Segment Customers of a E-Com Company by using RFM Approach

R- Recency (Recent customers who purchased the product)

F- Frequency (how frequently customer is coming to buy products)

M- Monetary value (how much money we are earning from a customer)

Prime Customers

R- less

F- high

M- high

In [1]:
```
#import basic package
import os,sys
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
import warnings
warnings.filterwarnings('ignore')
import datetime
```

In [2]:
```
#import dataset
dataset=pd.read_csv('E-com_Data.csv')
dataset.head()
```

Out[2]:

	CustomerID	Item Code	InvoieNo	Date of purchase	Quantity	Time	price per Unit	Price	Shipping Location	Cancelled
0	4355.0	15734	398177.0	29-10-2017	6.0	3:36:00 PM	321.0	1926.0	Location 1	
1	4352.0	14616	394422.0	05-10-2017	2.0	2:53:00 PM	870.0	1740.0	Location 1	
2	4352.0	14614	394422.0	12-10-2017	2.0	2:53:00 PM	933.0	1866.0	Location 1	
3	4352.0	85014B	388633.0	22-08-2017	3.0	2:47:00 PM	623.0	1869.0	Location 1	
4	4352.0	15364	394422.0	10-10-2017	2.0	2:53:00 PM	944.0	1888.0	Location 1	

In [3]:
```
dataset.shape
```

Out[3]:
```
(541116, 12)
```

Significant columns

1) **CustomerID** - to segment customers

2) **Date of Purchase** - to calculate recency

3) **Invoice No** - to find freqency

4) **Price**- to calculate Monetary value

In [4]:
```
dataset.info()     #missing values in most of columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541116 entries, 0 to 541115
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   CustomerID         404189 non-null  float64
 1   Item Code          537979 non-null  object 
 2   InvoieNo           537979 non-null  float64
 3   Date of purchase   537979 non-null  object 
 4   Quantity           537979 non-null  float64
 5   Time               537979 non-null  object 
 6   price per Unit     537979 non-null  float64
 7   Price              537979 non-null  float64
 8   Shipping Location  537979 non-null  object 
 9   Cancelled_status   8345 non-null    object 
 10  Reason of return   3 non-null       object 
 11  Sold as set        0 non-null       float64
dtypes: float64(6), object(6)
memory usage: 49.5+ MB
```

1. Drop duplicate data

In [5]:
```
dataset.duplicated().sum()
```

Out[5]:
```
3145
```

In [6]:
```
dataset=dataset.drop_duplicates(ignore_index=True)
```

In [7]:
```
dataset.duplicated().sum()
```

Out[7]:
```
0
```

2. Drop insignificant columns

In [8]:
```
dataset.columns
```

Out[8]:
```
Index(['CustomerID', 'Item Code', 'InvoieNo', 'Date of purchase', 'Quantity',
       'Time', 'price per Unit', 'Price', 'Shipping Location',
       'Cancelled_status', 'Reason of return', 'Sold as set'],
      dtype='object')
```

In [9]:
```
dataset=dataset.drop(['Item Code','Quantity',
       'Time', 'price per Unit','Shipping Location',
       'Cancelled_status', 'Reason of return', 'Sold as set'],axis=1)
dataset.head()
```

Out[9]:

	CustomerID	InvoieNo	Date of purchase	Price
0	4355.0	398177.0	29-10-2017	1926.0
1	4352.0	394422.0	05-10-2017	1740.0
2	4352.0	394422.0	12-10-2017	1866.0
3	4352.0	388633.0	22-08-2017	1869.0
4	4352.0	394422.0	10-10-2017	1888.0

In [10]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 537971 entries, 0 to 537970
Data columns (total 4 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   CustomerID        404181 non-null  float64
 1   InvoieNo          537970 non-null  float64
 2   Date of purchase  537970 non-null  object 
 3   Price             537970 non-null  float64
dtypes: float64(3), object(1)
memory usage: 16.4+ MB
```

3. Correcting data type

In [11]:
```
#renaming first
dataset=dataset.rename(columns={'Date of purchase':'Date','InvoieNo': 'InvoiceNo'})
```

In [12]:
```
dataset['Date']=pd.to_datetime(dataset['Date'])
```

In [13]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 537971 entries, 0 to 537970
Data columns (total 4 columns):
 #   Column      Non-Null Count   Dtype         
---  ------      --------------   -----         
 0   CustomerID  404181 non-null  float64       
 1   InvoiceNo   537970 non-null  float64       
 2   Date        537970 non-null  datetime64[ns]
 3   Price       537970 non-null  float64       
dtypes: datetime64[ns](1), float64(3)
memory usage: 16.4 MB
```

