In order to maintain a good CRM (Customer Relationship Management), a company should be aware of each customer's attitude towards the company. The company should know the answers to the following questions:

1. when did the customer last purchased? (Recency)
2. how often does the customer purchase? (Frequency)
3. how much money did the customer spend? (Monetary)

The answers to the above questions would make the customer be categorized and after this process, the company would be dealing with tens of segments instead of tens of thousands customers. **RFM** is an acronym that stands for **Recency**, **Frequency** and **Monetary**. In order to assign each customer into the appropriate segment, RFM metrics should be calculated and afterwards RFM scores should be computed.

## Getting to know the variables:

**InvoiceNo** : The number of the invoice, unique per each purchase. Refund invoice numbers contain "C"
**StockCode** : Unique code per each item
**Description** : Name of the item
**Quantity** : The number of items within the invoice
**InvoiceDate** : Date and time of the purchase
**UnitPrice** : Price of a single item, as of Sterlin
**CustomerID** : Unique id number per each customer
**Country** : The country where the customer is living

## install packages and set configurations

In [1]:
```
import numpy as np
import pandas as pd
import datetime as dt

pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

In [2]:
```
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
%matplotlib inline
import plotly.graph_objs as go
import plotly.offline as py
import plotly.tools as tls
import plotly.offline as offline
offline.init_notebook_mode(connected = True)

import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter(action='ignore', category=FutureWarning)
```

## Read data

In [3]:
```
df_ = pd.read_excel(r"C:\Users\raval\Downloads\Online Retail.xlsx")
df = df_.copy()
df.head()
```

Out[3]:

| | Invoice | StockCode | Description | Quantity | InvoiceDate | Price | Customer ID | Country |
|---|---|---|---|---|---|---|---|---|
| **0** | 536365 | 85123A | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55000 | 17850.00000 | United Kingdom |
| **1** | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39000 | 17850.00000 | United Kingdom |
| **2** | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75000 | 17850.00000 | United Kingdom |
| **3** | 536365 | 84029G | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 2010-12-01 08:26:00 | 3.39000 | 17850.00000 | United Kingdom |
| **4** | 536365 | 84029E | RED WOOLLY HOTTIE WHITE HEART. | 6 | 2010-12-01 08:26:00 | 3.39000 | 17850.00000 | United Kingdom |

# Data Understanding

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   Invoice      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   Price        541909 non-null  float64       
 6   Customer ID  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
```

how many countries in df:

In [5]:
```
df['Country'].nunique()
```

Out[5]:
```
38
```

the names of the countries with the total values:

In [6]:
```
df['Country'].value_counts()
```

Out[6]:
```
United Kingdom          495478
Germany                   9495
France                    8557
EIRE                      8196
Spain                     2533
Netherlands               2371
Belgium                   2069
Switzerland               2002
Portugal                  1519
Australia                 1259
Norway                    1086
Italy                      803
Channel Islands            758
Finland                    695
Cyprus                     622
Sweden                     462
Unspecified                446
Austria                    401
Denmark                    389
Japan                      358
Poland                     341
Israel                     297
USA                        291
Hong Kong                  288
Singapore                  229
Iceland                    182
Canada                     151
Greece                     146
Malta                      127
United Arab Emirates        68
European Community          61
RSA                         58
Lebanon                     45
Lithuania                   35
Brazil                      32
Czech Republic              30
Bahrain                     19
Saudi Arabia                10
Name: Country, dtype: int64
```

the most expensive products:

In [7]:
```
df.sort_values(by='Price', ascending=False).head()
```

Out[7]:

| | Invoice | StockCode | Description | Quantity | InvoiceDate | Price | Customer ID | Country |
|---|---|---|---|---|---|---|---|---|
| **222681** | C556445 | M | Manual | -1 | 2011-06-10 15:31:00 | 38970.00000 | 15098.00000 | United Kingdom |
| **524602** | C580605 | AMAZONFEE | AMAZON FEE | -1 | 2011-12-05 11:36:00 | 17836.46000 | NaN | United Kingdom |
| **43702** | C540117 | AMAZONFEE | AMAZON FEE | -1 | 2011-01-05 09:55:00 | 16888.02000 | NaN | United Kingdom |
| **43703** | C540118 | AMAZONFEE | AMAZON FEE | -1 | 2011-01-05 09:57:00 | 16453.71000 | NaN | United Kingdom |
| **15017** | 537632 | AMAZONFEE | AMAZON FEE | 1 | 2010-12-07 15:08:00 | 13541.33000 | NaN | United Kingdom |

number of unique products:

In [8]:
```
df['Description'].nunique()
```

Out[8]: 4223

most purchased items:

In [9]:
```
df.groupby("Description").agg({"Quantity": lambda x: x.sum()}).sort_values("Quantity", ascending=False).head()
```

Out[9]:

| Description | Quantity |
|---|---|
| **WORLD WAR 2 GLIDERS ASSTD DESIGNS** | 53847 |
| **JUMBO BAG RED RETROSPOT** | 47363 |
| **ASSORTED COLOUR BIRD ORNAMENT** | 36381 |
| **POPCORN HOLDER** | 36334 |
| **PACK OF 72 RETROSPOT CAKE CASES** | 36039 |

check the number of uniques for StockCode ve Description variables:

In [10]:
```
print(f"Number of uniques in StockCode: {df['StockCode'].nunique()}")
print(f"Number of uniques in Description:{df['Description'].nunique()}")
```

```
Number of uniques in StockCode: 4070
Number of uniques in Description:4223
```

the values were expected to be equal, so there must be more than one unique value in Description variable for one unique StockCode. let's check each StockCode value with the corresponding Description values, get every StockCode that has more than one unique Description in a list form

In [82]:
```
a =df.groupby('StockCode').agg({'Description': "nunique"})
a.reset_index(inplace=True)
a.head()
b = list(a.loc[a['Description'] > 1, 'StockCode'])

for x in b:
    print(f"{x} = {df.loc[df['StockCode'] == x, 'Description'].unique()}")
```

```
22197 = ['SMALL POPCORN HOLDER' 'POPCORN HOLDER']
22199 = ['FRYING PAN RED RETROSPOT' 'FRYING PAN RED POLKADOT ']
22246 = ['GARLAND, MAGIC GARDEN 1.8M' 'MAGIC GARDEN FELT GARLAND ']
22268 = ['EASTER DECORATION SITTING BUNNY' 'DECORATION SITTING BUNNY']
22285 = ['DECORATION HEN ON NEST, HANGING' 'HANGING HEN ON NEST DECORATION']
22286 = ['DECORATION , WOBBLY RABBIT , METAL ' 'DECORATION WOBBLY RABBIT METAL ']
22287 = ['DECORATION , WOBBLY CHICKEN, METAL ' 'DECORATION WOBBLY CHICKEN']
22383 = ['LUNCH BAG SUKI  DESIGN ' 'LUNCH BAG SUKI DESIGN ']
22407 = ['MONEY BOX FIRST ADE DESIGN' 'MONEY BOX FIRST AID DESIGN']
22416 = ['SET OF 36 DOILIES SPACEBOY DESIGN ' 'SET OF 36 SPACEBOY PAPER DOILIES']
22466 = ['FAIRY TALE COTTAGE NIGHTLIGHT' 'FAIRY TALE COTTAGE NIGHT LIGHT']
22502 = ['PICNIC BASKET WICKER SMALL' 'PICNIC BASKET WICKER 60 PIECES']
22584 = ['PACK OF 6 PANNETONE GIFT BOXES' 'PACK OF 6 PANETTONE GIFT BOXES']
22595 = ['CHRISTMAS GINGHAM HEART' 'GINGHAM HEART DECORATION']
22597 = ['CHRISTMAS MUSICAL ZINC HEART ' 'MUSICAL ZINC HEART DECORATION ']
22602 = ['CHRISTMAS RETROSPOT HEART WOOD' 'RETROSPOT WOODEN HEART DECORATION']
22632 = ['HAND WARMER RED POLKA DOT' 'HAND WARMER RED RETROSPOT']
22776 = ['SWEETHEART CAKESTAND 3 TIER' 'CAKESTAND, 3 TIER, LOVEHEART'
 'SWEETHEART 3 TIER CAKE STAND ']
22777 = ['GLASS BELL JAR LARGE' 'GLASS CLOCHE LARGE']
```

as an example derived from the above list, both the Descriptions: 'PINK SPOTTY BOWL' and 'PINK POLKADOT BOWL' have the same StockCode: 20677. This means that there are duplicates in Description variable (possibly due to manuel entries or merge) so it would be better to use StockCode.

In [14]:
```
df.loc[df['StockCode'] == 20677, 'Description'].unique()
```

Out[14]:
```
array(['PINK POLKADOT BOWL'], dtype=object)
```

# Data Preperation

drop na values

In [15]:
```
df.dropna(inplace=True)
```

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 406829 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Invoice      406829 non-null  object
 1   StockCode    406829 non-null  object
 2   Description  406829 non-null  object
 3   Quantity     406829 non-null  int64
 4   InvoiceDate  406829 non-null  datetime64[ns]
 5   Price        406829 non-null  float64
 6   Customer ID  406829 non-null  float64
 7   Country      406829 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 27.9+ MB
```

In [17]:
```
df.describe([0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 0.99]).T
```

Out[17]:

| | count | mean | std | min | 1% | 5% | 10% | 25% | 50% | 75% |
|---|---|---|---|---|---|---|---|---|---|---|
| **Quantity** | 406829.00000 | 12.06130 | 248.69337 | -80995.00000 | -2.00000 | 1.00000 | 1.00000 | 2.00000 | 5.00000 | 12.00000 |
| **Price** | 406829.00000 | 3.46047 | 69.31516 | 0.00000 | 0.21000 | 0.42000 | 0.55000 | 1.25000 | 1.95000 | 3.75000 |
| **Customer ID** | 406829.00000 | 15287.69057 | 1713.60030 | 12346.00000 | 12415.00000 | 12626.00000 | 12876.00000 | 13953.00000 | 15152.00000 | 16791.00000 |

there are negative values on Quantity variable, this is caused by the refund invoices (Invoices containing the letter "C"), reassign df without refund invoices

In [18]:
```
df = df[~df["Invoice"].str.contains("C", na=False)]
```

In [19]:
```
df.describe([0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 0.99]).T
```

Out[19]:

| | count | mean | std | min | 1% | 5% | 10% | 25% | 50% | 75% |
|---|---|---|---|---|---|---|---|---|---|---|
| **Quantity** | 397924.00000 | 13.02182 | 180.42021 | 1.00000 | 1.00000 | 1.00000 | 1.00000 | 2.00000 | 6.00000 | 12.00000 |
| **Price** | 397924.00000 | 3.11617 | 22.09679 | 0.00000 | 0.21000 | 0.42000 | 0.55000 | 1.25000 | 1.95000 | 3.75000 |
| **Customer ID** | 397924.00000 | 15294.31517 | 1713.16988 | 12346.00000 | 12415.00000 | 12627.00000 | 12883.00000 | 13969.00000 | 15159.00000 | 16795.00000 | 1 |

negative values are excluded. We are not removing outliers (such as the max value on Quantity and Price variables) because we will be scoring the dataset.

In [20]:
```
df['TotalPrice'] = df['Quantity'] * df['Price']
```

In [21]:
```
df.head()
```

Out[21]:

| | Invoice | StockCode | Description | Quantity | InvoiceDate | Price | Customer ID | Country | TotalPrice |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 536365 | 85123A | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55000 | 17850.00000 | United Kingdom | 15.30000 |
| **1** | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39000 | 17850.00000 | United Kingdom | 20.34000 |
| **2** | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75000 | 17850.00000 | United Kingdom | 22.00000 |
| **3** | 536365 | 84029G | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 2010-12-01 08:26:00 | 3.39000 | 17850.00000 | United Kingdom | 20.34000 |
| **4** | 536365 | 84029E | RED WOOLLY HOTTIE WHITE HEART. | 6 | 2010-12-01 08:26:00 | 3.39000 | 17850.00000 | United Kingdom | 20.34000 |

# RFM Metrics

the last date of purchase:

In [22]:
```
df['InvoiceDate'].max()
```

Out[22]:
```
Timestamp('2011-12-09 12:50:00')
```

assign "today's date" as 2 days after the last date of purchase to make sure that none of the Recency values become zero

In [23]:
```
today_date = df['InvoiceDate'].max() + dt.timedelta(days=2)
today_date
```

Out[23]:
```
Timestamp('2011-12-11 12:50:00')
```

create a new df called rfm in order to calculate Recency, Frequency and Monetary values.
df is grouped by customers and:

- the number of days between today_date and the last purchase date of this customer is **Recency**
- the number of unique invoices of this customer is **Frequency**
- the sum of TotalPrice is this customer's **Monetary**

In [24]:
```
rfm = df.groupby('Customer ID').agg({'InvoiceDate': lambda date: (today_date - date.max()).days,
                                     'Invoice': lambda inv: inv.nunique(),
                                     'TotalPrice': lambda price: price.sum()})
```

In [25]:
```
rfm.head()
```

Out[25]:

| Customer ID | InvoiceDate | Invoice | TotalPrice |
|---|---|---|---|
| **12346.00000** | 327 | 1 | 77183.60000 |
| **12347.00000** | 3 | 7 | 4310.00000 |
| **12348.00000** | 76 | 4 | 1797.24000 |
| **12349.00000** | 20 | 1 | 1757.55000 |
| **12350.00000** | 311 | 1 | 334.40000 |

renaming rfm columns:

In [26]:
```
rfm.columns = ['Recency', 'Frequency', 'Monetary']
rfm.head()
```

Out[26]:

| Customer ID | Recency | Frequency | Monetary |
|---|---|---|---|
| **12346.00000** | 327 | 1 | 77183.60000 |
| **12347.00000** | 3 | 7 | 4310.00000 |
| **12348.00000** | 76 | 4 | 1797.24000 |
| **12349.00000** | 20 | 1 | 1757.55000 |
| **12350.00000** | 311 | 1 | 334.40000 |

check if there are any zeros in rfm:

In [27]:
```
rfm.describe([0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 0.99]).T
```

Out[27]:

| | count | mean | std | min | 1% | 5% | 10% | 25% | 50% | 75% | 90% | 95 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Recency** | 4339.00000 | 93.51832 | 100.00975 | 2.00000 | 2.00000 | 4.00000 | 6.00000 | 19.00000 | 52.00000 | 143.00000 | 264.00000 | 313.000( |
| **Frequency** | 4339.00000 | 4.27195 | 7.70549 | 1.00000 | 1.00000 | 1.00000 | 1.00000 | 1.00000 | 2.00000 | 5.00000 | 9.00000 | 13.000( |
| **Monetary** | 4339.00000 | 2053.79302 | 8988.24838 | 0.00000 | 52.07600 | 112.24500 | 156.56600 | 307.24500 | 674.45000 | 1661.64000 | 3646.16400 | 5840.182( |

# RFM Scores

- the min number of Recency metric means that this customer has just purchased, so the highest score (5) should be given to the lower number of Recency.
- the max number of Frequency and Monetary metrics mean that the customer is purchasing frequently and spending more money, so the highest score (5) should be given to the highest Frequency and Monetary values.

In [28]:
```
rfm["RecencyScore"] = pd.qcut(rfm['Recency'], 5, labels=[5, 4, 3, 2, 1])

rfm["FrequencyScore"] = pd.qcut(rfm['Frequency'].rank(method="first"), 5, labels=[1, 2, 3, 4, 5])

rfm["MonetaryScore"] = pd.qcut(rfm['Monetary'], 5, labels=[1, 2, 3, 4, 5])
```

In [29]:
```
rfm["RFM_SCORE"] = (rfm['RecencyScore'].astype(str) +
                    rfm['FrequencyScore'].astype(str) +
                    rfm['MonetaryScore'].astype(str))

rfm.head()
```

Out[29]:

| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE |
|---|---|---|---|---|---|---|---|
| **12346.00000** | 327 | 1 | 77183.60000 | 1 | 1 | 5 | 115 |
| **12347.00000** | 3 | 7 | 4310.00000 | 5 | 5 | 5 | 555 |
| **12348.00000** | 76 | 4 | 1797.24000 | 2 | 4 | 4 | 244 |
| **12349.00000** | 20 | 1 | 1757.55000 | 4 | 1 | 4 | 414 |
| **12350.00000** | 311 | 1 | 334.40000 | 1 | 1 | 2 | 112 |

display some of the customers with the highest scores:

In [30]:
```
rfm[rfm['RFM_SCORE'] == "555"].head()
```

Out[30]:

| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE |
|---|---|---|---|---|---|---|---|
| **12347.00000** | 3 | 7 | 4310.00000 | 5 | 5 | 5 | 555 |
| **12362.00000** | 4 | 10 | 5226.23000 | 5 | 5 | 5 | 555 |
| **12417.00000** | 4 | 9 | 3649.10000 | 5 | 5 | 5 | 555 |
| **12433.00000** | 2 | 7 | 13375.87000 | 5 | 5 | 5 | 555 |
| **12437.00000** | 3 | 18 | 4951.41000 | 5 | 5 | 5 | 555 |

## ## Naming the RFM Scores

the following dict has been made according to the famous RFM graphic

In [31]:
```
seg_map = {
    r'[1-2][1-2]': 'Hibernating',
    r'[1-2][3-4]': 'At_Risk',
    r'[1-2]5': 'Cant_Loose',
    r'3[1-2]': 'About_to_Sleep',
    r'33': 'Need_Attention',
    r'[3-4][4-5]': 'Loyal_Customers',
    r'41': 'Promising',
    r'51': 'New_Customers',
    r'[4-5][2-3]': 'Potential_Loyalists',
    r'5[4-5]': 'Champions'
}
```

we will be using Recency and Frequency scores for customer segmentation. We are assuming that a customer who has recently purchased and who is often purchasing should have high RFM scores.

In [32]:
```
rfm['Segment'] = rfm['RecencyScore'].astype(str) + rfm['FrequencyScore'].astype(str)
rfm.head()
```

Out[32]:

| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE | Segment |
|---|---|---|---|---|---|---|---|---|
| **12346.00000** | 327 | 1 | 77183.60000 | 1 | 1 | 5 | 115 | 11 |
| **12347.00000** | 3 | 7 | 4310.00000 | 5 | 5 | 5 | 555 | 55 |
