RETAIL

Problem statement:

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

Variables Description

Invoice No **Invoice number. Nominal, a six-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation**

Stock Code **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**

Invoice Date **Invoice Date and time. Numeric, the day and time when each transaction was generated**

Unit Price **Unit price. Numeric, product price per unit in sterling**

Customer ID **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**

ANALYSIS:

Data Cleaning:

1. Perform a preliminary data inspection and data cleaning.

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

b. Remove duplicate data records.

c. Perform descriptive analytics on the given data.

]:
```
data = pd.read_excel('Online Retail.xlsx')
data.head()
```

]:

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

```
data.describe().T
```

	count	mean	min	25%	50%	75%	max	std
Quantity	541909.0	9.55225	-80995.0	1.0	3.0	10.0	80995.0	218.081158
InvoiceDate	541909	2011-07-04 13:34:57.156386048	2010-12-01 08:26:00	2011-03-28 11:34:00	2011-07-19 17:17:00	2011-10-19 11:27:00	2011-12-09 12:50:00	NaN
UnitPrice	541909.0	4.611114	-11062.06	1.25	2.08	4.13	38970.0	96.759853
CustomerID	406829.0	15287.69057	12346.0	13953.0	15152.0	16791.0	18287.0	1713.600303

```
# Dropping rows with negative quantity
data.drop(data[data['Quantity']<=0].index, inplace=True)
```

```
# Dropping rows with $0.00 sales
data.drop(data[data['UnitPrice'] == 0].index, inplace=True)
```

```
# Checking for duplicate rows in database

duplicate = data[data.duplicated()]
print(f'There are {len(duplicate)} duplacate rows in this data file')
```

There are 5226 duplacate rows in this data file

```
# Removing duplicate rows in database and re-checking to be sure the database is clear of duplicates.

data = data.drop_duplicates()
duplicate_check = data[data.duplicated()]
print(f'There are {len(duplicate_check)} duplacate rows in this data file')
```

```
There are 0 duplacate rows in this data file
```

```
# Checking for missing values

data.isna().any()
```

```
InvoiceNo      False
StockCode      False
Description    False
Quantity       False
InvoiceDate    False
UnitPrice      False
CustomerID      True
Country        False
dtype: bool
```

```
Customer_id_isna = data[pd.isnull(data['CustomerID'])]
print('There are: ' + str(len(pd.unique(Customer_id_isna['InvoiceNo']))) + ' Invoices with no Customer ID')
Customer_id_isna
```

```
There are: 1430 Invoices with no Customer ID
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
1443	536544	21773	DECORATIVE ROSE BATHROOM BOTTLE	1	2010-12-01 14:32:00	2.51	NaN	United Kingdom
1444	536544	21774	DECORATIVE CATS BATHROOM BOTTLE	2	2010-12-01 14:32:00	2.51	NaN	United Kingdom
1445	536544	21786	POLKADOT RAIN HAT	4	2010-12-01 14:32:00	0.85	NaN	United Kingdom
1446	536544	21787	RAIN PONCHO RETROSPOT	2	2010-12-01 14:32:00	1.66	NaN	United Kingdom
1447	536544	21790	VINTAGE SNAP CARDS	9	2010-12-01 14:32:00	1.66	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
541536	581498	85099B	JUMBO BAG RED RETROSPOT	5	2011-12-09 10:26:00	4.13	NaN	United Kingdom
541537	581498	85099C	JUMBO BAG BAROQUE BLACK WHITE	4	2011-12-09 10:26:00	4.13	NaN	United Kingdom
541538	581498	85150	LADIES & GENTLEMEN METAL SIGN	1	2011-12-09 10:26:00	4.96	NaN	United Kingdom
541539	581498	85174	S/4 CACTI CANDLES	1	2011-12-09 10:26:00	10.79	NaN	United Kingdom
541540	581498	DOT	DOTCOM POSTAGE	1	2011-12-09 10:26:00	1714.17	NaN	United Kingdom

132188 rows × 8 columns

```python
# Will drop all rows with no Customer ID

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

```python
# Checking for missing values again

data.isna().any()
```

```
InvoiceNo      False
StockCode      False
Description    False
Quantity       False
InvoiceDate    False
UnitPrice      False
CustomerID     False
Country        False
dtype: bool
```

Data Transformation:

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

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

b. Analyse the retention rate of customers.

```
data['Month'] = data['InvoiceDate'].dt.to_period('M')
data.head()
```

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

```
# Convert to InvoiceDate to Year-Month format
data['month_year'] = data['InvoiceDate'].dt.to_period('M')
data['month_year'].nunique()
```

```
13
```

```python
month_cohort = data.groupby('month_year')['CustomerID'].nunique()
month_cohort
```

```
month_year
2010-12     885
2011-01     741
2011-02     758
2011-03     974
2011-04     856
2011-05    1056
2011-06     991
2011-07     949
2011-08     935
2011-09    1266
2011-10    1364
2011-11    1664
2011-12     615
Freq: M, Name: CustomerID, dtype: int64
```

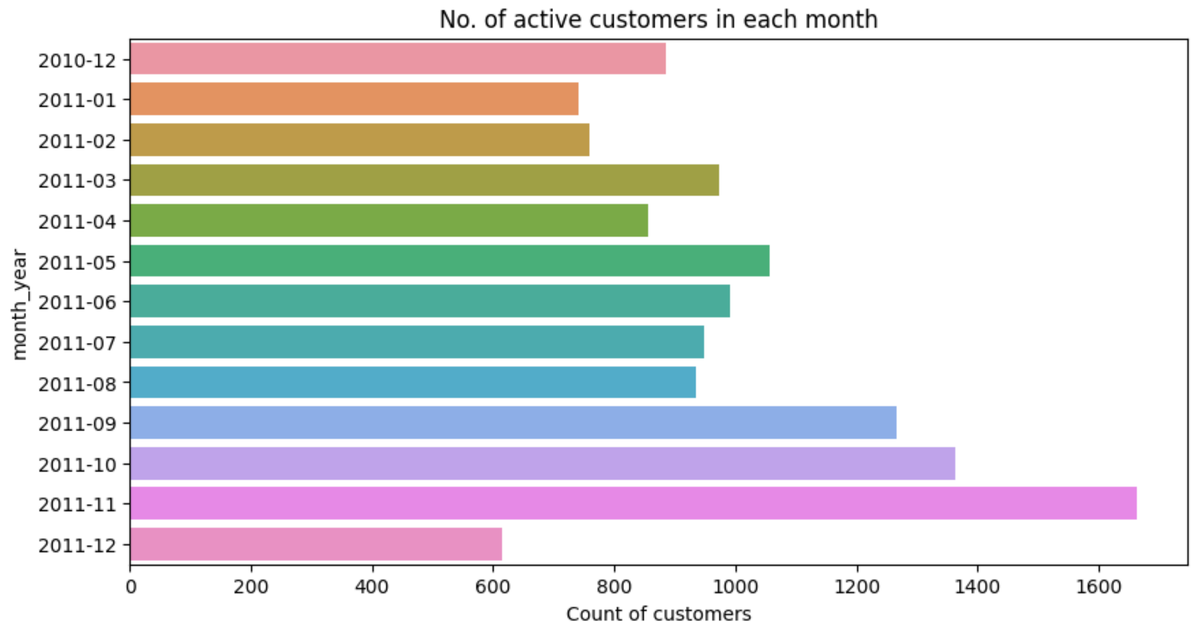
```python
data['cohort'] = data.groupby('CustomerID')['InvoiceDate'] \
               .transform('min') \
               .dt.to_period('M')
```

```python
data.tail(50)
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Month	month_year	cohort
541859	581580	37500	TEA TIME TEAPOT IN GIFT BOX	1	2011-12-09 12:20:00	4.95	12748.0	United Kingdom	2011-12	2011-12	2010-12
541860	581581	23562	SET OF 6 RIBBONS PERFECTLY PRETTY	6	2011-12-09 12:20:00	2.89	17581.0	United Kingdom	2011-12	2011-12	2010-12
541861	581581	23561	SET OF 6 RIBBONS PARTY	6	2011-12-09 12:20:00	2.89	17581.0	United Kingdom	2011-12	2011-12	2010-12
541862	581581	23681	LUNCH BAG RED VINTAGE DOILY	10	2011-12-09 12:20:00	1.65	17581.0	United Kingdom	2011-12	2011-12	2010-12
541863	581582	23552	BICYCLE PUNCTURE REPAIR KIT	6	2011-12-09 12:21:00	2.08	17581.0	United Kingdom	2011-12	2011-12	2010-12
541864	581582	23498	CLASSIC BICYCLE CLIPS	12	2011-12-09 12:21:00	1.45	17581.0	United Kingdom	2011-12	2011-12	2010-12
541865	581583	20725	LUNCH BAG RED RETROSPOT	40	2011-12-09 12:23:00	1.45	13777.0	United Kingdom	2011-12	2011-12	2010-12

```
plt.figure(figsize=(10,5))
sns.barplot(y = month_cohort.index, x = month_cohort.values);
plt.xlabel("Count of customers")
plt.title("No. of active customers in each month")
```

```
Text(0.5, 1.0, 'No. of active customers in each month')
```




```
from operator import attrgetter
data_cohort = data.groupby(['cohort', 'Month']) \
              .agg(n_customers=('CustomerID', 'nunique')) \
              .reset_index(drop=False)
data_cohort['period_number'] = (data_cohort.Month - data_cohort.cohort).apply(attrgetter('n'))
```

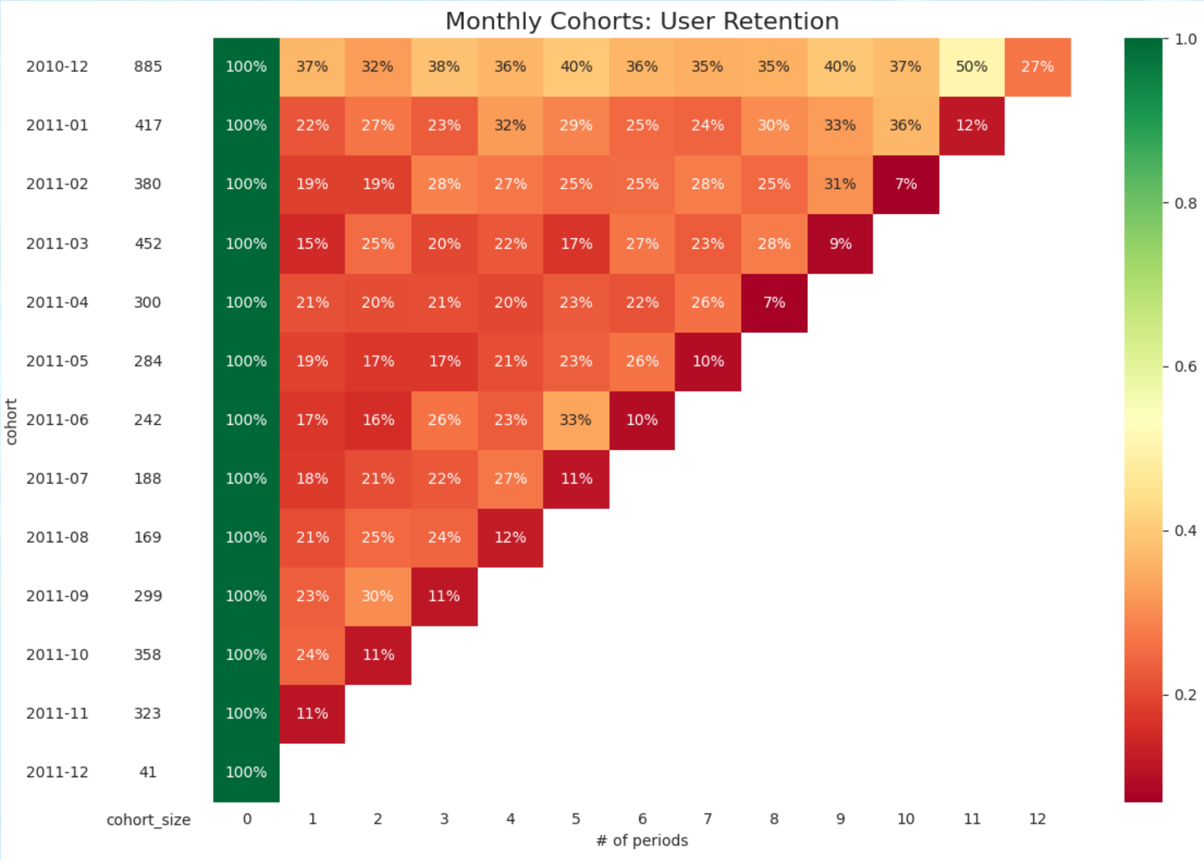
```
data_cohort.head()
```

	cohort	Month	n_customers	period_number
0	2010-12	2010-12	885	0
1	2010-12	2011-01	324	1
2	2010-12	2011-02	286	2
3	2010-12	2011-03	340	3
4	2010-12	2011-04	321	4

```python
cohort_pivot = data_cohort.pivot_table(index = 'cohort',
                                       columns = 'period_number',
                                       values = 'n_customers')
```

```python
cohort_size = cohort_pivot.iloc[:,0]
retention_matrix = cohort_pivot.divide(cohort_size, axis = 0)
```

```python
import seaborn as sns
import matplotlib.colors as mcolors

with sns.axes_style("white"):
    fig, ax = plt.subplots(1, 2, figsize=(12, 8), sharey=True, gridspec_kw={'width_ratios': [1, 11]})

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

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

    fig.tight_layout()
```



- There is a significant drop off in retention after the first month.
- Each subsequent month is about 20% to 30% retention
- The first cohort, 2010-12, seems to be the most consistent with the highest retention percent's
- December is the least consistent month with much lower retention percent than any other month.

Data Modelling :

1. Build a RFM (Recency Frequency Monetary) model. Recency means the number of days since a customer made the last purchase. Frequency is the number of purchase in a given period. It could be 3 months, 6 months or 1 year. Monetary is the total amount of money a customer spent in that given period. Therefore, big spenders will be differentiated among other customers such as MVP (Minimum Viable Product) or VIP.

2. Calculate RFM metrics.

3. Build RFM Segments. Give recency, frequency, and monetary scores individually by dividing them into quartiles.

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

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

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

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

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

```python
from datetime import datetime
recency_now_date = data['InvoiceDate'].max()
recency = data.groupby('CustomerID', as_index=False)['InvoiceDate'].max()
recency.columns = ['CustomerID','max_date']
recency['Recency'] = recency['max_date'].apply(lambda row: (recency_now_date - row).days)
recency.drop(['max_date'], axis=1, inplace=True)
recency.head()
```

	CustomerID	Recency
0	12346.0	325
1	12347.0	1
2	12348.0	74
3	12349.0	18
4	12350.0	309

```python
frequency = data.groupby('CustomerID', as_index=False)['InvoiceNo'].nunique()
frequency.columns = ['CustomerID', 'Frequency']
frequency.head()
```

	CustomerID	Frequency
0	12346.0	1
1	12347.0	7
2	12348.0	4
3	12349.0	1
4	12350.0	1

```python
data['OrderTotal'] = data['Quantity'] * data['UnitPrice']
monetary = data.groupby('CustomerID', as_index=False)['OrderTotal'].sum()
monetary.columns = ['CustomerID', 'Monetary']
monetary.head()
```

	CustomerID	Monetary
0	12346.0	77183.60
1	12347.0	4310.00
2	12348.0	1797.24
3	12349.0	1757.55
4	12350.0	334.40

```python
rfm_data["RecencyScore"] = pd.cut(rfm_data["Recency"],
                                  bins=[-1,
                                    np.percentile(rfm_data["Recency"], 25),
                                        np.percentile(rfm_data["Recency"], 50),
                                        np.percentile(rfm_data["Recency"], 75),
                                        rfm_data["Recency"].max()],
                                  labels=[4, 3, 2, 1]).astype("int")

rfm_data["FrequencyScore"] = pd.cut(rfm_data["Frequency"],
                                  bins=[-1,
                                    np.percentile(rfm_data["Frequency"], 25),
                                        np.percentile(rfm_data["Frequency"], 50),
                                        np.percentile(rfm_data["Frequency"], 75),
                                        rfm_data["Frequency"].max()],
                                  labels=[1, 2, 3, 4]).astype("int")

rfm_data["MonetaryScore"] = pd.cut(rfm_data["Monetary"],
                                  bins=[-1,
                                    np.percentile(rfm_data["Monetary"], 25),
                                        np.percentile(rfm_data["Monetary"], 50),
                                        np.percentile(rfm_data["Monetary"], 75),
                                        rfm_data["Monetary"].max()],
                                  labels=[1, 2, 3, 4]).astype("int")

rfm_data['RFM_Score'] = rfm_data['RecencyScore'] + rfm_data['FrequencyScore'] + rfm_data['MonetaryScore']
```

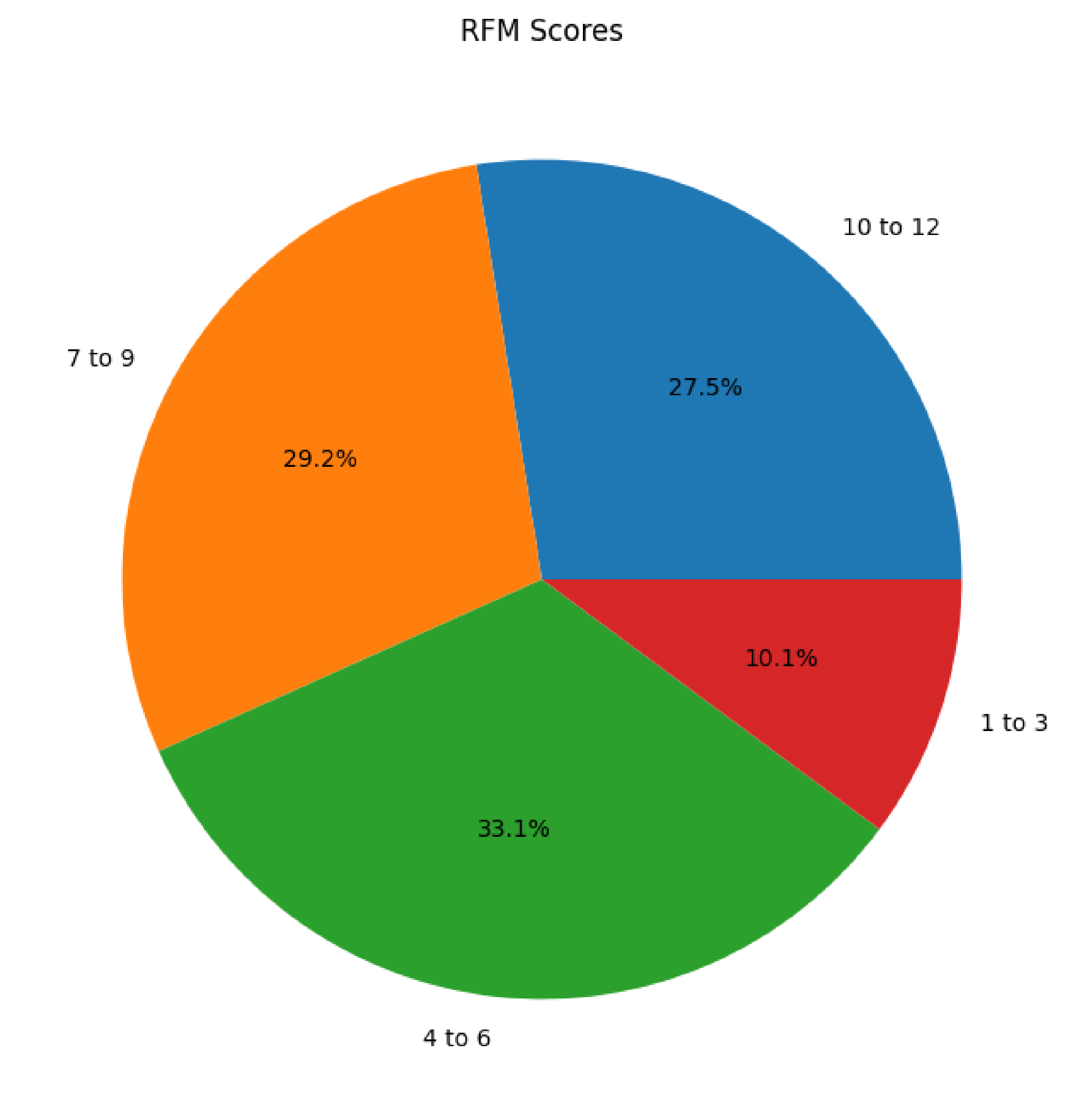
```python
# Looking at the RFM data to see how it was segmented.
rfm_segmentation = pd.DataFrame()
rfm_segmentation['RecencyMinValue'] = rfm_data.groupby('RecencyScore')['Recency'].min()
rfm_segmentation['RecencyMaxValue'] = rfm_data.groupby('RecencyScore')['Recency'].max()
rfm_segmentation['FrequencyMinValue'] = rfm_data.groupby('FrequencyScore')['Frequency'].min()
rfm_segmentation['FrequencyMaxValue'] = rfm_data.groupby('FrequencyScore')['Frequency'].max()
rfm_segmentation['MonetaryMinValue'] = rfm_data.groupby('MonetaryScore')['Monetary'].min()
rfm_segmentation['MonetaryMaxValue'] = rfm_data.groupby('MonetaryScore')['Monetary'].max()
rfm_segmentation
```

RecencyScore	RecencyMinValue	RecencyMaxValue	FrequencyMinValue	FrequencyMaxValue	MonetaryMinValue	MonetaryMaxValue
1	142	373	1	1	3.75	306.46
2	51	141	2	2	306.55	668.56
3	18	50	3	5	668.58	1659.75
4	0	17	6	209	1660.88	280206.02

Looking at the RFM Segments we can make the following observations:

- **25% of customers have been active in the last 17 days**
- **More than 25% of all customers have not been active in the last 4 and a half months**
- **More than 75% of customers have placed no more than 5 orders total**
- **Less than 25% of customers are responsible for the vast majority of overall sales at over $280k**