4. Missing values

In [14]:
```
dataset.isnull().sum()
```

Out[14]:
```
CustomerID    133790
InvoiceNo          1
Date               1
Price              1
dtype: int64
```

In [15]:
```
dataset.isnull().sum()/len(dataset)*100
```

Out[15]:
```
CustomerID    24.869370
InvoiceNo      0.000186
Date           0.000186
Price          0.000186
dtype: float64
```

In [16]:
```
# Nearly 25% data missing in Customer ID , talk to your stakeholder , drop this dat
```

In [17]:
```
dataset=dataset.dropna(subset=['CustomerID'])
dataset.isnull().sum()
```

Out[17]:
```
CustomerID    0
InvoiceNo     0
Date          0
Price         0
dtype: int64
```

5. How many customers we have in this given data

In [18]:
```
dataset['CustomerID'].value_counts()
```

Out[18]:
```
4043.0    7970
1896.0    5874
1301.0    5099
331.0     4615
1675.0    2779
          ...
2198.0       1
3209.0       1
2251.0       1
3127.0       1
3244.0       1
Name: CustomerID, Length: 4349, dtype: int64
```

In [19]:
```
dataset['CustomerID'].nunique()   #4349 customers data
```

Out[19]:
```
4349
```

RFM Approach

In [20]:
```
dataset['Date'].describe()
```

Out[20]:
```
count                  404181
unique                    381
top       2017-11-24 00:00:00
freq                     2522
first     2016-02-12 00:00:00
last      2017-12-19 00:00:00
Name: Date, dtype: object
```

last transaction date we can get from here (2017-12-19)

So, lets create a date object (2017-12-20) to calculate recency

2017-12-20 - 1 day old customer

2017-12-21 - 2 day old customer....

In [21]:
```
new_date= datetime.datetime(2017,12,20)
new_date
```

Out[21]:
```
datetime.datetime(2017, 12, 20, 0, 0)
```

Calculating Recency , Frequency, Monetary

In [22]:
```
dataset.head(2)
```

Out[22]:

	CustomerID	InvoiceNo	Date	Price
0	4355.0	398177.0	2017-10-29	1926.0
1	4352.0	394422.0	2017-05-10	1740.0

In [23]:
```
RFMScore=dataset.groupby('CustomerID').agg({'Date':lambda x:(new_date-x.max()).days
                                            'InvoiceNo': lambda x:x.count(),
                                            'Price': lambda x: x.sum()})
```

In [24]:
```
RFMScore=RFMScore.rename(columns={'Date':'Recency','InvoiceNo':'Frequency','Price':
RFMScore
```

Out[24]:

	Recency	Frequency	Monetary
CustomerID			
2.0	4	182	553704.0
3.0	77	27	257404.0
4.0	20	72	176613.0
5.0	18	16	41976.0
6.0	9	84	151822.0
...	...	...	...
4368.0	17	10	20480.0
4369.0	181	7	10774.0
4370.0	12	13	24962.0
4371.0	4	754	280608.0
4372.0	51	70	262820.0

4349 rows × 3 columns

In [ ]:
```

```

Good Customer

Recency - less

Frequency - high

Monetary- high

In [25]:
```
RFMScore.Recency.describe()
```

Out[25]:
```
count    4349.000000
mean       61.445160
std        89.656941
min         1.000000
25%        10.000000
50%        19.000000
75%        73.000000
max       617.000000
Name: Recency, dtype: float64
```

So, in recency ,

Recency < Q1 or 25% - good customers

Recency > Q3 or 75% - bad customers

In [26]:
```
RFMScore.Frequency.describe()
```

Out[26]:
```
count    4349.000000
mean       92.936537
std       232.086935
min         1.000000
25%        17.000000
50%        42.000000
75%       101.000000
max      7970.000000
Name: Frequency, dtype: float64
```

So, in Frequency ,

Freq. < Q1 or 25% - bad customers

Freq. > Q3 or 75% - good customers

In [27]:
```
RFMScore.Monetary.describe()
```

Out[27]:
```
count    4.349000e+03
mean     2.299380e+05
std      8.572589e+05
min     -5.037200e+04
25%      3.814800e+04
50%      8.365500e+04
75%      2.056120e+05
max      3.553619e+07
Name: Monetary, dtype: float64
```

