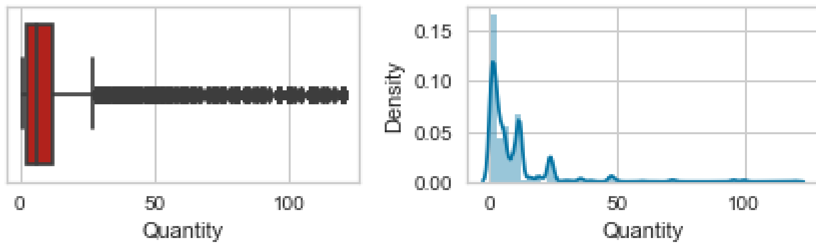
```
#Removing outliers - hard edges

lower_limit = dataretail.Quantity.quantile(0.01)
upper_limit = dataretail.Quantity.quantile(0.99)

dataretail = dataretail[(dataretail.Quantity >= lower_limit)
                        & (dataretail.Quantity <= upper_limit)]

lower_limit = dataretail.UnitPrice.quantile(0.01)
upper_limit = dataretail.UnitPrice.quantile(0.99)

dataretail = dataretail[(dataretail.UnitPrice >= lower_limit)
                        & (dataretail.UnitPrice <= upper_limit)]

print(dataretail[["Quantity"]].skew())
print(dataretail[["UnitPrice"]].skew())
```

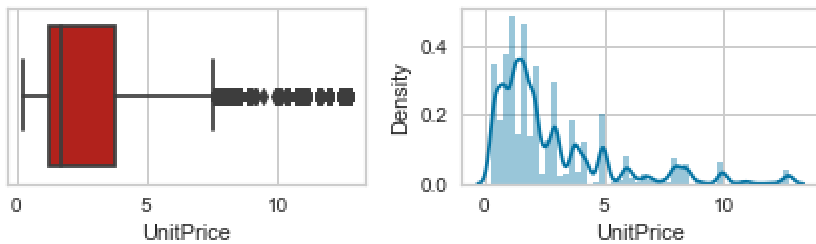
```
Quantity    3.94916
dtype: float64
UnitPrice    1.818721
dtype: float64
```

In [148…

```
#Visualizing Quantity and UnitPrice distributions and outliers after outliers removal

#Note: Metrics are positively skewed/right skewed.
```

```python
columns = ['Quantity','UnitPrice']

for i in columns:
    fig,axes = plt.subplots(1,2,figsize=(6,2))
    sns.boxplot(x=dataretail[i],orient = 'v',ax = axes[0],color = 'r')
    sns.distplot(dataretail[i],ax = axes[1])
    fig.tight_layout()
```





In [29]:

```python
#Changing data type to datetime
dataretail['InvoiceDate']=pd.to_datetime(dataretail['InvoiceDate'])
```

In [30]:

```python
#Extractin Months and Years for further analysis

dataretail['Month'] = pd.DatetimeIndex(dataretail['InvoiceDate']).month
dataretail['Month_name']=dataretail['InvoiceDate'].dt.month_name()
dataretail['Year']=dataretail['InvoiceDate'].dt.year
dataretail['Year_Month']=dataretail['Year'].apply(str)+' '+dataretail['Month_name'].apply

dataretail
```

Out[30]:

	index	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Montl
0	1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
1	5	536365	22752	SET 7 BABUSHKA NESTING BOXES	2	2010-12-01 08:26:00	7.65	17850.0	United Kingdom	12
2	6	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6	2010-12-01 08:26:00	4.25	17850.0	United Kingdom	12
3	7	536366	22633	HAND WARMER UNION JACK	6	2010-12-01 08:28:00	1.85	17850.0	United Kingdom	12
4	8	536366	22632	HAND WARMER RED POLKA DOT	6	2010-12-01 08:28:00	1.85	17850.0	United Kingdom	12

	index	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Montl
...	...	...	...	...	...	...	...	...	...	..
360723	541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680.0	France	12
360724	541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680.0	France	12
360725	541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680.0	France	12
360726	541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680.0	France	12
360727	541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680.0	France	12

350487 rows × 13 columns

In [31]:

```
# Loading cleaned data into the database
dataretail.to_sql('dimsales', con=conn, if_exists='replace')
```

In [32]:

```
dim_clean = Q("select*from dimsales ")
```

In [33]:

```
dim_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 350487 entries, 0 to 350486
Data columns (total 14 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   level_0      350487 non-null  int64  
 1   index        350487 non-null  int64  
 2   InvoiceNo    350487 non-null  object 
 3   StockCode    350487 non-null  object 
 4   Description  350487 non-null  object 
 5   Quantity     350487 non-null  int64  
 6   InvoiceDate  350487 non-null  object 
 7   UnitPrice    350487 non-null  float64
 8   CustomerID   350487 non-null  float64
 9   Country      350487 non-null  object 
 10  Month        350487 non-null  int64  
 11  Month_name   350487 non-null  object 
 12  Year         350487 non-null  int64  
 13  Year_Month   350487 non-null  object 
dtypes: float64(2), int64(5), object(7)
memory usage: 37.4+ MB
```

DATA EXPLORATION ANALYSIS

In [34]:

```
#Which product sells the most?

bestseller = Q("SELECT Description, sum(Quantity*UnitPrice) as Revenue,\
Count(InvoiceNo) From dimsales Group By Description Order by 2 desc Limit 10")
```

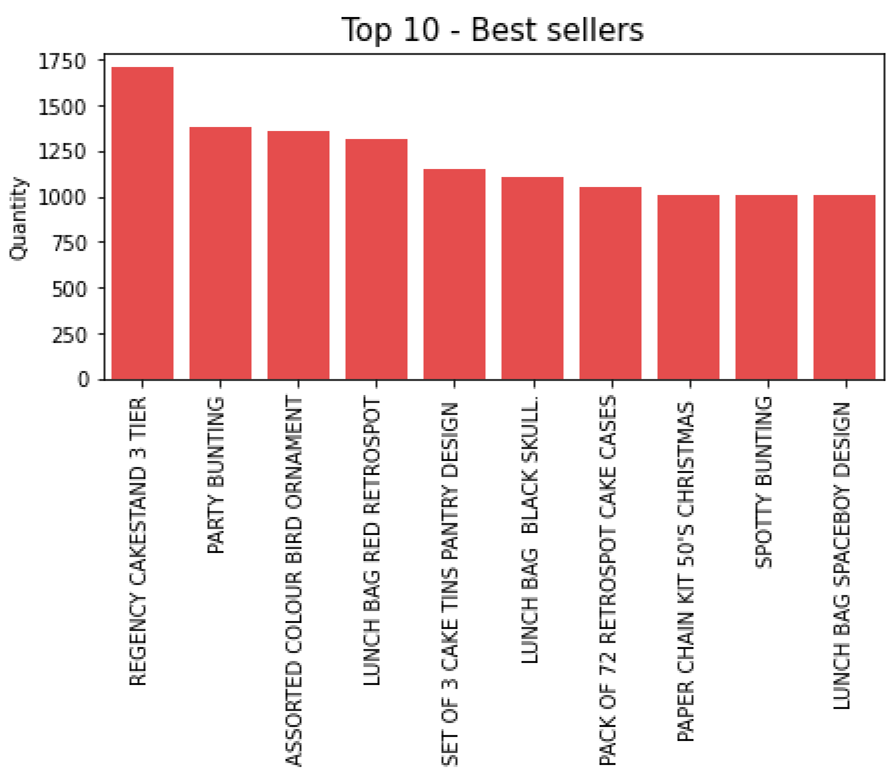
```
bestseller
```

Out[34]:

	Description	Revenue	Count(InvoiceNo)
0	REGENCY CAKESTAND 3 TIER	129122.35	1706
1	PARTY BUNTING	61166.83	1384
2	ASSORTED COLOUR BIRD ORNAMENT	37428.74	1355
3	CHILLI LIGHTS	36751.47	517
4	PAPER CHAIN KIT 50'S CHRISTMAS	35337.23	1011
5	SPOTTY BUNTING	30575.85	1010
6	JAM MAKING SET WITH JARS	30038.77	884
7	RABBIT NIGHT LIGHT	27158.88	819
8	SET OF 3 CAKE TINS PANTRY DESIGN	26974.48	1154
9	LUNCH BAG RED RETROSPOT	26960.95	1312

In [35]:

```
# Checking for most popular items

prod_seller= dim_clean[dim_clean['Quantity']>0]
prod_seller = prod_seller.groupby('Description')['Quantity'].count().sort_values(ascending

plt.figure(figsize=(7,3))
sns.barplot(x= prod_seller['Description'], y=prod_seller['Quantity'], color="red", alpha=(
plt.title("Top 10 - Best sellers", size=15)
plt.xticks(rotation=90)
plt.xlabel(" ")
plt.show()
```



In [37]:

```
#Which year generated more revenue
```

```
Q("SELECT Year, sum(Quantity*UnitPrice) as Revenue\
From dimsales Group By Year Order by 2 desc")
```

Out[37]:

	Year	Revenue
0	2011	5.798397e+06
1	2010	3.963944e+05

In [38]:

```
#Checking for the best month sales

Q("SELECT Month, Year, sum(Quantity*UnitPrice) AS Revenue,\
count(InvoiceNo) as TotalInvoices From dimsales Group \
By Month Order by 2 desc LIMIT 3")
```

Out[38]:

	Month	Year	Revenue	TotalInvoices
0	11	2011	906030.07	58063
1	10	2011	740535.01	44194
2	9	2011	676732.51	35626

In [39]:

```
# Visualisation of sales across months

month = dim_clean.groupby('Month')['Quantity'].count()
plt.figure(figsize=(7,3))
month.plot(marker='o', color="red", alpha=0.8)
plt.title("Sales across months", size=15)
plt.show()
```

In [40]:

```
#Which products was the best seller in November?

sellers = Q("SELECT Month, Description, sum(Quantity*UnitPrice) as Revenue,\
Count(InvoiceNo) From dimsales where Year ='2011' and Month_name = 'November'\
Group By Month_name,Description Order by 3 desc Limit 10")

sellers
```

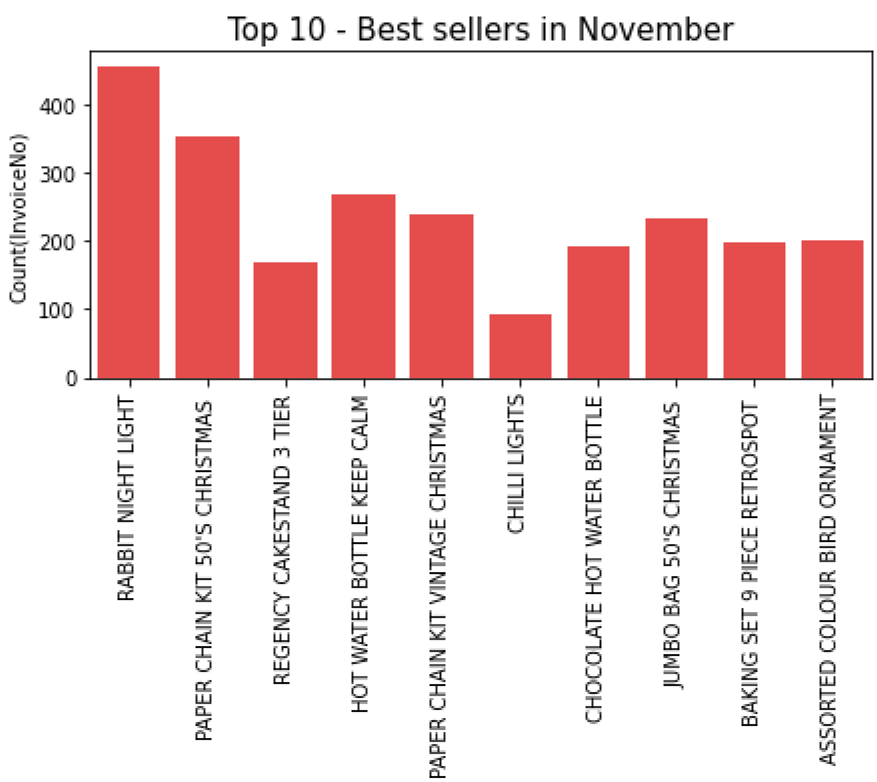
Out[40]:

	Month	Description	Revenue	Count(InvoiceNo)
0	11	RABBIT NIGHT LIGHT	14549.65	456
1	11	PAPER CHAIN KIT 50'S CHRISTMAS	12212.01	355
2	11	REGENCY CAKESTAND 3 TIER	10964.40	170

	Month	Description	Revenue	Count(InvoiceNo)
3	11	HOT WATER BOTTLE KEEP CALM	8006.10	270
4	11	PAPER CHAIN KIT VINTAGE CHRISTMAS	7736.11	238
5	11	CHILLI LIGHTS	7560.83	92
6	11	CHOCOLATE HOT WATER BOTTLE	6553.35	192
7	11	JUMBO BAG 50'S CHRISTMAS	5984.56	233
8	11	BAKING SET 9 PIECE RETROSPOT	5308.60	197
9	11	ASSORTED COLOUR BIRD ORNAMENT	5120.70	200

In [41]:

```
# Visualisation of best sellers products in November


sellerr= dim_clean[dim_clean['Quantity']>0]
sellerr = sellers.groupby('Description')['Count(InvoiceNo)'].count().sort_values(ascending

plt.figure(figsize=(7,3))
sns.barplot(x= sellers['Description'], y=sellers['Count(InvoiceNo)'],color="red", alpha=0.
plt.title("Top 10 - Best sellers in November", size=15)
plt.xticks(rotation=90)
plt.xlabel(" ")
plt.show()
```



In [45]:

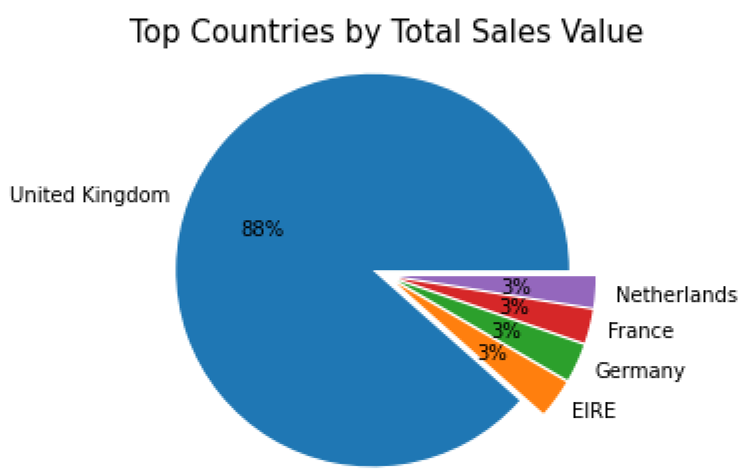
```
#Checking sales by Country

TC = Q("SELECT CustomerID, Country, sum(Quantity*UnitPrice) \
       as TotalSales,avg(Quantity*UnitPrice) as AvgSales, \
       Count(InvoiceNo) as Orders from dimsales GROUP BY CustomerID")

TC.head(5)
```

Out[45]:

	CustomerID	Country	TotalSales	AvgSales	Orders
0	12347.0	Iceland	3397.85	21.236563	160
1	12348.0	Finland	1186.68	56.508571	21
2	12349.0	Italy	1318.10	19.383824	68
3	12350.0	Norway	251.50	19.346154	13
4	12352.0	Norway	1373.24	18.068947	76

In [47]:

```
# Top countries by sales value

top_country = TC.groupby('Country')['TotalSales'].sum().sort_values(ascending=False)[:10]
labels = top_country[:5].index
size = top_country[:5].values

plt.figure(figsize=(5,4))
plt.pie(size, labels=labels, explode=[0.07]*5, autopct='%1.0f%%')
plt.title("Top Countries by Total Sales Value", size=15)
plt.axis('equal')
plt.show()
```



Recency, Frequency and Monetary - RFM analysis

In [46]:

```
#calculating Monetary (How much spent) and Frequency (how often the purchases)

R_df = Q("SELECT CustomerID, Country, sum(Quantity*UnitPrice) as Monetary,\
         avg(Quantity*UnitPrice) as AvgMonetaryValue, Count(InvoiceNo) as Frequency,\
         MAX(InvoiceDate) as last_order_date, (select MAX(InvoiceDate) from dimsales) as r
         from dimsales GROUP BY CustomerID")

R_df.head(5)
```

Out[46]:

	CustomerID	Country	Monetary	AvgMonetaryValue	Frequency	last_order_date	max_order_date
0	12347.0	Iceland	3397.85	21.236563	160	2011-12-07 15:52:00	2011-12-09 12:50:00
1	12348.0	Finland	1186.68	56.508571	21	2011-09-25 13:13:00	2011-12-09 12:50:00
2	12349.0	Italy	1318.10	19.383824	68	2011-11-21 09:51:00	2011-12-09 12:50:00
3	12350.0	Norway	251.50	19.346154	13	2011-02-02 16:01:00	2011-12-09 12:50:00
4	12352.0	Norway	1373.24	18.068947	76	2011-11-03 14:37:00	2011-12-09 12:50:00

In [48]:
```python
# Loading new data into the database

R_df.to_sql("rfmsales", con=conn, if_exists='replace')
```

In [49]:
```python
#Calculating Recency - How long ago was last order?

rfm_data = Q("SELECT CustomerID, Country, Frequency, Monetary,\
             round(JULIANDAY(max_order_date) - JULIANDAY(last_order_date))\
             AS Recency from rfmsales GROUP BY CustomerID")

rfm_data
```

Out[49]:

	CustomerID	Country	Frequency	Monetary	Recency
0	12347.0	Iceland	160	3397.85	2.0
1	12348.0	Finland	21	1186.68	75.0
2	12349.0	Italy	68	1318.10	18.0
3	12350.0	Norway	13	251.50	310.0
4	12352.0	Norway	76	1373.24	36.0
...	...	...	...	...	...
4265	18280.0	United Kingdom	9	165.30	277.0
4266	18281.0	United Kingdom	4	31.62	180.0
4267	18282.0	United Kingdom	12	178.05	7.0
4268	18283.0	United Kingdom	709	1872.03	3.0
4269	18287.0	United Kingdom	58	1220.06	42.0

4270 rows × 5 columns

In [50]:
```python
# Converting Days_from_last_purchase to int since this contains number of days

rfm_data['Recency'] = rfm_data['Recency'].astype(int)

rfm_data.head(5)
```

Out[50]:

	CustomerID	Country	Frequency	Monetary	Recency
0	12347.0	Iceland	160	3397.85	2
1	12348.0	Finland	21	1186.68	75
2	12349.0	Italy	68	1318.10	18
3	12350.0	Norway	13	251.50	310
4	12352.0	Norway	76	1373.24	36

In [51]:
```python
# Loading new data into the database

rfm_data.to_sql("rfms_new", con=conn, if_exists='replace')
```

In [52]:
```python
#calculate RFM scores
```

```
rfm_score = Q("SELECT CustomerID, R_score, F_score, M_score,\
             R_score*100 + F_score*10 + M_score AS RFM FROM ( SELECT CustomerID,\
             NTILE(4) OVER (ORDER BY Recency desc) AS R_score,\
             NTILE(4) OVER (ORDER BY Frequency) AS F_score,\
             NTILE(4) OVER (ORDER BY Monetary) AS M_score FROM rfms_new)")

cur.close()
```

In [53]:

```
rfm_score
```

Out[53]:

	CustomerID	R_score	F_score	M_score	RFM
0	13747.0	1	1	1	111
1	12791.0	1	1	1	111
2	15350.0	1	1	1	111
3	17643.0	1	1	1	111
4	14237.0	1	1	1	111
...	...	...	...	...	...
4265	17364.0	4	4	4	444
4266	17581.0	4	4	4	444
4267	16558.0	4	4	4	444
4268	15311.0	4	4	4	444
4269	12748.0	4	4	4	444

4270 rows × 5 columns

In [54]:

```
# Loading new data into the database

rfm_score.to_sql("rfms_s", con=conn, if_exists='replace')
```

In [55]:

```
#Creating RFM total score column

rfm_score = Q("Select CustomerID,\
              R_score, F_score, M_score, R_score + F_score+ M_score\
              as RFM_Score, RFM from rfms_s")

rfm_score
```

Out[55]:

	CustomerID	R_score	F_score	M_score	RFM_Score	RFM
0	13747.0	1	1	1	3	111
1	12791.0	1	1	1	3	111
2	15350.0	1	1	1	3	111
3	17643.0	1	1	1	3	111
4	14237.0	1	1	1	3	111
...	...	...	...	...	...	...
4265	17364.0	4	4	4	12	444

	CustomerID	R_score	F_score	M_score	RFM_Score	RFM
4266	17581.0	4	4	4	12	444
4267	16558.0	4	4	4	12	444
4268	15311.0	4	4	4	12	444
4269	12748.0	4	4	4	12	444

4270 rows × 6 columns

In [56]:

```
# loading new data into the database

rfm_score.to_sql("rfm_combo", con=conn, if_exists='replace')
```

In [57]:

```
#Checking data

Q("select*from rfm_combo LIMIT 5")
```

Out[57]:

	index	CustomerID	R_score	F_score	M_score	RFM_Score	RFM
0	0	13747.0	1	1	1	3	111
1	1	12791.0	1	1	1	3	111
2	2	15350.0	1	1	1	3	111
3	3	17643.0	1	1	1	3	111
4	4	14237.0	1	1	1	3	111

In [58]:

```
#Joinning tables to create new data w/ all columns

finalRFM = Q("SELECT rfms_new.CustomerID,rfms_new.Recency,\
              rfms_new.Frequency, rfms_new.Monetary, rfm_combo.R_score,\
              rfm_combo.F_score, rfm_combo.M_score, rfm_combo.RFM_Score, rfm_combo.RFM \
              FROM rfms_new INNER JOIN rfm_combo ON rfms_new.CustomerID = rfm_combo.Custor

finalRFM
```

Out[58]:

	CustomerID	Recency	Frequency	Monetary	R_score	F_score	M_score	RFM_Score	RFM
0	12347.0	2	160	3397.85	4	4	4	12	444
1	12348.0	75	21	1186.68	2	2	3	7	223
2	12349.0	18	68	1318.10	3	3	3	9	333
3	12350.0	310	13	251.50	1	1	2	4	112
4	12352.0	36	76	1373.24	3	3	3	9	333
...	...	...	...	...	...	...	...	...	...
4265	18280.0	277	9	165.30	1	1	1	3	111
4266	18281.0	180	4	31.62	1	1	1	3	111
4267	18282.0	7	12	178.05	4	1	1	6	411
4268	18283.0	3	709	1872.03	4	4	4	12	444
4269	18287.0	42	58	1220.06	3	3	3	9	333

4270 rows × 9 columns

In [59]:

```
#Checking data shape values

finalRFM.shape
```

Out[59]:

```
(4270, 9)
```

DATA ANALYSIS AND PREPROCESSING FOR CLUSTERING

In [60]:

```
#Making a copy of df

rfm_df = finalRFM.copy()
```

In [61]:

```
#Checking columns

rfm_df.columns
```

Out[61]:

```
Index(['CustomerID', 'Recency', 'Frequency', 'Monetary', 'R_score', 'F_score',
       'M_score', 'RFM_Score', 'RFM'],
      dtype='object')
```

In [62]:

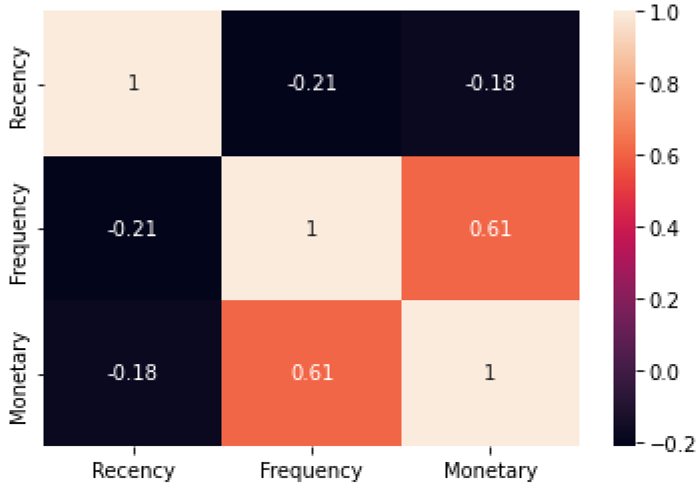
```
# RFM data Description/ Summary

rfm_df.iloc[:,[1,2,3]].describe()
```

Out[62]:

	Recency	Frequency	Monetary
count	4270.000000	4270.000000	4270.000000
mean	92.249883	82.081265	1450.770827
std	100.164482	200.912098	4337.494464
min	0.000000	1.000000	2.900000
25%	17.000000	15.000000	251.417500
50%	50.000000	37.000000	579.435000
75%	143.000000	90.000000	1395.330000
max	373.000000	6971.000000	143916.040000

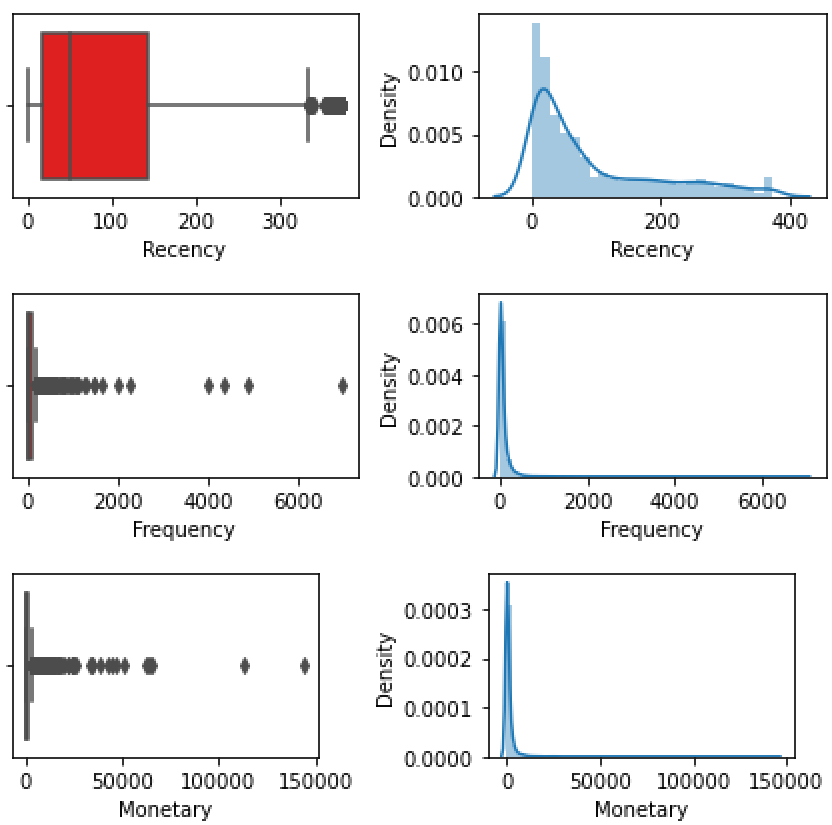
In [63]:

```
#checking correlation

sns.heatmap(rfm_df.iloc[:,[1,2,3]].corr(), annot=True)
plt.show()
```



In [65]:

```
#Visualizing the Recency, Frequency and Monetary distributions.

#Note: Metrics are positively skewed/right skewed.

columns = ['Recency','Frequency', 'Monetary']

for i in columns:
    fig,axes = plt.subplots(1,2,figsize=(6,2))
    sns.boxplot(x=rfm_df[i],orient = 'v',ax = axes[0], color = 'r')
    sns.distplot(rfm_df[i],ax = axes[1])
    fig.tight_layout()
```



Note:From the above figure, all the variables do not have a symmetrical distribution. As seen above, the variables are skewed to the right. It is also noted extremelly values (outliers) in Monetary and Frequency variables. Since clustering algorithms are sensitive to outliers and require a normal distribution, normalization of the data is required.

In [66]:

```
#Identifying upper & lower limits-Quantile-based hard edges
```

```
upper_limit = rfm_df.iloc[:,[1,2,3]].quantile(0.99)
lower_limit = rfm_df.iloc[:,[1,2,3]].quantile(0.01)


print("Highest allowed",upper_limit, '\n ')
print("Lowest allowed",lower_limit, '\n ')


print(rfm_df[["Recency"]].skew())
print(rfm_df[["Frequency"]].skew())
print(rfm_df[["Monetary"]].skew())
```

```
Highest allowed Recency       369.0000
Frequency      585.8600
Monetary     11924.8627
Name: 0.99, dtype: float64

Lowest allowed Recency       1.000
Frequency      1.000
Monetary     35.769
Name: 0.01, dtype: float64

Recency    1.243721
dtype: float64
Frequency    18.072126
dtype: float64
Monetary    17.169422
dtype: float64
```

In [67]:

```
#Capping outliers - Hard edge method

rfm_df[["Recency"]] = np.where(rfm_df[["Recency"]] <1.000, 1.000,rfm_df[["Recency"]])
rfm_df[["Recency"]] = np.where(rfm_df[["Recency"]] >369.0000, 369.0000,rfm_df[["Recency"]]

rfm_df[["Frequency"]] = np.where(rfm_df[["Frequency"]] <1.000, 1.000,rfm_df[["Frequency"]]
rfm_df[["Frequency"]] = np.where(rfm_df[["Frequency"]] >585.8600, 585.8600,rfm_df[["Freque

rfm_df[["Monetary"]] = np.where(rfm_df[["Monetary"]] <35.769, 35.769,rfm_df[["Monetary"]])
rfm_df[["Monetary"]] = np.where(rfm_df[["Monetary"]] >11924.8627, 11924.8627,rfm_df[["Mone

print(rfm_df[["Recency"]].skew())
print(rfm_df[["Frequency"]].skew())
print(rfm_df[["Monetary"]].skew())
```

```
Recency    1.240881
dtype: float64
Frequency    2.782755
dtype: float64
Monetary    3.397516
dtype: float64
```

Note : Since the dataset contain wholesale transactions - Decided to cap (hard-edges) the outliers instead of removing them completally and apply log transformation.

In [68]:

```
rfm_df.shape
```

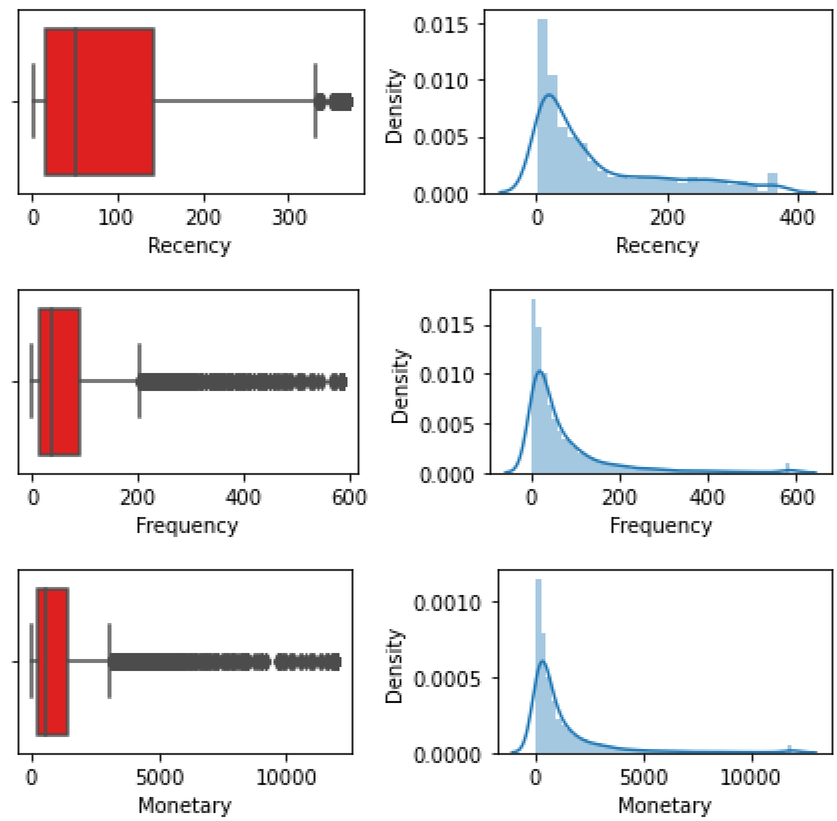
Out[68]:

```
(4270, 9)
```

In [70]:

```
#Note: Metrics are positively skewed or right skewed.

#Visualizing the Recency, Frequency and Monetary distributions.
```

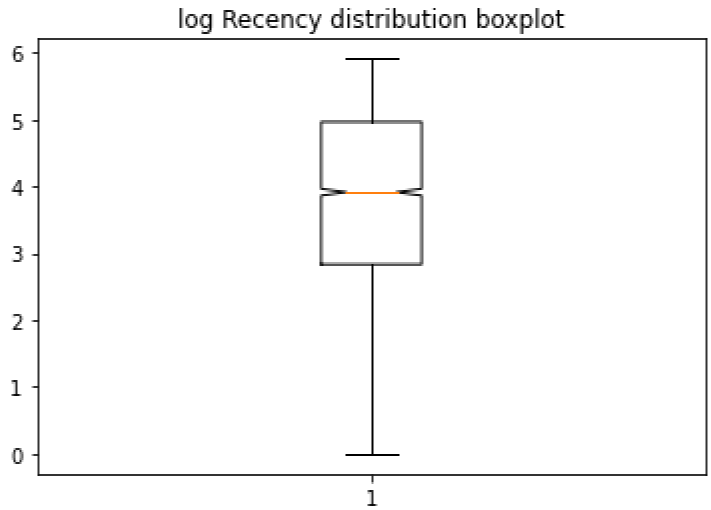
```
columns = ['Recency', 'Frequency','Monetary']

for i in columns:
    fig,axes = plt.subplots(1,2,figsize=(6,2))
    sns.boxplot(x=rfm_df[i],orient = 'v',ax = axes[0], color = 'r')
    sns.distplot(rfm_df[i],ax = axes[1])
    fig.tight_layout()
```

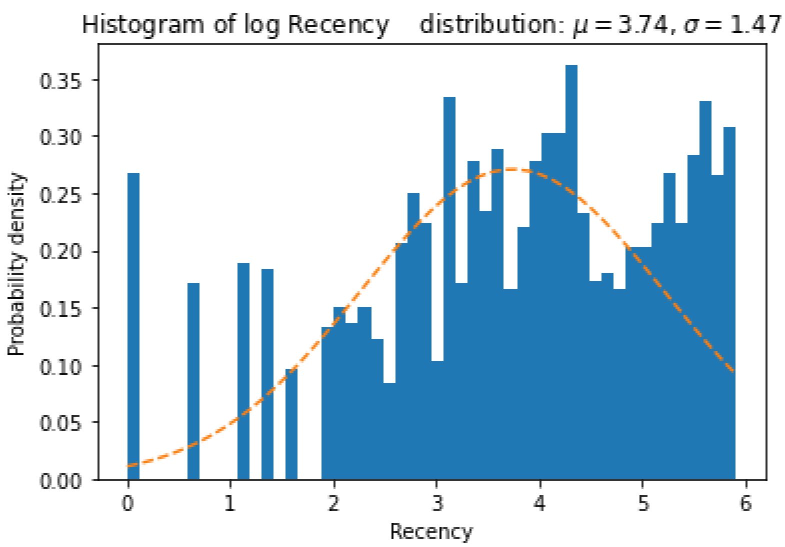


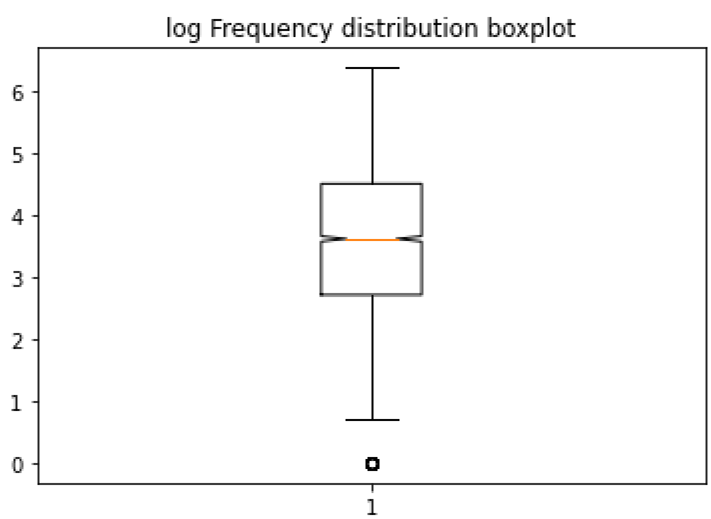
In [71]:

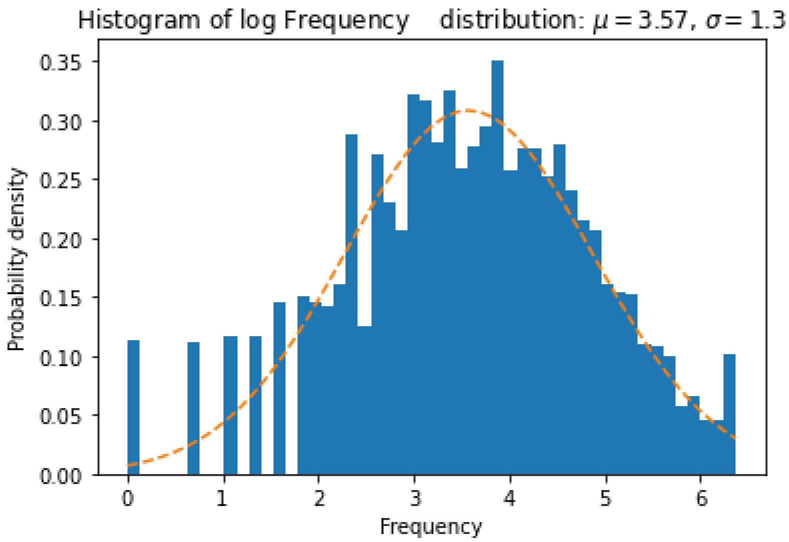
```
#checking distribution for log_transformation

from math import log

for col_name in ['Recency', 'Frequency','Monetary']:

    fig, ax = plt.subplots()

    x = rfm_df[col_name]

    ln_x = x.apply(lambda x: log(x))

    ax.boxplot(x=ln_x, notch=True)
    ax.set_title(f"log {col_name} distribution boxplot")

    mu = ln_x.mean()
    sigma = ln_x.std()
    num_bins = 50

    fig1, ax1 = plt.subplots()

    # the histogram of the data
    n, bins, patches = ax1.hist(ln_x, num_bins, density=True)

    # add a 'best fit' line
    y = ((1 / (np.sqrt(2 * np.pi) * sigma)) *
         np.exp(-0.5 * (1 / sigma * (bins - mu))**2))

    mu = round(mu, 2)
```

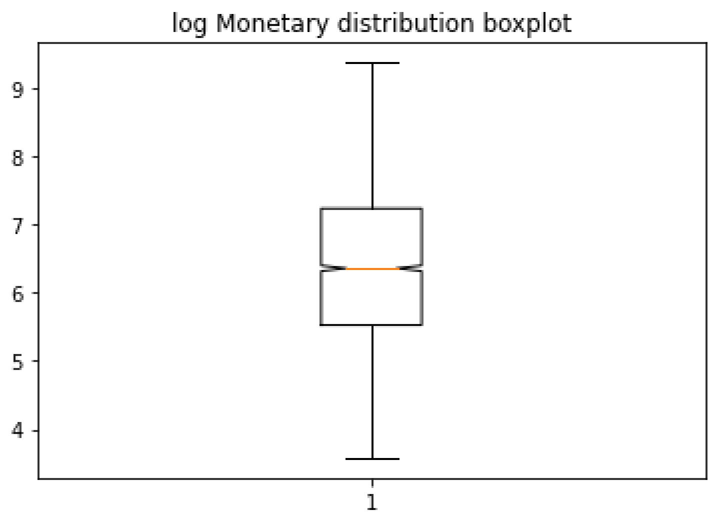
```
    sigma = round(sigma, 2)

    ax1.plot(bins, y, '--')
    ax1.set_xlabel(col_name)
    ax1.set_ylabel('Probability density')
    ax1.set_title(f'Histogram of log {col_name}\
    distribution: $\mu={mu}$, $\sigma={sigma}$')
```

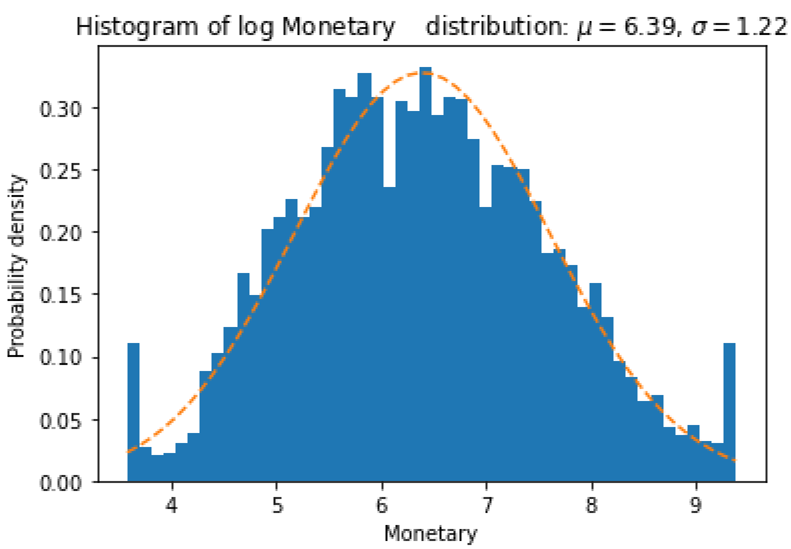












In [72]:

```
#Performing Log transformation to bring data into normal or near normal distribution

rfm_df['r'] =  np.log(rfm_df['Recency']+0.1) #log(0) is undefined
rfm_df['f'] =  np.log(rfm_df['Frequency']+0.1)
rfm_df['m'] = np.log(rfm_df['Monetary']+0.1)
```

In [73]:

```
#creating new dataframe

n_rfm = rfm_df[['r', 'f', 'm']]
```

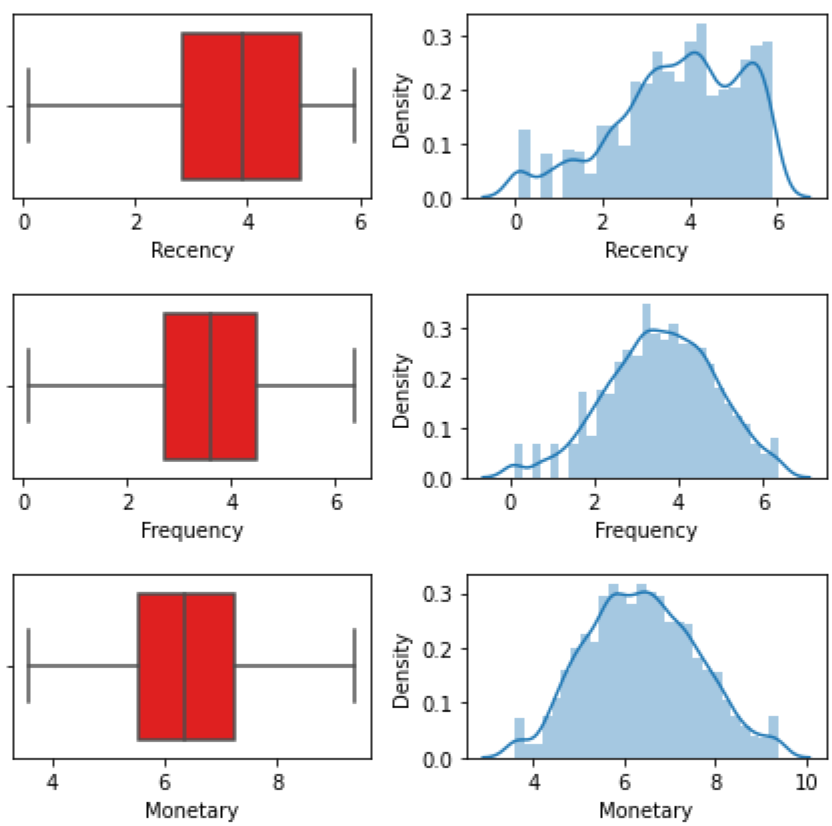
```
n_rfm = n_rfm.rename(columns={'r': 'Recency', 'f': 'Frequency', 'm': 'Monetary'})

n_rfm.describe()
```

Out[73]:

	Recency	Frequency	Monetary
count	4270.000000	4270.000000	4270.000000
mean	3.748487	3.581541	6.392635
std	1.459520	1.285637	1.217241
min	0.095310	0.095310	3.579873
25%	2.839078	2.714695	5.527513
50%	3.914021	3.613617	6.362226
75%	4.963544	4.500920	7.240958
max	5.911068	6.373252	9.386389

In [74]:

```
#Checking outliers and distributions after log transformation


columns = ['Recency', 'Frequency','Monetary']

for i in columns:
    fig,axes = plt.subplots(1,2,figsize=(6,2))
    sns.boxplot(x=n_rfm[i],orient = 'v',ax = axes[0], color = 'r')
    sns.distplot(n_rfm[i],ax = axes[1])
    fig.tight_layout()
```



In [75]:

```
#Making a copy of data

MM_scaled = n_rfm.copy()
```

In [76]:

```
from sklearn.preprocessing import StandardScaler

#Bringing the data on same scale
standscale = StandardScaler()
MM_scaled = standscale.fit_transform(MM_scaled)
```

In [77]:

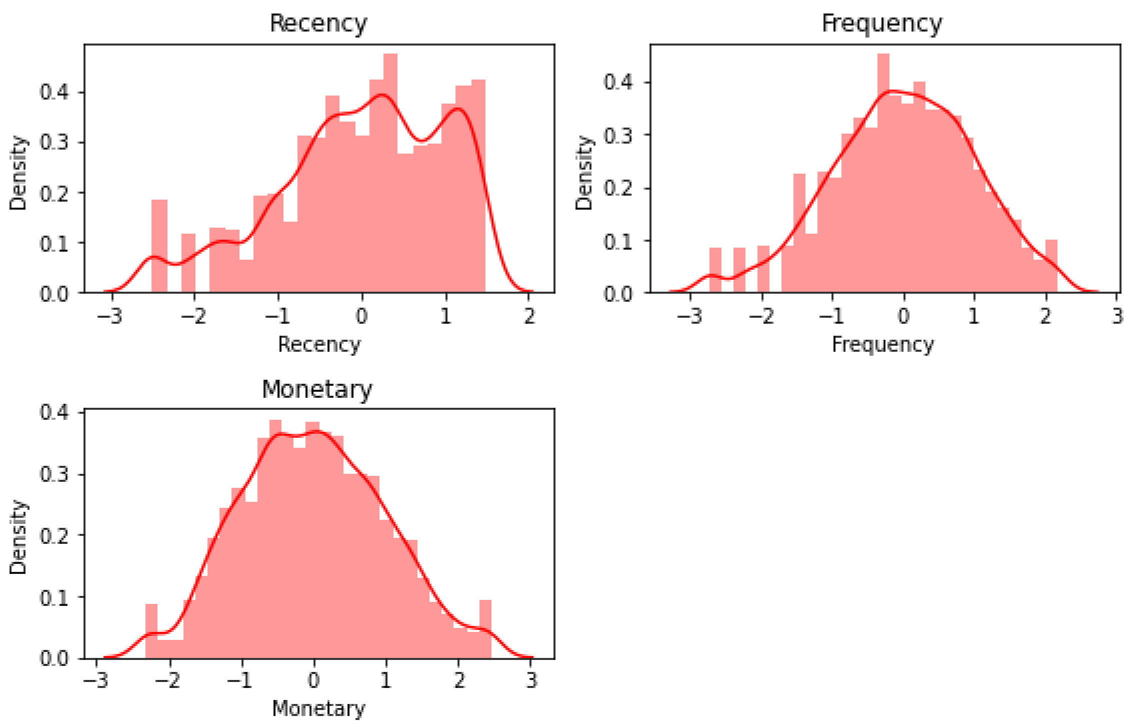
```
#Saving as dataframe

MM_scaled = pd.DataFrame(MM_scaled)
MM_scaled.columns = ['Recency','Frequency','Monetary']
MM_scaled.head()
```