```
top = len(rfm_data[rfm_data['RFM_Score'] >= 10])
mid_top = len(rfm_data[rfm_data['RFM_Score'].isin(range(7,10))])
mid_bottom = len(rfm_data[rfm_data['RFM_Score'].isin(range(4,7))])
bottom = len(rfm_data[rfm_data['RFM_Score'] <= 3])

pie_data = ([top, mid_top, mid_bottom, bottom])
labels = ['10 to 12', '7 to 9', '4 to 6', '1 to 3']
plt.figure(figsize=(8,8))
plt.title('RFM Scores')
plt.pie(pie_data, labels=labels, autopct='%1.1f%%');
```



Most of the RFM Scores are somewhat equally distributed among all customers with the exception of customers with RFM Scores of 1 to 3 which is only 10% of total customers.

Data Modelling :

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. Analyse these clusters and comment on the results.

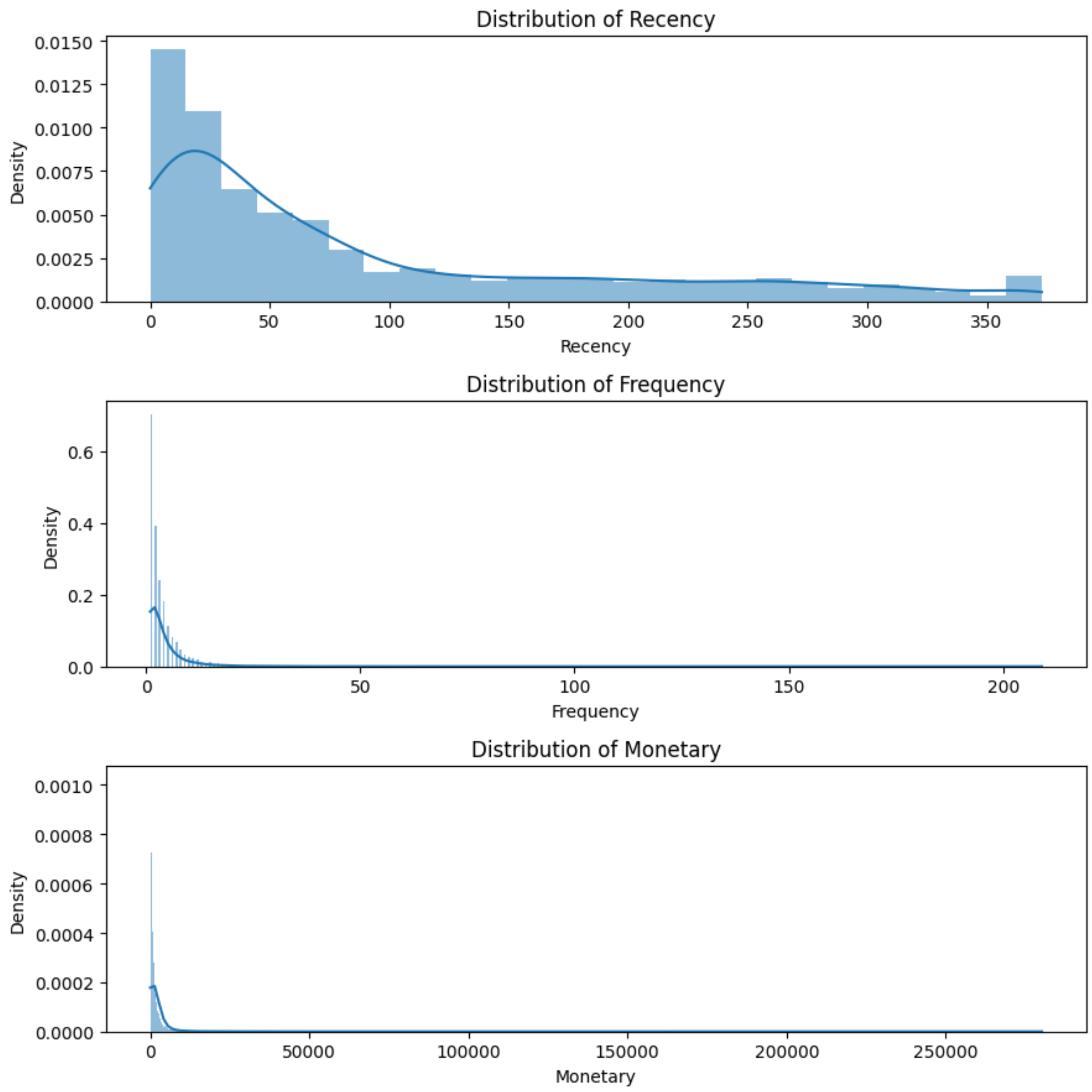
```
from scipy import stats

# Function to check for skewness
def check_skew(df_skew, column):
    skew = stats.skew(df_skew[column])
    skewtest = stats.skewtest(df_skew[column])
    plt.title('Distribution of ' + column)
    sns.histplot(df_skew[column], kde=True, stat='density', linewidth=0)
    print("{}'s: Skew {}, : {}".format(column, skew, skewtest))
    return
```

```
rfm_segments = rfm_data[['CustomerID', 'Recency', 'Frequency', 'Monetary']]
rfm_segments.head()
```

	CustomerID	Recency	Frequency	Monetary
0	12346.0	325	1	77183.60
1	12347.0	1	7	4310.00
2	12348.0	74	4	1797.24
3	12349.0	18	1	1757.55
4	12350.0	309	1	334.40

```
plt.figure(figsize=(9,9))

plt.subplot(3,1,1)
check_skew(rfm_segments, 'Recency')

plt.subplot(3,1,2)
check_skew(rfm_segments, 'Frequency')

plt.subplot(3,1,3)
check_skew(rfm_segments, 'Monetary')

plt.tight_layout()
```

```
Recency's: Skew 1.2456166142880103, : SkewtestResult(statistic=26.606793376917242, pvalue=5.664292789640091e-156)
Frequency's: Skew 12.062857869870964, : SkewtestResult(statistic=74.62743613377035, pvalue=0.0)
Monetary's: Skew 19.332680144099353, : SkewtestResult(statistic=85.01187149828888, pvalue=0.0)
```

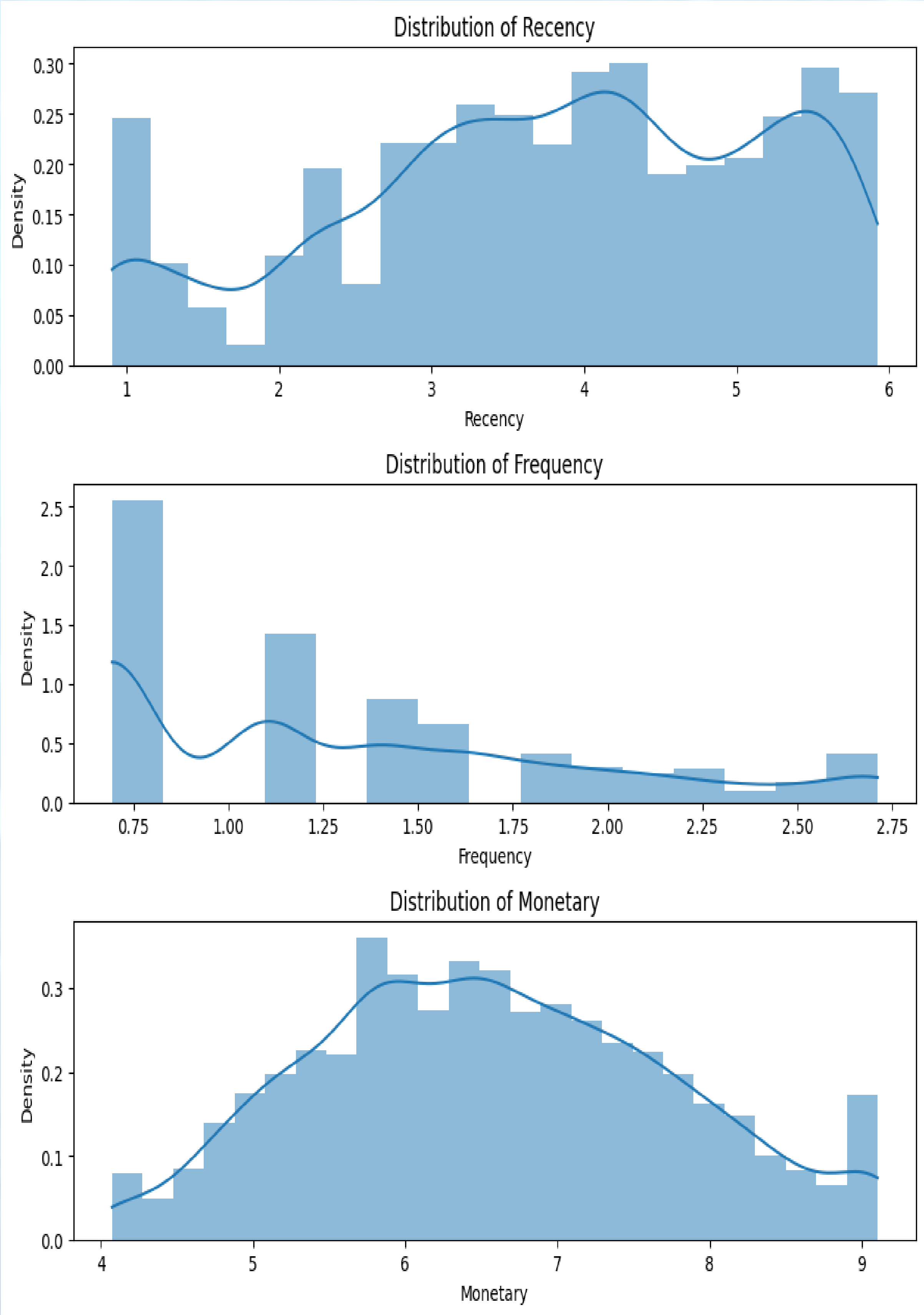