| **12348.00000** | 76 | 4 | 1797.24000 | 2 | 4 | 4 | 244 | 24 |
| **12349.00000** | 20 | 1 | 1757.55000 | 4 | 1 | 4 | 414 | 41 |
| **12350.00000** | 311 | 1 | 334.40000 | 1 | 1 | 2 | 112 | 11 |

in the last step, we will convert the metrics into category names

In [33]:
```
rfm['Segment'] = rfm['Segment'].replace(seg_map, regex=True)
rfm.head()
```

Out[33]:

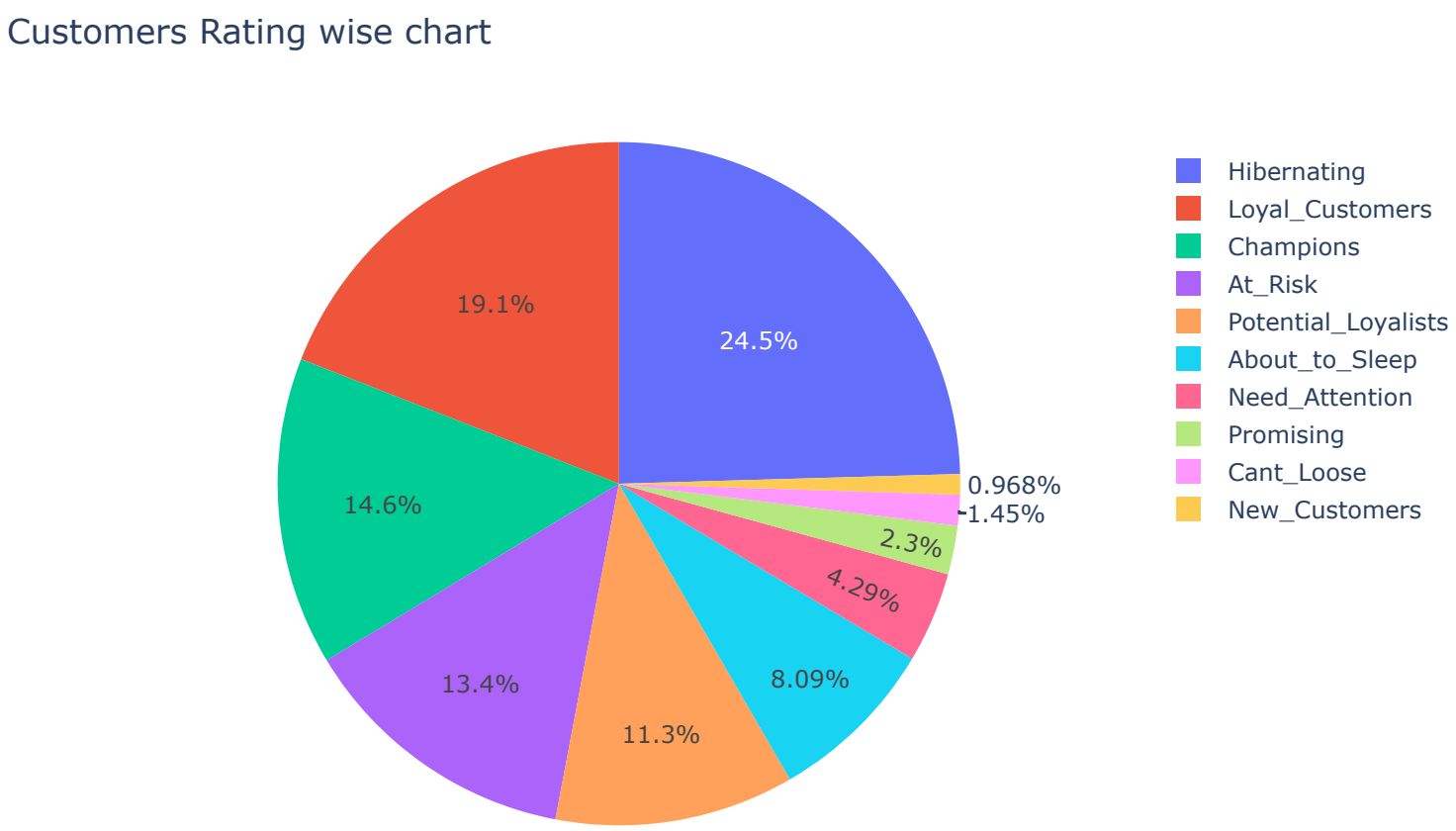
| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE | Segment |
|---|---|---|---|---|---|---|---|---|
| **12346.00000** | 327 | 1 | 77183.60000 | 1 | 1 | 5 | 115 | Hibernating |
| **12347.00000** | 3 | 7 | 4310.00000 | 5 | 5 | 5 | 555 | Champions |
| **12348.00000** | 76 | 4 | 1797.24000 | 2 | 4 | 4 | 244 | At_Risk |
| **12349.00000** | 20 | 1 | 1757.55000 | 4 | 1 | 4 | 414 | Promising |
| **12350.00000** | 311 | 1 | 334.40000 | 1 | 1 | 2 | 112 | Hibernating |

see the number of customers that fall into each category

In [34]:
```
rfm['Segment'].value_counts()
```

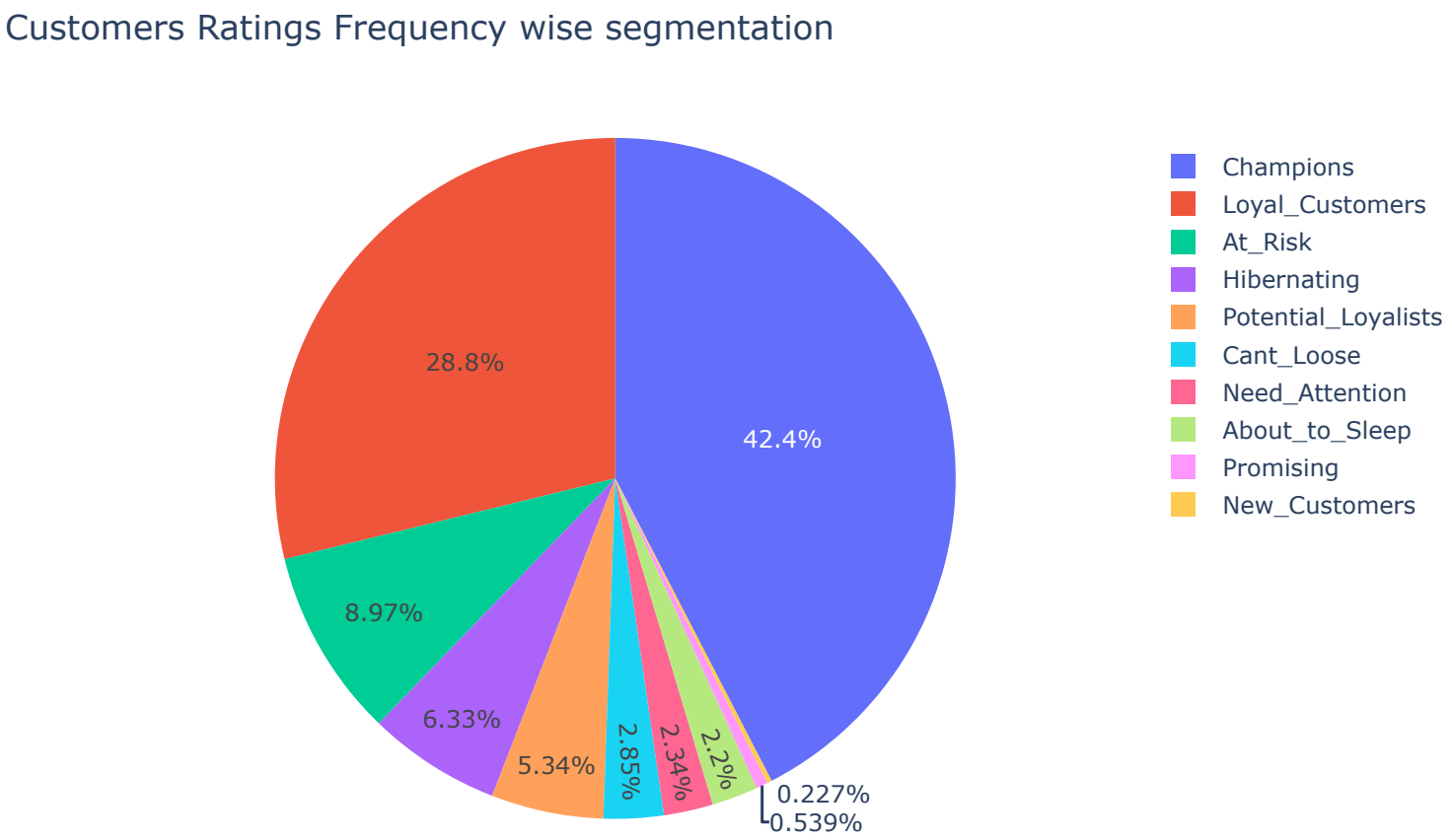
Out[34]:
```
Hibernating            1065
Loyal_Customers         827
Champions               633
At_Risk                 580
Potential_Loyalists     492
About_to_Sleep          351
Need_Attention          186
Promising               100
Cant_Loose               63
New_Customers            42
Name: Segment, dtype: int64
```

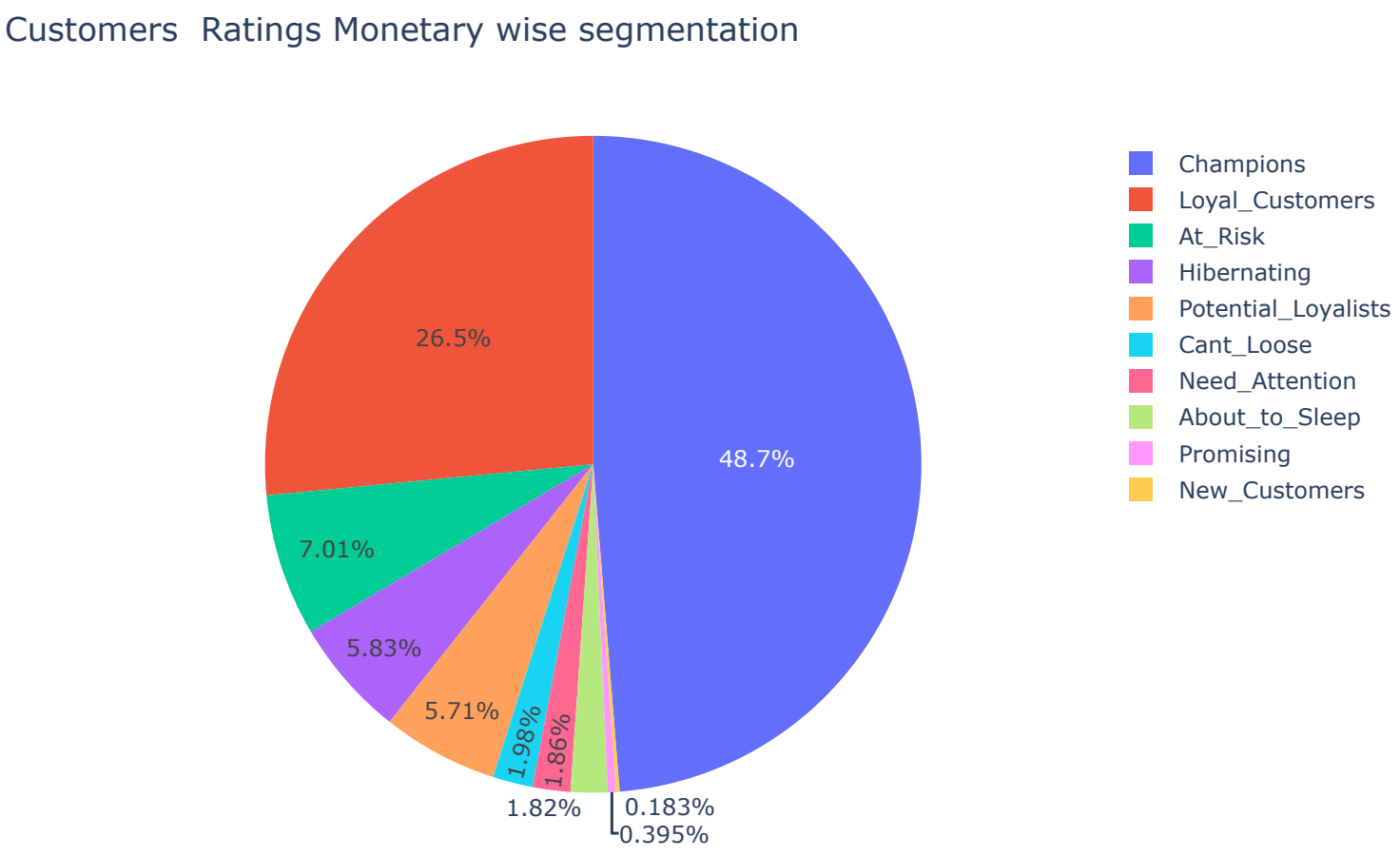
In [35]:
```
df_local =  pd.DataFrame(rfm["Segment"].value_counts() ).sort_values(by='Segment', ascending=False)
fig = px.pie(df_local , values='Segment', names=df_local.index, title='Customers Rating wise chart')
fig.show()
```

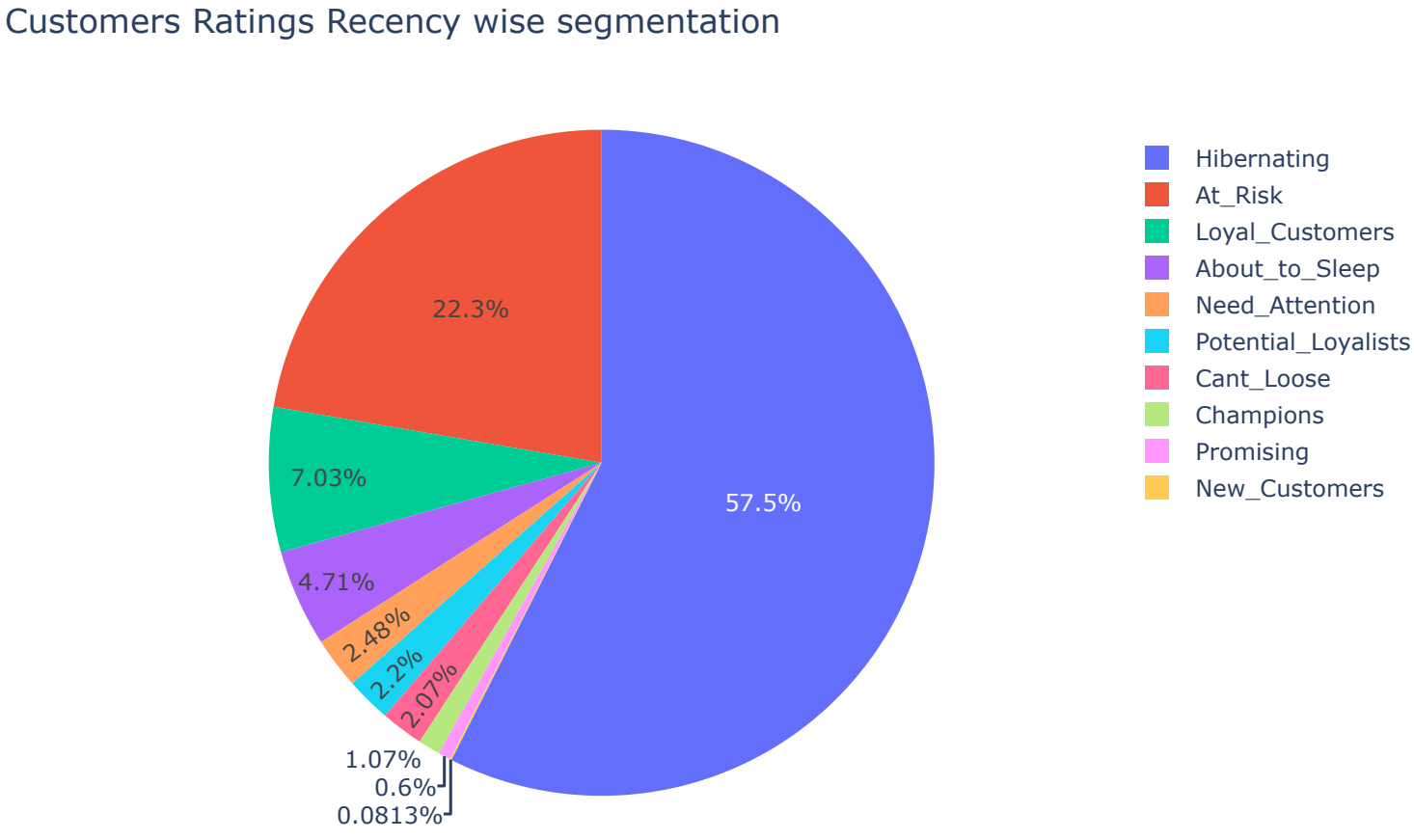



## Creating Frequency Monetary and Recency Plots Based on their Ratings

In [37]:
```
df_local =  rfm.groupby('Segment').agg({"Frequency" : "sum"}).reset_index()
fig = px.pie(df_local , values='Frequency', names="Segment", title='Customers Ratings Frequency wise segmentation')
fig.show()

df_local =  rfm.groupby('Segment').agg({"Monetary" : "sum"}).reset_index()
fig = px.pie(df_local , values='Monetary', names="Segment", title='Customers  Ratings Monetary wise segmentation')
fig.show()

df_local =  rfm.groupby('Segment').agg({"Recency" : "sum"}).reset_index()
fig = px.pie(df_local , values='Recency', names="Segment", title='Customers Ratings Recency wise segmentation')
fig.show()
```

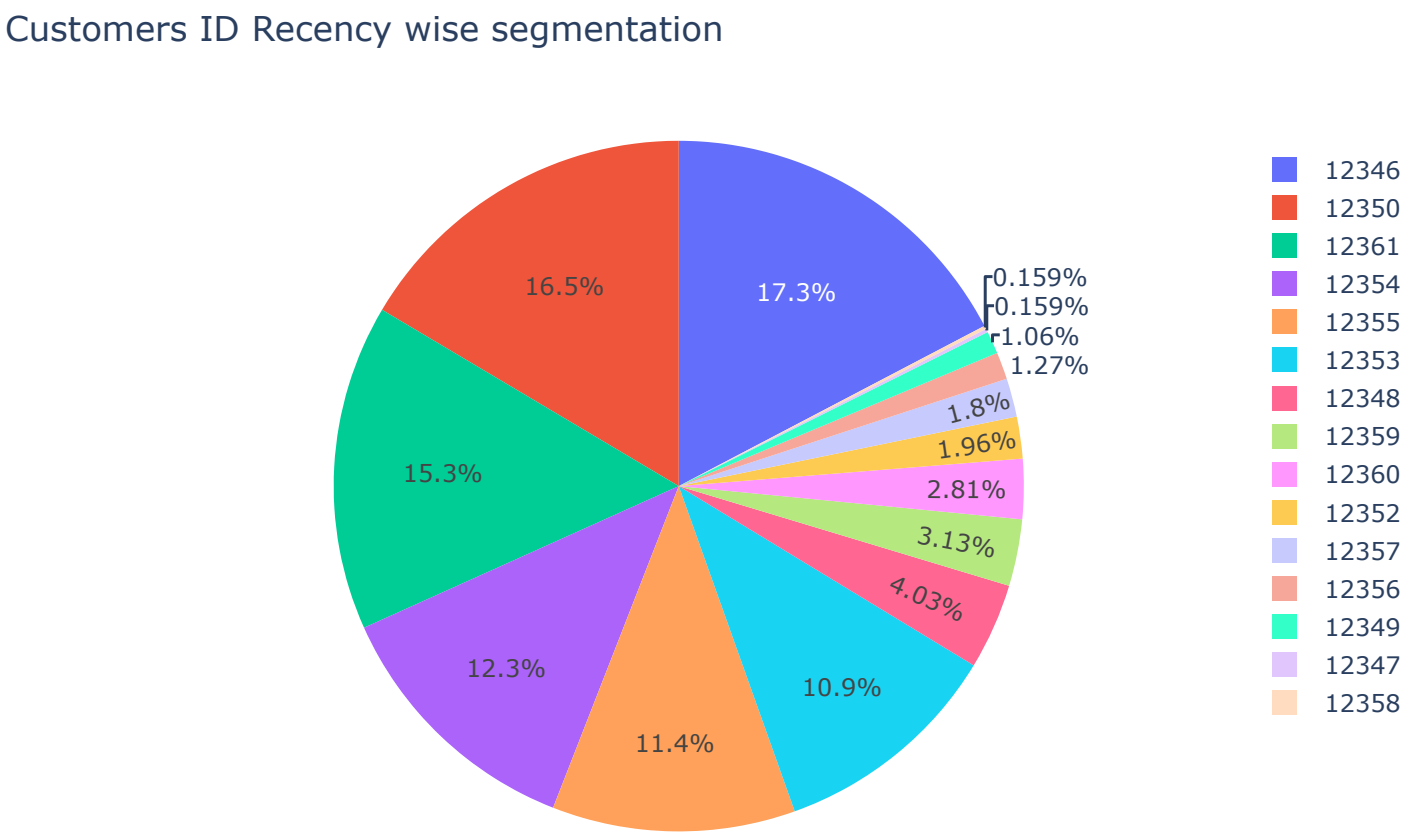


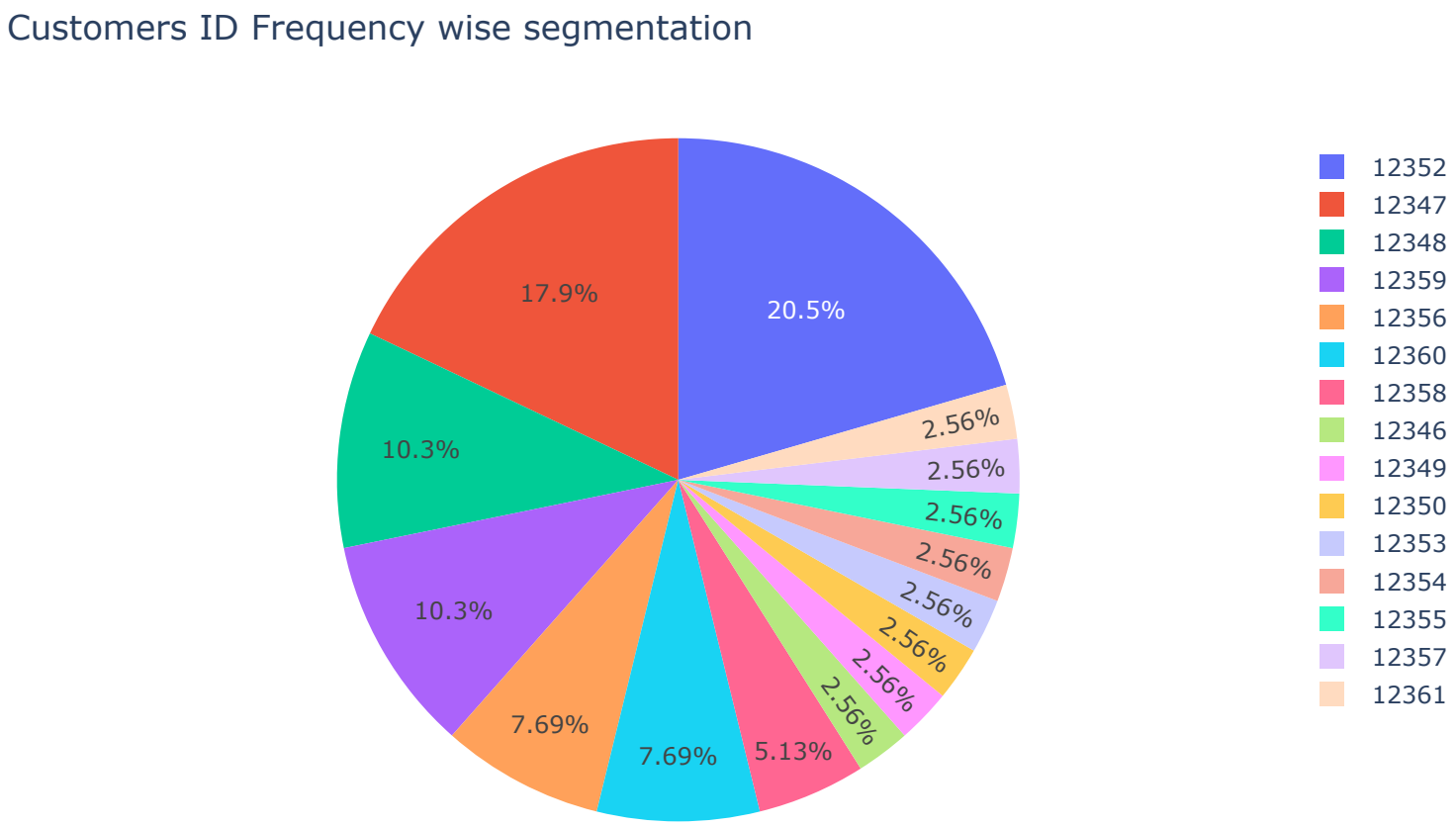



# Creating Frequency Monetary and Recency Plots Based on Customer IDS

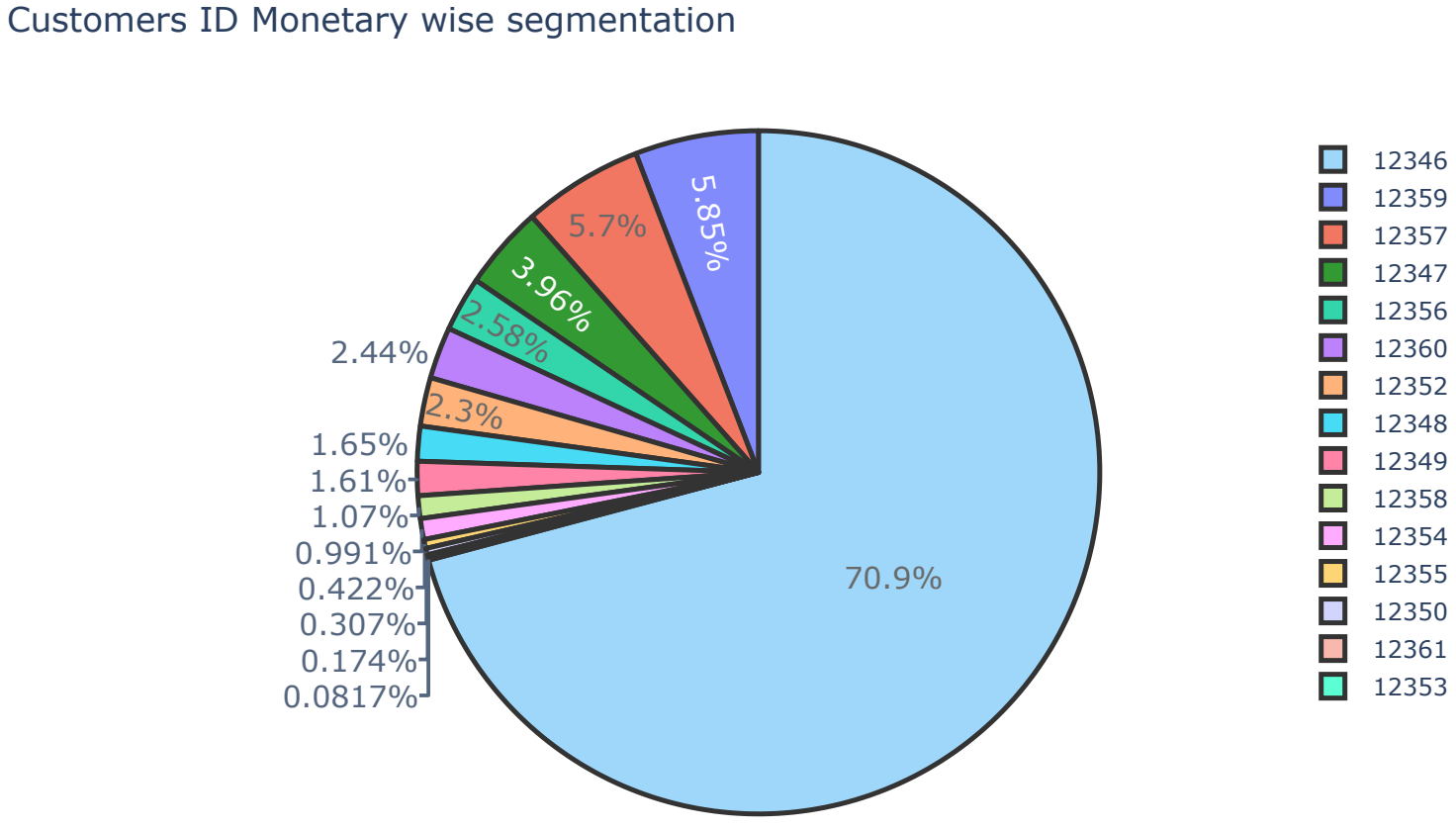
In [44]:
```
#grouping Customer Ids on basis of Recency and getting top 15 customers
df_local =  rfm.groupby('Customer ID').agg({"Recency" : "sum"}).reset_index()[:15]
fig = px.pie(df_local , values='Recency', names="Customer ID", title='Customers ID Recency wise segmentation')
fig.show()
```



In [42]:
```
#grouping Customer Ids on basis of Frequency and getting top 15 customers
df_local =  rfm.groupby('Customer ID').agg({"Frequency" : "sum"}).reset_index()[:15]
fig = px.pie(df_local , values='Frequency', names="Customer ID", title='Customers ID Frequency wise segmentation')
fig.show()
```

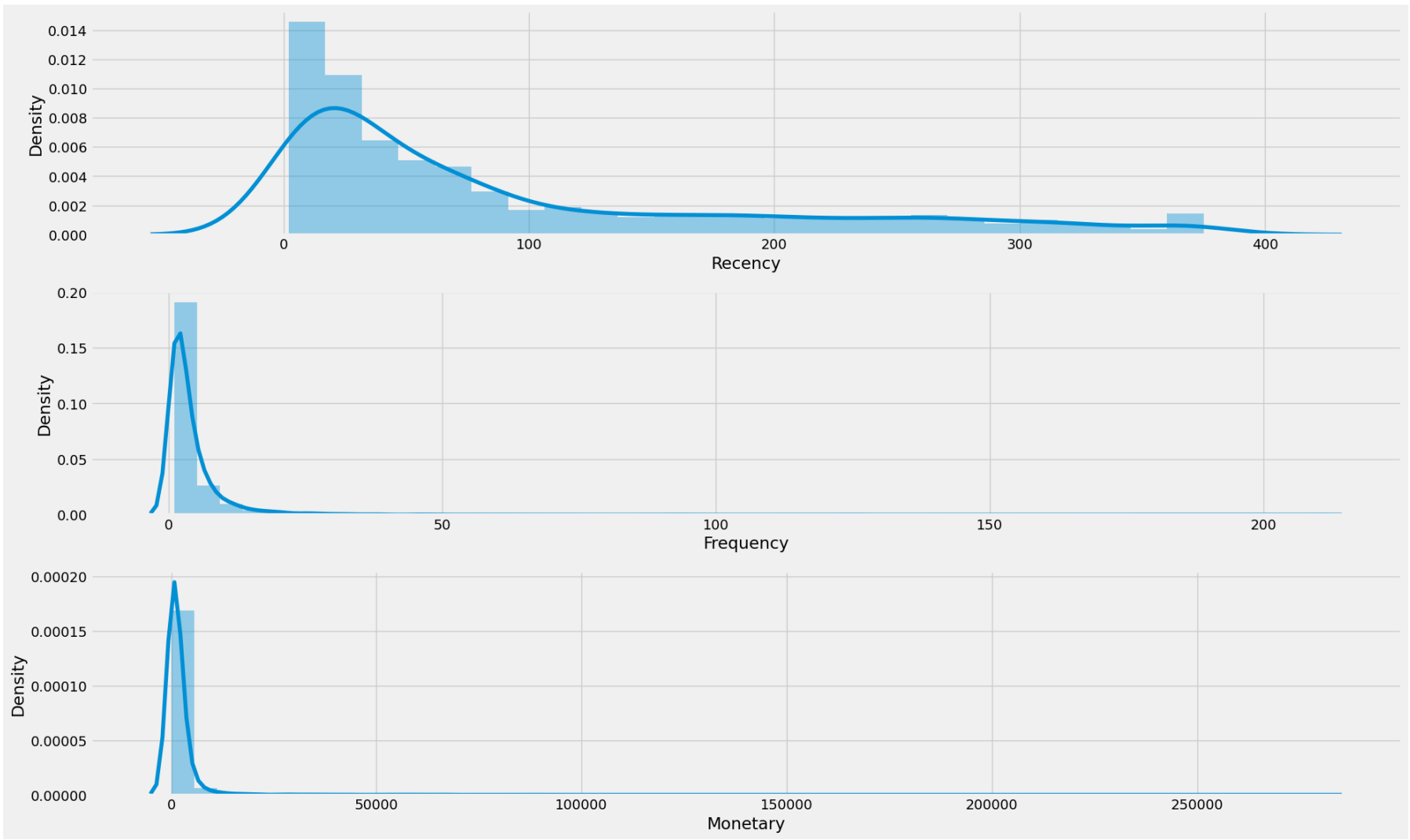



In [51]:
```
# #grouping Customer Ids on basis of Monetary and getting top 15 customers
df_local =  rfm.groupby('Customer ID').agg({"Monetary" : "sum"}).reset_index()[:15]
# fig = px.pie(df_local , values='Monetary', names="Customer ID", title='Customers ID Monetary wise segmentation')
# fig.show()

trace = go.Pie(labels = df_local["Customer ID"], values = df_local["Monetary"],
               textfont=dict(size=15), opacity = 0.8,
               marker=dict(colors=['lightskyblue', 'green'],
                           line=dict(color='#000000', width=2.5)))


layout = dict(title =  'Customers ID Monetary wise segmentation')

fig = dict(data = [trace], layout=layout)
py.iplot(fig)
```



# Plotting Distribution of Our Recency Frequency and Monetary

In [53]:
```
plt.style.use('fivethirtyeight')
f,ax = plt.subplots(figsize=(20, 12))
plt.subplot(3, 1, 1); sns.distplot(rfm.Recency, label = 'Recency')
plt.subplot(3, 1, 2); sns.distplot(rfm.Frequency, label = 'Frequency')
plt.subplot(3, 1, 3); sns.distplot(rfm.Monetary, label = 'Monetary')

plt.tight_layout()
plt.show()
```




# Applying Kmeans Clustering on Data

In [54]:
```
class Kmeans():
    def __init__(self,df):
        self.df = df
    def Scale_data(self):
        #Scaling Dataset
        self.df2 = pd.DataFrame()
        self.df2["Recency"]  = self.df.Recency
        self.df2["Frequency"]  = self.df.Frequency
        self.df2["Monetary"]  = self.df.Monetary
        #Applying Min Max Scaler
        sc = MinMaxScaler((0, 1))
        self.df3 = sc.fit_transform(self.df2)
        return self.df3
    def apply_kmeans(self):
        #initializing Kmeans object model
        kmeans = KMeans(n_clusters= 5, init= 'k-means++')
        kmeans.fit(self.Scale_data())
        clusters = kmeans.labels_
        self.df["Clusters"] = clusters+1
        return self.df
```

In [55]:
```
kmeans= Kmeans(rfm)
data1 = kmeans.apply_kmeans()
data1.head()
```

Out[55]:

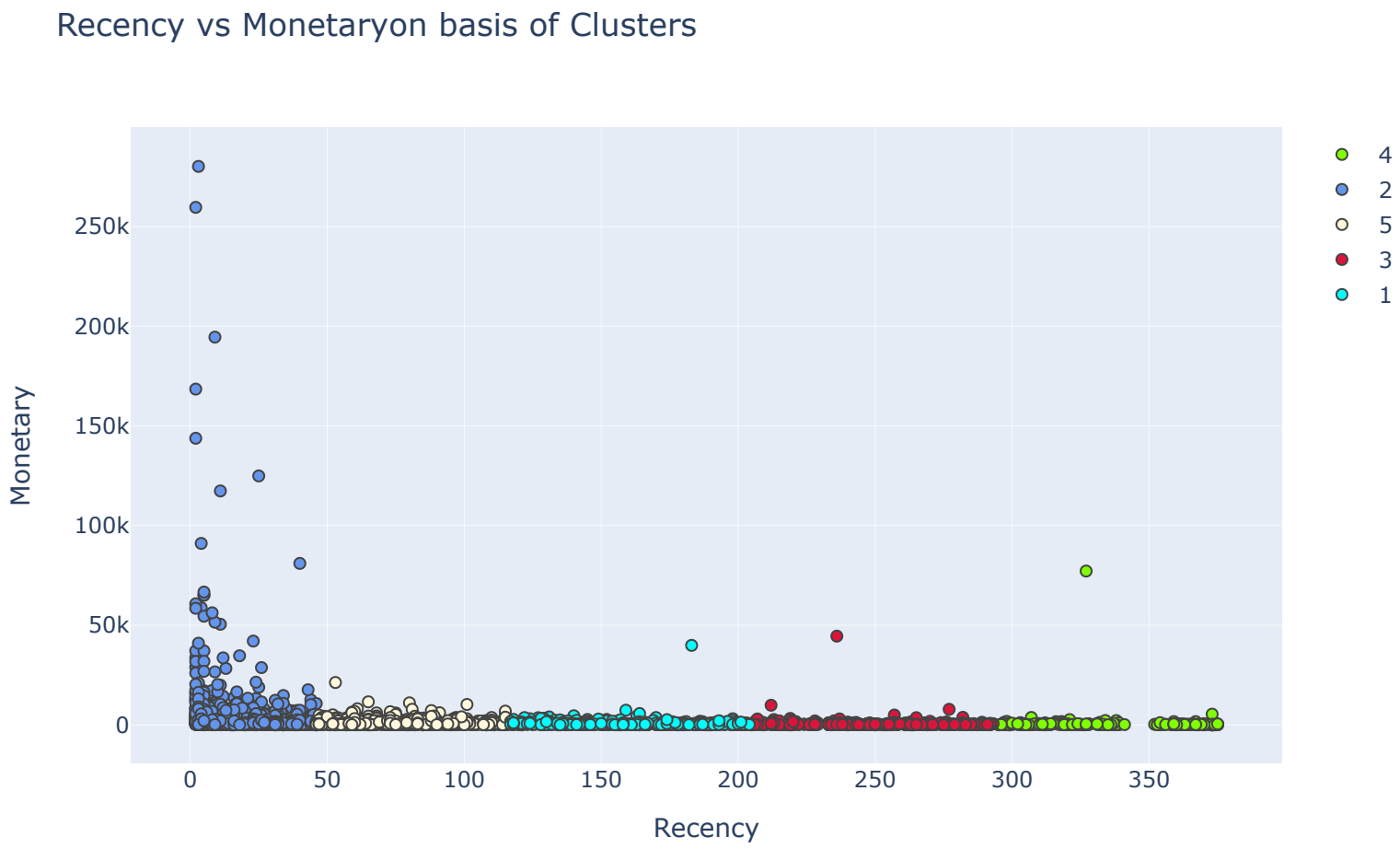
| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE | Segment | Clusters |
|---|---|---|---|---|---|---|---|---|---|
| **12346.00000** | 327 | 1 | 77183.60000 | 1 | 1 | 5 | 115 | Hibernating | 4 |
| **12347.00000** | 3 | 7 | 4310.00000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **12348.00000** | 76 | 4 | 1797.24000 | 2 | 4 | 4 | 244 | At_Risk | 5 |
| **12349.00000** | 20 | 1 | 1757.55000 | 4 | 1 | 4 | 414 | Promising | 2 |
| **12350.00000** | 311 | 1 | 334.40000 | 1 | 1 | 2 | 112 | Hibernating | 4 |

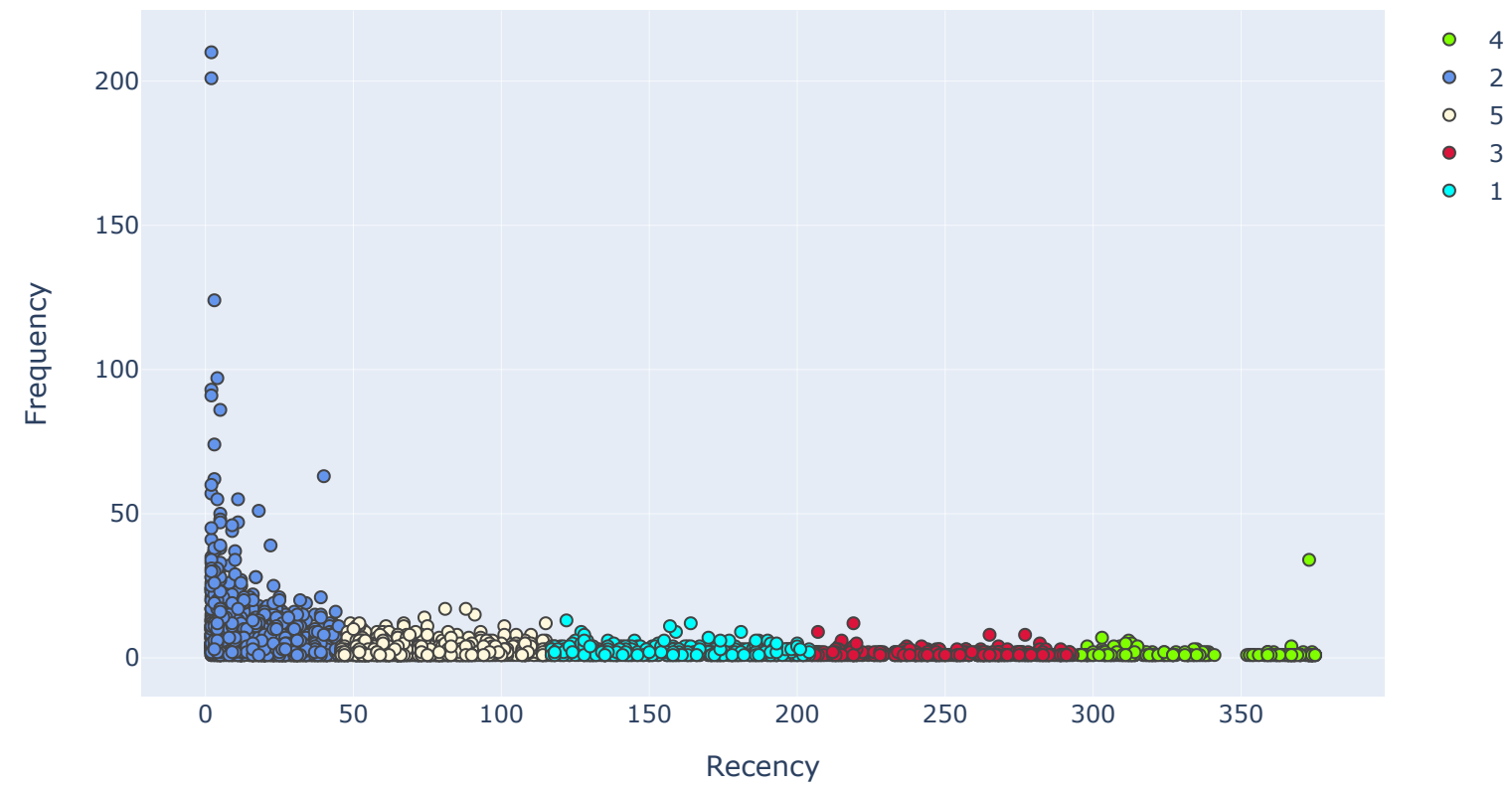
In [56]:
```
#Colors pallets for plots
s = '''
        chartreuse, cornflowerblue,
        cornsilk, crimson, cyan,aliceblue, antiquewhite, aqua, aquamarine, azure,
        beige, bisque, black, blanchedalmond, blue,
        blueviolet, brown, burlywood, cadetblue,darkblue, darkcyan,
        darkgoldenrod, darkgray, darkgrey, darkgreen,
        darkkhaki, darkmagenta, darkolivegreen, darkorange,
        darkorchid, darkred, darksalmon, darkseagreen,
        darkslateblue, darkslategray, darkslategrey,
        darkturquoise, darkviolet, deeppink, deepskyblue,
        dimgray, dimgrey, dodgerblue, firebrick,
        floralwhite, forestgreen, fuchsia, gainsboro,
        ghostwhite, gold, goldenrod, gray, grey, green,
        greenyellow, honeydew, hotpink, indianred, indigo,
        ivory, khaki, lavender, lavenderblush, lawngreen,
        lemonchiffon, lightblue, lightcoral, lightcyan,
        lightgoldenrodyellow, lightgray, lightgrey,
        lightgreen, lightpink, lightsalmon, lightseagreen,
        lightskyblue, lightslategray, lightslategrey,
        lightsteelblue, lightyellow, lime, limegreen,
        linen, magenta, maroon, mediumaquamarine,
        mediumblue, mediumorchid, mediumpurple,
        mediumseagreen, mediumslateblue, mediumspringgreen,
        mediumturquoise, mediumvioletred, midnightblue,
        mintcream, mistyrose, moccasin, navajowhite, navy,
        oldlace, olive, olivedrab, orange, orangered,
        orchid, palegoldenrod, palegreen, paleturquoise,
        palevioletred, papayawhip, peachpuff, peru, pink,
        plum, powderblue, purple, red, rosybrown,
        royalblue, saddlebrown, salmon, sandybrown,
        seagreen, seashell, sienna, silver, skyblue,
        slateblue, slategray, slategrey, snow, springgreen,
        steelblue, tan, teal, thistle, tomato, turquoise,
        violet, wheat, white, whitesmoke, yellow,
        yellowgreen
        '''
colors1=s.split(',')
colors1=[l.replace('\n','') for l in colors1]
colors1=[l.replace(' ','') for l in colors1]
```

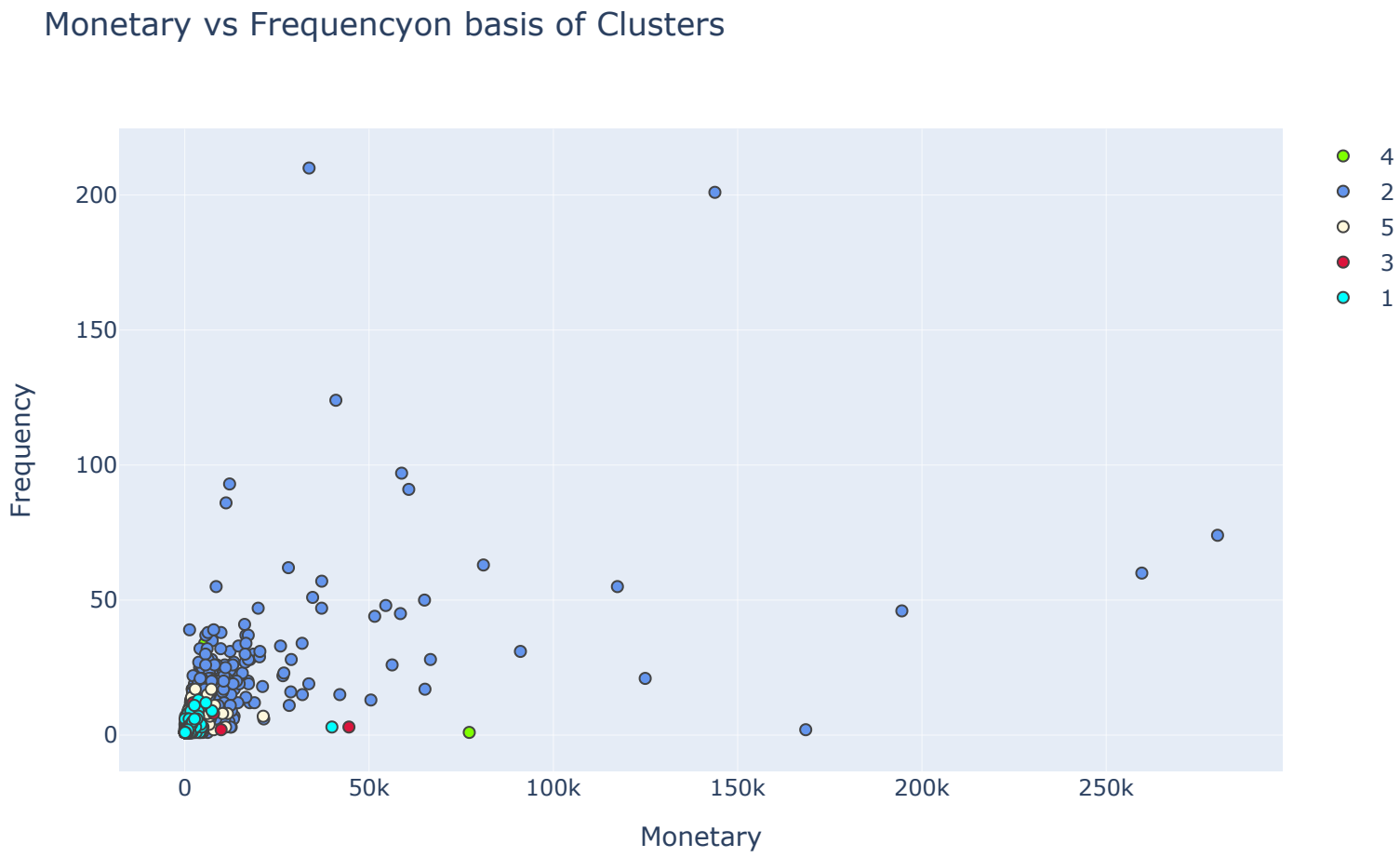
# Creating Frequency Monetary and Recency Scatter Plots with relation with eachother with Clusters

In [57]:
```
def plot_feat1_feat2(feat1, feat2,seg_col ="rfm_rate_customers") :
    t = []
    #creating Scatter plots iterating data frames and plotting
    for pos,n in enumerate(data1[seg_col].unique()):
        d = data1.loc[data1[seg_col]==n]
        trace1 = go.Scatter(
            x = d[feat1],
            y = d[feat2],
            name = str(n),
            mode = 'markers',
            marker = dict(color = colors1[pos],
                line = dict(
                width = 1)))
    t.append(trace1)
layout = dict(title = feat1 +" "+"vs"+" "+ feat2+f"on basis of {seg_col}",
                yaxis = dict(title = feat2,zeroline = False),
                xaxis = dict(title = feat1, zeroline = False)
               )

plots = t

fig = dict(data = plots, layout=layout)
py.iplot(fig)
```

In [58]:
```
plot_feat1_feat2("Recency","Monetary","Clusters")
plot_feat1_feat2("Recency","Frequency","Clusters")
plot_feat1_feat2("Monetary","Frequency","Clusters")
```






## Time for Action

Now that we have all the scores for the customers and we have been able to categorize them into 10 groups, it's time for action. We will be using metrics for this process, not scores. We will be focusing on the groups that need a better customer relationship and try to figure out what we can do in order to make that specific segment purchase more frequently and become loyal. Thanks to RFM scores of the segments, we know what exactly that segment needs.

In [ ]:
```
rfm[["Segment", "Recency", "Frequency", "Monetary"]].groupby("Segment").agg(["mean", "count"])
```

take a closer look at the customers that need attention:

In [ ]:
```
rfm[rfm["Segment"] == "Need_Attention"].head()
```

**Need_Attention** segment has 207 customers that last purchased nearly 2 months ago, despite the fact that they don't frequently purchase, they spend quite a good amount of money. So we should be focusing on this group. In order to make them transform into a customer that purchases frequently, we can offer them some discount with a time limit of 30 days. So that they would revisit and purchase.

**Can't_Loose** segment has purchased for 9 times this year but the last date of this was nearly 4 months, they spend a good amount of money and they used to be our loyal customers, we can't loose them. We should put this 77 customers into our loyalty program, offer them seasonal discounts, make them feel special while purchasing from our company and make them loyal again. We can export the customer id list into an excel file and pass this file to our Marketing Department.

In [ ]:
```
marketing_df = pd.DataFrame()
marketing_df["Cant_Loose"] = rfm[rfm["Segment"] == "Cant_Loose"].index
```

In [ ]:
```
marketing_df.head()
```

change the dtype of Customer ID variable in order to get rid of the decimal part:

In [ ]:
```
marketing_df['Cant_Loose'] = marketing_df['Cant_Loose'].astype(int)
marketing_df.head()
```

In [ ]:
```
marketing_df.info
```

In [59]:
```
# marketing_df.to_csv("cant_loose.csv")
```

In [71]:
```
# customer_df = rfm.sort_values(by='Recency')
# top_15_customers = customer_df.head(15)
# top_15_customers
# colors = ['red', 'blue', 'green', 'purple', 'orange', 'gray', 'pink', 'brown', 'yellow', 'teal', 'magenta', 'cyan',
# # plt.pie(top_15_customers['Recency'], labels=top_15_customers.index, colors=colors, autopct='%1.1f%%')
# plt.pie(top_15_customers['Recency'], labels=top_15_customers.index, autopct='%1.1f%%')
# plt.title('Top 15 Customers by Recency')
# plt.show()
```

In [78]:
```
customer_df1 = rfm.sort_values(by='RecencyScore')
customer_df2 = rfm.sort_values(by='FrequencyScore')
customer_df3 = rfm.sort_values(by='MonetaryScore')
top_15_customers1 = customer_df1.head(15)
top_15_customers2 = customer_df2.tail(15)
top_15_customers3 = customer_df3.tail(15)
top_15_customers1
```

Out[78]:

| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE | Segment | Clusters |
|---|---|---|---|---|---|---|---|---|---|
| **15344.00000** | 2 | 3 | 563.94000 | 5 | 3 | 3 | 533 | Potential_Loyalists | 2 |
| **13297.00000** | 9 | 4 | 2089.85000 | 5 | 4 | 5 | 545 | Champions | 2 |
| **13298.00000** | 2 | 1 | 360.00000 | 5 | 1 | 2 | 512 | New_Customers | 2 |
| **15555.00000** | 13 | 16 | 4805.17000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **17350.00000** | 9 | 4 | 1286.07000 | 5 | 4 | 4 | 544 | Champions | 2 |
| **17346.00000** | 5 | 15 | 2676.56000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **13305.00000** | 5 | 10 | 2000.86000 | 5 | 5 | 4 | 554 | Champions | 2 |
| **14321.00000** | 12 | 5 | 1530.75000 | 5 | 4 | 4 | 544 | Champions | 2 |
| **13309.00000** | 8 | 5 | 1456.79000 | 5 | 4 | 4 | 544 | Champions | 2 |
| **16353.00000** | 5 | 23 | 6675.71000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **13311.00000** | 5 | 2 | 598.57000 | 5 | 2 | 3 | 523 | Potential_Loyalists | 2 |
| **13314.00000** | 3 | 3 | 775.94000 | 5 | 3 | 3 | 533 | Potential_Loyalists | 2 |
| **16358.00000** | 2 | 4 | 2027.50000 | 5 | 4 | 4 | 544 | Champions | 2 |
| **13318.00000** | 2 | 3 | 640.76000 | 5 | 3 | 3 | 533 | Potential_Loyalists | 2 |
| **13319.00000** | 6 | 26 | 10845.55000 | 5 | 5 | 5 | 555 | Champions | 2 |

In [79]:
```
top_15_customers2
```

Out[79]:

| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE | Segment | Clusters |
|---|---|---|---|---|---|---|---|---|---|
| **17191.00000** | 29 | 7 | 2095.13000 | 4 | 5 | 5 | 455 | Loyal_Customers | 2 |
| **17193.00000** | 37 | 7 | 1699.30000 | 3 | 5 | 4 | 354 | Loyal_Customers | 2 |
| **14704.00000** | 12 | 9 | 1546.91000 | 5 | 5 | 4 | 554 | Champions | 2 |
| **14702.00000** | 2 | 17 | 3292.14000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **14701.00000** | 12 | 9 | 2549.37000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **17203.00000** | 37 | 6 | 3563.85000 | 3 | 5 | 5 | 355 | Loyal_Customers | 2 |
| **14696.00000** | 5 | 7 | 2078.95000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **17211.00000** | 28 | 8 | 2317.22000 | 4 | 5 | 5 | 455 | Loyal_Customers | 2 |
| **14688.00000** | 9 | 21 | 5630.87000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **17213.00000** | 41 | 7 | 2781.23000 | 3 | 5 | 5 | 355 | Loyal_Customers | 2 |
| **17214.00000** | 61 | 6 | 1069.12000 | 3 | 5 | 4 | 354 | Loyal_Customers | 5 |
| **17218.00000** | 5 | 10 | 1960.72000 | 5 | 5 | 4 | 554 | Champions | 2 |
| **14680.00000** | 26 | 16 | 28754.11000 | 4 | 5 | 5 | 455 | Loyal_Customers | 2 |
| **14676.00000** | 32 | 6 | 2548.24000 | 4 | 5 | 5 | 455 | Loyal_Customers | 2 |
| **15299.00000** | 68 | 7 | 4507.01000 | 3 | 5 | 5 | 355 | Loyal_Customers | 5 |

In [80]:
```
top_15_customers3
```

Out[80]:

| Customer ID | Recency | Frequency | Monetary | RecencyScore | FrequencyScore | MonetaryScore | RFM_SCORE | Segment | Clusters |
|---|---|---|---|---|---|---|---|---|---|
| **15321.00000** | 72 | 3 | 2748.31000 | 3 | 3 | 5 | 335 | Need_Attention | 5 |
| **15311.00000** | 2 | 91 | 60767.90000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **15301.00000** | 52 | 12 | 5070.35000 | 3 | 5 | 5 | 355 | Loyal_Customers | 5 |
| **18283.00000** | 5 | 16 | 2094.88000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **15298.00000** | 3 | 12 | 4799.90000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **15296.00000** | 52 | 6 | 3672.86000 | 3 | 5 | 5 | 355 | Loyal_Customers | 5 |
| **15291.00000** | 27 | 15 | 4668.30000 | 4 | 5 | 5 | 455 | Loyal_Customers | 2 |
| **15290.00000** | 6 | 18 | 7943.22000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **15288.00000** | 44 | 5 | 2306.52000 | 3 | 4 | 5 | 345 | Loyal_Customers | 2 |
| **15281.00000** | 60 | 9 | 2332.15000 | 3 | 5 | 5 | 355 | Loyal_Customers | 5 |
| **15271.00000** | 8 | 15 | 2507.07000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **15270.00000** | 17 | 7 | 2379.49000 | 4 | 5 | 5 | 455 | Loyal_Customers | 2 |
| **15251.00000** | 10 | 11 | 10484.99000 | 5 | 5 | 5 | 555 | Champions | 2 |
| **15245.00000** | 135 | 3 | 2515.84000 | 2 | 3 | 5 | 235 | At_Risk | 1 |
| **15299.00000** | 68 | 7 | 4507.01000 | 3 | 5 | 5 | 355 | Loyal_Customers | 5 |

In [ ]:
```

```