So, in Monetary ,

Monetary < Q1 or 25% - bad customers

Monetary > Q3 or 75% - good customers

So, when we do clustering, our clusters could be like

1. R- min , F- max, M- max (good customers)
2. R-min, F- max, M-max
3. R-max, F-min, M-max
4. R-max, F-min, M-min (bad customers)

Split into four clusters/segments on basis of quantile method

In [28]:
```
quantiles=RFMScore.quantile(q=[0.25,0.50,0.75])
quantiles=quantiles.to_dict()
quantiles
```

Out[28]:
```
{'Recency': {0.25: 10.0, 0.5: 19.0, 0.75: 73.0},
 'Frequency': {0.25: 17.0, 0.5: 42.0, 0.75: 101.0},
 'Monetary': {0.25: 38148.0, 0.5: 83655.0, 0.75: 205612.0}}
```

In [29]:
```python
#x-value, p - recency,frequency,monetary, d- quantile dict
def RScore(x,p,d):
    if x<=d[p][0.25]:
        return 1
    elif x<=d[p][0.50]:
        return 2
    elif x<=d[p][0.75]:
        return 3
    else:
        return 4
```

In [30]:
```python
#function to calculate fre, monetary score
def FMScore(x,p,d):
    if x<=d[p][0.25]:
        return 4
    elif x<=d[p][0.50]:
        return 3
    elif x<=d[p][0.75]:
        return 2
    else:
        return 1
```

In [31]:
```python
RFMScore.columns
```

Out[31]:
```
Index(['Recency', 'Frequency', 'Monetary'], dtype='object')
```

In [32]:
```python
RFMScore['R']=RFMScore['Recency'].apply(RScore,args=('Recency',quantiles))
RFMScore['F']=RFMScore['Frequency'].apply(FMScore,args=('Frequency',quantiles))
RFMScore['M']=RFMScore['Monetary'].apply(FMScore,args=('Monetary',quantiles))
RFMScore
```

Out[32]:

	Recency	Frequency	Monetary	R	F	M
CustomerID						
2.0	4	182	553704.0	1	1	1
3.0	77	27	257404.0	4	3	1
4.0	20	72	176613.0	3	2	2
5.0	18	16	41976.0	2	4	3
6.0	9	84	151822.0	1	2	2
...	...	...	...	...	...	...
4368.0	17	10	20480.0	2	4	4
4369.0	181	7	10774.0	4	4	4
4370.0	12	13	24962.0	2	4	4
4371.0	4	754	280608.0	1	1	1
4372.0	51	70	262820.0	3	2	1

4349 rows × 6 columns

RFM Score

= (1,1,1) - good customer

= (4,4,4) - bad customer

In [33]:
```
#combining R,F,M values to 1 column

RFMScore['RFMGroup']=RFMScore.R.map(str)+RFMScore.F.map(str)+RFMScore.M.map(str)
RFMScore['RFMScore']=RFMScore[['R','F','M']].sum(axis=1)
RFMScore=RFMScore.reset_index()
RFMScore.head()
```

Out[33]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFMGroup	RFMScore
0	2.0	4	182	553704.0	1	1	1	111	3
1	3.0	77	27	257404.0	4	3	1	431	8
2	4.0	20	72	176613.0	3	2	2	322	7
3	5.0	18	16	41976.0	2	4	3	243	9
4	6.0	9	84	151822.0	1	2	2	122	5

RFMScore- sum=3 (Prime customers)

Now, we have **10 clusters** , from RFMScore equal 3 to 12

Categorize Customers basis RFM Score in 4 clusters

In [34]:
```
loyality_level=['Prime','Gold','Silver','Bronze']
score_cuts=pd.qcut(RFMScore.RFMScore,q=4,labels=loyality_level)
RFMScore['Loyality Level']=score_cuts.values
RFMScore.head()
```

Out[34]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFMGroup	RFMScore	Loyality Level
0	2.0	4	182	553704.0	1	1	1	111	3	Prime
1	3.0	77	27	257404.0	4	3	1	431	8	Gold
2	4.0	20	72	176613.0	3	2	2	322	7	Gold
3	5.0	18	16	41976.0	2	4	3	243	9	Silver
4	6.0	9	84	151822.0	1	2	2	122	5	Prime

In [35]:
```
#report to share
RFMScore.to_csv('Customer Segmentation.csv')
```

Number of customers in each cluster

In [56]:
```
final_details=RFMScore.groupby('Loyality Level')[['Recency','Frequency','Monetary',
    'Recency':'mean','Frequency':'mean','Monetary':'mean','CustomerID':'nunique'
})
final_details=final_details.reset_index()
```

In [57]:
```
final_details
```

Out[57]:

	Loyality Level	Recency	Frequency	Monetary	CustomerID
0	Prime	10.200000	227.785496	585979.422137	1310
1	Gold	32.593629	57.475524	124481.796426	1287
2	Silver	84.019169	25.174654	56236.376038	939
3	Bronze	163.617466	10.051661	23804.766298	813

In [58]:

```
final_details=final_details.rename(columns={'CustomerID':'No. of Buyers'})
final_details
```

Out[58]:

	Loyality Level	Recency	Frequency	Monetary	No. of Buyers
0	Prime	10.200000	227.785496	585979.422137	1310
1	Gold	32.593629	57.475524	124481.796426	1287
2	Silver	84.019169	25.174654	56236.376038	939
3	Bronze	163.617466	10.051661	23804.766298	813

In [59]:

```
#percentage of buyers

final_details['Percent']=final_details['No. of Buyers']/final_details['No. of Buyer
final_details['Percent']=round(final_details['Percent'],2)
final_details
```

Out[59]:

	Loyality Level	Recency	Frequency	Monetary	No. of Buyers	Percent
0	Prime	10.200000	227.785496	585979.422137	1310	30.12
1	Gold	32.593629	57.475524	124481.796426	1287	29.59
2	Silver	84.019169	25.174654	56236.376038	939	21.59
3	Bronze	163.617466	10.051661	23804.766298	813	18.69

In [60]:

```
final_details1=final_details[['Loyality Level','No. of Buyers','Percent']]
final_details1
```

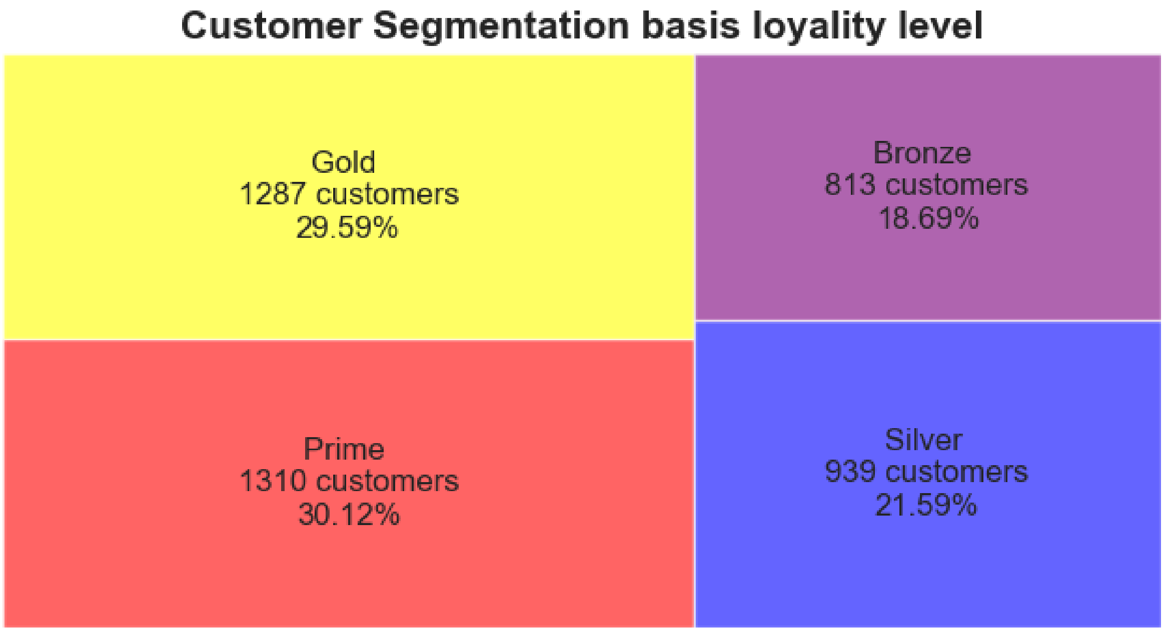
Out[60]:

	Loyality Level	No. of Buyers	Percent
0	Prime	1310	30.12
1	Gold	1287	29.59
2	Silver	939	21.59
3	Bronze	813	18.69

In [61]:

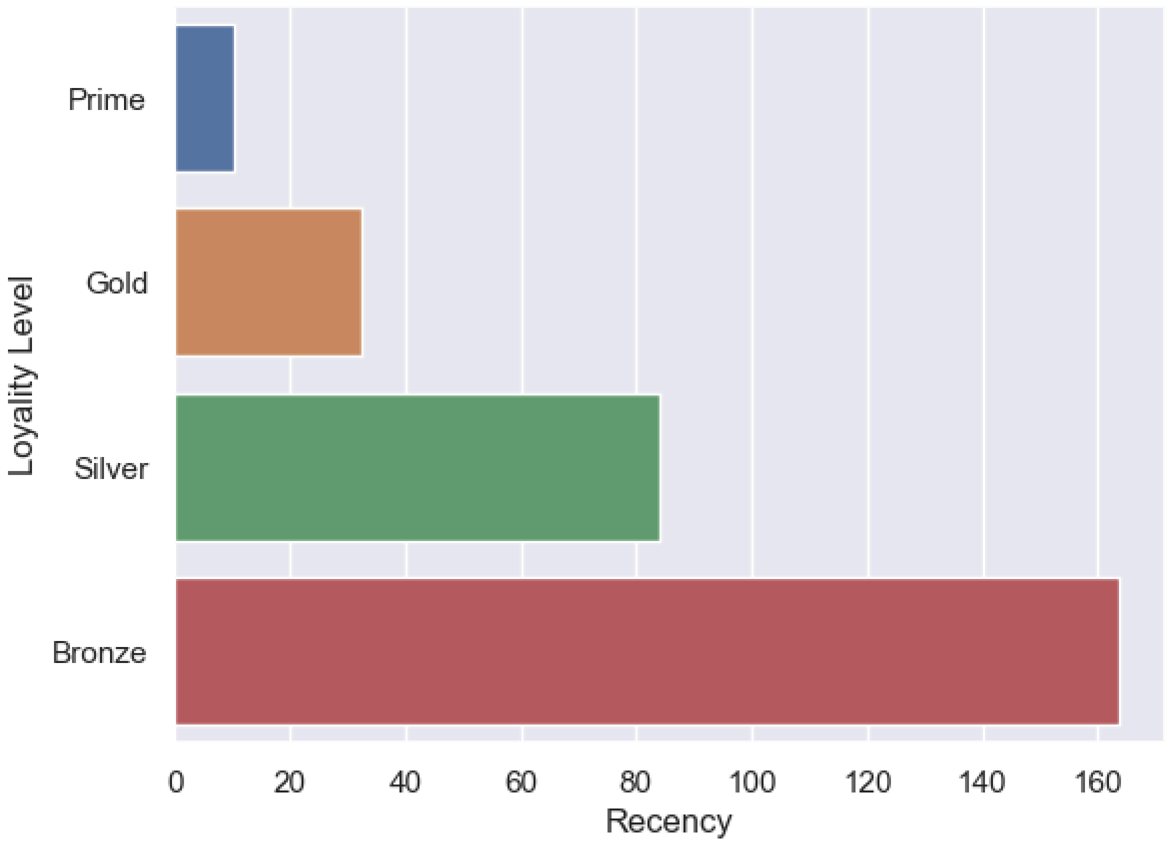
```
#Tree Map
import squarify
fig=plt.gcf()
ax=fig.add_subplot()
fig.set_size_inches(8,4)
color_dict={'Prime':'red','Gold':'yellow','Silver':'blue','Bronze':'Purple'}

squarify.plot(sizes=final_details['No. of Buyers'],color=color_dict.values(),
              label=['{} \n{:.0f} customers\n{}%'.format(*final_details1.iloc[i]) f
             alpha=0.6)
plt.title('Customer Segmentation basis loyality level',fontsize=15,fontweight='bolc
```

```
plt.axis('off')
plt.show()
```



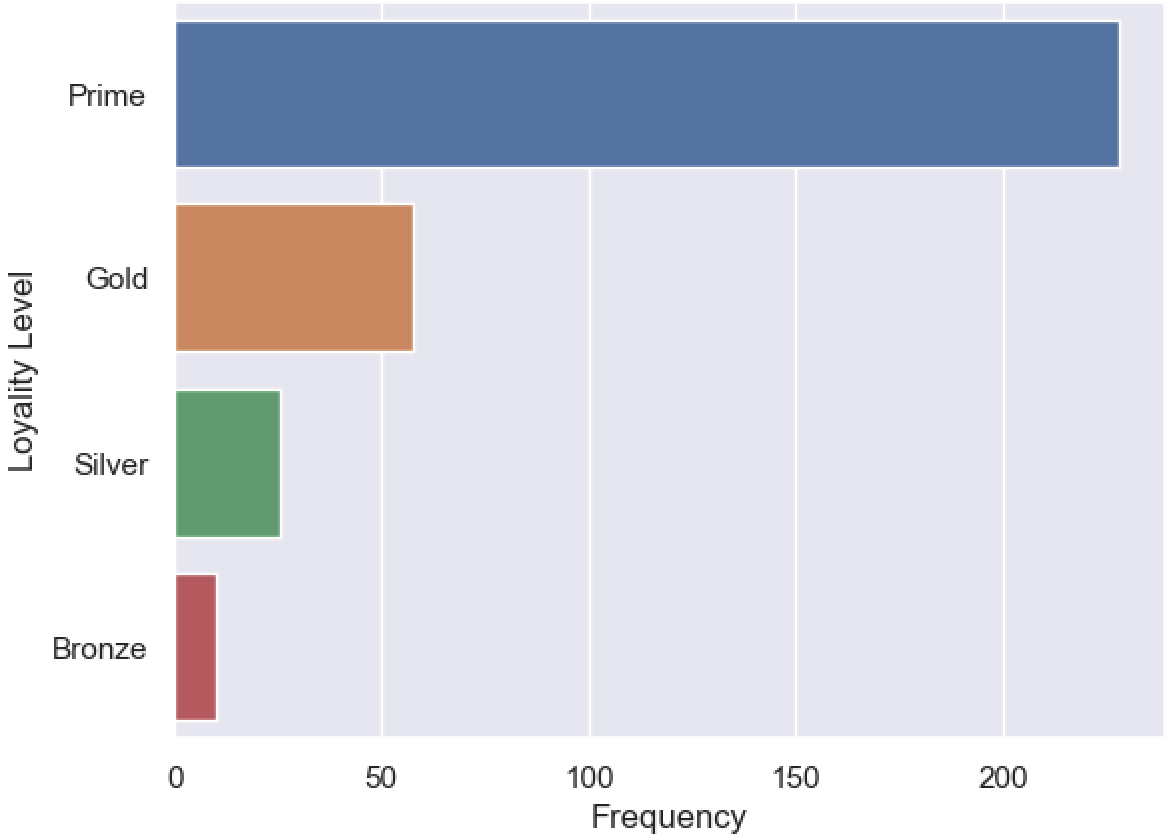
In [62]:
```
sns.barplot(x='Recency',y='Loyality Level',data=final_details)
```

Out[62]: <AxesSubplot:xlabel='Recency', ylabel='Loyality Level'>



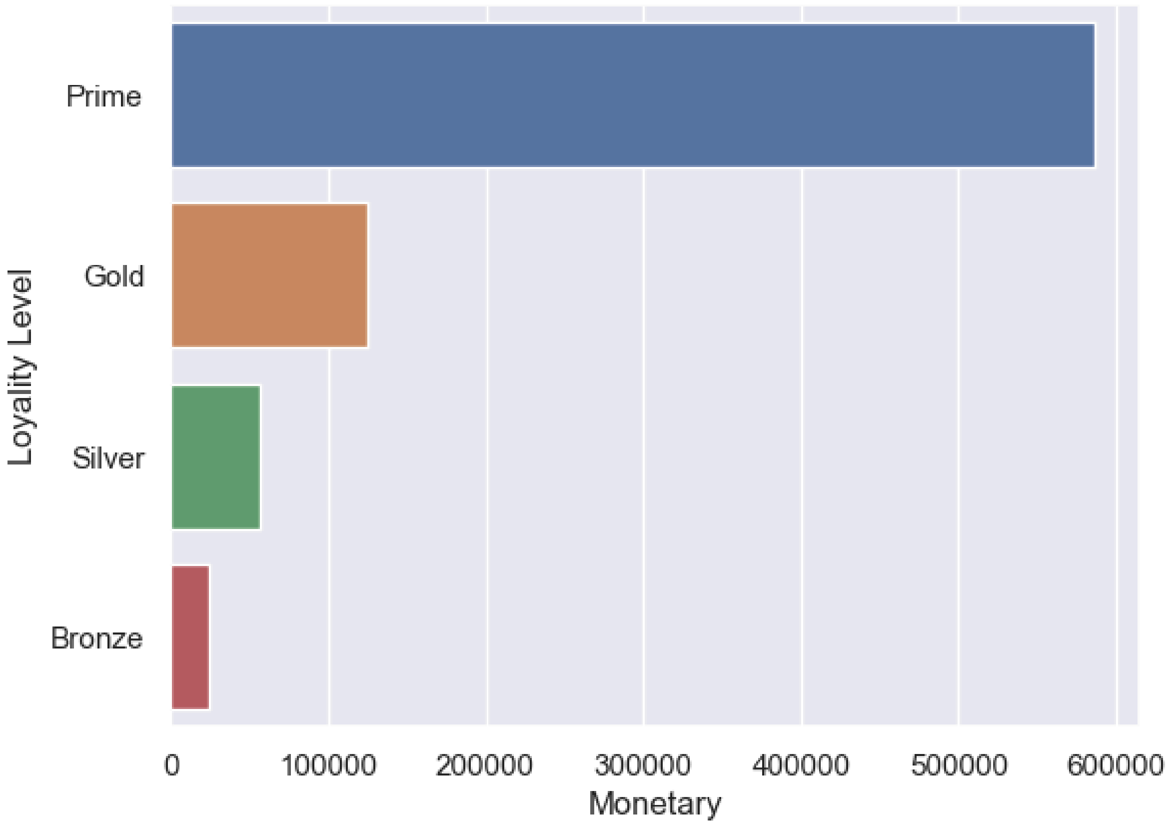
In [64]:
```
sns.barplot(x='Frequency',y='Loyality Level',data=final_details)
#average visit of prime customers more than all others
```

Out[64]: <AxesSubplot:xlabel='Frequency', ylabel='Loyality Level'>



In [65]:
```
sns.barplot(x='Monetary',y='Loyality Level',data=final_details)
#75% of our revenue from 30% of total customers (Prime Customers)
#similar to Pareto rule, (80/20 rule) - 80% of revenue from 20% of customers
```

Out[65]: <AxesSubplot:xlabel='Monetary', ylabel='Loyality Level'>



K-Means Clustering Method

In [42]:
```
RFMScore.head(2)
```

Out[42]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFMGroup	RFMScore	Loyality Level
0	2.0	4	182	553704.0	1	1	1	111	3	Prime
1	3.0	77	27	257404.0	4	3	1	431	8	Gold

In [43]:
```
#create a new dataset
RFMScore1=RFMScore.iloc[:,1:4]
RFMScore1.head(2)
```

Out[43]:

	Recency	Frequency	Monetary
0	4	182	553704.0
1	77	27	257404.0

In [46]:
```
from sklearn.preprocessing import StandardScaler,MinMaxScaler
scaler=MinMaxScaler()
scaled_data=scaler.fit_transform(RFMScore1)
scaled_data
```

Out[46]:
```
array([[0.00487013, 0.02271301, 0.01697483],
       [0.12337662, 0.00326264, 0.00864866],
       [0.03084416, 0.00890952, 0.00637839],
       ...,
       [0.01785714, 0.00150584, 0.00211692],
       [0.00487013, 0.09449115, 0.0093007 ],
       [0.08116883, 0.00865855, 0.00880085]])
```

In [47]:
```
scaled_data=pd.DataFrame(scaled_data,index=RFMScore1.index,columns=RFMScore1.columr
scaled_data.head(2)
```

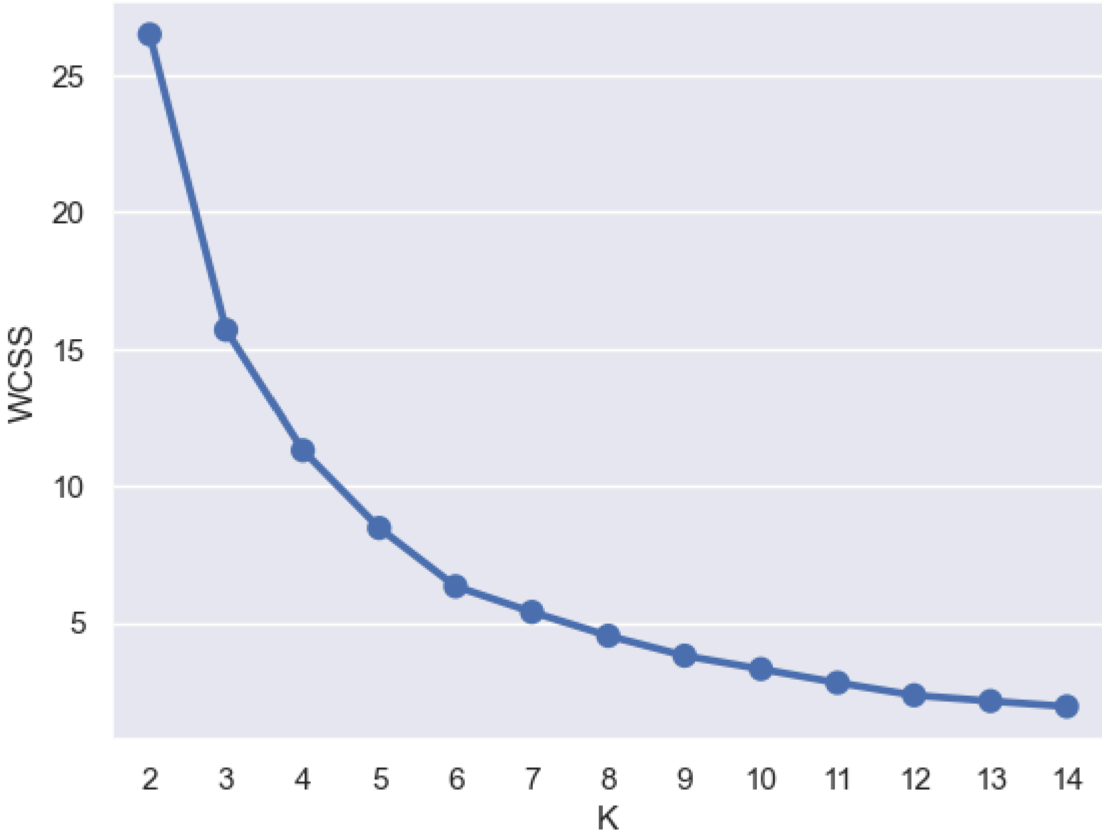
Out[47]:

	Recency	Frequency	Monetary
0	0.004870	0.022713	0.016975
1	0.123377	0.003263	0.008649

In [48]:
```
#Building K-means Cluster
from sklearn.cluster import KMeans
wcss=[]
for i in range(2,15):
    km=KMeans(n_clusters=i,random_state=101)
    km.fit(scaled_data)
    wcss.append(km.inertia_)

wcss
```

Out[48]:
```
[26.485217504119646,
 15.687959620731913,
 11.303285271307187,
 8.46637132255194,
 6.332840126192597,
 5.398201839257956,
 4.526043086435308,
 3.799728902981923,
 3.3115341695512788,
 2.811586088258872,
 2.3539787791775506,
 2.142332696144651,
 1.9442274929747922]
```

In [49]:
```
#elbow method to find K-value
abc=[2,3,4,5,6,7,8,9,10,11,12,13,14]
sns.pointplot(abc,wcss)
plt.xlabel('K')
plt.ylabel('WCSS')
plt.show()
```



In [50]:
```
#K=6
#building model
km=KMeans(n_clusters=6,random_state=101)
y_kmeans=km.fit_predict(scaled_data)
y_kmeans
```

Out[50]:
```
array([0, 3, 0, ..., 0, 0, 3])
```

In [51]:
```
RFMScore1['Clusters']=km.labels_
RFMScore1.head(10)
```

Out[51]:

	Recency	Frequency	Monetary	Clusters
0	4	182	553704.0	0
1	77	27	257404.0	3
2	20	72	176613.0	0
3	18	16	41976.0	0
4	9	84	151822.0	0
5	208	4	9410.0	1
6	234	58	135550.0	1
7	15	13	65832.0	0
8	16	58	331601.0	0
9	9	131	771439.0	0

In [52]:

```
RFMScore1['Clusters'].value_counts()
```

Out[52]:

```
0    2672
3     844
5     374
1     274
2     173
4      12
Name: Clusters, dtype: int64
```

In [55]:

```
final_details_km=RFMScore1.groupby('Clusters').agg({
    'Recency':'mean','Frequency':'mean','Monetary':'mean'
})
final_details_km['No. of Buyers']=RFMScore1['Clusters'].value_counts()
final_details_km
```

Out[55]:

Clusters	Recency	Frequency	Monetary	No. of Buyers
0	12.675524	117.780314	2.778854e+05	2672
1	242.802920	20.751825	4.747083e+04	274
2	365.878613	18.554913	2.960067e+04	173
3	60.520142	38.598341	9.600645e+04	844
4	4.000000	3131.833333	1.108638e+07	12
5	140.117647	27.852941	6.763825e+04	374

So, we have segmented our clients in 6 clusters,

Cluster 4 - Prime customers (with most profitable and regular clients)

Cluster 2 - does not contribute much to company's market, low expenditure and least visiting customers