```python
rfm_data_log = rfm_segments.copy()
rfm_data_log.head()
```

	CustomerID	Recency	Frequency	Monetary
0	12346.0	325	1	77183.60
1	12347.0	1	7	4310.00
2	12348.0	74	4	1797.24
3	12349.0	18	1	1757.55
4	12350.0	309	1	334.40

```python
import feature_engine
from feature_engine.outliers import Winsorizer

rfm_data_log = np.log(rfm_data_log+1)

winsorizer = Winsorizer(tail='both', fold=2, variables=['Recency', 'Frequency', 'Monetary'])
winsorizer.fit(rfm_data_log)

rfm_data_log = winsorizer.transform(rfm_data_log)

plt.figure(figsize=(9,9))

plt.subplot(3,1,1)
check_skew(rfm_data_log, 'Recency')

plt.subplot(3,1,2)
check_skew(rfm_data_log, 'Frequency')

plt.subplot(3,1,3)
check_skew(rfm_data_log, 'Monetary')

plt.tight_layout()
```

```
Recency's: Skew -0.3863807061514661, : SkewtestResult(statistic=-10.055002925140908, pvalue=8.731884165686116e-24)
Frequency's: Skew 0.7220853981502767, : SkewtestResult(statistic=17.54001378255881, pvalue=7.091019464639143e-69)
Monetary's: Skew 0.16491244333780397, : SkewtestResult(statistic=4.412400335006802, pvalue=1.0223085847018888e-05)
```

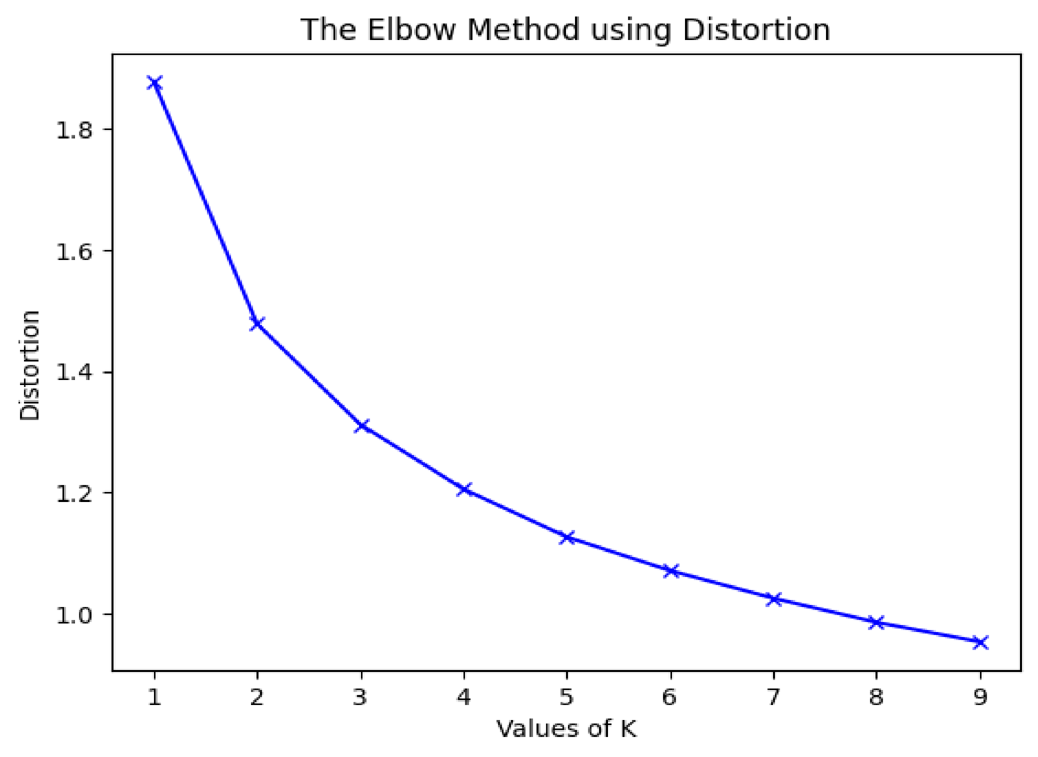


Distribution of Recency
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
1
2
3
4
5
6
Recency
Distribution of Frequency
Density
0.0
0.5
1.0
1.5
2.0
2.5
0.75
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
Frequency
Distribution of Monetary
Density
0.0
0.1
0.2
0.3
4
5
6
7
8
9
Monetary

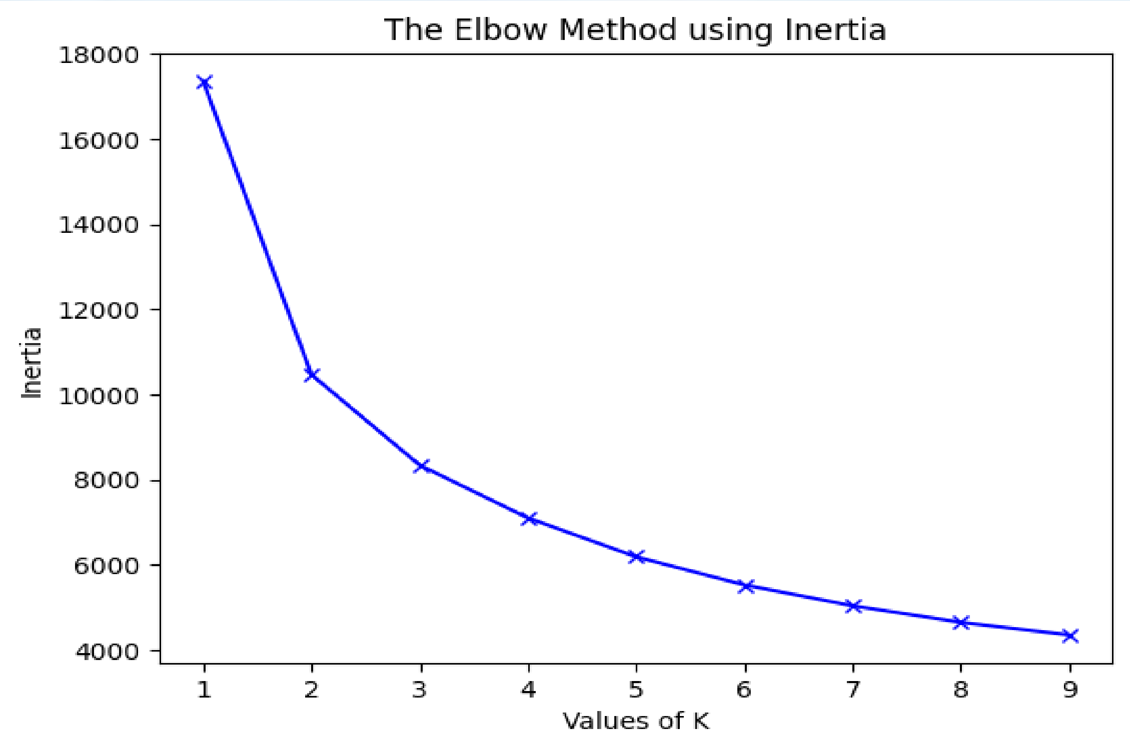
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(rfm_data_log)
rfm_data_scaled = scaler.transform(rfm_data_log)
```

```python
from sklearn.cluster import KMeans

from scipy.spatial.distance import cdist
distortions = []
inertias = []
mapping1 = {}
mapping2 = {}
K = range(1, 10)

for k in K:
    # Building and fitting the model
    kmeanModel = KMeans(n_clusters=k).fit(rfm_data_scaled)
    kmeanModel.fit(rfm_data_scaled)

    distortions.append(sum(np.min(cdist(rfm_data_scaled, kmeanModel.cluster_centers_,
                                        'euclidean'), axis=1)) / rfm_data_scaled.shape[0])
    inertias.append(kmeanModel.inertia_)

    mapping1[k] = sum(np.min(cdist(rfm_data_scaled, kmeanModel.cluster_centers_,
                                   'euclidean'), axis=1)) / rfm_data_scaled.shape[0]
    mapping2[k] = kmeanModel.inertia_
```

```python
plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```

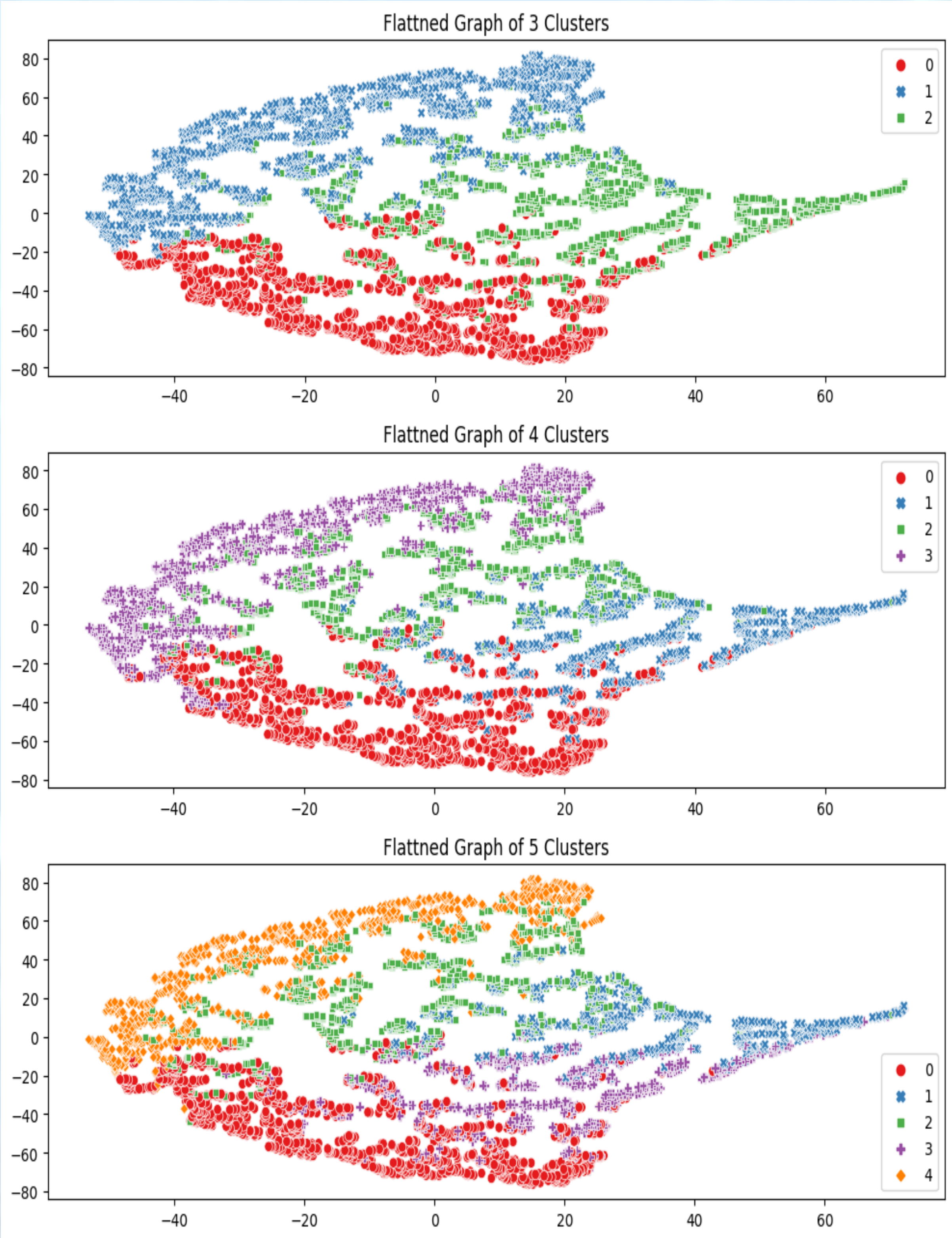



```
plt.plot(K, inertias, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```



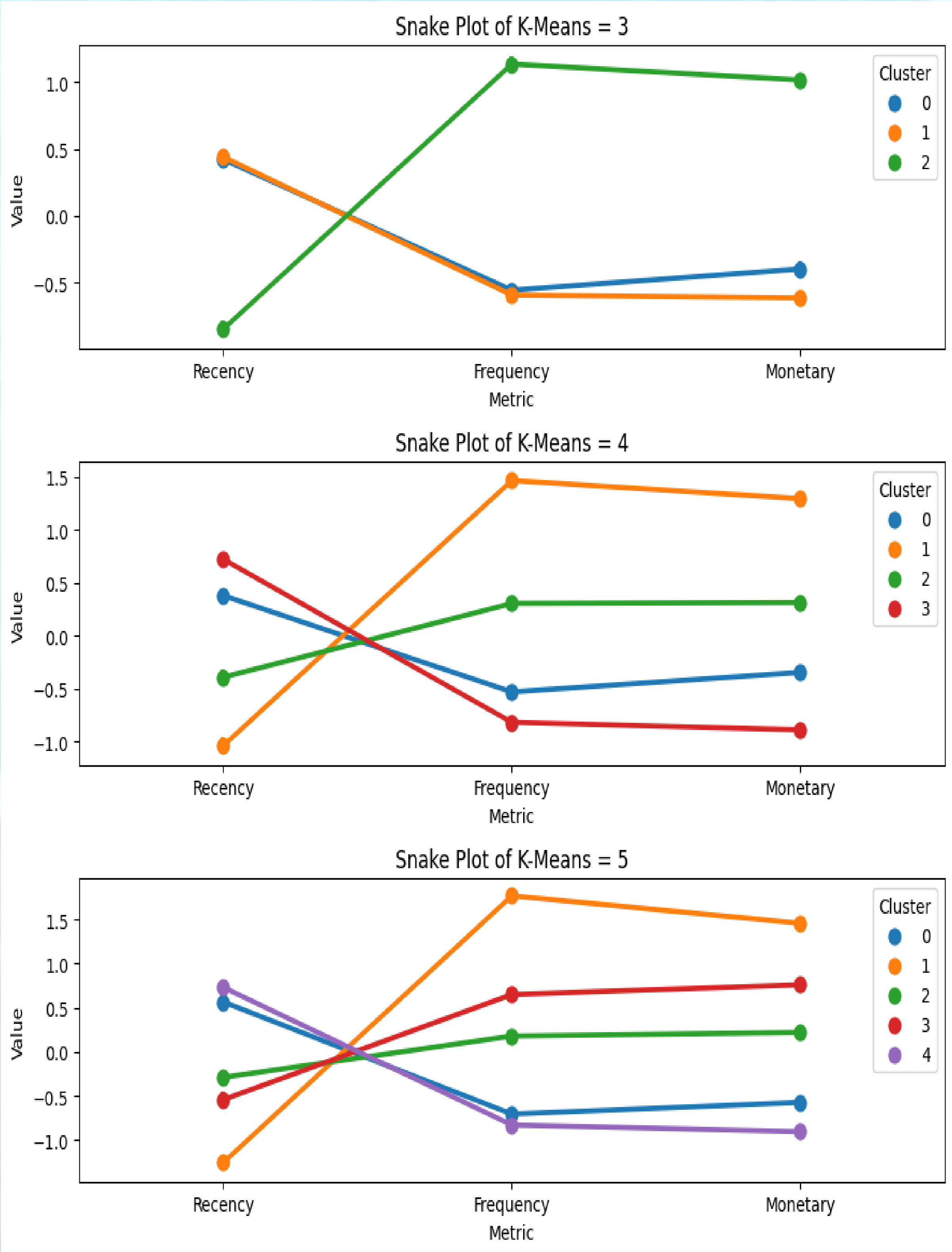
```python
from sklearn.manifold import TSNE

def kmeans(normalised_df_rfm, clusters_number, original_df_rfm):
    kmeans = KMeans(n_clusters = clusters_number, random_state=1)
    kmeans.fit(normalised_df_rfm)

    cluster_labels = kmeans.labels_

    df_new = original_df_rfm.assign(Cluster = cluster_labels)

    model = TSNE(random_state=1)
    transformed = model.fit_transform(df_new)

    plt.title('Flattned Graph of {} Clusters'.format(clusters_number))
    sns.scatterplot(x=transformed[:,0], y=transformed[:, 1], hue=cluster_labels, style=cluster_labels, palette='Set1')

    return df_new
```

```python
import warnings
warnings.filterwarnings('ignore')

plt.figure(figsize=(10,10))

plt.subplot(3,1,1)
df_rfm_k3 = kmeans(rfm_data_scaled, 3, rfm_segments)

plt.subplot(3,1,2)
df_rfm_k4 = kmeans(rfm_data_scaled, 4, rfm_segments)

plt.subplot(3,1,3)
df_rfm_k5 = kmeans(rfm_data_scaled, 5, rfm_segments)

plt.tight_layout()
```


Flattned Graph of 3 Clusters
0
1
2
Flattned Graph of 4 Clusters
0
1
2
3
Flattned Graph of 5 Clusters
0
1
2
3
4

```python
def snake_plot(normalised_df_rfm, df_rfm_kmeans, df_rfm_original):
    normalised_df_rfm = pd.DataFrame(normalised_df_rfm,
                                     index=rfm_segments.index,
                                     columns=rfm_segments.columns)
    normalised_df_rfm['Cluster'] = df_rfm_kmeans['Cluster']

    df_melt = pd.melt(normalised_df_rfm.reset_index(),
                      id_vars=['CustomerID', 'Cluster'],
                      value_vars=['Recency', 'Frequency', 'Monetary'],
                      var_name='Metric',
                      value_name='Value')
    plt.xlabel('Metric')
    plt.ylabel('Value')
    sns.pointplot(data=df_melt, x='Metric', y='Value', hue='Cluster')

    return
```

```python
plt.figure(figsize=(9,9))

plt.subplot(3,1,1)
plt.title('Snake Plot of K-Means = 3')
snake_plot(rfm_data_scaled, df_rfm_k3, rfm_segments)

plt.subplot(3,1,2)
plt.title('Snake Plot of K-Means = 4')
snake_plot(rfm_data_scaled, df_rfm_k4, rfm_segments)

plt.subplot(3,1,3)
plt.title('Snake Plot of K-Means = 5')
snake_plot(rfm_data_scaled, df_rfm_k5, rfm_segments)

plt.tight_layout()
```


Snake Plot of K-Means = 3
Value
Recency
Frequency
Monetary
Metric
Cluster
0
1
2
Snake Plot of K-Means = 4
Value
Recency
Frequency
Monetary
Metric
Cluster
0
1
2
3
Snake Plot of K-Means = 5
Value
Recency
Frequency
Monetary
Metric
Cluster
0
1
2
3
4

```python
df_rfm_k4.groupby('Cluster').agg({
    'Recency':'mean',
    'Frequency':'mean',
    'Monetary':['mean', 'count']
}).round(0)
```

	Recency	Frequency	Monetary	
	mean	mean	mean	count
Cluster				
0	117.0	2.0	747.0	1234
1	18.0	12.0	6967.0	888
2	42.0	4.0	1362.0	1033
3	164.0	1.0	315.0	1183

Based on the resulting clustered data and going with the 4-cluster selection as that seems to be most appropriate separation of data, we can make the following statements regarding the clusters.

- **Cluster 0. Less Recently Active - Less Frequent - Medium Monetary Value.**
- **Cluster 1. Most Recently Active - Most Frequent - Highest Monetary Value**
- **Cluster 2. Recently Active - Frequent - Good Monetary Value**
- **Cluster 3. Least Recently Active - One Time Frequency - Least Monetary Value**
- **Cluster 1 and 3 are the current valued customers worth trying to retain, with Cluster 1 being the Most Valued Customers.**
- **Clusters 0 and 3 are most likely passer-by customers that are possibly already lost or on the verge of being lost**

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

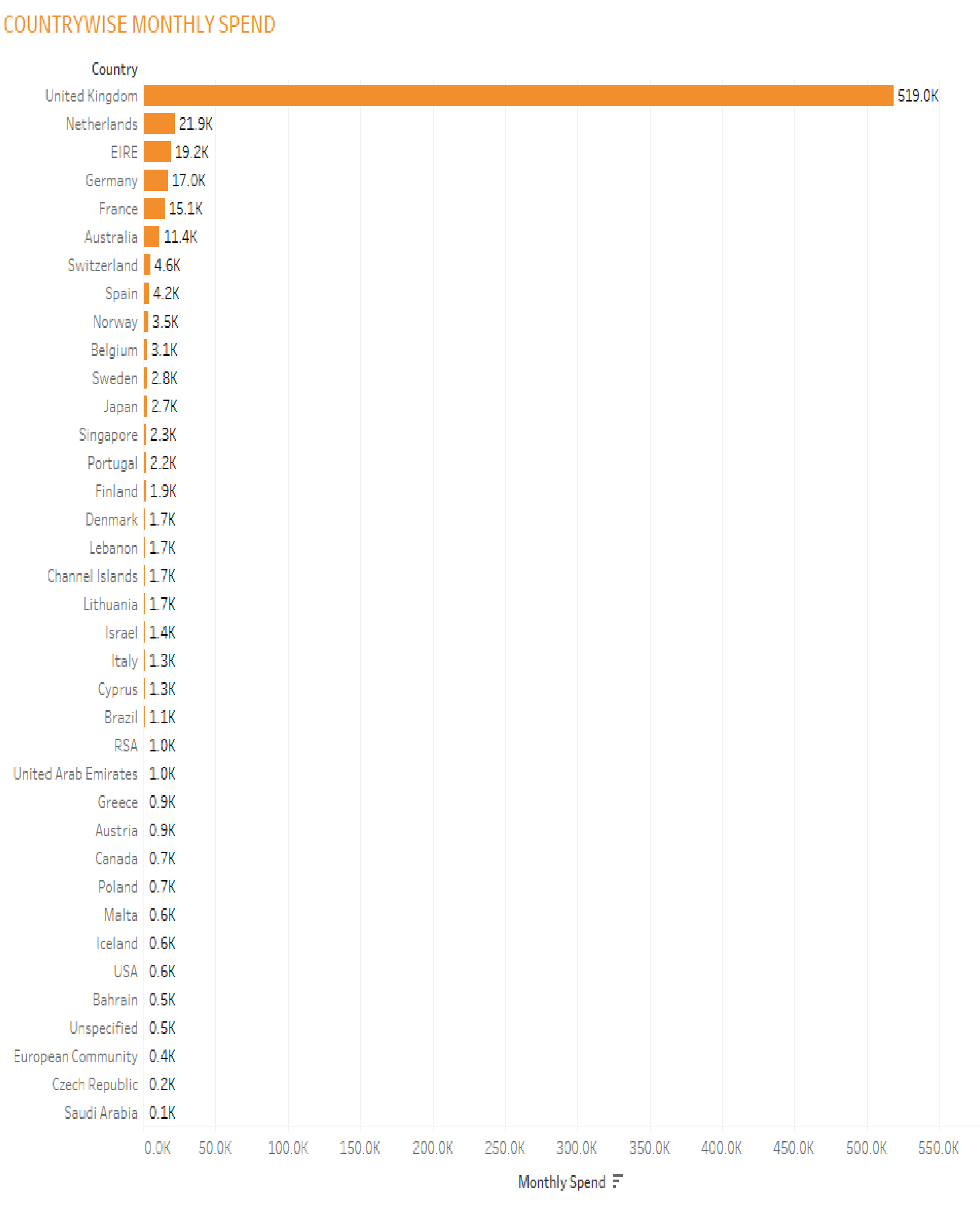
c. Bar graph to show the count of orders vs. hours throughout the day

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

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

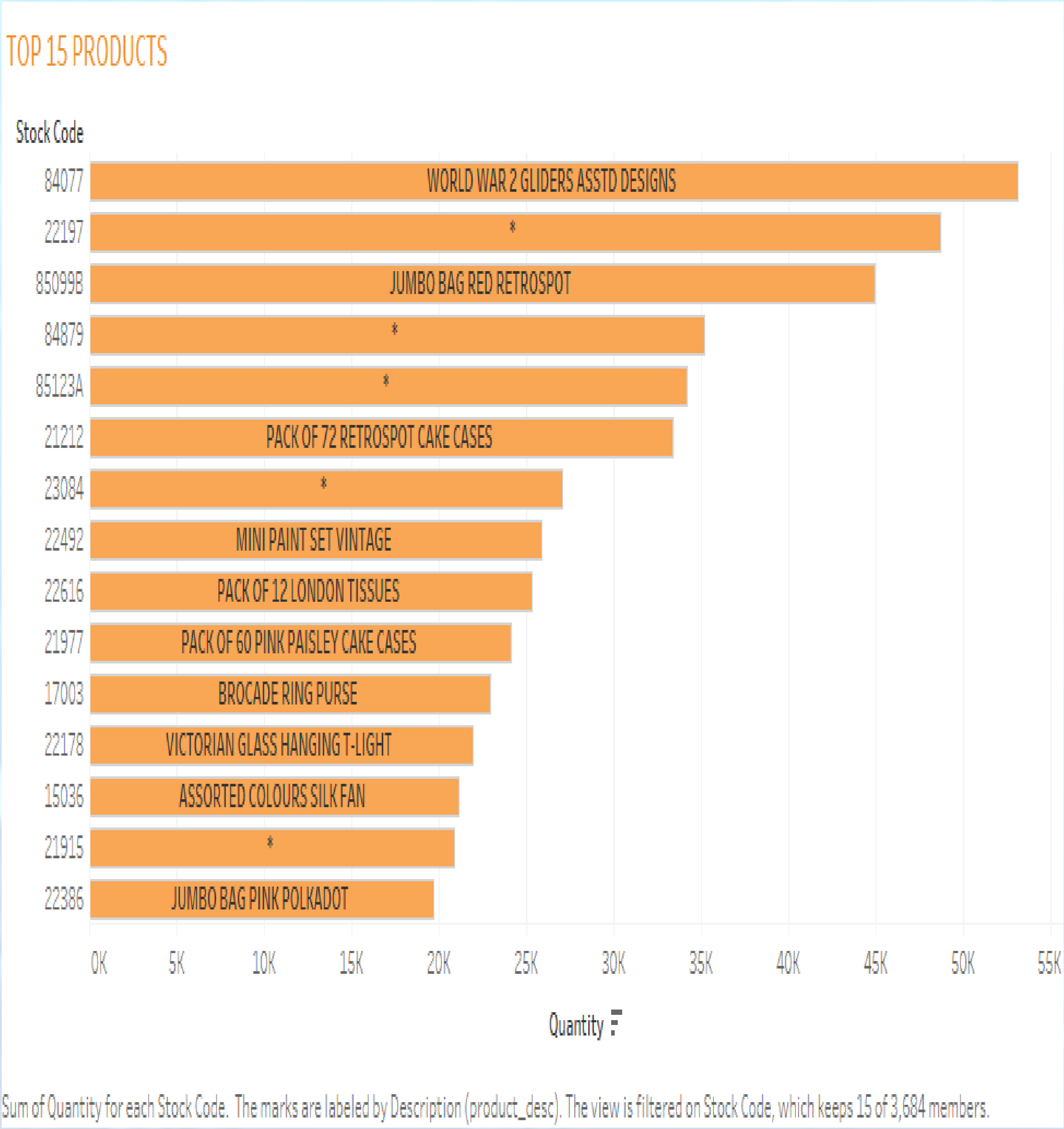
f. Visualize to compare the RFM values of the clusters using heatmap

Country wise Monthly Spend

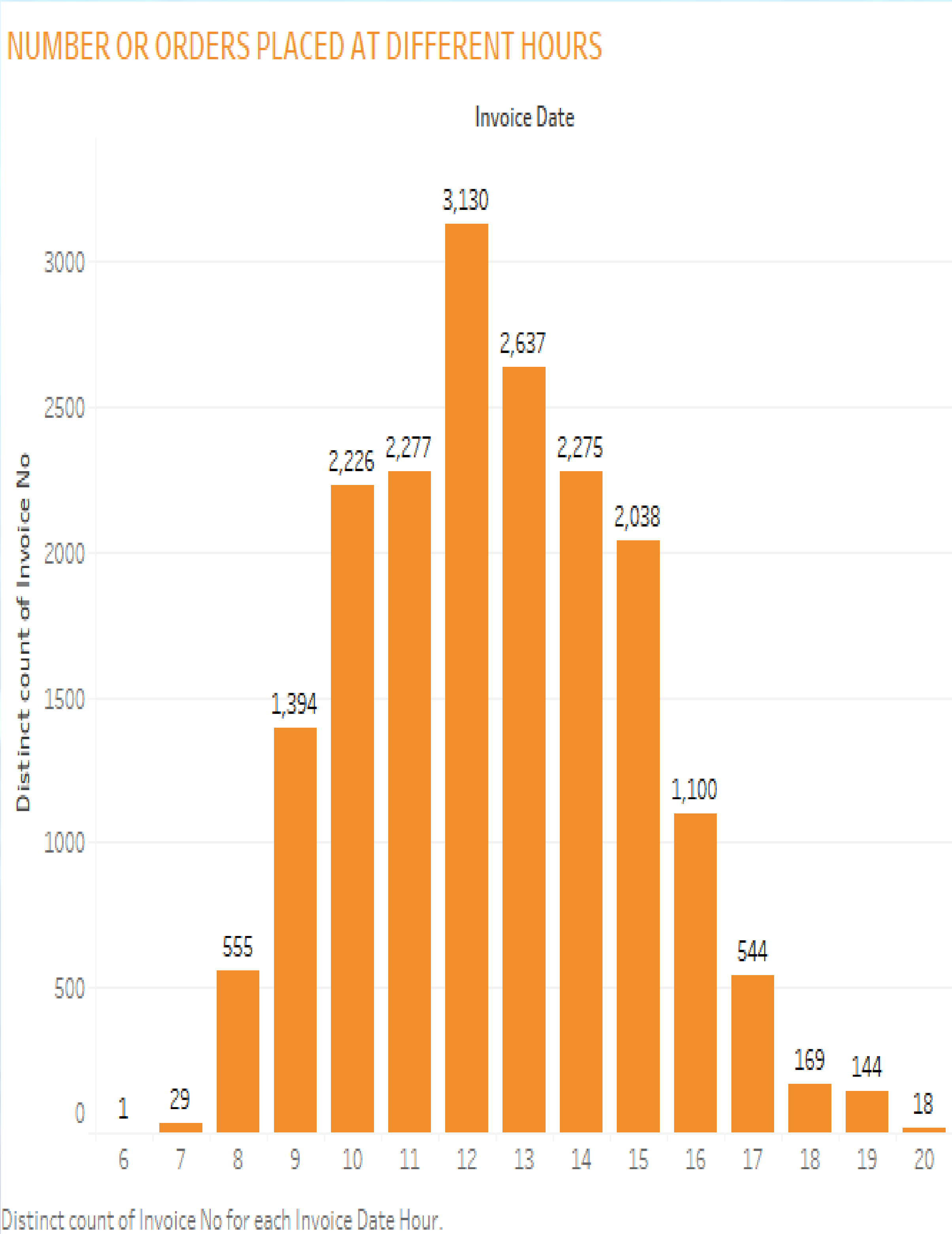


Monthly Spend for each Country.

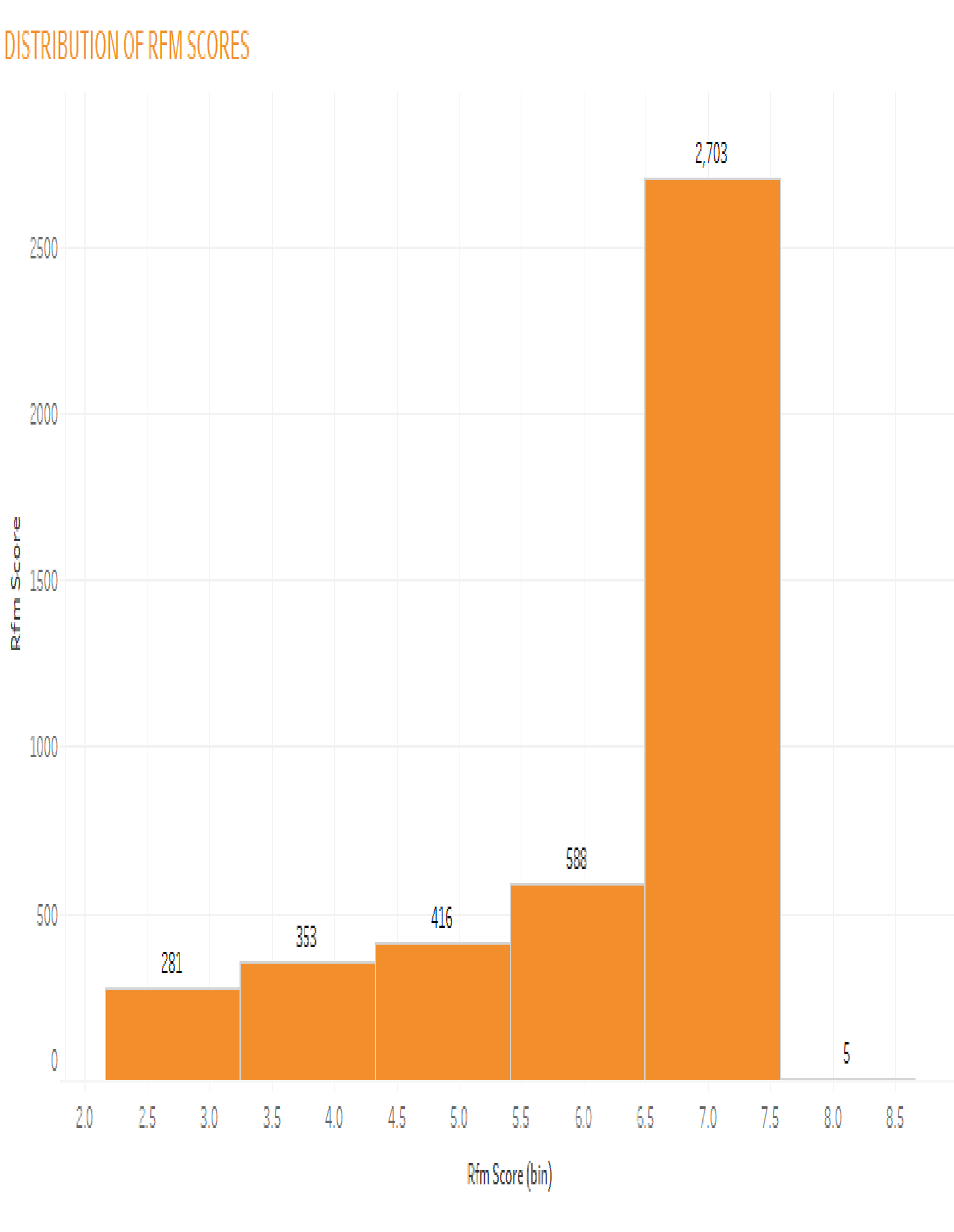
Top 15 Products



Number Or Orders Placed at Different Hours

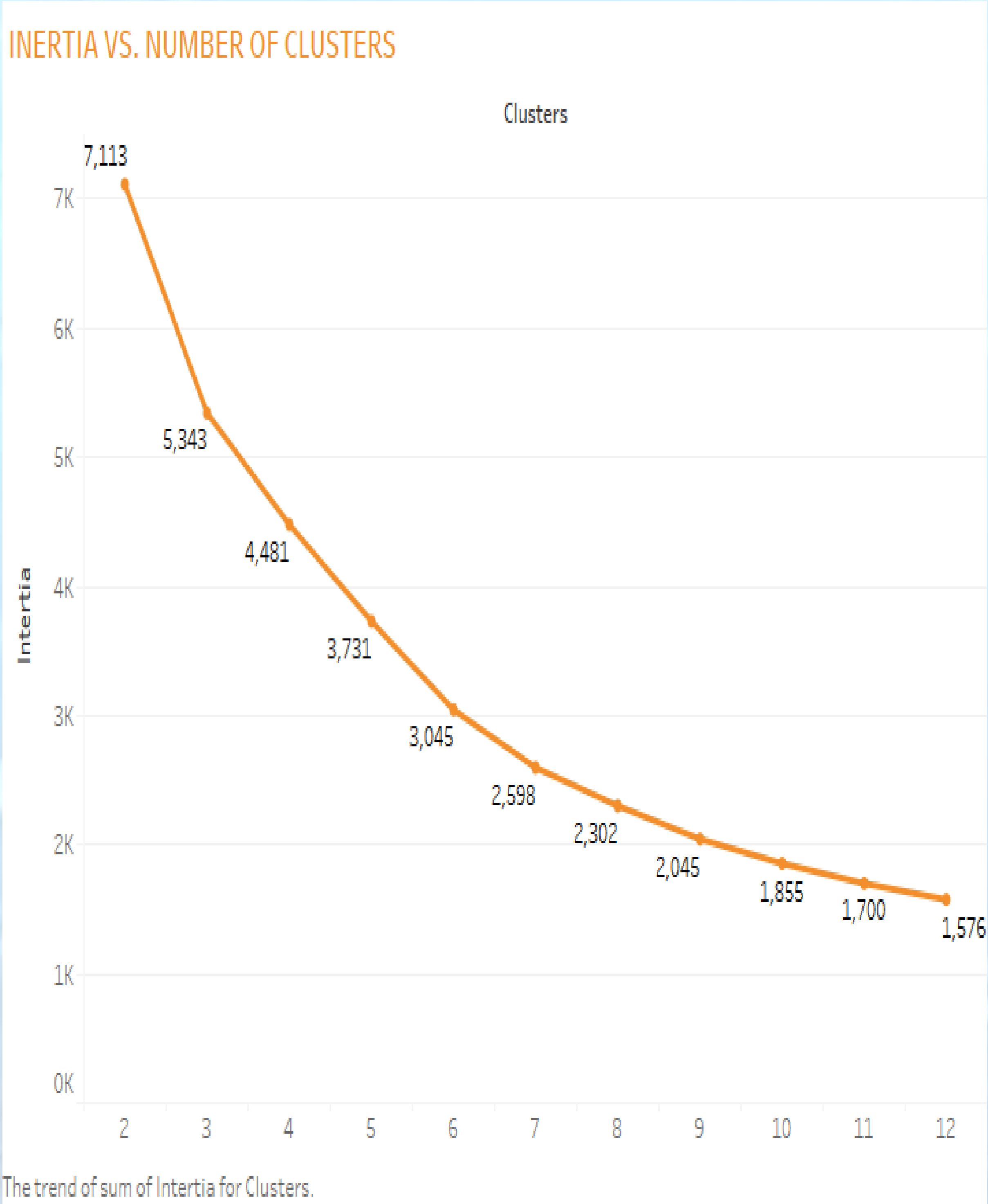


Distribution Of RFM Scores

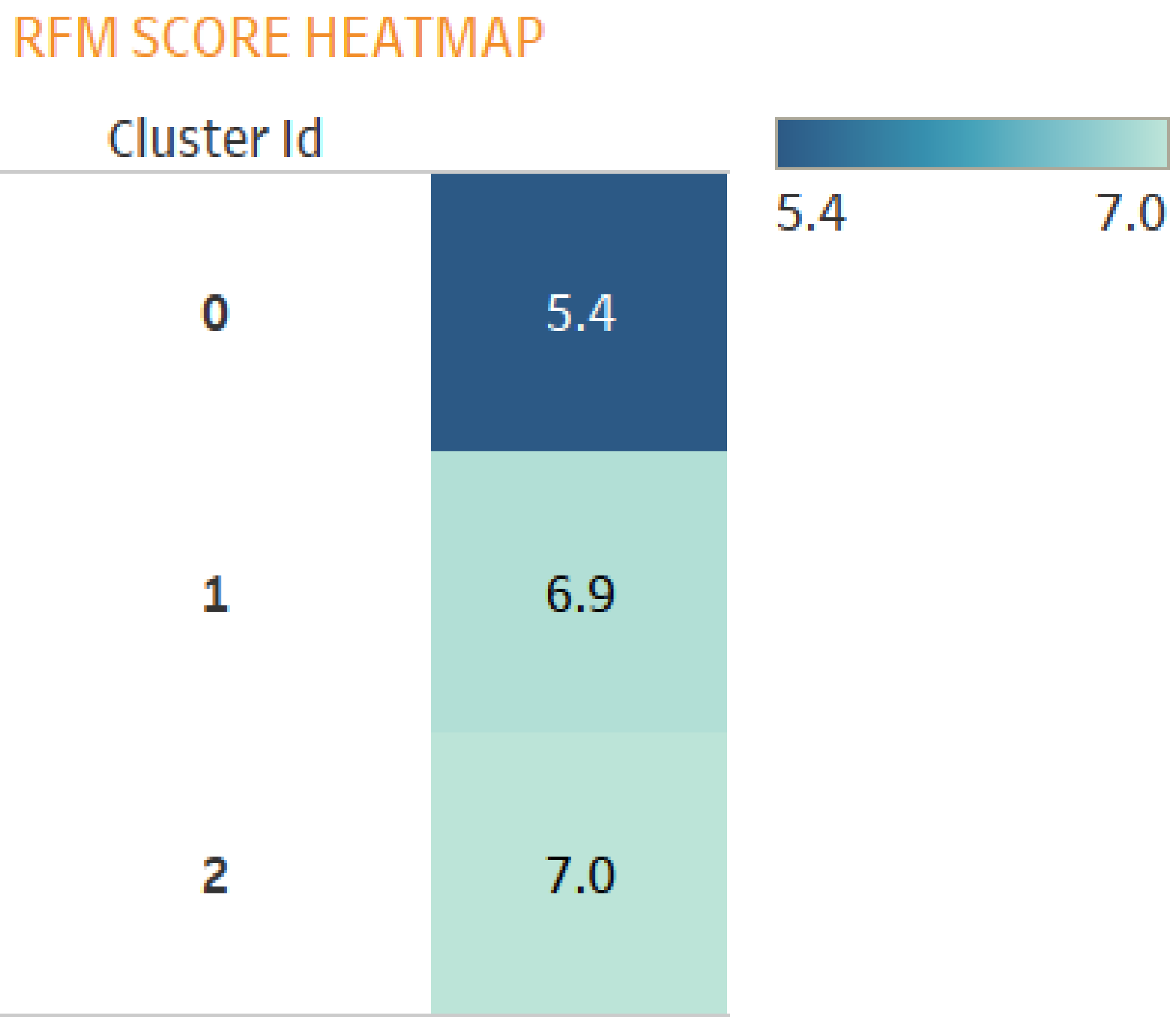


The trend of count of Rfm Score for Rfm Score (bin).

Inertia vs. Number of Clusters

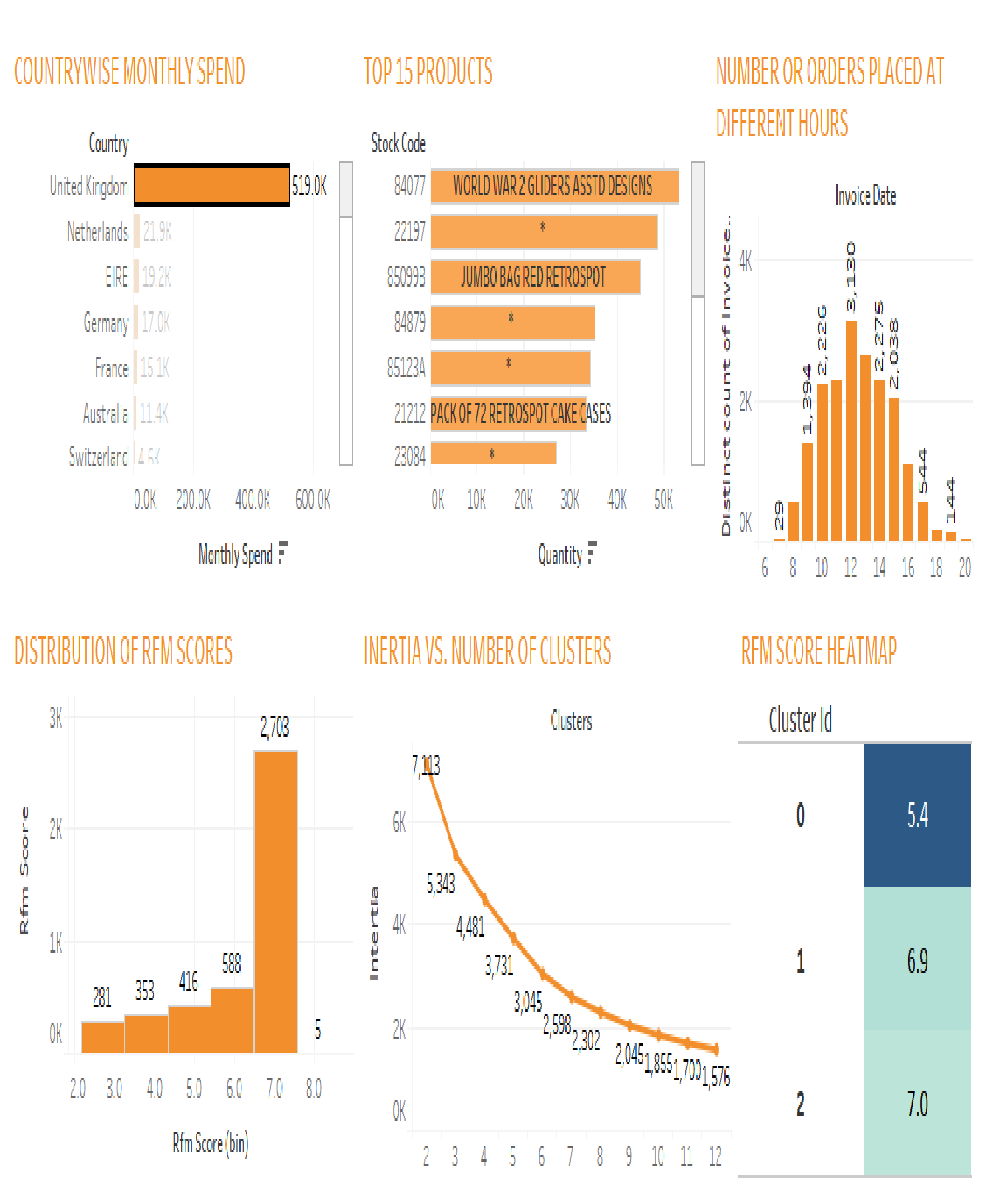


RFM Score Heatmap



Average of Rfm Score broken down by Cluster Id. Color shows average of Rfm Score. The marks are labeled by average of Rfm Score.

Dash Board



COUNTRYWISE MONTHLY SPEND
Country
United Kingdom 519.0K
Netherlands 21.9K
EIRE 19.2K
Germany 17.0K
France 15.1K
Australia 11.4K
Switzerland
0.0K 200.0K 400.0K 600.0K
Monthly Spend
TOP 15 PRODUCTS
Stock Code
84077 WORLD WAR 2 GLIDERS ASSTD DESIGNS
22197 *
85099B JUMBO BAG RED RETROSPOT
84879 *
85123A *
21212 PACK OF 72 RETROSPOT CAKE CASES
23084 *
0K 10K 20K 30K 40K 50K
Quantity
NUMBER OR ORDERS PLACED AT DIFFERENT HOURS
Invoice Date
Distinct count of Invoice..
4K 2K 0K
29 1,394 2,226 3,130 2,275 2,038 544 144
6 8 10 12 14 16 18 20
DISTRIBUTION OF RFM SCORES
Rfm Score
3K 2K 1K 0K
281 353 416 588 2,703 5
2.0 3.0 4.0 5.0 6.0 7.0 8.0
Rfm Score (bin)
INERTIA VS. NUMBER OF CLUSTERS
Clusters
Inertia
6K 4K 2K 0K
7,113 5,343 4,481 3,731 3,045 2,598 2,302 2,045 1,855 1,700 1,576
2 3 4 5 6 7 8 9 10 11 12
RFM SCORE HEATMAP
Cluster Id
0 5.4
1 6.9
2 7.0

THANK YOU