Out[77]:

	Recency	Frequency	Monetary
0	-2.060198	1.162407	1.428227
1	0.390814	-0.414059	0.563935
2	-0.584216	0.497428	0.650225
3	1.362530	-0.784861	-0.710538
4	-0.111141	0.583832	0.683894

In [78]:

```
# Visually checking distribution after Scale

columns = ['Recency','Frequency','Monetary']

plt.figure(figsize = (8, 20))
for i in range(len(columns)):
  plt.subplot(8, 2, i+1)
  sns.distplot(MM_scaled[columns[i]], color = 'r');
  plt.title(columns[i])

plt.tight_layout()
```



In [79]:

```
from sklearn.cluster import KMeans
from sklearn import metrics
```

```python
#Kmeans clustering (checking for number of k')

# definying a dictionary
results_dict = {}

# definying how many clusters.
num_of_clusters = 10

# runing through each instance of K
for k in range(2, num_of_clusters):

    print("-"*100)

    # definying a dictionary to hold the results.
    results_dict[k] = {}

    # fiting the training data
    kmeans = KMeans(n_clusters=k, random_state=0).fit(MM_scaled)

    # definying the silhouette score
    sil_score = metrics.silhouette_score(MM_scaled, kmeans.labels_, metric='euclidean')

    # storying the different metrics
    results_dict[k]['silhouette_score'] = sil_score
    results_dict[k]['inertia'] = kmeans.inertia_
    results_dict[k]['score'] = kmeans.score
    results_dict[k]['model'] = kmeans

    # printing the results
    print("Number of Clusters: {}".format(k))
    print('silhouette_score', sil_score)
    print('inertia', kmeans.inertia_)
```

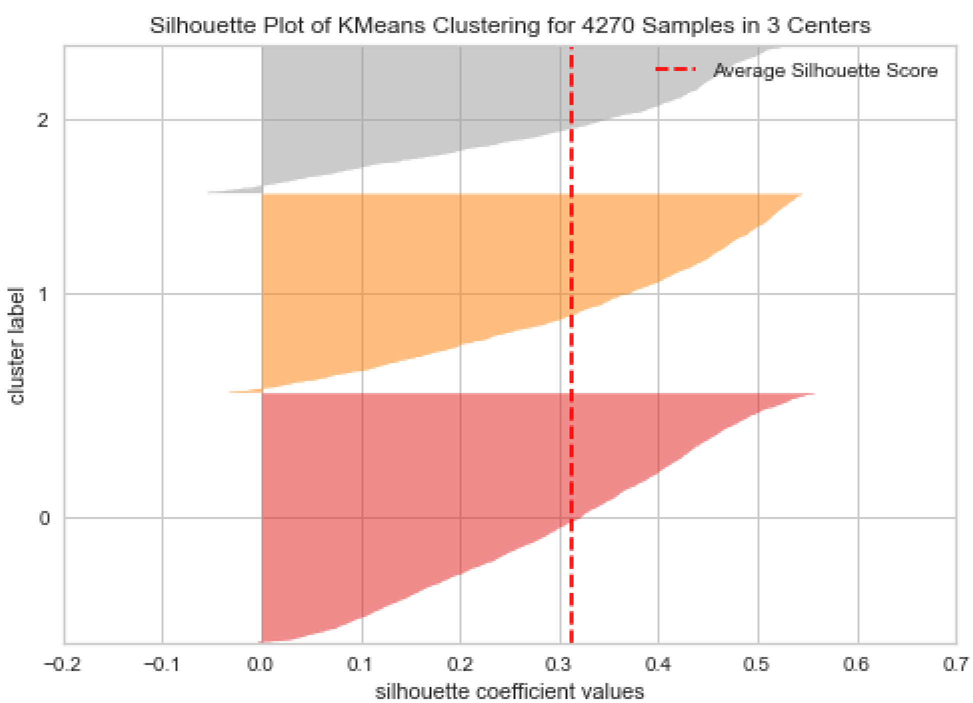
```
------------------------------------------------------------------------------------------
----------
Number of Clusters: 2
silhouette_score 0.404815000726263
inertia 6502.357762105064
------------------------------------------------------------------------------------------
----------
Number of Clusters: 3
silhouette_score 0.3129503661039162
inertia 4902.752239712742
------------------------------------------------------------------------------------------
----------
Number of Clusters: 4
silhouette_score 0.3097959436582124
inertia 4071.456076511653
------------------------------------------------------------------------------------------
----------
Number of Clusters: 5
silhouette_score 0.29101829578044736
inertia 3378.9833627138673
------------------------------------------------------------------------------------------
----------
Number of Clusters: 6
silhouette_score 0.28844026355965025
inertia 3005.55797063973
------------------------------------------------------------------------------------------
----------
Number of Clusters: 7
silhouette_score 0.27704843986053557
inertia 2676.1395589469466
------------------------------------------------------------------------------------------
```

```
----------
Number of Clusters: 8
silhouette_score 0.2746721151170784
inertia 2442.5518821632977
------------------------------------------------------------------------------------------
----------
Number of Clusters: 9
silhouette_score 0.27118484673897864
inertia 2265.604804848713
```

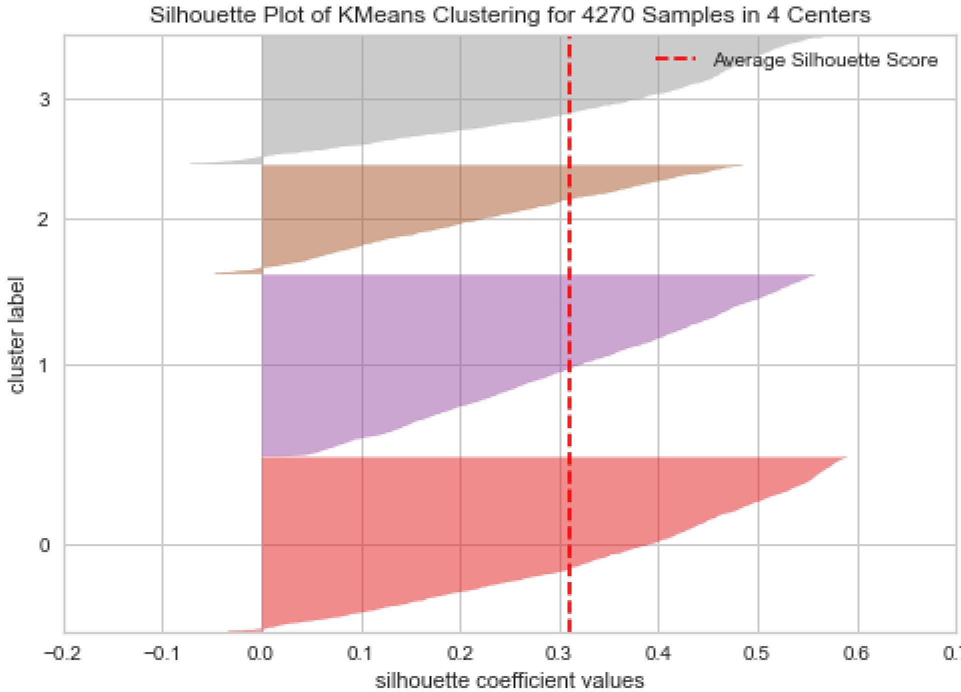
In [81]:

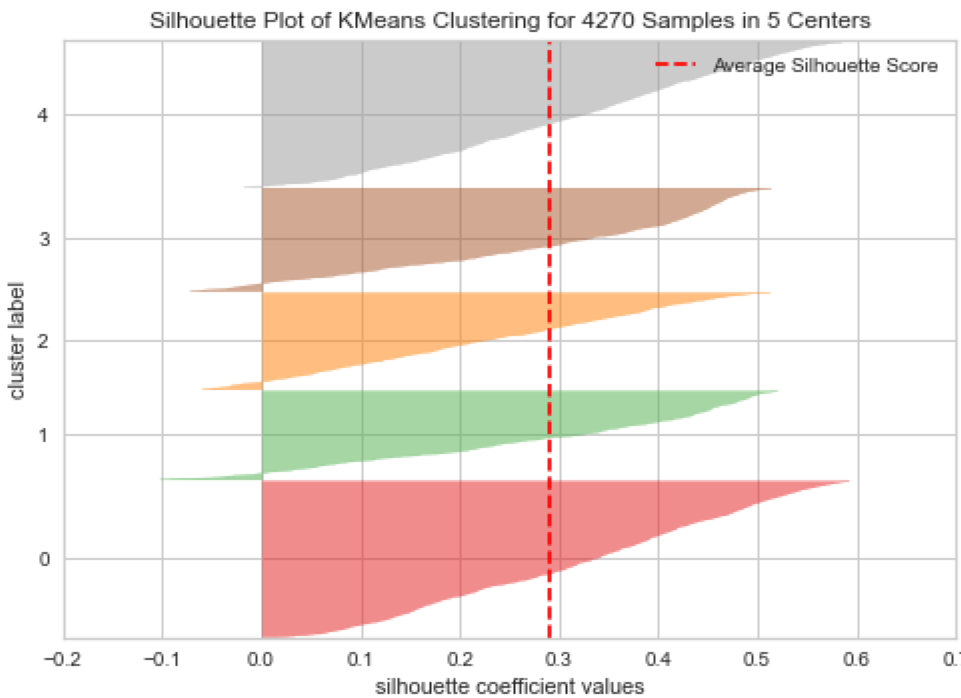
```python
#Checking for best number of K' based on silhouette_score

from yellowbrick.cluster import SilhouetteVisualizer

clusters = [3,4,5]

for cluster in clusters:

    print('-'*100)

    # defining the model for K
    kmeans = KMeans(n_clusters = cluster, random_state=0)

    # passing the model through the visualizer
    visualizer = SilhouetteVisualizer(kmeans)

    # fiting the data
    visualizer.fit(MM_scaled)


    visualizer.poof()
```

```
------------------------------------------------------------------------------------------
----------
```




```
------------------------------------------------------------------------------------------
----------
```



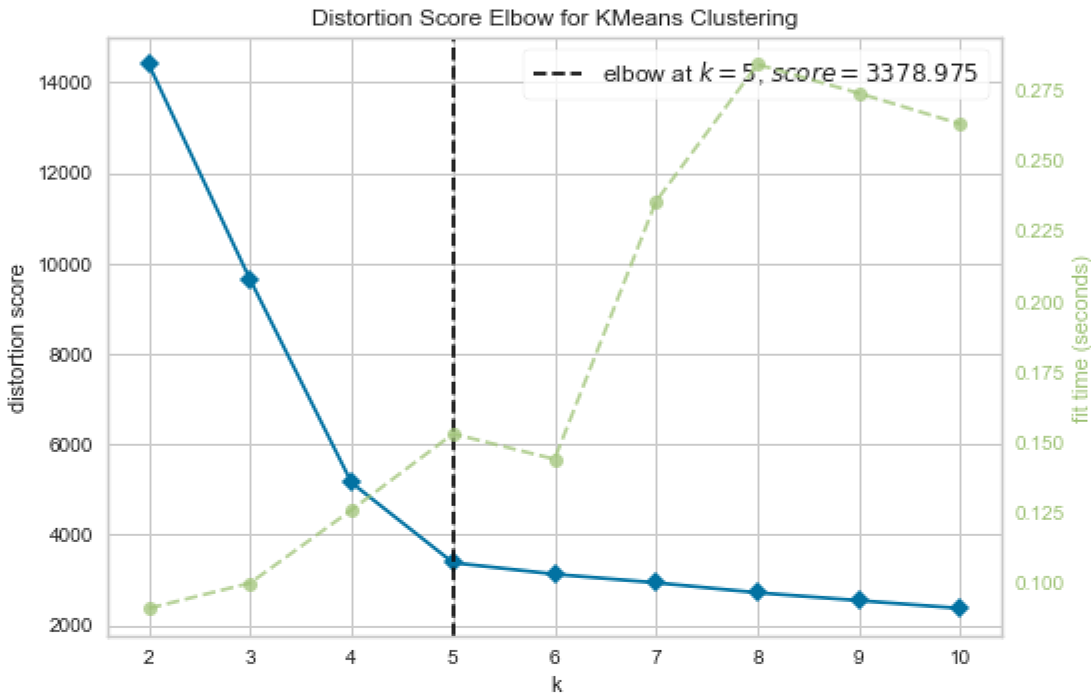


In [147…

```
##Checking for best number of K' based on Elbow method

from yellowbrick.cluster import KElbowVisualizer
clusters = [10]

for cluster in clusters:

    print('-'*100)


    kmeans = KMeans(n_clusters = cluster, random_state=0)


    visualizer = KElbowVisualizer(kmeans)


    visualizer.fit(MM_scaled)
```

```
    visualizer.poof()
```

```
----------------------------------------------------------------------------------------------------
```

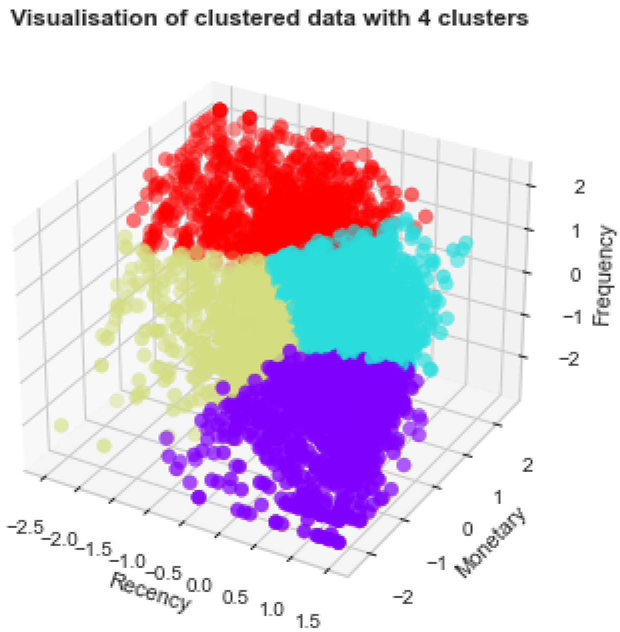


In [83]:

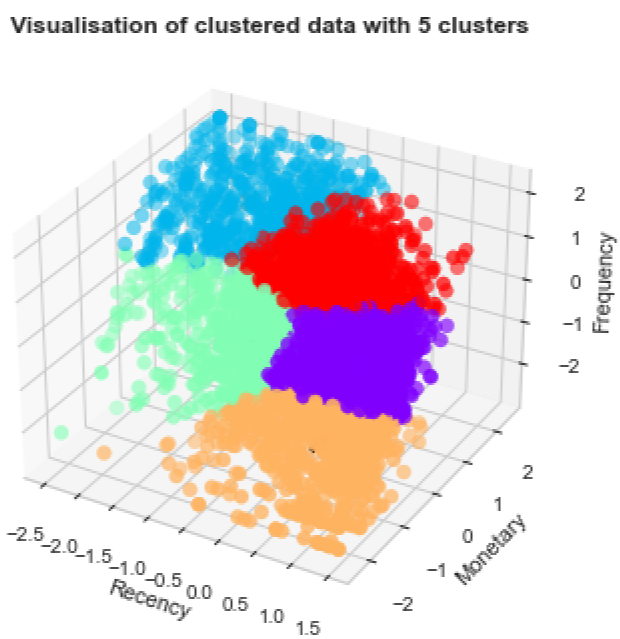
```
#Visualisation of K'means clusters

clusters = [4,5]

for cluster in clusters:

    print('-'*100)

    kmeans = KMeans(n_clusters= cluster, random_state=0).fit(MM_scaled)


    cluster_centers = kmeans.cluster_centers_
    C1 = cluster_centers[:, 0]
    C2 = cluster_centers[:, 1]
    C3 = cluster_centers[:, 2]


    fig = plt.figure(figsize=(4,5))
    ax = Axes3D(fig)


    x = MM_scaled['Recency']
    y = MM_scaled['Monetary']
    z = MM_scaled['Frequency']



    column_names = MM_scaled.columns
    ax.set_xlabel(column_names[0])
    ax.set_ylabel(column_names[2])
    ax.set_zlabel(column_names[1])

    ax.scatter(x, y, z, c = kmeans.labels_.astype(float), cmap='rainbow', s=50)
    ax.scatter(C1, C2, C3, marker="X",s=100, color='black')
```

```
    plt.title('Visualisation of clustered data with {} clusters'.format(cluster), fontweig
    plt.show()
```

```
--------------------------------------------------------------------------------------------
----------
```




```
--------------------------------------------------------------------------------------------
----------
```



Note: Based on Elbow method and silhouette_score it seens that the best number of clusters for k-maens are 5. Hierarchical Agglomerative Clustering will also be performed..

Hierarchical Agglomerative Clustering analysis

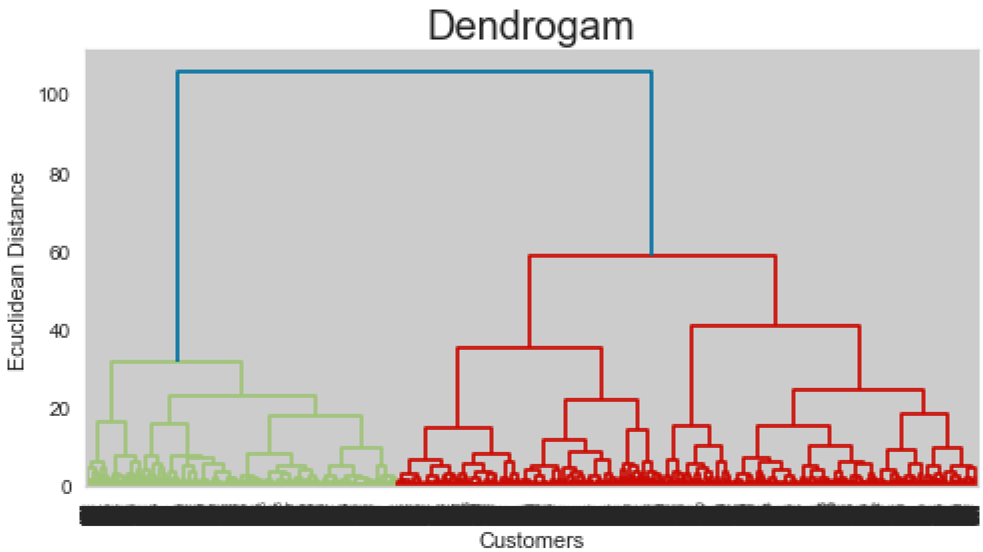
In [84]:

```
#copying data for Hierarchical Agglomerative Clustering
rfm_h = MM_scaled.copy()
```

In [85]:

```
#Visualisation Hierarchical clusters
import scipy.cluster.hierarchy as sch
```

```python
plt.figure(figsize=(8,4))
dendrogram = sch.dendrogram(sch.linkage(rfm_h, method = 'ward'))
plt.title('Dendrogam', fontsize = 20)
plt.xlabel('Customers')
plt.ylabel('Ecuclidean Distance')
plt.show()
```

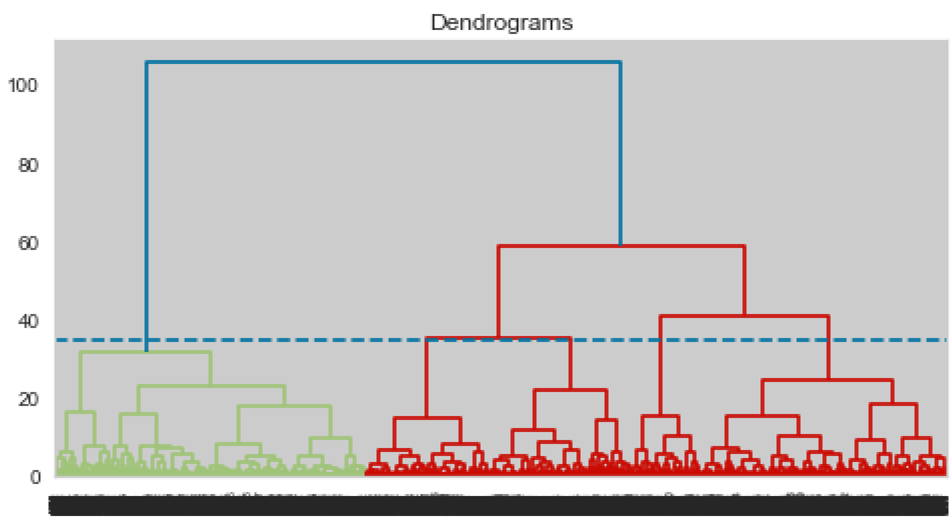


In [86]:

```python
#Best number Hierarchical clusters - potting line to identify

plt.figure(figsize=(8,4))
plt.title("Dendrograms")
hir_df = sch.dendrogram(sch.linkage(rfm_h, method='ward'))
plt.axhline(y=34.9, color='b', linestyle='--')
```

Out[86]:

```
<matplotlib.lines.Line2D at 0x19b2bf27a90>
```



In [87]:

```python
#Fitting predicting the model

from sklearn.cluster import AgglomerativeClustering

hir_cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='ward')
hir_cluster.fit_predict(rfm_h)
```

Out[87]:

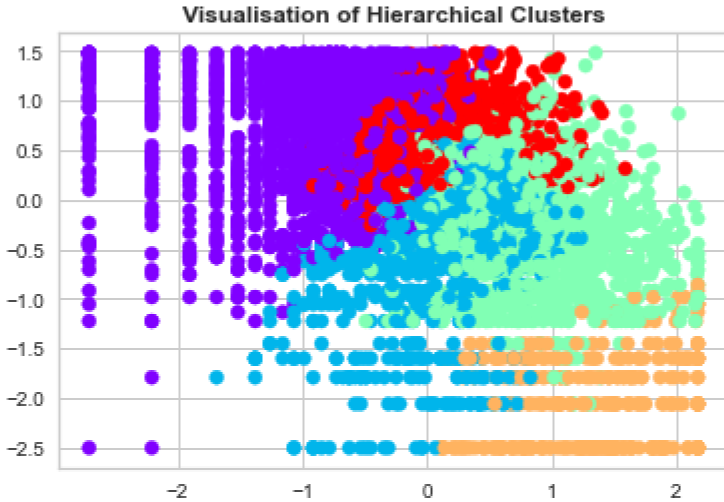
```
array([3, 4, 2, ..., 1, 3, 2], dtype=int64)
```

In [121…

```
#Visualisation Hierarchical clusters - scatter plot

plt.figure(figsize=(6, 4))
plt.scatter(rfm_h['Frequency'], rfm_h['Recency'], c=hir_cluster.labels_, cmap='rainbow')
plt.title('Visualisation of Hierarchical Clusters', fontweight='bold')
```

Out[121…

```
Text(0.5, 1.0, 'Visualisation of Hierarchical Clusters')
```



In [89]:

```
#Fitting and predicting K'means clustering

kmeans = results_dict[5]['model']

y_kmeans = kmeans.predict(MM_scaled)
```

In [90]:

```
#Checking shape

kmeans.cluster_centers_.shape
```

Out[90]:

```
(5, 3)
```

In [91]:

```
centroids = kmeans.cluster_centers_
```

In [92]:

```
#Saving to dataframe

cluster_centers = pd.DataFrame(data = kmeans.cluster_centers_, columns = [MM_scaled])
cluster_centers
```

Out[92]:

	Recency	Frequency	Monetary
0	0.796102	-0.262857	-0.315019
1	-1.471832	1.272049	1.369212
2	-0.763763	-0.258385	-0.399335
3	0.794714	-1.439455	-1.299548
4	-0.010974	0.705230	0.696225

In [93]:

```
labels = kmeans.labels_
```

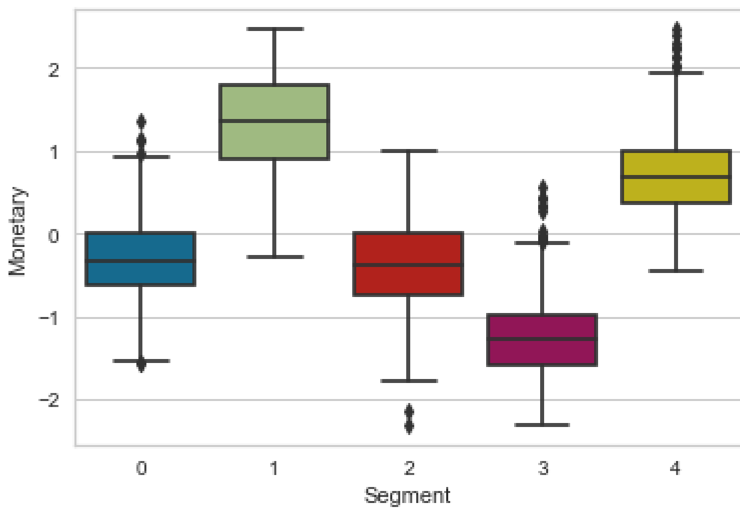
In [94]:
```
## Appending clusters (segment) to input features table

MM_scaled['Segment'] = y_kmeans
MM_scaled.head()
```

Out[94]:

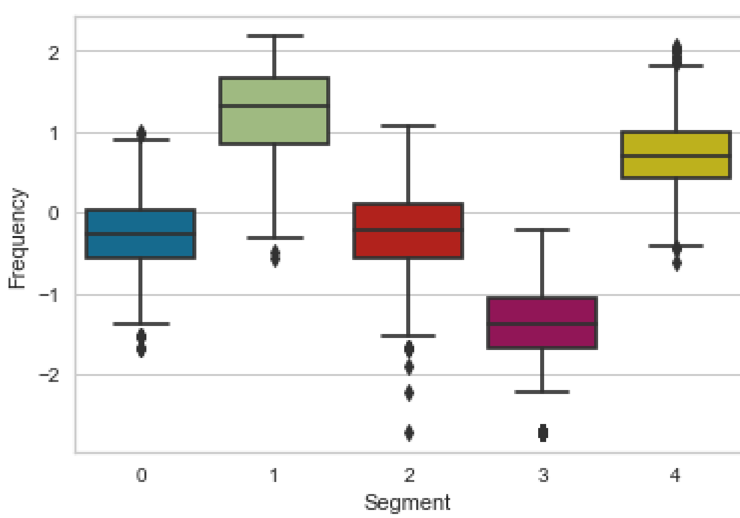
	Recency	Frequency	Monetary	Segment
0	-2.060198	1.162407	1.428227	1
1	0.390814	-0.414059	0.563935	0
2	-0.584216	0.497428	0.650225	4
3	1.362530	-0.784861	-0.710538	0
4	-0.111141	0.583832	0.683894	4

In [139…
```
#segement analysis - Customers on segment 1 are the ones who spends the most

plt.subplots(figsize=(6,4))
sns.boxplot(x='Segment', y='Monetary', data=MM_scaled)
```

Out[139…
```
<AxesSubplot:xlabel='Segment', ylabel='Monetary'>
```



In [140…
```
#segement analysis - Customers on segment 1 are the ones who bought the most

plt.subplots(figsize=(6,4))
sns.boxplot(x='Segment', y='Frequency', data=MM_scaled)
figsize=(6,2)
```

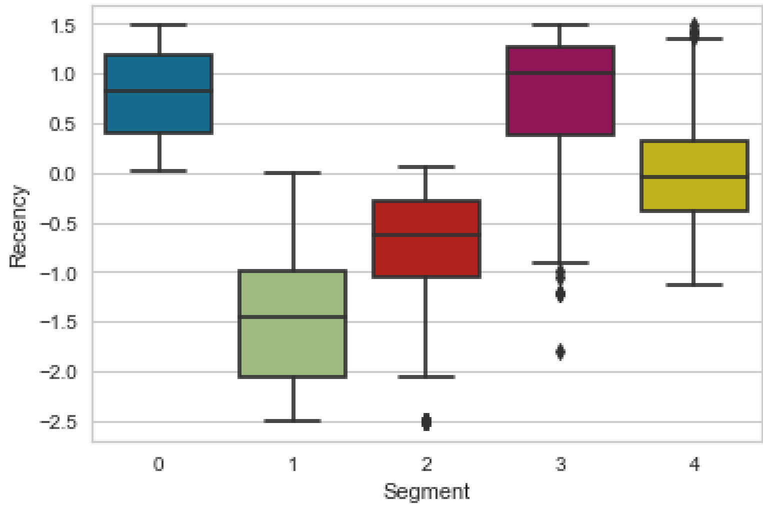


In [142…

```
#segement analysis - Customers on segment 1 are the ones who buy with more frequency

plt.subplots(figsize=(6,4))
sns.boxplot(x='Segment', y='Recency', data=MM_scaled)
```

Out[142…

```
<AxesSubplot:xlabel='Segment', ylabel='Recency'>
```



In [98]:

```
#Inverting data to normal scale

invert_rfm = standscale.inverse_transform(MM_scaled[['Recency', 'Frequency', 'Monetary']])

invert_rfm = pd.DataFrame(invert_rfm)
invert_rfm.columns = ['Recency', 'Frequency', 'Monetary']

invert_rfm = pd.concat([invert_rfm, MM_scaled[['Segment']]], axis=1)

invert_rfm.head()
```

Out[98]:

	Recency	Frequency	Monetary	Segment
0	0.741937	5.075799	8.130928	1
1	4.318821	3.049273	7.078999	0
2	2.895912	4.220977	7.184022	4
3	5.736895	2.572612	5.527841	0
4	3.586293	4.332048	7.225001	4

In [99]:

```
#AntiLog trasnformation to bring data back to original distribution and values

invert_rfm['r'] = invert_rfm['Recency'].apply(lambda x: np.exp(x))
invert_rfm['f'] = invert_rfm['Frequency'].apply(lambda x: np.exp(x))
invert_rfm['m'] = invert_rfm['Monetary'].apply(lambda x: np.exp(x))
```

In [100…

```
#creating new dataframe

rfm = invert_rfm[['r', 'f', 'm', 'Segment']]

rfm = rfm.rename(columns={'r': 'Recency', 'f': 'Frequency', 'm': 'Monetary'})

rfm.describe()
```

Out[100…

	Recency	Frequency	Monetary	Segment
count	4270.000000	4270.000000	4270.000000	4270.000000
mean	92.326464	74.676342	1253.693820	1.986183
std	100.070746	101.239233	1906.505297	1.538313
min	1.100000	1.100000	35.869000	0.000000
25%	17.100000	15.100000	251.517500	0.000000
50%	50.100000	37.100000	579.535000	2.000000
75%	143.100000	90.100000	1395.430000	3.000000
max	369.100000	585.960000	11924.962700	4.000000

In [101…

```
# Converting invoiceDate to int since this contains number of days

rfm['Recency'] = rfm['Recency'].astype(int)
rfm['Frequency'] = rfm['Frequency'].astype(int)
rfm['Monetary'] = rfm['Monetary'].astype(float).round(2)


rfm.head(5)
```

Out[101…

	Recency	Frequency	Monetary	Segment
0	2	160	3397.95	1
1	75	21	1186.78	0
2	18	68	1318.20	4
3	310	13	251.60	0
4	36	76	1373.34	4

In [145…

```
## Appending results and creating new table

Countries = rfm_data.loc[:,['Country']]

DataFinal = pd.concat([rfm, finalRFM[['CustomerID','R_score','F_score',
                                      'M_score','RFM_Score', 'RFM']],
                                       Countries[['Country']]], axis=1)


#rearreenging data

RFM_final = DataFinal.reindex(columns=['CustomerID','Recency','Frequency',
                                       'Monetary','R_score','F_score', 'M_score','RFM_Scor
                                       'RFM','Segment', 'Country'])


RFM_final
```

Out[145…

	CustomerID	Recency	Frequency	Monetary	R_score	F_score	M_score	RFM_Score	RFM	Segment	Country
0	12347.0	2	160	3397.95	4	4	4	12	444	1	Icelanc
1	12348.0	75	21	1186.78	2	2	3	7	223	0	Finlanc
2	12349.0	18	68	1318.20	3	3	3	9	333	4	Italy

	CustomerID	Recency	Frequency	Monetary	R_score	F_score	M_score	RFM_Score	RFM	Segment	Country
3	12350.0	310	13	251.60	1	1	2	4	112	0	Norway
4	12352.0	36	76	1373.34	3	3	3	9	333	4	Norway
...	...	...	...	...	...	...	...	...	...	...	...
4265	18280.0	277	9	165.40	1	1	1	3	111	3	United Kingdom
4266	18281.0	180	4	35.87	1	1	1	3	111	3	United Kingdom
4267	18282.0	7	12	178.15	4	1	1	6	411	2	United Kingdom
4268	18283.0	3	585	1872.13	4	4	4	12	444	1	United Kingdom
4269	18287.0	42	58	1220.16	3	3	3	9	333	4	United Kingdom

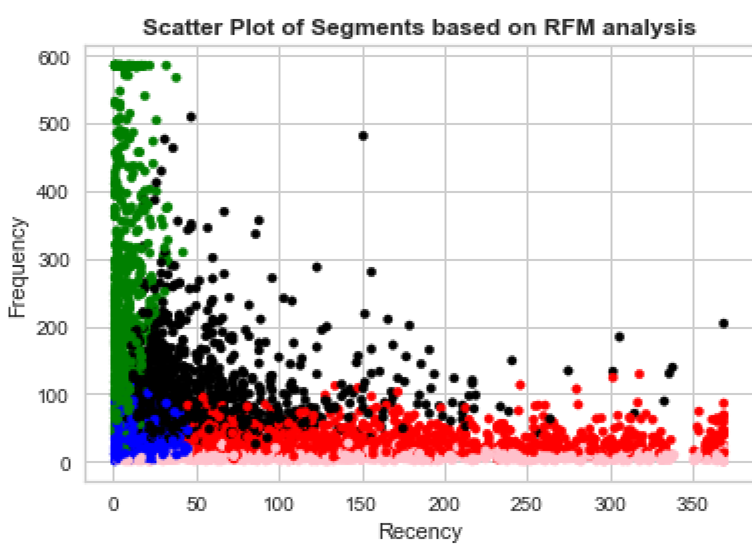
4270 rows × 11 columns

In [103…

```
#Visualisation of segments to validate results

from matplotlib import pyplot as plt


##Scatter Plot Frequency Vs Recency

Colors = (["red", "green", "blue","pink","black"])
rfm['Color'] = rfm['Segment'].map(lambda p: Colors[p])
ax = rfm.plot(kind="scatter", x="Recency", y="Frequency", figsize=(6,4), c = rfm['Color'])
plt.title('Scatter Plot of Segments based on RFM analysis', fontweight='bold')
```

Out[103…

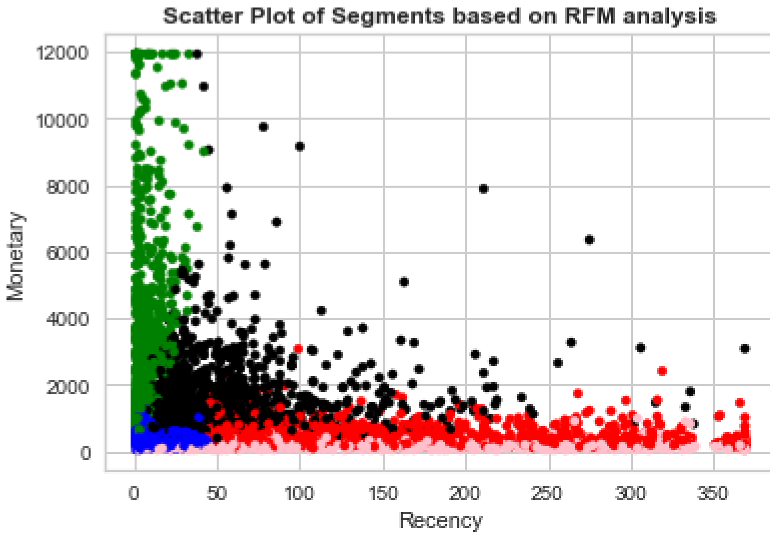
```
Text(0.5, 1.0, 'Scatter Plot of Segments based on RFM analysis')
```



In [104…

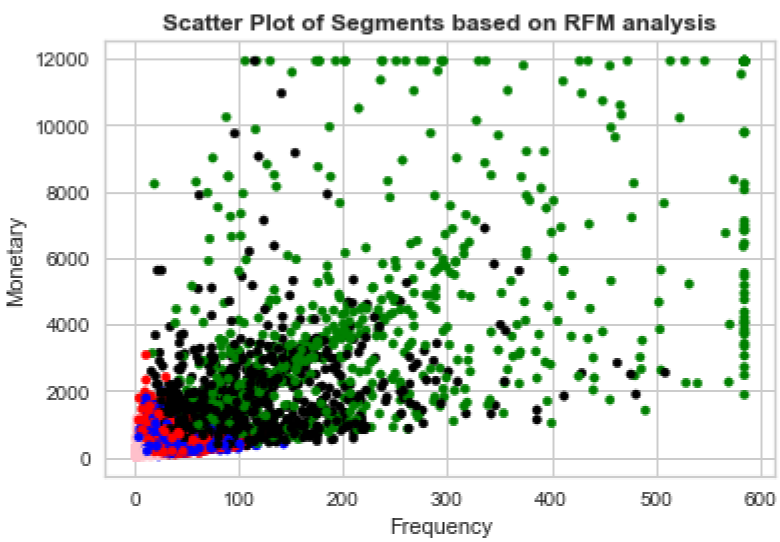
```
##Scatter Plot Monetary Vs Recency

Colors = (["red", "green", "blue","pink","black"])
rfm['Color'] = rfm['Segment'].map(lambda p: Colors[p])
ax = rfm.plot(kind="scatter", x="Recency", y="Monetary", figsize=(6,4), c = rfm['Color'])
plt.title('Scatter Plot of Segments based on RFM analysis', fontweight='bold')
```

Out[104… Text(0.5, 1.0, 'Scatter Plot of Segments based on RFM analysis')



In [105…
```
##Scatter Plot Monetary Vs Frequency

Colors = (["red", "green", "blue","pink","black"])
rfm['Color'] = rfm['Segment'].map(lambda p: Colors[p])
ax = rfm.plot(kind="scatter", x="Frequency", y="Monetary", figsize=(6,4), c = rfm['Color']
plt.title('Scatter Plot of Segments based on RFM analysis', fontweight='bold')
```

Out[105… Text(0.5, 1.0, 'Scatter Plot of Segments based on RFM analysis')



In [106…
```
#checking colors each segment belongs too

rfm.groupby("Color").mean()
```

Out[106…

Color	Recency	Frequency	Monetary	Segment
black	55.242366	104.035305	1651.986746	4.0
blue	18.601997	31.631954	444.265621	2.0
green	7.558320	230.841369	4142.059705	1.0
pink	179.324866	6.974599	149.082968	3.0
red	162.723894	29.692920	474.072372	0.0

In [107…

```
#Taking averages to label cust segmentation

RFM_final.groupby("Segment").mean()
```

Out[107…

Segment	CustomerID	Recency	Frequency	Monetary	R_score	F_score	M_score	RFM_Score	RFM
0	15275.698230	162.723894	29.692920	474.072372	1.549558	2.082301	2.106195	5.738053	177.884956
1	15193.342146	7.558320	230.841369	4142.059705	3.911353	3.835148	3.855365	11.601866	433.342146
2	15354.206847	18.601997	31.631954	444.265621	3.495007	2.101284	2.002853	7.599144	372.516405
3	15338.501337	179.324866	6.974599	149.082968	1.568182	1.040107	1.105615	3.713904	168.324866
4	15280.722328	55.242366	104.035305	1651.986746	2.656489	3.437977	3.418893	9.513359	303.447519

In [108…

```
#Labelying Clusters based on scatter and averages

segment = {1:"Platinum",4:"Diamond", 2:"Gold" , 0:"Silver", 3:"Bronze"}
RFM_final["Segment"].replace(segment,inplace=True)
RFM_final
```

Out[108…

	CustomerID	Recency	Frequency	Monetary	R_score	F_score	M_score	RFM_Score	RFM	Segment	Country
0	12347.0	2	160	3397.95	4	4	4	12	444	Platinum	Iceland
1	12348.0	75	21	1186.78	2	2	3	7	223	Silver	Finland
2	12349.0	18	68	1318.20	3	3	3	9	333	Diamond	Italy
3	12350.0	310	13	251.60	1	1	2	4	112	Silver	Norway
4	12352.0	36	76	1373.34	3	3	3	9	333	Diamond	Norway
...	...	...	...	...	...	...	...	...	...	...	...
4265	18280.0	277	9	165.40	1	1	1	3	111	Bronze	United Kingdom
4266	18281.0	180	4	35.87	1	1	1	3	111	Bronze	United Kingdom
4267	18282.0	7	12	178.15	4	1	1	6	411	Gold	United Kingdom
4268	18283.0	3	585	1872.13	4	4	4	12	444	Platinum	United Kingdom
4269	18287.0	42	58	1220.16	3	3	3	9	333	Diamond	United Kingdom

4270 rows × 11 columns

In [109…

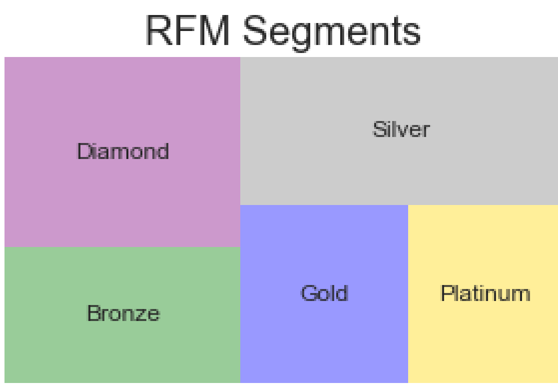
```
# Calculate total customers in each segment
rfm_agg = RFM_final.groupby('Segment').agg({'CustomerID':'count'})
print(rfm_agg)
```

```
          CustomerID
Segment
Bronze           748
Diamond         1048
```

```
Gold            701
Platinum        643
Silver         1130
```

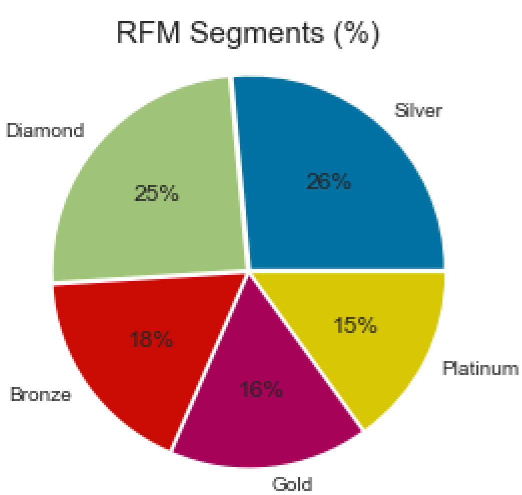
In [144…

```python
#RFM visualization of customers on each segmentation
import squarify

fig = plt.gcf()
ax = fig.add_subplot()
fig.set_size_inches(5, 3)
squarify.plot(sizes=rfm_agg['CustomerID'],
              label=['Bronze',
                     'Diamond',
                     'Gold',
                     'Platinum',
                     'Silver'], color=["green","purple","blue", "gold","grey"], alpha=0.4)
plt.title("RFM Segments",fontsize=20)
plt.axis('off')
plt.show()
```



In [111…

```python
# visualisation of total Customer by segments

top_seg = RFM_final.groupby('Segment')['CustomerID'].count().sort_values(ascending=False)
labels = top_seg[:5].index
size = top_seg[:5].values

plt.figure(figsize=(5,4))
plt.pie(size, labels=labels, explode=[0.02]*5, autopct='%1.0f%%')
plt.title("RFM Segments (%)", size=15)
plt.axis('equal')
plt.show()
```



In [112…

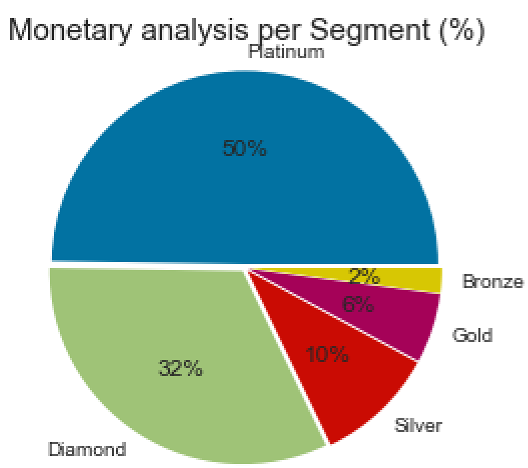
```python
RFM_final.groupby('Segment').agg({'CustomerID':'count'})
```

Out[112...

	CustomerID
Segment	
Bronze	748
Diamond	1048
Gold	701
Platinum	643
Silver	1130

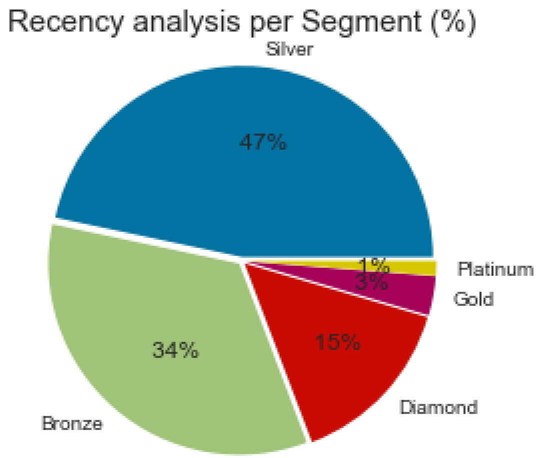
In [113...

```
# visualisation Monetary analysis per Segment

top_seg = RFM_final.groupby('Segment')['Monetary'].sum().sort_values(ascending=False)[:10]
labels = top_seg[:5].index
size = top_seg[:5].values

plt.figure(figsize=(5,4))
plt.pie(size, labels=labels, explode=[0.02]*5, autopct='%1.0f%%')
plt.title("Monetary analysis per Segment (%)", size=15)
plt.axis('equal')
plt.show()
```



In [114...

```
# visualisation Recency analysis per Segment

top_seg = RFM_final.groupby('Segment')['Recency'].sum().sort_values(ascending=False)[:10]
labels = top_seg[:5].index
size = top_seg[:5].values

plt.figure(figsize=(5,4))
plt.pie(size, labels=labels, explode=[0.02]*5, autopct='%5.0f%%')
plt.title("Recency analysis per Segment (%)", size=15)
plt.axis('equal')
plt.show()
```



In [115…

```
# visualisation Frequency analysis per Segment

top_seg = RFM_final.groupby('Segment')['Frequency'].sum().sort_values(ascending=False)[:1(
labels = top_seg[:5].index
size = top_seg[:5].values

plt.figure(figsize=(5,4))
plt.pie(size, labels=labels, explode=[0.02]*5, autopct='%1.0f%%')
plt.title("Frequency analysis per Segment (%)", size=15)
plt.axis('equal')
plt.show()
```