In [2]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [80]:

```
data = pd.read_csv(r'G:\FSDA\INEURON-INTERNSHIP-PROJECT-01\DATASET\MASTER.CSV',encoding = 'latin-1')
```

In [81]:

```
data.head()
```

Out[81]:

	ORDER_DATE	SHIPED_DATE	SalesOrderNumber	CUSTOME_BIRTHDAY	NAME_CUSTMOER	OrderQuantity	UnitPrice	TotalProductCost	SalesAmount
0	2014-01-22	2014-01-29	SO43793	57	Jon Yang	2	1699.995	1912.1544	3399.99
1	2016-01-22	2016-01-29	SO51522	57	Jon Yang	1	2319.990	1265.6195	2319.99
2	2016-01-22	2016-01-29	SO51522	57	Jon Yang	1	21.980	8.2205	21.98
3	2016-05-04	2016-05-11	SO57418	57	Jon Yang	1	2384.070	1481.9379	2384.07
4	2016-05-04	2016-05-11	SO57418	57	Jon Yang	1	28.990	10.8423	28.99

In [10]:

```
data.isnull().sum()
```

Out[10]:

```
ORDER_DATE             0
SHIPED_DATE            0
CUSTOME_BIRTHDAY       0
NAME_CUSTMOER          0
OrderQuantity          0
UnitPrice              0
TotalProductCost       0
SalesAmount            0
TaxAmt                 0
MaritalStatus          0
Gender                 0
Education              0
Occupation             0
DATE_FIRST_PURCHASE    0
ProductName            0
country                0
dtype: int64
```

In [11]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58189 entries, 0 to 58188
Data columns (total 16 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ORDER_DATE           58189 non-null  object 
 1   SHIPED_DATE          58189 non-null  object 
 2   CUSTOME_BIRTHDAY     58189 non-null  int64  
 3   NAME_CUSTMOER        58189 non-null  object 
 4   OrderQuantity        58189 non-null  int64  
 5   UnitPrice            58189 non-null  float64
 6   TotalProductCost     58189 non-null  float64
 7   SalesAmount          58189 non-null  float64
 8   TaxAmt               58189 non-null  float64
 9   MaritalStatus        58189 non-null  object 
 10  Gender               58189 non-null  object 
 11  Education            58189 non-null  object 
 12  Occupation           58189 non-null  object 
 13  DATE_FIRST_PURCHASE  58189 non-null  object 
 14  ProductName          58189 non-null  object 
 15  country              58189 non-null  object 
dtypes: float64(4), int64(2), object(10)
memory usage: 7.1+ MB
```

In [12]:

```
data['ORDER_DATE'] = pd.to_datetime(data['ORDER_DATE'])
data['SHIPED_DATE'] = pd.to_datetime(data['SHIPED_DATE'])
data['DATE_FIRST_PURCHASE'] = pd.to_datetime(data['DATE_FIRST_PURCHASE'])
```

EXPLORATORY DATA ANALYSIS

In [13]:

```
data['order_year'] = data['ORDER_DATE'].dt.year
data['order_month'] = data['ORDER_DATE'].dt.month
data['order_day'] = data['ORDER_DATE'].dt.day
```

In [14]:

```
data.head()
```

Out[14]:

ME_BIRTHDAY	NAME_CUSTMOER	OrderQuantity	UnitPrice	TotalProductCost	SalesAmount	TaxAmt	MaritalStatus	Gender	Education	Occupation	DATE_
57	Jon Yang	2	1699.995	1912.1544	3399.99	271.9992	M	M	Bachelors	Professional	
57	Jon Yang	1	2319.990	1265.6195	2319.99	185.5992	M	M	Bachelors	Professional	
57	Jon Yang	1	21.980	8.2205	21.98	1.7584	M	M	Bachelors	Professional	
57	Jon Yang	1	2384.070	1481.9379	2384.07	190.7256	M	M	Bachelors	Professional	
57	Jon Yang	1	28.990	10.8423	28.99	2.3192	M	M	Bachelors	Professional	

In [25]:

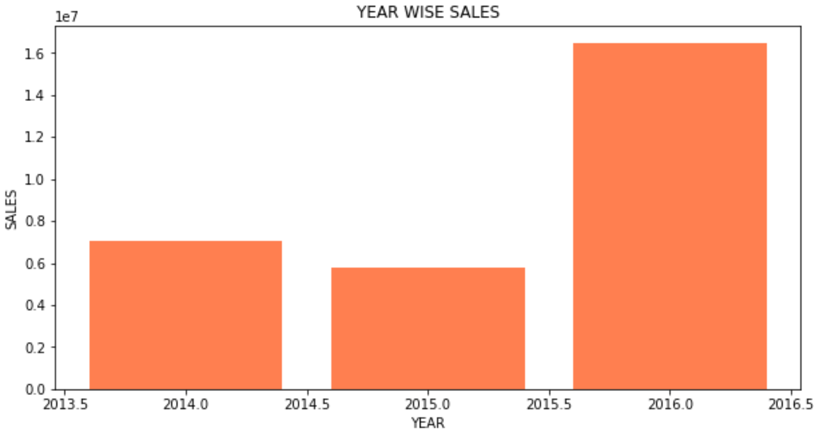
```
year_wise_sales=data.groupby(['order_year'])['SalesAmount'].sum().to_frame().reset_index()
year_wise_sales
```

Out[25]:

	order_year	SalesAmount
0	2014	7.072084e+06
1	2015	5.762134e+06
2	2016	1.647362e+07

In [102]:

```
plt.figure(figsize = (10,5))
plt.bar(year_wise_sales['order_year'],year_wise_sales['SalesAmount'],color='coral')
plt.xlabel('YEAR')
plt.ylabel('SALES')
plt.title('YEAR WISE SALES')
plt.show()
```



In [36]:

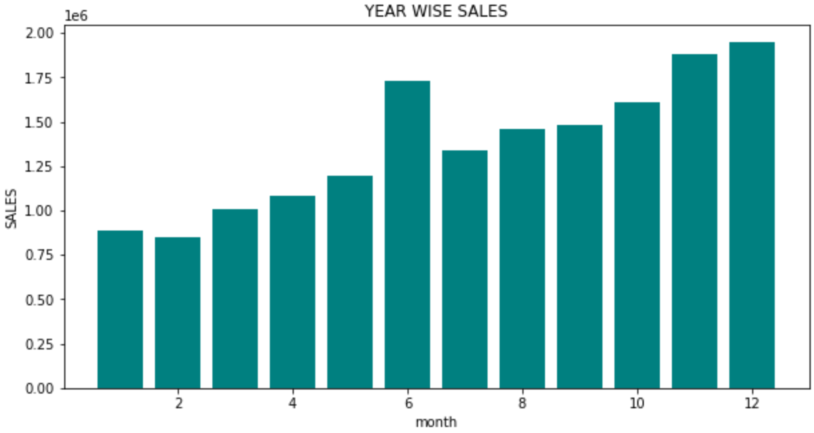
```
year_month_wise_sales=data.groupby(['order_year','order_month'])['SalesAmount'].sum().to_frame().reset_index()
year_month_wise_sales
```

Out[36]:

	order_year	order_month	SalesAmount
0	2014	1	4.733882e+05
1	2014	2	5.061917e+05
2	2014	3	4.739430e+05
3	2014	4	5.133295e+05
4	2014	5	5.439934e+05
5	2014	6	7.555279e+05
6	2014	7	5.967466e+05
7	2014	8	5.508167e+05
8	2014	9	6.441352e+05
9	2014	10	6.636923e+05
10	2014	11	6.735562e+05
11	2014	12	6.767636e+05
12	2015	1	5.003652e+05
13	2015	2	5.460015e+05
14	2015	3	3.504670e+05
15	2015	4	4.153902e+05
16	2015	5	3.350951e+05
17	2015	6	5.773140e+05
18	2015	7	4.388652e+05
19	2015	8	4.890903e+05
20	2015	9	4.855748e+05
21	2015	10	5.063993e+05
22	2015	11	5.627726e+05
23	2015	12	5.547992e+05
24	2016	1	8.866688e+05
25	2016	2	8.474135e+05
26	2016	3	1.010258e+06
27	2016	4	1.080450e+06
28	2016	5	1.196981e+06
29	2016	6	1.731788e+06
30	2016	7	1.340245e+06
31	2016	8	1.462480e+06
32	2016	9	1.480905e+06
33	2016	10	1.608751e+06
34	2016	11	1.878318e+06
35	2016	12	1.949361e+06

In [103]:

```
plt.figure(figsize = (10,5))
plt.bar(year_month_wise_sales['order_month'],year_month_wise_sales['SalesAmount'],color='teal')
plt.xlabel('month')
plt.ylabel('SALES')
plt.title('YEAR WISE SALES')
plt.show()
```



In [48]:

```
data.groupby(['country','order_year'])['SalesAmount'].sum().unstack().reset_index()
```

Out[48]:

order_year	country	2014	2015	2016
0	Australia	2.568701e+06	2.099585e+06	4383479.54
1	Canada	5.731010e+05	3.050107e+05	1088879.50
2	France	4.142453e+05	6.333997e+05	1592880.75
3	Germany	5.133532e+05	5.932472e+05	1784107.09
4	United Kingdom	5.505073e+05	6.965950e+05	2140388.50
5	United States	2.452176e+06	1.434296e+06	5483882.67

In [55]:

```
data['Gender'].value_counts()
```

Out[55]:

```
M    29314
F    28875
Name: Gender, dtype: int64
```

In [58]:

```
male=data[data['Gender']=='M']
female = data[data['Gender']=='F']
```

In [64]:

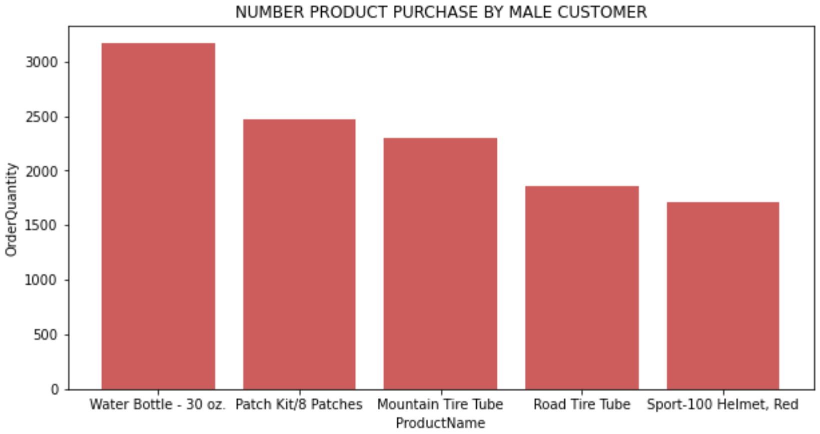
```
male_pro=male.groupby(['ProductName'])['OrderQuantity'].sum().nlargest(5).to_frame().reset_index()
male_pro
```

Out[64]:

	ProductName	OrderQuantity
0	Water Bottle - 30 oz.	3169
1	Patch Kit/8 Patches	2475
2	Mountain Tire Tube	2301
3	Road Tire Tube	1853
4	Sport-100 Helmet, Red	1712

In [66]:

```
plt.figure(figsize = (10,5))
plt.bar(male_pro['ProductName'],male_pro['OrderQuantity'],color='indianred')
plt.xlabel('ProductName')
plt.ylabel('OrderQuantity')
plt.title('NUMBER PRODUCT PURCHASE BY MALE CUSTOMER')
plt.show()
```



In [68]:

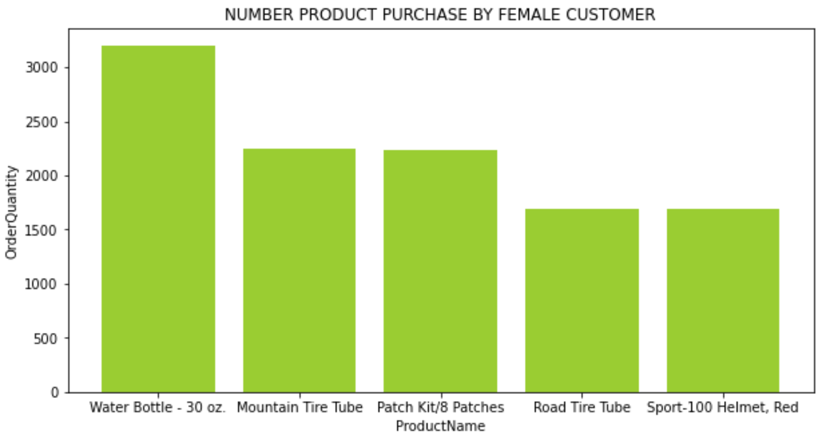
```
female_pro=female.groupby(['ProductName'])['OrderQuantity'].sum().nlargest(5).to_frame().reset_index()
female_pro
```

Out[68]:

	ProductName	OrderQuantity
0	Water Bottle - 30 oz.	3201
1	Mountain Tire Tube	2250
2	Patch Kit/8 Patches	2230
3	Road Tire Tube	1691
4	Sport-100 Helmet, Red	1686

In [104]:

```
plt.figure(figsize = (10,5))
plt.bar(female_pro['ProductName'],female_pro['OrderQuantity'],color='yellowgreen')
plt.xlabel('ProductName')
plt.ylabel('OrderQuantity')
plt.title('NUMBER PRODUCT PURCHASE BY FEMALE CUSTOMER')
plt.show()
```



In [70]:

```
age_bins=[0,40,50,60,70,80,100]
groupnames= ["0-40","40-50", "50-60", "60-70", "70-80", "80-100"]
```

In [73]:

```
data["age category"]=pd.cut(data.CUSTOME_BIRTHDAY, age_bins, right= False, labels= groupnames)
```

In [76]:

```
data["age category"].value_counts().to_frame().reset_index()
```

Out[76]:

	index	age category
0	50-60	20288
1	60-70	16473
2	70-80	9128
3	40-50	8202
4	80-100	4021
5	0-40	0

In [ ]:

```

```

In [77]:

```
data.head()
```

Out[77]:

OrderQuantity	UnitPrice	TotalProductCost	SalesAmount	TaxAmt	MaritalStatus	Gender	Education	Occupation	DATE_FIRST_PURCHASE	ProductName
2	1699.995	1912.1544	3399.99	271.9992	M	M	Bachelors	Professional	2014-01-22	Mountain-100 Silver, 38
1	2319.990	1265.6195	2319.99	185.5992	M	M	Bachelors	Professional	2014-01-22	Mountain-200 Silver, 38
1	21.980	8.2205	21.98	1.7584	M	M	Bachelors	Professional	2014-01-22	Fender Set - Mountain
1	2384.070	1481.9379	2384.07	190.7256	M	M	Bachelors	Professional	2014-01-22	Touring-1000 Blue, 46
1	28.990	10.8423	28.99	2.3192	M	M	Bachelors	Professional	2014-01-22	Touring Tire

RFM analysis

What is RFM Analysis? RFM analysis is a marketing technique used to quantitatively rank and group customers based on the recency, frequency and monetary total of their recent transactions to identify the best customers and perform targeted marketing campaigns.

Recency: How recently has the customer made a transaction?

Frequency: How frequently does the customer place an order?

Monetary: How much money has the customer spent on products ?

In [79]:

```
#Renaming the column:
#Grouping the data by Customer Unique ID to find the latest order of each customer:
df_recency = data.groupby(by = 'NAME_CUSTMOER', as_index = False)['ORDER_DATE'].max()

df_recency.rename(columns = {"ORDER_DATE": "LastPurchaseDate"}, inplace = True)

#Removing time and extracting only date from the datetime field:
df_recency["LastPurchaseDate"] = df_recency["LastPurchaseDate"].dt.date

#Using the last order in the entire dataset as a reference point to calculate recency:
recent_date = data['ORDER_DATE'].dt.date.max()
df_recency['Recency'] = df_recency['LastPurchaseDate'].apply(lambda x: (recent_date - x).days)

df_recency.head()
```

Out[79]:

	NAME_CUSTMOER	LastPurchaseDate	Recency
0	Aaron Adams	2016-04-30	244
1	Aaron Alexander	2016-12-15	15
2	Aaron Allen	2014-12-04	757
3	Aaron Baker	2016-09-12	109
4	Aaron Bryant	2016-07-27	156

In [87]:

```
## calculating the frequency
frequency_df = data.groupby(['NAME_CUSTMOER']).agg({'SalesOrderNumber':'nunique'}).reset_index()
## renaming the columns
frequency_df.rename(columns={'SalesOrderNumber':'frequency'},inplace=True)

frequency_df.head()
```

Out[87]:

	NAME_CUSTMOER	frequency
0	Aaron Adams	1
1	Aaron Alexander	1
2	Aaron Allen	1
3	Aaron Baker	1
4	Aaron Bryant	2

In [88]:

```
## calculating Monetary
monetary_df=data.groupby(by='NAME_CUSTMOER',as_index=False)['SalesAmount'].sum()
# renaming the column
monetary_df.rename(columns={'SalesAmount':'monetary'},inplace=True)

monetary_df.head()
```

Out[88]:

	NAME_CUSTMOER	monetary
0	Aaron Adams	117.96
1	Aaron Alexander	69.99
2	Aaron Allen	3399.99
3	Aaron Baker	1750.98
4	Aaron Bryant	133.96

In [89]:

```
rfm = df_recency.merge(frequency_df,on='NAME_CUSTMOER').merge(monetary_df,on='NAME_CUSTMOER')

rfm.drop('LastPurchaseDate',axis=1,inplace=True)

rfm.head()
```

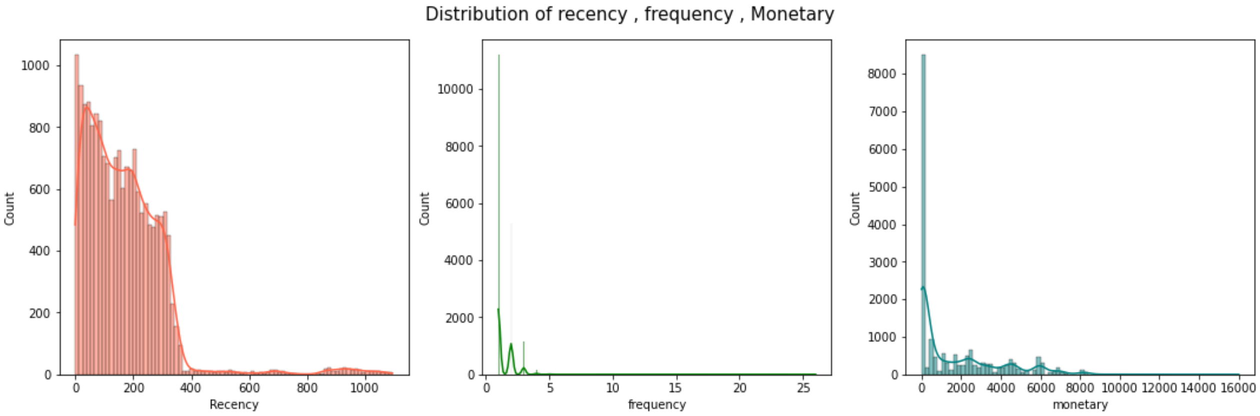
Out[89]:

	NAME_CUSTMOER	Recency	frequency	monetary
0	Aaron Adams	244	1	117.96
1	Aaron Alexander	15	1	69.99
2	Aaron Allen	757	1	3399.99
3	Aaron Baker	109	1	1750.98
4	Aaron Bryant	156	2	133.96

In [112]:

```
fig,ax=plt.subplots(nrows=1,ncols=3,figsize=(15,5))
#sns.set_palette('BrBG')
sns.histplot(rfm['Recency'],kde=True,ax=ax[0],color = 'tomato')
sns.histplot(rfm['frequency'],kde=True,ax=ax[1],color='green')
sns.histplot(rfm['monetary'],kde=True,ax=ax[2],color='teal')

plt.suptitle('Distribution of recency , frequency , Monetary',fontsize=15)
plt.tight_layout(pad=1)
plt.show()
```



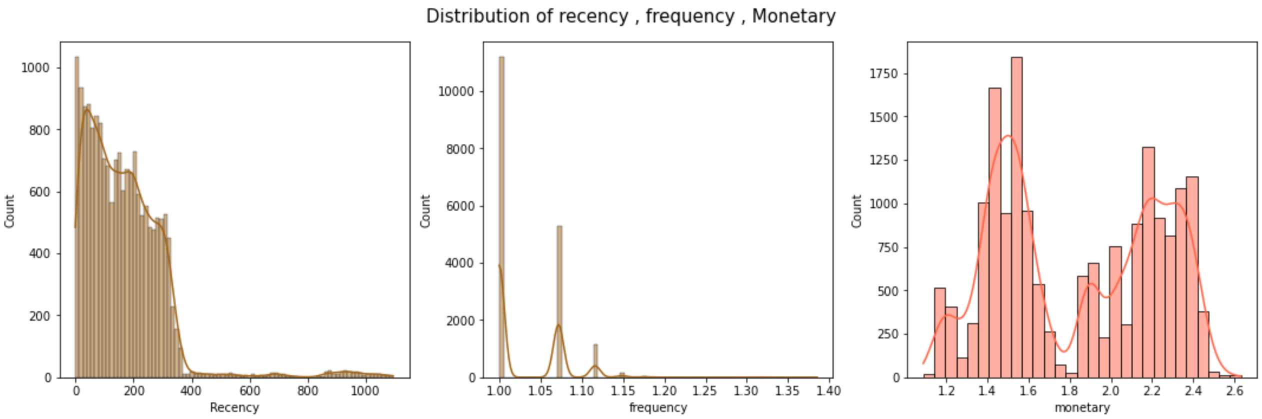
In [91]:

```
rfm_transformed = rfm.copy()
for feature in rfm.columns[2:]:
    rfm_transformed[feature]=rfm_transformed[feature].apply(lambda X:np.power(X,(1/10)))
```

In [113]:

```
fig,ax=plt.subplots(nrows=1,ncols=3,figsize=(15,5))
sns.histplot(rfm_transformed['Recency'],kde=True,ax=ax[0])
sns.histplot(rfm_transformed['frequency'],kde=True,ax=ax[1])
sns.histplot(rfm_transformed['monetary'],kde=True,ax=ax[2],color = 'tomato')

plt.suptitle('Distribution of recency , frequency , Monetary',fontsize=15)
plt.tight_layout(pad=1)
plt.show()
```



In [93]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled_rfm = scaler.fit_transform(rfm.drop('NAME_CUSTMOER', axis = 1))

scaled_rfm_df = pd.DataFrame(scaled_rfm, columns = rfm.columns[1:])
```

In [95]:

```
from sklearn.cluster import KMeans

final_model = KMeans(n_clusters = 5, random_state = 10)
final_model.fit(scaled_rfm_df)
```

Out[95]:

```
KMeans
KMeans(n_clusters=5, random_state=10)
```

In [96]:

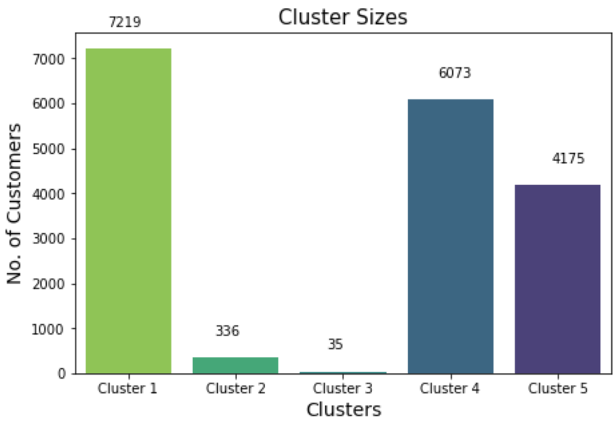
```
data_output = rfm.copy()
data_output['Cluster'] = final_model.labels_
data_output.sample(5)
```

Out[96]:

	NAME_CUSTMOER	Recency	frequency	monetary	Cluster
12279	Marshall Xu	180	2	564.9800	0
12015	Marcus Thomas	311	1	38.9800	3
1842	Bailey Adams	240	2	4558.5225	4
17144	Tyler Jackson	216	1	1735.9800	3
3566	Chloe Gonzalez	169	2	3310.4075	4

In [97]:

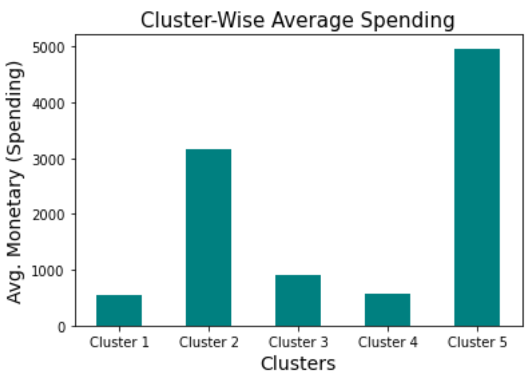
```
sns.countplot(data = data_output, x = 'Cluster', palette = 'viridis_r')
plt.title('Cluster Sizes', fontsize = 15)
plt.xlabel('Clusters', fontsize = 14)
plt.ylabel('No. of Customers', fontsize = 14)
plt.xticks([0, 1, 2, 3, 4], ['Cluster 1', 'Cluster 2', 'Cluster 3', 'Cluster 4', 'Cluster 5'], rotation = 0)
plt.text(x = 0 - 0.2, y = data_output.Cluster.value_counts()[0] + 500, s = data_output.Cluster.value_counts()[0])
plt.text(x = 1 - 0.2, y = data_output.Cluster.value_counts()[1] + 500, s = data_output.Cluster.value_counts()[1])
plt.text(x = 2 - 0.15, y = data_output.Cluster.value_counts()[2] + 500, s = data_output.Cluster.value_counts()[2])
plt.text(x = 3 - 0.12, y = data_output.Cluster.value_counts()[3] + 500, s = data_output.Cluster.value_counts()[3])
plt.text(x = 4 - 0.05, y = data_output.Cluster.value_counts()[4] + 500, s = data_output.Cluster.value_counts()[4])
plt.tight_layout(pad = -1)
plt.show()
```



In [98]:

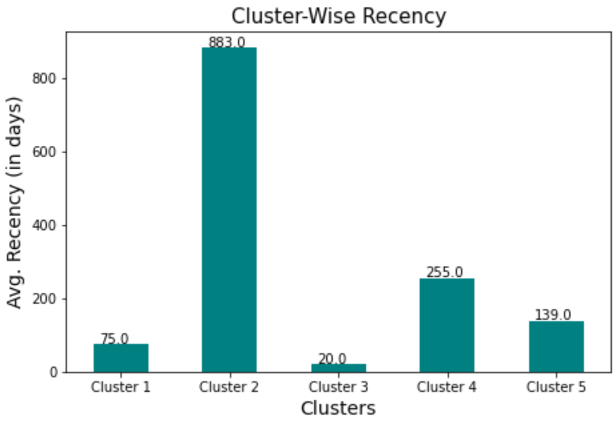
```
monetary_averages = pd.Series(data_output.groupby(by = 'Cluster')['monetary'].mean())
monetary_averages.plot(kind = 'bar', color = 'teal')
plt.title('Cluster-Wise Average Spending', fontsize = 15)
plt.xlabel('Clusters', fontsize = 14)
plt.ylabel('Avg. Monetary (Spending)', fontsize = 14)
plt.xticks([0, 1, 2, 3, 4], ['Cluster 1', 'Cluster 2', 'Cluster 3', 'Cluster 4', 'Cluster 5'], rotation = 0)

plt.show()
```



In [99]:

```
recency_averages = pd.Series(data_output.groupby(by = 'Cluster')['Recency'].mean())
recency_averages.plot(kind = 'bar', color = 'teal')
plt.title('Cluster-Wise Recency', fontsize = 15)
plt.xlabel('Clusters', fontsize = 14)
plt.ylabel('Avg. Recency (in days)', fontsize = 14)
plt.xticks([0, 1, 2, 3, 4], ['Cluster 1', 'Cluster 2', 'Cluster 3', 'Cluster 4', 'Cluster 5'], rotation = 0)
plt.text(x = 0 - 0.2, y = recency_averages[0] + 3, s = "{}".format(recency_averages[0].round(0)))
plt.text(x = 1 - 0.2, y = recency_averages[1] + 3, s = "{}".format(recency_averages[1].round(0)))
plt.text(x = 2 - 0.2, y = recency_averages[2] + 3, s = "{}".format(recency_averages[2].round(0)))
plt.text(x = 3 - 0.2, y = recency_averages[3] + 3, s = "{}".format(recency_averages[3].round(0)))
plt.text(x = 4 - 0.2, y = recency_averages[4] + 3, s = "{}".format(recency_averages[4].round(0)))
plt.tight_layout(pad = -1)
plt.show()
```



In [100]:

```
rfm_agg = data_output.groupby(['Cluster']).agg({
    'Recency': 'mean',
    'frequency': 'mean',
    'monetary': 'mean',
    'Cluster': 'count'
}).round(1)

rfm_agg.rename(columns = {"Recency": "Avg. Recency",
                          "frequency": "Avg. Frequency",
                          "monetary": "Avg. Monetary",
                          "Cluster": "Customer Count"
                         }, inplace = True)

rfm_agg
```

Out[100]:

Cluster	Avg. Recency	Avg. Frequency	Avg. Monetary	Customer Count
0	75.1	1.3	554.3	7219
1	883.3	1.0	3151.0	336
2	19.6	19.1	898.5	35
3	255.1	1.1	573.9	6073
4	139.2	2.3	4965.6	4175

```
Recency: How recently has the customer made a transaction?

Frequency: How frequently does the customer place an order?

Monetary: How much money has the customer spent on products ?
```

```
 cluster 0 :  Moderate customer
cluser 1 : occainsal customer
cluster 2 : Loyal customer
cluster 3: failed conversation with customers
cluster 4: Avoid and Higher spender customers
```

In [ ]: