ScalerMart

Data Analytics Case Study

Solving this case study will showcase your analytical skills, problem-solving abilities, and communication expertise, making you a strong contender for any consulting position.

Tips for Candidates:

● Take your time to understand the business problem before diving into data analysis. ● Document your thought process and assumptions clearly throughout your analysis. ● Use clear and concise language in your report, avoiding technical jargon where possible. ● Focus on actionable insights and data-driven recommendations that can be implemented to improve user engagement.

Problem Statement

ScalerMart, a leading global electronics retailer, has experienced a significant downturn in sales, with a nearly 50% decline in revenue in 2020 compared to the previous year.

In response to this challenge, the company is actively seeking a sharp Data Analyst to join their growing team.

You have been assigned the task of analyzing the customer-level transactional data to identify potential reasons behind the decline in sales.

Your objective is to recommend data-driven strategies aimed at improving sales performance.

Data Provided:

● Customers Table: Contains information about customers, including customer key, demographics (age, gender, location), and last purchase date.

● Products Table: Contains information about products, including product key, category, unit price, and brand.

● Sales Table: Contains information about orders placed, including order number, order date, and quantity.

1. Data Exploration and Cleaning:

○ Describe the data cleaning steps you would take to ensure data quality before analysis. (This assesses understanding of data pre-processing)

○ How would you explore the distribution of customer demographics? What visualization techniques would you employ? (This assesses proficiency in data exploration and visualization)

2. User Segmentation:

○ What customer segmentation techniques would you recommend to group users with similar characteristics? Why is segmentation crucial for this analysis? (This assesses knowledge of segmentation and its benefits)

○ Segment customers based on factors that might influence purchase behavior. Analyze purchase patterns within each segment. Are there any significant differences?

3. Engagement Analysis:

○ Stakeholders have noted that a substantial portion of the company's revenue is attributed to repeat purchases from our loyal customer base. Devise a metric to quantify customer loyalty and analyze trends over time? (This assesses understanding of customer loyalty metrics)

○ Correlate user demographics with purchase behavior. Do you observe any patterns? Formulate and test hypotheses to identify statistically significant relationships. (This assesses ability to perform hypothesis testing and identify correlations)

4. Recommendations:

○ Based on your analysis, what are some potential explanations for the decline in sales?

○ Recommend specific, data-driven strategies to improve sales across different customer segments. (This assesses problem-solving skills and ability to translate insights into actionable recommendations)

Deliverables:

A well structured report (slide deck) with clear explanations of

In [ ]:

In [ ]:

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:

Loading Customers data in jupyter notebook

In [2]:

```
Customers = pd.read_csv('Customers.csv',encoding= 'unicode_escape')
```

In [3]:

```
Customers
```

Out[3]:

	CustomerKey	Gender	Name	City	State Code	State	Zip Code	Coun
0	301	Female	Lilly Harding	WANDEARAH EAST	SA	South Australia	5523	Austra
1	325	Female	Madison Hull	MOUNT BUDD	WA	Western Australia	6522	Austra
2	554	Female	Claire Ferres	WINJALLOK	VIC	Victoria	3380	Austra
3	786	Male	Jai Poltpalingada	MIDDLE RIVER	SA	South Australia	5223	Austra
4	1042	Male	Aidan Pankhurst	TAWONGA SOUTH	VIC	Victoria	3698	Austra
...	...	...	...	...	...	...	...	
15261	2099600	Female	Denisa Du□ková	Houston	TX	Texas	77017	Unit Stat
15262	2099618	Male	Justin Solórzano	Mclean	VA	Virginia	22101	Unit Stat
15263	2099758	Male	Svend Petrussen	Wilmington	NC	North Carolina	28405	Unit Stat
15264	2099862	Female	Lorenza Rush	Riverside	CA	California	92501	Unit Stat
15265	2099937	Male	Zygmunt Kaminski	Bloomfield Township	MI	Michigan	48302	Unit Stat

15266 rows × 10 columns

Converting Birthday column in it to datetime format to be able to calculate age

In [4]:
```
Customers['Birthday']=pd.to_datetime(Customers['Birthday']) # converting
```

In [5]:
```
Customers['Age'] = 2020-Customers['Birthday'].dt.year
```

In [6]:
```
Customers['Age']
```

Out[6]:
```
0        81
1        41
2        73
3        63
4        55
         ..
15261    84
15262    28
15263    83
15264    83
15265    55
Name: Age, Length: 15266, dtype: int32
```

In [7]:
```
Customers.dtypes
```

Out[7]:
```
CustomerKey              int64
Gender                  object
Name                    object
City                    object
State Code              object
State                   object
Zip Code                object
Country                 object
Continent               object
Birthday        datetime64[ns]
Age                      int32
dtype: object
```

Loading Sales data in jupyter notebook

In [8]:
```
Sales = pd.read_csv('Sales.csv')
```

In [9]:
```
Sales['Order Date'] = pd.to_datetime(Sales['Order Date'])
Sales['Delivery Date'] = pd.to_datetime(Sales['Delivery Date'])
```

In [10]:
```
Sales.dtypes
```

Out[10]:
```
Order Number              int64
Line Item                 int64
Order Date       datetime64[ns]
Delivery Date    datetime64[ns]
CustomerKey               int64
StoreKey                  int64
ProductKey                int64
Quantity                  int64
Currency Code            object
dtype: object
```

Loading Customers data in jupyter notebook

In [11]:
```
Products = pd.read_csv('Products.csv')
```

In [12]:
```
Products.dtypes
```

Out[12]:
```
ProductKey         int64
Product Name      object
Brand             object
Color             object
Unit Cost USD     object
Unit Price USD    object
SubcategoryKey     int64
Subcategory       object
CategoryKey        int64
Category          object
dtype: object
```

Converting string data into integer which is necessary to be able to calculate Total Sales

In [13]:
```
Products['Unit Cost USD'] = Products['Unit Cost USD'].str[1:] # Slicing
```

In [14]:
```
Products['Unit Cost USD'] =Products['Unit Cost USD'].str.replace(',','')
Products['Unit Cost USD'] =Products['Unit Cost USD'].str.replace(' ','')
```

In [15]:
```
Products['Unit Price USD'] = Products['Unit Price USD'].str[1:]  # Slici
```

In [16]:
```
Products['Unit Price USD'] =Products['Unit Price USD'].str.replace(',','
Products['Unit Price USD'] =Products['Unit Price USD'].str.replace(' ','
```

In [17]:
```
Products['Unit Price USD'] = Products['Unit Price USD'].astype('float')
Products['Unit Cost USD'] = Products['Unit Cost USD'].astype('float')
```

In [18]:
```
Products['Sales'] = Products['Unit Price USD'] * Products['Unit Cost USD
```

In [19]:
```
Products.isna().sum() # there is no null values in the products data
```

Out[19]:
```
ProductKey        0
Product Name      0
Brand             0
Color             0
Unit Cost USD     0
Unit Price USD    0
SubcategoryKey    0
Subcategory       0
CategoryKey       0
Category          0
Sales             0
dtype: int64
```

There are 49,719 null values in the delivery date column

In [20]:
```
Sales.isna().sum()
```

Out[20]:
```
Order Number          0
Line Item             0
Order Date            0
Delivery Date     49719
CustomerKey           0
StoreKey              0
ProductKey            0
Quantity              0
Currency Code         0
dtype: int64
```

In [21]:
```
diff = Sales['Delivery Date'] - Sales['Order Date']
```

In [22]:
```
diff.value_counts().sort_values(ascending=True)
```

Out[22]:
```
17 days       5
14 days       7
15 days       8
13 days      17
12 days      45
11 days      81
10 days     173
9 days      280
8 days      519
1 days      549
7 days      967
2 days     1480
6 days     1592
5 days     2189
3 days     2518
4 days     2735
Name: count, dtype: int64
```

Type *Markdown* and LaTeX: α^2

In [23]:
```
Sales.head()
```

Out[23]:

	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	StoreKey	ProductKey	Quantity	Currei Cc
0	366000	1	2016-01-01	NaT	265598	10	1304	1	C
1	366001	1	2016-01-01	2016-01-13	1269051	0	1048	2	U
2	366001	2	2016-01-01	2016-01-13	1269051	0	2007	1	U
3	366002	1	2016-01-01	2016-01-12	266019	0	1106	7	C
4	366002	2	2016-01-01	2016-01-12	266019	0	373	1	C

In [ ]:

In [24]:
```
Customers.isna().sum()
```

Out[24]:
```
CustomerKey     0
Gender          0
Name            0
City            0
State Code     10
State           0
Zip Code        0
Country         0
Continent       0
Birthday        0
Age             0
dtype: int64
```

In [25]:
```
# To Determine which join to choose :-
# we will consider the problem statement which states that we want to
```

In [26]:
```
Join_data = pd.merge(Sales,Products, on = 'ProductKey',how = 'left')
```

In [27]:
```
Join_data = pd.merge(Join_data, Customers, on ='CustomerKey', how = 'lef
```

In [28]:
```
Join_data.isna().sum()
```

Out[28]:
```
Order Number           0
Line Item              0
Order Date             0
Delivery Date      49719
CustomerKey            0
StoreKey               0
ProductKey             0
Quantity               0
Currency Code          0
Product Name           0
Brand                  0
Color                  0
Unit Cost USD          0
Unit Price USD         0
SubcategoryKey         0
Subcategory            0
CategoryKey            0
Category               0
Sales                  0
Gender                 0
Name                   0
City                   0
State Code            30
State                  0
Zip Code               0
Country                0
Continent              0
Birthday               0
Age                    0
dtype: int64
```

In [29]:
```
Join_data[Join_data['Delivery Date'].isna()][['Delivery Date','Sales']]
```

Out[29]:

	Delivery Date	Sales
0	NaT	2126.3600
6	NaT	839933.2660
7	NaT	29903.8500
8	NaT	101153.9200
9	NaT	1546.5933
...	...	...
62867	NaT	130252.9800
62868	NaT	8.4042
62869	NaT	12406.6800
62872	NaT	50.8491
62879	NaT	9850.9300

49719 rows × 2 columns

Imputation Treatment of the null values in the sales data :-

- # It has been observed that for every records where there is null values in the delivery date we are having StoreKey which is non-zero
- # Also there is a actual sale for the related sales records in the Sales data hence

It can be assumed that the such sales are directly deliverd / purchased from Store

hence we can impute such delivery date by the order date of such records and so on.

In [30]:
```
Join_data['Delivery Date'].fillna(Join_data['Order Date'],inplace=True)
```

In [31]:
```
Join_data
```

Out[31]:

	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	StoreKey	ProductKey	Quantity	C
0	366000	1	2016-01-01	2016-01-01	265598	10	1304	1	
1	366001	1	2016-01-01	2016-01-13	1269051	0	1048	2	
2	366001	2	2016-01-01	2016-01-13	1269051	0	2007	1	
3	366002	1	2016-01-01	2016-01-12	266019	0	1106	7	
4	366002	2	2016-01-01	2016-01-12	266019	0	373	1	
...	...	...	...	...	...	...	...	...	
62879	2243030	1	2021-02-20	2021-02-20	1216913	43	632	3	
62880	2243031	1	2021-02-20	2021-02-24	511229	0	98	4	
62881	2243032	1	2021-02-20	2021-02-23	331277	0	1613	2	
62882	2243032	2	2021-02-20	2021-02-23	331277	0	1717	2	
62883	2243032	3	2021-02-20	2021-02-23	331277	0	464	7	

62884 rows × 29 columns

In [32]:
```
Join_data[Join_data['Delivery Date'] == Join_data['Order Date']].shape
```

Out[32]:
```
(49719, 29)
```

Delivery Date Imputation Done Sucessfully

In [33]:
```
Join_data[Join_data["State Code"].isna()][['State']].value_counts()
```

Out[33]:
```
State
Napoli    30
Name: count, dtype: int64
```

In [34]:
```
Join_data[Join_data["State Code"].isna()][['State']].value_counts().sum(
```

Out[34]: 30

In [35]:
```
Join_data[Join_data["State"]== 'Napoli']['State'].count()
```

Out[35]: 30

Imputation Technique for 30 records of State code

It has been Observed that State Code for all the records with state 'Napoli' has been stated as null and

we will replace NAP with shortform for Napoli

In [36]:
```
Join_data['State Code'].fillna('NAP',inplace = True)
```

In [37]:
```
Join_data[Join_data["State Code"].isna()][['State Code']].value_counts()
```

Out[37]: 0

In [38]:
```
Join_data[Join_data['State Code']=='NAP'].value_counts().sum()
```

Out[38]: 30

State Code Imputation Done Sucessfully

In [39]:
```
Join_data.isna().sum().sum()
```

Out[39]: 0

There is no null value in entire dataframe

Now starting with EDA

As the problem statement clearly specified that there was a significant downturn in sales, with a nearly 50% decline in revenue in 2020 compared to the previous year. ie 2019 So we will filter the data based on year 2019 and 2020 only

In [40]:
```
Join_data = Join_data[(Join_data['Order Date'].dt.year == 2019) | (Join_
```

In [41]:
```
sales_2019 =Join_data[Join_data['Order Date'].dt.year==2019]['Sales'].su
sales_2019
```

Out[41]:
```
1669925150.2814
```

Sales for the year 2019 was 1669925150.2814

In [42]:
```
sales_2020=Join_data[Join_data['Order Date'].dt.year==2020]['Sales'].sum
sales_2020
```

Out[42]:
```
834943994.6052
```

Sales for the year 2020 was 834943994.6052

- ## Hence we came to know there was a actual decline in sales in 2020 as compared to 2019.

In [43]:
```
Join_data['Order Year'] = Join_data['Order Date'].dt.year
```

In [44]:
```
Join_data['Order Year'].value_counts()
```

Out[44]:
```
Order Year
2019    21611
2020    11026
Name: count, dtype: int64
```

- ## It has been Observed that the Order Quantity for the year 2020 is decline to 50 % as compared to 2019

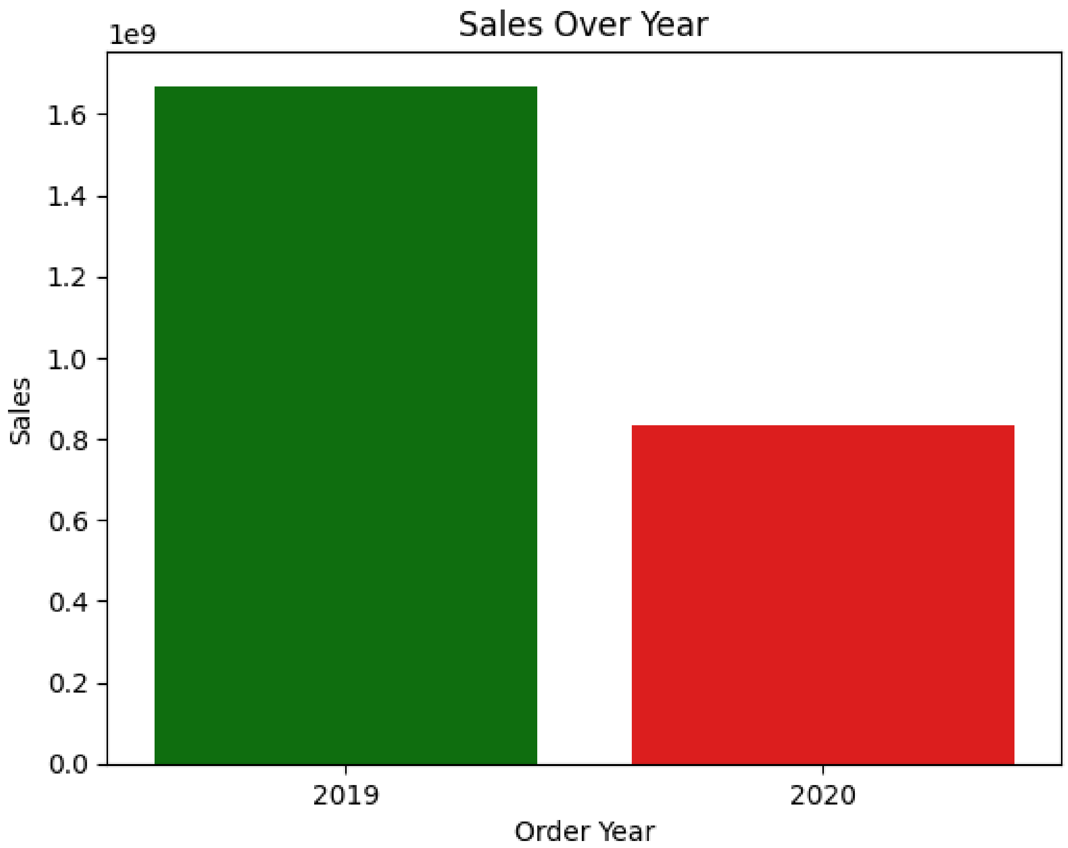
Aggregating data for better visualization

In [45]:
```
Group_data = Join_data.groupby('Order Year')[['Sales']].sum()
```

Graphical representation of the Total sales for the two years

In [46]:

```
plt.xlabel = ('Year')
plt.ylabel = ('Sales')
plt.title('Sales Over Year')
palette = {'2019':'green','2020':'red'}
sns.barplot(Group_data,x='Order Year',palette = palette, y = 'Sales')
plt.show()
```

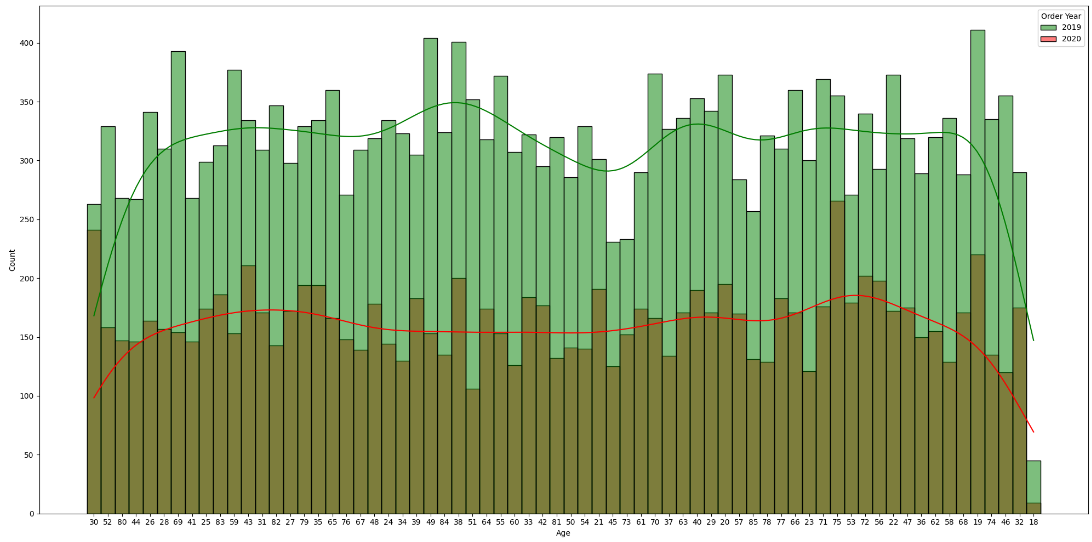


In [47]:

```
Join_data['Age']=Join_data['Age'].astype('str')
```

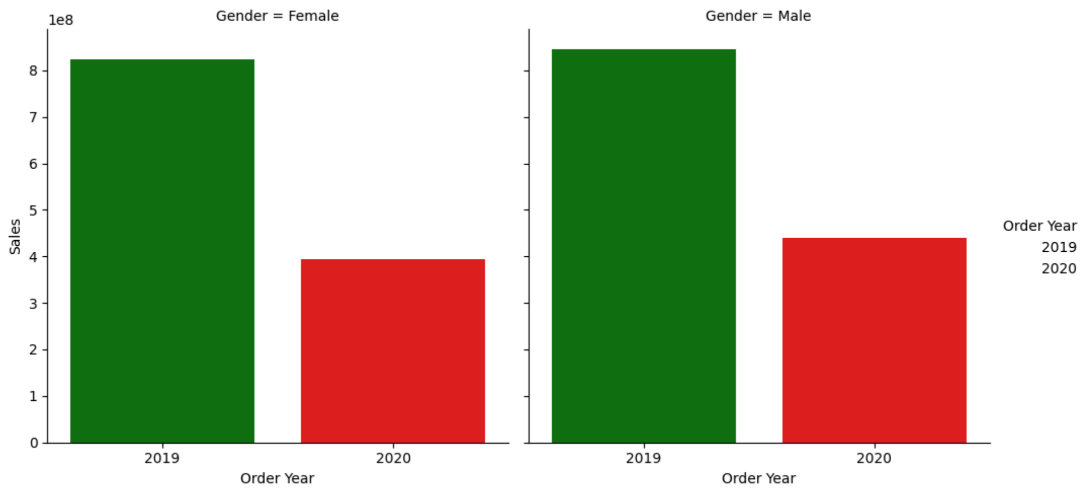
Graph To identify whether Customer Sales are evenly distributed throughout different 'Age' of Customers

In [48]:
```
plt.figure(figsize=(20,10))
palette={2019:'green',2020:'red'}
sns.histplot(data=Join_data, x='Age', bins=30, kde=True,hue='Order Year'
plt.tight_layout()

plt.show()
```



To identify whether Customer Sales are evenly distributed throughout the 'Gender' of Customers

In [49]:
```
group_gender = Join_data.groupby(['Gender','Order Year'])[['Sales']].sum
palette={'2019':'green','2020':'red'}
sns.catplot(data=group_gender, y= 'Sales',x='Order Year',col='Gender',ki
plt.show()
```



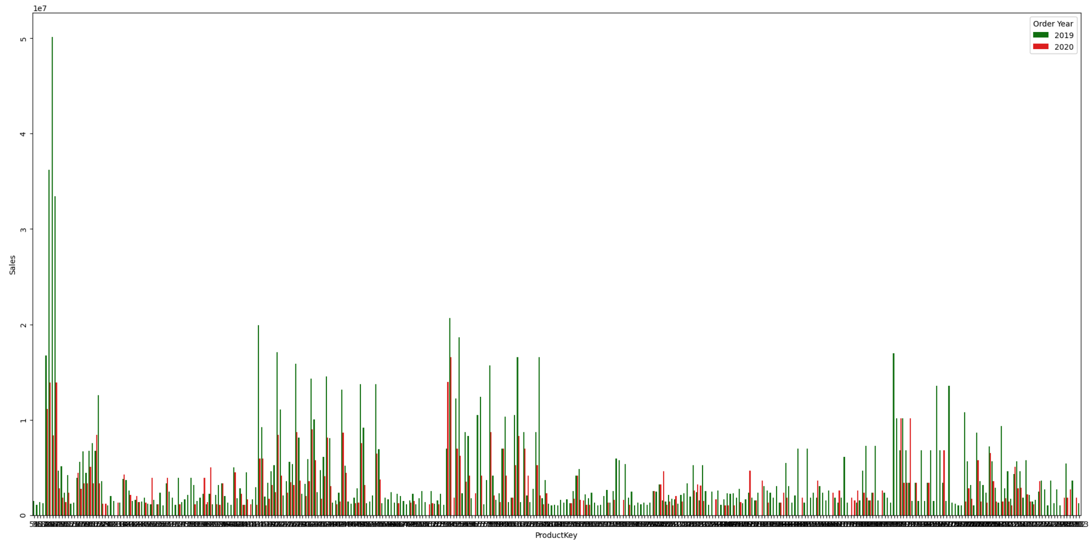
Products Performance Analysis

In [50]:
```
Join_data.columns
```

Out[50]:
```
Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'Product Name', 'Brand', 'Color', 'Unit Cost USD', 'Unit Price
USD',
       'SubcategoryKey', 'Subcategory', 'CategoryKey', 'Category', 'Sa
les',
       'Gender', 'Name', 'City', 'State Code', 'State', 'Zip Code', 'C
ountry',
       'Continent', 'Birthday', 'Age', 'Order Year'],
      dtype='object')
```

Below graph to identify the distribution of sales(amount)for each productKey

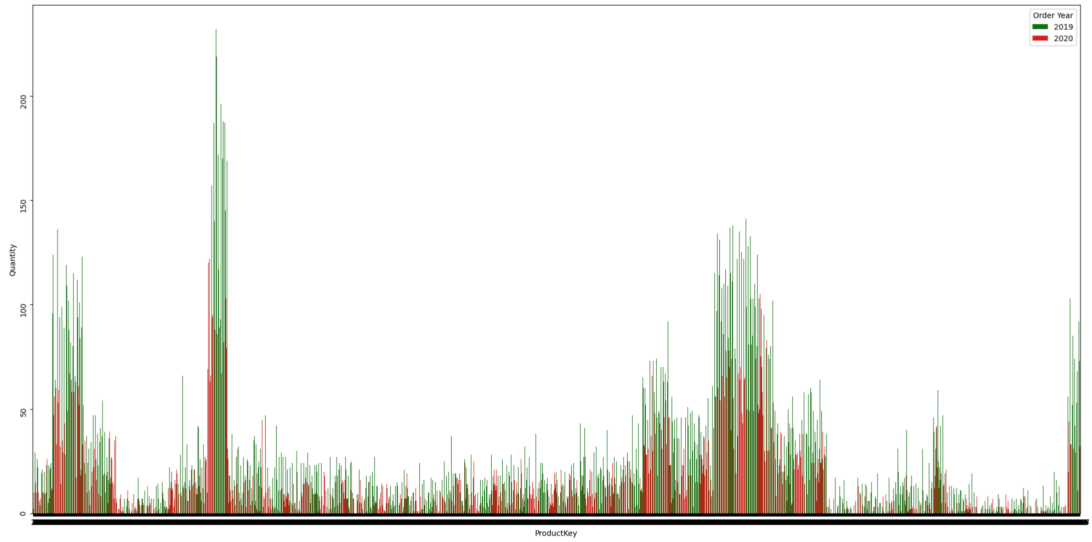
In [51]:
```
ProductKey_data = Join_data.groupby(['ProductKey','Order Year'])[['Sales

plt.figure(figsize=(20,10))
palette = {2019: 'green', 2020: 'red'}

sns.barplot(data = ProductKey_data, x='ProductKey',y = 'Sales',hue='Orde
palette = {2019: 'green', 2020: 'red'}

plt.yticks(rotation=90)
plt.tight_layout()

plt.show()
```



Below graph to identify the distribution of Sales (Quantity) for each productKey

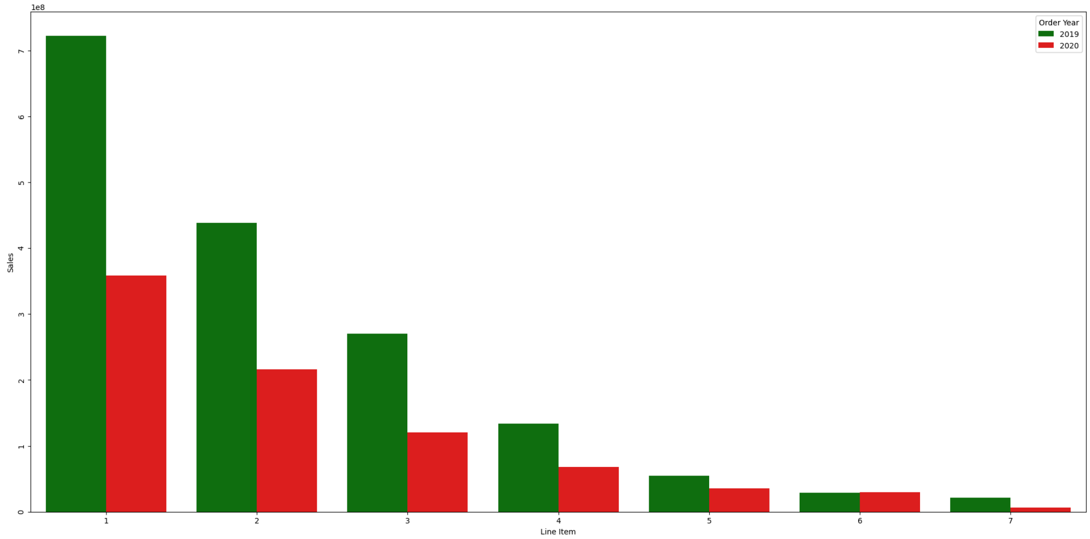
In [52]:

```
Quantity_data = Join_data.groupby(['ProductKey','Order Year'])[['Quantit

plt.figure(figsize=(20,10))
palette = {2019: 'green', 2020: 'red'}

sns.barplot(data = Quantity_data, x='ProductKey',y = 'Quantity',hue='Ord
palette = {2019: 'green', 2020: 'red'}

plt.yticks(rotation=90)
plt.tight_layout()

plt.show()
```



Below graph to identify the distribution of Sales (amount) for each Line Item.

In [53]:
```
Line_item_data = Join_data.groupby(['Line Item','Order Year'])[['Sales']

plt.figure(figsize=(20,10))
palette = {2019: 'green', 2020: 'red'}

sns.barplot(data = Line_item_data, x='Line Item',y = 'Sales',hue='Order
palette = {2019: 'green', 2020: 'red'}

plt.yticks(rotation=90)
plt.tight_layout()

plt.show()
```



In [ ]:

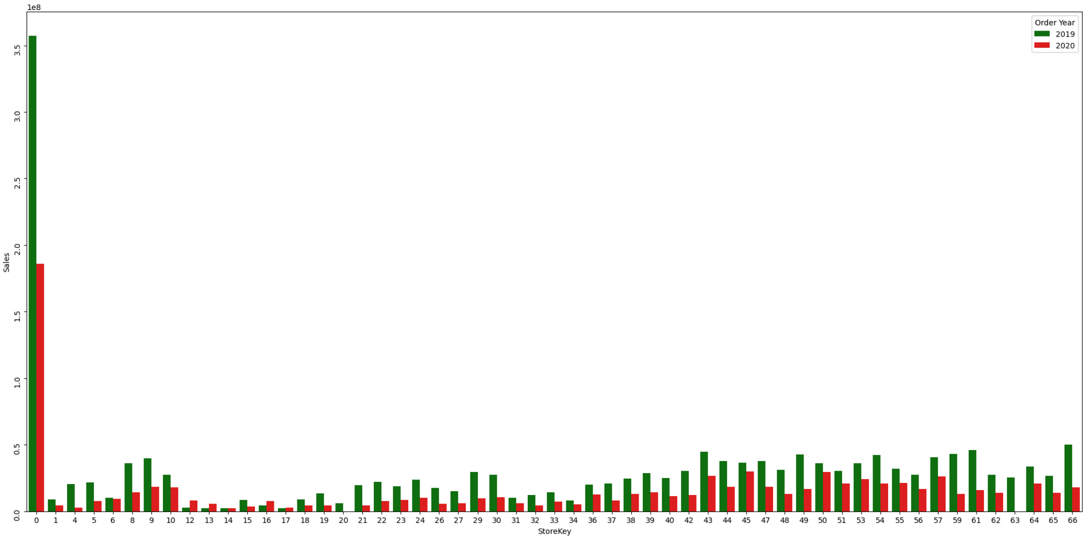
In [54]:
```
Join_data.columns
```

Out[54]:
```
Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'Product Name', 'Brand', 'Color', 'Unit Cost USD', 'Unit Price
USD',
       'SubcategoryKey', 'Subcategory', 'CategoryKey', 'Category', 'Sa
les',
       'Gender', 'Name', 'City', 'State Code', 'State', 'Zip Code', 'C
ountry',
       'Continent', 'Birthday', 'Age', 'Order Year'],
      dtype='object')
```

Below graph to identify the distribution of Sales (amount) for each StoreKey.

In [55]:

```
StoreKey_data = Join_data.groupby(['StoreKey','Order Year'])[['Sales']].

plt.figure(figsize=(20,10))

palette = {2019: 'green', 2020: 'red'}

sns.barplot(data = StoreKey_data, x='StoreKey',y = 'Sales',hue='Order Ye
palette = {2019: 'green', 2020: 'red'}

plt.yticks(rotation=90)
plt.tight_layout()

plt.show()
```



In [56]:

```
Join_data.columns
```

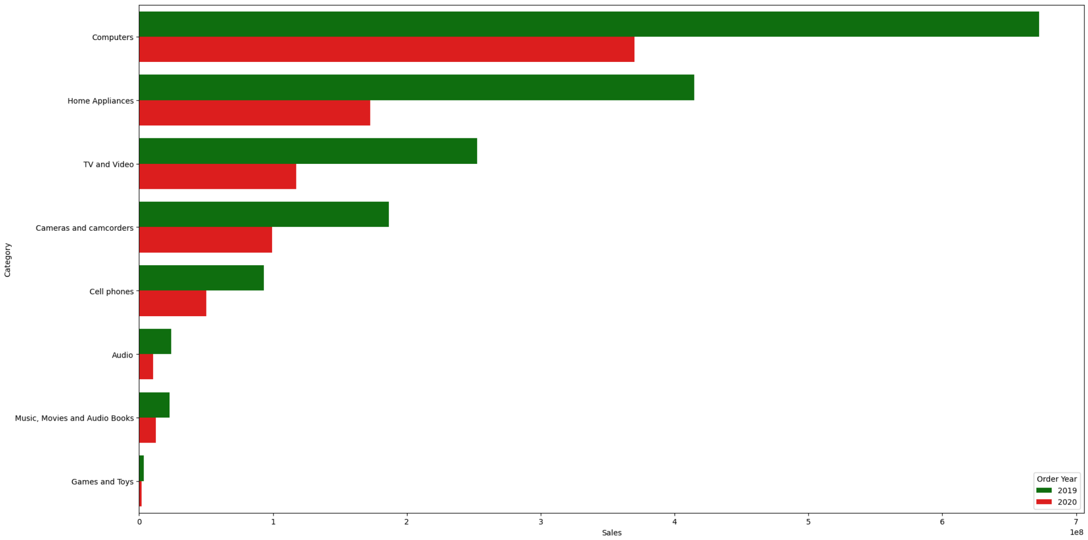
Out[56]:

```
Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'Product Name', 'Brand', 'Color', 'Unit Cost USD', 'Unit Price
USD',
       'SubcategoryKey', 'Subcategory', 'CategoryKey', 'Category', 'Sa
les',
       'Gender', 'Name', 'City', 'State Code', 'State', 'Zip Code', 'C
ountry',
       'Continent', 'Birthday', 'Age', 'Order Year'],
      dtype='object')
```

Below graph to show distribution of Sales(amount) for each Category

In [57]:

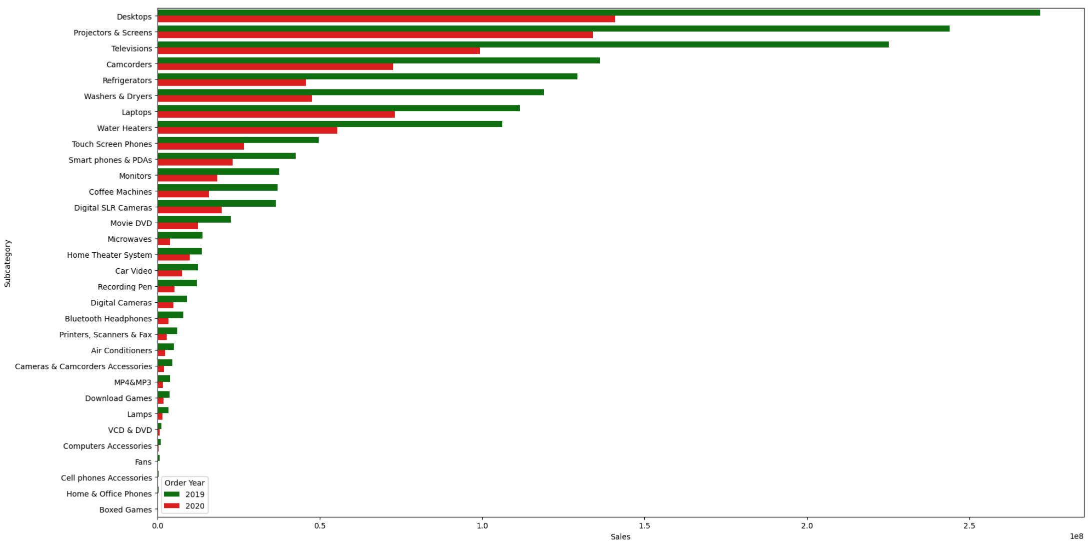
```
Category_sub_data = Join_data.groupby(['Category','Order Year'])[['Sales
plt.figure(figsize=(20,10))
palette = {2019: 'green', 2020: 'red'}
sns.barplot(data=Category_sub_data, y='Category', x='Sales', hue= 'Order

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



Below graph to show distribution of Sales(amount) for each Subcategory

In [58]:

```
Category_sub_data = Join_data.groupby(['Subcategory','Order Year'])[['Sa
plt.figure(figsize=(20, 10))
palette = {2019: 'green', 2020: 'red'}
sns.barplot(data=Category_sub_data, y='Subcategory', x='Sales', hue= 'Or

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



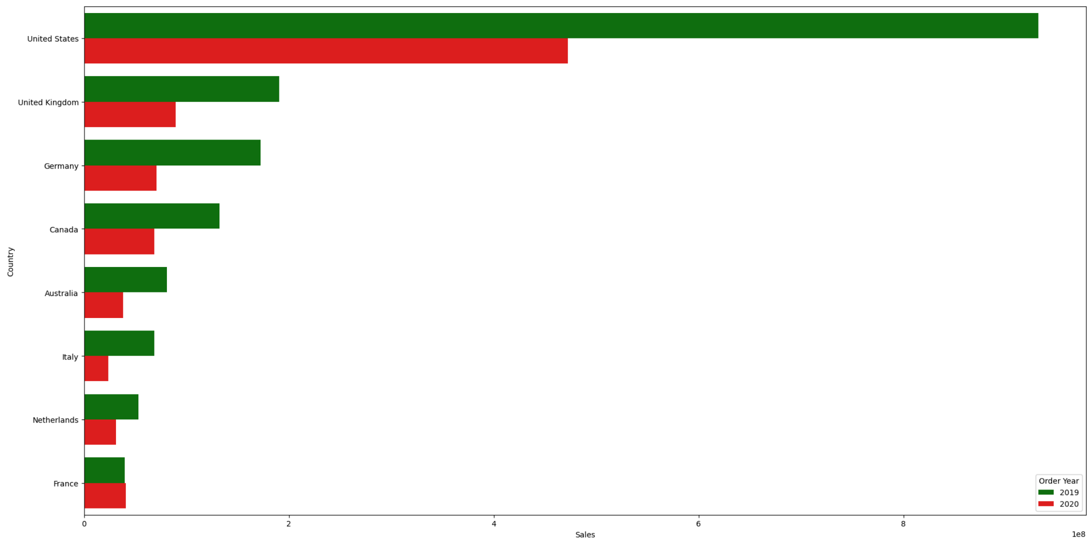
In [59]:
```
Join_data.columns
```

Out[59]:
```
Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'Product Name', 'Brand', 'Color', 'Unit Cost USD', 'Unit Price
USD',
       'SubcategoryKey', 'Subcategory', 'CategoryKey', 'Category', 'Sa
les',
       'Gender', 'Name', 'City', 'State Code', 'State', 'Zip Code', 'C
ountry',
       'Continent', 'Birthday', 'Age', 'Order Year'],
      dtype='object')
```

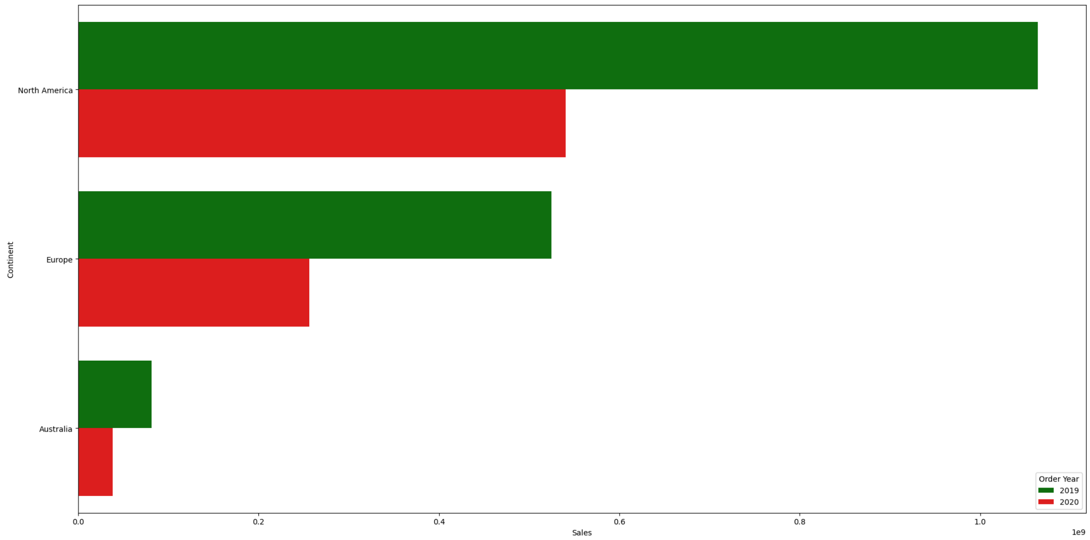
In [60]:
```
Join_data['Country'].value_counts()
```

Out[60]:
```
Country
United States     18228
United Kingdom     3688
Germany            3212
Canada             2699
Australia          1494
Italy              1223
Netherlands        1177
France              916
Name: count, dtype: int64
```

In [61]:
```
Country_data = Join_data.groupby(['Order Year','Country'])[['Sales']].su

palette= {2019:'green',2020:'red'}
plt.figure(figsize=(20,10))
sns.barplot(data=Country_data, x='Sales',y='Country',hue='Order Year',pa
plt.tight_layout()
plt.show()
```



In [62]:
```
Continent_data = Join_data.groupby(['Order Year','Continent'])[['Sales']

palette= {2019:'green',2020:'red'}
plt.figure(figsize=(20,10))
sns.barplot(data=Continent_data, x='Sales',y='Continent',hue='Order Year
plt.tight_layout()
plt.show()
```



In [63]:
```
Join_data.to_csv('Join_data.csv')
```

In [64]:
```
Join_data.columns
```

Out[64]:
```
Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'Product Name', 'Brand', 'Color', 'Unit Cost USD', 'Unit Price
USD',
       'SubcategoryKey', 'Subcategory', 'CategoryKey', 'Category', 'Sa
les',
       'Gender', 'Name', 'City', 'State Code', 'State', 'Zip Code', 'C
ountry',
       'Continent', 'Birthday', 'Age', 'Order Year'],
      dtype='object')
```

Customer Segmentation

Customer Segmentation Using RFM Analysis (Quantiles Method and K-Means Clustering

1. Data Preparation - Creating Recency DataFrames - Creating Frequency DataFrames - Creating Monetary DataFrames - Creating RFM DataFrames 2. RFM Analysis with Quantiles Method - Calculate RFM Quantiles - Creating Segments using Quantiles - Create RFM Segmentation Table - Calculate RFMScore and Generate Clusters 3. RFM Analysis Using K-Means Clustering - Define K Value for clustering - Fitting Model

Predicting CLuster - Cluster Visualization - Cluster Evaluation 4. Cluster Exploration - How many Customer for each group/cluster? - How does each cluster/group contribute to the company's revenue? - What is the common stock ordered in each group - When does each cluster usually made an order? - How does each cluster react on a discounts?

In [65]:
```
refrence_date = pd.to_datetime('2021-01-01')
```

In [66]:
```
rfm = Join_data.groupby('CustomerKey').aggregate({'Order Date':lambda x:
                                                  'Order Number':'count',
```

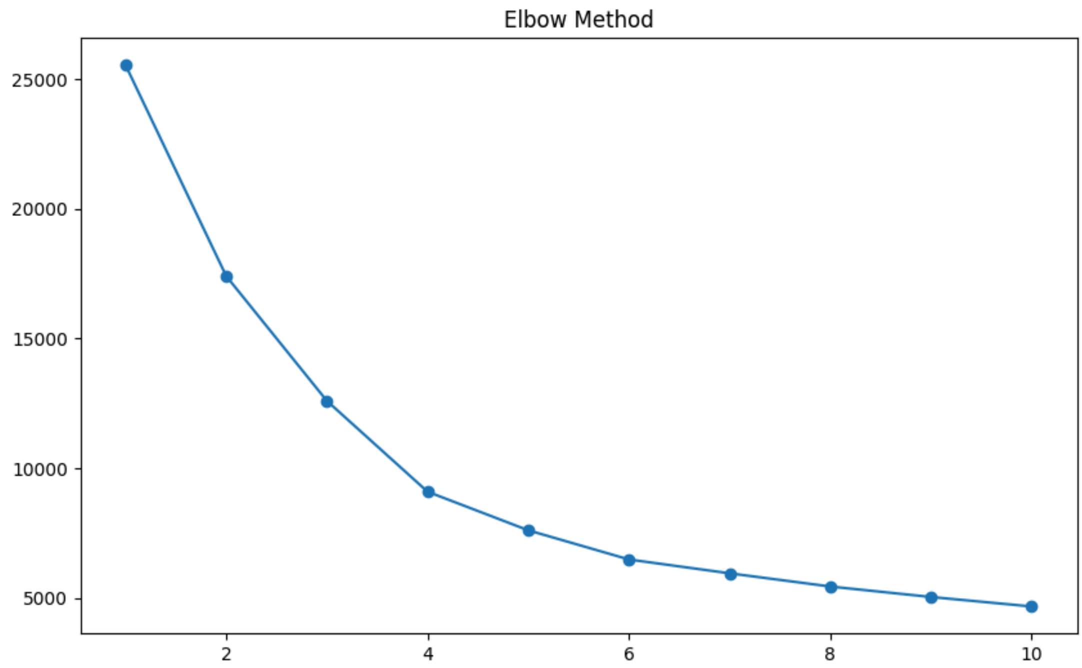
In [67]:
```
rfm.rename(columns={'Order Date': 'Recency','Order Number': 'Frequency',
rfm['Recency'] = rfm['Recency'].dt.days
```

In [68]:
```
rfm.dtypes
```

Out[68]:
```
Recency        int64
Frequency      int64
Monetory     float64
dtype: object
```

In [69]:
```
Scaler = StandardScaler()
rfm_scaled = Scaler.fit_transform(rfm[['Recency','Frequency','Monetory']
```

In [70]:
```
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(rfm_scaled)
    wcss.append(kmeans.inertia_)

# Plotting the Elbow Curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), wcss, marker='o')
# plt.xlabel("Number of clusters")

plt.title('Elbow Method')
# plt.ylabel('WCSS')
plt.show()
```



hence from the above elbow method we can determine a optinum number of cluster to choose for the data

In [71]:
```
kmeans = KMeans(n_clusters = 4 , random_state = 42)
rfm['Segment'] = kmeans.fit_predict(rfm_scaled)
```

In [72]:

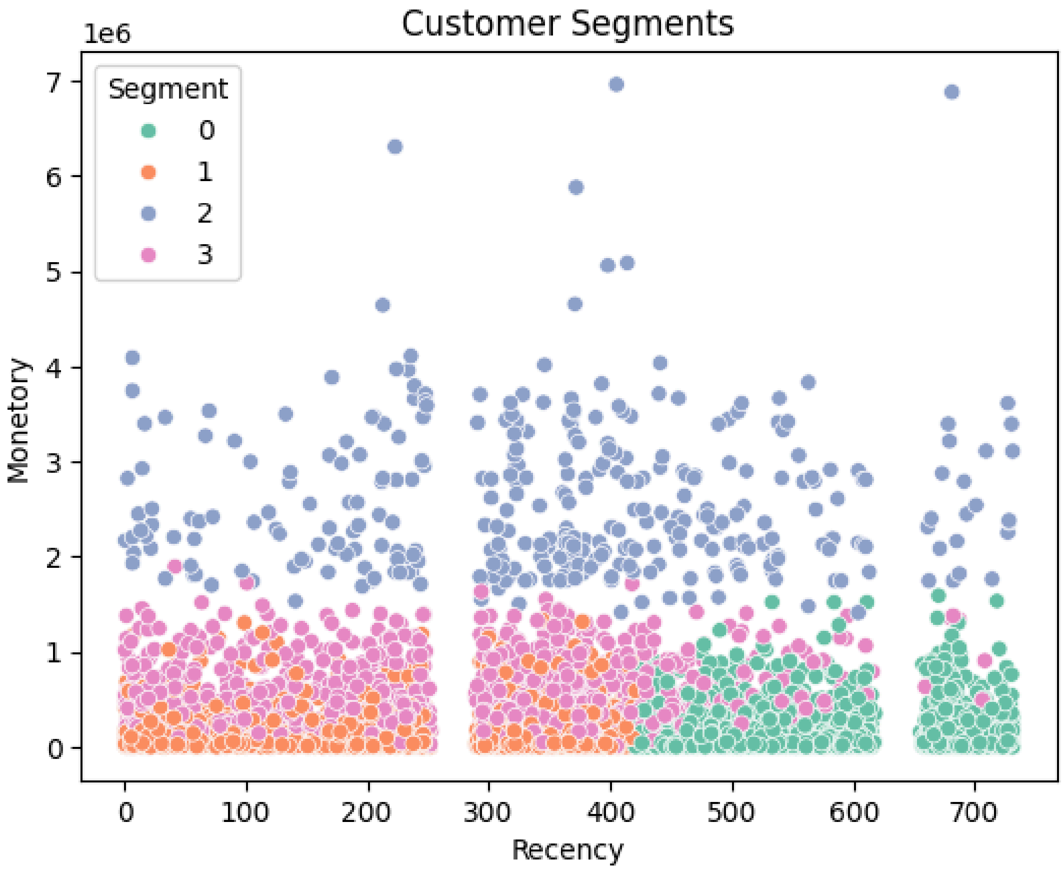
```
segment_analysis = rfm.groupby('Segment').mean()
segment_analysis
```

Out[72]:

Segment	Recency	Frequency	Monetory
0	567.583527	2.532713	1.283568e+05
1	275.911316	2.680392	1.351360e+05
2	359.116618	6.189504	2.579010e+06
3	296.099703	8.058754	4.536849e+05

In [73]:

```
sns.scatterplot(x='Recency', y='Monetory', hue='Segment', data=rfm, pale
plt.title('Customer Segments')
plt.show()
```



The above diagram show the customer segment as per the KMeans Clustering algorithm

- # We can also do customer segmentation on the basis of their RFM scores by adding it manually and divide then by group (manually).

In [74]:
```
refrence_date = pd.to_datetime('2021-01-01')
```

In [75]:
```
rfm = Join_data.groupby('CustomerKey').aggregate({'Order Date':lambda x:
                                                   'Order Number':'count',
```

In [76]:
```
rfm.rename(columns={'Order Date': 'Recency','Order Number': 'Frequency',
rfm['Recency'] = rfm['Recency'].dt.days
```

In [77]:
```
quantiles = rfm.quantile(q=[0.25,0.5,0.75])
```

In [78]:
```
quantiles
```

Out[78]:

	Recency	Frequency	Monetory
0.25	300.0	2.0	26268.490000
0.50	377.0	3.0	98787.326150
0.75	510.0	5.0	322656.996625

In [79]:
```
#CREATING SEGMENTS USING QUANTILES
def RScore(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
# Arguments (x = value, p = recency, monetary_value, frequency)
def FMScore(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 [80]:
```
rfm['R'] = rfm['Recency'].apply(RScore,args=['Recency',quantiles])
rfm['F'] = rfm['Frequency'].apply(FMScore,args=['Frequency',quantiles])
rfm['M'] = rfm['Monetory'].apply(FMScore,args=['Monetory',quantiles])
```

In [81]:
```
rfm
```

Out[81]:

CustomerKey	Recency	Frequency	Monetory	R	F	M
301	417	1	29028.7200	2	1	2
325	363	7	117052.3404	3	4	3
554	393	3	18746.0287	2	2	1
1568	132	5	198292.9802	4	3	3
1585	673	3	173411.1079	1	2	3
...	...	...	...	...	...	...
2099252	90	3	55746.8500	4	2	2
2099383	216	3	95129.1300	4	2	2
2099758	205	4	6299.6450	4	3	1
2099862	366	3	48795.3500	3	2	2
2099937	321	2	167262.2325	3	1	3

8512 rows × 6 columns

In [82]:
```
rfm['RFM'] = rfm['R'] + rfm['F'] + rfm['M']
rfm['RFM']
```

Out[82]:
```
CustomerKey
301         5
325        10
554         5
1568       10
1585        6
           ..
2099252     8
2099383     8
2099758     8
2099862     7
2099937     7
Name: RFM, Length: 8512, dtype: int64
```

In [83]:
```
def rfm_segments(Score):
    if Score < 5:
        return 'Low_value'
    elif Score < 9 :
        return 'Medium_value'
    else:
        return 'High_value'
```

In [84]:
```
rfm['Segments'] = rfm['RFM'].apply(rfm_segments)
```

In [85]:
```
rfm_seg_counts = rfm['Segments'].value_counts().reset_index()
```

In [86]:
```
rfm_seg_counts
```

Out[86]:

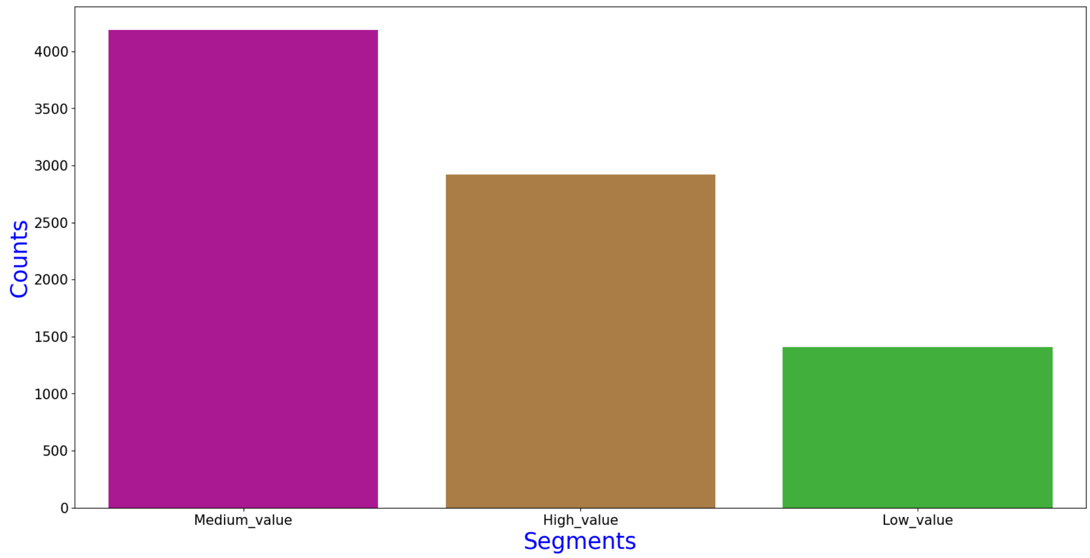
	Segments	count
0	Medium_value	4184
1	High_value	2922
2	Low_value	1406

In [87]:
```
rfm_seg_counts.columns = ['Segments','Counts']
rfm_seg_counts
```

Out[87]:

	Segments	Counts
0	Medium_value	4184
1	High_value	2922
2	Low_value	1406

In [88]:
```
np.random.seed(10)
plt.figure(figsize=(20,10))
random_palette = np.random.rand(len(rfm_seg_counts),3)
ax = sns.barplot(data= rfm_seg_counts,x='Segments',y = 'Counts',palette
ax.set_xlabel('Segments',fontsize=25,color = 'blue')
ax.set_ylabel('Counts',fontsize=25,color = 'blue')
plt.xticks(fontsize=15)  # X-axis label with larger font size
plt.yticks(fontsize=15)    # Y-axis label with larger font size
plt.show()
```



In [89]:
```
rfm
```

Out[89]:

CustomerKey	Recency	Frequency	Monetory	R	F	M	RFM	Segments
301	417	1	29028.7200	2	1	2	5	Medium_value
325	363	7	117052.3404	3	4	3	10	High_value
554	393	3	18746.0287	2	2	1	5	Medium_value
1568	132	5	198292.9802	4	3	3	10	High_value
1585	673	3	173411.1079	1	2	3	6	Medium_value
...	...	...	...	...	...	...	...	...
2099252	90	3	55746.8500	4	2	2	8	Medium_value
2099383	216	3	95129.1300	4	2	2	8	Medium_value
2099758	205	4	6299.6450	4	3	1	8	Medium_value
2099862	366	3	48795.3500	3	2	2	7	Medium_value
2099937	321	2	167262.2325	3	1	3	7	Medium_value

8512 rows × 8 columns

In [90]:
```


rfm['RFM_customer_segment'] = ''
rfm
```

Out[90]:

CustomerKey	Recency	Frequency	Monetory	R	F	M	RFM	Segments	RFM_cu
301	417	1	29028.7200	2	1	2	5	Medium_value	
325	363	7	117052.3404	3	4	3	10	High_value	
554	393	3	18746.0287	2	2	1	5	Medium_value	
1568	132	5	198292.9802	4	3	3	10	High_value	
1585	673	3	173411.1079	1	2	3	6	Medium_value	
...	...	...	...	...	...	...	...	...	
2099252	90	3	55746.8500	4	2	2	8	Medium_value	
2099383	216	3	95129.1300	4	2	2	8	Medium_value	
2099758	205	4	6299.6450	4	3	1	8	Medium_value	
2099862	366	3	48795.3500	3	2	2	7	Medium_value	
2099937	321	2	167262.2325	3	1	3	7	Medium_value	

8512 rows × 9 columns

In [91]:
```
rfm.dtypes
```

Out[91]:
```
Recency                  int64
Frequency                int64
Monetory               float64
R                        int64
F                        int64
M                        int64
RFM                      int64
Segments                object
RFM_customer_segment    object
dtype: object
```

In [92]:
```
rfm.loc[rfm['RFM'] >= 9,'RFM_customer_segment'] = 'VIP / Loyal'
rfm.loc[(rfm['RFM'] >= 6) & (rfm['RFM'] < 9),'RFM_customer_segment'] = '
rfm.loc[(rfm['RFM'] >= 5) & (rfm['RFM'] < 6), 'RFM_customer_segment'] =
rfm.loc[(rfm['RFM'] >= 4) & (rfm['RFM'] < 5),'RFM_customer_segment'] = '
rfm.loc[(rfm['RFM'] >= 3) & (rfm['RFM'] < 4),'RFM_customer_segment'] = '
rfm
```

Out[92]:

	Recency	Frequency	Monetory	R	F	M	RFM	Segments	RFM_cu
CustomerKey									
301	417	1	29028.7200	2	1	2	5	Medium_value	/
325	363	7	117052.3404	3	4	3	10	High_value	
554	393	3	18746.0287	2	2	1	5	Medium_value	/
1568	132	5	198292.9802	4	3	3	10	High_value	
1585	673	3	173411.1079	1	2	3	6	Medium_value	
...	...	...	...	...	...	...	...	...	
2099252	90	3	55746.8500	4	2	2	8	Medium_value	
2099383	216	3	95129.1300	4	2	2	8	Medium_value	
2099758	205	4	6299.6450	4	3	1	8	Medium_value	
2099862	366	3	48795.3500	3	2	2	7	Medium_value	
2099937	321	2	167262.2325	3	1	3	7	Medium_value	

8512 rows × 9 columns

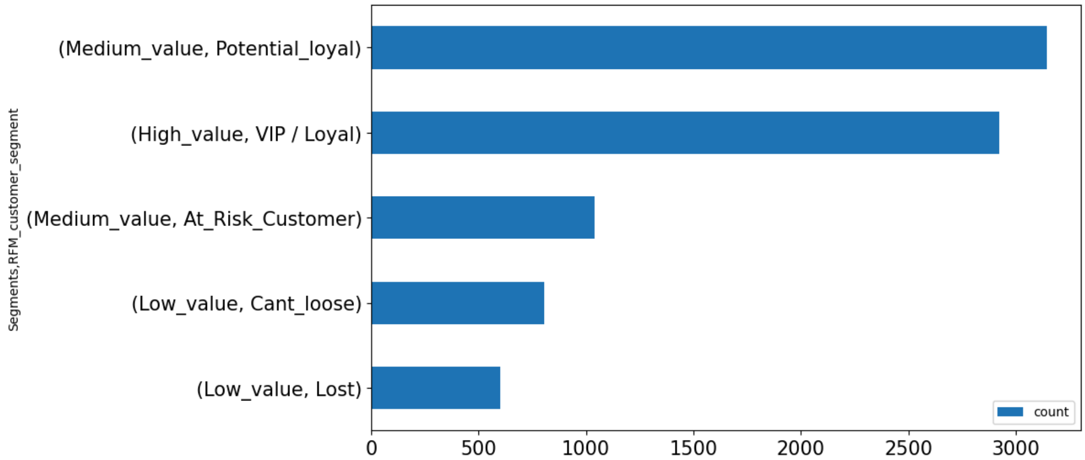
In [93]:
```
seg_data = rfm.groupby(['Segments','RFM_customer_segment'])
seg_data = pd.DataFrame(seg_data['RFM_customer_segment'].value_counts())
seg_data.sort_values(ascending=True,by ='count',inplace = True)
seg_data
```

Out[93]:

Segments	RFM_customer_segment	count
Low_value	Lost	600
	Cant_loose	806
Medium_value	At_Risk_Customer	1041
High_value	VIP / Loyal	2922
Medium_value	Potential_loyal	3143

In [94]:
```
np.random.seed(10)
plt.figure(figsize= (20,10))
random_palette = np.random.rand(len(seg_data-1),3)
seg_data.plot(kind = 'barh',stacked=True,figsize = (10,6))
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.show()
```

```
<Figure size 2000x1000 with 0 Axes>
```



Hypothesis Testing

Hypothesis: Repeat customers have declined

H0: No significant difference in customer frequency between 2019 and 2020

H1: Significant decline in customer frequency in 2020

Explanation:

- **common_customers: This variable contains the list of customer IDs that are present in both 2019 and 2020.**
- **Filtering and Aligning: We filter the sales data to include only these common customers and then ensure that the freq_2019 and freq_2020 arrays are aligned by customer ID.**
- **Performing the Test: With the arrays now of equal length and aligned, the paired t-test can be performed without error.**
- **This approach should resolve the ValueError and allow you to proceed with the hypothesis testing.**

In [121]:
```
customer_2019 = Join_data[Join_data['Order Year'] == 2019]['CustomerKey'
customer_2019.shape
```
Out[121]:
```
(6497,)
```

In [122]:
```
customer_2020 = Join_data[Join_data['Order Year'] == 2020]['CustomerKey'
customer_2020.shape
```
Out[122]:
```
(3868,)
```

In [123]:
```
common_customers = np.intersect1d(customer_2019,customer_2020)
common_customers.shape
```
Out[123]:
```
(1853,)
```

In [124]:
```
freq_2019 = Join_data[(Join_data['CustomerKey'].isin(common_customers))
freq_2020 = Join_data[(Join_data['CustomerKey'].isin(common_customers))
```

In [125]:
```
Join_data.columns
```
Out[125]:
```
Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'Product Name', 'Brand', 'Color', 'Unit Cost USD', 'Unit Price
USD',
       'SubcategoryKey', 'Subcategory', 'CategoryKey', 'Category', 'Sa
les',
       'Gender', 'Name', 'City', 'State Code', 'State', 'Zip Code', 'C
ountry',
       'Continent', 'Birthday', 'Age', 'Order Year'],
      dtype='object')
```

In [128]:
```
ttest_stats , p_value  = stats.ttest_rel(freq_2019,freq_2020)
```

In [131]:
```
if p_value < 0.05:
    print('Reject the null hypothesis : There is significant decline in
else:
    print('Fail to reject the null hypothesis : There is no significant
```

```
Reject the null hypothesis : There is significant decline in the frequ
ency of customers in 2020
```

H0 is rejected

There is significant decline in the frequency of the no. of orders in 2020 as compared to 2019

- # Hence there is a significant decline because of the decline in the frequency of customers

Overall findings

Findings from the Analysis

Overall Sales Decline:

* Total sales revenue dropped nearly 50% from 2019 to 2020.

* Sales in 2019 were 1.66 billion USD, which declined to 834 million USD in 2020

Order Volume:

The number of orders decreased significantly:

21,611 orders in 2019 versus 11,026 in 2020.

This represents a 50% drop in order quantity

Customer Frequency:

Analysis indicates a substantial decline in repeat customers in 2020 compared to 2019.

Hypothesis testing revealed a statistically significant decline in customer frequency for repeat purchases

Customer Segmentation:

RFM Analysis (Recency, Frequency, Monetary):

Many customers were categorized as "at risk" or "lost customers."

High-value and loyal customers represented a smaller percentage in 2020 compared to 2019

Demographics and Behavior:

Age and gender distributions showed no significant anomalies, but lower purchasing trends were noted across all demographics.

There was no evident recovery in engagement among younger or older age groups

Product Performance:

Certain product categories and subcategories underperformed.

Substantial drops in sales volume were observed for high-ticket items

Regional Performance:

Declines were observed across multiple regions, with the most significant impacts in countries like the United States, Canada, and Germany.

Global disruptions, possibly due to external factors like the pandemic, may have contributed to this

Operational Issues:

Delivery challenges were identified:

A significant number of orders lacked proper delivery dates (imputed to store pickups).

This could reflect operational inefficiencies impacting customer satisfaction

Potential Minor Causes

Macroeconomic Trends:

The pandemic or other economic downturns likely contributed to reduced consumer spending.

Product Relevance:

Declines in demand for certain product categories could indicate shifting consumer preferences.

In [ ]: